THE INTERPLAY OF PERSONAL PREFERENCE AND SOCIAL INFLUENCE IN SHARING NETWORKS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

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August 2015

THE INTERPLAY OF PERSONAL PREFERENCE AND SOCIAL INFLUENCE IN SHARING NETWORKS

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Cornell University 2015

Identifying social influence among people is a problem that has vexed sociologists, social psychologists and marketers for decades. As more and more of our activities are mediated by online sharing networks, there is a unique opportunity in terms of large-scale access to data about people's decisions, but also new challenges around understanding how interfaces and algorithms on these socio-technical systems affect people's decision-making on items. This thesis presents a mixed-methods analysis of social influence on the two decisions that comprise much of online information exchange: adoption and sharing.

First, we show the prevalence of *preference locality*—similarity in item preferences among friends—for two popular sharing networks, Twitter and Facebook. We find that friends' data alone can be used for recommendation algorithms that predict people's actions as good as those using the full network's data. We then present a sequence of experimental and data mining efforts that help us in explaining how such preference locality emerges in social networks, specifically on the interplay between people's personal preference and social influence.

We present two experimental studies using the Facebook platform that examine the role of people's personal preference and social influence on their decisions to adopt or share items such as movies or musical artists. For adoption, we study the influence effect of showing social information about a recommendation—such as "*X* and *n* others like this"—and find that people's

own preferences play a primary role in their adoption decision, even when information about the item is scarce. Similarly, people tend to share items that they like, even when they are targeting shares to specific recipients. Both studies indicate that people's own preferences are the dominant force for shaping their decisions.

To see how these findings extend to other websites and item domains, we analyze traces of activity on a broad range of sharing networks: Last.fm, Goodreads, Flickr and Flixster. On all the websites we studied, not more than 3% of a user's actions are copies of their friends' actions and thus potentially attributable to influence. Further, using a novel statistical procedure for estimating influence that controls for underlying preference locality among friends, we find that we can attribute influence as a cause for only about 1% of total user actions on these websites.

Our findings present a contrasting picture to the popular narrative of the huge role of influence in online social networks. While influence does exist, it only affects a minority of people's actions and most of the locality in preferences can be explained as a result of homophily selection processes where people form connections with others of similar preference (and subsequently follow their own preferences). These results on influence, based on an explicit modeling of people's personal preferences, have a practical import for designing future socio-technical interactions: through recommender systems that model social processes and through accurate diffusion models that incorporate people's past preferences. Further, this thesis demonstrates a mixed-methods analysis pipeline—a combination of experimental rigor with large-scale data mining—that is necessary for answering complex social science questions through the messy, incomplete picture that trace data from socio-technical systems provide.

Dedicated to my parents.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dan Cosley, for being an amazing mentor, collaborator and friend for the last 4 years. This thesis would not have been possible without Dan taking the time to introduce me to the world of user experiments, his helpful advice on scoping research problems, and his thoughtful feedback on my work throughout. I am especially grateful for the freedom and encouragement that Dan gave me in pursuing my research ideas. I would also like to thank my committee members, Johannes Gehrke and Levent Orman, for their useful advice and feedback as I navigated my way through the Ph.D. journey.

I had the good fortune of spending my summers with some excellent collaborators in industry. I thank Baoshi Yan and Anmol Bhasin (LinkedIn), Gueorgi Kossinets and Ed Chi (Google), and Jake Hofman and Duncan Watts (Microsoft Research) for believing in me and providing me the opportunity to work on interesting, practical problems around recommendation systems and sharing networks (which, unfortunately, are not in this thesis).

During my time at Cornell, I had the benefit of learning from some brilliant graduate students. I would like to mention Chenhao Tan and Karthik Raman, with whom I had many conversations about research, including on some of the work presented in this thesis. I also worked with some amazing undergraduate and Master's students: Mevlana Gemici, Meethu Malu and Yulan Miao, and Benjamin Schulman.

I am grateful to Partha Pratim Chakrabarty, my undergraduate advisor, whose introductory algorithms course exposed me to the wonderful world of algorithms and computer science.

Finally, I thank my parents and my sisters, Neha and Mohita, for their endless love and support towards my education, continuing to this day that brings me here, writing this acknowledgment to the thesis that follows.

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Introduction

CHAPTER 1

INTERPLAY OF PERSONAL PREFERENCE AND SOCIAL INFLUENCE

> In 2011, an unknown singer called Rebecca Black burst onto the music scene when her song, *Friday*, went "viral" on social media and collected over 167 million views on YouTube in three months. 87% of the feedback on her song was negative, which is rare for popular musical videos on YouTube[1]. Why were so many people drawn to a song that was not liked by most people? Perhaps more puzzlingly, why were people sharing a song they evidently did not like to their friends on social media, so much so that it became widely popular within a span of days?

Answers to the above questions require an understanding of people's decision-making on such cultural items and how knowledge of others' activities influences these decisions. This thesis sheds light on how people make decisions on items—what to adopt and what to share to others—in social networking websites.

Such questions on processes of decision-making and influence from others' actions have been studied for decades in the social sciences including psychology, sociology and economics [1, 2, 3, 4]. In general, social influence can lead to powerful effects on people's decisions, making them more likely to *conform* to a group's opinion, follow activities of others due to *social proof* or change their decision based on interpersonal influence from some specific individuals [1].

[1] http://en.wikipedia.org/wiki/Friday_(Rebecca_Black_song)

Social networking websites provide an opportunity to understand how these effects of influence affect people's decision-making in online settings. On websites such as Facebook and Twitter, exposure to activities from others influences our decisions in a wide range of contexts such as our consumption of information [5], adoption of new products [6], and even decisions like going out to vote [7] or making health choices [8, 9]. In addition, as usage of online social networks becomes ubiquitous in society—from sharing entertainment-centric items to boosting productivity in the workplace [10, 11], from being the global cultural commons to enhancing local community networks [12, 13]—understanding how these processes of influence impact people's consumption and sharing decisions on such networks becomes an important endeavor.

In many ways, activities on online social networks are similar to that in the offline world. However, being socio-technical systems, people's activities are mediated and influenced by system interfaces which presents unique challenges and opportunities. Similar to the offline world, people form connections with each other within online social networks. They also interact with items: a person expresses her evaluation of an item by liking it (or *adopting* it) and/or *sharing* it to their social connections on social networks like Facebook. These two actions—adopting and sharing an item—form key decisions in an online social network, collectively deciding how and which items spread among people.

Unlike offline settings, however, online systems afford new ways to engineer or mediate these adoption and sharing decisions. Specifically, the system design, user interface and underlying algorithms of these socio-technical systems affect which items and whose activities people get exposed to, which in turn, affects which items are adopted or shared. Most sharing networks employ an activity feed interface that shows recent activities of others. They also show item recommendations based on activities of others. These feed and recommendation interfaces may influence people's decisions on items. For example, a feed showing popular content may encourage behaviors based on social proof, while one that shows activities of friends may emphasize interpersonal influence.

Estimating the power of such social influence in social networks can help us become aware of the influence of such engineered system features and allow system designers to evaluate and better support user goals around adopting and sharing. Further, understanding people's motivations, considerations and the role of social influence in adoption and sharing decisions can help to understand how items become popular (or not)—such as Black's *Friday* song above—and be of practical import to content creators, marketers and change-makers that aim to spread their message to a wider audience.

1.1 Factors affecting sharing and adoption decisions

To focus on people's decision-making on items in social networking websites, let us first introduce the term *sharing network* to denote a network of people who adopt and share items of a certain domain. For example, YouTube may be considered as a sharing network for videos, Twitter for tweets or hashtags, Last.fm for songs, Goodreads for books, Flickr for photos, and so on.

In sharing networks, almost all information exchange between people involves two decisions: adopting and/or sharing an item. Typically, adoption refers to the use of a certain item or technology, but in the context of sharing networks, we define adoption as a specific feedback by an individual that conveys that she consumed the item and liked it. For example, Favoriting a song on Last.fm, Liking a URL on Facebook, and Upvoting a video on YouTube are examples of adopting an item in sharing networks[2]. Sharing an item means to send it directly to another person or broadcast it to a group of people, typically friends or followers of an individual on a sharing network.

These two fundamental decisions for information exchange—sharing and adopting an item—are expected to be guided by people's personal preference. Intuitively, a person may be more likely to adopt or share an item if it aligns with her preferences. The concept of *personal preference* relates to the decision a person would make on an item in the absence of any external factors.

However, this is rarely the case in sharing networks. In fact, most sharing networks thrive on exposing people to others' activities, thus helping them to find and discover new items. Some of this is manually initiated, such as when people share items directly to specific social connections. A major part of exposure to activity from others happens automatically though, through feeds or recommendations that show adoptions and broadcast activity from other people, as we discussed above.

Adoption

Given such exposure to others' activities, decisions to adopt an item depend not just on personal preferences, but also on social influence. Recent experiments in online sharing networks demonstrate this effect. In one of the first experiments on influence through online systems, Salganik et al. constructed alternative iso-

[2]Whenever we use a term to refer to its meaning specific to an online sharing network, we capitalize the first letter to differentiate from its general English usage.

lated worlds in a music discovery system and found that showing current popularity information about songs changed which songs became the most popular [14]. Similarly, on Reddit, a news aggregation website where people can upvote or downvote stories, manipulating the number of upvotes to a story changes people's likelihood of clicking on it [15].

Based on theories of interpersonal influence and conformity [1], these effects may even be stronger when information about friends' activities are shown to a user, instead of overall activity. An experiment on Facebook showed that showing names of friends associated with an advertisement can boost click-through rates [16]. Similarly, an experiment during the 2012 United States election demonstrated that showing a user that their friends had voted increased her chances of voting as well [7]. Influence effects also vary from person to person. The role of social influence in a person's decisions depends on the strength of her relationship with people associated with an item [1, 17], and her susceptibility to social influence in general [18, 19, 20, 21].

Sharing

The decision to share is also guided by social forces. Motivations such as the need to express oneself [22, 23], provide information [24], demonstrate expertise [25] or help others [26], and concerns such as self-presentation [27, 28] influence people's sharing decisions and their propensity to share [29]. In addition, sharing decisions are guided by the nature of relationship between sharer and recipient, including how close they are [30] and whether they trust each other [31].

Thus, understanding how items are adopted and shared requires modeling both people's personal preferences as well as the social forces that guide their decisions. This thesis tackles questions on the interplay of people's personal preferences, social influence and recommendations in sharing networks: how they impact people's decision-making on adopting and sharing items and in turn, guide the bigger picture of influence and virality in sharing networks.

To explore this interplay, we will draw on two main fields of study around people's decision-making on items: information diffusion and recommender systems. Diffusion models provide mathematical abstractions for the spread of items—and implicitly, the impact of social influence—within a sharing network. Recommender systems suggest new items to users by modeling their preferences toward items.

1.2 Models for information diffusion

Most of the current models for diffusion fall into two major categories: threshold models and independent cascade models. Inspired by epidemiology, threshold models [32, 33, 34] assume an individual adopts an item once a certain number of her neighbors adopt it, or more generally, her exposure to the item exceeds her threshold. These models are informed by theories of social proof and conformity [1], that suggest that individuals are likely to adopt an item if they see many others have done so or conform to the opinions of people in a group. Empirically, the threshold for each individual can be estimated using a k-exposure curve [35, 36], which shows the probability of adopting an item given some k number of friends have adopted the item.

In contrast, independent cascade models [37, 38, 39] assume transmission parameters for each directed edge in a social network that indicate the probability of an item being adopted through that edge. These models emphasize the effect of interpersonal influence. The transmission probability between a sharer and a recipient can be considered as an indicator of the influence exerted by the sharer on the recipient. They may also account for the the nature of relationship between the sharer and the recipient, which threshold models are unable to do. Given data on past adoption decisions in a sharing network, machine learning models can estimate the most likely transmission probabilities for edges in the sharing network [38].

Formulation of information diffusion based on these models have been used to theoretically identify structural conditions for an item to spread in a social network [34] and users who are likely to influence the maximum number of users [39]. However, the models are not well-suited for online sharing networks [40], because they assume (re)transmission is automatic; all adopted items are shared. This viral analogy breaks down when, unlike diseases, nodes of the network can voluntarily decide what to share and to whom. Similarly, people can also decide whether to adopt items shared to them and later share them to others.

Model-free analysis of data from online sharing networks avoids the above limitations. Instead of parametrically restricting diffusion mechanisms, empirical studies on networks such as Twitter [36], Facebook [41] and others [35, 42, 43, 44] study actual trends in people's activity data and yield insights about the temporal, network-structural and content-based properties of diffusion of items in a sharing network.

Still, a major limitation of both empirical and theoretical approaches is that they consider the spread of items one at a time. On sharing networks, each item is not shared in a vacuum; the same people act on different items in sharing networks, likely informed by their personal preferences. Therefore, accounting for people's personal preferences is important for building accurate models of diffusion.

1.3 Recommender systems for sharing networks

Happily, recommender systems are all about modeling personal preference. Based on the assumption that past activities of people are a good proxy for their preferences, one can create models of what a person is likely to consume next. Recommender systems fueled by such models are widely successful, contributing to page visits and revenue for many e-commerce (e.g., Amazon), media (e.g., The New York Times) and content-streaming (e.g., Netflix) websites.

A popular class of models for recommendation is collaborative filtering, which is based on recommending items liked by people similar to the current user [45, 46]. Typically, collaborative filtering accounts for similarity in preferences across the full population of users. For example, memory-based algorithms [47] are based on finding items liked by others that most similar to the items already liked by a user. Model-based algorithms like matrix factorization and its variants [45] approximate a user's preferences—the objective is to minimize the global error between her predicted and actual rating for each item—and consequently, find items liked by others with a high predicted rating.

With the advent of sharing networks, new models have been proposed that utilize people's social connections as an additional signal for learning what people will like [48]. These models augment collaborative filtering by adding assumptions about the social network, such as friends should be similar to each other [49, 50, 51] or that trust between people flows through network edges [52, 53, 54, 55]. However, incorporating social data into collaborative filtering algorithms offers varying, often modest improvements [56]. This leads us to question whether the assumptions about social influence encoded in these algorithms actually capture the dynamics of preferences in sharing networks.

Apart from boosting accuracy of recommendations, using people's social connections can also improve the utility and user experience of recommender systems [57, 58]. Recommender systems within a sharing network provide a social context for recommendations and influence how we think about them: seeing familiar people associated with items makes recommendations more persuasive, informative or trustworthy [59, 60, 61, 62]. For example, providing additional social information about an item might influence people's willingness to try out an item because a trusted friend has endorsed it or they want to be able to talk about it with their friends. They might influence people's ratings, just as displaying predicted ratings in a recommender system affects people's actual ratings [20]. Finally, they might even influence our opinion of the recommender system itself, by making its recommendation algorithm more transparent [63].

1.4 Accounting for both personal preferences and influence

Owing to their singular focus on either modeling the spread of items or people's preferences, however, current work on diffusion and recommendation fails to present a complete picture on people's decision processes that involves *both* personal preference and social influence.

To understand the interplay between the effects of personal preference and social influence on people's adoption and sharing decisions, we will need to tackle a new set of questions straddling social psychology, interface design and algorithms [64]. These are questions around how exposure to social information impacts people's adoption decisions, how personal preferences impact people's sharing decisions and how recommendation systems and activity feeds mediate these decisions. Answers to such questions can, in turn, help advance the study of information diffusion and recommender systems within sharing networks.

For adoption, we argue that accounting for people's personal preference, as in the recommender systems literature, can lead to a more accurate understanding of people's decision processes. In addition to the number of friends who have adopted an item (threshold) or the transmission probability from friends to an individual, the adoption decision likely depends on how well an item aligns to the individual's personal preferences. Recommender systems will also improve through a deeper understanding of the extent of influence effects when adopting items. Better models of susceptibility to influence [21] will help design recommendations with more useful social information. For instance, systems can personalize the kind of social information shown (e.g., overall activity-based versus activities of certain friends) based on what information is most useful or persuasive to an individual.

Explicit modeling of personal preference will also help to understand sharing decisions. Sharing is largely ignored by models for diffusion and recommendation, both of which focus on adoption decisions. Both threshold and independent cascade models for diffusion implicitly assume no distinction between adoption and sharing—any item that is adopted automatically becomes a candidate for sharing. In the recommender systems literature, while the merits of suggesting items to social connections has been studied [26], little is known about how to model and predict people's sharing decisions. Models of personal preference, for both sharer and the recipient, can be useful to operationalize people's motivations for sharing and predict which items get shared and to whom. Such models can also help to support more effective sharing by recommending what to share to whom.

More generally, while past work on diffusion and recommendation deals with adoption and sharing, the underlying processes of people's decision-making—what to adopt, what to share and to whom—are less understood. Based on studies on information diffusion in multiple sharing networks and item domains [7, 14, 15, 42, 65, 66], we expect social influence to play an important role. Based on the success of recommender systems, people's personal preferences should also matter in making such decisions. Understanding the interplay of personal preference and social influence in people's decisions can provide a viable framework for studying how items are adopted and shared in sharing networks.

In the next chapter, we will discuss why estimating the role of influence in sharing networks is a tricky problem and describe how we make progress by defining influence in terms of personal preferences of people in a sharing network. To do this, first we will introduce the concept of preference locality—preferences of people closer to each other in a sharing network tend to be more similar—and present evidence for it in popular sharing networks.

CHAPTER 2

PREFERENCE LOCALITY: TO WHAT EXTENT ARE PEOPLE'S PREFERENCES SIMILAR TO THEIR FRIENDS'?

> In 2012, Facebook launched a widget called "Recommendations box"[1] for website owners that presents content recommendations for a user based on activities of her friends on the same website (see Figure 2.1). A driving assumption for such recommendations is that people would enjoy content that their friends also enjoyed on that website. Do friends always like similar content? Given that there are thousands of people (and often more) using a sharing network, could there be some strangers who are more similar to a user in their preferences than the user's friends?

In this chapter, we investigate preference similarity between a user and her friends in a sharing network and compare that to the similarity between the user and strangers. In doing so, we introduce the concept of *preference locality*, which suggests that people with similar preferences are clustered together within a sharing network.

In general, friends tend to be similar to each other in their demographic profile, attitudes, beliefs and behavior [67]. Multiple studies on sharing networks show that friends adopt similar items and that a person's probability of adopting an item increases as more of her friends adopt that item [36, 66]. However, the predictive power of friends' preferences is less understood: how well can a user's actions be predicted from her friends' actions? Answers to this

[1] http://mashable.com/2012/07/26/facebook-recommendation-bar/

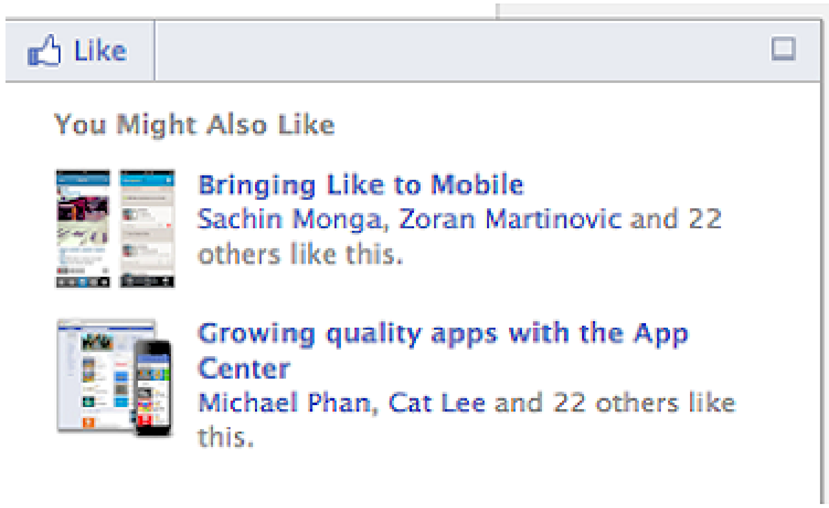

Figure 2.1: An example screenshot of the Facebook recommendation widget. The widget recommends articles from the same website that have been Liked by friends of the current user. Screenshot from www.allthingsd.com, a website for technology news.

question can help reason about the efficacy of using data from social ties in recommendation—in what domains and networks might they be relevant—as well as provide preliminary evidence for understanding how an individual's preferences become similar to her friends' preferences.

To this end, we compare how recommendations based on only friends compare with those computed from the entire network of users. Using datasets from popular sharing networks such as Facebook and Twitter, we find that recommendations computed from friends perform comparably to those computed from strangers (where a stranger is anyone in the dataset who is not a friend). This is a surprising result, especially because friends are fewer than strangers and further, we find that the k-most similar strangers are more similar to a user than k-most similar friends. As an attempt to explain the goodness of friend-based recommendations, we propose metrics that quantify the notion of preference locality in a sharing network.

While these metrics help us characterize observed locality, they expose little about *how* preferences of friends become similar to a user's preferences and how the effects of personal preference and social influence play out. Two social processes are likely to contribute to such similarity in preferences: homophily, which suggests that people make connections with others who are similar to them, and social influence, which suggests that knowing about others' adoption of some content makes it more likely for people to adopt that content. Due to the homophily selection process, it is possible for friends' preferences to be more similar to a user's preference than non-friends' preferences, even in a network where everyone follows their personal preference (and thus, void of any influence effects). This problem of disentangling influence and homophily has vexed sociologists for decades. We will lay the foundation for reasoning about the contributing social processes of homophily and influence, and outline our contributions—involving both behavioral experiments and data mining—at the end of this chapter.

2.1 Basic definitions

Let us start with some definitions. For the purposes of this thesis, we use the term *item* to denote any entity or content that people may adopt or share in a sharing network. These could be cultural items such as books, movies or songs, entities such as musical artists or bands, or domain-specific artifacts such as hashtags on Twitter.

We assume preferences of people are proxied by their past actions, usually as a set of items they have already adopted. This can be thought of as a unary rating, well-suited for decisions in sharing networks where a person may either adopt an item or not. Similarity between preferences is measured using the Jaccard measure [68], a common measure for similarity between sets and for unary ratings in recommender systems [69]. For two users u_1 and u_2, it is given by:

$$JS = \frac{|Adopts(u_1) \cap Adopts(u_2)|}{|Adopts(u_1) \cup Adopts(u_2)|}$$

Our insight is that a comparison of measures of interest for friends versus non-friends can be useful for reasoning about preference locality in sharing networks. We use an *ego network*—a subgraph of the social network containing a user and her friends—as our unit of study. In contrast to analyzing full networks, considering ego networks provides an apt focus for studying the processes that lead to locality—most sharing networks only show friends' activities to a user—while also reducing data collection and computation costs.[2] Further, such networks are commonly used in the social sciences to estimate network properties and peer effects on an individual [70, 71]. Figure 2.2 shows an example of a ego network, where the central node in the star-shaped graph is the ego user, or a *core* user.

[2]Most online sharing networks offer APIs that expose data in an ego-centric way, providing data about friends for each user. This makes ego networks especially suitable for collection and analysis from sharing networks.

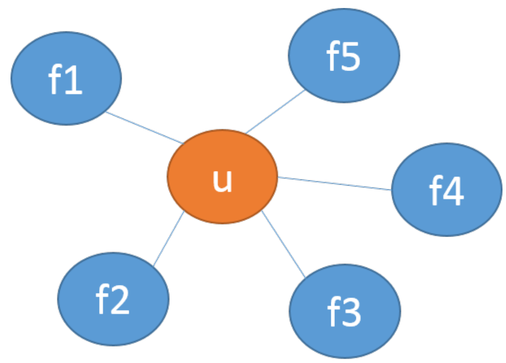

Figure 2.2: An ego network showing the ego user (u) and her friends. Note that friends of a user may also be connected to each other but we ignore such connections and focus only on the connections of the ego user.

2.2 Comparing social and non-social recommenders

A number of recommender systems that use only the ego network for generating recommendations have been proposed [60, 64, 72]. Through user studies, such friend-based recommendations are reported to be more trustworthy [61] or interesting [60, 62] than those based on people's preferences alone. In addition, recommendations based on the ego network are faster to compute since they avoid the the computational costs of processing all users of a sharing network. However, in these studies, users know which recommendations are sourced from friends, which may introduce influence effects in their feedback.

A more neutral comparison would be to compare how friend-based algorithms compare with typical collaborative filtering techniques when people do not know whether a recommendation is sourced from someone they know. In such a setting, it is less clear whether friend-based recommendations would be more relevant than those computed from all the non-friends [60, 66, 73]. To answer this question for sharing networks, we examine the performance of recommendation systems that rely only on friends' preferences versus those that rely on all of non-friends' preferences on three different item domains. First let us describe the datasets that we use.

2.2.1 Data from Facebook and Twitter

We use three datasets: two from Facebook (one for movies, one for musical artists) and one from Twitter (hashtag use). The Facebook datasets were collected as a part of user studies involving university students [64, 74], while the Twitter data was collected using their public API [75]. In all three cases, data was collected in an ego-centric fashion: each consenting participant would allow access to her past activity on items in the sharing network as well as her friends' or followees'[3] activity.

Thus, the datasets are a collection of individual ego networks, where each *core user* is expected to have all his first-degree connections. The preference data is a set of user-item pairs, where items are movies or musical artists Liked in Facebook or hashtags used in Twitter. We use the term *adoption* to refer to a Like on Facebook or usage of a hashtag.

Table 2.1 shows the statistics for the three datasets. The two Facebook networks have both a higher average number of friends than Twitter and a higher average adoptions per item. The distribution of adoptions for items (Figure 2.3) shows that adoptions for artists and movies are concentrated toward the most popular items: the 10% most popular artists and movies receive around 5/6

[3]Throughout the rest of the thesis, we use the term *friend* to denote reciprocal social connection between two people in a sharing network and follower/followee to denote directed social connections.

	Artists	Movies	Hashtags
Total users	63230	51365	69414
Total core users	153	149	935
Friends/user ($\mu;\sigma$)	(499; 341)	(352; 156)	(126; 61)
Total items	139986	78244	214941
Total adoptions	1289340	873261	1230169
Adoptions/user ($\mu;\sigma$)	(20; 34)	(17; 33)	(17; 17)
Adoptions/item ($\mu;\sigma$)	(9; 117)	(11; 96)	(6; 29)

Table 2.1: Overview of datasets. Both the Facebook artists and movies datasets have a higher friend average and average number of adoptions per item compared to Twitter.

of the adoptions, versus about half for hashtags. This is a common, *long-tail* distribution [43, 76, 77] of activity over items in a population.

Artists and movies have fairly similar profiles with a long tail and an uneven distribution of popularity. We suspect that this happens because of exogenous effects such as media exposure for the most popular artists and movies that generates large amounts of attention for a relatively small number of items. Hashtag use in Twitter, on the other hand, is much more evenly distributed, perhaps because hashtags receive less exposure outside of Twitter itself and so must spread largely inside the Twitter network.

2.2.2 Comparing recommendation quality

We now use these datasets to examine the basic assumption of recommender systems that use friend information, that such information provides useful signal. We use the k-nn recommender algorithm [78] for reporting our results because it provides a transparent interpretation into how it computes its recommendations using similarity between users. We also tried other collaborative

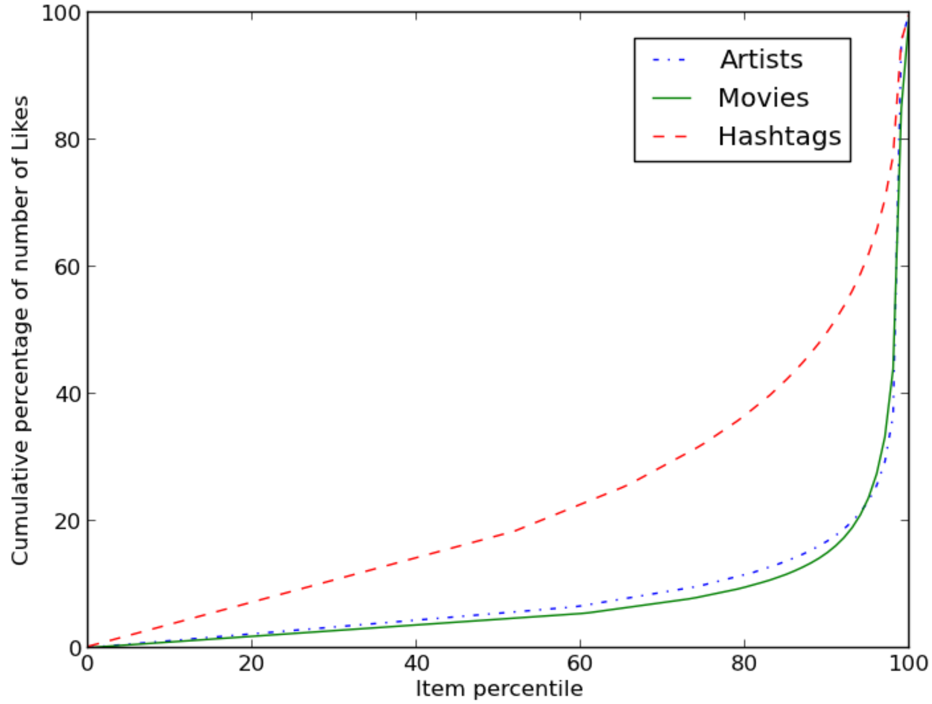

Figure 2.3: Distribution of item adoptions for the three domains, showing the cumulative percentage of total adoptions for items in the kth percentile of popularity. Compared to hashtags, adoptions for artists and movies are skewed toward popular items.

filtering algorithms such as matrix factorization; the patterns were similar to k-nn.

