ORIE 565

Financial Engineering Project

Grupo Uno
Credit Card Analysis

Equipo Nueve Consulting

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Executive Summary

Grupo Financiero Uno (GFU), the largest credit card issuer in Central America, offering a wide variety of products, has more than 700,000 customers. GFU would like to continue improving their understanding of the customers in order to increase their market penetration. To achieve these goals, the following three important questions were currently identified:

- Who is using our rewards programs?
- Are we rewarding the right behavior? Which reward scheme should we use?
- Is higher spent a consequence of redemption activity or vice versa?

To determine who is taking most advantage of the rewards we segmented the customers based on demographics, payment type, and credit card type, in addition to performing a cluster analysis customer base. We hypothesized that there were two distinct redemption behaviors, so to prove ff this was correct we also performed a redemption behavior analysis. The two groups we believed that existed were customers that redeemed frequently to get smaller prizes (the ER group) and customers that redeemed less often but got the larger-ticket items (the SG group). Had these two groups existed, GFU could target the two redemption behavior separately.

To test if GFU was rewarding the correct behavior we looked into how many points customers of each payment type earned for each dollar they contributed to GFU. If each group earned roughly the same points, then we could assume that each group was being rewarded fairly and thus GFU was indeed reward the right behavior. We also looked into if there was a significant difference in those customers that accumulated a lot of point and those that did not, and we also looked into the proportion of customers that were actually redeeming their points.

To see which reward scheme GFU should use, we ran a cost-benefit analysis to see whether or not a scheme rewarding only balance was profitable. We also ran a cost-benefit analysis on a hybrid scheme which rewarded the greater of balance or purchase to see if this was less costly as the current scheme and the scheme that only rewarded balance.

Finally, we tested the cause and effect relationship between spending and redemption. To analyze this relation, we ran a lagged regression on both spending and redemption to determine the direction of the causation. Redemption leading to spending is beneficial to GFU as it validates the effectiveness of its loyalty program.

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1 Introduction

1.1. Problem description

Grupo Financiero Uno (GFU), the largest credit card issuer in Central America, offering a wide variety of products, has more than 700,000 customers and has seen 25% annual growth over the last 3 years. GFU would like to continue improving its understanding of the customers in order to increase their market penetration. The credit card industry has seen many changes since its inception, and nowadays for a credit card issuer to survive it must provide an effective loyalty program that is of value to both itself and its customers. As a result of this, GFU has asked us to evaluate the effectiveness of its current loyalty program and to come up with recommendations of how to tweak the rewards program to better suit the needs of its customers. To guide us with our analysis, the following three important questions were currently identified:

- Who is using the rewards programs?
- Is GFU rewarding the right behavior? Which reward scheme should GFU use?
- Is higher spent a consequence of redemption activity or vice versa?

A brief summary of our answers to the preceding questions is provided in the next section in addition to our recommendations of how to improve the loyalty program.

1.2. Summary of Findings

To tackle the first question of who is using the reward we performed three types of analysis: a top-down analysis, a bottom-up analysis, and a redemption behavior analysis. The top-down analysis consisted of segmenting users of the loyalty program based on demographics, payment behavior, and credit card type. For payment behavior, we expanded the given definition of revolvers and transactors by defining three levels of revolvers and two levels of transactors (a formal definition of the various levels of these two payment types can be found in chapter 5). We also found that the different levels of gender and marital status did not show distinct differences in redemption behavior, so only age was included in the results. From our top-down analysis, we concluded in terms of amount of points redeemed, the group that used the loyalty program was between the ages of 61 to 70, held a Platinum card, and exhibited payment behavior consistent with a Medium Revolver; in terms of percentage of

total accumulated points that were redeemed (redemption rate), the group that used the loyalty program was between the ages of 31 to 40, held a Platinum card, and exhibited payment behavior consistent with a Strong Revolver. Both of these groups make up an extremely small proportion of GFU's customers, so this suggests that its loyalty program must be changed in order for more customers to use the program. In our bottom-up analysis, we did a cluster analysis by looking at revenue, redemption rate, credit usage, and attrition probability. In our analysis, we were able to identify four distinct groups: two groups that used the loyalty program and two groups that did not use the loyalty program. The two groups that did not use the program showed stark differences; one of the groups provided GFU with the greatest revenue in addition to high credit usage, while the other group provided very little revenue and hardly used its credit card. Thus, we were able to identify a group of customers that were basically dead weight to GFU. In addition to this, we saw as redemption rate increased the likelihood of customers leaving GFU decreased, so this suggests the loyalty program is effective when used. Finally, in the redemption behavior analysis, we only concentrated on the customers that redeemed their points in the hopes of finding whether or not there were two distinct redemption behaviors as hypothesized (the SG group which accumulates points over a long time horizon in order to redeem big-ticket items, and the ER group which accumulates points but redeems frequently to get smaller ticket items). Our analysis concluded that the two redemption behaviors did not exist, and for the most part the customers that did redeem were only concerned with the smaller tickets items. In addition to this, we found as the frequency of redemptions increases among customers, they bring in increased revenue to GFU, so we recommend GFU make more of an effort to promote the redemption of its smaller ticket items.

For the second task of determining of whether GFU was rewarding the right behavior and which rewarding scheme it should use, we found that it was not rewarding the right behavior. Intuitively, this is easy to see because revolvers provide GFU with a majority of its revenue, but with the current reward scheme, customers only earn points on purchase, so this primarily benefits transactors. To analytically prove that the GFU was not rewarding the right behavior, we looked at how many points each of the five payment groups (three levels for revolvers and 2 levels for transactors) redeemed for contributing one dollar of revenue to GFU. We found there were significant differences among the five groups, so all the groups were not fairly rewarded. We also found that customers that had accumulated a lot of points, only redeemed 30% of their points, and 1/3 of all the customers ever redeemed their points, so this suggests that customers are not really being rewarded properly and the items available for redemption are not of value to the customers. Instead of earning points on purchases, we

looked into earning points on an outstanding balance. To better market this scheme, we decided to look at the average balance per month for each customer. After making certain assumptions, we did a cost-benefit analysis to see if the new scheme was economically feasible. We saw that by varying how many points it takes to earn one loyalty point, we found that GFU could earn a profit with the new scheme. However, in an attempt to not alienate users of the current loyalty program and to try reward both types of payment behavior, we suggested a tiered reward scheme which takes the maximum of points earned from a customer's average balance and the points earned from the customer's purchases per month. From a cost-benefit analysis similar to the other suggested reward scheme, we found that the tiered reward scheme was even more profitable than the scheme that rewarded only average balance. Thus we recommend GFU to switch its loyalty to our suggested tiered reward scheme.

Finally, to answer the third question of whether redemption spurs spending or vice versa, we performed the Granger Causality Test to analyze that cause-effect relationship between spending and redemption. What we found was that increased redemption will forecast increased spending, but also increased spending will forecast increased redemption. Stronger conclusions could not be made because the cause-effect relationship existed in both directions and the Granger Causality Test requires us to make additional assumptions about the underlying causes of changes in redemption and spending. Our result, however, does confirm that the loyalty program is effective because users of the loyalty program will spend more and thus bring in more revenue to GFU. We also found that an increase in spending occurs primarily one month after redemption was increased, and that Gold and Platinum members spend more after redeeming than do Classic members. Thus we suggested that GFU modify its loyalty program to better suit the needs of Gold and Platinum members, so they can redeem more and thus enabling GFU to extract greater value from this group of customers. However, because Classic members make up the greatest proportion of GFU's customers, we think it would be wise for GFU to modify the loyalty program to better suit their needs in attempt increase correlation between spending and redemption amongst this customer group.

2 Database

2.1 Data Sources

All data used in this project was provided by GFU. The data consists of six GFU institutions spanning three countries, Costa Rica, Nicaragua, and Honduras. The data was gathered for a 24 month time period and can be categorized into the following five groups:

- **Customer and account information**
  - Table: ACCOUNT_CUSTOMER and ACCOUNT_CUSTOMER_CA
- **Balance information**
  - Table: BALANCE and BALANCE_CA
- **Statement information (summary and transaction details)**
  - Table: STATEMENT_HEADER and STATEMENT_HEADER_CA
  - Table: STATEMENT_DETAIL and STATEMENT_DETAIL_CA
- **Loyalty information (balance, accrual, redemption)**
  - Table: LOYALTY_BALANCE and LOYALTY_BALANCE_CA
  - Table: LOYALTY_ACUMULATION and LOYALTY_ACUMULATION_CA
  - Table: LOYALTY_REDEMPTIOM and LOYALTY_REDEMPTIOM_CA
- **Behavior scores (risk, revenue, attrition)**
  - Table: SCORE and SCORE_CA
  - Table: EXTRA and EXTRA_CA

2.2 Database

A database is an organized collection of data. A database management system (DBMS) such as Access (Microsoft) or Oracle provides us with the software tools we need to organize that data in a flexible manner. It includes facilities to add, modify or delete data from the database, a query tool to extract and analyze a certain subset of the data, and a mechanism to produce reports that summarize selected contents of the data.

In this project, we use Microsoft Access as our DBMS because it provides users with one of the simplest and most flexible DBMS solutions.

2.3 Database Analysis and Design

Data Type Definition

The data provided by GFU was broken into several text files, so it first had to be imported into the database. Each text file corresponds to a different table in the database, and in order to ensure that no data is lost during importation, we must define each field of each table with the correct data type. Data type is the characteristic of a field that determines what type of data it can hold. Data types include Boolean, Integer, Long, Currency, Single, Double, Date, String, and Variant. An example of how data can be lost with the incorrect specification of the data type is to consider the example when we define the data type of a field to be of type Integer but in actuality the field's data type should be Double. During importation we would lose data because Access would truncate all decimal numbers, and since Integer values are not as large as Double values, Access would refuse to import all data whose value is greater than the maximum value for an Integer. The data types of each field of each table in the database can be found in Appendix I.

ER Diagram

To easily extract and conveniently analyze data, we must properly design the interrelationships betweens tables. This is most often done by making a primary key of one table a foreign key of another table. Proper design of the relationships between tables will ensure that data of one table is not replicated in another table and that the user can extract the data he or she needs in one pass rather that multiples passes. GFU provided us with most of the relationship specifications, but we had to create a few extra tables to make sure that all the data was connected. The tables we created can be found in the Appendix I. An entity-relationship (ER) diagram is a specialized graphic that illustrates the interrelationships between the tables of the database. The ER diagram will show which tables are connected with each other, and it will also show what kind of relationship exists between entries of one table and the entries of another; whether it is a one-to-one relationship, a one-to-many relationship, or a many-to-many relationship. The ER diagram for our database can also be found in Appendix I.

2.4 Data Cleaning

Once the data was imported into the database and all the tables were properly connected, the next task was to "clean" the data. The data to be used for the project came from multiple sources as data from six different institutions was collected, and each source may have its own

convention for data entry, so there may be inconsistencies among the sources of data entry. Moreover, the person inputting the data might make a mistake during the process, so there is possibility the data give is not entirely correct. High quality data is essential for this project so that the end users of our analysis, Grupo Uno, can accept our results and conclusions with a high degree of confidence. Therefore, a significant effort was made to detect and correct errors and inconsistencies in the data. However, the cleaning was not done in the database, rather in the statistical software we used, primarily R, because if we changed the data in the database, we would be left with very little usable data.

Since the types of errors and inconsistencies can be domain-specific, it is important to develop generic domain-independent data cleansing solutions. Our goal in this part of the project was to develop a set of domain-independent rules which could be used for developing effective and efficient data cleaning solutions.

More specific data cleaning rules can be found in Appendix II.

2.5 Data Query

Users of a database have different requirements and uses for the data within the database. Users may want to examine only a certain subset of the data under a particular view, or they may want to manipulate the data a certain way for analysis purposes. Thus, database management systems such as Access are equipped with utilities to search for any record a user needs and manipulate the data in many different ways. The aforementioned tasks are completed through the use of queries.

Once the tables have been established inside of a database, a person can develop a query to select a group of fields from those tables or select only records that adhere to a specific set of criteria, and then ready those records for use in reports. Queries can also be used to aggregate records and create new tables which contain manipulated records of the data.

In this project, we used queries to obtain account and customer information, to calculate the revenue and net present worth of each account, and pull up purchase and loyalty redemption amounts for each account month by month. A list of all the queries used in our project can be found in the Appendix III.

2.6 Database Management

For our project, the rough system framework is described in the figure below. There are three parts to our framework:

- **Data Collection Area**: the collection and storage for the data from the six institutions.
- **Data Repository Area**: the repository scheme for input, output and results data.
- **Process and Analysis Engine Area**: calculation engines and processing systems to handle and manipulate the data.

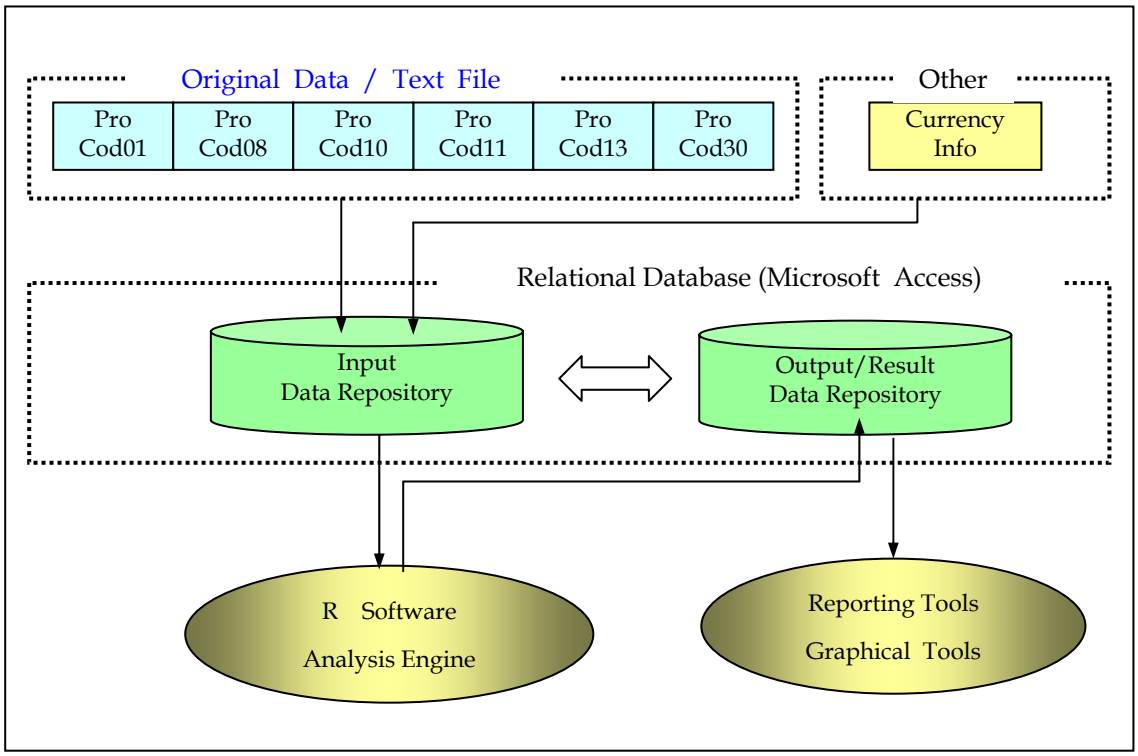


Figure (2.1) System Framework

3 Terminology and Definition

3.1 Introduction to Customer Segmentation

In regards to our project, customer segmentation describes the division of customers into homogeneous groups with respect to different behaviors pertaining to credit card usage such as spending, loyalty accumulation and/or redemption, and carrying a balance. Each group, or "segment," can be targeted by different variables because the segments are created to minimize inherent differences between respondents within each segment and maximize differences between each segment.

