

# CS7880: Rigorous Approaches to Data Privacy, Spring 2017

## POTW #1

Instructor: Jonathan Ullman

**Due Sun, Jan 22th, 11:59pm**  
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- **You may work on this homework in pairs if you like. If you do, you must write your own solution and state who you worked with.**
- Solutions must be typed in L<sup>A</sup>T<sub>E</sub>X.
- Aim for clarity and brevity over low-level details.

**Problem 1** (Random Subsampling). Given a dataset  $x \in \mathcal{X}^n$ , and  $m \in \{0, 1, \dots, n\}$ , a *random  $m$ -subsample of  $x$*  is a new (random) dataset  $x' \in \mathcal{X}^m$  formed by keeping a random subset of  $m$  rows from  $x$  and throwing out the remaining  $n - m$  rows.

- (a) Show that for every  $n \in \mathbb{N}$ ,  $|\mathcal{X}| \geq 2$ ,  $m \in \{1, \dots, n\}$ ,  $\varepsilon > 0$ , and  $\delta < m/n$ , the algorithm  $A(x)$  that outputs a random  $m$ -subsample of  $x \in \mathcal{X}^n$  is *not*  $(\varepsilon, \delta)$ -differentially private.
- (b) Although random subsamples do not ensure differential privacy on their own, a random subsample does have the effect of “amplifying” differential privacy. Let  $A : \mathcal{X}^m \rightarrow \mathcal{R}$  be any algorithm. We define the algorithm  $A'(x) : \mathcal{X}^n \rightarrow \mathcal{R}$  as follows: choose  $x'$  to be a random  $m$ -subsample of  $x$ , then output  $A(x')$ .

Prove that if  $A$  is  $(\varepsilon, \delta)$ -differentially private, then  $A'$  is  $(\frac{e^\varepsilon - 1}{n}m, \frac{\delta m}{n})$ -differentially private. Thus, if we have an algorithm with the relatively weak guarantee of 1-differential privacy, we can get an algorithm with  $\varepsilon$ -differential privacy by using a random subsample of a dataset that is larger by a factor of  $1/(e^\varepsilon - 1) = O(1/\varepsilon)$ .

- (c) (**Optional.**) We can also show that some sort of converse is true—for many tasks achieving  $(\varepsilon, \delta)$ -differential privacy *requires*  $\Omega(1/\varepsilon)$  more samples than achieving  $(1, \delta)$ -differential privacy. Let  $\mathbf{q}(x) = (q_1(x), \dots, q_k(x))$  be a collection of statistical queries.<sup>1</sup> Assume that there is *no*  $(1, \delta)$ -differentially private algorithm  $A : \mathcal{X}^n \rightarrow \mathbb{R}^k$ , such that

$$\forall x \in \mathcal{X}^n \quad \mathbb{E}[\|A(x) - \mathbf{q}(x)\|_\infty] \leq 1/100.$$

Show that for some  $n' = \Omega(n/\varepsilon)$ , there is *no*  $(\varepsilon, \varepsilon\delta/100)$ -differentially private algorithm  $A : \mathcal{X}^{n'} \rightarrow \mathbb{R}^k$  such that

$$\forall x' \in \mathcal{X}^{n'} \quad \mathbb{E}[\|A(x') - \mathbf{q}(x')\|_\infty] \leq 1/100.$$

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<sup>1</sup>Recall that a statistical query  $q(x)$  takes a dataset  $x = (x_1, x_2, \dots) \in \mathcal{X}^*$  of arbitrary size, and outputs  $\mathbb{E}_{x_i \sim x}[\phi(x_i)]$  for some function  $\phi : \mathcal{X} \rightarrow [0, 1]$ .