We divide each core user's preference data into 70:30 train-test splits, because using 30% test items means even users with few adoptions have at least one in the test set. For each user, we compute top-10 recommendations using items adopted by the k nearest neighbors, weighted by Jaccard similarity. For evaluation, we use normalized discounted cumulative gain (NDCG), a common metric used to compare ranked results [79, 80]:

$$\text{NDCG} = \frac{Rel_1 + \sum_{2..N} Rel_i / \log_2 i}{1 + \sum_{2..N} 1/\log_2 i}$$

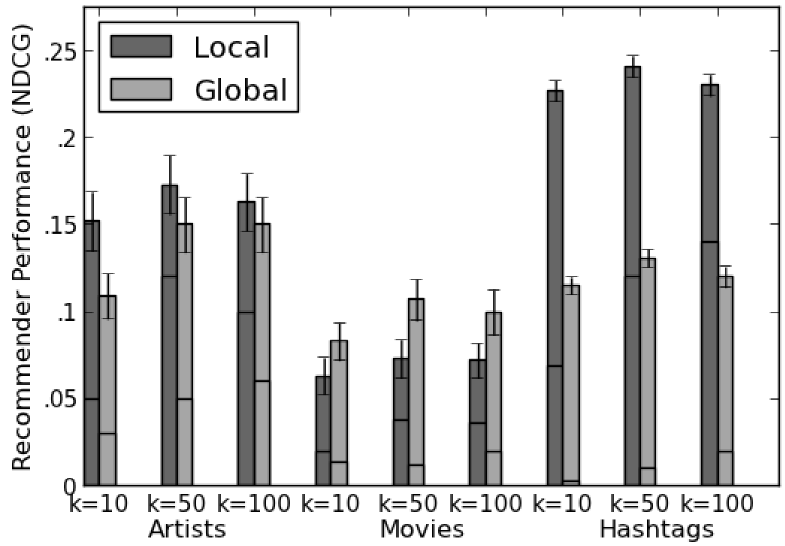

Figure 2.4: NDCG for *k*-nn recommender using only friends (Local) versus non-friends (Global). On average, friends are better for artists and hashtags, worse for movies. The black marker within each bar represents a recommender choosing people randomly. Error bars represent standard deviation of the mean.

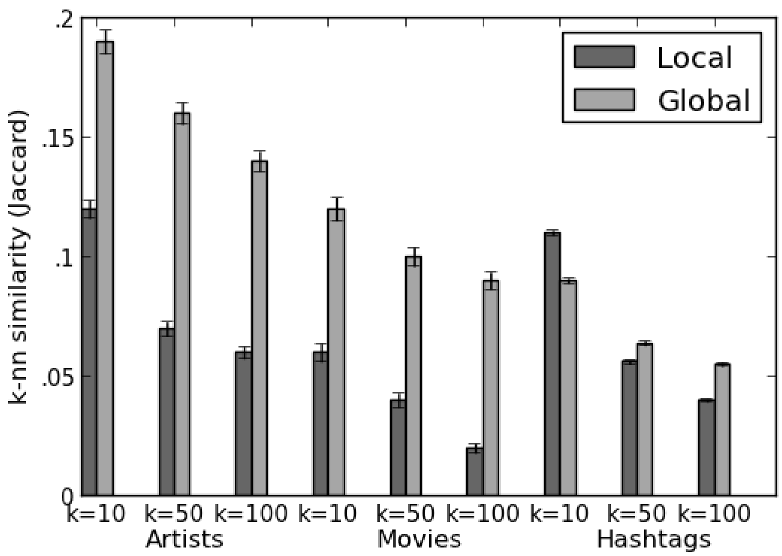

Figure 2.5: Average Jaccard similarity of a user with her top-*k* friends (Local), and her top-*k* non-friends (Global). For the Facebook datasets, non-friends are more similar at all values of *k*. For hashtags on Twitter, friends appear to be more similar than non-friends at $k = 10$, but non-friends are still more similar otherwise.

where $N = \{min(10, |TestSet|)\}$ and $Rel_i = 1$ if the ith ranked item is in the test set and 0 otherwise.

To focus on the effect of friends, we compare ego-centric recommendations based on only friends to recommendations that use only non-friends from the full network. Figure 2.4 shows NDCG values averaged across 10 random 70:30 splits. Compared to non-friends, friends are comparable for making recommendations for movies and artists, even though they are much fewer in number. In particular, NDCG values for friend-based recommendations are higher for artists at $k = 10$ and lower for movies at $k > 10$. For hashtags, friend-based recommendations are better than those based on non-friends.

2.2.3 Comparing preference similarity

A likely reason for the goodness of friend-based recommendations could be that friends' preferences are more similar to a user's preferences than those of non-friends. We examine this hypothesis by comparing average preference similarity between a user and her friends, and between her and comparable non-friends.

Random Similarity. We first look at how similar a person is to his friends versus an equal number of randomly selected people in the full dataset. We measure this directly by comparing the average Jaccard similarity between a core user and his friends versus that between the core user and an equal number of randomly chosen non-friends.

	Friends	Non-Friends
Artists	0.040	0.023
Movies	0.020	0.013
Hashtags	0.043	0.002

Table 2.2: Average pairwise Jaccard similarity between a user and her friends, or an equal number of randomly selected non-friends. Friends are, on average, more similar to a user than random non-friends.

Table 2.2 shows the results averaged over 10 random sets of non-friends. In all three datasets, friends are in fact more similar. The effect is strongest with hashtags, consistent with our expectation of relatively strong endogenous effects in the adoption of hashtags compared to artists or movies.

k-nn similarity Recommender algorithms (like the k-nearest neighbor algorithm we chose above) typically choose the most similar neighbors, so we now look at how a user's k most similar friends compare to the most similar k non-friends in the network. We use the Jaccard measure to compute similarity.

Figure 2.5 shows the results. As expected, average similarity decreases as k increases. However, for artists and movies, top-k friends are less similar than top-k non-friends. Hashtags offer a similar scenario where top-k non-friends are more similar than top-k non-friends (except at $k = 10$).

These trends in k-nn similarity show that recommendation performance does not align directly with preference similarity. Even for movies where recommender performance (as measured by NDCG) is slightly higher for non-friends, the difference between the NDCG values for friends and non-friends is much lower than might be expected based on the large differences in k-nn similarities.

2.3 Why friend-based recommendations are effective

The above results are counter-intuitive for two reasons:

- Top-k non-friends are more similar compared to top-k friends of a core user. Yet, when we make recommendations based on adoptions by top-k friends, the recommendations turn out to be better (or comparable) predictors of a user's actions than combined items from top-k non-friends.
- Friends are much fewer compared to non-friends which should make it harder to find users with similar preferences. We have over 50k non-friends for all three datasets, while only hundreds of friends for each user.

2.3.1 The preference locality observation

Together, the two observations suggest that the goodness of friend-based recommendations involves additional factors that are not fully explained by pairwise preference similarity alone. We find that preferences of friends taken together are good predictors of a user's preference, but the most similar friend is not necessarily more similar to a user than any non-friend.

A possible explanation would be that preferences are clustered within an ego network: rather than pairwise similarity, preferences within an ego network as a whole might be a better proxy for recommender accuracy. Then, the extent of such clustering in a sharing network, which we call *preference locality*, could drive the effectiveness of friend-based recommendations. For instance, a high preference locality would imply that a lot of the decisions on items made by a user are also common to her friends, which would lead to a low sparsity in the user-item matrix for any ego network. A less sparse matrix would, in turn, help to better model the user's preferences [46]. Another way to think about locality is in terms of the number of ego networks that an item is adopted in. In a sharing network with high preference locality, it is likely that an item adopted by an individual is adopted in few other ego networks. This raises the chances that recommendations based on friends would also include that item and thus lead to a higher NDCG score for friend-based recommendation.

	Friends	**Non-Friends**
Artists	0.73%	0.01%
Movies	0.87%	0.02%
Hashtags	3.60%	0.01%

Table 2.3: Density of the user-item matrix in ego networks versus the network as a whole (excluding friends). A higher density implies higher preference locality.

2.3.2 Characterizing preference locality

Specifically, we define *preference locality* as the observation that friends of a user are more likely to have similar adoptions to a user than a comparable set of non-friends.[4] This definition allows us to propose measures for locality based

[4]Note that this definition can be extended to friends of friends (second-degree connections) and so on outwards from the core user, but we restrict ourselves to first-degree preference locality since a major feature of sharing networks is enabling exposure to friends' or followees' actions on items.

on comparing friends and non-friends, that can be computed from adoption data from a sharing network.

Sparsity. Ratings sparsity is common in preference datasets [81], including ours, which have an average user-item matrix density of 0.02% or less. However, preference locality suggests that this sparsity should be unevenly distributed. Table 2.3 shows that this is in fact the case: for all datasets, ratings for the items in a given ego network are two orders of magnitude denser than in the full dataset. The effect is stronger for hashtags than for movies or artists, demonstrating their higher locality. These values align with recommendation accuracy in Figure 2.4, reflecting that a denser preference matrix for ego networks increases the chances that friends of a user would have adopted a relevant item before the user.

Ego Coverage Metrics. Another way to think about preference locality is to look at coverage, or what percentage of available items can be potentially recommended to a user. This is a common way of evaluating a recommender system and aims to maximize the number of items over which it can make recommendations [82, 83]. Here we consider coverage metrics for each item and then average them over the entire set of items. Intuitively, as people's preferences for an item are more localized, it will be adopted in fewer ego networks, reducing coverage of the item across the sharing network. There are a number of ways we might formalize this notion.

The simplest approach is to look at the percentage of ego networks in which at least one person adopts a given item. Averaging this over all items gives us a measure of ego network coverage: what percent of possible ego network-item pairs exist in the dataset? We then subtract from 100 so that higher numbers correspond to increased locality, and call this the *Uncovered Ego* of the network.

Uncovered Ego, however, does not account for item popularity. For instance, items with one adoption will look maximally local—true but uninformative—while an item with many adoptions should appear in many networks, and thus appear less local even if its preferences are more concentrated than we expect. Thus, we might want to account for the expected number of ego networks an item should appear in. To do this, we compare ego coverage with a random network, which we construct by randomly distributing the items among users. Such *null* models have been useful in the past in modeling network growth [84], as well as testing similarity in networks [85]. Here we create a network with identical friend connections and number of adoptions per node, but with the items randomly distributed (subject to the constraint that each node can only adopt a given item once). Dividing the number of ego networks that contain a given item in the randomized network by the number of ego networks that contain it in the real network gives a measure of how much preferences deviate from what we would expect if they were distributed without reference to the friend network. We call this metric *Random Item/Ego*, with higher numbers indicating greater locality.

In some ways, that approach is too random because it doesn't account for patterns of individual preferences—that, as Amazon reminds us, people who bought X also tend to buy Y. One way to account for this is to randomize at the network level rather than the item level: keeping the same number of friends for each core user and the same itemsets, but randomly reassigning the friend links. We call this metric *Random Friend/Ego*.

	Uncovered Ego	Random Item/Ego	Friend/Ego
Artists	97.4%	1.19	1.16
Movies	96.3%	1.20	1.28
Hashtags	99.7%	1.78	1.79

Table 2.4: Ego network coverage by dataset. Compared to random, hashtags exhibit the highest locality for all three metrics. Between artists and movies, the metrics are divided.

Table 2.4 shows these metrics averaged across all items in each dataset. All datasets exhibit more locality than random. As with the sparsity and similarity measures, hashtags are more local than movies or artists. The effect of randomizing by friend versus by item varies by network, indicating that the amount of item-item correlation in the networks is also different.

Putting our recommendation and locality results together implicates preference locality as an important reason why using social network information can improve recommendations [49, 72], as ego-centric recommender performance roughly correlates with preference locality. Because of the high locality in the sharing networks we studied, friend-based recommendations are comparable in accuracy to algorithms that use the full network's preference data even though any given ego network, on average, only contains a small fraction of items potentially available to a user. It seems likely that social network information becomes more valuable for recommendation as locality increases.

2.4 Understanding how preference locality emerges

Still, locality metrics do not capture fully why social information matters—some metrics show higher locality for artists versus movies, and vice versa, despite the higher performance of local k-nn for artists over movies. Knowing more about why and how people decide to adopt items may help us understand locality and the resulting recommendation results better.

In this sense, our findings generate more questions than answers: how does locality emerge in sharing networks? What is the role of social influence in leading to locality? What factors lead to the variance that we see between Twitter and Facebook? We discuss these questions next, and keep coming back to them in the rest of the thesis.

2.4.1 Emergence of locality: A tricky problem

Understanding how preference locality emerges is a tricky problem because there can be multiple social processes that lead to a common item adoption between two friends. These processes fall under two major classes: homophily and social influence.

Homophily. Homophily refers to the social processes by which people connect to other people who are similar to them [67]. Homophily is seen in social networks on different dimensions, such as race, gender, age, socio-economic status and personal preferences or opinions. On average, these dimensions tend to correlate with each other, so people who connect based on having the same demographics are also more likely to have similar preferences on items.

Thus, due to the homophily selection process through which people form ties with similar people, friends are more likely to have similar preferences.

Social Influence. Observing others' actions may cause a person to be influenced by those actions, through the general process of *social influence* [1]. Social influence operates through many sub-processes, such as being swayed through *social proof* of an action endorsed by others, *conforming* to a group's opinion, or being influenced by a certain individual's actions (interpersonal influence).

Most online sharing networks thrive off exposing people to their friends' activities. Based on the processes of social influence, such exposure would influence a person to copy her friends' actions and thus increase preference locality.

Therefore, a high preference locality could be due to homophily or influence; it is hard to tell them apart given only observational data such as the datasets from Facebook and Twitter. For example, if a person (let us call her A) adopts a song on Friday and her friend (B) does so on Tuesday, was B influenced by A's adoption, or do they both happen to have a personal preference for that song? What if B adopts the song a few minutes after A? In general, without either strong assumptions about influence mechanisms (e.g., [86, 87, 88]) or strong knowledge of latent variables that indicate homophily (e.g., [6]), distinguishing them from observational data alone is somewhere between impractical and impossible [89].

2.4.2 Towards identifying the role of influence and homophily

While sharing networks offer unprecedented data about people's activities, these data hide the underlying decision process—why and how do people decide to adopt or share an item—that is important to flesh out accurate models of their actions. As we saw above, logs may indicate that two friends adopted the same item, but it is unclear whether they both discovered the item by themselves or one influenced the other.

In this thesis, we develop algorithms and experimental designs to understand the role of influence and homophily in two fundamental decisions on items in sharing networks: adopting or sharing. To fully understand people's decision-making on items, we need to understand people's motivations and considerations for sharing and adopting items, in addition to studying the data generated from their actions. Therefore, we employ a *mixed-methods approach*. We use behavioral experiments to understand people's decision-making and build individual-level models of how people adopt and share items. We use data mining to see how our experimental findings extend to large-scale activity on different sharing networks.

2.4.3 Influence in terms of personal preference

A common thread throughout our work is the use of preference models that allow us to characterize and tackle questions around social influence. By using personal preferences, we obtain specific, operational definitions of influence that can be mapped into specific domains and that make the processes and measures clear. This allows for more accurate measurement (as we will see, naive measures of "influence" overstate it), better connection of influence to the theories that underlie it, consideration of the role of systems in mediating influence, and perhaps a better ability to compare results from other studies.

Using the lens of personal preference, we define social influence as follows. A person's current preferences provide a prior for his future decisions on items.

Any deviation from this prior caused by exposure to friends' activities can be considered as social influence. Thus, using past activity of users to construct preference models gives us a way of isolating the effect of influence: change in activity that is not expected from following one's past actions.

Admittedly, this is not always feasible. For example, when studying the effect of influence in activities that do not happen often, such as starting to smoke [89], it is hard to construct a reliable prior for a person's own preference for smoking. However, when relevant past activity data is available, influence can be estimated with less stringent assumptions. This is common in online sharing networks (especially for domains like music, movies, games and apps) where we have multiple data points about a user's past activities, which we exploit in our work.

2.5 Contributions

The rest of the thesis is organized in three parts. In Part II, we present experimental evidence that shows that personal preference is the dominant factor in helping people decide to adopt and share items. These results gain external validity in Part III, where we estimate the extent of influence on log data from a broad range of websites and find that only a small minority of people's actions (and thus preference locality) can be attributed to influence. In Part IV, we discuss the implications of our results.

We make the following contributions.

Part II. First, we describe a social recommendation platform, *PopCore*, that acts as an experimentation platform as well as a recommender system in its own right (Chapter 3). Through a pair of experiments on PopCore, we demonstrate that personal preference is the dominant force in people's decision-making on adopting or sharing an item.

In Chapter 4, we conduct a randomized experiment to study the effect of exposing an individual to others' activity on a recommended item.

- We find that the effect of social influence—as embodied by additional social information shown alongside items—is secondary to that of people's personal preference, even when minimum information about the item is shown.
- We build a generative mixture model for rating that combines the effect of people's personal preference and social influence. Estimates from the fitted mixture model confirm the finding that social influence has a relatively minor effect.
- Although the relative contribution of social influence due to explanations is minor overall, the effect on each individual varies widely. Based on our generative model, we suggest strategies to find the more susceptible people to influence and further personalize the kind of social explanation for those users.
- Different kinds of explanations have different effects in aggregate—some are just more influential—but even those that are most influential don't appear to help people make good decisions with respect to their preferences, further suggesting that preference and influence have a complicated relationship.

The dominant role of personal preference is also seen when people share items to others (Chapter 5). Through a paired experiment that allows friends to share items to each other from a list of recommended items, we find that:

- Even when people share items to a specific known recipient, which may allow them to personalize their shares based on the recipient's preferences, their own preferences dominate in deciding what is shared.
- An individual's personal preference over items, in conjunction with her promiscuity (or frequency) of sharing, can predict more than two-thirds of her sharing decisions.
- Still, a majority of participants claimed that they were personalizing their shares for the recipient. We propose a preference-salience sharing model that explains these contrasting results: people share what they like themselves, but may select the actual item to share based on salience due to the recipient or exposure from the user interface of a system.
- When shown items aligned with the recipient's preferences, people shared items that were liked comparably by the recipients and themselves. This suggests that salience of items through the system interface can alter what gets shared, which can be utilized by recommender systems to encourage effective sharing among people.

Part III. In Part III, we consider a common situation in online sharing networks that Part II characterizes, where people adopt and broadcast—share to their social connections—what they like and their activities are shown to their social connections in the form of an activity feed with a social explanation (*"X liked this item"*) for each item [24, 41, 77]. We are interested in how such exposure to friends' recent activity influences people's adoption (and thus, implicitly, resharing) behavior.

To tease out the effect of people's personal preference and social influence from activity feeds, we introduce a general statistical procedure, *Preference Matching Estimation (PME)*, in Chapter 6.

- By controlling for preference similarity among friends due to homophily, the PME procedure estimates the fraction of actions taken due to influence from social feeds in sharing networks. The use of preference data as a proxy for homophily allows a precise specification for influence yet broad applicability of the PME procedure on different sharing networks.
- Unlike past work on estimating influence [6], our procedure relies on commonly available data from sharing networks: user activity and social connections among people.
- The PME procedure is able to provide both individual and network-level estimates for the effect of social influence from exposure to friends' activities in a sharing network. This enables personalized models of susceptibility to influence that can useful for making recommendation and understanding diffusion processes more accurately.

In Chapter 7, we apply the PME procedure to data from sharing networks that cover a wide range of item domains such as books, photos and music.

- We find that estimates of social influence used in past work [90, 91], such as the fraction of common adoptions between friends within a certain time period, overestimate the extent of influence in sharing networks, often substantially.

- Further, our results show a subdued effect of influence on people's adoption decisions. Influence accounts for less than 1% of the total users' activity on items in these domains.
- Finally, we find a wide variation in individuals' susceptibility to influence. The majority of users in all four networks appear not to be influenced by activity feeds at all.

These findings confirm the results from our experiments in Part II, indicating that the effect of influence in sharing networks might be overrated; personal preference of people dominates a vast majority of their actions, at least in these feed contexts on sharing networks.

Part IV. Overall, our empirical results indicate a modest effect of influence, questioning the popular wisdom around influence and contagion in online sharing networks. In this sense, our work joins recent work [40, 92] in uncovering the relatively low effect of influence in sharing networks and demonstrating that even with continuous exposure to others' activities on social media, people's personal preferences largely dictate their online activities on items.

We discuss implications of these results in Chapter 8. Our work opens up new questions around diffusion and recommendation models for sharing networks, informed by better models of personal preference and social influence. We demonstrate how modeling an individual's personal preference when sharing, and her susceptibility to influence when adopting can lead to better models of her decisions on items. Our findings are also useful for advancing recommender systems within sharing networks, such as by personalizing social explanation strategies in adoption or modeling people's preferences in sharing decisions.

More generally, our work points to the merits of using precise, context-specific definitions of influence rather than aiming for a grand unified theory. Our results on the interplay of personal preference and social influence in people's adoption and sharing decisions are made possible by a precise operationalization of influence in terms of deviation from people's personal preference. For any given sharing network, such a formulation for influence is easily adaptable, concretely defined and thus testable using data on people's activities. Rather than general theories about influence, we believe that formulations based on specific processes and contexts—like we did with social influence within a sharing network—are more likely to advance our understanding of people's decision processes.

Finally, we demonstrate the value of combining research methods—experimentation and data mining—to tackle tricky questions about social processes in online sharing networks. The combination of experimental rigor in Part II and large-scale external validation in Part III allowed us to identify the effects of personal preference and social influence at the individual as well as the aggregate level, thus enriching our understanding of adoption and sharing decisions in a way that neither experimentation or data mining efforts alone would have been able to.

Part II

Experimental Evidence: Modeling adoption and sharing decision processes

In this part, we study the two fundamental decisions that people make on items in sharing networks: adoption and sharing. Different sharing networks may have different ways or nomenclature on how people interact with items, but at their core, almost all of the decisions can be thought of in terms of adoption or sharing. For instance, adoption may be referred to as *Liking* an item on Facebook, *Loving* a song on Last.fm, *Favoriting* a photo on Flickr, rating highly a book on Goodreads and so on. Sharing has fewer names (*retweeting* or simply *sharing*), but differs in how people select recipient(s) to share to. People may broadcast to their social connections such as when posting a status update on Facebook or Twitter, or share items directed to certain friends in a *direct message* on Twitter or a *recommendation* on Goodreads.

Still, on all sharing networks, adoption and sharing decisions of each user propagate to their social connections, who may then adopt and/or share too. If we ignore the effects of external forces (e.g., advertisements, featured lists, and/or algorithmic sorting of items), these two decisions—sharing and adopting—decide the fate of an item in a sharing network.

Through online experiments on a social recommendation platform, we will study the processes by which people decide to adopt or share. Experiments provide us a window into the motivations, processes and social influences in these decisions in ways that data mining of log data cannot. For adoption, we are interested in how exposure to friends' activities influences a person's decision. For sharing, we are interested in how people consider their friends' likes and dislikes when making their decisions.

Additionally, underlying both these decisions—adopting and sharing—in a sharing network is the personal preference of each individual. Despite the presence of social influence around adoption, and the potential consideration of friends' interests when sharing, we will see that people's personal preference plays a dominant role in both decision processes.

CHAPTER 3

POPCORE: A SOCIAL RECOMMENDATION PLATFORM

To facilitate behavioral experiments on adoption and sharing of items, we built a recommendation system on top of the Facebook social network. Instead of aiming for individual consumption as most recommender systems available at the time (early 2011) did, we developed our system, *PopCore*[1], as a social platform that provides people recommendations based on their friends' activities while facilitating awareness of others' activities and sharing of items [93].

This chapter describes the relevant features of the system. As a research platform, the goal was to push forward friends-based recommendation algorithm development, understand how people perceive recommendations associated with their friends, and how people share items to each other [64]. In addition, the system also served to collect useful data about people's social connections and their past activities. The Facebook data used in the preference locality study (Chapter 2) was captured through the system, notably via a study on people's adoption decisions that we will see in Chapter 4.

3.1 System design

PopCore is implemented as a Facebook application that provides recommendations in the entertainment domain, covering music artists, movies, books and television shows. We chose Facebook as the underlying social network because it provides us both network and preference data (through Likes), and also supports a diverse set of domains for items. We chose the entertainment domain

[1]A delightful twist on the word *popcorn*, symbolic of watching entertainment.

due to its relative popularity of Likes on Facebook compared to items from other domains.

A user logs in to PopCore using her Facebook credentials and gives the app permission to access her Likes and her friends' Likes in movies, music, books and TV shows. Once the appropriate data permissions are obtained, the system uses her Likes and her friends' Likes to compute recommendations.

3.1.1 Friend-based recommendations

PopCore provides a general framework for plugging in different recommendation algorithms, which was used to compare different friend-based algorithms in earlier work [64]. Since recommendations need to be computed with minimal delay once a user logs in and provides access to their Likes, an algorithm that can compute recommendations online is ideal. For the experiments presented in the thesis, the system uses the k-nearest neighbors algorithm [78, 94] over friends' data, a memory-based technique [45, 46]. At this scale (people tend to have hundreds of friends on average), k-nn runs reasonably fast. In Chapter 2, we also saw that k-nn recommendation accuracy based only on friends' data is comparable to that based on a much larger preference dataset.

3.1.2 User interface

Figure 3.1 shows how the recommendations are presented. The recommendations may also have some optional social information that adds social context. These convey the number of friends who have Liked the item, names of spe-

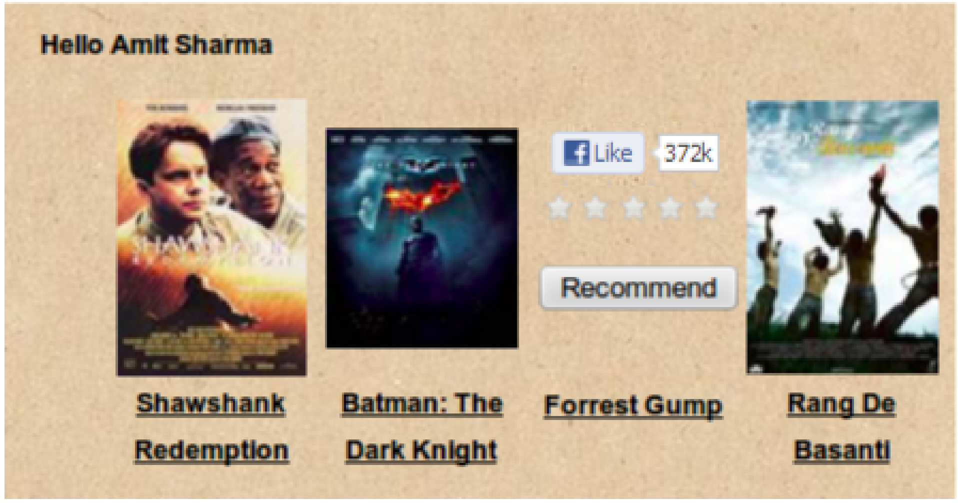

Figure 3.1: PopCore interface. Recommendations are computed based on Likes of friends of a user. Upon clicking an item, its thumbnail is replaced by the possible actions a user may take: Like, rate or share ("Recommend") that item to her friend(s).

cific friends who have done so and/or the overall number of Facebook Likes for the item. This is a common feature in many recommender systems and activity feeds in popular sharing networks such as Facebook, Goodreads or Last.fm.

Users may give feedback on the recommended items, and share some of those items to their friends.

Feedback on items

There are two ways of giving feedback on an item, as shown in Figure 3.1. A user may rate an item on a scale of 0.5-5 stars or choose to Like it on Facebook (which is added to her Facebook profile and accessible according to her privacy settings). Though the Like button and a high rating both can be used for positive feedback on an item, they convey different signals. To Like an item is to publicly identify oneself with it, while a rating serves as a private affirmation of interest [64].

Directed sharing

Direct person-to-person sharing is a natural part of social communication. To facilitate such sharing, the system recommends candidate people to share to when a user clicks the *Recommend* button. This is computed based on the friends whose preference is closest to the current item, but have not already Liked the item on Facebook. This is just a default suggestion; the user is free to choose any friend that they wish to share to.

3.2 PopCore as an experimental platform

One of the goals for the PopCore system was to serve as a useful recommendation system, but the system failed to gain much traction among people. Nevertheless, its infrastructure and interface elements remained useful for conducting behavioral experiments. We did so by creating custom interfaces and inviting study participants to use those versions of the system. We explicitly ask for consent before people participate in experiments, and these experiments have been approved by Cornell's IRB.