Customer segmentation is important to GFU because by analyzing its loyalty program, it can bolster its marketing strategy by taking advantage of differentiation and it can better serve its customers by better understanding them. Good customer segmentation can also serve as stepping-stone to expanding revenues and obtaining competitive advantages over its competitors. In the age of modern marketing, marketing professionals use many sophisticated techniques, such as customer segmentation, to reach potential users by offering the most customized products possible.

3.2 Reasons to use customer segmentation

There are many good reasons for dividing all customers into smaller segments. The primary reasons are as follows:

- **Easier marketing:** "Who is using GFU rewards programs" is a key question in this project. GFU believes it can effectively apply its rewards programs by knowing which group or groups use or do not use the programs. Furthermore, GFU will gain a better understanding of how and why the different groups use the loyalty programs. Additionally, it is easier to address the needs of smaller groups of customers, particularly if they have many characteristics in common (e.g. seek the same benefits, or are of the same age, gender, etc.).
- **Efficient:** Segmentation also provides more efficient use of marketing resources by focusing on the best segments for GFU's offering— reward program, price, and

promotion. Furthermore, segmentation can help avoid sending the wrong message or sending the message to the wrong people.

- **Find niches:** Segmentation can also identify under-served or un-served customers. Using "niche marketing," segmentation can allow GFU to target less contested users or credit card holders, and thus enabling a mature program seek new customers. This is something we will further explore in the project because GFU wants know if changing the rewards program will stimulate more spending and/or loyalty program usage, and also if it should modify its product offering based on demographics and/or transactional behavior.

3.3 Segmentation in this project

There are four major ways of segmenting a market according to the level of precision we require and the type of data available about the customers. They four methods are:

1) A Priori segmentation
2) Usage segmentation (also known as decile analysis or Pareto analysis)
3) Attitudinal research and cluster analysis,
4) Needs based segmentation.

For our project, we will be utilizing the third method of cluster analysis to segment the customers. The reason for this is that cluster analysis provides the most convenient and efficient way of segmenting the customers based on the size and nature of the data. Cluster analysis divides the customers into groups or "clusters" based a on specified variables, and it provides a bottom-to-top approach to segmenting the data. To further refine the clusters, a top-to-bottom approach will be undertaken.

In the top-to-bottom approach, the total portfolio will be segmented with respect to **demographics, products, revolvers/transactors,** and then each sub-segment will be profiled with respect to:

1) NPV
2) Current revenue
3) Number of cards
4) Balance
5) Spent
6) Behavior scores
7) Utilization rate
8) Redemption behavior

In addition to the cluster analysis and the top-to-bottom analysis, we hypothesize that we may be able to identify groups with respect to loyalty redemption behavior. We believe that there exist two distinct groups based on loyalty accrual and redemption behavior: the Earn-it-and-Redeem-it group (ER group), which earns reward mileage and frequently redeems them over a certain defined redemption interval; and the Save-it-and-Get-big group (SG group), which earns and saves reward mileage to get big items over the same interval.

3.3.1 Revolvers / Transactors

A **revolver,** as defined by GFU, is a customer who generates interest charges because they carry over a balance from one cycle to the next. Revolvers are beneficial to GFU because they provide revenue in the form of the interest payments. For our analysis, we thought it would be beneficial to break down revolvers into three levels. The three levels are Strong Revolver (SR), Medium Revolver (MR), and Weak Revolvers (WR). They three levels are formally defined in chapter 5.

A **transactor**, as defined by GFU, is a customer who pays his balance in full at the end of a cycle and had card activity during that cycle. In terms of generating revenues, transactors are not as beneficial as revolvers because they do not provide interest payment as they do not carry a balance. For our analysis purposes, we thought it would be beneficial to break down transactors into two levels. The two levels are Strong Transactor (ST) and Weak Transactor (WT). A formal definition of these two levels is provided in chapter 5.

3.3.2 Current Revenue

To calculate the current revenue for each customer, GFU has provided a document "Revenue Formula" that details which fields are relevant to calculate this value. The reason we need this document is that current revenue is simply not a field which you can find in one of the tables of the database. Basically, this value is computed by using three interests and transaction values under certain conditions.

3.3.3 Balance

For each customer, monthly balance information can be found in the "Statement Header" table and overall balance can be found in the "Balance" table. By observing the balance information for each customer, we can see which customers are inclined to paying their

balance in full (transactors) and those who do not pay in full (revolvers). As a result, these two behaviors will lead to different revenues for GFU.

3.3.4 Purchase

Purchase is basically how much a customer spent per month. This data is primarily used in the analysis of whether redemption spurs spending or spending spurs redemption. The purchase data for each customer can be obtained from the "Statement Header" table and "Statement Detail" table.

3.3.5 Behavior Scores

The "Score" table details several behavior score values for each of GFU's customers. The technical report "Credit Card Behavior Scorecard Development" by FairIsaac consulting firm documents the meaning and calculations for each behavior score. FairIsaac developed five scorecards for GFU's credit card portfolio.

The behavior scores analyze past customer account behavior to predict a certain behavior in the future. The three main behavior scores analyzed in the project are Risk, which predicts future likelihood of delinquency or risk, Revenue, which predicts future revenue potential, and Attrition, which predicts the future likelihood that a customer will leave GFU for one of its competitor. These three behavior scores were used to determine GFU's most desirable customer, so they will also be beneficial in analyzing GFU's loyalty program

For each score, the way you get probability of a negative event happening, such as a person defaulting, is first you calculate the odds of the event by using the following formula:

$$ODDS = 60 \times 2^{\frac{Score-600}{20}}$$

Then you get the probability of the event by using the following formula:

$$P(event) = \frac{ODDS}{ODDS + 1}$$

And finally to the probability of the negative event happening is 1 – *P(event)*.

Below are figures that show who the risk, revenue, and attrition probabilities scores vary with age and credit card type.

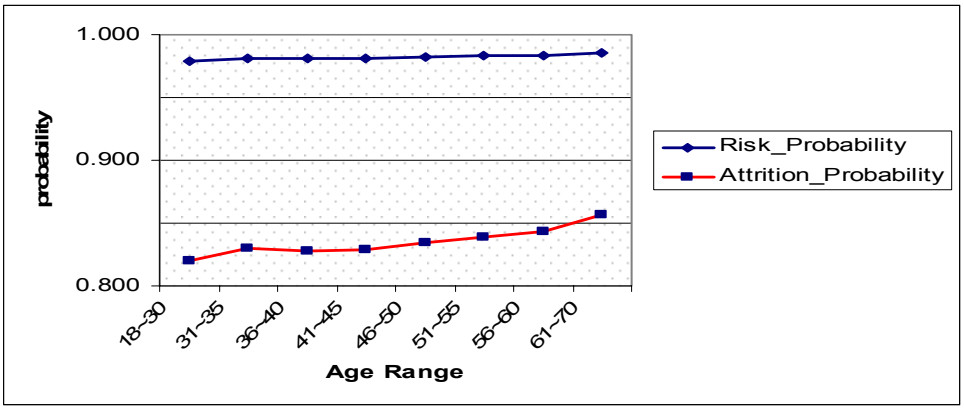


Figure 3-1

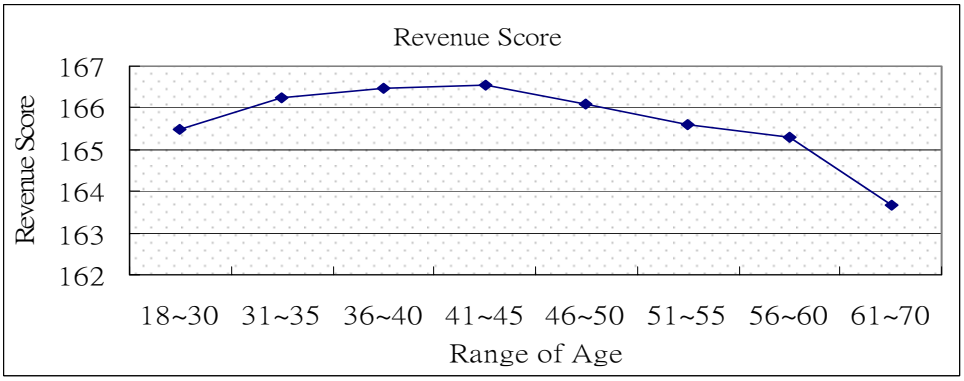


Figure 3-2

Product Type	Risk Probability	Attrition Probability	Revenue Score
C	0.981	0.820	167.082
G	0.983	0.847	163.280
P	0.987	0.891	160.877

Table 3-1

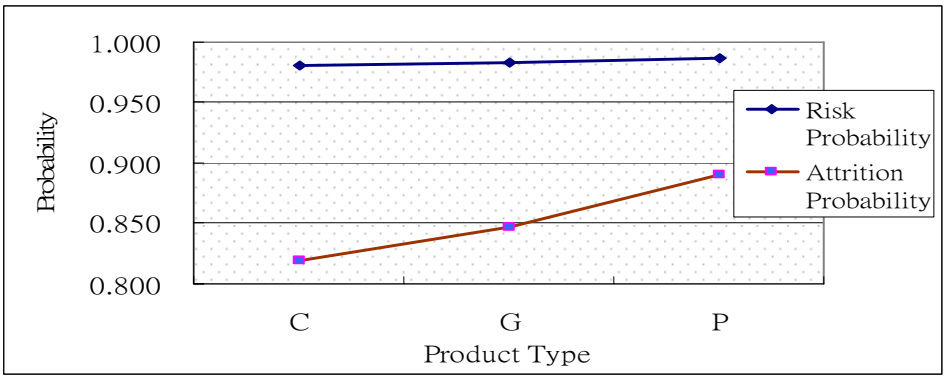


Figure 3-3

We see from the preceding figures and table that card type and age do no really have a major impact on the risk of default. The likelihood of a customer leaving GFU decreases as he or she becomes older and also when going from Classic to Gold to Platinum. Finally, the revenue score first increases and then decreases with age, but when going form Classic to Gold and Platinum, this strictly decreases.

3.3.6 Credit Usage

Credit usage is a way to measure how much a customer uses his or her card, and how much of the credit limit was used to finance a customer's debt. There are many ways to define credit usage, but one popular way is to define it as balance / credit limit. In our analysis, we used the end of the month balance for each customer as the value of balance used in the computation of credit usage. For revolvers, we want to see what percentage of the credit is used for purchases and what percentage is used to carry over balances. Credit usages is also one of the variables use in our cluster analysis

3.3.7 Loyalty Program in GFU and Redemption Behavior

In this section we start analyzing the loyalty program by looking at the six different institutions. For each institution, we look at how many loyalty programs it offers, the total loyalty balance amount, the total loyalty accumulation amount, the total loyalty redemption amount, and a new metric, redemption rate. We define redemption rate as lifetime loyalty redemption over lifetime loyalty accumulation, and this metric is used in subsequent analyses of the loyalty program.

The table below shows our findings for the six institutions.

	PRoCod 01	ProCod 08	ProCod 10	ProCod 11	ProCod 13	ProCod 30
Country	Costa Rica	Nicaragua	Nicaragua	Honduras	Honduras	Costa Rica
Program Number	**20**	**5**	**5**	**9**	**10**	**7**
Loyalty Balance	63041	60220	42951	32081	31118	22065
Loyalty Accumulation	1496453	1575970	1061360	749302	804594	485892
Loyalty Redemption	82938	39741	18835	20724	24592	35824
Redemption Rate	**5.54%**	**2.52%**	**1.77%**	**2.77%**	**3.06%**	**7.37%**

Table 3-2

Each institution's redemption rate has been calculated and shown in this table. We find that the overall redemption rate is very low, which suggests that loyalty program is not very well utilized. We also see that there is a difference in loyalty program usage among the three countries. We see Costa Rica has the highest redemption rate in, while Nicaragua has the lowest. This might indicate that there is a difference in behavior within the three countries, or maybe the loyalty program is marketed differently in each of the countries

4 Groups Using GFU's Rewards Programs

4.1 Groups from Segmentation

To begin with the top-down analysis of who is using GFU's loyalty program, we proceeded to segment the data by demographics. We grouped the data by age, gender, and marital status. However, only when we segment by age do we see interesting results which is demonstrated by significant differences in redemption rate for different levels of age. The table below shows the average redemption amount and average redemption rate, in addition to revenue, for different ranges of age.

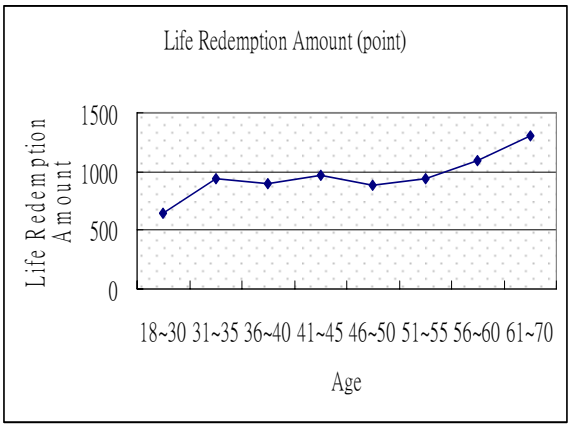
Range of Age	Life Accumulated	Life Redemption	Redemption Rate	Revenue
18~30	2284	646	17.01%	$817
31~35	3222	935	17.81%	$1,171
36~40	3476	890	16.68%	$1,352
41~45	3702	967	15.92%	$1,485
46~50	3873	886	15.37%	$1,621
51~55	4277	934	14.79%	$1,738
56~60	5224	1087	12.82%	$1,935
61~70	6715	1301	12.40%	$2,187

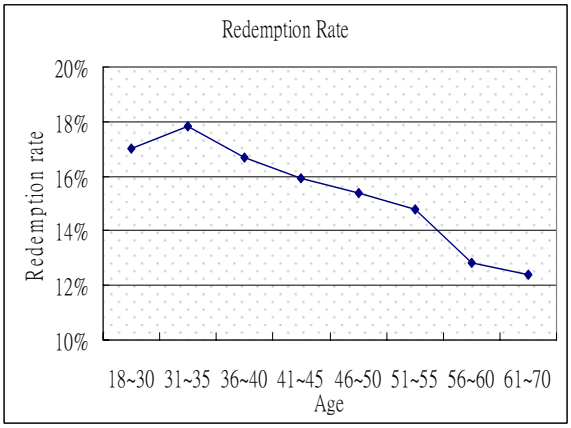
Table 4-1

From the table above, we make the following observations:

1) Revenue per customer increases as age increases.
2) Although on average the amount of points redeemed increases with age, the redemption rate decreases with age. This means older people are redeeming more but are not fully utilizing all the points they have accumulated. This might suggest that possibly older people might find it a hassle to redeem or the items that can be redeemed are of little value to them.

