yesterday

DP definition, properties

Randomized Response

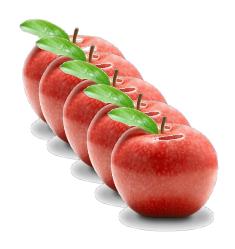
Laplace Mechanism

reportNoisyMax

Ok, but I wanted to use my data for a scenario where direct noise addition doesn't make sense

selecting from among discrete set of alternatives

small perturbation in outcome space could be disastrous for outcome quality Example: Items for sale



Could set the price of apples at \$1.00 for profit: \$4.00

Could set the price of apples at \$4.01 for profit \$4.01

Best price: \$4.01

2nd best price: \$1.00

Profit if you set the price at \$4.02: \$0 Profit if you set the price at \$1.01: \$1.01



- A mechanism $M: \mathbb{N}^{|X|} \to R$ for some abstract range R.
 - i.e. $R = \{\text{Red, Blue, Green, Brown, Purple}\}$
 - $R = \{\$1.00, \$1.01, \$1.02, \$1.03, \dots\}$
- Paired with a quality score:

$$q: \mathbb{N}^{|X|} \times R \to \mathbb{R}$$

q(D,r) represents how good output r is for database D.

- Relative parameters for privacy, solution quality:
 - Sensitivity of q:

$$GS(q) = \max_{r \in R, D, D': ||D - D'||_{1} \le 1} |q(D, r) - q(D', r)|$$

- Size and structure of R.
 - How many elements of R are high quality? How many are low quality?

Exponential($D, R, q: \mathbb{N}^{|X|} \to R, \epsilon$):

- 1. Let $\Delta = GS(q)$.
- 2. Output $r \sim R$ with probability proportional to:

$$\Pr[r] \sim \exp\left(\frac{\epsilon q(D,r)}{2\Delta}\right)$$

$$\Pr[r] = \frac{\exp(\frac{\epsilon q(D, r)}{2\Delta})}{\sum_{r' \in R} \exp(\frac{\epsilon q(D, r')}{2\Delta})}$$

Exponential($D, R, q: \mathbb{N}^{|X|} \to R, \epsilon$):

- 1. Let $\Delta = GS(q)$. 2. Output $r \sim R$
 - 2. Output $r \sim R$ with probability proportional to:

$$\Pr[r] \sim \exp\left(\frac{\epsilon q(D, r)}{2\Delta}\right)$$

Idea: Make high quality outputs exponentially more likely at a rate that depends on the sensitivity of the quality score (and the privacy parameter)

Thm. The exponential mechanism preserves $(\epsilon, 0)$ -differential privacy.

Exponential
$$(D, R, q: \mathbb{N}^{|X|} \to R, \epsilon)$$
:

- 1. Let $\Delta = GS(q)$.
- 2. Output $r \sim R$ with probability proportional to:

$$\Pr[r] \sim \exp\left(\frac{\epsilon q(D,r)}{2\Delta}\right)$$

Theorem: The Exponential Mechanism preserves $(\epsilon, 0)$ -differential privacy.

Proof: Fix any $D, D' \in \mathbb{N}^{|X|}$ with $\big| |D, D'| \big|_1 \le 1$ and any $r \in R$...

 $\Pr[\mathsf{Exponential}(D,R,q,\epsilon)=r]$

 $\frac{1}{\Pr[\text{Exponential}(D', R, q, \epsilon) = r]} =$

$$\frac{\left(\frac{\exp(\frac{\epsilon q(D,r)}{2\Delta})}{\sum \exp(\frac{\epsilon q(D',r')}{2\Delta})}\right)}{\left(\frac{\exp(\frac{\epsilon q(D',r')}{2\Delta})}{\sum \exp(\frac{\epsilon q(D',r')}{2\Delta})}\right)} = \left(\frac{\exp(\frac{\epsilon q(D,r)}{2\Delta})}{\exp(\frac{\epsilon q(D',r)}{2\Delta})}\right) \left(\frac{\sum_{r'} \exp(\frac{\epsilon q(D',r')}{2\Delta})}{\sum_{r'} \exp(\frac{\epsilon q(D,r')}{2\Delta})}\right)$$

Exponential $(D, R, q: \mathbb{N}^{|X|} \to R, \epsilon)$:

- Let Δ = GS(q).
 Output r ~ R with probability proportional to:

$$\Pr[r] \sim \exp\left(\frac{\epsilon q(D, r)}{2\Delta}\right)$$

Theorem: The Exponential Mechanism preserves $(\epsilon, 0)$ -differential privacy. **Proof**:

$$= \left(\frac{\exp(\frac{\epsilon q(D,r)}{2\Delta})}{\exp(\frac{\epsilon q(D',r)}{2\Delta})} \right) =$$

$$\exp\left(\frac{\epsilon(q(D,r) - q(D',r))}{2\Delta} \right) \le$$

$$\exp\left(\frac{\epsilon\Delta}{2\Delta} \right) = \exp\left(\frac{\epsilon}{2} \right)$$