CHAPTER 4

HOW DO SOCIAL EXPLANATIONS AFFECT PEOPLE'S LIKELIHOOD TO ADOPT

> In recent years, every major website seems to be in a mad scramble to tell us what our friends did. Not just in sharing networks like Facebook and Twitter, explanations of the form "X, Y and 10 other friends endorse this" accompany products on Amazon and search results on Google (Figure 4.1). How much does such additional social information affect people's decisions? If all your friends jumped off a bridge, would you jump too?

A major component of online sharing networks is that they provide awareness about our friends' activities. This may be manifested in the form of feed interfaces which show recent actions on items by our friends, recommendations that show which of our friends like an item, and even advertisements that use our friends' information. Often, each item is accompanied by the name(s) and/or number of friends who have already adopted that item.

This extra social information can be thought of as a *social explanation* for the item, borrowing the name from explanations—supporting information—in the context of recommendation systems [95, 96]. Facebook provides probably the most ubiquitous context in which we see such social explanations, powered by the *Like* button. Users on Facebook can Like status updates, Facebook pages representing entities such as products, movies, music, and books, and even external URLs as long as they are appropriately coded[1]. These items are then presented

[1]Applicable for webpages that support the Open Graph protocol (http://ogp.me/)

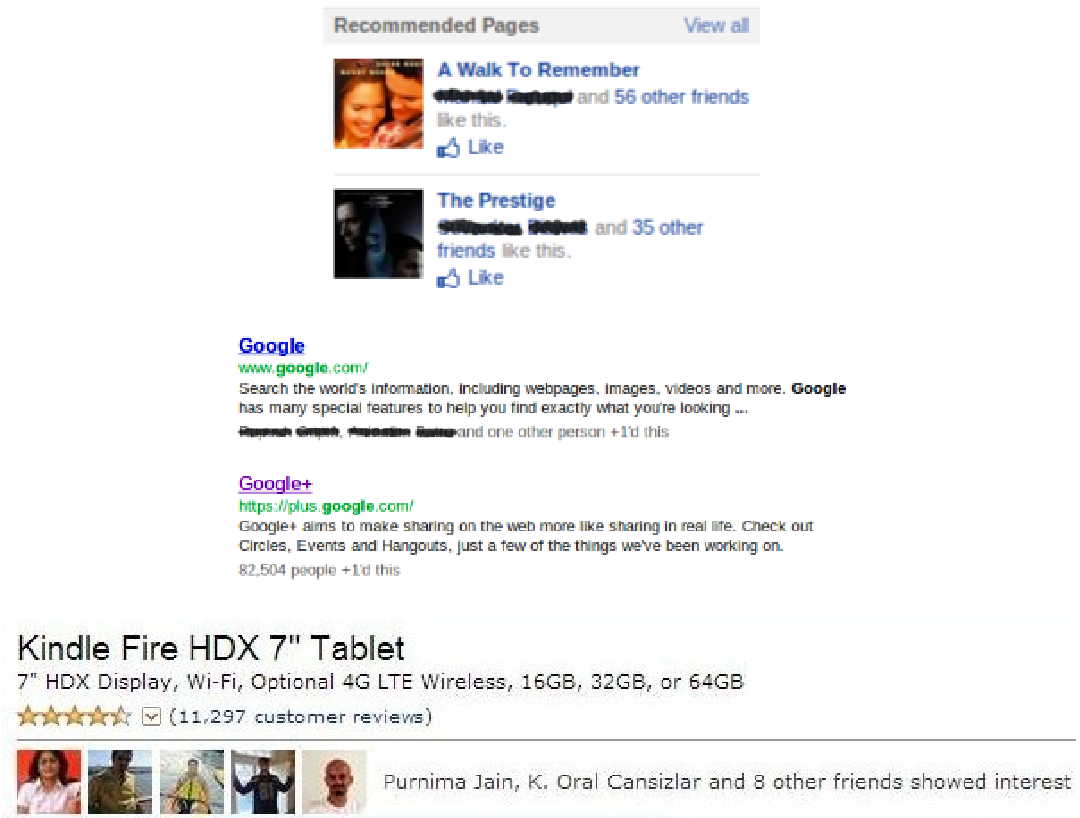

Figure 4.1: An example of social explanations typically found online. Here we show screenshots from Facebook's page recommender, Google's search engine and Amazon's product page. Names and counts of friends, and number of people who like an item are presented to the user.

along with information about how many people in general, or how many of a person's own friends, have Liked them on Facebook, as shown in Figure 4.1.

In general, these social explanations follow a few basic forms that theories of social influence suggest might impact people's decision-making [1]. Such explanations rest on the idea of social proof, that people follow other people's behaviors because they assume that others have reasons for doing those things [19]. Other social explanations provide the names of particular friends who have Liked the item; particularly if the names chosen are good friends, this might tap into the idea that people we like are more persuasive [60, 97]. Social explanations can also combine these kinds of information, for instance, providing both names and counts of others' activity around items (see Figure 4.1).

Influence due to such social explanations in sharing networks could be a cause of the preference locality in sharing networks that we saw in Chapter 2. Seeing their friends' actions on recommended items may increase the likelihood that people adopt the recommendations shown, thus leading to common adoptions between friends. However, such influence is hard to identify from log data of people's adoptions, because homophily might also lead to common adoptions between friends. Further the logs typically do not show the explanations presented along with a recommendation.

In this chapter, we present a randomized experiment that controls for personal preference effects and captures how different kinds of social information influence people's decisions. Using the PopCore platform, the first phase of our experiment showed people social explanations for musical artists that they knew little about (assuming that this would remove the effect of personal preference in their decision) and asked them to rate their *likelihood* of trying out those artists. In the second phase of the experiment, they return about a week later and actually listen to music by artists (without any social explanation) they had been exposed to earlier and provide a *consumption* rating.

We are interested in how influence from social explanations impacts a person's likelihood to try out an item, and how actual consumption ratings—when no social explanations are shown—correlate with likelihood ratings. We summarize results from both phases of the experiment below.

Likelihood phase. We find that different kinds of social explanations do have different effects on likelihood ratings. However, it is only a secondary effect, with the dominant influence on most people's likelihood ratings being their inherent expectations of how they will like the item, even with minimal available information about the artist. Further, social explanations are not always persuasive. People's comments show that a trusted friend's name can increase the credibility of a recommendation, but a friend whose interests are unknown or incompatible negatively influences likelihood ratings. More generally, when people identify with the source of the explanation, they tend to give it more credibility.

Based on these insights, we present a generative model that explains much of the interplay between social explanations and inherent preferences on likelihood ratings, a model that can be generalized to include other sources of explanation as well. There is a wide variation in how susceptible people are to the effect of social explanation and to different kinds of social explanation, which is also reflected in people's comments about having different strategies for making sense of social explanations. These findings suggest that personalizing strategies for explanations might have real value.

Consumption phase. We find that the effect of different kinds of social explanations does not transfer to the consumption phase. In fact, like past work on explanations in recommender systems [59], we find a low correlation between likelihood and consumption ratings people give to the same artist. This suggests that there are different motivations and goals for the two phases, and further, that although explanations are persuasive, they are not very informative and may lead people astray.

4.1 Background: How explanations affect people's adoption of recommendations

We build on existing work that shows the value of explaining recommendations in general and the growing trend to use social information in sharing networks for explaining recommendations.

4.1.1 Effect of explanations for recommendations

Deciding whether to consume a recommended item is not done in isolation, but in a situated context [98]. Terming rating as a cognitive process, Lueg argues that the ratings are a dynamic result of the interaction of an individual with an "information situation". In our context, an explanation is part of the information presented about a recommendation, and studies show that explanations play an important role in helping a user evaluate a recommendation [57, 99]. In one of the first studies of explanations, Herlocker et al. evaluated 21 types of explanation interfaces for a movie recommender system [95]. Similar to our study, they presented no actual information about the item and found that a histogram showing the ratings of similar users is the most persuasive for users when asked about their likelihood to see a movie.

However, being persuasive has drawbacks. Another study found that although explanations might persuade a user to try an item, they were not good for accurately estimating the quality of an item [59]. The authors further argue the goal of a recommender should not be to persuade people to adopt a recommended item (which they call *promotion*), but rather to enable a user to make a more accurate judgment on the true quality of the item for that person (which they call *satisfaction*).

Besides helping users make an informed choice, explanations may also increase the acceptability of a recommender system overall, by communicating why an item has been recommended to a user [100] and thus helping them understand the system. These explanations and other presentational choices can be designed to increase the system's trustworthiness [101], and a number of real systems incorporate explanations (e.g., Amazon's explanation of "Customers who bought this also bought these", and Netflix's explanation by genres). Tintarev et al. provide a number of desirable attributes of explanations, including transparency, scrutability, trustworthiness, effectiveness, persuasiveness, efficiency, and satisfaction [96].

One outstanding problem it that is not clear how to characterize explanations' influence on either likelihood or consumption ratings. Computing persuasiveness is difficult because people's likelihood decisions are also informed by the merits of the recommended item and by other information presented in the interface. And, though Cosley et al. found that displaying predicted ratings caused people to change their own ratings of movies [20], this was likely a short-term effect caused by displaying the predicted rating at the same time as the user the rated movie. Here, we attempt to tease out persuasiveness through comparing a number of different social explanation strategies, by putting a substantial delay between the likelihood and consumption ratings and, like Herlocker et al. [95], by minimizing people's ability to judge the merits of the item.

4.1.2 Using social information for explanations

Social information can also be used to explain a recommendation, as with the neighbor-based ratings in Bilgic and Mooney [59]. Using user-generated tags, based on their popularity and relevance, is another source of social information that has also been studied for explanation in a sharing network [102]. More recently, friends' activities on an item have been used for explaining search engine results [103, 104] and news articles [105], where they have been found to be useful for providing social context.

Our work directly addresses the effects of such social explanations on people's adoption decisions. A fundamental question is whether, and how, these social explanations influence user decisions. In addition, we would like to investigate how different types of social information vary in their impact. Analogous to the likelihood and consumption phases of the experiment, we are interested in both the *persuasive* power of such explanations, as well as their *informative* power (whether they lead to satisfying choices). Based on the discussion above, we articulate four high-level research questions:

RQ1: How do different social explanation strategies influence likelihood ratings?

RQ2: How do social explanations interact with an individual's personal preferences?

RQ3: How can we model the influence of explanations on likelihood ratings?

RQ4: Do high likelihood ratings translate to high consumption ratings in the absence of any social explanation?

4.2 Description of the user study

We now describe the details of our experiment for estimating influence due to social explanations on the decision to adopt musical artists. We chose the music domain for this experiment because it is relatively easy to acquire consumption ratings of previously unknown artists (three minutes per song, versus two hours per movie, for example), allowing us to explore whether explanations would influence consumption ratings.

4.2.1 Experiment design

The experiment proceeds in two main phases. We initially collect the artists that the participant and her friends Liked. We then show all the artists the participant's friends Like that she hasn't yet Liked and ask her to identify a minimum of 30 that she is not familiar with. We ask for this information to minimize the effects of prior knowledge or personal preference. To minimize position bias, we ordered artists randomly.

Phase I

Phase I begins immediately after the initial selection. The experiment is a within-subjects design, where each participant sees the artists they selected, randomly assigned to one of five explanation strategies:

- **Friend Popularity**: The number of friends of a user who Like an artist (*FriendPop*, Figure 4.2(a)).

- **Overall Popularity**: The number of Likes by all Facebook users for an artist (*OverallPop*, Figure 4.2(b)).
- **Random Friend**: The name of a particular friend, chosen from those that Like an artist (*RandFriend*, Figure 4.2(c)).
- **Good Friend**: The name of a "close" friend, chosen from those that Like an artist (*GoodFriend*, Figure 4.2(c)).
- **Good Friend & Count** A combination of Good Friend and Friend Popularity (*GoodFrCount*, Figure 4.2(d)).

These roughly align with commonly used social explanation strategies described earlier. Given a user and an item, *OverallPop* and *FriendPop* explanations are straightforward to compute using the total number of Facebook users or friends who Like an artist, respectively. For *RandFriend*, we choose a friend at random among all the friends that Like an artist. For *GoodFriend* and *GoodFrCount*, we choose the friend with the highest tie strength who Likes the artist, assuming there exists such a friend with non-zero tie-strength. Using a rough proxy of interaction frequency, loosely inspired by Gilbert and Karahalios' work on predicting tie strength in Facebook [106], we define tie strength between a user and a given friend as the number of interactions (likes, comments, and wall posts) between them among the last 500 interactions involving the user.

For each artist, we show the artist's name, their profile picture on Facebook, and the associated explanation. For *GoodFriend* and *GoodFrCount*, it was often the case that there were no friends with non-zero tie strength who had Liked the item. In these cases, we skipped the item, leading us to show fewer artists in these conditions; we saw this as preferable to assigning artists that random friends had Liked because we were afraid that might dilute the effects of close

(a) Friend Popularity

(b) Overall Popularity

(c) Good/Random Friend

(d) Good Friend & Count

Figure 4.2: Different explanation strategies used in the experiment, shown along with an artist's name and profile picture. This setup was chosen as a tradeoff between realistic recommendation scenarios (artist information shown) and ideal experiment conditions (no other information).

friendship. For each recommendation, we ask the user how likely is she to check out the recommended artist and how sure is she about her answer. We use a 0-10 (inclusive) Likert scale to collect these answers[2]. To reduce order effects of either artist or explanation strategy, we randomize the order of presentation for artists.

[2]The initial slider value is 5 and participants usually moved the slider, leading to a relative lack of 5 ratings.

Once all artists are shown, the user fills out a questionnaire that asks about their reaction to the explanations: which ones were more convincing or effective and why, and how she used the information presented to think about the recommended items.

Phase II

In the second phase, users listen to songs by a randomly chosen subset of the artists they had rated in Phase I. Explanations are not shown in this phase. We also required participants to wait at least three days between Phase I and Phase II. The goal of this delay, and of not re-showing the social explanation during Phase II, was to see whether there was a lasting effect of the explanation on people's consumption ratings [20]. Participants could choose their date for Phase II; the average delay was 5.2 days.

We used Grooveshark[3] to provide the top three songs for a musician, assuming that a musician's best songs are a reasonable representation of the artist. Since listening to the top three songs for a given artist takes 6-9 minutes, we randomly chose two artists from each explanation strategy from Phase I to keep the experiment between 60 and 90 minutes. This meant that participants listened to 10 songs in total. After listening to the songs, we asked the user to rate how much they liked the artist and their surety about the rating. As before, feedback was collected on a 0-10 Likert scale.

[3] `http://en.wikipedia.org/wiki/Grooveshark`. A popular music service at the time, ceased operations in April 2015.

4.2.2 Participants and descriptive overview

Participants were drawn from two on-campus experimental subject pools covering undergraduate and graduate students as well as staff at the university. Participants were compensated with either money or with experiment participation credits required by some courses. A total of 237 users took part. Out of these, 175 people completed both phases, while the rest completed only Phase I. The gender ratio was 68% female, 32% male and the average age 20.5 years. We collected a total of 4458 ratings for Phase I and 835 for Phase II.

4.3 Influence of different social explanation strategies on likelihood ratings

First, we address **RQ1:** How do different social explanation strategies influence likelihood ratings? Table 4.1 shows the mean likelihood ratings for different explanation strategies[4]. *GoodFrCount* and *GoodFriend* have relatively high mean ratings, while *FriendPop* and *RandFriend* have relatively low ones, suggesting that good friends are more persuasive than counts or random friends. An ANOVA with repeated measures shows that there is a significant difference between the different explanation strategies ($F(4, 763) = 4.96, p = 0.0006$). A post-hoc Tukey test shows that *GoodFrCount* is significantly higher than *RandFriend* ($p = 0.002$) and *FriendPop* ($p = 0.006$).

[4]As a reminder, the good friends-based strategies have fewer ratings because many of the items that were randomly assigned to them hadn't been Liked by a good friend and so were skipped.

Explanation Strategy	N	Mean	Std. Dev.
Friend Popularity (*FriendPop*)	1203	2.12	2.42
Random Friend (*RandFriend*)	1225	2.08	2.49
Overall Popularity (*OverallPop*)	1191	2.36	2.69
Good Friend (*GoodFriend*)	434	2.52	2.69
Good Friend & Count (*GoodFrCount*)	405	2.71	2.90

Table 4.1: Likelihood ratings for different explanation strategies. Strategies based on good friends have higher ratings.

Answer Theme	Prevalence (%)
Good Friends	26
Similar Friends	18
Overall Popularity	13
Expert Friends	12
Popular Among Friends	12
Artist Name and Cover	10
None	9

Table 4.2: Answer themes and their prevalence for the kinds of information participants found most convincing. Some of these were explicitly shown (e.g., overall popularity), while others were raised by participants (e.g., friends having similar taste in music, or perceived to be experts).

Users' qualitative responses give confirmation, explanation, and depth to these differences, showing the importance of good friends and, no matter which explanation strategy, the importance of identifying with the source of the recommendation. Table 4.2 shows how useful people saw the different information available to them in explanations, based on coding their responses to a question about what aspects of explanations they found most powerful. We used inductive coding to arrive at the six categories, using two researchers to code participants' answers.

4.3.1 Showing the right friends matters

The most important source of information was the name of the friend who liked the item: *"The best recommendation was the showing which one of my friends liked a song. I didn't really care when I was vaguely told '2 friends'. It was important to see names because I know some of my friends' music tastes."* (P78)

Good friends were seen as more influential and informative than others: *"I would only be interested in the recommendations based on people who are relatively close to me (compared to random individuals/acquaintances on my friends list)."* (P23)

This is likely because people are better able to think about whether they know and trust good friends' tastes, as suggested by [107]: *"I found it most powerful when I could see what friend likes the artist. I know what kind of music my friends listen to and that helps me know if I would like the artist or not."* (P105)

As Table 4.2 shows, people also trusted those friends more who were perceived to have similar interests, or a good taste in music: *"Certain friends who I'm close with and have similar interests/music tastes to mine made me feel more likely to listen to a band."* (P141) *"I found the recommendation for Falluah most convincing because it was liked by one of my close friends who has great taste in music."* (P51)

Disagreement, on the other hand, could lead an explanation to be less persuasive: *"Sometimes I judged the artist solely based on which friend liked it. If it was a friend that I did not think I would have similarly music taste too, then I immediately ruled the artist out which may be an incorrect judgment."* (P15)

4.3.2 Popularity only matters if people identify with the crowd

People were more divided about the efficacy of popularity-based explanations. For some, social proof was clearly an important influence: *"The recommendations that had more 'likes' were most powerful. I assume that there is a reason that so many people like that music."* (P172)

This is particularly true when people see the crowd as providing useful information, as with this person who found recommendations through his friends: *"The recommendations that were most convincing to me were the ones that displayed that a decent number of my friends listened to or liked the artist. I often like to hear my friends' feedback on certain artists and music tastes so that I might get a better idea of what is out there that I might like as well."* (P32)

However, when people don't see their friends as informative for them, they dismissed friend count information: *"Me and my friends' music tastes rarely match up, so I've learned to not care about what music my friends like. Since I mostly listen to mainstream music that means that I would more likely listen to artists with more likes."* (P96)

4.4 Interaction of social explanations with people's personal preferences

We have seen that different kinds of social explanations are differently persuasive, and further, that there is variation between individuals in how useful they

Answer Theme	Prevalence (%)
Helped make decision	34
Useful information	40
No use or influence	20
Other	6

Table 4.3: Answer themes and prevalence for how much participants thought they were influenced by social explanations overall. On balance, people saw them as presenting some useful information, though the amount of influence varied.

find different kinds of social explanations. We now look at **RQ2:** How do explanations interact with an individual's personal preferences?

4.4.1 People are differently susceptible to social explanation

Table 4.3 shows three main groups that emerged when we asked people how they felt about the social explanations and coded their responses. On balance, people felt that social explanations could influence their decisions about artists, but the amount of influence varied quite a bit between people.

As with their reactions to particular kinds of explanation, the differences appear to hinge on whether people expect the social information to be informative: *"I think that it influenced my choice on the degree to which I thought I would search the artist and how confident I felt in that decision. If I knew the person well, trusted them, or was friends with them, or if a lot of my Facebook friends liked that artist, I was definitely more likely to think about researching the artist and feeling confident about it."* (P22)

4.4.2 Social explanation is only part of the story

Although not cited as important as the social information, the artist's name and photo had an effect too: *"What influenced me the most was the picture associated with the band or artist."* (P66)

For most (Table 4.2), social explanations were useful, but they were just a part of a story in which other factors also mattered: *"The albums with the most interesting picture, or interesting name, with a lot of likes. If the name struck me, such as 'Formidable Joy', I found myself wondering more. If a lot of my friends liked it, it must be good!"* (P7)

And, as we saw earlier with friends who had incompatible preferences in music, people would sometimes combine social explanation with artist information in order to reject a recommendation: *"The recommendations didn't really convince me that much. It more mattered what my interests were, not my friends'. If anything, some of the recommendations convinced me not to look up the bands; if the artist looked like a rapper, and the kid who suggested it was a younger boy from my high school who thinks he is cool I was positive that I was not going to look it up."* (P59)

4.4.3 Influence from social explanations is a second order effect

Our final observation is that, based on our data, influence from social explanations is a second order effect. The standard deviations for likelihood rating shown in Table 4.1 were high and the effect size is small (Cohen's $d \approx 0.2$[5]) even between the most and least persuasive social explanation strategies, *GoodFriend*

[5] We report Cohen's-d [108] as a measure of effect size throughout.

Explanation	**Fraction** > 5
Friend Popularity	0.137
Random Friend	0.141
Overall Popularity	0.175
Good Friend	0.200
Good Friend & Count	0.239

Table 4.4: Fraction of likelihood ratings above 5 (neutral rating) for each explanation strategy. Good friends-based strategies have higher fractions of ratings above 5.

and *RandFriend*. This suggests that other factors play an important role in people's decision-making around recommendations.

Participants' responses comments confirmed that the effect of explanations may depend on pre-conceived notions of quality or prior information, both of which would be informed by people's personal preferences: *"Recommendations of artists that seemed established AND were endorsed by people who I respect were the most powerful. Even if they were endorsed by someone I know and respect, if they seemed to be a garage band, I did not find the recommendation powerful."* (P117) *"I tended to find the most powerful recommendations were the ones whose genre I knew in advance and were liked by my Facebook friends that were closest to me."* (P132)

Further evidence is provided by the distribution of likelihood ratings (Figure 4.3), which shows that most ratings are below 2. This trend is consistent across explanation strategies, which suggests that in addition to explanation, underlying every rating there is a base decision process, that on average, leans towards rejection.

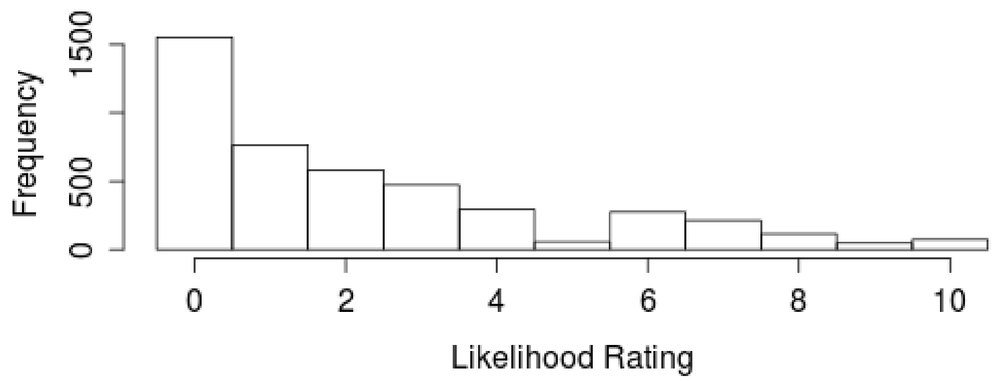

Figure 4.3: Overall distribution of likelihood ratings across explanation strategies. The mode is 0; frequencies decrease thereafter except for the anomalous 5 and a bump around 6.

4.5 A generative model for likelihood ratings

In this section we address **RQ3:** How can we model the influence of explanations on likelihood ratings? Figure 4.4 shows the overall distribution of likelihood ratings, along with the distribution for each social explanation strategy. Although *GoodFrCount* and *GoodFriend* have a higher proportion of likelihood ratings over 5 (see Table 4.4), it's clear that no matter which explanation strategy is used, people have an underlying model of likelihood that has a stronger influence on their ratings than explanations. This also came out through people's comments in Section 4.4.

Both the graphs and the comments suggest that a mixture model for the ratings might be appropriate, thus, we assume that a person's likelihood rating is derived from a probability distribution that is a mixture of two independent distributions. One represents her inherent likelihood estimate for the item, and the other describes the effect of the social explanation. The density function h

for the ratings can be written as:

$$h(x) = af(x) + (1 - a)g(x)$$

where $f(x)$ and $g(x)$ are continuous density functions representing the inherent preferences and explanations respectively. We model x as a continuous variable, although it is discrete in the data. a is a parameter that represents the *rigidness* of the underlying likelihood model, compared to explanations; the higher a is, the less effect explanations have on people's decision-making.

We first specify the base likelihood model, $f(x)$, which in this case includes both a person's personal preferences and the effect of showing an artist's name and photo. Note that we are not modeling actual preferences; rather, we are estimating whether the user is likely to try out an artist. Our data shows a large percentage of artists with very low ratings. This is not surprising, since we chose artists that users claimed they knew little about. Thus, we model $f(x)$ as an exponentially decaying function controlled by α, the *discernment* of an individual; discerning individuals tend to give relatively few high ratings.

$$f(x) = \alpha e^{-\alpha x} \tag{4.1}$$

We now turn to modeling the influence due to social explanations, $g(x)$. People described how explanations with specific friends' names had both positive and negative effects, depending on their perception of that friend's usefulness as a source of information. Those who valued popularity-based explanations mentioned how the number of people associated with an explanation helped them decide. It seems plausible that most explanations, whether names or counts, will only be average in their persuasion, as opposed to very convincing ones on either side. Thus we model the effect of explanations by a μ-centered distribution, as shown in equation 4.2. The center of the distribution gives a sense

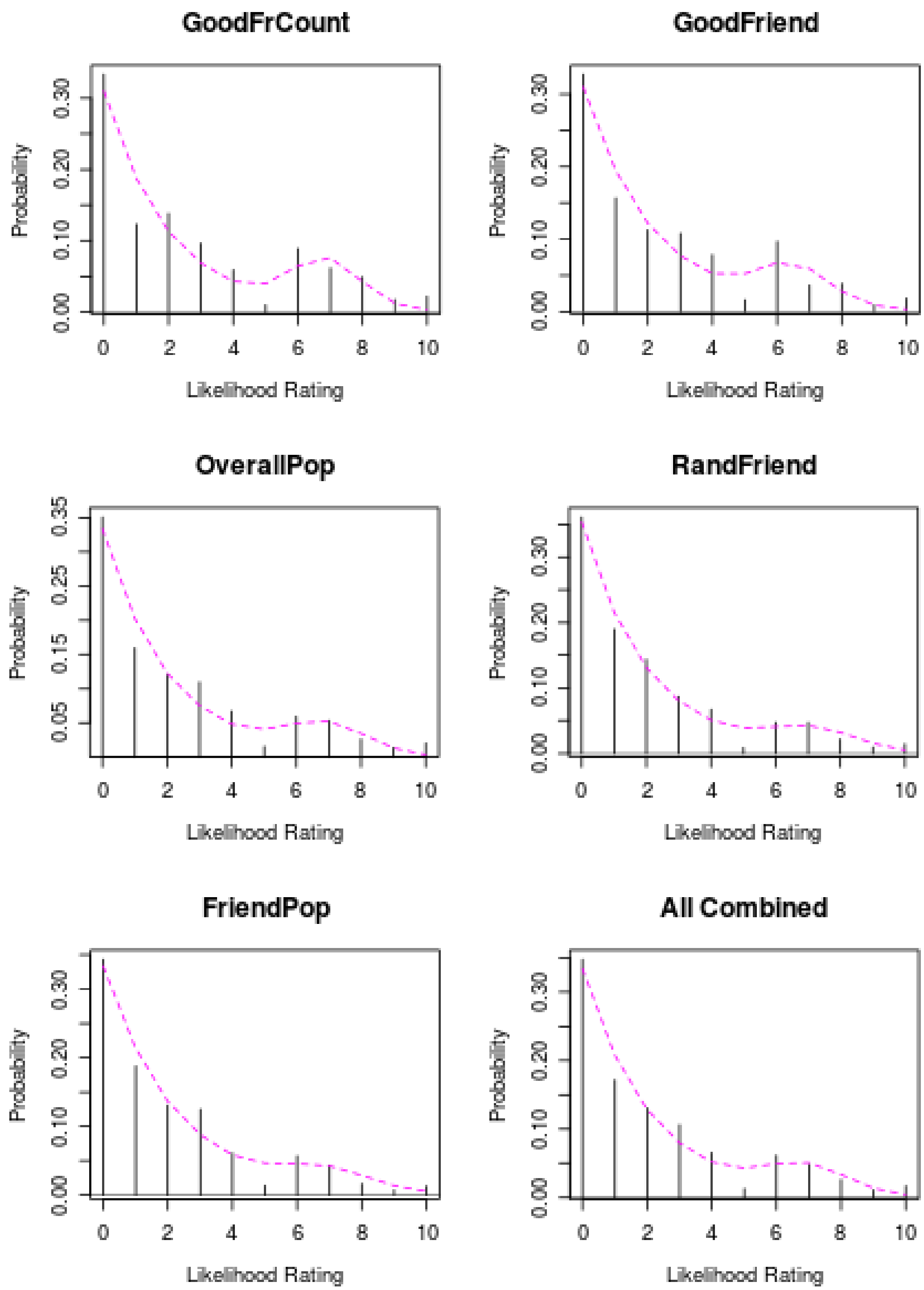

Figure 4.4: Likelihood densities for different explanation strategies. Note how *GoodFrCount* and *GoodFriend* have higher bumps after 5 than others. The line plot shows the fit of our proposed mixture model.

of the *receptiveness* of an individual, while the standard deviation σ represents how different explanations of the same type might affect them differently, the person's *variability*.

