Review of Local Private Hypothesis Testing: χ^2 tests.

May 30, 2018

1 The BibTex

First, this has the following BibTex:

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@ARTICLE{2017arXiv170907155G,
author = {{Gaboardi}, M. and {Rogers}, R.},
title = "{Local Private Hypothesis Testing: Chi-Square Tests}",
journal = {ArXiv e-prints},
archivePrefix = "arXiv",
eprint = {1709.07155},
primaryClass = "math.ST",
keywords = {Mathematics - Statistics Theory, Computer Science - Cryptography an
    year = 2017,
    month = sep,
    adsurl = {http://adsabs.harvard.edu/abs/2017arXiv170907155G},
    adsnote = {Provided by the SAO/NASA Astrophysics Data System}}
```

2 The Paper

We'll try to answer the following questions:

1. What new background is needed for this article?

This uses the concept of concentrated differential privacy. This is a variant of differential privacy where the "defining inequality" doesn't hold for all events. Recall that for (ϵ, δ) differential privacy, we say that for any two neighboring databases that:

$$\Pr[M(x) \in S] \le e^{\epsilon} \Pr[M(y) \in S] + \delta \tag{1}$$

must hold for all subsets $S \subseteq \text{Range}(M(x))$.

Concentrated differential privacy instead says that:

$$\mathbb{E}_{y \sim \mathcal{M}(x)}[\exp(t \ln(\frac{\Pr[M(x) = y}{\Pr[M(y) = y}) - \rho)] \le e^{t^2 \rho}, \quad \forall t \ge 0$$
 (2)

Note that the $\ln \frac{f(x)}{f(y)} - \rho$ quantity is essentially the same thing as ϵ in the definition of (ϵ, ρ) differential privacy. If M(x) was (ϵ, ρ) differentially private, we'd have that this inequality is just (bounded by):

$$\mathbb{E}[\exp(t\epsilon)] \le \exp(t^2 \rho) \tag{3}$$

We can view the Advanced Composition Theorem as a *concentration inequality*, saying that *privacy loss* is concentrated about the mean.

Concentrated Differential privacy makes a new (incomparable) definition of differential privacy, with the intent that it satisfies a concentration inequality under composition. The tradeoffs are that in (ϵ, δ) DP, with probability δ privacy loss can be $arbitrarily\ bad$. Concentrated differential privacy essentially says that the $privacy\ loss$ is small mean, and subgaussian.

- 2. What new techniques do the authors apply?
- 3. What new results do the authors qet?

They develop a χ^2 test for *local*, *concentrated* differential privacy. This is the first of its kind (other concentrated differential privacy ones existed,