Exponential($D, R, q: \mathbb{N}^{|X|} \to R, \epsilon$):

- 1. Let $\Delta = GS(q)$. 2. Output $r \sim R$ with probability proportional to:

$$\Pr[r] \sim \exp\left(\frac{\epsilon q(D,r)}{2\Delta}\right)$$

Theorem: The Exponential Mechanism preserves $(\epsilon, 0)$ -differential privacy. **Proof**:

$$= \left(\frac{\sum_{r'} \exp(\frac{\epsilon q(D', r')}{2\Delta})}{\sum_{r'} \exp(\frac{\epsilon q(D, r')}{2\Delta})}\right) \le \left(\frac{\sum_{r'} \exp(\frac{\epsilon q(D, r') + \Delta}{2\Delta})}{\sum_{r'} \exp(\frac{\epsilon q(D, r')}{2\Delta})}\right) = \left(\frac{\exp(\frac{\epsilon q(D, r')}{2\Delta})}{\sum_{r'} \exp(\frac{\epsilon q(D, r')}{2\Delta})}\right) = \exp(\frac{\epsilon q(D, r')}{2\Delta})$$

Exponential $(D, R, q: \mathbb{N}^{|X|} \to R, \epsilon)$:

- 1. Let $\Delta = GS(q)$. 2. Output $r \sim R$ with probability proportional to:

$$\Pr[r] \sim \exp\left(\frac{\epsilon q(D, r)}{2\Delta}\right)$$

Theorem: The Exponential Mechanism preserves $(\epsilon, 0)$ -differential privacy.

Proof: Recall:

$$\frac{\Pr[\text{Exponential}(D,R,q,\epsilon)=r]}{\Pr[\text{Exponential}(D',R,q,\epsilon)=r]} = 4$$

$$\leq \exp\left(\frac{\epsilon}{2}\right) \exp\left(\frac{\epsilon}{2}\right)$$

$$= \exp(\epsilon)$$

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Exponential(D, R, q: \mathbb{N}^{|X|} \to R, \epsilon):

1. Let \Delta = GS(q).

2. Output r \sim R with probability proportional to:

\Pr[r] \sim \exp\left(\frac{\epsilon q(D, r)}{2\Delta}\right)
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But is the answer any good?

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Exponential(D, R, q: \mathbb{N}^{|X|} \to R, \epsilon):

1. Let \Delta = GS(q).

2. Output r \sim R with probability proportional to:

\Pr[r] \sim \exp\left(\frac{\epsilon q(D, r)}{2\Delta}\right)
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But is the answer any good?

It depends...

Define:

$$OPT_q(D) = \max_{r \in R} q(D,r)$$

 $R_{OPT} = \{r \in R : q(D,r) = OPT_q(D)\}$
 $r^* = \text{Exponential}(D,R,q,\epsilon)$

Theorem:

$$\Pr\left[q(r^*) \le OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log\left(\frac{|R|}{|R_{OPT}|}\right) + t\right)\right] \le e^{-t}$$

Theorem:

$$\Pr\left[q(r^*) \le OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log\left(\frac{|R|}{|R_{OPT}|}\right) + t\right)\right] \le e^{-t}$$

Corollary:

$$\Pr\left[q(r^*) \le OPT_q(D) - \frac{2\Delta}{\epsilon}(\log(|R|) + t)\right] \le e^{-t}$$

Proof:

 $|R_{OPT}| \ge 1$ by definition.

Theorem:

$$\Pr\left[q(r^*) \le OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log\left(\frac{|R|}{|R_{OPT}|}\right) + t\right)\right] \le e^{-t}$$

Corollary:

$$E[q(r^*)] \ge OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log(|R|) + \log(OPT_q(D)) \right) - 1$$

Proof:

$$\begin{split} &\Pr\left[q(r^*) \leq OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log(|R|) + \log(OPT_q(D))\right] \leq \frac{1}{OPT_q(D)} \\ &\Pr\left[q(r^*) \geq OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log(|R|) + \log(OPT_q(D))\right] \geq 1 - \frac{1}{OPT_q(D)} \end{split} \right] \end{split}$$

Theorem:

$$\Pr\left[q(r^*) \le OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log\left(\frac{|R|}{|R_{OPT}|}\right) + t\right)\right] \le e^{-t}$$

Corollary:

$$E[q(r^*)] \ge OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log(|R|) + \log(OPT_q(D)) \right) - 1$$

Proof:

$$\begin{split} &E[q(r^*)] \geq (x \cdot \Pr[q(r^*) \geq x]) \\ &\geq \left(OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log(|R|) + \log\left(OPT_q(D)\right) \right) \right) \cdot \left(1 - \frac{1}{OPT_q(D)} \right) \\ &> OPT_q(D) - \frac{2\Delta}{\epsilon} \left(\log(|R|) + \log\left(OPT_q(D)\right) \right) - 1 \end{split}$$