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}} \tag{4.2}$$

Putting things together, we get the following mixture model.

$$h(x) = a(\alpha e^{-\alpha x}) + (1-a)(\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}) \tag{4.3}$$

The mean of density $h(x)$ is given by $a/\alpha + (1-a)\mu$. Constraining the mean to be equal to the mean of the original likelihood distribution (c), we have

$$\alpha = \frac{a}{c-(1-a)\mu}$$

Thus, the parameters of the model are the receptiveness (μ), the variability (σ), and the rigidness (a) of an individual. Given an artist and an explanation, a user draws her rating from the distribution $h(x)$ as a mixture of her preference and explanation models specified by the triplet (μ, σ, a). Over a set of the user's ratings, the prevalence of a certain rating x can be approximated by $h(x)$.

4.5.1 Aggregate effects of explanation strategies

We first see how well the model explains the aggregate ratings. For the average user represented by these ratings, we fit the model parameters for ratings from each explanation strategies separately, as well as for the combined case (Figure 4.4). We evaluate the fits using residual standard error.

Explanation	**Error**	α*(computed)*	μ	σ	a
Friend Popularity	0.022	0.44	6.85	3.61	0.74
Random Friend	0.018	0.49	7.10	3.57	0.71
Overall Popularity	0.026	0.49	6.89	3.10	0.66
Good Friend	0.030	0.46	6.46	2.51	0.66
Good Friend & Count	0.034	0.50	6.84	2.26	0.61
Combined	0.022	0.47	6.88	3.05	0.69

Table 4.5: Fit parameters for likelihood densities of different explanation strategies. *GoodFrCount* has the lowest rigidness (a), which suggests people were more swayed by this explanation strategy.

Cl#	**N**	**Ratings**	**Error**	μ	σ	a
1	89	1817	0.001	0.05	78.82	0.62
2	84	1610	0.01	1.43	1.98	0.50
3	64	1119	0.04	4.99	3.22	0.08

Table 4.6: Fitted parameters for three clusters of users. The effect of explanations increases from Cluster 1 to 3, as shown by the values for a.

Table 4.5 shows the fitted parameters for the different explanation strategies. First, we observe that values for α are very close to one another for all strategies, giving weight to the assumption of an inherent discernment parameter for the average user that does not depend on explanation strategy. *GoodFrCount* exhibits the lowest value of a, suggesting that explanations of that type influence user ratings more. The receptiveness (μ) and variability (σ) scores together explain how *GoodFrCount* and *GoodFriend* have more ratings above 5, and hence are more consistently persuasive than the others (and giving further support to our earlier findings).

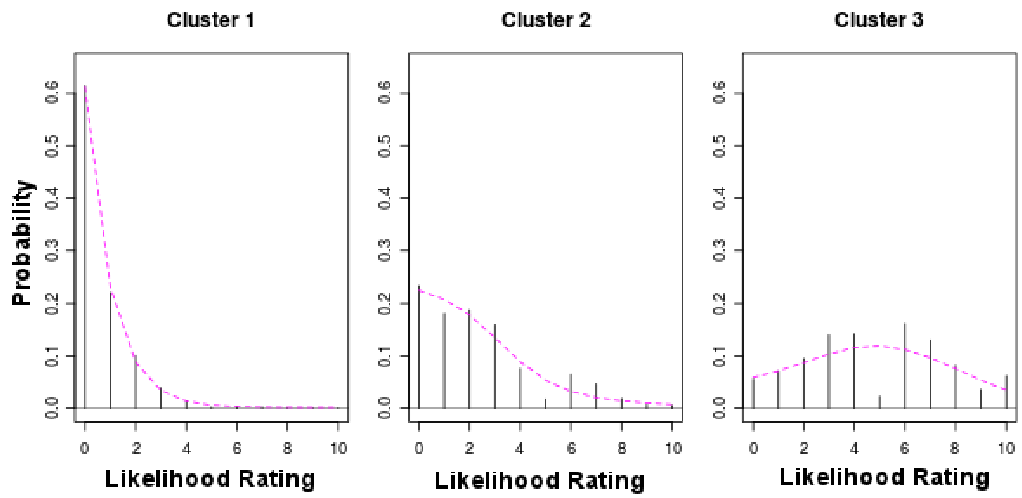

Figure 4.5: Likelihood rating distributions for three clusters of users. These distributions bring out the three types of users: ones on whom explanations had no effect, those who found them useful and those who relied on them more heavily. As before, the line plots show the fitted mixture models.

4.5.2 Different users, different models

Until now, we have analyzed the distribution of the aggregate population. However, as we saw earlier, people are differently influenced by explanations; we now look at how we might refine the models by exploiting the differences in susceptibility to explanations demonstrated by Table 4.3. To do this, we group users into three clusters using a standard k-means algorithm, representing users by their mean and variance of ratings. The mean ratings in the three computed clusters are 0.67, 2.44, and 4.89 respectively. Figure 4.5 shows the distribution of likelihood ratings for the three clusters, and Table 4.6 shows the fitted parameters (we do not fit for individuals for fear of overfitting, since users have about 30 ratings).

The plots give evidence of these three types of users in the data, with cluster 1 roughly representing the "no use or influence" case, cluster 2 representing "useful information", and cluster 3 representing "helped make decision". Parameter a decreases from cluster 1 to 3, suggesting the decreasing rigidness of individuals towards explanations. Clusters 1 and 3 serve as composing examples of the mixture model: cluster 1 illustrates the dominance of the exponential distribution, while cluster 3 is highly gaussian.

Personalization. In Section 4.4, we observed how people are differently susceptible to influence from social explanation. The above data provides weight to that observation, and opens up opportunities for personalization of explanations. In a practical system, this could be done in multiple stages. When users first join the system, they can be assigned population averages for these parameters for each explanation strategy. As they encounter explanations, their preferences can be either explicitly captured (e.g., through rating whether an explanation is helpful, as with Amazon reviews) or inferred based on their reaction to the explained recommendation. As we build up data, we can compare them to cluster models such as those described here to see whether explanations are helpful at all, or have individual models for each user. Eventually, we can infer which types of explanations are the most appropriate for an individual user and prefer showing them when possible.

Explanation	N	Mean	Std. Dev.	Mean (Likelihood)
Friend Popularity	190	4.14	2.85	2.12
Random Friend	192	4.57	3.09	2.08
Overall Popularity	198	4.86	2.92	2.36
Good Friend	133	4.57	2.86	2.52
Good Friend & Count	122	4.63	2.84	2.71

Table 4.7: Listening ratings for artists, binned by explanation strategy. *OverallPop* performs the best in Phase II, but we found no significant difference between the ratings.

4.6 Comparing likelihood and consumption ratings

Having analyzed likelihood ratings, we now focus on **RQ4:** Do high likelihood ratings translate to high consumption ratings in the absence of social explanation? First, we study how the different explanation strategies shown in Phase I affected consumption ratings in Phase II. We then contrast the overall consumption ratings with likelihood ratings.

4.6.1 Do explanations affect consumption ratings?

Table 4.7 shows the consumption ratings for different explanation strategies. We note that the means for consumption are higher than for likelihood. While *GoodFrCount* performed best for likelihood, we find that *OverallPop* records the highest mean for consumption. However, we must be careful with making conclusions since (except for *FriendPop*), the means for different strategies are quite close, and an ANOVA with repeated measures confirms the differences are not significant ($F(4, 378) = 1.64$, $p = 0.2$).

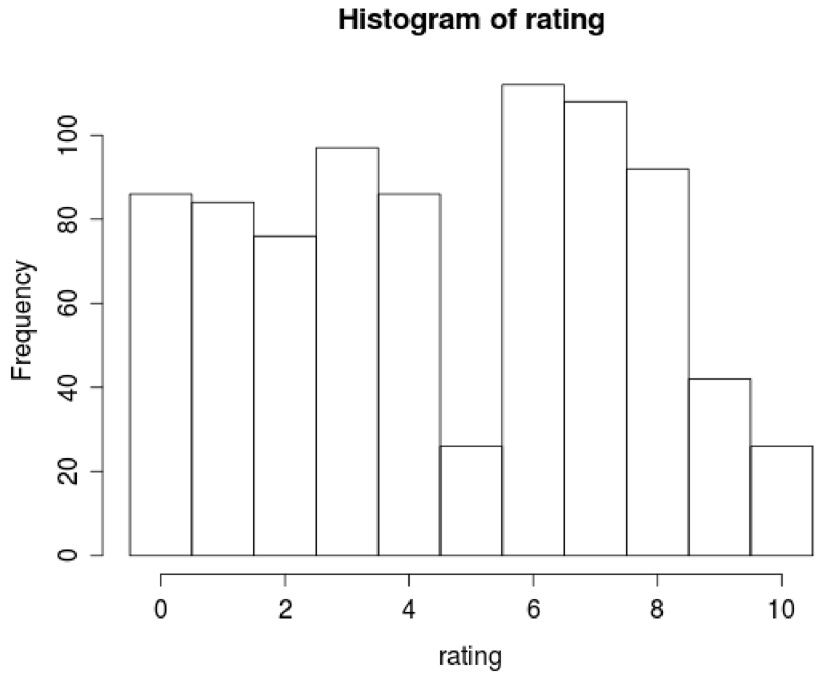

Figure 4.6: Distribution of consumption ratings for all users. Apart from very high ratings {9,10} and the anomalous 5, ratings are evenly distributed.

Since *OverallPop*, *GoodFrCount* and *GoodFriend* all have comparable ratings, this implies that explanations lose their influence on a user's decision after a delay of a few days. This is also shown in figure 4.6 where ratings are close to uniformly distributed across the 11-point scale (except ratings above 8 which show a dip, and the anomalous 5). The different explanation strategies exhibit similar distributions.

4.6.2 Does likelihood predict consumption?

We next look at whether likelihood ratings can predict later consumption ratings. Figure 4.7 shows how the two compare, z-score adjusted to control for

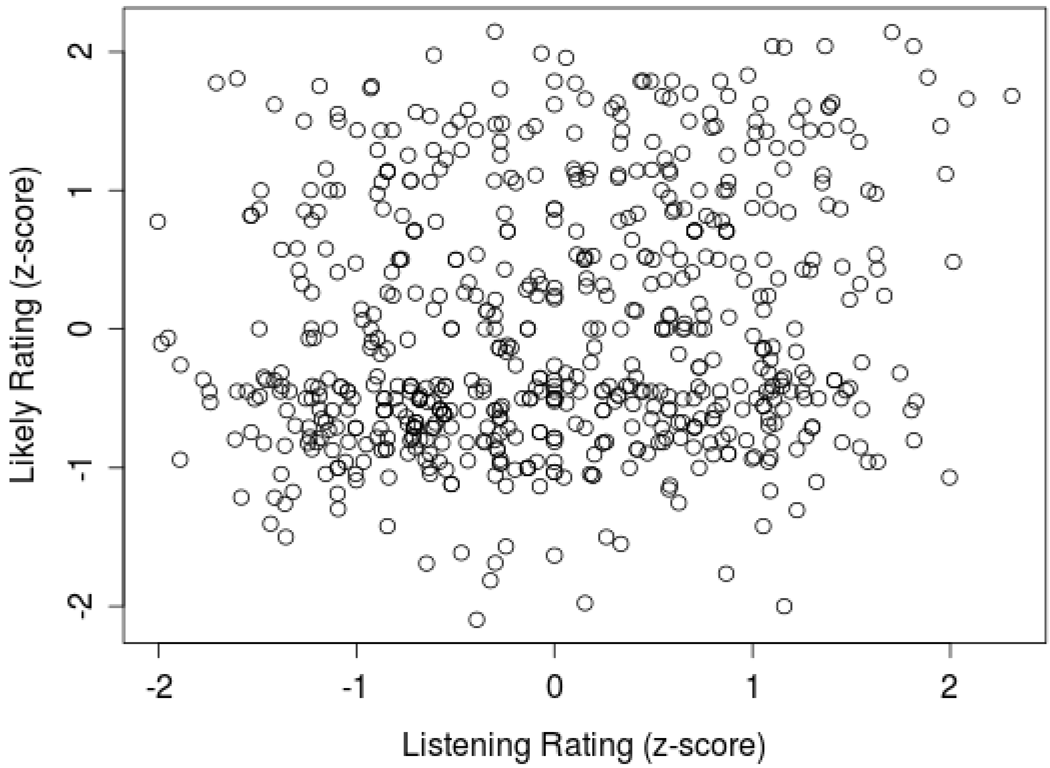

Figure 4.7: Z-scores of likelihood and listening ratings. The two ratings show little correlation (correlation coeff=0.17)

individual biases in numerical ratings. It is apparent that there is little correlation between likelihood and consumption ratings (r = 0.17), suggesting that the persuasiveness and informativeness of an explanation are quite different [59]. In the limiting case where we provide almost all the information about an item in a recommendation (such as recommending pictures), these ratings should be close together. But our results show that these two ratings can be quite far apart, suggesting that it will be useful to think about the two kinds of rating independently.

Considering them separately gives designers more freedom to optimize users' experiences and support different recommendation goals [109]. Our initial proposed model suggests that increasing persuasiveness might increase overall user activity and consumption, though at some risk of eroding trust if the system persuades users to consume items they don't actually like. Systems might also effectively support serendipity by increasing the persuasiveness of explanations for items where the consumption model predicts high ratings and the likelihood model predicts low ratings. Tuning the likelihood threshold might also support users who prefer either riskier or more conservative recommendations.

As a practical import, the notions of likelihood and consumption are natural parallels to the ideas of click-throughs and purchases online. Scenarios of two-phase recommendation are common on the web—for example, clicking a movie recommendation on Netflix and rating it after watching, or clicking a Page recommendation on Facebook and deciding to Like it. In general, current approaches to information filtering assume that the two ratings are correlated (or have access to only one), and hence optimize only one of the rating objectives. For example, recommender systems research focuses mainly on consumption ratings [45], while ad systems typically optimize click-through rates [76, 110]. The gap between likelihood and consumption suggests that rather than optimizing one or the other, it would be fruitful to model both.

4.6.3 Modeling likelihood and consumption separately

One way we could make use of modeling both likelihood and consumption is by conceptualizing the decision-making as a sequential process. A user proceeds to consume an artist recommendation only after he evaluates a high enough likelihood for liking that artist. Thus we could set up an optimization framework:

$$\texttt{maximize } R \; s.t. \; L > \epsilon_u$$

where L and R are the likelihood and consumption ratings for an artist respectively[6]. ϵ can be initialized to a reasonable global value (such as 5 in our case), or a user-specific ϵ_u. Models could iteratively decrement ϵ in case enough recommendations cannot be retrieved, or depending on recommendation goals, may use alternate values for ϵ. For serendipity, one may prefer may prefer to set ϵ lower, for instance. Note that in a domain where R and L are highly correlated, equation reduces to the standard one-phase optimization, maximizing R.

L may depend on the explanation shown, in which case there will be multiple likelihood values for a single item. The models for L and R can be based on standard collaborative filtering models [45] or socially enhanced variants [49].

4.7 Opportunities for improving explanations

We find that social explanations, especially ones involving close friends, are persuasive, though they have secondary effects compared to other sources of information about recommended items. However, our data also shows that persuasive explanations may not be informative—that people's ratings of expected

[6]Our formulation is different from multiple objective optimization [111, 112], since the two objectives are sequential.

liking aren't good proxies of their actual liking of the artists. In this section, we discuss the opportunities for designing explanations that our findings point to.

4.7.1 Improving expectations of informativeness for social explanations

One major finding is that the effect of social explanations is based heavily on a user's expectations of how informative the explanation will be: how they perceive a friend's music tastes to be similar to theirs, or how much they expect to agree with the crowd. Our explanation interfaces were fairly minimal because, as shown in Figure 4.1, many real social explanation settings—particularly those that present a list of recommended items—convey little additional information beyond a title and a social explanation.

Our results suggest that this might be a mistake, and that systems should design explanation interfaces to increase the informativeness of the explanation. For instance, the interface could show information about similarity to people used in social explanations, either by translating similarity metrics into legible indicators (as with some of the explanation interfaces shown in [95]) or by using representative examples of items liked. It could also show information designed to convey expertise, such as the quantity, diversity, or rarity of items an explainer likes. Based on our results, an effective display of this kind of information might make both individual-based and crowd-based social explanations more useful.

4.7.2 Increasing informativeness of explanations

Our results also call the difference between persuasiveness and informativeness into sharp focus [59], showing that social explanations along with basic artist information have a limited ability to help people predict their actual liking of a recommended item. Section 4.6.3 talks about one way to deal with this difference, by modeling persuasiveness (likelihood) and informativeness (consumption) separately.

An alternative approach to managing the gap between likelihood and consumption ratings would be to enrich explanations in order to close the gap. Our suggestions above about increasing the informativeness of social explanation are one such strategy. However, as we've seen, social explanations are just one part of people's decision-making process. A number of other interface elements have been proposed that might help explain recommendations, including tags associated with the item [102], indicators of the system's confidence in the recommendation [109], and the predicted rating itself [20].

These interface elements fall into four main classes: tokens of the item itself (such as genres or music clips for music, or trailers, genres, and actors for a movie); data that people attach to the item (ratings, tags, reviews); metadata about those people (similarity information, their ratings); and information about the recommendation system's algorithms (confidence, predicted ratings). Our hypothesis is that item information is more informative, and social and algorithm information are more persuasive, but this is an open question. The space for designing explanations is rich, and more work is needed to explore the effect of these sources of information on both the persuasiveness and the informativeness of explanations of these various types.

4.8 Summary

We want to point out four main factors around our study that readers should bear in mind when applying our results. First, our users are fairly young and primarily drawn from a single university. Older users might have different perceptions of the usefulness and acceptability of social explanations. Second, we focused on the music domain. This was intentional, to support the collection of consumption ratings, but does mean that our results may not apply in domains where consuming items is more costly in terms of money or time. Third, although we took care not to include artists familiar to a user, they were all chosen from her friends' Likes. This might have introduced a selection bias, especially if a few friends Liked most of the artists. Finally, although we chose a representative sample of social explanation strategies, we did not cover the entire space. Interfaces might show multiple names, or combine other sources of social information.

Still, our results suggest that when it comes to adopting an item in a sharing network like Facebook, preferences of people play a bigger role than social influence due to other people's involvement or endorsement of that item. Even in the presence of explanations and when people presumably are not familiar with the item, their own preferences towards an item play a significant role in deciding their actions despite minimal information being available to guide those preferences.

In the next chapter, we will see how strongly this observation holds for sharing decisions.

CHAPTER 5

HOW DO PREFERENCES AFFECT PEOPLE'S SHARING DECISIONS

> *"I tend to share ... when I understand something about the other person and I think that a certain movie, book, song, etc., might interest that person, whether it be to challenge what someone is saying or feeling, or to reinforce and reaffirm what someone is thinking or feeling. Sure, with close friends, with whom you maintain a close relationship, you might just say, 'hey I liked this movie. check it out.' But I think we do that because we already know the person and the person already knows us. There's a certain level of mutual understanding and respect already established. I say I don't recommend 'all willy-nilly' and I mean that I don't run up to strangers and recommend they read George Orwell, because I don't know anything about that person or how they feel. Unfortunately, to some extent, we do do just that, we all do that sometimes, when we recommend in order to show off our own interests, to show how cool we are, to show how much we know, to show how diversified our interests are, to show how much niche-specific music we listen to. You know, when we're self-interested assholes."* (P23)

Apart from adopting (or liking) an item, sharing it to others is the second fundamental decision on items in sharing networks. Many people get recommendations for movies, music, articles, and products through their social connections both online and off. Online, we often think of sharing primarily as a public broadcast through tweets, status updates, and the like. Much online sharing, however, is narrower, targeted at specific audiences (as with Google+ circles or Pinterest boards) or *directed* [26] at specific individuals through email, chat, and person-to-person messages (e.g., suggesting movies on Netflix [113]).

Further, recent studies show that sharing content through email is still popular [26, 114], surpassing social media in certain product categories [115].

While there is extensive research on understanding people's adoption behavior and predicting their ratings or feedback for items, primarily in the recommender systems community [45], little is known about people's online sharing behavior and its predictability. Sharing to others is a surprisingly complex process affected by a number of considerations, as illustrated by the quote from a study participant above. Untangling this complexity is important for understanding how items are shared (and potentially diffused through a sharing network).

In this chapter, we make progress toward both that question and our larger question about the interplay of preference and influence by examining the role of personal preferences in sharing. To do that, we conducted an empirical study on the PopCore platform where pairs of friends were independently shown the same set of movies and asked to rate those movies and/or share them with their friend. 87 pairs of Facebook friends took part in the study, providing rating and sharing data along with answers to open-ended questions about their sharing behavior. Our results provide several concrete findings about person-to-person sharing.

First, a sharer's personal preference is the dominant factor for sharing items. Shared items are rated significantly higher by sharers than items that aren't shared. Further, sharers' ratings are significantly higher than recipients' ratings for shared items.

Second, participants describe customizing their recommendations based on the recipient, consistent with results from earlier studies [26, 116]. We argue that these two seemingly contrary results—people claiming to personalize but still sharing items that they themselves like—can be best explained by the following decision process: people choose items to share based on their preferences and context, then decide to share or not depending on the recipient. We formalize this process as the *preference-salience* model of sharing and provide some evidence for it.

Third, we show that we can (noisily) predict which items a person might share in the context of the experiment. A model using sharers' and recipients' preferences for movies along with sharers' promiscuity—their overall tendency to share—can predict shares by study participants with more than 75% precision. We also find that item characteristics such as average rating and popularity play little role in predicting sharing decisions compared to people's own preferences for an item.

5.1 Background: Why do people share?

5.1.1 Motivations of individuation and altruism

From past research on word-of-mouth product sharing and information sharing on the web, we know that people share items for many reasons: enhancement of personal image, personal interest in the item, helping others, a desire to help or harm the item's producer, seeking advice, and so on [22, 117, 118]. On balance, these motivations can be seen as special cases of two primary drivers of sharing proposed by Ho and Dempsey: *individuation*, the need to establish a distinct identity for oneself, and *altruism*, the desire to help others [23].

Based on the primary motivations of individuation and altruism, we can expect people to share content that is some balance of their own and others' interests. What that balance is, and how it comes to be so, however, is an open question. A recent study on Twitter suggests that the balance is tilted toward the self: around 80% of people primarily share content about their activities and opinions, while only 20% share informational content more likely to be useful to others [24]. However, this may be because of the broadcast nature of sharing on Twitter where in the absence of a specific recipient, sharing becomes an expression of one's thoughts and ideas [119]. When people share to specific recipients, they may be more likely to think about usefulness for the recipient (and thus be more altruistic) than when they share to larger groups [26, 116].

5.1.2 Mapping motivations to preferences

When sharing items such as movies, these two motivations of individuation and altruism can be mapped to sharing based on one's own preferences or the audience's. These can be estimated from the rich preference data available online. Ratings for movies by the sharer can be considered as a proxy for her preference in movies, which in turn is expected to reflect her self-image (individuation). Similarly, we regard sharing movies that align with the recipient's preferences as other-oriented altruistic behavior. We are interested in studying the relative effect of these two factors.

RQ1: To what extent do people tend to share items that they like themselves (individuation) versus those that they perceive to be relevant for the recipient (altruism)?

In addition, we aim to build models of sharing that account for the role of personal preference in sharing. If successful, these models can explain how people weigh their own and recipients' preferences when sharing items and present a computational framework for predicting future shares. This model can be used to estimate sharing probabilities for different recipients and items; diffusion models can leverage these probabilities to better account for these influences and make more accurate predictions around diffusion. Recommender systems within sharing networks will also benefit from better models of sharing decisions. These models can be used to support sharing online by suggesting which items to share and who to share them with [26, 120].

RQ2: How well can we predict whether an item is shared using readily available information about people's preferences and properties of people and items?

5.2 Description of the user study

To tackle the above questions, we conducted an empirical study on the PopCore platform where pairs of friends were independently shown the same set of movies and asked to rate those movies and/or share them with their friend. 87 pairs of Facebook friends took part in the study, providing rating and sharing data along with answers to open-ended questions about their sharing behavior.

We chose movies as the item domain for several reasons. Movies are a common domain in recommender systems research and an important cultural item that people often share and discuss, making them a natural domain for studying sharing. They are also fairly popular to Like on Facebook [64] (among our participants, $\mu = 18.2, \sigma = 31.8$), allowing us build reasonable user profiles for making recommendations.

5.2.1 Experiment design

Figure 5.1 shows an overview of the experiment, which proceeded in three main stages. In the first stage, a participant (A) signs up for the study and invites one of her Facebook friends as a partner (B) through email sent by our system. When Person B accepts the invitation, the second stage starts. Person B is shown a set of movie recommendations which he is asked to rate and/or share with Person A, followed by a questionnaire that asks about B's relationship with A and his practices around sharing items in general. Person A then gets a notification and, in the third stage, performs the same tasks on the same items, then answers the same questions as Person B.

Showing both partners the same items allows us to get overlapping sharing and rating data to address the research questions. The asynchronous design allows partners to participate independently, making the study easier to complete. To minimize explicit social influence that might affect sharing and rating behaviors [74], participants do not see information about their partner's ratings or shares.

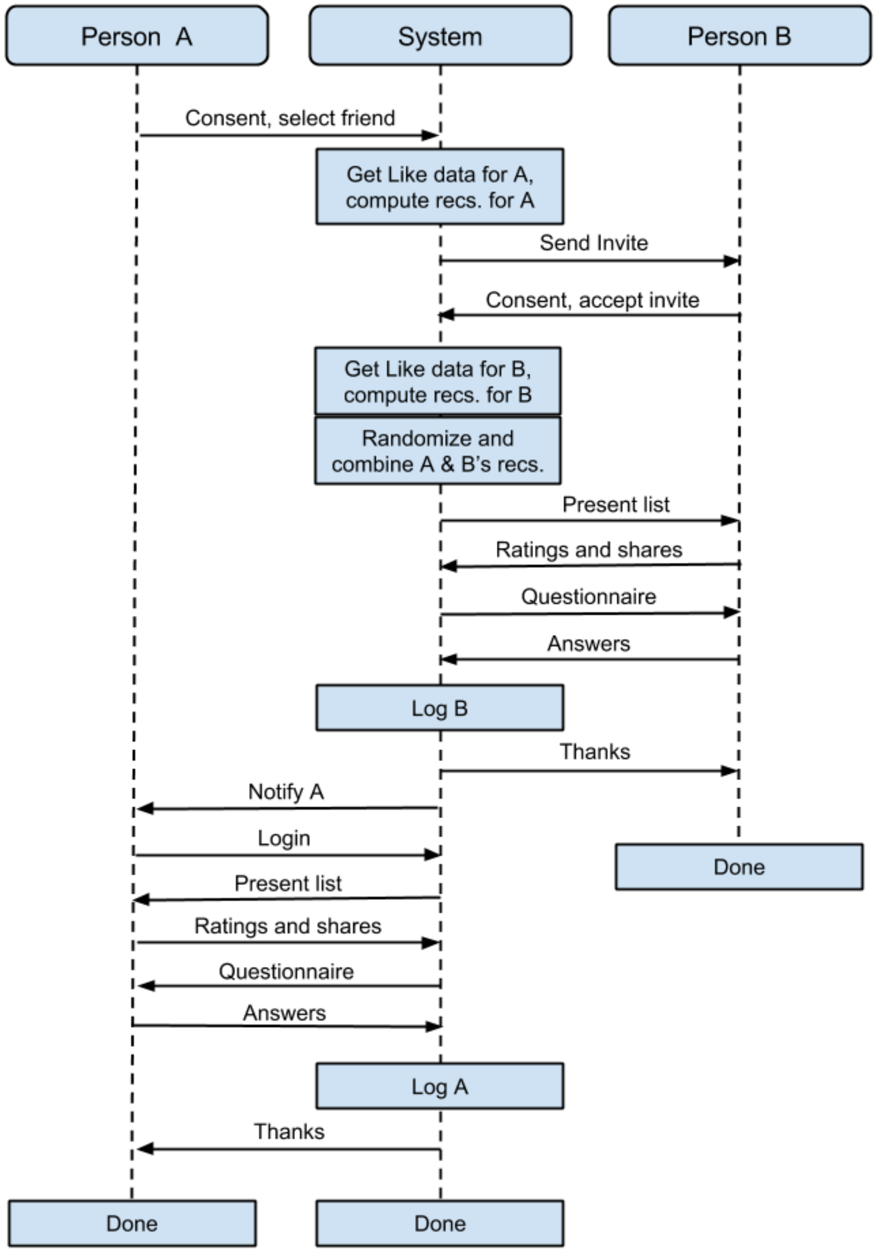

Figure 5.1: The flow of the experiment. Person A invites a Facebook friend (B) to take part in the study. Once B accepts, B rates and shares recommendations computed from both A and B's past movie Likes. Finally, person A logs into the study again and rates and shares an identical set of recommendations. To reduce effects of social influence, there is no direct communication between A and B and the system presents no information about the other person's decisions.