The following graphs illustrate the relationship between redemption amount and age, and the relationship between redemption rate and age.



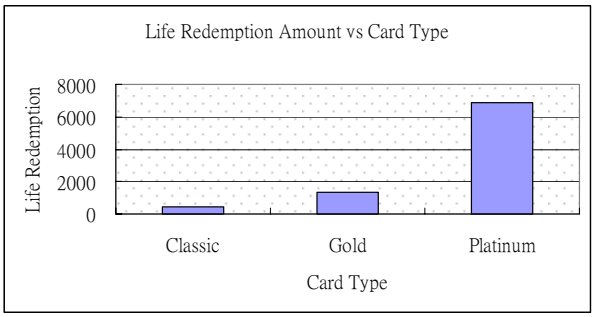


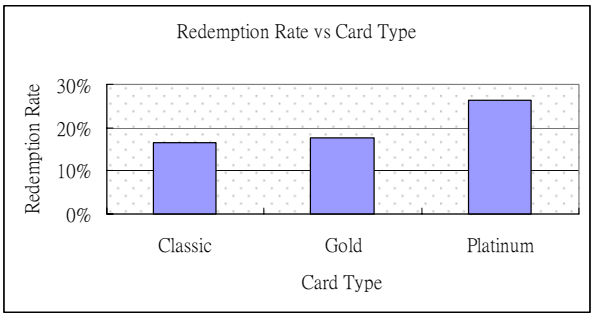
Next we proceeded to segment the customers by credit card type (Classic, Gold, and Platinum). The reason for segmenting based on this variable is that each type has a different credit limit and its constituents are of different social statuses, so their spending and possibly their redemption behavior will be different. The follow table below shows the average redemption amount and average redemption rate of the three card types.

Product Type	Percentage of customers	Life Accumulated	Life Redemption	Redemption Rate
Classic	**75.56%**	**1592**	**463**	**16.51%**
Gold	**19.49%**	**4369**	**1314**	**17.61%**
Platinum	**4.95%**	**15321**	**6858**	**26.41%**

Table 4-2

From the table above, we see that as we go from Classic to Gold to Platinum, redemption amount and redemption rate increases. This is not surprising because Platinum are the most affluent customers, so their purchasing power is greater thus allowing them to make larger redemptions. The graphs below show the relationship between credit card type and redemption amount, and the relationship between credit card type and redemption rate.





Finally, we segmented customers based on payment type. For payment type, there are three levels of revolvers (Strong, Medium, and Weak) and two levels of transactors (Strong and Weak) and they are formally defined in chapter 5. The current reward scheme rewards transactors because points are only earned purchases, so we wanted to see how the two payment types used the current reward scheme. The table below shows the relationship between payment type and average redemption amount, and the relationship between payment type and redemption rate.

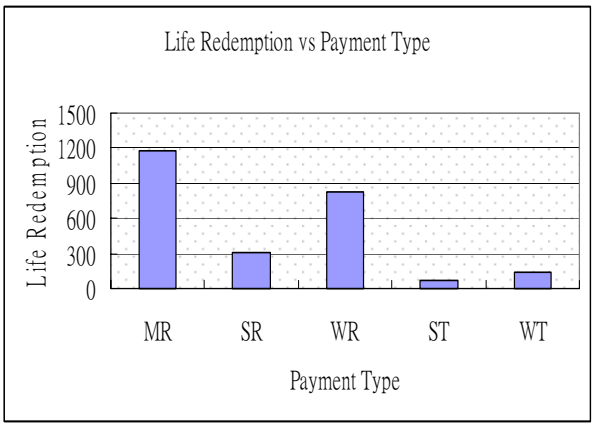
Payment Type	Percentage of customers	Life Accumulated	Life Redemption	Redemption Rate
MR	59.79%	4243	1171	24.59%
SR	2.96%	1029	305	26.60%
WR	21.30%	4172	826	16.80%
ST	7.03%	784	68	7.69%
WT	8.92%	1515	143	8.43%

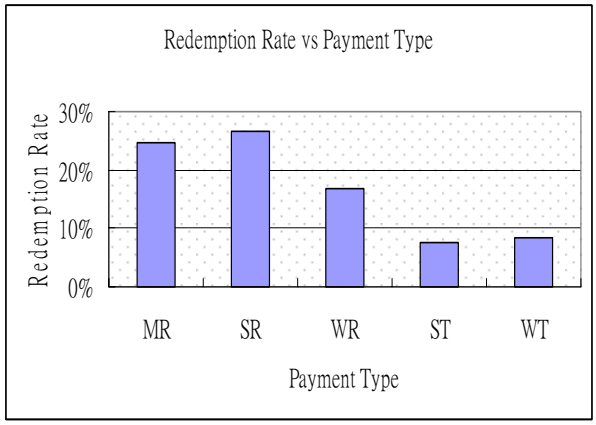
Table 4-3

From the preceding table, we make tow interesting observations:

1) Medium revolvers on average redeem the greatest amount of points, but strong revolvers have the greatest redemption rates which suggest that they are utilizing the reward program the most.
2) Both level transactors have low redemption amounts and redemption rates, which means they are not really using the reward program. This is surprising because the current reward scheme benefits transactors more than revolvers.

The graphs below show the relationship between payment type and redemption amount, and the relationship between payment type and redemption rate.





From the preceding segmentation, we can make the following conclusions about the people who are using the loyalty program the most:
In terms of REDEMPTION AMOUNT

Age: 61-70
Card type: Platinum
Payment Behavior: Medium Revolver

In terms of REDEMPTION RATE

Age: 31-40
Card type: Platinum
Payment Behavior: Strong Revolver

However, because Platinum card holders and Strong Revolver make up such a small proportion of the customers, it would not make sense for GFU to target these customers. It would be more worthwhile for GFU to learn why Classic card holders are not redeeming, and how the rewards should be modified to be suit their needs. GFU also should consider altering their reward to better suit medium revolvers because they already make considerable redemptions and make up the greatest proportion of the customer population, so a better reward program may bring even more revenue into GFU

4.1.1 Groups segmented by redemption behaviors

Earlier we suggested that there may exist two distinct behaviors for people who utilize the loyalty rewards program. One is the Earn-it-and-Redeem-it group (ER group) which accumulates loyalty points and frequently redeems them over a certain redemption interval, and the other is the Save-it-and-Get-big group (SG group), which earns and saves reward point to get big items over the same interval. If these two behaviors were to exist, then we should see two distinct patterns when plotting loyalty accumulation versus time. Both patterns would resemble each other because loyalty accumulation would increase with time, but there would be a drastic jump downwards every time the loyalty points would be redeemed. However, for the SG group the period for the aforementioned pattern would be longer and the amplitude would be greater than for the ER group

To see if these two behaviors actually exist, we first divided the customers into two distinct groups: one consisting of customers who have redeemed their loyalty points at least once, and the other group consisting of customers who never redeemed their loyalty points. Then we further analyzed the group of customers who have redeemed at least once, as this will tell us who is using the loyalty in addition to providing evidence to either corroborate or dismiss our hypothesis.

Below is a histogram of redemption rate, and we see that approximately two-thirds of the customers have never redeemed as they a have a redemption rate of zero. However for our analysis purposes, it is the remaining one-third of customers that will provide useful information.

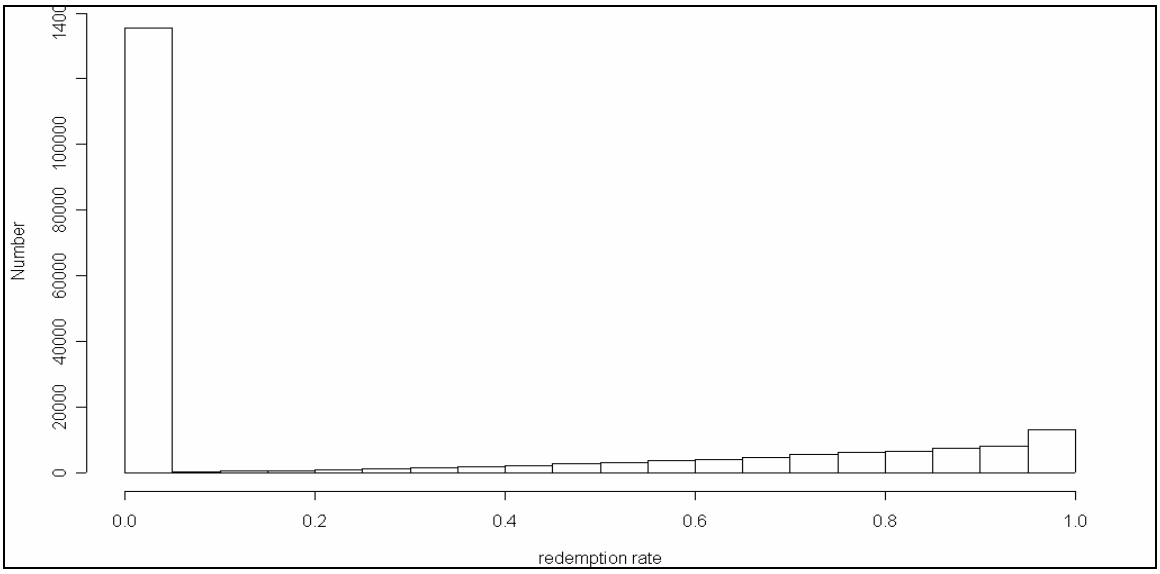


Figure 4-1

Approximately 59101 customers have redeemed at least once, and a histogram for the redemption rate for these customers can be found below. The histogram is similar to that of an exponential distribution. The meaning of this could be that when customers do redeem, they basically cash out all of the loyalty points that they have accumulated. This suggests that these customers make a conscious decision to accumulate points and they redeem once they have reached a desired level. This would imply that these customers actively use the loyalty program and believe that the loyalty program is of some value to them.

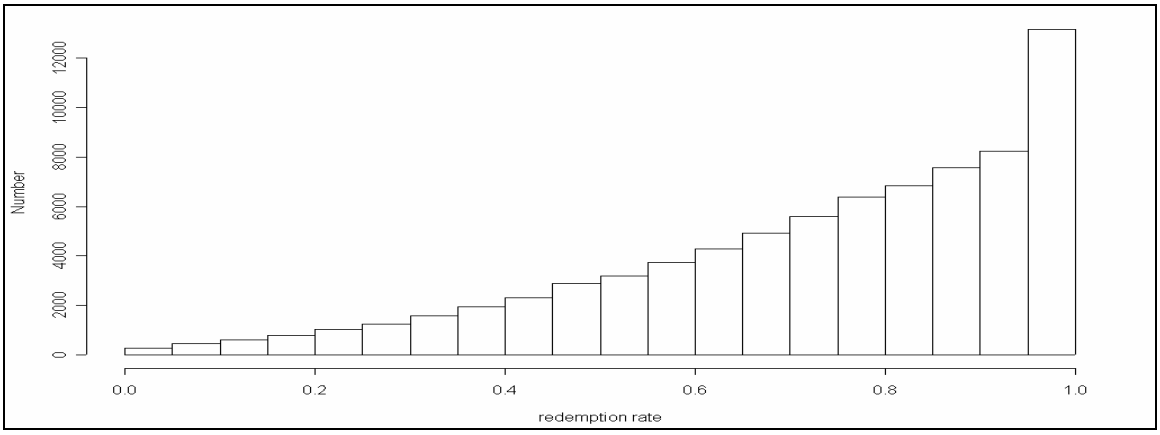


Figure 4-2

After analyzing the redemption rate of the customers who actually use the loyalty program, we thought it would be beneficial to see how many times these customers actually redeem their loyalty points. We see from the chart below that about 60% of the customers only redeemed once during the analysis period, and an additional 20% of the customer redeemed twice. This might suggest that the loyalty program is not as effective as GFU would like because multiple redemptions by a majority of the customers would more indicative of customers finding the loyalty program beneficial. However, if the less-frequent redeemers make redemptions that are of larger order of magnitude than frequent redeemer, then they would be extracting the same value as the frequent redeemers.

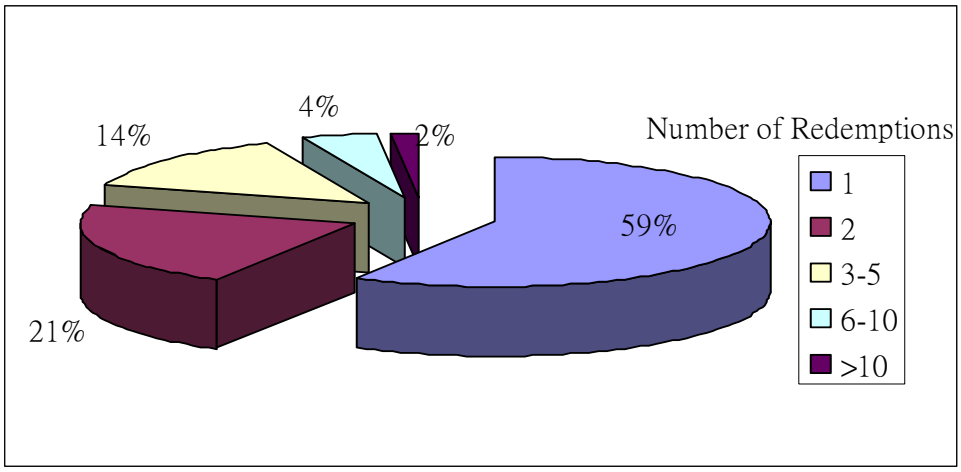


Figure 4-3

We also looked at the relationship between redemption rate and the number of times a customer redeemed his or her points. From the chart below we see that redemption rates increases when the frequency of redemptions increases. This would imply that frequent redeemers are consciously saving up their points and redeeming every time they reach their desired level of points. This means the products of the loyalty program are of value to the customers and they want the products multiple times and not just once.

