

Differential Privacy in the Industry: Challenges and Successes

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Modalities of Privacy

		Data	
		Distributed	Centrally stored
Functionality	Statistics / Analytics		
	Machine Learning		

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Distributed Analytics

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Distributed Analytics

- Google Chrome's RAPPOR (2014 – 2019)
 - Based on randomized response
 - Supported more than 200 metrics
- Inspired plenty of follow-up in theory and applications
- Main challenges
 - Utility (absolute error $\sim N^{1/2}$)
 - Privacy loss over time

Distributed Analytics

- Fuchsia OS' Cobalt (in development)
 - Based on randomized response + anonymization channel
- Interesting theory work
- Main challenge
 - Who is doing anonymization?

Analytics over Collected Data

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Analytics over Collected Data

- The “standard” setting for differential privacy:
 - McSherry’s PINQ (2009),..., Uber’s Flex (2018)
 - US Census Bureau
- Main challenges:
 - Mission creep
 - Business imperatives
 - Who is keeping the budget?

Differentially private ML

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Differentially Private ML

- Two main approaches: PATE and DP-SGD
- DP-SGD is a better fit for standard ML pipeline
- TensorFlow implementation: 800+ stars, 100+ forks
- Challenges:
 - Slower!
 - Learning to learn **with privacy**

References

RAPPOR

“RAPPOR: Randomized Aggregatable Privacy-Preserving Ordinal Response”,
Erlingsson, Pihur, Korolova, ACM CCS 2014

Shuffle Model

“Prochlo: Strong Privacy for Analytics in the Crowd”, Bittau et al., SOSP 2017

PATE:

“Semi-supervised Knowledge Transfer for Deep Learning from Private Training Data”,
Papernot et al., ICLR 2017

DP-SGD:

“Deep Learning with Differential Privacy”, Abadi et al., ACM CCS 2016