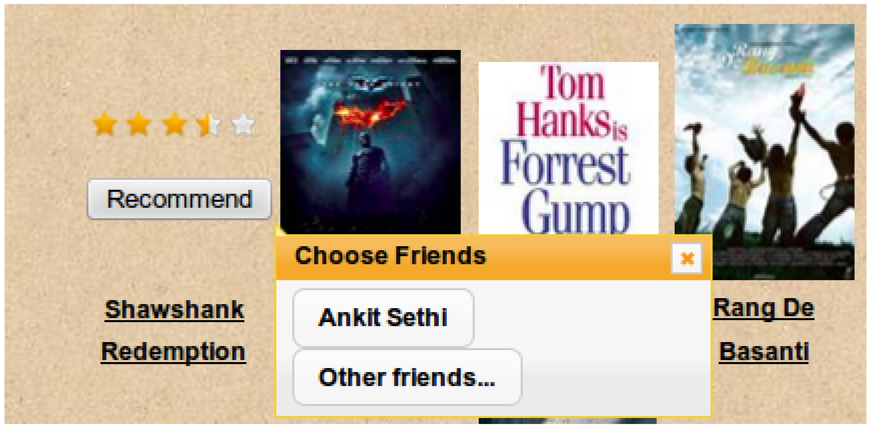

Figure 5.2: A screenshot of the interface. A maximum of 20 movies was shown; participants rate and/or share as many movies as they wish. The study partner was shown as the default recipient.

Figure 5.2 shows a screenshot of the interface, based on PopCore and designed to broadly resemble other systems that recommend lists of items. Participants were free to choose the movies to rate or share among the movies shown. All ratings are on a Likert scale from 0.5-5, with half ratings allowed. Movies are shared by clicking on the Recommend button and providing a short message explaining the recommendation. The system showed the study partner as the default choice for sharing; all but four shares were to their partner so we removed those four shares from the dataset.

After the rating and sharing task, participants completed a short questionnaire asking how close they were to their study partner, as well as open-ended questions about how and why they suggest items, and how and when they receive suggestions from others.

5.2.2 Computing recommendations

For each user, we computed recommendations using PopCore's friends-based k-nearest neighbors algorithm (Chapter 3). We first selected the user's $k = 20$ most similar friends based on Jaccard similarity of their Likes with the user. We then computed a score for each movie based on its similarity-weighted popularity among the k friends:

$$Score(item_i, u) = \frac{\sum_{j=1}^{k} JSim(u, f_j) Likes(f_j, item_i)}{\sum_{j=1}^{k} JSim(u, f_j)}$$

where $Likes$ is 1 if friend f_j likes $item_i$ and 0 otherwise.

The ten highest scoring movies for each user that were not already liked by her were chosen as recommendations. Some users may have less than 10 recommendations because they do not have enough friends or enough Likes in their profile to compute recommendations. Further, Facebook API errors and rate limits prevented some users' Likes from being fetched. Thus, participants saw between 0 and 20 movies; we pruned those who saw less than 10.

Recommendations for both partners were computed and stored in the second stage, ensuring that both saw the same set. Each pair's recommendations were combined and presented in a randomized order to minimize presentation order effects.

5.2.3 Participation

We recruited participants through two sources, a pool of participants at a large northeastern U.S. university and Amazon Mechanical Turk. The university pool consists of students and staff who elect to take part in user studies. We conducted a drawing with a 1/3 chance of winning \$10 gift cards to motivate participation inside the university and paid Mechanical Turk users a flat \$2.50. There were no significant differences in terms of the number of shares, ratings, or Facebook Likes between the groups so we treat them as a composite sample (Table 5.1).

After pruning people who saw fewer than ten recommendations, a total of 87 pairs took part, 59% female. Due to turnover between the three stages, only 142 participants saw recommendations. Figure 5.3 shows the distribution of number of ratings and shares by the participants. 118 participants rated at least one movie and 86 shared at least one movie for a total of 966 ratings and 314 shares to their partner; each session took 11 minutes on average. These are the data that we consider for our analysis.

We expected pairs to know each other (and their preferences) well since people chose their own partners. When asked to evaluate the statement "We are very close to each other", 83% of participants answered "Agree" or "Completely Agree", indicating that most pairs were close ties.

5.2.4 Three non-randomized participant groups

Participants were divided into three groups based on the recommendations they saw during the experiment. Note that these groups are not randomly assigned; as mentioned earlier, Liking behavior and API errors in data fetching affected the recommendations any participant saw and thus which group they are in.

Participants' statistics	**MTurk**	**Univ**	**All**
Number of users who rated at least once	36	82	118
Number of users who shared at least once	28	58	86
Number of ratings/person	6.83	8.81	8.18
Mean rating/person	3.82	3.87	3.85
Number of shares/person	2.69	2.64	2.66
Number of Likes/person	16.2	19.1	18.2

Table 5.1: Aggregate statistics for participants recruited from Amazon Mechanical Turk and the university. About a third of the participants were recruited through Mechanical Turk. There was no significant difference in study activity between the two populations.

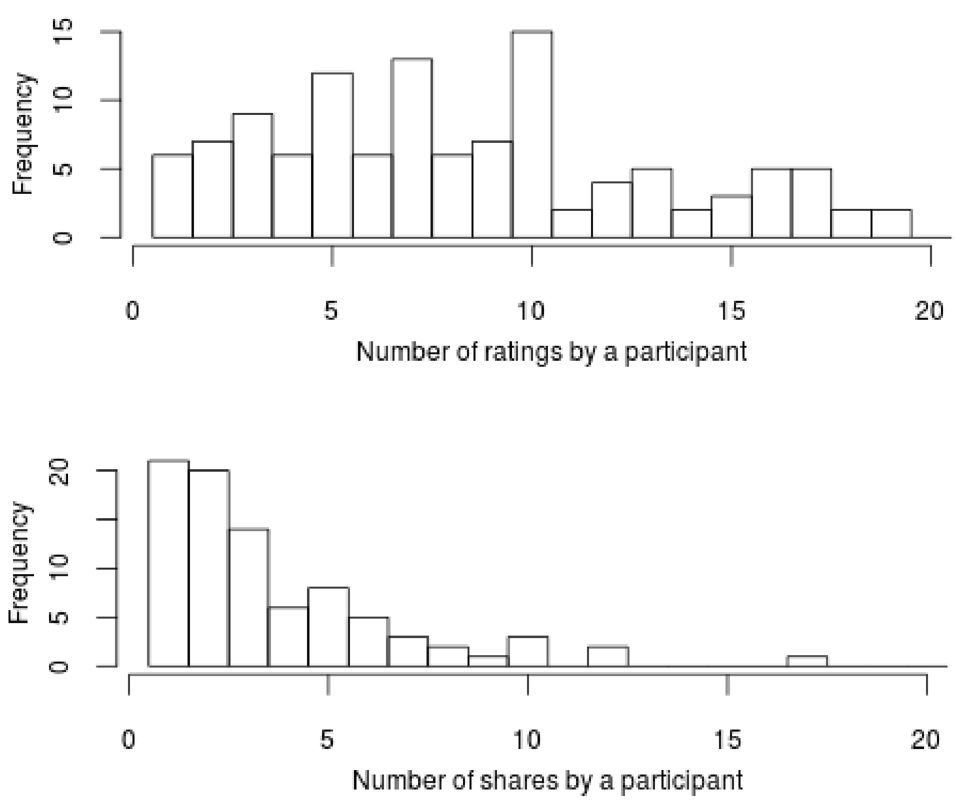

Figure 5.3: Distribution of ratings and shares per participant. On average, people rated about three times more items than they shared.

Condition	**No. of Users**	**Ratings**	**Shares**
Both-Shown	60	609	141
Own-Shown	29	179	96
Other-Shown	29	178	77
All users	118	966	314

Table 5.2: Aggregate rating and sharing statistics for users in the three groups. *Both-Shown* participants saw a mix of recommendations for themselves and their partner, *Own-Shown* participants saw only recommendations made for themselves, and *Other-Shown* only saw recommendations made for their partners.

- *Both-Shown*: All participants who saw more than 10 movies belong to this group. Since our algorithm computes a maximum of 10 recommendations for each user, this means they saw movies recommended based on both their own profile and their partner's. The least number of movies shown is 14 for this group.
- *Own-Shown*: These participants saw 10 movies that were recommended based on their own profile.
- *Other-Shown*: These participants saw 10 movies that were recommended based on their partner's profile. Since both participants in a pair see the same movies, this means that partners of participants in *Own-Shown* are in *Other-Shown* and vice versa.

Table 5.2 shows the breakdown of participants between the three groups.

5.2.5 Sanity checks

Before we discuss factors affecting sharing, a couple of sanity checks for our study design are in order. The first concerns the efficacy of our recommendation algorithm. The average rating of items recommended using a participant's own Likes is significantly higher than those recommended for her partner ($\mu = 3.93, \sigma = 1.00, N = 515$; $\mu = 3.76, \sigma = 1.17, N = 451$; $t(887) = 2.37, p = 0.02; d = 0.2$). This indicates that the algorithm does capture users' preferences to some extent.

Second, while we designed the study so that participants do not have an incentive to tell their partners about their shares (compensation was for completing the study, not for agreeing on movie ratings with their partners), nothing prevents participant B from disclosing her shares to A before A logs on to the study again (especially if they are close to each other). To check whether our study results may have been impacted by such information exchange, we compared the average ratings for received movies (i.e., those that were shared by their partner) between participants who completed the experiment first and those that completed the experiment after their partner. A t-test revealed no significant difference ($\mu_A = 3.87$, $\mu_B = 3.89$), which makes us believe that such disclosure between A and B was not prevalent.

5.3 Sender's preferences and the sharing decision process

We start with **RQ1**, examining the extent to which people share items they like themselves versus those they perceive to be relevant for the recipient. We use both people's sharing data and their open-ended answers to the question: "How/why do you suggest items to people?"

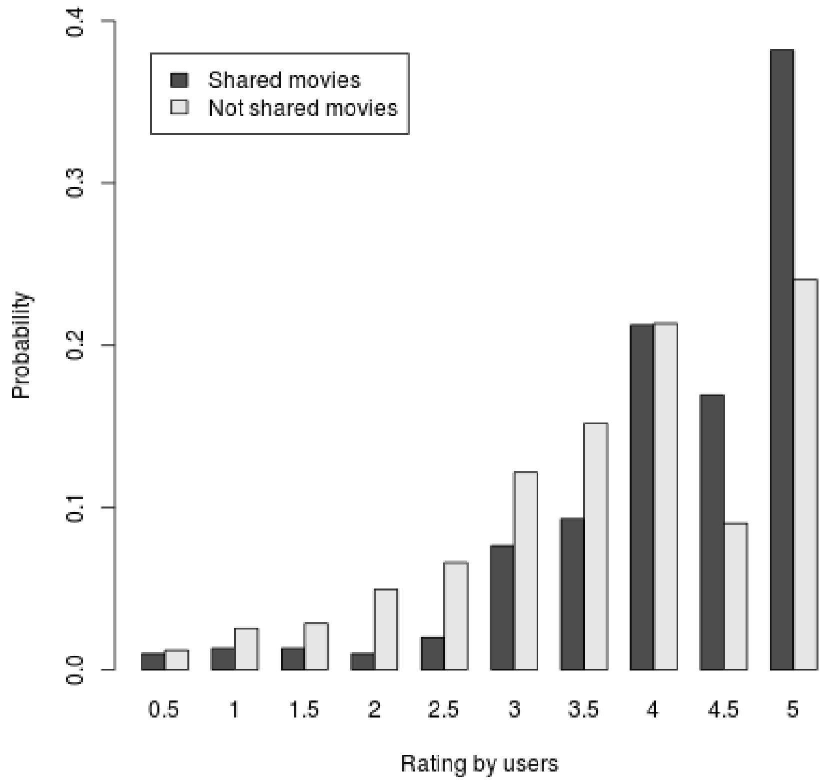

Figure 5.4: Probability of different sharer ratings for shared and non-shared items. Highly rated items are more likely to be shared than lower-rated items.

5.3.1 Senders' own preference matters

We first analyze whether senders tend to share movies they like by comparing their ratings for shared and non-shared movies. The overall distribution of ratings for shared and non-shared movies is shown in Figure 5.4. On average, shared movies are rated higher: 77% of the shared movies are rated 4 or above.

Using the t-test, Table 5.3 shows that for all three groups of participants, shared movies are rated significantly higher than those that are not shared. The effect size is biggest for the *Other-Shown* group. For this group, we would expect the overall average rating to be lower because those movies are targeted at the

Group	Shared			Non-Shared			Significance	Effect Size
	N	μ	σ	N	μ	σ		
Both-Shown	140	4.20	0.93	469	3.81	1.07	$t(258) = 4.20; p < 10^{-4}$	0.4
Own-Shown	90	4.16	0.87	89	3.56	1.05	$t(170) = 4.14; p < 10^{-4}$	0.6
Other-Shown	71	4.18	1.08	107	3.31	1.24	$t(164) = 4.92; p < 10^{-4}$	0.7
All users	301	4.18	0.95	665	3.70	1.11	$t(671) = 6.98; p < 10^{-4}$	0.5

Table 5.3: Comparison of sender ratings for shared and non-shared movies, along with results of an unpaired t-test and Cohen's-d effect size measure. In all three groups, shared movies are significantly higher rated than non-shared movies.

recipient not the sharer, but the mean rating for shared movies ($\mu = 4.18$) is as high as for other groups. This suggests that people still only share the movies they like a lot.

We must caution here that ratings are not strictly normal and independent, which are assumptions for conducting standard significance tests such as the t-test. There is a skew towards higher ratings and ratings for the same movie or by the same user may be interdependent. Thus, we also considered a linear mixed-effects model to account for sender and item variability as a random effect with sharing as a fixed effect.

Mixed-effects analysis (or hierarchical regression) [121] accounts for the interdependence in data by identifying the fixed and random effects on the dependent variable (in our case, people's ratings). We can encode the dependence between ratings by the same user or for the same item as random effects due to user and item, and consider our specific experimental manipulation as the

Group	N	$\chi^2(1)$	p-value
Both-Shown	609	6.6	< 0.01
Own-Shown	179	5.4	0.02
Other-Shown	178	13.6	< 0.001
All users	966	23.5	< 0.001

Table 5.4: Significance tests using a linear mixed-effects analysis for comparing senders' ratings of shared and non-shared movies. Across all groups, shared movies are rated significantly higher.

fixed effect. Being a form of regression, the specific assumptions made are that the residual errors have expectation zero, are independent, and have equal variances.

When comparing ratings given by senders for shared and non-shared movies as in Table 5.3, whether a movie was shared or not can be considered as a fixed effect on the rating. The sender and the movie are random effects on the rating, which leads us to the following model:

$$rating \sim shared\_or\_not + (1|participant) + (1|movie) + \epsilon$$

where ϵ denotes the random error. Using this formulation, we compare this model against a null model which does not incorporate the sharing variable.

$$rating \sim (1|participant) + (1|movie) + \epsilon$$

We analyze the significance of whether a movie was shared or not by comparing the likelihood of the observed data given our model and the null model. Table 5.4 shows the results, using *lme4* in R[1], including by-participant and by-movie random slopes for the effect of sharing. As before, shared movies are rated significantly higher than non-shared ones in all three groups.

[1] `http://CRAN.R-project.org/package=lme4`

5.3.2 Item characteristics are not informative

One possible explanation for shared movies having higher ratings is that sharers may only share high quality or popular movies. To check this, we collected average rating and popularity data from the popular movie reviewing website IMDB[2]. For each movie, IMDB reports an average rating on a scale of 1-10 (*IMDB rating*) and the number of people who have rated that movie (*IMDB popularity*).

We find that there is no significant difference between shared and non-shared movies for either IMDB rating ($\mu = 7.64, \sigma = 1.23; \mu = 7.48, \sigma = 1.20$) or IMDB popularity ($\mu = 11.2M, \sigma = 9.68M; \mu = 13.1M, \sigma = 10M$). This indicates that aggregate opinions about items such as average rating or popularity did not matter much when sharing movies. These results align well with the motivation of individuation, which suggests that people will share items that help establish a distinct identity for themselves.

5.3.3 Participants' responses support individuation

These results are supported by participants' accounts of how they select items to share. For more than half of the participants, liking the item themselves is the most important factor in sharing an item with someone.

> *"Usually when I suggest, it depends on the item, not the target individual, because I want to share what I enjoyed."* (P8)

[2] Internet Movie Database www.imdb.com, accessed Feb. 2014.

Sharing items that one likes may also signal expertise [122].

> *"I suggest items to people because in my case, I've usually seen more movies than they have and I have a better relative perspective of what is considered good or bad."* (P61)

It can also be a useful way to have shared experiences and discussions around items.

> *"I suggest because I like something and I want to see if other people feel the same way about an item. When I suggest items to my friends we are able to talk and laugh about the certain item."* (P91)

All of the above can be connected to individuation, or personal preference, as the guiding motivation for sharing.

5.3.4 Sharing promiscuity varies widely

While all participants tended to share movies that matched their preferences, we saw great variability in how much people shared, or their sharing *promiscuity*. Among the users who shared movies, the minimum number of movies shared was 1 and the maximum was 17 ($\mu = 3.65, \sigma = 3.05$), as shown in Figure 5.3.

For many people, sharing is reserved only for *"something I really, really enjoy"* in part because sharing too frequently *"tends to water down my stamp of approval."* (P16)

Selective sharing is also connected to the common problem of managing one's image in social media [123].

> *"Sometimes I'm paranoid that if I suggest items to someone I don't know very well, they will change their perception of me."* (P15)

A likely hypothesis connected to sharing promiscuity is that people tend to select items for sharing in decreasing preference order. This suggests that sharing more items should lead to lower average ratings by both senders and recipients. This is borne out in the data: there is a negative correlation between the number of items shared and both average sender ($corr = -0.31$) and recipient ($corr = -0.36$) ratings.

5.4 How useful are shares for the recipient?

Analysis of recipients' ratings for shared items reveals more about the relative effects of senders' and recipients' personal preference (individuation and altruism, **RQ1**).

5.4.1 Senders rate shared items higher than recipients

A total of 171 shares were rated by both sharers and recipients. Figure 5.5 shows the difference between their ratings. About half of the shares have a higher sender rating and a quarter have equal ratings. A paired t-test for these shares shows that senders' ratings are significantly higher than recipients' ($\mu = 4.19, \mu = 3.88$; $t(170) = 2.90$; $p = 0.002$).

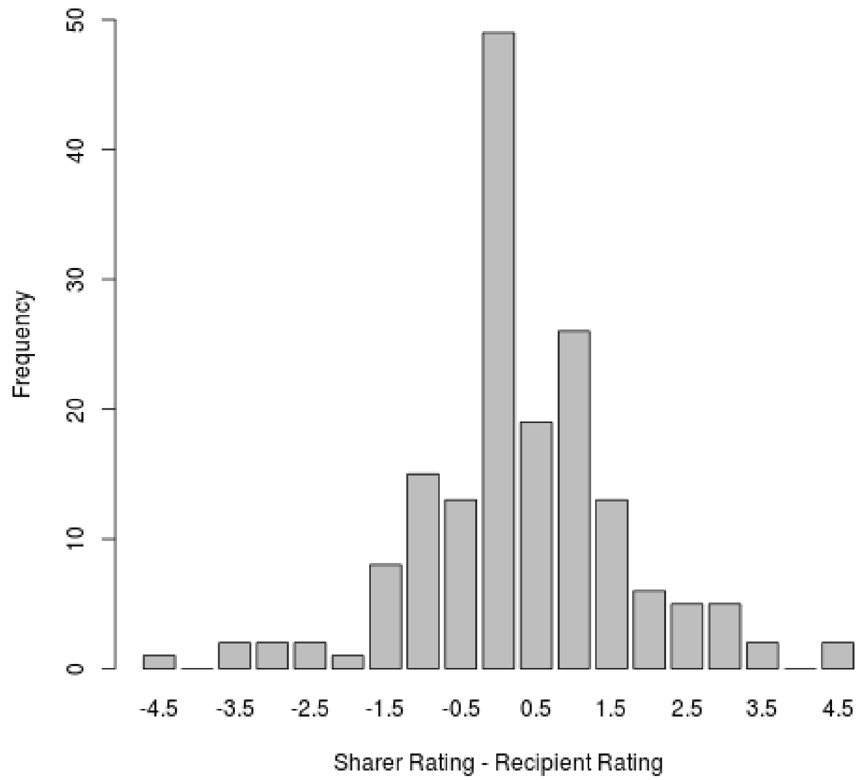

Figure 5.5: Comparison of sender and recipient ratings for shared movies. The x-axis represents the difference between the sender and recipient rating; on average, sender ratings are higher than recipient ratings.

Although recipients' ratings for shared items are lower than senders', many participants claimed that they consider the recipient's preferences before sharing an item.

> *"I make suggestions to people if I think they might gain enjoyment. Obviously it really depends on their personality and their likes/dislikes."* (P22)

This disconnect between people's self-reports and actual sharing behavior is surprising; we will consider likely explanations for it later in Section 5.6.

		Sender Rating		Recipient Rating			
Group	N	μ	σ	μ	σ	Significance	Effect Size
Both-Shown	81	4.12	0.95	3.80	1.05	$t(80) = 2.19; p = 0.01$	0.3
–Own Algorithm	38	4.14	0.94	3.71	1.27	$t(37) = 1.93; p = 0.03$	0.4
–Other Algorithm	43	4.10	0.97	3.88	0.81	$t(42) = 1.14; p = 0.13$	0.2
Own-Shown	49	4.40	0.75	3.67	1.34	$t(48) = 3.52; p < 0.001$	0.7
Other-Shown	41	4.06	1.09	4.28	0.70	$t(40) = 1.10; p = 0.14$	0.2
All users	171	4.19	0.94	3.88	1.09	$t(170) = 2.90; p = 0.002$	0.3

Table 5.5: Comparison of sender and receiver ratings for shared movies using a paired t-test. Across all groups, shared movies have a significantly higher rating from the sender than the recipient when the sender shares from a list close to her movie preferences. The difference is not significant when a sender shares from a list close to the recipient's movie preferences; still, sender ratings in this case are high ($\mu > 4$).

5.4.2 Recipients' ratings depend on the item set shown

When senders saw recommendations from both algorithms (*Both-Shown* group), sender rating is significantly higher than the recipient rating for a shared item (Table 5.5). However, when we break up the shares in the *Both-Shown* condition by algorithm, a more complex picture emerges. Although participants shared movies about equally from both sets of recommendations, the difference in sender and receiver ratings is significant only for the movies selected by sender's *Own Algorithm*.

We see a similar pattern when we compare the *Own-Shown* and *Other-Shown* groups. As shown in Table 5.5, participants in the *Own-Shown* group had significantly higher ratings than the recipient, but not those in the *Other-Shown* group. In fact, recipients' ratings were higher than senders' ratings for shares in the *Other-Shown* group (but, not significantly higher).

It is not surprising that recipient ratings are higher when shares come from movies recommended by *Other Algorithm* because those recommendations are based on the recipient's past Likes. Still, senders' rating for shares is high across groups and algorithms. These findings, coupled with higher ratings by senders for shares versus non-shares, lead us to conclude that one's personal preferences (and thus individuation) are the dominant criterion when choosing movies to share.

5.5 Predicting shares

From the last two sections, it seems that senders' own preferences for movies matter more than the recipients' in sharing decisions. To know more about how senders' and recipients' preferences contribute to a sharing decision, we now examine how well we can predict sharing decisions (**RQ2**) using information about senders, recipients, and items. We build a series of models—starting from simple ones that use a single feature—to predict shares.

5.5.1 Data and method

We have 279 shares for movies that also have IMDB rating and popularity data. We use these shares to create 10 balanced datasets by randomly sampling sets of 279 non-shares. For each model, we perform 10 cross-fold validation in each dataset and average the results. For ease of interpretability, we use a decision tree classifier from the WEKA machine learning toolkit [124].[3]

Computing features. Based on our results earlier, we consider a sharer's own preferences and the recipient's preferences for the item as features for prediction. We also consider the sharer's sharing promiscuity, which is simply the number of shares by her in the training dataset. In addition to these features, we add preference similarity between the sharer and recipient to examine effects of homophily, along with IMDB rating and IMDB popularity to examine effects of item characteristics.

The sharer's and recipient's rating are not available for every item, so we estimate their preference for a movie through a method similar to item-based collaborative filtering [47]. Since Likes on Facebook—which appear on the individual's profile and may be shared automatically to her friends—are typically reserved for items that people really, really liked [64], we convert ratings in the study to a unary scale by denoting each rating 4 or above as a Like and combine those with the people's Likes before the study. We chose 4 as a useful threshold between admissibility and filtering: a threshold of 4.5 would admit too few items and a threshold below 4 may not convey a high degree of preference for the item. For people who did not take part in the experiment but were friends

[3]We also tried random forests, logistic regression, and support vector machines. Results were qualitatively similar.

Features	Precision	Recall	Accuracy
Item-based			
Average IMDB Rating	49.5	61.9	50.1
Popularity	51.8	60.6	51.1
Both	51.8	62.1	50.9
Recipient-based			
Recipient-Item Similarity	64.0	38.5	58.7
Sender-Recipient Similarity	64.8	41.2	58.7
Both	62.9	54.1	60.5
Sender-based			
Sender-Item Similarity	66.3	**79.2**	68.4
Sharing Promiscuity	69.0	72.1	69.1
Both	72.3	74.9	72.7
Sender+Recipient	**78.4**	70.8	**75.7**

Table 5.6: Precision, recall, and accuracy for predicting whether an item is shared. Bold numbers are per-metric maximums. Item features such as popularity and average rating do little better than random guesses. Recipient-based features improve precision, but the most predictive features are connected to the sharer.

of one of the participants, we consider only their Likes before the study, giving a total of 43K users and 785K likes on all movies.

We represent each movie as a set of users who Liked the movie and compute Jaccard similarity between each pair of movies. To estimate a user's preference for a movie, we compute the average Jaccard similarity between the given movie and the movies that a user had Liked. We use this similarity score between a user and a movie as a feature denoting their preference for the movie, computing both the sender's and recipient's preference for each movie.

Finally, we compute the sender-recipient similarity feature as the Jaccard similarity between sets representing each user's movie Likes as defined above.

5.5.2 Prediction performance

Table 5.6 shows each model's precision, recall, and accuracy, common metrics for evaluating such models. Accuracy is the overall fraction of correct predictions of whether an item is shared or not. Sometimes it makes sense to focus only on predicted or actual shares; to do this, we also compute precision and recall. Precision is the fraction of correct predictions among all the items predicted as shares and recall is the fraction of true shares that were correctly predicted.

Item-based features of movies such as quality or popularity have little predictive power, with accuracy close to the 50% that a random predictor would achieve on the balanced dataset we created.

Using only recipients' similarity with a movie gives a precision of 64%, but the recall is low (38%). This is because sharers tend to share what they like, as we found in Section 5.3. Thus, while a high recipient rating is a better than random predictor of a share, it does not cover many other shares that may have lower recipient ratings (which in turn, leads to low recall). If we use the similarity between Likes of the sharer and the recipient directly, then we get comparable precision and recall to a model using recipients' similarity.

Sender-based features are more useful. A sender's similarity with a movie is able to predict whether a movie is shared or not with 66% precision and 79% recall, higher than recipient-based features. These results are consistent with the results around individuation described earlier.

Sharing promiscuity of a sender is also important; shares can be predicted with 69% precision based only on promiscuity. The model, though, is trivial,

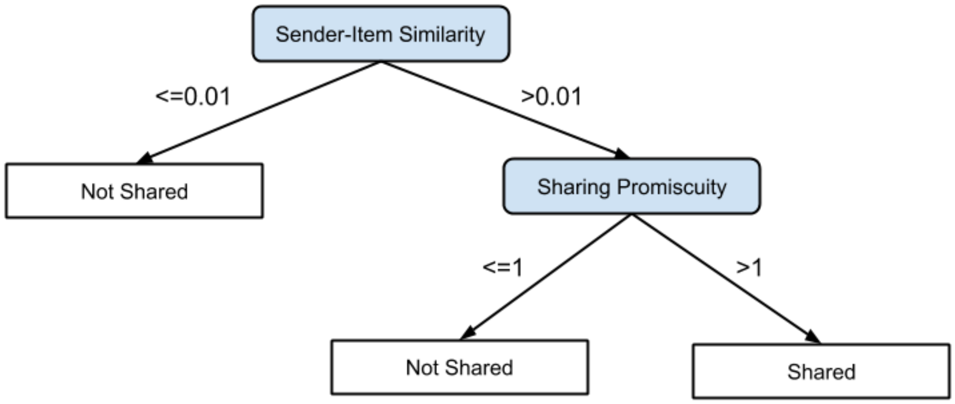

Figure 5.6: Fitted decision tree model based only on sender-based features. Sender-item similarity, corresponding to the sender's own preference for the item, is the most discriminating feature.

predicting that users above a certain threshold of promiscuity would share all movies shown to them while those below the threshold will share none.