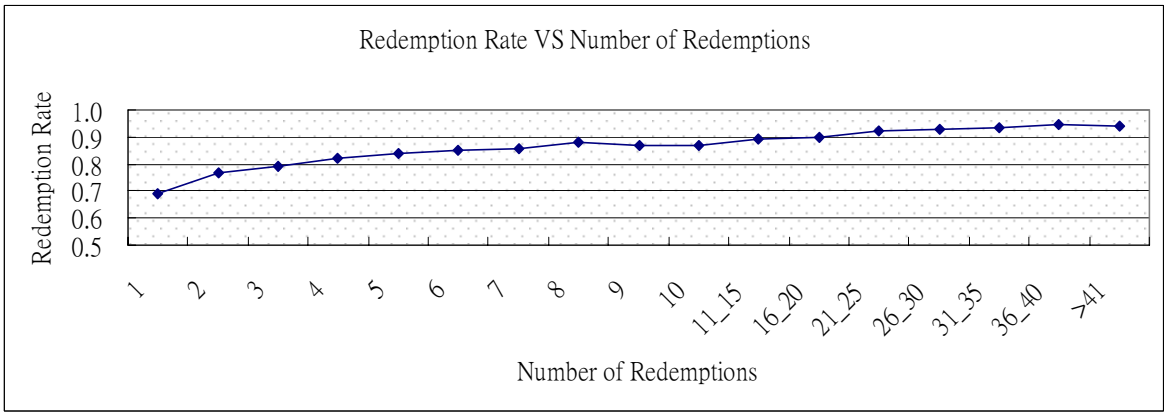


Figure 4-4

We also want to see which customer was more beneficial to GFU. Was it the customer who only redeemed once, or was it the customer who redeems frequently? From the graph below of revenue (to GFU) versus redemption times we see a general trend of revenue increasing with redemption times. This means as a customer becomes more valuable to GFU, he or she uses the loyalty program more often. This is a good thing, assuming the loyalty program

actually does bolster loyalty, because the more valuable customers are also the more loyal customers.

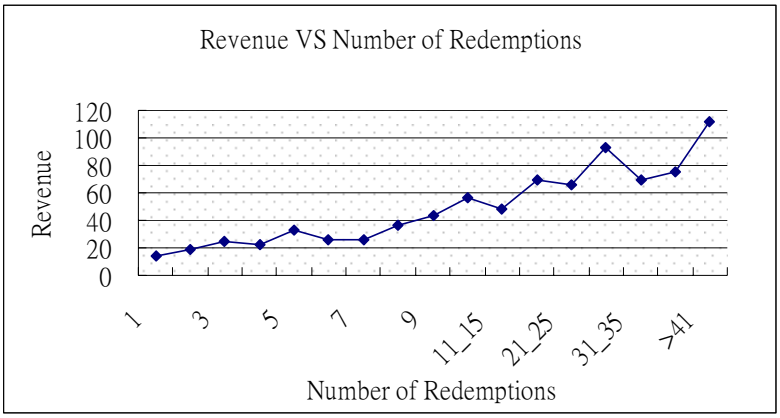


Figure 4-5

Finally, we looked at the relationship between the redemption amount per redemption and the number of times a redemption was made. We see from the chart below that generally redemption amount decreases slightly as frequency of redemptions increases. Between one redemption and ten redemptions, we see there is not a significant change in the redemption amount. The redemption amount is of the same order of magnitude, so this evidence against our hypothesis that there is an ER group and a SG group. The reason for this is that under our hypothesis the less frequent redeemer would be the SG customer, so when he or she made a redemption, the amount that was redeemed should have been much greater than for the more frequent redeemer (or ER customer). However, this is not what we see in the chart, so we must reject our hypothesis.

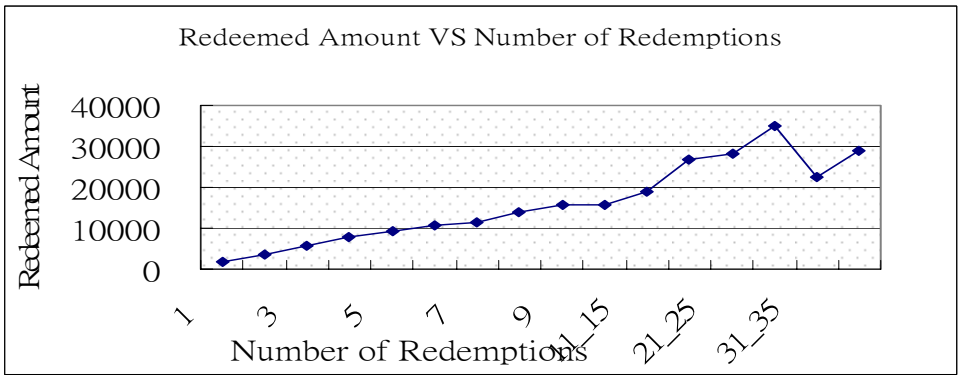


Figure 4-6

4.2 Groups from Cluster Analysis

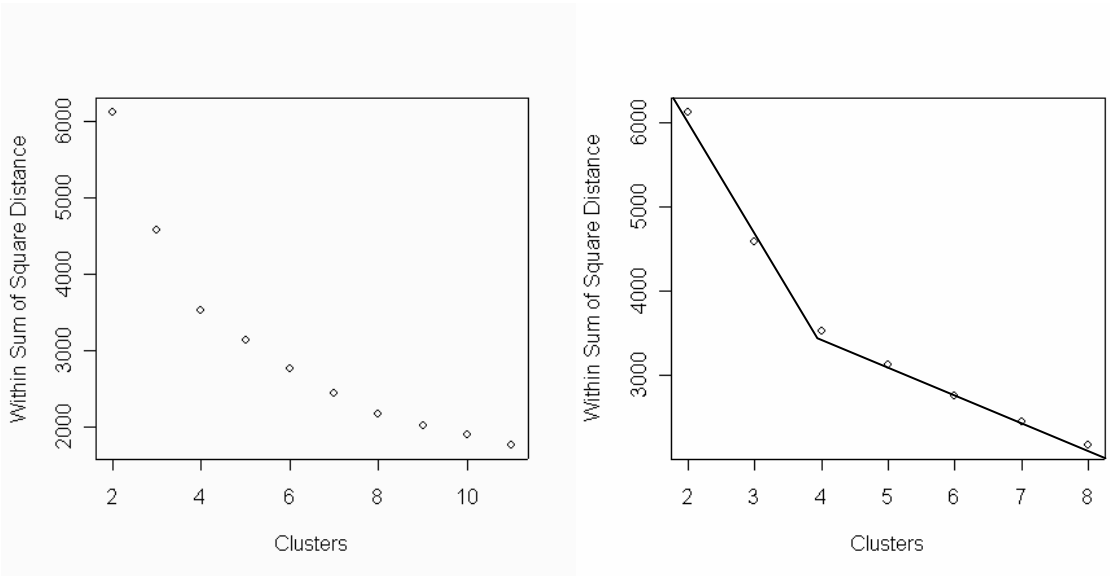
To determine the optimal number of clusters fitting the data we utilized the K-Means algorithm. The way this algorithm works is that first you fit the data to an increasing number of clusters, so first you fit the data to two clusters, then to three clusters, and so forth. The range of the numbers of clusters should not be too wide as having many clusters is not useful because the analysis becomes cumbersome. A statistical package like R or SAS is the most convenient way for actually segmenting your data into the specified number of clusters. For each iteration, you determine the total sum of squared distance from the centers of each cluster to all the points of each cluster. Then you plot total sum of squared distances versus the number of clusters, and try to find a "kink" in the plot. If the plot has an elbow shape, then the number of clusters corresponding to the point where the kink occurs will be the optimal number of clusters.

In our analysis, the range for the number of clusters was from two to eleven clusters. The reason for choosing this is that after ten clusters the analysis would not be useful to GFU. It would be difficult for GFU to specifically target so many groups, and the size of some of the groups might be so small that targeting would not bring realizable benefits to GFU.

We chose to do the cluster analysis by looking at the following four variables: redemption rate, credit usage, revenue, and attrition score. The reason for choosing these four variables is that this set gives a good picture how well the loyalty program is working. Credit usage tells us how much the cards are being used, redemption rate tells us to what extent the loyalty programs are being utilized, revenue tells us the benefits coming into GFU, and attrition score will help us determine if the loyalty program is actually effective in creating loyalty. We would have looked at risk scores also but all the data was bunched up in a very small range, so we thought the K-Means algorithm would not be effective in detecting the differences in the points. GFU also wished to do the cluster analysis with respect to payment behavior, but we decided not to include this in our analysis. The reason is that payment behavior is a qualitative characteristic and not quantitative, so it would be hard to implement this specification into the K-Means algorithm. We used R as our statistical package to do the clustering, and before running the algorithm, we had to normalize all the data with respect to each variable so that each dimension was of equal magnitude.

4.2.1 The result from K-Means analysis

Below you will find two plots of the results of our cluster analysis. The first plot is the total sum of squared distance versus the number of cluster for the range of two to eleven clusters. We saw two kinks in this plots at four clusters and eight clusters, so we decided to refine our analysis by only clustering the data within the range of two to eight clusters. The results of this analysis can be seen in the second plot. The actual R code used for the analysis can be found in the appendix as well as the R outputs corresponding to the code.



Figures 4-7 & 4-8

The reason we decided to focus on the four clusters rather than the eight clusters is that we thought it would be more useful for GFU. It will be easier for them to target four groups of customers rather than eight groups of customer, and also some of the clusters in the eights clusters were so small that analyzing them would not provide any added benefits.

After segmenting the data into the four clusters, we decided to look at the characteristics defining each cluster. At the onset we saw that the four clusters fell into two groups: one group that used the loyalty program (as seen by a relatively high redemption rate) and another group that did not use the loyalty program. Because two clusters fell into each of the group, we decided to compare clusters within the same group rather than comparing each cluster with all the other clusters. The quantitative results of our comparison can be found below, and in the next section we qualitatively define each cluster.

Non-users of Loyalty Program:

	Cluster 1	Cluster 3
Redemption Rate	0.006315	0.005348
Redemption Amount	1.27	1.18
Credit Usage	0.460	0.096
Revenue (per year)	$69.18	$7.84
Risk of Default	2.90%	1.55
Risk of Attrition	17.53%	17.64%
Product:		
Classic	66%	72%
Gold	17%	17%
Platinum	4%	3%
Revolver:		
Strong	2%	0%
Medium	80%	19%
Weak	15%	44%
Transactor:		
Strong	0%	10%
Weak	2%	28%
Age	33-47	32-47
Gender:		
Male	62%	58%
Female	38%	42%
Marital Status:		
Single	40%	42%
Married	52%	51%
Divorced	2%	2%

Table 4-4

Users of the loyalty program:

	Cluster 4	Cluster 2
Redemption Rate	0.882800	0.544100
Redemption Amount	1,348.37	1,564.91
Credit Usage	0.431	0.400
Revenue	$51.85	$51.80
Risk of Default	1.99%	1.86%
Risk of Attrition	11.72%	13.88%
Product:		
Classic	69%	70%
Gold	24%	23%
Platinum	6%	7%
Revolver:		
Strong	2%	2%
Medium	74%	71%
Weak	19%	22%
Transactor:		
Strong	1%	1%
Weak	4%	5%
Age	32-46	32-46
Gender:		
Male	57%	57%
Female	43%	43%
Marital Status:		
Single	40%	41%
Married	53%	51%
Divorced	2%	2%

Table 4-5

4.2.2 Characteristics of each group

Non-Users of Loyalty Program

Type I: A majority of GFU's customers fall into this segment. On average, each customer provides GFU with revenue of $68 and utilizes his or her credit to a fair extent. More than 95% of the customers are revolvers, meaning that they carry a balance from one cycle to the next, so they are an asset to GFU as they provide the company with additional revenue through interest payments. Their risk of attrition is 17.53% and their risk of default is 2.9%, so they are not likely to default on their payments but there is a sizable risk that they might leave the company

Type II: These customers do not use the loyalty program while also not utilizing their credit limit to a significant extent. They do not provide a lot of revenue, close to only $8, and about 40% of the customers are some sort of transactors, which is not beneficial to GFU because they do not provide the company with additional revenue. Compared to Type I Non-Users, these customers are less likely to default, but there is a slightly increased risk that these customers will leave GFU.

Type I Non-Users are more desirable than the Type II because they provide GFU with a significant amount of revenue and they actually use the products offered by GFU. Type II customers for the most part are useless because they do not provide much revenue and do not use the product. GFU could easily live without Type II customers, but they would not exist with the Type I customers.

Users of Loyalty Program

Type I: This group of Users is larger than Type II User and they utilize the loyalty program to a greater extent than Type II Users. In addition to using the loyalty program more, these customers also utilize their credit limit to a greater extent. They provide GFU with almost as much revenue as Type II Users, the percentage of customers who carry a balance is almost the same as the Type II Users. However, they are less like likely to leave GFU, but there is a slightly greater risk they will default.

Type II: This is the smallest segment of GFU's customer. They utilize the loyalty program to a fair extent, while also utilizing their credit to a good extent. On average each customer provides GFU with revenue of about $52, and about 95% of these customers are revolvers.

This implies they are an asset to GFU because they provide additional revenue through interest payments. They are not likely to default, and compared to Non-Users they are less likely to leave GFU.

Interestingly, even though Type II Users utilize the loyalty program to a lesser than Type I's, they redeem a greater amount. This would imply that there is a difference in spending behavior between these two groups. The data also provide evidence that the loyalty program is effective in creating loyalty to GFU because we see as loyalty program utilization increases, the likelihood of the customers leaving GFU decreases. However, one alarming observation is that largest group of customers is not using the loyalty program even though they provide GFU with the greatest revenue. This would imply GFU is not rewarding its greatest asset and needs to modify its loyalty program to better serve this segment.

5 Analysis of GFU's Reward Schemes

5.1 Reasons GFU does not reward the right behavior

There are two reasons why we believe that GFU is not rewarding the right behavior:

1) Customers who carry balances are profitable but they are not rewarded
2) A significant percentage of customers have amassed a lot of points but have never redeemed.

The following two sections will provide evidence to what we feel is wrong with the current reward scheme.

5.1.1 Customers who carry balances are profitable but not rewarded

As we discussed earlier, customers who carry an outstanding are more beneficial to GFU because they provide additional revenue in the form of interest payments. As a result, these customers should be rewarded more so that they do not leave GFU. To see if this is the case we looked at the redemption behavior of transactors and revolvers. In our analysis, we defined three levels for revolvers and two levels for transactors. The way we determined which payment type and which level a customer fell under is as follows:

1) For each month for each customer, determine his or her credit usage:

   Credit usage = balance / credit limit
2) Then for each customer, determine the average credit usage by taking the arithmetic average of the credit over all months of data. If the average credit usage is:

- Less than 0.01, then define customer as ST (strong transactor)
- Between 0.01 and 0.05, then define customer as WT (weak transactor)
- Between 0.05 and 0.20, then define customer as WR (weak revolver)
- Between 0.20 and 0.50, then define customer as MT (medium transactor)
- Greater than 0.50, then define customer as ST (strong revolver)

Below, you will find a table of summary statistic of each different. Some interesting findings in this table are:

1) The revenue contributed to GFU by revolvers dwarfs the revenue transactors.
2) SR is the group that contributes the greatest revenue to GFU. One SR customer contributes over 10 times revenue than each of the groups of transactors.