The model that includes both promiscuity and similarity (the sender-both line in the table) is more interesting. Precision increases to 72% compared to either alone; a fitted decision tree is shown in Figure 5.6. Similar movies above a threshold are shared depending on the sharer's promiscuity, but not those below it.

Finally, combining sender-based and recipient-based features leads to a decision tree (Figure 5.7) that achieves an accuracy of 76% and precision of 78%. Knowledge about preference similarity between the sender and the recipient helps; however, the decision tree ignores a recipient's similarity to the item.

Although our experiment design restricted the set of movies that can be shared and we used a modified, balanced dataset of shares and non-shares, these results demonstrate the potential of predicting sharing decisions using people's preferences.

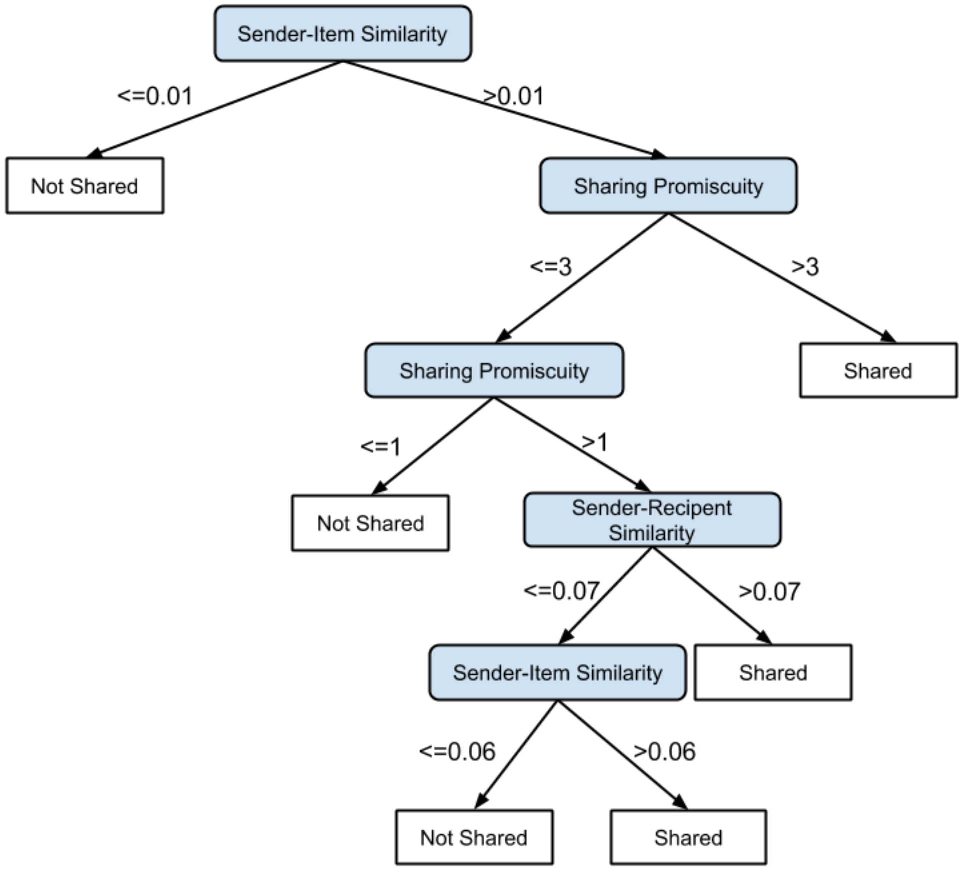

Figure 5.7: Fitted decision tree model based on both sender's and recipient's features. Sender-item similarity, sender's sharing promiscuity and similarity between the sender's and the recipient's preferences are the three features used by the model.

5.6 A preference-salience model for sharing

When broadcasting as on Twitter, past research shows that most people post messages about themselves rather than sharing information [24]. Based on results in communication around tuning messages for the audience [125] and recent work showing that people think more about usefulness for the recipient as the audience size decreases [116], we expected people would weigh recipients' preferences more when sharing to an individual. However, all three signals from our study—people's sharing data, their self-reports and prediction results—underscore the importance of their own preferences. For **RQ1**, the answer is clearly that sharing is more driven by people's own preferences than recipients'.

Yet people claimed to customize their shares for the recipient. Looking at recipients' ratings for shared items, we find that the items shown to a person affected their sharing behavior. When restricted to a set of items recommended for the recipient, people share items that are on average rated comparably by the recipient than their own rating, but not when they are shown a mix of recommendations for them and and their partner. This suggests that while sharing decisions are driven by a sender's own preference, the salience of items shown to the sender can influence what items are shared and consequently, how well those shares are received.

To explain these results, we propose a novel process model based on preference and salience and provide some evidence for it. One way of explaining the disconnect between people's data and descriptions of how they personalize shares for recipients is that people do not really try to balance individuation and altruism when they share items. Rather, they share based on their preference for items and what is salient to them at the moment. Here salience denotes the particular items and recipient that the sharer is thinking of.

> *"I try to assess if the individual that I am recommending to would like the movie that I am suggesting. Otherwise, I do not tell them about the movie, and may think of someone else who would like the movie."* (P5)

In addition to their own preferences, people's selection of a candidate item for sharing also depends on the context that makes a certain item salient. When asked "When do you suggest items to others?", participants responded that they share just after consuming an item, during conversations when a relevant topic comes up, or when asked explicitly.

> *"I usually suggest either after I see the content or if something related comes up in conversation."* (P82)

Thus, a likely process for sharing can be described as follows. People's personal preferences determine shareable items. Among these candidates, some items become salient based on the context and then are shared or not depending on whether the sharer thinks they are suitable for the recipient[4].

This process can explain how participants shared items that they like, yet claim to be personalizing for the recipient. Out of the movies shown, participants considered the movies that they like for sharing, and then decided to share or not in part based on their perception of their partner's preferences. The increase in recommendation quality for shares when selecting from items tuned to recipients underscores the saliency aspect: showing items appropriate for the sharing task led to shares that recipients rated higher.

The preference-salience process is also supported by the structure of the sharing prediction decision tree in Figure 5.7. The biggest factor in deciding whether an item is shared is the sender's personal preference for that item. Additionally, if sender's and recipient's preferences happen to be similar, the chances of sharing an item are higher since the recipient is expected to like what

[4]This is somewhat the dual of the FeedMe system's making possible recipients for an item salient by recommending them as targets [26].

the sender shares. In this model, each sender's sharing promiscuity limits the number of items that she shares.

5.6.1 Comparison with other candidate models

We believe our preference-salience model presents a reasonable abstraction of people's sharing decisions that has more empirical support than two other models we considered:

- *High Quality Model.* It is possible that people simply share higher quality items which are likely to be liked by all. This is supported by the fact that shares are rated highly by the senders, are comparable to recommended items in matching recipients' preferences, and are significantly higher-rated on IMDB than recommendations. However, there is no difference between overall IMDB ratings for shared and non-shared movies, which led us to reject this model.
- *Misguided Altruism Model.* It could also be that people do try to customize shares to recipients but fail because of imperfect knowledge [125]. This is supported by participants' accounts of how they personalize for recipients and the fact that shared items are not rated as highly by recipients as they are by sharers. However, across all groups of participants, senders' own ratings are significantly higher for shares than for non-shares, which indicates that even if people do try to personalize for the recipient, their own preferences still play an important role.

5.6.2 Still, a simplification of a complex process

While we propose the preference-salience model as a likely explanation of our observations, our binarization of motivations into individuation and altruism is a simplification that does not account for other motivations (e.g., to dissuade people from trying an item) or factors (e.g., relationships between people) that affect sharing behavior.

In particular, the closeness of ties between most of our participants might have played a role in people's decisions. Knowing a recipient well increases people's chances of knowing his preferences and customizing their suggestions.

> *"I'll only recommend a movie to a close friend or relative because I know them well enough to know what they would like in a movie."* (P54)

Close ties may also allow people to be more open about their preferences.

> *"With my close friend I feel like I can share anything, but with an acquaintance, I will feel less open to sharing my interests."* (P71)

Finally, people don't just share good items; sharing may also warn others about bad items.

> *"if i really liked something i want others to experience it too...if i hated it i want to help them avoid it."* (P34)

5.7 Limitations and open questions

It is also important to keep in mind the limitations of our study while interpreting the above results. First, although we broadened our sample by recruiting from two different participant pools in the U.S., differences in demographics and culture may affect people's decisions around sharing.

The design of our experiment may also have affected people's sharing behavior. We allow participants to invite their own partners so they can choose people with whom they feel comfortable sharing and whose preferences they would be more likely to know. This led to high tie strength for most of the participant pairs; understanding more about sharing between weaker ties would be an interesting area to study.

We also restricted the set of items in order to get ratings from both members of a pair. Many real contexts also make subsets of an item domain salient, such as in recommendation lists and filtered activity feeds, and we expect our results apply best there. Studying scenarios where items are not made explicitly salient (e.g., searching for an item and sharing) would tell us more the relative effects of salience and personal preferences.

Finally, we studied movies as a specific domain. Though a reasonable choice, sharing decisions in other domains such as news or photos might be different because of differences in cost of consuming an item or ease of sharing items. Our results may also less readily apply to knowledge sharing scenarios where goals may be more strategic and individual preference may be expected to be less discriminating (such as sharing job information or advice).

5.8 Summary

Still, our results demonstrate connections between people's preferences and their sharing behavior that pave the way for better models of sharing in sharing networks. Personal preferences of senders appear to dominate, despite the fact that altruism (and other considerations such as the nature of the relationship and identity management) are both theoretically and self-reportedly present. The preference-salience model serves to explain why this may be so. We posit that people select an item to share based on a combination of their personal preference for it and what is salient at the moment and show that this information can help to predict sharing decisions.

Combined with our results on adopting items from Chapter 4, these findings demonstrate that even though sharing networks are designed around friends and their activities, people's personal preferences play the biggest role in making decisions about adopting and sharing items. For adoption, we saw that even when people saw unfamiliar items and had little accompanying information about the items, their personal preferences towards items dominated their decision. For sharing too, even when sharing to a specific recipient—which increases the chances of consideration for the recipient's preferences as opposed to broadcast sharing—people's personal preferences emerge as the dominant driver of their decisions.

Further, note that in the sharing experiment, recipients did not know which items were shared to them. Thus, we conclude that even without knowledge of who shared an item and any possibility of being influenced by it, changes in the system interface, such as making certain items less or more salient to the sender, can influence what gets shared and consequently, the recipient's response. This finding reveals the intricate interplay between system interfaces (such as recommendations and activity feeds), personal preference and social influence in a sharing network. Algorithms for selecting recommendations and feed items influence which items an individual shares and adopts. These items are then shown to her friends with social explanations, which are adopted (or reshared) based on a combination of personal preferences and social influence (Chapter 4). These adoptions are further shown to friends of friends and the interplay of the feed, personal preference and social influence continues.

Part III

Observational Evidence: Estimating the extent of influence from activity feeds

Both studies on adoption and sharing suggest that personal preferences play a dominant role in people's decisions on items. This indicates that a large part of observed preference locality between friends might just be due to the homophily selection process—people with similar preferences tend to befriend each other—and not due to any social influence from their friends' activities.

It would be useful to see how these results extend to other sharing networks beyond Facebook and for other item domains. In this part of the thesis, we use large-scale observational data from a broad range of sharing networks to attack the question about separating out the effects of homophily and influence. Such an analysis is made possible through public APIs of sharing networks that provide data about people's activities on items as well as their social network relationships. For each user, we obtain data in the form of triplets, *<user, item, timestamp>*, that tell us exactly which items she acted on and when.

We propose a statistical procedure to estimate the extent of influence in people's decisions from such activity data. This procedure utilizes the fact that many sharing networks employ an activity feed—a list of recent actions by friends—as a primary interface element that exposes users to their friends' activities. If we can make a realistic model of a user's feed from the activity data, we can use it to estimate the extent of influence from such feeds. Based on our observations so far, a key issue will be to account for preference similarity between friends, which forms the major endeavor of Chapter 6.

Estimates of influence on data from the sharing networks we studied—Last.fm, Goodreads, Flickr and Flixster—show that personal preferences of people can explain a majority of people's adoption decisions on items. In fact, the effect of influence is not just secondary, it is genuinely small: only about 1% of people's actions on items in these sharing networks are attributable to influence. While these results confirm and extend our experimental findings, they seem contrary to popular perception and scholarly work around influence which do find significant effects of social influence in different decisions that people make. Towards the end of this part, we will discuss how to reconcile the general perception of the power of social influence with the subdued findings from our analysis on a broad range of online sharing activity.

CHAPTER 6

PREFERENCE-BASED MATCHED ESTIMATION (PME): A PROCEDURE FOR ESTIMATING THE EFFECT OF INFLUENCE

> Varun is a Facebook user. He views the articles, pictures or videos that his friends post in Facebook's aggregated news feed and routinely Likes them. Would he have Liked the same posts had Facebook not shown him information about his friends' endorsements of the content? How much do his friends' activities influence what he Likes?

Answering questions like the above requires distinguishing between influence and personal preference in sharing networks. In Part II, we described behavioral experiments that allow us to study the relative effect of personal preference in adopting or sharing items. While experiments provide a clean, controlled setup to study people's decision processes, they are often hard to pull off on online sharing networks. Experiments may be costly or infeasible without access to the network, and can raise ethical concerns around consent even with such access.

It is relatively easy to obtain data (for example, through server logs or from web-based APIs of sharing networks) about people's actions, which make it enticing to develop methods for distinguishing between influence and personal preference using observational data alone. However, outside of controlled experiments, identification of influence is not straightforward. Naive measures, such as simply counting the number of common actions between friends within a given time period likely overestimate influence, as any observed data is simultaneously affected by both influence and personal preference (Chapter 2).

Due to the homophily selection process, people select friends similar to them, and thus when a person copies her friend's action, it is hard to tell whether it is because of underlying similarity in personal preferences or social influence.

Further, even when people are not similar to each other, they may be exposed to the same item through media outside of the sharing network, through a process called *external exposure* [66]. For example, two friends may like the same item after watching an advertisement for it. While some external exposure (such as mass media) does not depend on social ties, other kinds of exposure (such as co-location or shared contexts) are likely to be correlated among friends more than among strangers, in part due to the homophilous nature of social ties. Thus, there might be a similarity in two friends' adoptions even when the main influence for both was an external event. In general, without making broad, parametric assumptions about the influence process or observing all the homophilous attributes (covariates) of people that lead to similarity in actions, a simple analysis of the causal graphical model encoding influence and homophily [126] shows that it is impossible to distinguish influence from homophily and external exposure [89].

One way to get around this problem is to identify and formulate specific mechanisms for influence, based on the context in which decisions on items are made. Instead of a general test for influence, pinning influence down to specific mechanisms can enable methods for estimating influence based on salient features of each mechanism, such as the nature of the system interface and how users interact with it.

In this chapter, we look specifically at influence from activity feeds—a list of recent actions by a user's friends. We choose exposure from feeds as the influ-

Figure 6.1: A reverse chronological feed of songs loved by friends of a user on Last.fm. This interface is shown as a widget on the home page for each logged-in user, along with a similar widget for recent songs listened to by friends.

ence mechanism because these feeds are a primary interface element in many online sharing networks through with people come to know (and are possibly influenced by) their friends' actions [41]. For example, on Last.fm, a sharing network we will study, people leave a trail of their music consumption by *loving* or *listening* to songs. These actions on songs are shared to their friends or followers through an aggregate feed in which each user sees the actions by her friends (Figure 6.1).

Given the prevalence of feed interfaces, we propose an influence estimation procedure which follows directly from a model of the mechanism through which influence from feeds operates in online sharing networks and only requires access to past activity data of users. To do this, we construct a model of how people are exposed to others' activities through such feeds and define a specific process of influence within the context of our model: the *copy-process* of influence, by which people copy or mimic their friends' actions in the feed. Using the assumptions in the model, we estimate the extent to which exposure to friends' activities through an aggregated feed influences a user. Unlike past work on estimating influence [6, 86, 127], our procedure is broadly applicable—requiring only social network and past activity data—and provides both individual-level and network-level estimates. We also present a validation of our procedure that shows that it provides a better estimate of copy-influence than simply tracking common activities between friends within a certain time duration.

6.1 Background: Estimating influence from observational data

There are two major approaches to obtain estimates of influence from observational data. In the first approach, controlling for influence mechanisms, for example, by reversing the direction of directed connections [86], provides conditions for estimating the extent of influence. In the second approach, influence is identified by controlling for homophily, such as by matching up activities of comparable individuals [6] or by shuffling network edges randomly [128].

6.1.1 Controlling for influence

One way to estimate influence is to compare the observed data with an alternative world with no influence and attribute the differences to influence. A core part of such a test is to obtain, or create, data for the alternative world.

For directed edges, Christakis et al. presented an edge-reversal test, where if person A has an edge to B but not vice-versa, then comparing B's influence on A with that of A on B would give us a measure of influence due to the directed edge [86]. The intuition behind the test for influence is that there cannot be any influence from A to B if B does not consider A as a social connection. This test was used to examine whether obesity is contagious: if someone's friend becomes obese, does it influence her to become obese too? Applying this test to health data for people at two different time steps revealed that influence is significantly higher in the direction of the directed edge than the opposite direction.

However, there are methodological and data quality issues with the method [129]. For example, since participants self reported only up to 3 social connections, it is likely that many actual friends were not reported in the data. Further, continuing with the example above, the efficacy of the test depends on the assumption that B has little chance of being influenced by A. This could be relevant when directed edges control exposure to information such as on Twitter, where people do not see their followers' updates. For networks with undirected edges, this method is not useful.

Randomized statistical tests overcome some of the shortcomings of Christakis et al. in creating alternative worlds with zero influence. Randomization, for instance, can remove the causality aspect of influence, as with Anagnostopoulos et al.'s shuffling of all actions by users randomly in time [87]. In the absence of influence, the expected probability of a user acting upon an item given some number of their friends have already done so—called *k*-exposure in other studies [36, 66]—should be the same in the observed data and the time-shuffled data.

Comparing the rate at which the probability of adoption increases with the number of friends in the observed and time-shuffled data can be used to detect the presence of influence. Applying this method to data from Flickr showed no significant difference in the rate coefficient for the two worlds, suggesting the increase in probability of adoption with the number of friends who have already adopted an item may just be due to preference locality. However, the authors do not rule out influence, giving examples from their dataset which demonstrate influence effects, and concede that their method is unable to estimate the extent of such effects.

6.1.2 Controlling for homophily

Randomization may also be used to control for preference similarity and thus estimate influence. La Fond and Neville [128] use shuffling of social network edges to estimate influence given activity data at two time intervals. They first calculate the average correlation in activity between friends. To control for preference similarity due to homophily, they randomize the edges between people and inspect whether friends' actions are correlated even when people form edges randomly. To control for preference similarity due to external exposure, they also subtract out the correlation effect when both edges and preferences are randomized. Any difference that one finds then, must be due to influence; this intuition can be formalized as a randomized test for detecting influence.

Using data on Facebook groups joined by students at a public university at two different timestamps (a year apart), La Fond and Neville found that the relative effect of homophily or influence varies with the group: some groups exhibited a significant influence effect, while others exhibited a significant homophily effect.

Another way to control for preference similarity would be to directly account for its indicators. If we are able to observe underlying attributes (such as demographics, and other features that affect people's preferences) that could lead to similarity in preferences, then we can identify influence by controlling for these observed attributes. Using this intuition, Aral et al. [6] used propensity score matching on such attributes to create matched pairs of users, such that one of them had been exposed to an item through at least one of her friends, and the other had not. Then, the difference in adoption rates within each group should give the relative impact of influence due to friends. This method was applied to adoption data for a new web service on Yahoo network. To control for homophily, Aral et al. listed out 46 attributes based on both personal and network characteristics and found that a majority of adoptions can be explained without any influence effects.

A fundamental problem with their method, however, is that it depends heavily on the choice of underlying similarity attributes, which are often not available for each user. Even if they are, one needs to be convinced that the set of attributes are sufficient for explaining the similarity in actions between people.

6.2 Using personal preferences to control for homophily

Combining ideas from the above two lines of work, we present a broadly applicable statistical procedure for estimating the extent of copy-influence in sharing networks. We control for preference similarity while also limiting the time duration of exposure to friends' actions to model the mechanism of copy-influence in feeds than *k*-exposure models [35, 87]. Further, our estimation procedure for distinguishing between the effects of homophily and the influence of friends' behavior in online social networks does not require a comprehensive list of indicators of homophily and makes reasonable assumptions about influence mechanisms in these systems.

For estimating homophily, we borrow from the recommender systems literature [45] and use similarity metrics based on past activity. This avoids cost and methodological issues around using panel data collected at fixed intervals [88, 127, 128]. Using similarity metrics also allows broader application of the matching technique from Aral et al. [6] that required additional person-level and network attributes, because continuous streams of data about people's actions on online social networks are often publicly available. Specifically, these activity data can be used to construct preference models, which allow us to control for homophily by serving as individual-specific priors for expected actions of people without the effects of social influence.

As for the influence mechanism, we consider copy-influence from feeds as the primary mechanism within sharing networks. Admittedly, feeds are not the only such interface elements: profile pages, collaborative filtering-based recommendations lists, social explanations of presented content, and out-of-system interaction may all convey information and perhaps influence from friends. However, feeds are ubiquitous and commonly studied as conveyors of influence [41, 65, 77], and we argue that they are the dominant feature through which people see behaviors enacted by friends in social networks, and thus the dominant feature through which influence might be conveyed in these networks.

Below we present a model for how people make actions on items in social network feeds and then provide an overview of the copy-influence estimation procedure given the model assumptions.

6.2.1 A simple model for users' interaction with feeds

Let us start by formally defining what we mean by a *feed* within a sharing network. As defined in Chapter 2, the term *friend* refers to a social connection of an individual in a sharing network. We define the feed to be the aggregated activity of all of a user u's friends presented in reverse chronological order. This is an approximation: feeds can contain advertisements or content from outside of a person's chosen friends (e.g., sometimes Facebook presents actions from friends of friends), while algorithmic filtering can hide or reorder items shown in the feed. Still, in many networks it is a very good approximation; we consider how to handle situations where the feed is algorithmically filtered or reordered in Section 6.5.

As shown in Figure 6.1, users often see a feed interface showing their friends' activities whenever they use online social networks. We assume that friends' activities are shown in a reverse chronological order and that users scan the feed from top to bottom. Thus, when a user adopts an item, she may have been recently exposed to some number M of friends' recent actions in their feed. In contrast to k-exposure models [35, 87] that assume people attend to all of their friends' actions, the parameter M represents a user's attention budget for friends' actions and we argue this more realistically models copy-influence in social network feeds. That said, M is also an approximation; in practice users likely have different cutoffs and modeling those would be interesting future work.

We define *copy-actions* as actions by a user which are also listed in the last M items in her feed (e.g., loving one of the songs in Figure 6.1). A baseline measure of copy-influence could be the fraction of actions by a user that are copy-actions, as reported in some studies [90, 91]. Note, however, that all copy-actions may not be due to copy-influence. They could be based on her personal preferences (and common to the friends' feed due to homophily), or driven by common external exposure (e.g., seeing an advertisement or being present at a local music event). Our goal is to estimate which actions are due to *copy-influence*: copy-actions that can't be attributed to personal preferences or external influences, and thus are more likely to represent situations in which a friend's activity influenced the user's.

6.2.2 Basis for estimation of copy-influence

As we argued above, even without any copy-influence, it is possible for friends' actions to be more correlated than non-friends' because of homophily selection processes. Let us now consider a hypothetical feed constructed from users who are not friends with the user u. When non-friends' feed actions are correlated with a user's actions, that is most likely due to following their own preferences or having a common external exposure. Influence between the two is ruled out because within our model, a user does not see the non-friends' actions. This intuition drives our procedure for estimating copy-influence: if we can find non-friends who are as similar to a user as that user's friends, we may use them to control for the effects of homophily. Note that this is similar to how La Fond and Neville [128] control for homophily. However, instead of choosing the non-friends randomly, we choose non-friends that are as similar in preferences to a user as her actual friends, to better control for preference similarity.

Our insight is that in a network with a history of activity, we can directly use users' observed activities to represent their preferences and measure similarity between them. These past actions implicitly capture factors such as demographics, prior external and social influence, and other hidden factors that determine people's preferences on items [130, 131]. In other words, the list of past actions provides a reasonable proxy for personal preferences and can be used to control for underlying homophily—any two users with identical action history could be considered to have the same probability of acting on an item in the future, minus any social influence. Thus, we estimate the extent of copy-influence by comparing the number of copy-actions between a user and her friends' feed with the number of copy-actions between a user and the synthetic non-friends' feed—activities from a matched set of non-friends who are as similar to a user as the friends.

In addition to controlling for homophily, our procedure can also control for some kinds of external exposure for the same reason as explained above. These would include mass advertisements or widely popular items where any two users with the same personal preference would have an equal probability of acting on the item, irrespective of the distance between them in the social network. However, for cases where exposure is due to shared context (two friends attending the same music concert), our estimation procedure will not be able to control for it. Thus, the proposed estimate is expected to be a tighter overestimate on the extent of copy-influence than simply counting the fraction of common actions between an individual and her friends.

6.3 Estimating copy-influence from feeds

Our proposed copy-influence estimation procedure proceeds in two phases: *Matching* and *Estimation*. We divide the data into two parts at a fixed time T, performing the matching phase on data before T and the estimation phase on the data after T. In the matching phase, for each user u, we generate a set of non-friends ("similar strangers") who at time T are as close in preferences to the user as their friends. In the estimation phase, we compute the percentage of actions taken after time T by u that are copy-actions of a feed based on friends (F) and copy-actions of a feed based on the pre-computed similar strangers (S). We call the fraction of actions that are common between a user and her friends Friends-Overlap and the fraction of actions that are common between a user and similar strangers Strangers-Overlap.

6.3.1 Preference-based Matched Estimation (PME) procedure

We now formally describe our copy-influence estimation procedure, which we call Preference-based Matched Estimation (PME).

Matching Phase

For each friend f of a core user u, we find a matching non-friend w at random such that both of the following conditions are satisfied:

- The similarity between the non-friend w and u is approximately equal to the similarity between f and u. We compute similarity between two users by using the Jaccard measure between their activity streams up to time T. Let $A^{(u)}_{0,T}$ denote the activity stream of a user u consisting of all her actions until time T. Then, we compute the similarity between two users u and v as:

$$Sim(u,v) = J(A^{(u)}_{0,T}, A^{(v)}_{0,T}) = \frac{|A^{(u)}_{0,T} \bigcap A^{(v)}_{0,T}|}{|A^{(u)}_{0,T} \bigcup A^{(v)}_{0,T}|}$$

- The number of actions by the non-friend $|A^{(w)}|$ is approximately equal to the number of actions by the friend $|A^{(f)}|$, up to time T. Assuming that the rate of activity stays the same before and after T, this condition ensures the non-friend and friend are expected to have an equal number of actions that will appear in u's feed after T.

We compute both these conditions on data prior to time T to ensure that we do not peek into the future: matched non-friends are dependent only on activity prior to the copy-influence estimation phase.

To implement the matching phase, we sample a non-friend randomly (without replacement) and check whether it matches with an unmatched friend until there are no more unmatched friends left, or no more non-friends to choose. We allow matches to be approximately equal: ϵ_s is the allowed percentage difference in similarity between matched non-friends and friends. Using a percentage instead of the raw difference helps to normalize for different levels of similarity. Similarly, the percentage difference in the number of actions between non-friend and friend should be at most ϵ_a.

Estimation Phase

For the data after time T, we compute the percentage of actions taken by u that copied recent actions by either the set of friends (F) or similar strangers (S) that we computed in the matching phase. Because we assume that people have a finite amount of attention for their feed, we only consider the M most recent actions by the set before each action of u.

More formally, let $A^{(u)}_{T,\infty}$ denote u's activity stream after time T, and $Feed^{(u,W)}_M$ denote the most recent M actions taken by a set of users W before u acts on a given item. We define the *Overlap* between u and the users in W as:

$$Overlap^{(u,W)}_M = \frac{\sum_{a \in A^{(u)}_{T,\infty}} 1\{a \in Feed^{(u,W)}_M\}}{|A^{(u)}_{T,\infty}|}$$

where $1\{x\}$ represents the indicator function which is 1 whenever x is true and 0 otherwise.