3) MR is the group that contributes the second highest revenue. The number is about two-third of that of SR group.
4) Even the ER group contributes significantly more than transactor with an average revenue three times as the revenue from the WT group.

Payment Type	Count	%	Avg Life Redeemed	%	Avg Redemption Rate	Avg Total Revenue	%
MR	130352	59.8%	1170.80	46.6%	0.21	315.55	31.3%
SR	6449	3.0%	304.58	12.1%	0.08	466.03	46.2%
WR	46446	21.3%	826.16	32.9%	0.14	162.24	16.1%
ST	15329	7.0%	68.08	2.7%	0.02	15.98	1.6%
WT	19438	8.9%	142.78	5.7%	0.05	49.27	4.9%

Table 5-1

Next we calculate the percentage of revenue that each group contributed and the percentage of the total lifetime redemption points redeemed by each group. Then we take the ratio of the percentage of lifetime redeemed points to the percentage of contributed revenue. This ratio gives us how many reward points each group redeemed for each dollar of contributed revenue. The result of the aforementioned calculation is shown in the table below. For example, the SR group contributed one dollar but only redeemed 0.18 points, while the WR group contributed one dollar but redeemed 1.37 points.

Payment Type	Count	%	Avg. Life Redeemed	Life Redeemed* Weight	%	Avg Redemption Rate	Avg Total Revenue	Revenue* Weight	%	Redeem Amount/ Revenue
MR	130352	59.8	1170.80	700.03	78	.21	315.55	188.67239	78	1.00
SR	6449	3.0	304.58	9.01	1	.08	466.03	13.785584	6	.18
WR	46446	21.3	826.16	176.01	20	.14	162.24	34.56298	14	1.37
ST	15329	7.0	68.08	4.79	1	.02	15.98	1.123561	<1	1.14
WT	19438	8.9	142.78	12.73	1	.05	49.27	4.390301	<2	.78

Table 5-2

The smaller the ratio, the less costly this group is to GFU. Because the values of the ratios vary greatly, it means that GFU did not reward all groups fairly. That means that the GFU did not reward the right behavior. Below is a chart of the ratio for each payment type.

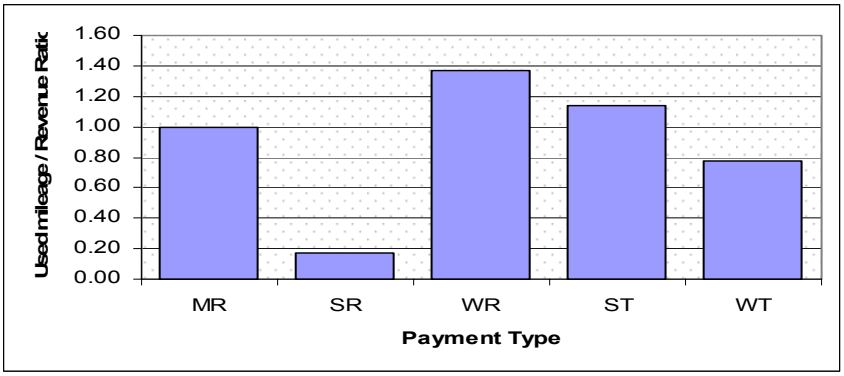


Figure 5-1

Furthermore, the revolvers contribute to almost 98% of the revenue, while the transactors (16% of total number of customers) less contribute than 3% of the revenue. This fact shows that revolvers contribute much more revenue to GFU, so they are more vital customers and they should be rewarded accordingly.

5.1.2 Significant Percentage of People Do Not Redeem

In this section, we investigate how many points customers have accumulated in their lifetime and how many of those points were redeemed. We broke the accumulation amount into levels and the results for each level can be found in the table below. We find for the group of customers that have accumulated the greatest amount of point, their redemption rate is only about 29%. This is problematic because this suggests people are not taking advantage of the points they have. This in addition to the fact that approximately two-thirds of the customers never redeem suggests that customer are not really rewarded because many of them never use the points they earned. This is further evidence the GFU's present loyalty program is not rewarding the right behavior.

Life Accumulated	Percentage of customer	Life Accumulated	Life Redemption	Redemption Rate
<1000	41.41%	238	12	**9.91%**
[1000,5000]	44.45%	2167	455	**17.92%**
[5000,10000]	6.86%	6958	2068	**29.74%**
[10000,15000]	2.56%	12174	3639	**29.88%**
>15000	4.71%	38119	9778	**28.37%**

Table 5-3

5.2 Current Reward Scheme: Rewarding Purchases

Under the current reward scheme, GFU rewards its customers when they make a purchase. Thus, the transactors primarily benefit from the reward scheme because they pay their balance in full in each cycle, so their contribution to GFU in each cycle is their purchases, which is what currently earns points. Revolvers also earn points on purchases, but their primary contribution to GFU is their interest payments, so they are being rewarded for a secondary contribution. Presently, a customer earns one point for each dollar of purchase made, so the total amount of purchase made during a cycle is how many points a customer earns during the cycle. The cost to GFU for each mile differs from country to country, and the rates are as follows:

- Nicaragua: $0.013/point
- Honduras: $0.016/point
- Costa Rica: $0.018/point

Thus if customers in Nicaragua earn a total of 100,000 points during a cycle, it will cost GFU $1300 for those points.

5.2.1 Evaluation of the current reward scheme

Presently, GFU has 204,002 effective customers, who have made purchases totaling $588,319,908 over the 2 year analysis period. Below is table the breaks down these purchases by payment type (Strong Transactor, Weak Transactor, Strong Revolver, Medium Revolver, and Week Revolver) and product type (Classic, Gold Platinum). This means total number of points redeemed during the period was 588,319,908 points. This amounts to an approximate cost of $10,589,758 for GFU ($0.018/point*588,319,908points).

Payment Behavior	Product Type	Purchase
ST	P	$1,906,875.61
ST	G	$1,765,795.48
ST	C	$1,764,432.90
WT	P	$5,482,642.03
WT	C	$5,526,363.70

WT	G	$7,352,550.25
SR	P	$2,283,387.97
SR	G	$1,062,423.46
WR	P	$46,157,409.28
WR	G	$52,982,825.21
WR	C	$41,424,922.58
SR	C	$2,558,081.01
MR	P	$118,930,575.19
MR	G	$126,272,300.85
MR	C	$172,849,322.17
Total		**$588,319,907.70**

Table 5-4

5.3 Possible Reward Scheme: Rewarding customers carrying balances as well

As it has already been stated, customers carrying an outstanding balance are more beneficial to GFU. As a result, there should be more of an effort to making sure that they do not leave GFU. This is our greatest motivation for promoting a reward scheme that rewards people carrying an outstanding balance. This scheme will reach a greater proportion of GFU's customers and will be affecting a group of customers that is vital to GFU's existence.

5.3.1 Benefits of this reward scheme

We believe that if customers are rewarded for carrying a balance, then the following changes in behavior will occur:

1) Customers will carry a greater balance from cycle to cycle.
Because customers will earn points for having a balance, this will increase the attractiveness for maintaining a balance. Thus, this could cause a certain percentage of customers to maintain a larger balance or induce them from not carrying a balance to carrying balance. More customers that have a greater balance would be beneficial for GFU because that means they earn more revenue as greater balances imply greater interest payments from customers. Unfortunately, this could be a mixed blessing for GFU because a greater balance also implies a greater risk that the customer may default on his payment, so in this case GFU will actually lose potential revenue. However, there will probably be a only a slight increase in risk

because it is highly doubtful rewarding customers to carry a balance will outweigh the inconvenience of paying higher interest payments that comes with greater balances.

In our analysis of a reward scheme for carrying a balance, we make the following assumptions about changes in payment behavior:

1) 1/10 of customers will change from ST group (strong transactors) to WT group (weak transactors).
2) 1/10 of customers will change from WT group to WR group (weak revolvers).
3) 1/10 of customers will change from WR group to MR group (medium revolvers).
4) 1/10 of customers will change from MR group to SR group (strong revolvers).
5) Customers will be unchanged if they are in the SR group originally.

With these assumptions, we will be able to calculate the change in revenue resulting from rewarding balance instead of purchases.

2) Customer will spend more.

One way for customers to increase their balance is to make more purchases or spend more using GFU's card. This is good for GFU because its customers will be using its cards more, and thus bringing in more revenue to GFU. However, the downside is that customers may go overboard with their spending and will not be unable to make their payments, but the possibility for this is slight

3) Customers less likely to leave Grupo.

Because more customers will be rewarded by earning points on balances rather than purchases and assuming the loyalty program actually does increase customer loyalty, then GFU will have a greater proportion of customers who will not defect to one of its competitors. This is always good for business because loyal customers provide more revenue and keep potential revenue away from competitors.

5.3.2 Evaluation of this reward scheme

Cost to GFU

Because it would be bad business practice for GFU to explicitly support customers having an outstanding balance, we must find another way to reward revolvers. The solution we came up with was for customer to earn points on their average balance for any given month. This still rewards the behaviors of revolvers, but it does not openly promote carrying a greater outstanding balance. The way we calculate average balance is that we have beginning

balance and ending balance for each customer for each month of the analysis period, so we take the average of the month's beginning and ending balance. By calculating the average balance for each customer for each month, we get the following table (which groups customers by payment behavior and product type):

Payment Behavior	Product Type	Total Average Balance	Total Purchases
ST	P	**$1,525,975.00**	$1,906,875.61
ST	G	**$2,504,971.00**	$1,765,795.48
ST	C	**$2,632,525.00**	$1,764,432.90
WT	P	**$12,502,366.00**	$5,482,642.03
WT	C	**$18,002,127.00**	$5,526,363.70
WT	G	**$19,599,138.00**	$7,352,550.25
SR	P	**$49,371,538.00**	$2,283,387.97
SR	G	**$88,006,360.00**	$1,062,423.46
WR	P	**$125,332,793.00**	$46,157,409.28
WR	G	**$175,523,272.00**	$52,982,825.21
WR	C	**$181,646,786.00**	$41,424,922.58
SR	C	**$249,160,924.00**	$2,558,081.01
MR	P	**$706,880,272.00**	$118,930,575.19
MR	G	**$1,349,681,418.00**	$126,272,300.85
MR	C	**$2,347,156,518.00**	$172,849,322.17
	Total	**$5,329,526,983.00**	$588,319,907.70

Table 5-5

From the table above, it is clear to see that that revolvers carry a greater average balance and thus will benefit more from the new scheme. This is what GFU should strive for because revolvers provide GFU with a majority of its revenue, so they should be rewarded for their contribution. We also see that the total for average balance for all customers is roughly nine times the value of the total purchase amounts for all customers. Thus, in the average balance rewards scheme, customers would be receiving nine times the amount of points if we still give still go with a point for one dollar scheme. However, GFU will want to give out points of the same magnitude as the purchase rewards program, so we need to scale the point for dollar ratio. Below is a cost analysis for the average balance redemption by varying how many dollars it takes to accumulate a point. The first row represents the cost, and the second row corresponds to how many times more costly the average balance is to the purchase scheme.

We see with the ten dollars for one point scheme, the cost of average balance program is almost equal to the purchase program.

	1 dollar/point	2 dollars/point	3dollars/point	5 dollars/point	10 dollars/point
cost	$95,931,486	$47,965,743	$31,977,162	$19,186,297	$9,593,149
times	9.06	4.53	3.02	1.81	0.91

Table 5-6

Revenue for GFU

If we follow the assumptions about the shift in payment behavior scheme, then following table shows how much revenue GFU should expect to see per customer. We see from the table that GFU should see each customer contribute about $96 with the average balance scheme. Considering on average GFU is roughly earning $52 dollar from the customers using the present reward, the new scheme will provide excellent returns if our assumptions holds and GFU can actually capture the new revenue.

Payment Type	Old revenue	New revenue	Revenue Increase(RI)	Percentage of Customer in this group	RI*Percentage * 10%
SR	$2,960	$2,960	$0	2.96%	$0.00
MR	$1,851	$2,960	$1,110	59.79%	$66.34
WR	$722	$1,851	$1,128	21.30%	$24.04
WT	$260	$722	$462	8.92%	$4.12
ST	$69	$260	$191	7.03%	$1.36
Total	$5,862.04				$95.86

Table 5-7

Assuming each of the 204002 customers provide GFU with revenue of $95.86, we can expect to see total revenue of $19,555,034. If we compare this revenue value to the costs of the different dollar-for-point schemes for the average balance rewards program, we can see how much of a profit GFU can expect to make from the new rewards program. The table below shows the results of this analysis.

	1dollar/point	2dollar/point	3dollar/point	5dollar/point	10dollar/point
Cost	$95,931,486	$47,965,743	$31,977,162	$19,186,297	$9,593,149
Revenue	$19,555,034	$19,555,034	$19,555,034	$19,555,034	$19,555,034
Profit	-$76,376,452	-$28,410,709	-$12,422,128	$368,737	$9,961,885

%Revenue	-27.21%	-10.12%	-4.43%	**0.13%**	**3.55%**

Table 5-8

GFU should go with the 10 dollars-for-one point schemes as provides the greatest profits, in addition to tracking the most closely with the previous rewards program.

5.4 Tiered Reward Scheme: Rewarding both behaviors with less cost

The previous section showed that GFU can have a new loyalty scheme that rewards people carrying a balance. The major problem with using the new scheme is that it might alienate the people using the old scheme. These customers had already found the old loyalty program to be of value to them, so it would be bad business to sacrifice one group of customers in the hopes obtaining greater value from another group of customers. Another problem with the new scheme is that it has a cost much greater than the old scheme, so a high ratio of dollars of balance to accumulated points is needed for break-even.

Thus we suggest a tiered reward scheme for taking advantage of both the old scheme and new scheme. The tiered reward scheme is a modified way to reduce the cost but still keep the additional revenue GFU could earn. The idea is that GFU could have both reward schemes (rewarding purchase and outstanding balance) and give customers the greatest number of miles they would get under each scheme (e.g. each month you earn a mile per dollar spent, or a mile per dollar in your balance, whichever is greater).