The difference in *Overlap* between a user and her friends ($FriendsOverlap$) versus the similar strangers ($StrangersOverlap$) should give us an estimate of the copy-influence due to the friends' activity feed, over and above the homophily effects captured by similarity in preferences with the non-friends, and over and above any external influences that affect both friends and non-friends.

$$CopyInfluence_u = Overlap_M^{(u,F)} - Overlap_M^{(u,S)}$$

where F denotes the friends of a user and S denotes the non-friends, or the similar strangers.

The mean of this per-user copy-influence estimate over all users gives us an average estimate of copy-influence in a sharing network.

6.3.2 Interpretation

Note that this estimate ranges between -1 and 1, since the estimate is just the difference between two fractions for each user. An estimate close to 1 implies that copy-influence is the dominant force driving people's actions, while an estimate close to zero implies that all of Friends-Overlap can be explained by underlying similarity in preferences. In cases where friends have lower overlap with a user than non-friends, the estimate can also be negative. This indicates that Friends-Overlap is no better than Strangers-Overlap from similar non-friends (e.g., when a person tends to adopt items that are popular outside her ego network), and thus we consider copy-influence to be zero in such cases.

6.4 Validation on semi-synthetic data

To check the efficacy of the proposed procedure in identifying copy-influence, we first run it on simulated worlds based on data from Last.fm, where we fix the

Feature	Listen	Love
Number of users with ≥ 10 actions	312461	437299
Number of core users	96029	141346
Mean number of friends per user (with standard error)	(75;0.7)	(70;0.6)
Number of actions	656M	140M
Mean number of actions per user	2101	320
Number of songs	23M	13M
Mean number of actions per song	28	10.8

Table 6.1: Descriptive statistics for the Last.fm dataset. On average, each user listened to 2101 songs during the 3 month period and loved a total of 320 songs during his lifetime.

relative effects of copy-influence, personal preference and external exposure by generating simulated activity streams of users. We consider six cases for evaluation: three cases where only one of the three processes is active in the sharing network, and three when there is a mixture of copy-influence and personal preference active.

Let us first describe how we collected social network and preference data from Last.fm, a sharing network for music. Using the underlying social network thus obtained, we present a sanity check for our influence estimation method in Section 6.4.2.

6.4.1 Describing the Last.fm dataset

Last.fm is a music service that records the songs that its users listen to on the last.fm website or supported desktop/mobile devices. Users can listen to, love, or ban songs. It also allows users to add other users as friends; both parties have to agree, so these links are undirected. Each user sees her friends' recent activity (songs listened to and loved) on her last.fm homepage (see Figure 6.1), aggregated and presented in two reverse chronologically ordered widgets—one for friends' loves and one for listens—in the way our model of copy-influence assumes.

We used Last.fm's API to collect listens, loves and network data for users. Because Last.fm's API (and many other APIs) only returns the current list of friends for each user without timestamps for when links were created, we run the risk of incorrectly considering someone as a friend of a user before the actual link was made. To reduce this problem, we randomly selected 1000 user ids of people who joined before 2010, with the thought that these older members of the system would tend to have more stable friend networks.

Starting with this seed set, we followed a weighted breadth-first search to obtain other users, adding friends to the search queue weighted by the number of already-found users they were friends with. This weighting resulted in a reasonably well-connected component of the last.fm social graph. The crawl was completed over the months of April-June 2014.

In addition to the social network, we also collected users' timestamped actions on items through the end of February 2014. For loves, we collected the user's entire history since they joined; for listening, which is much more frequent, we collected songs they had listened to starting in November 2013 to keep the dataset size reasonable. For both listen and love actions, we filtered out any users with less than 10 actions. Table 6.1 shows some statistics for the data we collected. Although listening is a more frequent activity, the number of users with at least 10 listen actions is fewer than the corresponding number for the love action (Table 6.1). This is because we collected listening data for only

3 months, so users who were inactive during the period will not appear in the listening dataset.

Since we collected a sample of the entire social network, some users do not have all of their friends in the dataset. We fetched the actual number of friends for each user from the Last.fm API and labeled users that have at least 75%[1] of their friends in the dataset as *core users*. We apply the PME procedure to only such core users, for whom we have a reasonable sample of the their total friends.

6.4.2 Generating semi-synthetic data

The three processes are operationalized as follows:

- **Copy-influence**: Analogous to a reverse chronological feed, a user selects an item at random from a set containing the last M items acted upon by her friends.
- **Personal preference**: First, we select the k most similar users to the current user by comparing the Jaccard similarity of their current activity streams. A user then selects an item at random from the last M items acted upon by these k most similar users.
- **External exposure**: We model such exposure by assuming that a user selects the next item to act upon randomly from the set of all items, weighted by their current popularity.

[1]We chose the threshold percentage 75% as a tradeoff between having a representative sample for friends and being too restrictive for filtering. We also tried thresholds of 50, 90 and 100 and did not see a significant change in our analysis.

For our experiments, we selected time T at three equally-spaced timestamps: 2014/01/01, 2013/10/01 and 2013/07/01. We choose values closer to our crawl date so that the friend set that we use for estimation is closest to the actual friend set. To generate synthetic data, we start from the state of the Last.fm loves dataset at time T, after which we replace the songs that users actually loved with songs generated by either the copy-influence, personal preference or external exposure process, while maintaining the original social network and timestamps of actions. For cases where we have a mixture of copy-influence and personal preference, we fix the relative probability of selecting copy-influence over personal preference and each user decides which of the processes to use for his next action based on this probability.

For the results presented, we set $M = 10$, although we also tried $M = \{3, 15, 20\}$ and get the same general results. For the personal preference process, we choose a low value of $k = 10$ as these users are more likely to be actually similar to a user's personal preference. Both ϵ_s and ϵ_a were set to 0.1, thus ensuring that the differences are within 10% of the corresponding similarity and activity for friends of a user. To get reliable estimates for similarity and copy-influence before and after time T respectively, we consider only those users who have at least 10 actions both before and after T. Finally, we generated data 100 times using each process and ran the PME procedure for determining the extent of copy-influence in each. Results shown are averaged across the 100 runs and across all three timestamps.

Process	**Friends-Overlap**	**Copy-Influence**	**Std. Error**
External Exposure (EE)	0.0001	$-2.4 * 10^{-5}$	$8.1 * 10^{-6}$
Personal Preference (PP)	0.04	0.001	0.0001
Copy-Influence (CI)	1.00	1.00	0.0004
CI-PP (50%-50%)	0.529	0.501	0.0001
CI-PP (10%-90%)	0.156	0.102	0.0001
CI-PP (1%-99%)	0.055	0.011	0.0002

Table 6.2: Sanity check on the proposed PME procedure using loves on songs, showing Friends-Overlap, copy-influence estimate and standard error on the copy-influence estimate for each process. Each dataset simulates either external exposure, personal preference, copy-influence or a mixture of personal preference and influence processes. The test correctly does not ascribe most of the copy-actions in homophily and external exposure processes to copy-influence. For mixtures involving copy-influence, the test retrieves the true probability of copy-influence with a lower error than Friends-Overlap.

6.4.3 PME procedure recovers simulated copy-influence

Observed Friends-Overlap

Before we report the copy-influence estimates, let us first look at the observed Friends-Overlap. This would be the naive estimate of copy-influence in case we do not control for homophily effects. Comparing the value of Friends-Overlap and the actual copy-influence estimate gives the amount of correlation that the PME procedure is able to rule out copy-influence for. We would expect relatively high Friends-Overlap for the copy-influence process, and a low Friends-Overlap in the external exposure process. In addition, due to latent homophily between friends, we expect Friends-Overlap for the personal preference process to be greater than that for external exposure.

Table 6.2 shows the mean Friends-Overlap for all three processes. Friends-Overlap for copy-influence is 1 because users always selected songs from their friends' feed, while Friends-Overlap for external exposure is less than 10^{-4}. Friends-Overlap for personal preference is higher than that for external exposure, giving evidence that an individual's preferences are similar to her friends' preferences. However, this measure does not tell us whether preferences became similar due to homophily or due to copy-influence from exposure to friends' actions.

Copy-influence estimate

We now use our PME procedure over the semi-synthetic data to estimate the effect of copy-influence due to exposure to friends' actions. As the third column in Table 6.2 shows, our copy-influence estimate is able to correctly rule out most of the correlated actions in external exposure and personal preference processes, while it still shows a high copy-influence estimate (rounded to 1.00) for the copy-influence process.

Likewise, the PME procedure is able to provide better estimates of the true copy-influence than Friends-Overlap in the cases with a mixture of personal preference and copy-influence. However, for all the cases, the copy-influence estimate is slightly higher than the true extent of copy-influence that we fixed while generating the data. Even for the personal preference process, our test is not able to rule out copy-influence completely and provides a copy-influence estimate of 0.001. The reason is that our matching may be inexact: in theory, for the personal preference process, matched non-friends should have an equal correlation with the user as her friends, but in practice, our measure of preference similarity may not be able to capture their preferences completely.

Nevertheless, the observed error is much lower than that obtained with Friends-Overlap, so accounting for preference similarity provides a more accurate estimate of copy-influence.

6.5 Applicability to online sharing networks

We presented a simple estimation procedure for separating copy-influence from preference behavior in online sharing networks that does not need any additional person-level attributes, does not depend on the directionality of edges, and provides both overall and person-level estimates of not just the presence but the amount of copy-influence. Additionally, the procedure requires only activity data and social network data for users, which is easily available through activity logs (and for many sharing networks, publicly available through web APIs), thus making it a well-suited procedure to apply to online sharing networks.

Before applying the PME procedure to an online sharing network, it is important to verify whether the specific network is amenable to the assumptions laid out in our model. We make two major assumptions: use personal preferences and matching as a proxy for homophily, and consider a reverse chronological feed.

Preference and matching as proxy for homophily. We use preference similarity as a proxy for modeling underlying similarity between people. To do this, one needs to have sufficient data to make reasonable preference models; this appears to be not a problem for many online social networks in which users generate large volumes of activity.

We also chose to account for personal preference by matching friends with non-friends. A natural alternative would be to directly compute a user's affinity for an item (e.g., using a recommender algorithm [45]) and use that to control for a user's own preference. However, the drawback is that the interpretation of influence estimates would depend strongly on the quality of the recommender algorithm as a proxy for personal preference, while such a recommender would not be able to account for external influences that might be evident in other users' activities.

Reverse chronological feed. It is also important to verify that a sharing network does not violate the reverse chronological feed assumption that exposes users to actions by their friends. For instance, the assumption is less appropriate for networks with opaque feed ranking algorithms such as Facebook. In such cases it would be important to capture data about which feed items are actually shown to a user or use knowledge about the algorithm to approximate the real feed from the chronological timestamps.

Still, there are many websites for which such assumptions hold. In the next chapter, we will apply the PME procedure to data from four such websites spanning a broad range of online sharing activity: actions on books, movies, songs and photos.

CHAPTER 7

HOW MUCH DOES INFLUENCE FROM AN ACTIVITY FEED AFFECT PEOPLE'S ADOPTION DECISIONS

> If you read news headlines about the power of influence through sharing networks—e.g., "Facebook as tastemaker", "Does social media influence your buying habits?", "How Facebook can influence your vote this election day", and "Does Facebook's news feed control your world view?"[1]—you might start to get excited (or worried) about the influence from your friends on social media. How powerful is this influence? Here's a simple question to ponder: How many of the recent articles, videos or products that you saw were due to influence from your friends?

Using our preference-based influence estimation procedure (PME), we now estimate the extent of copy-influence due to feeds on different sharing networks. We consider data from four sharing networks: Last.fm for songs, Goodreads for books, Flickr for photos and Flixster for movies. In Chapter 6, we already saw that Last.fm is a sharing network where people *listen* to and *love* songs. Similarly, Goodreads allows users to *rate* books, Flixster allow users to *rate* movies and Flickr allows users to *favorite* photos that other users post on the website. As on Last.fm, on each of these websites, users can act upon items and form (undirected) connections with other users. Finally, all of these websites satisfy

[1]Full articles available at the following URLs:
www.nytimes.com/2011/09/23/technology/facebook-makes-a-push-to-be-a-media-hub.html
www.huffingtonpost.ca/parmjit-parmar/social-media-shopping_b_6306234.html
www.pcworld.com/article/2842958/how-facebook-can-influence-your-vote-this-election-day.html
www.cbsnews.com/news/facebooks-news-feed-limits-your-world-view/

our model assumptions by having a similar feed mechanism, where a user sees aggregated activity by her friends in a (loosely) reverse chronological order[2].

For these sharing networks, our main research goal is to estimate the extent by which activity feeds influence people to copy their friends' actions on items. Copy-influence estimates from the PME procedure highlight two major observations.

First, we find that naive estimates of copy-influence do overestimate such influence, often substantially. The degree of overestimation, however, varies widely across the different datasets. This variation is likely due to differences in characteristics such as item domain, ease of consumption of items and feed design between sharing networks that might affect the prevalence of copy-influence. In addition, we find a wide variation in copy-influence estimates for people.

Second, despite these differences, we find a consistently low overall estimate for the extent of copy-influence: less than 1% of the total user actions in these sites can be attributed to copy-influence from the feed. Even the more generous Friends-Overlap estimate, which, by definition, is an upper bound on the actual copy-influence, indicates that copy-influence accounts for no more than about 3% of total user actions on items.

Overall, these findings show a subdued picture of the role of copy-influence in these sharing networks. At least for the websites we study, personal preferences account for a majority of the actions on items on these sharing networks,

[2]Flixster changed its website after 2010 and moved away from being a sharing network for movies. This dataset was collected before the change and thus, satisfies our assumptions.

confirming and extending our experimental findings on the dominant role of personal preferences in people's decisions from Part II.

7.1 Copy-influence from the friends' feed on Last.fm

We first apply the PME procedure to the actual observed activity of users on Last.fm for both love and listen actions. We used the same parameters as we did for validation on semi-synthetic data (Section 6.4), setting $M = 10$ and $\epsilon_s = \epsilon_a = 0.1$. Since we have listens data only for three months, we set T differently for listen and love actions. For love actions, we set $T = 2013/07/01$ as before, and for listen actions, we set $T = 2014/01/01$. We discuss the robustness of our estimates to changes in these parameters at the end of this section.

A user may listen to the same song more than once, raising the question of how to treat repeated activity. One option would be to only look at the first time a user heard a song, on the assumption that copy-influence plays a minimal role in re-experiencing the song versus a user's own preferences about the song after listening to it. On the other hand, a user might be influenced to re-listen to a song they like by seeing it in their feed; in this case, we would want to measure copy-influence on all actions. For our copy-influence estimates, we consider all actions taken by users, including re-listens.

7.1.1 Friends-Overlap overestimates copy-influence

Our first major observation is that for both listens and loves, Friends-Overlap tends to overestimate copy-influence. Table 7.1 shows the mean effect of copy-

Action on song	Friends-Overlap	Copy-influence	Std. Error
Listen	0.004	0.001	$2.5 * 10^{-5}$
Love	0.023	0.004	$7.8 * 10^{-5}$

Table 7.1: A comparison of copy-actions from the friends' feed (Friends-Overlap) with the proposed copy-influence estimate on Last.fm. For both actions, Friends-Overlap overestimates copy-influence.

influence, along with Friends-Overlap, for listening to or loving songs. In particular, our copy-influence estimate indicates that on average, only 0.4% of the actions by users can be attributed to influence for loves. Note that the copy-influence estimate is only about one-fifth of the naive Friends-Overlap.

Friends-Overlap and copy-influence for loves is higher than those for listens, indicating first, that a higher fraction of love actions are correlated among friends than for listens, and second, a higher fraction among love actions are also copied from friends than for listens. A possible reason could be that loves are rarer, and thus spend a longer time in a user's feed compared to listens. We might also expect loves by other users to be considered as stronger endorsements, and thus, have a higher copy-influence effect than listens.

7.1.2 Variation in the effect of copy-influence within users

In addition to estimating network-level effects of copy-influence, in many cases, it is useful to estimate copy-influence on individual users. One way to interpret individual estimates is that we are measuring the *susceptibility* to copy-influence for an individual [21]. Such an estimate can be used in diffusion models to set personalized thresholds or transmission probabilities, and in recommendation

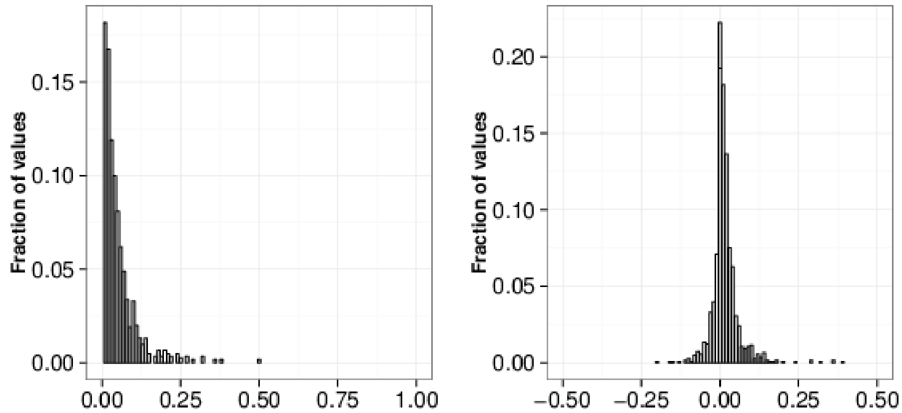

Figure 7.1: Per-user variation of Friends-Overlap (left panel) and copy-influence (right panel) for loves on songs, among users with non-zero Friends-Overlap. Even among the users with non-zero Friends-Overlap, about a third of them have a zero or negative copy-influence estimate, indicating that their actions are not influenced by a feed of their friends' actions.

systems to employ more of friend-based information for more susceptible people, as we showed in Section 4.5.2.

We look into how the effect of copy-influence varies on different users for the *love* action on songs and find a wide variation in the effect of copy-influence among users. A striking feature of Friends-Overlap values over users is that a majority (over 54%) of the values are zero. This implies that more than half of users on Last.fm are not influenced *at all* from the feed of their friends' loves. The high number of zeros makes visual inspection of the full distribution of Friends-Overlap and copy-influence difficult. Thus, we show the distribution of Friends-Overlap and the copy-influence estimate only for users with $Friends - Overlap > 0$ in Figure 7.1. Among these users with non-zero Friends-Overlap, about a third of the users have their copy-influence estimate less than or equal to zero, which indicates that even with non-zero Friends-Overlap, all of their actions can be explained by preference similarity alone.

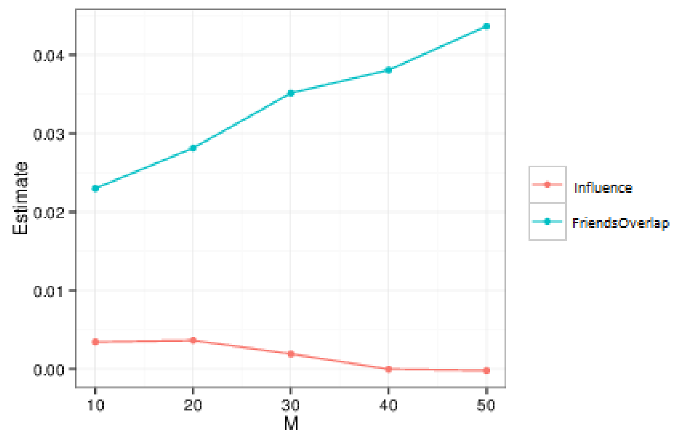

Figure 7.2: Variation of Friends-Overlap and copy-influence for loves on songs as we increase M, the length of the feed from friends that we consider for estimating copy-influence. Blue line shows the Friends-Overlap which increases with increase in M. On the other hand, we observe that the copy-influence estimate (in red) decreases as we increase M.

Overall, the copy-influence estimate is zero or negative for about 70% of core users. This helps to explain the low overall effect we see for copy-influence, as well as providing additional empirical evidence of a wide range of susceptibility among users of a given system [21, 87].

7.1.3 Variation with PME parameters

The parameters we use in the PME procedure are T, M and the two error thresholds, ϵ_s and ϵ_a. To check whether our results are robust to changes in parameters, we tried a range of values for each of the parameters. Let us first consider the two cutoff parameters for the matching phase, ϵ_s and ϵ_a. Increasing ϵ_s allows less similar people to be matched, since a random individual is more likely to be dissimilar than similar to an individual. Similarly, people with a higher number of actions are rarer, and thus increasing ϵ_a allows people with fewer actions than actual friends to be matched. These observations suggest that increasing ϵ_s and ϵ_a should decrease the extent to which we can rule out copy-influence and vice versa, which we do find on varying these parameters. Nevertheless, the high-level finding that most actions could be ruled out as not due to copy-influence stays consistent.

We find an interesting variation on the extent of copy-influence with M, the number of recent past actions by friends that we consider for copy-influence estimation. Figure 7.2 show the variation of both Friends-Overlap and the copy-influence estimate as we increase M. Friends-Overlap increases along with M, which is not surprising as increasing M allows each action from a user to be compared to a larger pool of actions from friends. However, our copy-influence estimate decreases. We are not sure why this happens. It could be that having a larger time window increases our chances of detecting actions due to common external exposure, or that a longer non-friend feed more accurately depicts a person's preferences.

This change in the copy-influence estimate with M underscores a key assumption of our test: a truncated reverse chronological feed. Future work on setting M to personalized values for each user might lead to more fine-grained estimates of susceptibility and copy-influence.

7.2 Estimating copy-influence on other sharing networks

We have focused so far on Last.fm as a running example for explaining and exploring the PME procedure. We now we apply it to compute copy-influence

Feature	Goodreads	Flixster	Flickr
Number of users with $\geq$ 10 actions	252K	50.0K	183K
Number of users with friendship data	252K	48.8K	175K
Average number of friends per user	29	13	74
Number of actions	28M	7.9M	33M
Average number of actions per user	112	157	182
Number of items	1.3M	48.4K	10.9M
Average number of actions per item	21	163	3

Table 7.2: Descriptive statistics for the datasets from Goodreads, Flixster and Flickr. Flixster data has the lowest number of items and consequently, more actions per item (163) than Goodreads (21) and Flickr (3). The average number of actions per user is above 100 for all three datasets.

estimates on other sharing networks and see how our results generalize to different item domains, feed interfaces and system designs.

We use existing datasets from Goodreads [132], Flixster [53] and Flickr [44]. These datasets cover a diverse set of item domains: Goodreads is a sharing network for books, Flixster for movies, and Flickr for photos. As on Last.fm, on each of these websites, users can act upon items and form (undirected) connections with other users. In addition, each sharing network has a feed interface that shows friends' rating or favoriting activities, aggregated and presented in a (loosely) reverse chronologically order in the way our model of copy-influence assumes.

7.2.1 Describing the datasets

We present aggregate statistics for each of the datasets in Table 7.2. The number of items available and the number of actions per item both vary among the three datasets. On average, an item is acted on 3 times on Flickr, 21 times on

Goodreads, and 163 times on Flixster (the same average was 11 loves per song on Last.fm, which is the most similar activity to rating or favoriting items on these websites). In comparison, per-user activity is similar: in all datasets, each user rates or favorites an average of more than 100 items. More details about each dataset can be found in the papers that introduced them [44, 53, 132].

Unlike unary adopt actions on Last.fm and Flickr, Goodreads and Flixster allow users to rate items on a scale of 0.5-5. A higher rating by a friend is indicative of a strong preference for the item, although a rating is shown in a user's feed irrespective of whether it was high or low and is thus a candidate for influencing the user. For the results presented next, we consider all ratings by users of Goodreads and Flixster for our analysis. To better account for preference similarity, we also tried a variation where we filtered out any rating below 3 or 4. The results are qualitatively the same.

Further, since we do not know the real number of friends for each user in these datasets, we consider any user with a non-zero number of friends as a *core* user. All friend relations are still without timestamps, so we assume a static social network and set T so that only 10% of the actions are after time T. For consistency, we use the same values for all other parameters as for Last.fm.

7.2.2 Vast majority of actions are due to personal preference

We now present the results of applying the PME procedure to these datasets. Each user is expected to rate or favorite an item only once, so all of these datasets contain actions on unique items for each user.

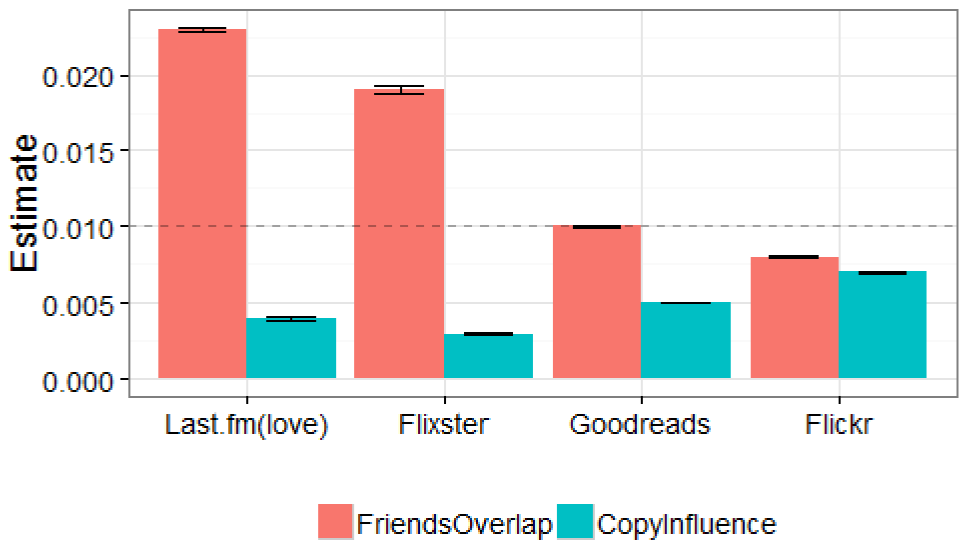

Figure 7.3: Friends-Overlap and copy-influence estimates on different social networks. While both Friends-Overlap and the ratio of Friends-Overlap to copy-influence varies, the copy-influence estimates for all websites fall below 0.01, or less than 1% of the user actions on items on these social networks.

Figure 7.3 shows the Friends-Overlap and copy-influence estimates for all four datasets, along with the standard error on the copy-influence estimate.

We find varying estimates for Friends-Overlap on these datasets, from 0.023 on Last.fm to 0.008 on Flickr. Similarly, the amount of Friends-Overlap explained by preference similarity varies widely; the copy-influence estimate is 15% of Friends-Overlap for Flixster and over 85% of Friends-Overlap for Flickr. Such differences are plausible, and in fact, expected: except for the fact that they are all online sharing networks, these websites differ from each other in many characteristics: their item domains, types of actions, distribution of the actions on items with respect to users, and system interfaces. We will talk about these characteristics in the next section.

However, after controlling for preference similarity, we find that the copy-influence estimates for all four domains fall into a narrow range between 0.003-0.007. This is a surprising result, given the differences between these websites. Interpreting the copy-influence estimate as the average fraction of user actions due to copy-influence, these results imply that less than 1% of the total user actions in these sites can be attributed to copy-influence from the feed.

7.2.3 Copy-influence from feeds is overrated (?)

The above results suggest a subdued picture of the role of copy-influence in online sharing networks. Even without controlling for homophily, we find the percentage of copy-actions (which is an upper bound on the *actual* copy-influence) is low: less than 3% of users' actions are copy-actions on all four datasets (Figure 7.3). While we do not rule out the existence of copy-influence, our estimates indicate that more than 99% of all actions on these websites can be explained without copy-influence. Finally, when we break up the copy-influence estimate for each user (as for song loves on Last.fm), we find that a majority of the users are not influenced by the feed of their friends' activities at all.

In this sense, our work joins past work in questioning the extent of influence-based contagion in online social networks. Just as viral retweets in Twitter are rare and a vast majority of tweets do not even breach the ego network of a Twitter user [40], influence-based copying is a rare event in comparison to all of users' actions on items and affects only some susceptible users of a website. We conclude that even when exposed to feeds, most of people's actions are driven by their current personal preference.

7.3 Factors that affect the extent of copy-influence

That said, we do observe variations in the degree of over-estimation for copy-influence between different actions (listen and love on Last.fm) and between different websites and it will be useful to understand the reasons for these differences. Two factors play a prominent role in affecting users' exposure to their friends on online sharing networks: characteristics of the item space and the design of the feed.

7.3.1 Characteristics of the item space

One set of factors that might affect estimates of copy-influence have to do with properties of the items and domain. For example, photos on Flickr, being user-generated items, are numerous compared to the relatively mass-consumed items such as movies, music or books that we studied on other websites. This leads to the low mean popularity of 3 for a photo that we see in Table 7.2. Further, photos, like songs, are quick consumption items and thus are more amenable to mimicry on exposure from friends' feeds than a book or a movie. A user may favorite a photo right after viewing it in her feed, or love a song after listening to it for a few minutes. For domains like books or movies which take hours to consume, we would expect less of such spontaneous mimicry. Finally, items like books, movies and songs have a well-defined existence outside of the sharing networks we study that might lead to more effects from external exposure. Photos, on the other hand, often exist only on Flickr (like Twitter hashtags in Chapter 2) and thus it may be harder to discover new ones from outside the sharing network's system interfaces.

Item properties	Flickr	Goodreads	Last.fm	Flixster
No external existence	Yes	No	No	No
Sparse actions/item	Yes	Yes	Yes	No
Quick consumption	Yes	No	Yes	No

Table 7.3: A summary of item properties for the four datasets that we studied. Photos on Flickr score well on each of the properties that promotes copy-influence. On the other hand, Flixster does not satisfy any of these properties and delivers the lowest copy-influence estimate among our datasets.

These characteristics of the item space can affect the amount of correlation in activity between friends, as well as the actual copy-influence flowing between them. Table 7.3 summarizes these factors for the four websites we studied. We note that implications from the item characteristics roughly match the copy-influence estimates. The column for Flixster in the table suggests why movie ratings on Flixster may have a low copy-influence: the dataset does not qualify for any of the three factors that promote the likelihood of copy-influence. On the other hand, Flickr, where preference similarity could rule out only a small fraction of Friends-Overlap, satisfies all these criteria. Finally, Last.fm and Goodreads lie somewhere in the middle.

7.3.2 Feed Design

These websites also differ in how they show friends' activities to a user. Since users are typically exposed to their friends' activity through the feed, the design of the feed interface and the algorithms behind ranking of the activities in a feed likely impact the extent of copy-influence in a network.

We showed in Figure 6.1 one example of a feed for love actions. However, Last.fm shows activities of friends in different ways on different webpages. For example, on the page for an artist, it shows the recent loves or listens by friends for that artist. On Last.fm, all of these feeds occupy small widgets in the user interface. Further, the interface is often in the background while people listen to music and attend to other tasks, rather than the interface itself, likely reducing the feed's influence relative to other sites. The interface for Flickr lies on the other side of the spectrum: most of the available space is devoted to a feed of others' photos, and using the interface is a focal activity that concentrates attention on the photos shown in the feed.

Further, some feeds might make consumption or endorsement actions for items quicker or easier, which increases the likelihood of capturing influence effects and may compensate for specific item properties. We already saw how listening and loving a song have different estimates of copy-influence. In general, making it easy to convey interest in an item might increase our ability to record the effect of copy-influence: a user might not read a book or watch a movie right away, but if the interface lets her put it in a queue, that might support more rapid consumption of others' items (and thus, likely increase estimates of copy-influence when measured on the *queuing* action).

Finally, this is not an exhaustive account of reasons why copy-influence might differ between domains and individuals (in particular, network factors such as tie strength and knowledge of friends also affects people's copying decisions [5, 7, 74, 133]). We presented these factors to call attention to the need for nuance in thinking about how copy-influence arises in sharing networks. The system design and characteristics of the item space impact people's relative exposure and ability to act on items from their friends, thus impacting what we *measure* as copy-influence in these sharing networks. Even though the PME procedure is broadly applicable to sharing networks—requiring only social network edges and preference data—it is important to interpret the resultant influence estimates with respect to the design and context of the sharing network.

7.4 Limitations and future work

It is also important to keep in mind the assumptions inherent in our copy-influence estimate. In Chapter 6, we discussed two assumptions that a sharing network must satisfy for the PME procedure to be applicable: appropriate data such that preference matching can be used as a proxy for homophily and a reverse chronological feed. Here, we consider two additional assumptions of the procedure that help in computing the estimate; these are not strictly necessary and may be lifted in future work to better estimate copy-influence. Specifically, the PME procedure considers a reasonably static network and does not differentiate between different friends of a user.

7.4.1 A reasonably static network and preferences

The datasets we studied didn't have timestamps for tie formation, so we assumed a static social network. When timestamps for edge formation are available, we can make a simple modification in the procedure to consider only the friends of a user up to time T when computing the similarity and considering the current friends of a user when computing Friends-Overlap.

Another limitation of our estimation procedure is that by considering all actions in the Matching phase (before time T) as proxy for personal preference, we miss out on the effects of copy-influence in those actions. If copy-influence is higher early in someone's life in a sharing network, we might end up underestimating copy-influence, as the effects of any early copy-influence would merge into an individual's personal preference. Models that relax the time T assumption and compute both preferences and friend sets across the history of the dataset are computationally expensive, but possible—and would be interesting for bringing simulation-based results around contagion and network change toward real datasets [134, 135], as well as understanding how users' susceptibility changes as a function of their time in the system and their networks.

7.4.2 All friends being equal

Finally, by comparing all friends of a user in aggregate with their matched non-friends, we do not consider the individual differences in copy-influence due to a friend, which is an important factor for influence: people perceive actions by different friends differently based on their relationship with them, as we saw in Chapter 4. In our current datasets, we did not have any good principled ways to estimate tie strength. Future work would include accounting for these tie-specific variations in influence estimation.

7.5 Summary

Our results extend past work [6, 87, 127] that suggests that accounting for homophily is an important factor in estimating influence from feeds, demonstrating this in a variety of systems and domains and providing a method for doing so using publicly available data (requiring only activity data and social connections). We also find that the extent of overestimation varies widely with different websites, raising questions around how characteristics of the item domain and design of the feed impact the extent of copy-influence in sharing networks.

As for the interplay between personal preference and influence, estimates from the PME procedure show that copy-influence accounts for a just a tiny fraction of total people's actions on items, across a broad range of sharing networks and types of actions. Often, what appears to be someone copying a friend's action is more likely driven by shared preferences rather than influence. These results are even stronger than what we found experimentally from Part II, where influence was found to be a secondary effect to people's personal preference.

At first, these results may seem contrary to both popular perception and scholarly work on social influence. The idea of a particular item or opinion starting from a few sources and spreading *virally* to a large component of a sharing network is riveting and often highlighted in mainstream media. Further, social influence on sharing networks has been shown to be potent for diverse activities including reading articles [15], adopting new products [43], adopting healthy practices [9], emotional well-being [136] and even voting [7].

Our results do not necessarily contradict such findings nor rule out the effect of influence. In Chapter 4, for instance, we do find that named friend-based social explanations are more persuasive than other explanation strategies and demonstrate their influence on people's likelihood ratings.[3] But our results do call out attention to the tiny role of copy-influence in affecting the routine, overall activity around items in the sharing networks we study.

Most discussion of influence and diffusion focuses on the unusual: events where people do adopt their friends' behaviors and items spread widely. However, the mundane reality is when we consider people's entire action history over items, we find that most of their actions are not affected by copy-influence at all, rather guided by their own preference. This is supported by recent work by Flaxman et al. [92], who shows that only about 3-4% of online news consumption is referred through social media, thus giving an upper bound on the fraction of news articles read due to influence from others in a social network. This study, like our work, is able to put the effect of social media on news consumption in perspective by comparing it against the total number of news articles visited by users and not just focusing on the ones shared within social networks. Likewise, the vast majority of tweets never breach the sender's ego network [40].

We conclude that influence from the feed does exist and may lead to significant changes for susceptible people and some of their actions, but at least for the websites we studied, a vast majority of people's adoptions can be explained without any social influence effects.

[3] It could also be that we are missing the aggregation of influence over time: 1% of all actions seems tiny, but 1 influenced action out of 100 may aggregate to be a significant effect on people's decisions.

Part IV

Discussion and Conclusion

CHAPTER 8
DISCUSSION

> "Measurement is the first step that leads to control and eventually improvement. If you can't measure something, you can't understand it. If you can't understand it, you can't control it. If you can't control it, you can't improve it." – H. James Harrington [137]

We started out with the goal of understanding the interplay between personal preferences and social influence in shaping people's decisions on items in sharing networks. Influence from exposure to friends' activities may lead to the widely-observed locality of preferences in sharing networks, but it could also be that people largely follow their own preferences and locality emerges due to similar people becoming friends through the homophily selection process.

To understand how people make decisions on items, we looked at two fundamental processes of information exchange in sharing networks: adoption and sharing. We found that social influence through interface elements such as explanations plays a secondary role in deciding which items to try out. People's own preferences toward items have a bigger effect, even when people know little about items (Chapter 4). Similarly, when sharing, personal preferences of the sender play a dominant role in deciding what to share (Chapter 5). These empirical observations provided evidence for a smaller role of influence than people's own preferences when it comes to making decisions on items, even though awareness of others' activities and information sharing among friends are key features of any sharing network.

In Chapter 7, we found that our empirical claim about the small role of influence generalizes to a broad range of online sharing networks that differ in their item domains, purpose and system interfaces. Using a novel statistical procedure to estimate the effect of copy-influence from observational data (introduced in Chapter 6), we saw that on average, influence from the feed accounts for less than 1% of the total actions on items in sharing networks. Even without controlling for homophily through the PME procedure, data from the four different sharing networks shows that common actions within reasonable time-windows between friends—and thus a natural upper bound on the actual copy-influence—are not more than 3% of the actions an average user makes. Combined with our experimental findings, these results demonstrate a subdued effect of copy-influence in adoption decisions on sharing networks. The effect of copy-influence is not just secondary to personal preference: it is genuinely small since the vast majority of people's actions on items can be explained without any influence from the feed.

Overall, our findings run contrary to the general wisdom around online sharing networks that portrays them as a hotbed of influence. In this regard, we join recent work in questioning the virality and extent of influence in sharing networks [40, 92]. Influence may be still a powerful force in many scenarios, but at least for the contexts in online sharing networks that we studied, its effect pales in comparison to that of people's own preferences for items.

While the average effect of influence is low, the effect of influence from friends' activities varies widely for different users, as we demonstrated with the variance in people's susceptibility to social explanation (Chapter 4) and influence from feeds (Chapter 7), and their promiscuity for sharing items (Chapter 5). This underscores the importance of modeling individual-level variations in people's decision-making.

Finally, rather than a grand unifying theory of influence, our results point to the importance of scoping the study of influence to clearly defined mechanisms and contexts. In this chapter, we first discuss how our preference-based definition of influence provides a concrete, testable framework for studying influence. Tractable estimates of influence, in turn, promise to improve both models of behavior and design for online sharing networks. We will discuss how such estimates can lead to better models for diffusion in online contexts as well as better personalization in recommendation systems. Knowledge about the effect of influence would also be useful for system designers, marketers and change-makers, and users of a sharing network. We will end our discussion by arguing for the importance of modeling underlying processes that guide people's behavior—as we did for influence—rather than simply relying on observational estimates. To this end, our mixed-methods approach, combining experimental and data mining methods, can be a promising way forward.

8.1 Towards testable formulations of influence

Since social influence operates in diverse scenarios and contexts, it is hard to pin it down to general, tractable measures and mechanisms. Theories of influence provide a general compass to design and formulate measures of influence; however, what those measures mean vary with studies and their specific contexts.

Our definition of influence—as the deviation from expected behavior based on following personal preference—provides a concrete framework for operationalizing theories of influence [1] in sharing networks. In this framework, the specific process of influence under study is specified by two components: a model of people's personal preference and the mechanism by which influence is expected to operate. Depending on how one specifies the preference model and the influence mechanism, our preference-based framework for influence leads to specific claims that can be verified from available data.

8.1.1 Personal preference model

The personal preference model characterizes expected behavior of an individual in the absence of any social or external influences. Models of personal preference allow for a data-driven estimation of influence, making recent definitions of influence based on utility theory—influence changes the utility a person expects from acting on an item [138]—more amenable to empirical methods. They also allow us to utilize the rich knowledge from advances in recommender systems, where preference models are widely used [45].

The idea of the preference model is general, but needs to be specialized to context. For our first experiment on adoption, we showed people unfamiliar items and thus our preference model simply predicted an exponential distribution over ratings from 0-10. When past activities of people are available, they are valuable for building preference models. For instance, for the sharing study, our preference model was based on the ratings and Likes by participants and for our observational study, it was based on people's past adoptions in each sharing network.

Such formulations can be easily extended to other settings to set more accurate priors for activity without any influence effects. For example, instead of assuming that all common URLs between friends are due to influence as in Bakshy et al. [65], constructing a preference model based on a user's past tweets can lead to better estimates of actual influence between Twitter users. Preference models can also be included in generative models of activity that seek to explain effects of influence. For example, Crandall et al.'s generative model for edits on Wikipedia [66] may be augmented by positing that people choose a biased sample of actions based on their preferences, rather than sampling uniformly from others' activities in the absence of influence.

8.1.2 Influence mechanism

In addition to personal preferences, it is important to specify the mechanism by which we expect influence to operate. Having a clear formulation for the influence mechanism allows us to encode the implicit assumptions in our methods for estimation, based on specific system interfaces, and data and expectations around people's behavior.

Defining the influence mechanism involves two parts: identifying the key elements of a system interface and formulating a user behavior model around it. For instance, in Chapter 4, we identified social explanations for recommendations as the key interface element, and assumed a model where people look at each recommendation and its explanation sequentially. For developing the PME procedure in Chapter 6, we identified the activity feed as the key interface element and assumed a behavior model where people looked at items from top to bottom up to a cutoff for the number of items.

Often, these mechanisms are implicit in past studies on influence. For example, k-exposure models [36]—counting the number of friends who have already adopted an item—implicitly assume that people are equally exposed to all activities of their friends, which may or may not apply to a given sharing network. For instance, such a mechanism may not be appropriate for algorithmically filtered feeds as employed by Facebook. In such a case, we may either obtain the actual items shown to a user through server logs of the feed (as discussed in Chapter 6), or model the important properties of the feed such as increased focus for popular items or those from close friends. Making the mechanism explicit allows one to evaluate whether the resultant influence estimate would be reasonable in the specific context under study.

More generally, for specifying the influence mechanism, we are interested in *how* people are exposed to others' activities. This can include consideration for the system interface as well as the background algorithms that decide which items are shown to users.

8.1.3 Combining preference model and influence mechanism

Combined, specifying a personal preference model and an influence mechanism operationalizes social influence to a set of data-driven and testable claims. For our experiment on adoption, we considered any change in rating from the exponential preference model as evidence for the effect of influence due to social explanation. With observational data, we were able to derive estimates for feed influence by using preference models that control for a user's tendency to choose items that align with preferences common to the user and her friends. These claims can be easily verified in other sharing networks that satisfy our formulation of the influence process, as we showed for four different sharing networks in Chapter 7. Further, our framework is general enough to support scenarios where the mechanisms of influence change—e.g., exposure to a filtered feed on Facebook—or when a different preference model is used—e.g., translating past adoptions to latent feature spaces—and allows for a principled comparison of influence effects in these different contexts.

Rather than aiming for a unified theory of influence, we believe that scoping social influence problems within well-defined contexts will allow us to better understand what's really happening. We studied the effect of influence on people's decision-making in a specific context: exposure to friends' activities through recommendations or feeds within online sharing networks. We do believe, however, that our preference-based framework for influence, and associated methodological contributions such as the PME procedure, can be viable tools for identifying social influence effects in diverse contexts.

8.2 Implications for diffusion models

By demonstrating the effect of people's preferences on adoption and sharing decisions, this thesis joins recent work in questioning assumptions used in general diffusion models [40, 92]. Much of the scholarly work on diffusion—deriving from threshold and cascade models—assumes that all adopted items are shared, items are adopted independent of each other, people are equally susceptible to influence, and all friends' activities are equally shared to a user. Our results show that these are seldom true in sharing networks.

8.2.1 Separating out adopting and sharing

A major drawback of current diffusion models is that they make no distinction between adopting and sharing. If an item is adopted by a person, it automatically is assumed to be shared to her neighbors, inspired from how diseases spread in epidemiology [33] and social scenarios where neighbors can transparently see an individual's actions [32]. In some sharing networks, this assumption holds; people's adoptions are automatically transmitted through activity feeds, as we saw in Chapter 7. However, a lot of sharing is based on explicit choices: for example, people decide of their own volition to retweet on Twitter or share a URL on Facebook.

One way to account for people's volition would be to assume that people share only the most liked items. However, in Chapter 5, we found that not all highly rated items were shared, indicating that there is more to sharing decisions than simply a strong alignment with personal preference. In addition to the sender's personal preference, sharing depends on the recipient's preference and the sender's sharing promiscuity, which in turn is informed by concerns around identity management and consideration for others.

Acknowledging the difference between sharing and adopting can be useful for modeling diffusion accurately. In such a model, each person makes two separate decisions on an item: adoption and sharing. This can be realized through a fruitful combination of threshold and cascade models. Implicitly, these classes of diffusion models simulate either of adoption or sharing: threshold models focus on the process of adoption based on exposure to neighbors' activities, while cascade models focus on the process of sharing between a sender and a recipient. Combined, they can become the constituents of an integrated diffusion model, where a person decides to adopt based on a threshold number of adoptions by her friends, and decides to share based on the transmission probabilities between her and the recipient.

8.2.2 Using preferences to model people's decisions on items

Combining the two models would lead to added complexity in modeling diffusion. Fortunately, the concept of personal preference provides tractable ways of instantiating the integrated model, while also allowing us to reason about the diffusion of multiple items simultaneously through a sharing network. As we argued in Chapter 1, people do not make decisions on items in a vacuum; these decisions are guided by their personal preference. Thus, instead of independently focusing on the spread of one item at a time as current diffusion models do, using people's preferences can lead to better models of people's decisions.

For adoption, this implies relaxing thresholds for an individual based on how close an item is to her personal preference. To account for differences in friends' influence over an individual (such as the effect of activities from close friends as we saw in Chapter 4), the threshold may be a weighted sum instead of a simple count. For sharing, rather than having independent transmission probabilities for each network edge, we may specify the probability in terms of the sender's preference, recipient's preference and the item, as we do in our prediction model (Section 5.5).

8.2.3 Modeling differences in susceptibility and sharing promiscuity

In addition to their personal preference of items, our results indicate that people differ in their overall *susceptibility* to influence and tendency to share (sharing *promiscuity*). For instance, we saw a wide variation in people's susceptibility to influence from the feed in Chapter 7 and found sharing promiscuity to be an important predictor of people's sharing decisions in Chapter 5. Thus, accounting for these individual-level variations in people's decision-making can further improve our understanding of diffusion. This would mean having a personalized threshold for susceptibility to influence and a cutoff for sharing promiscuity for each individual, as proposed in a recent study on diffusion within blog networks [139].

8.2.4 Accounting for salience from system interfaces

Finally, our results also show the importance of accounting for the effects of salience of items, as described in the preference-salience model from Section 5.6. Unlike the assumption in diffusion models, all friends' activities do not receive equal visibility in a sharing network. What gets shared, and consequently how recipients react to the shared items depends, in part, on which items are made salient by system interfaces. For example, an individual's adoptions may be automatically broadcast to her friends through the feed interface, or selectively shown to others as recommendations.

Thus, apart from explicit decisions by people, system elements such as activity feeds and recommendation systems also determine the spread of items in a sharing network. In Chapter 7, we studied the impact of salience from unfiltered, reverse chronological feeds on people's adoption decisions. When feeds are algorithmically filtered, as on Facebook, the nature of filtering can further affect people's decisions, and potentially, their preferences; this has led to growing concerns about the biases due to filtering algorithms [140, 141]. Going forward, modeling the effect of different kinds of feed filters and recommendation algorithms on items' salience—and consequently, their adoption and sharing—are interesting, open questions and we believe that our preference-based formulation for influence provides a suitable basis for tackling such questions.

8.3 Implications for recommender systems in sharing networks

Our work also suggests that recommender systems should explicitly consider social influence. Even though social influence is not a dominant factor, it does contribute to people's behavior as we saw with the effect of explanations in Chapter 4. Modeling the effect of such influence can help recommendation systems utilize social information better and also lead to personalized explanation strategies, based on individuals' susceptibility to influence. Our work also points to the value of recommending items to share, not just consume, in sharing networks.

8.3.1 Using social information in recommendation algorithms

Prior work on incorporating social information, such as by Ma et al. [55, 142], considers it as additional signal for improving matrix-based collaborative filtering models for recommendation. Results from this thesis suggest alternative strategies for making use of social information in recommendation algorithms.

Our first major strategy is that recommendations based on only ego networks can be effective, even though they use much less data than typical collaborative filtering systems, as we saw in Chapter 2. Such recommendations can be useful in contexts where computational power is limited or preferences from only the ego networks are available. For example, when data or computation is local to a mobile device (such as peer to peer recommenders, or mobile recommenders that keep data local to support privacy, as in PocketLens [137]), it may be infeasible or undesirable to compute on a large dataset. Likewise, many websites such as Flixster, TripAdvisor, and CNET use existing social networks such as Facebook to support their user accounts. These sites essentially see individual ego networks drawn from the underlying full Facebook network; our results show that those views may be valuable for recommendation.[1]

Coverage for ego-network only recommendations, however, may be a problem, leading to concerns that people may be restricted to a narrow set of items liked by their friends [140, 141]. Further, as we saw in Chapter 4, some people are not influenced by social explanations at all and may not find value in recommendations based on their friends' preferences. Thus, our second major strategy is to have decoupled, hybrid recommenders [143] that balance the role

[1]Facebook changed its API policy in April 2015, which makes it harder to obtain all friends' activities. Still, APIs from many other networks such as Twitter continue to provide ego-centric slices of a user's network.

of friends-based versus collaborative filtering recommendations. This has the added benefit of allowing personalized weighting of social versus preference-based signals, instead of matrix-based models that assume the same weights for every user [55]. Such flexibility in increasing the social component of recommendations will help in accounting for differences in susceptibility to influence from friends. It will also help in alleviating the *cold start* problem of having little preference data [144], as an individual transitions from being a new user to an experienced user of the system.

8.3.2 Personalizing explanation strategies

In addition to the recommendation algorithm, we could also personalize the explanation strategies shown alongside recommendations, since the effect of influence from social explanations and activity feeds varies widely between people (Chapter 4).

The generative model for the effect of social explanations that we presented in Section 4.5 provides a basis for such personalization. Using such a model, recommender systems can personalize the *kinds* of explanations shown to users (not just the explanation) based on which explanation strategy is the most useful for an individual. Although we considered only social explanations, such personalization could be extended to non-social explanation strategies as well. For example, we found that some users (cluster 1, Figure 4.5) do not seem to be affected by social explanations at all, but it is possible they may find other explanations (such as tags, genres) useful.

8.3.3 Recommending for different goals: adoption and sharing

As we saw in Chapters 4 and 5, people's decision process for trying out items can be different from actually liking them, which are in turn, different from the processes for sharing items. In the case of optimizing for discovery versus consumption, tuning the relative contribution of social and collaborative recommendations can be useful. For example, if the goal is to expose users to new items, showing more recommendations from slightly dissimilar friends and providing persuasive explanations could be a good strategy. If the goal is to maximize consumption, it would make sense to give preference-based collaborative filtering more importance. Often, we would like a balance, since maximizing the likelihood of trying out an item might increase overall user activity and consumption, but also erode trust if the system persuades users to consume items they don't actually like. In such cases, a two-phase optimization framework that models likelihood and consumption separately like the one we proposed in Section 4.6.3 can be useful.

For sharing, we would need to model both senders' and recipients' preferences as we saw that both are important factors for modeling people's shares in Section 5.5. Such preference-based models can be valuable for recommending which items to share, a design goal that is often overlooked in the recommender systems community (perhaps because of the traditional focus on e-commerce applications). They may also be used to suggest who to share items to, using similarity between potential items and recipients (as in FeedMe [26]). In the case of broadcast sharing, where we have multiple recipients, modeling aggregate preferences of the ego network can help in recommending items that are expected to be received well by a user's audience as a whole.

In addition, we saw that the results of sharing differed based on which items were shown to a sender as candidates for sharing. Shares were well-received when a sender was restricted to sharing items based on the recipient's preference than when she saw a mix of items based on both of their preferences (Section 5.4). This effect of salience can be used profitably in recommender systems to feature task-appropriate items: systems could recommend items for self in consumption contexts and items for others in sharing contexts. That is, when the goal is sharing, giving more weight to recipients' preferences will likely lead to shares that are well-liked. For example, when a user browses her friend's profile, systems could recommend items based on the friend's preferences to encourage effective sharing.

8.4 Towards better models of activity in sharing networks

More generally, our work points to the importance of modeling underlying processes such as influence for understanding people's decisions on items. Rather than simply computing observational estimates, such models are likely to convey more accurate and generalizable insights about adoption and sharing activity in sharing networks. Below, we discuss why modeling underlying processes of decision-making matters, and how our mixed methods methodology can be useful to make progress on understanding people's activity in sharing networks.

8.4.1 Importance of modeling underlying processes

The popularity of sharing networks allows access to unprecedented scales and granularity of data about people's decisions and activities. These data can be used to make observations about people's decisions and their aggregate effects, such as tracking locality of preferences (Chapter 2), spread of items like the song *Friday* [41, 77], and identifying well-connected or far-reaching people in a network [39, 145]. However, such analyses gloss over the underlying processes that lead to the observed data. These processes hold the key to causal questions—*how* and *why* do people make the decisions they do—that are important to making sense of activity on sharing networks.

In this thesis, we focused on understanding people's adoption and sharing decisions. Observational data from sharing networks showed high locality of preferences which may be attributed to social influence between friends. However, when we accounted for the role of preferences in decision-making, we found that influence accounts for only a small fraction of people's actions on items. Thus, developing measures of the effect of influence led to a better understanding of people's decision-making. This can in turn, inform advancement of theory about influence and other social processes in technology-mediated contexts such as sharing networks.

Interpretable estimates of influence are also of practical import for a number of stakeholders including system designers, marketers and change-makers, and users of a sharing network. System designers can use our methods to analyze the effect of influence in their sharing networks and improve user experiences. They can learn more about how interface elements like social explanations and activity feeds influence their users' activity and make informed evaluations of changes in those interfaces. This would be based on system goals: for example, a news website may want to decrease social influence to prevent balkanization [146], while a fashion discovery website may want to promote more social influence. Marketers and change-makers would also benefit from having accurate estimates about the effect of influence in swaying people's decisions. Instead of relying on observational data on adoption and sharing activity which may lead to incorrect conclusions, estimates of influence can help them evaluate the effectiveness of different strategies and spread their message better. Finally, like Cialdini[2], we hope that the results from this thesis are useful for users of sharing networks too, making them aware of (and perhaps adapt to) the factors that influence their decisions.

8.4.2 Mixed-methods: a viable methodology for understanding online activity

To understand the role of influence in people's decision-making on items, we used a mix of experimentation and data mining efforts. We used data mining, specifically recommendation algorithms, to demonstrate locality of preferences in sharing networks. Since the available activity data from sharing networks could not tell us more about *how* preference locality emerges, we turned to experimental methods to understand people's motivations and considerations for adopting and sharing items. To gain external validity for our results, we turned back to data mining and devised a computational procedure to estimate the extent of influence in a variety of online sharing networks.

[2] Robert Cialdini. Author of a widely-read book on social influence [1].

We argue that *mixed-methods* approaches are more likely to lead to real insights about people's behavior in online contexts and make progress on the general goals of computational social science [147]. As more and more of our activities shift online, we need to develop new computational methods to process the data being generated and make sense of the underlying processes. At the same time, we need experiments to investigate *how* that data was generated (identify the processes) and provide assumptions and guiding theories for developing the computational methods. Experiments also provide qualitative data about people's activities, which reveal people's rationale and concerns that might otherwise be missed in data analysis. For instance, people's comments about the effect of social explanations in Section 4.3 guided our formulation of the mixture-based generative model for their rating.

Finally, we hypothesize that tighter integration of these methods—experimentation and data mining—can be a big win, as with the idea of using models of sharing behavior and social influence derived from experimental work to set (or add) parameters of diffusion models. We leave these investigations for future work.

CHAPTER 9

CONCLUSION

We presented a mixed-methods analysis of the role of personal preference and social influence in shaping people's decisions in sharing networks. Even though sharing networks are built around showing friends' activities through system elements such as feeds, social explanations and recommendations, the main result from both experimental and observational studies is that personal preferences dominate people's decisions to adopt or share items; influence only plays a minor role.

Besides demonstrating our main result in a variety of sharing networks, we made a number of concrete contributions that will help advance the understanding of influence. First, our preference-based formulation of influence provides a viable framework to scope influence problems to specific contexts and develop tractable methods for its estimation. Second, our generative model for adopting items presents a general approach to estimate both network-level and individual-level effects of personal preference and social influence. Third, we proposed a decision-tree model based on sender's and recipient's preferences that can be used to model people's sharing decisions. Finally, we presented the Preference-based Matched Estimation (PME) procedure for estimating the extent of influence from feeds in sharing networks, based only on observational data on people's activities.

More generally, our journey through understanding the role of influence and personal preference in sharing networks underscores the importance of modeling the processes behind people's decision-making and their interplay with system design and interfaces. Estimates of the effect of underlying processes provide a deeper understanding about people's decisions, as well as make it possible to evaluate the effect of current system elements—such as feeds, recommendations and other social algorithms [148]—on people's decisions and the goals of both designers and users of sharing networks. To that end, we hope that the mixed-methods methodology that we demonstrated, combining experimental and data mining efforts, will be a viable approach for answering questions about people's behavior from the noisy, incomplete picture that data from sharing networks provide.

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