The way the tiered loyalty program could come into fruition is by using the reward function:

Max (Average Balance per month, Purchase per month)

5.4.1 Benefits of this reward scheme

The main benefit of the tiered reward scheme is that it allows us to take advantage of all the benefits of the purposed loyalty rewarding an outstanding balance, while reducing costs and not alienating users of the current reward scheme. For example, when one customer purchases more in one month, he will be rewarded for purchasing, but if this customer carries more balance than purchase the next month, then he will be rewarded for carrying a balance.

Therefore, we can still assume the same behaviors as the analysis in former sections.

5.4.2 Evaluation of this reward scheme

The following table shows a sensitivity analysis for the cost of the tiered loyalty program by varying how many dollars it takes to accumulate one loyalty point. Because we are using the MAX function, the cost will include already include the cost of purchases, so the second "Times" row in the table is additional cost for customers carrying a balance.

Pay	Card	1 Dollar / Point	2 Dollar / Point	3 Dollar / Point	5 Dollar / Point	10 Dollar / Point
ST	P	$2,688,861	$2,213,244	$1,875,598	$2,013,089	$1,958,883
ST	G	$3,444,380	$2,504,931	$1,751,608	$2,026,516	$1,890,104
ST	C	$3,453,603	$2,501,534	$1,740,251	$2,017,823	$1,884,355
WT	P	$13,376,984	$8,420,048	$7,119,692	$6,359,563	$5,897,420
WT	C	$19,372,495	$11,557,982	$9,138,447	$7,561,018	$6,490,065
WT	G	$20,782,475	$12,761,268	$10,472,617	$9,082,696	$8,173,125
SR	P	$49,445,617	$24,987,628	$17,003,375	$10,597,733	$6,225,585
SR	G	$88,033,950	$44,104,010	$29,485,904	$17,782,115	$9,202,598
WR	P	$128,228,727	$75,099,342	$62,313,614	$54,054,131	$49,731,716
WR	G	$180,069,592	$102,899,666	$82,212,664	$67,926,437	$59,827,384
WR	C	$185,778,770	$103,054,262	$78,624,544	$61,150,346	$50,577,605
SR	C	$249,191,711	$124,812,516	$83,393,431	$50,286,016	$25,934,888
MR	P	$712,872,941	$379,849,715	$280,801,226	$205,034,290	$158,180,992
MR	G	$1,355,643,950	$699,123,535	$491,106,223	$327,569,213	$219,733,997
MR	C	$2,354,684,003	$1,203,176,991	$831,321,799	$537,685,998	$342,891,750
	Total	**$5,367,068,067**	**$2,797,066,672**	**$1,988,360,993**	**$1,361,146,992**	**$948,600,467**
	Times	**9.12**	**4.75**	**3.38**	**2.31**	**1.61**
(current sche me excluded)		8.12	3.75	2.38	1.31	0.61

Table 5-9

The total costs for each payment type and card type was obtained by using the reward function on each customer's data for each month, and summing over all months and all customers. Again, the most expensive cost for point (Nicaragua: $0.018/point) we used to approximate the total cost.

The following graph shows the cost of the tiered reward scheme compared to the current scheme and the scheme just rewarding average balance from the previous section. The graph shows that the tiered is less costly as the scheme in previous section and it will converge to the cost of the current scheme.

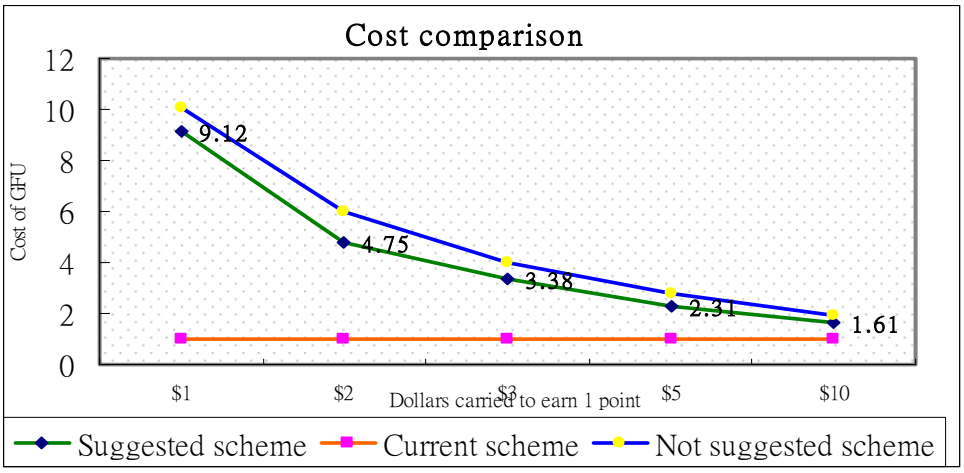


Figure 5-2

Next we look at the revenue of the tiered scheme while varying how dollars of balance it takes to accumulate one point. The table summarizes our findings. We see that GFU can save over the scheme in the previous section, and that the tiered program will bring in more money than the current reward scheme. To make sure our previous assumption, GFU is better off being conservative and going with the 5 dollar per point scheme.

	1dollar/point	2dollars/point	3dollars/point	5dollars/point	10dollars/point
Cost	$86,017,467	$39,757,442	$25,200,740	$13,910,888	$6,485,050
Revenue	$19,555,034	$19,555,034	$19,555,034	$19,555,034	$19,555,034
Profit	**-$66,462,433**	**-$20,202,408**	**-$5,645,706**	**$5,644,146**	**$13,069,984**
%Revenue	**-23.68%**	**-7.20%**	**-2.01%**	**2.01%**	**4.66%**

Table 5-10

5.5 Other Possible Reward Schemes

In order to induce customers that have accumulated a lot of points to redeem, GFU may consider two more reward schemes.

1) Allow customers to transfer their mileage
2) Allow customers to use their mileage to carry some balance

By using the first reward scheme, customers have more flexibility to use their mileage. Not only can they redeem items provided by GFU, but they can transfer their mileage to their family members and friends, or even they sell it in the internet. The second reward scheme is really useful for customers especially for revolvers, which could increase customer loyalty. However, the shortcoming is it would reduce GFU's revenue.

6 Relationship between Redemption Activity and Spent

6.1 Introduction

To answer the question, is higher spent a consequence of redemption activity or vice versa, we used the Granger Causality Test. Proposed by Granger (1969), the Granger Causality Test is a time series analysis to test causality of whether lagged variable Y helps forecast X, or vise versa. The models to test if X granger-causes Y are as follows:

$$Yt = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \beta_p X_{t-p} + e_t \quad (1)$$

$$Yt = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \tilde{e}_t \quad (2),$$

where p is the number of time units the time-series data should be lagged. We use the two models to test the following hypothesis:

H_0: $\beta_1 = \beta_2 = \cdots = \beta p = 0$

H_A: at least one $\beta i \neq 0$

If we accept the null hypothesis, then we conclude X is not helpful in forecasting Y, but if we reject the null hypothesis, then we accept that there exists at least one lagged series of X that is helpful in predicting Y. To test the null hypothesis, we run two regressions on the data based on the two models stated above and, then compare the sum of squared residuals of these two regressions. We use the following test statistic to accept or reject the null hypothesis:

$$F^* = \{[SSR(2) - SSR(1)]/p\} / \{SSR(1) / [T - (2p-1)]\},$$

where SSR is sum of squared residuals of the regression model, T is length of the dataset, and p is defined as above. The test statistic follows a F{p, T-(2p-1)} distribution, so if the p-value for our test statistic is less than our specified level of significance, then we reject the null hypothesis, else we accept the null hypotheis.

Similarly, the models to test if Y granger-causes X are as follows:

$$Xt = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots \beta_p Y_{t-p} + e_t \quad (1)$$

$$Xt = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \tilde{e}_t \quad (2)$$

By switching the variables X and Y, you can test if Y is helpful in forecasting X the same way as above and thus obtain the results for causality in the opposite direction. If only one direction has results which are significant, you have unidirectional causality; if both directions direction are significant, you have bidirectional causality; and finally if neither of the two directions are significant, the variables are independent.

The Granger Causality Test can be a useful test to predict whether a particular series Y helps forecast X. It, however, does not take into account other macroeconomic variables, so the correlation between the two variables could be caused by other unrelated factors. Thus, we use the word, "granger-cause" instead using "cause" to distinguish the Granger causation from the true causation. However, if we make some additional assumptions, then we can conclude that Granger causation is true causation. Also, when there is unidirectional causation, then we can make stronger conclusions.

To analyze the cause and effect relationship between spending and redemption activities of customers, we used the two variables, "Purchase" for spending and "Redemption" for redemption activities. In our analysis, we lagged each customer's spending and redemption data by one month, two months, and three months, and then for each lag, we concatenated each individual's monthly data into one. This enabled us to run a regression analysis using all the customer's data for each of the three lags.

We first ran Granger Causality Test using only a one month lag, and then we ran separate tests for a two month lag and a three month lag. Moreover, we separated the test by card type such as Classic, Gold, and Platinum because we assumed that different type of card holders have different spending behaviors and possibly different redemption behaviors. Thus, we conducted nine Granger Causality Tests, three lags for each card type. The following shows the models for the Granger Causality Test using a one month lag:

$$\text{Purchase}_t = \alpha_1\text{Purchase}_{t-1} + \beta_1\text{Redemption}_{t-1} + e_t,$$

$$\text{Purchase}_t = \alpha_1\ \text{Purchase}_{t-1} + \tilde{e}_t$$

and by switching the variables to get the causality results in the opposite direction:

$$\text{Redemption}_t = \alpha_1\text{Redemption}_{t-1} + \beta_1\text{Purchase}_{t-1} + e_t,$$

$$\text{Redemption}_t = \alpha_1\text{Redemption}_{t-1} + \tilde{e}_t$$

Similarly, when we ran the Granger Causality Test with a two and three month lags, we used the following models:

$$\text{Purchase}_t = \alpha_1\text{Purchase}_{t-1} + \alpha_2\text{Purchase}_{t-2} + \beta_1\text{Redemption}_{t-1} + \beta_2\text{Redemption}_{t-2} + e_t,$$

$$\text{Purchase}_t = \alpha_1\text{Purchase}_{t-1} + \alpha_2\text{Purchase}_{t-2} + \tilde{e}_t$$

for a lag by 2 months, and

$$\text{Purchase}_t = \alpha_1\text{Purchase}_{t-1} + \alpha_2\text{Purchase}_{t-2} + \alpha_3\text{Purchase}_{t-3} + \beta_1\text{Redemption}_{t-1} + \beta_2\text{Redemption}_{t-2} + \beta_3\text{Redemption}_{t-3} + e_t,$$

$$\text{Purchase}_t = \alpha_1\text{Purchase}_{t-1} + \alpha_2\text{Purchase}_{t-2} + \alpha_3\text{Purchase}_{t-3} + \tilde{e}_t$$

for a lag by 3 months. By switching the two variables, we obtained the opposite causality models for the two month lag and three month lag as well.

In our analysis of whether redemption spurs spending or vice versa, we wanted our test to take into account each customers behavior separately, rather than the broad behavior of the customer group as a whole. This is the reason we concatenated each customer's 24 monthly data into one and ran a regression on this entire dataset. By doing, each customer contributed equally to testing whether or not some for correlation existed between spending and redemption. Alternatively, we could have calculated the average spending and average redemption for all the customers for each month, and then ran a lagged regression on this average data. However, we felt some information would be lost with this method because the behavior of the high spenders and high redeemer would have overpowered the behavior of the small spenders and small redeemers. Therefore, to obtain results that better reflected each customer's behavior, we chose to test in the former way. However, because our sample size was so enormous, it was easy for the test to show a significant relationship between spending and redemption.

6.2 Cause-Effect Relationship Analysis

The results of all nine tests are summarized in the table below..

Summary of Result of Granger Causality Test:			
1 Month Lag	**Classic**	**Gold**	**Platinum**
Redemption causes Spending			
Test Statistic	648.3877	1576.9950	819.4744
P-value	0	0	0
Spending causes Redemption			
Test Statistics	1250.5110	3922.9450	1935.482
P-value	0	0	0
2 Month Lag	**Classic**	**Gold**	**Platinum**
Redemption causes Spending			
Test Statistic	222.0577	778.6442	325.7067
P-value	0	0	0
Spending causes Redemption			
Test Statistic	566.7780	2240.8380	1123.7970
P-value	0	0	0

3 month lag	Classic	Gold	Platinum
Redemption causes Spending			
Test Statistic	121.7130	476.5466	219.2673
P-value	0	0	0
Spending causes Redemption			
Test Statistic	318.3087	1418.5520	765.2127
P-value	0	0	0

Table 6-1

For the nine Granger Causality Tests in both directions, we see that all P-values close to zero, so this means we can even reject the null hypothesis at significance level of 0.1%, in addition to the standard significance levels of 5% and 1%. Therefore, the results of the nine tests are all significant and there exists a bidirectional causality relationship between spending and redemption. As we mentioned earlier the abnormally small P-values could have been the result of having a large amount of data. In our Granger Test, the length of the data was 48,659 for Platinum card members, 89,686 for Gold card members, and 150,980 for Classic card member. This large amount of data makes the significance much easier to detect.

In conclusion, for all three card types of our Granger Causality Test, there exists strong correlation between spending and redemption activities. In other words, spending can help forecast redemption, while redemption can also help forecast spending.

Now that it has been established that there exists a bidirectional causality directional relationship, GFU must be able to find ways to exploit this relationship. The purpose of the loyalty program is to prevent customers from leaving GFU, while also trying to extract greater value from the customers who are using the loyalty program. As a result, we focused on the relationship of increased redemption spurring spending. The results to following questions will help GFU to better utilize its loyalty program to improve business performance:

1. How much does spending increase by a one point increase in redemption?
2. Will the spending increase more, one month after redemption has been spurred, or is it more observable two or three months after redemption has been spurred?
3. Which card type of customers' spending is most affected by an increase in redemption?

Before answering these questions, we must remember that the Granger Causality Test merely tells that there evidence of a lagged correlation between two time series; our quantitative

interpretation here is just an estimate based on the evidence of the correlation. Thus, the estimates are on average likely have a certain amount of error, and we must assume the customers' behavior is predictable with respect to increases in spending and redemption activities.

To answer the question proposed above, we examined the coefficients of the lagged regressions we ran previously because the coefficient of each variable measures the degree of correlation between spending and redemption activities. The table below summarizes the value of the coefficients for each of the three time lags which were done for each of three card types. We also include the coefficient for the test in the other direction (spending spurring redemption) for thoroughness.

Summary of the Coefficients:		**Classic**	**Gold**	**Platinum**
Redemption(x) granger-causes Spending(Y):				
lag by 1month	Coefficient:	0.0114	0.0501	0.0517
lag by 2 months	Coefficients: 1 month lag	0.0073	0.0359	0.0351
	2 month lag	0.0041	0.0322	0.0273
	TOTAL	0.0114	0.0681	0.0624
lag by 3 months	Coefficients: 1 month lag	0.0066	0.0329	0.0332
	2 month lag	0.0027	0.0287	0.0236
	3 month lag	0.0018	0.0169	0.0210
	TOTAL	0.0111	0.0785	0.0778
Spending(x) granger-causes Redemption(y):				
lag by 1month	Coefficient:	0.4453	0.4853	0.4469
lag by 2 months	Coefficients: 1 month lag	0.3227	0.3645	0.3608
	2 month lag	0.1744	0.2612	0.2240
	TOTAL	0.4971	0.6257	0.5848
lag by 3 months	Coefficients: 1 month lag	0.2821	0.3241	0.3098
	2 month lag	0.1222	0.2151	0.1993
	3 month lag	0.0944	0.1453	0.1560
	TOTAL	0.4987	0.6845	0.6651

Table 6-2

From the table, we can easily provide answers to three questions:

1) The table shows that for a Classic cardholder a one point increase in redemption forecasts $ 0.0114 increase in spending next month. For the Gold cardholder, if

we use the two-month lag model, a one point increase in redemption forecasts $0.0359 increase in spending next month and $0.0322 increase in spending two months later. For the Platinum cardholder, if we use the three-month lag mode, a one point increase in redemption forecasts $0.0332 increase in spending after one month, $0.0236 two month later, and $0.021 three months later.

2) By looking at three-month lag model, we see the value for coefficient for the one-month lag is the greatest for all three card types. This means most of the increase in spending is seen one month after redemption has been spurred.
3) By summing up the coefficients of each time lag model for each of the three card types, we see a greater impact on spending from increased redemption for Platinum and Gold cardholders than for Classic cardholders. Thus we can conclude that increased redemption has more of an effect on Platinum and Gold member, than Classic members

Finally, we can make the following conclusions from our analysis of the cause-effect relationship between spending and redemption:

1) GFU's loyalty program is indeed effective. The reason for this is if a customer is happy with the loyalty program, he or she will redeem his or her point. This will GFU to see an increase in the customer's spending which translate into more money coming into GFU. Consequently, if the customer spends more, he or she will also redeem more, so we will see a cyclical effect.
2) GFU now has a model to forecast future spending by looking at the past redemption activity of its customer. This will allow GFU to have a more accurate picture how much money is coming into the company, and it will also allow GFU to target specific groups for spurring spending.
3) GFU now also knows which card types show the greatest increase in spending by using the loyalty program, so GFU should modify its loyalty program to better suit the needs of Platinum and Gold members, so they redeem more and thus spend more. GFU should also modify its loyalty program to better suit the needs of it Classic members so that it can extract more value from its largest customer base.

6.3 Extensions of Cause-Effect Relationship

After establishing that increased redemption forecasts increased spending, GFU requested the model be sliced with respect to other factor such as gender, age, and payment, to see if certain crosses of factor showed relatively high increasing in spending from increased redemption. The following three tables summarize some results for gender, age and payment type.

By Gender, Card Type (Y: Purchase)	Classic Man	Classic Woman	Gold Man	Gold Woman	Platinum Man	Platinum Woman
Coefficients:						
redemption lagged by 1 month	0.0192	0.0030	0.0360	0.0233	0.0321	0.0358
redemption lagged by 2 months	0.0101	0.0014	0.0251	0.0367	0.0229	0.0255
redemption lagged by 3 months	0.0065	0.0009	0.0200	0.0093	0.0203	0.0230
TOTAL REDEMPTION	**0.0357**	**0.0054**	**0.0810**	**0.0693**	**0.0752**	**0.0844**

Table 6-3

By Age, Card Type = Classic, Gender = Male (Y:Purchase)	18-30	31-40	41-50	51-100
Coefficients:				
redemption lagged by 1 month	0.0245	0.0255	0.0090	0.0309
redemption lagged by 2 months	0.0083	0.0179	0.0058	0.0081
redemption lagged by 3 months	0.0068	0.0104	0.0052	0.0068
TOTAL REDEMPTION	**0.0395**	**0.0537**	**0.0200**	**0.0458**

Table 6-4

By Gender, Card Type, Age = 51-100 (Y:Purchase)	Classic Man	Classic Woman	Gold Man	Gold Woman	Platinum Man	Platinum Woman
Coefficients:						
redemption lagged by 1 month	0.0309	0.0081	0.0330	0.0176	0.0333	0.0342
redemption lagged by 2 months	0.0081	0.0087	0.0426	0.0261	0.0253	0.0276
redemption lagged by 3 months	0.0068	0.0140	0.0259	0.0203	0.0161	0.0272
TOTAL REDEMPTION	**0.0458**	**0.0308**	**0.1015**	**0.0639**	**0.0747**	**0.0890**

Table 6-5

By Payment Type, Card Type = Classic,	MR	SR	ST	WR	WT

Gender = Male (Y:Purchase)					
Coefficients:					
redemption lagged by 1 month	0.0155	-0.0010	0.0507	0.0521	0.0585
redemption lagged by 2 months	0.0101	0.0014	0.0340	0.0085	0.0326
redemption lagged by 3 months	0.0060	0.0028	-0.0257	0.0118	0.0126
TOTAL REDEMPTION	**0.0316**	**0.0032**	**0.0591**	**0.0724**	**0.1038**

Table 6-6

By Gender, Card Type, Payment Type = WR (Y:Purchase)	**Classic Man**	**Classic Woman**	**Gold Man**	**Gold Woman**	**Platinum Man**	**Platinum Woman**
Coefficients:						
redemption lagged by 1 month	0.0521	0.0008	0.0306	0.0385	0.0319	0.0346
redemption lagged by 2 months	0.0085	0.0002	0.0248	0.0222	0.0235	0.0279
redemption lagged by 3 months	0.0118	0.0003	0.0196	0.0097	0.0331	0.0076
TOTAL REDEMPTION	**0.0724**	**0.0013**	**0.0750**	**0.0704**	**0.0884**	**0.0701**

Table 6-7

A few interesting observation that can be made for each of the three categories are:

- By gender: We see that both genders of Platinum cardholders and male Gold cardholders have higher coefficients than Classic cardholders.
- By age: We first analyze male Classic cardholders separated by four age groups, under 30, 31-40, 41-50, and more than 50. We see that the group of more than 50 years old has the highest coefficients for the four age groups. We then added the age element of more than 50 years old into card type and gender, and then looked at the coefficients. For the group of more than 50 years old, we can see that although the coefficients for male Gold cardholders and male Platinum cardholder decreased, the coefficients for the other four groups increased.
- By payment type: We first analyzed male Classic cardholders separated by the five payment types (MR, SR, ST, WR, WT), similar to what we did with age. We found that the WR and WT groups have higher coefficients. We used WR group to further analyze the effect of card type and gender because we previously found revolvers were more profitable. For the WR group, we see both increases and decreases in the coefficients, and for both genders of Gold cardholders and Platinum cardholder have coefficients greater than the coefficients for Classic cardholders.

Overall, we found four higher coefficient groups. Platinum card holders of both genders, male Gold cardholders, the age group of more than 50 years old, and payment type of WR and WT. Therefore, we conclude that GFU would be able to expect to see a greater increase in spending if GFU specifically targets these groups for increased redemption.

7 Conclusion and Recommendations

7.1 Conclusion

We have found that in terms of amount of points redeemed, the group that used the loyalty program the most can be characterized as being between the ages of 61 to 70, having Platinum card, and exhibiting payment behavior consistent with a Medium Revolver; in terms of redemption rate, the group that used the loyalty program the most can be characterized as being between the ages of 31 to 40, having a Platinum card, and exhibiting payment behavior consistent with a Strong Revolver. Both of these groups are small groups within GFU's customer base, so this means most of customers are not utilizing loyalty program which could mean they do not find the program to be of value to them. From our cluster analysis, we were able to break the customers into four distinct groups. Two of the four groups used the loyalty program quite extensively; the differences between these two groups are that one group redeems a greater percentage of its total accumulated points but redeems a lesser amount of points and has a lesser likelihood of leaving GFU than the other group. The other two groups barely use the loyalty program, but there are stark differences among these two groups; one of the groups is GFU's greatest asset because its constituents provide the greatest per customer revenue and have the highest credit usage, while the other provides GFU with little or no benefits as they provide a small per customer revenue and barely use their credit card. Because the majority of the customers fall into the two groups that do not use the loyalty, this is evidence that loyalty program is not effective in rewarding its customers. From the redemption behavior analysis, we were forced to reject our hypothesis that there existed two distinct redemption behaviors; one than accumulated a lot of points but did not redeem frequently in order to redeem bigger prizes, and the other that redeemed frequently to get the smaller ticket items. We only found evidence that customers primarily redeemed the smaller items. However, some interesting observations that came out of the analysis is that the customers that do redeem find the loyalty program to be of value to them because, when they redeem their points, they redeem most of their points, and also frequent redeemers provide GFU with greater revenue.

Because so few customers were utilizing the loyalty program, there was already evidence that GFU was not rewarding the right behavior. Intuitively, this made sense because the current scheme primarily benefits transactors, while the revolvers make up most of GFU's customer based and provide GFU with a majority of its revenue. We looked at how many points each

of the five payment groups redeemed for every one dollar contribution of revenue to GFU, and found there were significant differences among the five groups, so all the groups were not fairly rewarded. This led us to see if it was possible for GFU to reward people carrying an outstanding balance instead of earning points on purchases. By having customers earn points on their average balance per month, we not only found that it is economically possible for GFU to use such a scheme, but we also found that it could turn more of a profit that the current rewards scheme. In an attempt to reward both payment behaviors, we looked into a tiered scheme which rewards the greater of average balance and purchase for each customer per month. We found this scheme was also economically viable, and was less costly than the scheme that just rewards the average balance.

Finally, when analyzing that cause-effect relationship between spending and redemption, we found that an increase in redemption will show an increase in spending, but also an increase in spending will show an increase in redemption. Thus, our analysis does confirm the loyalty program is effective because users of the loyalty program will spend more and thus bring in more revenue to GFU. Additionally, because increased spending will show additional redemption, both redemption and spending feed each other, which is advantageous to GFU because it can extract greater value from its customer by riding the cycle until it finally breaks. Our analysis also provides GFU with a model to forecast future spending by using past redemption activity. This gives GFU a more accurate way to gauge its revenue stream, and also see how targeting specific subgroups can have an effect on the bottom line. We also found that an increase spending occurs primarily one month after redemption was increased, and that Gold and Platinum members spend more after redeeming than do Classic members.

7.2 Recommendations

Because a majority of the customers are not using the loyalty program, GFU needs to improve its relationship with its customers to find out what they really want of the rewards program. Because we have seen that increased redemption will show an increase in spending, it would be beneficial for GFU to find out how to spur redemption in order extract greater value from its customers. We also saw that frequent redeeming customers bring in more revenue, so this is another reason for GFU to make an effort for GFU to induce redemption among the customers who are not using the loyalty program. In addition, we saw that the customers

that do redeem their points do not redeem a lot of points at once, so GFU should consider scrapping some of its more costly prizes and primarily promote the redemption of its smaller-ticket items.

Also, as stated many times, revolvers benefit GFU, so it should have a loyalty that rewards their payment behavior. The current reward scheme primarily benefits transactors, thus GFU is at risk of losing its most important customers. The scheme of earning points on the average balance will cause a shift from transactors being rewarded to revolvers being rewarded. Because of this, GFU should strongly consider rewarding average balance rather than purchases. In an attempt to prevent users of the current scheme from being displeased with the new scheme, GFU should consider implementing the proposed tiered scheme, which rewards the greater of average balance and purchase. This scheme will be attractive to both transactors and revolvers, so GFU will be reaching a much larger portion of its customer base. In addition to this, the tiered reward is less costly than the reward scheme that only rewards average balance, and if the dollar per point ratio is large enough, then the tiered scheme is even less costly than the current reward scheme. GFU could also get a little creative with its reward scheme by allowing customers to transfer or sell their accumulated point to the customers of GFU. This might spur redemption of the larger ticket item, and at the least the customer could extract some form of value from his or her accumulated point. Another idea is to let the accumulated points pay off a portion of the customer's outstanding balance. This would mean less revenue for GFU but could mean increased loyalty amongst its customers.

In closing, GFU's loyalty program is effective when used, but the problem lies in that many customers are not using the program. If GFU could get more customers to use its program then its benefits would be twofold: a majority of its customer would be more loyal and it would be extracting greater value from a larger proportion of its customers. GFU needs to spend time and resources in understanding what its Classic and Gold members want from the reward program because they make up most of its customer base and the Platinum members are already using the loyalty program.

Appendix I ER Diagram and data type definition

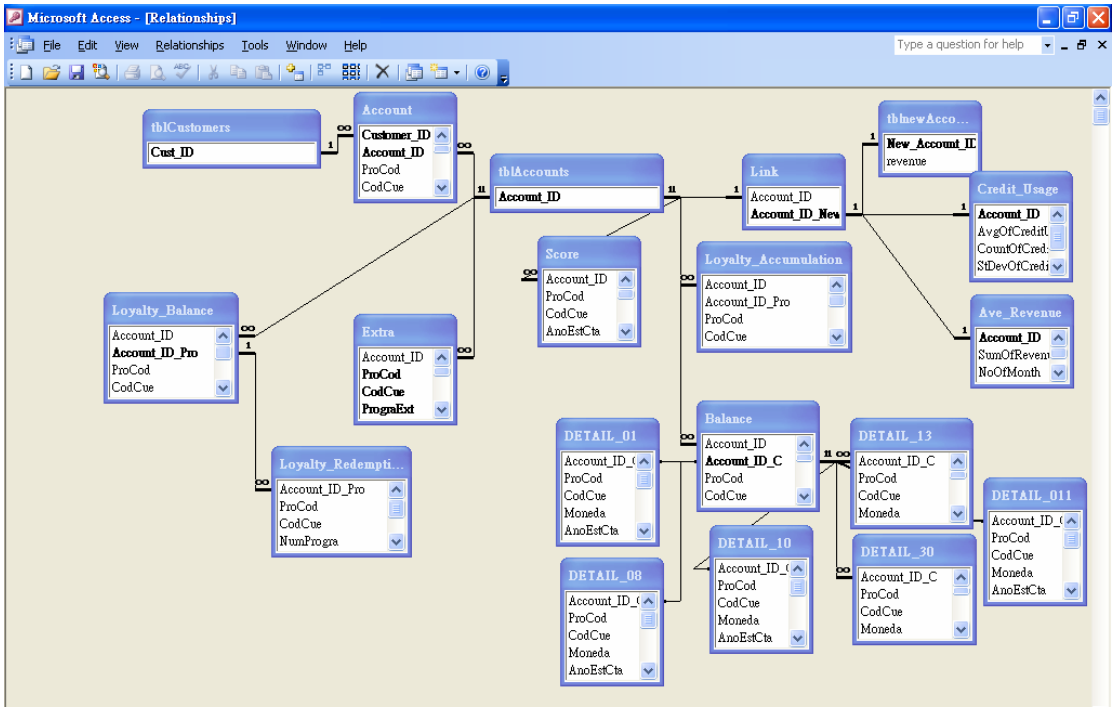


Figure: ER Diagram

ACCOUNT:	
Customer_ID	Text
Account_ID	Text
ProCod	Integer
CodCue	Long Integer
CodCli	Long Integer
SdoOpeCta	Integer
PlanCta	Integer
LimCredito	Long Integer
FecUltAuLC	Long Integer
MtoUltLC	Double
Categoria	Text
EstCivil	Text
Sexo	Text
FecNacmto	Long Integer
FecApeCta	Long Integer
Product_Type	Text
Age	Long Integer

EXTRA:	
Account_ID	Text
ProCod	Integer
CodCue	Long Integer
PrograExt	Integer
PlanExt	Integer
Moneda	Integer
Certificado	Long Integer
NoCertifUs	Integer
MtoUtil	Double
MtoInt	Double
CuotaGen	Integer
MtoCuota	Double
FecUltCuot	Long Integer

LOYALTY_ACCUMULATION:	
Account_ID	Text
Account_ID_Pro	Text
ProCod	Integer
CodCue	Long Integer
NumProgra	Integer
AnoEstCta	Integer
MesEstCta	Integer
MtoPuntos	Double
MtoPenal	Integer
MtoNeto	Double

SCORE:	
Account_ID	Text
ProCod	Integer
CodCue	Long Integer
AnoEstCta	Integer
MesEstCta	Integer
Risk	Integer
Revenue	Integer
Attrition	Integer
ExclusionRisk	Integer
ExclusionRevenue	Integer
ExclusionAttrition	Integer
ScoreCardType	Integer

LOYALTY_REDEMPTION:	
Account_ID_Pro	Text
ProCod	Integer
CodCue	Long Integer
NumProgra	Integer
AnoEstCta	Integer
MesEstCta	Integer
MtoUtili	Double

LOYALTY_BALANCE:	
Account_ID	Text
Account_ID_Pro	Text
ProCod	Integer
CodCue	Long Integer
NumProgra	Integer
MtoGanado	Double
MtoPenal	Integer
MtoNeto	Double
MtoUtili	Double

STATEMENT_DETAIL:	
Account_ID_C	Text
ProCod	Integer
CodCue	Long Integer
Moneda	Integer
AnoEstCta	Integer
MesEstCta	Integer
Secuencia	Integer
CodTra	Integer
CodConcept	Integer
MtoTra	Double
Comision	Double
Sobrecargo	Integer
Category	Long Integer
OriTra	Integer
Time	Integer
Account_ID_CT	Text

STATEMENT_HEADER:	
Account_ID_C	Text
ProCod	Integer
CodCue	Long Integer
Moneda	Integer
AnoEstCta	Integer
MesEstCta	Integer
Status	Text
SdoUltCort	Double
DebitosMes	Double
CreditMes	Double
NvoSaldo	Double
MtoPagoMes	Double
MtoRetMes	Double
NumRetMes	Integer
MtoCompMes	Double
NumCompMes	Integer
SaldoMora	Double
Intereses	Double
IntBonific	Integer
IntMorator	Double
LimCredito	Long Integer
NumPagVenc	Integer
PagoMinMes	Double
PlanCta	Integer
Ciclo	Integer

Appendix II Data Error

Some errors are found in the data GFU provides.

(1) GENDER

6 English letters used for presenting the GENDER.

F, H, M, N, X, S

(2) MARITAL STATUS

14 English letters used for presenting the MARITAL STATUS

0, 3, A, C, D, I, L, M, N, O, Q, S, U, V

(3) BIRTH DATE

Some customers whose birth data is 19000101

(4) REDEMPTION AMOUNT

Value form redemption amount per month shows below 200

Redemption rate for some customers are over than 1. This means life accumulated amount is less than life redemption amount

(5) LOYALTY DATA

Loyalty data are provided not from 11/2002, but from1996. Revenue data are only provided from 11/2002.

Appendix III Data Query

The most queries used in this project are “Make Table Query”, “Update Query”, and “Select Query”. “Make Table Query” is used to extracted data from one or more databases and put queried data in a new table. “Update Query” is used when we want to identify data into several types. “Select Query” is like “Make Table Query”. The difference is this query will produce a temporary table which is used to export data into a file with “txt” or “excel” format.

Currency conversion query:

```
UPDATE DETAIL_01 SET DETAIL_01.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];

UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]
WHERE (([Moneda]=2));

UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]*0.002779
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]*0.002508
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]*0.002275
WHERE (([AnoEstCta]=2004 And [Moneda]=1));


UPDATE DETAIL_08 SET DETAIL_08.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];
UPDATE DETAIL_08 SET DETAIL_08.Account_ID_CT = [Account_ID_C] & "_" & [Time];


UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]
WHERE (([Moneda]=2));

UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]*0.070169
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]*0.066205
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]*0.062746
WHERE (([AnoEstCta]=2004 And [Moneda]=1));
```

```
UPDATE DETAIL_10 SET DETAIL_10.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];
UPDATE DETAIL_10 SET DETAIL_10.Account_ID_CT = [Account_ID_C] & "_" & [Time];


UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]
WHERE (([Moneda]=2));


UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]*0.070169
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]*0.066205
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]*0.062746
WHERE (([AnoEstCta]=2004 And [Moneda]=1));

UPDATE DETAIL_11 SET DETAIL_11.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];
UPDATE DETAIL_11 SET DETAIL_11.Account_ID_CT = [Account_ID_C] & "_" & [Time];


UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]
WHERE (([Moneda]=2));

UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]*0.060852
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]*0.057653
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]*0.054926
WHERE (([AnoEstCta]=2004 And [Moneda]=1));
```

Another currency conversion query:

```
UPDATE DETAIL_01 SET DETAIL_01.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];

UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]
WHERE (([Moneda]=2));
```

```
UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]*0.002779
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]*0.002508
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_01 SET DETAIL_01.Commission = [Comision]*0.002275
WHERE (([AnoEstCta]=2004 And [Moneda]=1));


UPDATE DETAIL_08 SET DETAIL_08.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];
UPDATE DETAIL_08 SET DETAIL_08.Account_ID_CT = [Account_ID_C] & "_" & [Time];


UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]
WHERE (([Moneda]=2));

UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]*0.070169
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]*0.066205
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_08 SET DETAIL_08.Commission = [Comision]*0.062746
WHERE (([AnoEstCta]=2004 And [Moneda]=1));

UPDATE DETAIL_10 SET DETAIL_10.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];
UPDATE DETAIL_10 SET DETAIL_10.Account_ID_CT = [Account_ID_C] & "_" & [Time];


UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]
WHERE (([Moneda]=2));


UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]*0.070169
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]*0.066205
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_10 SET DETAIL_10.Commission = [Comision]*0.062746
WHERE (([AnoEstCta]=2004 And [Moneda]=1));
```

```
UPDATE DETAIL_11 SET DETAIL_11.[Time] = ([AnoEstCta]-2002)*12+[MesEstCta];
UPDATE DETAIL_11 SET DETAIL_11.Account_ID_CT = [Account_ID_C] & "_" & [Time];


UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]
WHERE (([Moneda]=2));

UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]*0.060852
WHERE (([AnoEstCta]=2002 And [Moneda]=1));
UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]*0.057653
WHERE (([AnoEstCta]=2003 And [Moneda]=1));
UPDATE DETAIL_11 SET DETAIL_11.Commission = [Comision]*0.054926
WHERE (([AnoEstCta]=2004 And [Moneda]=1));
```

Appendix IV Segmentation of Products and Country

Product Segmentation:

Classic	Redemption Rate	Redemption Amount	Sample Size
MULTIPREMIOS	0.26	1,128.47	127107
DISTANCIA	0.00	10.35	1152
CASHBACK	0.32	8.55	23879
ESSO CARD	0.20	989.43	8486

Gold	Redemption Rate	Redemption Amount	Sample Size
MULTIPREMIOS	0.35	3649.47	34143
DISTANCIA	0.00	48.15	3164
CASHBACK	0.42	42.10	4219
ESSO CARD	0.36	5254.97	857

Platinum	Redemption Rate	Redemption Amount	Sample Size
MULTIPREMIOS	0.38	12533.54	9594
DISTANCIA	-	-	-
CASHBACK	0.46	47.03	619
ESSO CARD	-	-	-

	Redemption Rate	Redemption Amount	Sample Size
BUDP	0.00	2.94	10689

Country Segmentation:

Country	**Redemption Rate**	**Sample Size**
Costa Rice	0.3215	77869
Nicaragua	0.2173	97017
Honduras	0.2527	55351

Appendix V Cluster Analysis Methodology

A Bottom-Up Approach

Cluster analysis is the most frequently used method of segmenting a market. The underlying definition of cluster analysis procedures mimic the goals of market segmentation: to identify groups of respondents in a manner that minimizes differences between members of each group while maximizing differences between members of a group and those in all other groups. However, there is one key difference between clustering and segmenting respondents — clusters produce groups of respondents who have similar responses on key variables while segmentation finds groups of respondents who have similar behaviors when purchasing and seeking products in the market.

Both hierarchical and iterative cluster analysis procedures can be used, but hierarchical procedures are difficult to evaluate once you exceed 100 or 200 survey respondents. A mong the various iterative cluster analysis procedures, the K-Means method is most of ten used. K-Means cluster analysis can be found in all of the most popular statistical programs (SAS, SPSS, and R). Software R would be used in this project.

R Statistics Software

S is a high level language and an environment for data analysis and graphics developed at AT&T Bell Laboratories, lead by John M. Chambers who, in 1998, received the ACM Software System Award where S was cited as "The S system, which has forever altered how people analyze, visualize, and manipulate data."

S-Plus and R are two implementations and preferred statistics software tools. They already be widely used for many data analyses, and also for research and teaching. R is free to get including source code, and it's protected to remain free in the future. Besides, it is easily to find usage manual in the web sites and numerous statistical professionals are familiar with R.

K-Mean Algorithm

The K-Means clustering algorithm chooses a pre-specified number of cluster centers to minimize the with-in class sum of squares from those centers. The algorithm needs a starting point, so we choose the means of the clusters identified by group-average clustering. Generally speaking, four steps are iterated:

1. Randomly pick K cluster centers
2. Assign each point to the cluster whose mean is closest in Euclidean distance
3. Compute the mean vectors of the points in each cluster
4. Use these as new cluster centers and iterate the algorithm

K-Means Algorithm: Pseudo-Code

```
for k=1,…,K, let r(k) be a randomly chosen point from D
while changes in cluster C_k happen do
    form clusters:
    for k=1,…,K do
        C_k={x in D | d(r_k,x)≤d(r_j,x)} for all j=1,…,K, j≠k}
    end
    compute new cluster centers:
    for k=1,…,K do
        r_k = (1/n_k) Σ_{x_i∈C_k} x_i
    end
end
```

Application in this project

In this project, cluster analysis plays an important role as a tool to find optimal segmentation. Especially for multi-dimensional variables, K-means could help us identify clusters and tell us the characteristics of our target group. Detail process of all the analyses and results would be put in later chapters in this document.

Appendix VI R Code for Granger Test

```
card_type_C<-read.csv("card_C_300_3TIMES.txt")
colnames(card_type_C)<-c("accountid","purchase","redemption","time")
attach(card_type_C)


mylag<-function(x,n){
      if(n<length(x)){
          return(x[(1+n):length(x)])
       }
   }


LagDataByThree<-function(x){
       regressiondata = NULL;
       uniqueIDs<-unique(x[,1]);
       for(i in 1:length(uniqueIDs)){
              subset<-x[x[,1]==uniqueIDs[i],];
              n=length(subset[,1])
              if(n>3){
                     purchase1<-mylag(subset[,2],1);
                     purchase2<-mylag(subset[,2],2);
                     purchase3<-mylag(subset[,2],3);
                     redemption1<-mylag(subset[,3],1);
                     redemption2<-mylag(subset[,3],2);
                     redemption3<-mylag(subset[,3],3);
                     temp<-cbind(subset[1:(n-3),2],purchase1[1:(n-
3)],purchase2[1:(n-3)],purchase3,subset[1:(n-3),3],redemption1[1:(n-
3)],redemption2[1:(n-3)],redemption3);
                     regressiondata<-rbind(regressiondata,temp);
              }
       }
       return (regressiondata)
}



relevantdata<-card_type_C[,1:3]
regressiondata<-LagDataByThree(relevantdata)
regressiondata[1:30,]
```

```
classic_Regression_Lag3<-lm(regressiondata[,1] ~ regressiondata[,2] +
regressiondata[,3] + regressiondata[,4] + regressiondata[,6] +
regressiondata[,7] + regressiondata[,8])
classic_Regression_Lag3
summary(classic_Regression_Lag3)
anova(classic_Regression_Lag3)

classic_Regression1_Lag3<-lm(regressiondata[,1] ~ regressiondata[,2] +
regressiondata[,3] + regressiondata[,4])
classic_Regression1_Lag3
summary(classic_Regression1_Lag3)
anova(classic_Regression1_Lag3)

T<-length(regressiondata[,1])
T
RSS1<-sum(residuals(classic_Regression_Lag3)^2)
RSS1
RSS0<-sum(residuals(classic_Regression1_Lag3)^2)
RSS0

test_statistics_Lag3<-((RSS0-RSS1)/3)/(RSS1/(T-7))
test_statistics_Lag3
p_value<-(1-pf(test_statistics_Lag3,3,T-7))
p_value

swclassic_Regression_Lag3<-lm(regressiondata[,5] ~ regressiondata[,6]+
regressiondata[,7] + regressiondata[,8] + regressiondata[,2] +
regressiondata[,3] + regressiondata[,4])
swclassic_Regression_Lag3
summary(swclassic_Regression_Lag3)
anova(swclassic_Regression_Lag3)

swclassic_Regression1_Lag3<-lm(regressiondata[,5] ~ regressiondata[,6]
+ regressiondata[,7] + regressiondata[,8])
swclassic_Regression1_Lag3
summary(swclassic_Regression1_Lag3)
anova(swclassic_Regression1_Lag3)

swRSS1<-sum(residuals(swclassic_Regression_Lag3)^2)
swRSS1
swRSS0<-sum(residuals(swclassic_Regression1_Lag3)^2)
```

```
swRSS0

swtest_statistics_Lag3<-((swRSS0-swRSS1)/3)/(swRSS1/(T-7))
swtest_statistics_Lag3
1-pf(swtest_statistics_Lag3,3,T-7)
```

Appendix VII References

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Damodar N. Gujara