TTIC 31250: An Introduction to the Theory of Machine Learning

Machine Learning and Differential Privacy

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Learning and Privacy

- To do machine learning, we need data.
- What if the data contains sensitive information?
- Even if the (person running the) learning algo can be trusted, perhaps the output of the algorithm reveals sensitive info.
- E.g., using search logs of friends to recommend query completions:

Why are _
Why are my feet so itchy?

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Learning and Privacy

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- Even if the (person running the) learning algo can be trusted, perhaps the output of the algorithm reveals sensitive info.
- E.g., SVM or perceptron on medical data:
  - Suppose feature j is has-green-hair and the learned w has $w_j \neq 0$.
  - If there is only one person in town with green hair, you know they were in the study.

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Learning and Privacy

- To do machine learning, we need data.
- What if the data contains sensitive information?
- Even if the (person running the) learning algo can be trusted, perhaps the output of the algorithm reveals sensitive info.
- An approach to address these problems:

Differential Privacy

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A preliminary story

- A classic result from theoretical crypto:
  - Say you want to figure out the average numeric grade of people in the room, without revealing anything about your own grade other than what is inherent in the answer.

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A preliminary story

- A classic result from theoretical crypto:
  - Say you want to figure out the average numeric grade of people in the room, without revealing anything about your own grade other than what is inherent in the answer.
- Turns out you can actually do this. In fact, any function at all. "secure multiparty computation".
  - It's really cool. Want to try?
- Anyone have to go to the bathroom?
  - What happens if we do it again?

Differential privacy "lets you go to the bathroom in peace"

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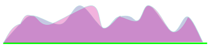
Differential Privacy

High level idea:

- What we want is a protocol that has a probability distribution over outputs:



  such that if person i changed their input from x_i to any other allowed x_i', the relative probabilities of any output do not change by much.
- This would effectively allow that person to pretend their input was any other value they wanted.

Bayes rule: $\frac{\Pr(x_i|output)}{\Pr(x_i'|output)} = \frac{\Pr(output|x_i)}{\Pr(output|x_i')} \cdot \frac{\Pr(x_i)}{\Pr(x_i')}$

(Posterior $\approx$ Prior)

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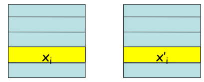
Differential Privacy: Definition

It's a property of a protocol A which you run on some dataset X producing some output A(X).

- A is ϵ-*differentially private* if for any two neighbor datasets S, S′ (differ in just one element $x_i \to x_i'$),



for all outcomes v,

$e^{-\epsilon} \le \Pr(A(S)=v)/\Pr(A(S')=v) \le e^{\epsilon}$

$\approx 1-\epsilon$ | probability over randomness in A | $\approx 1+\epsilon$

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View as model of plausible deniability

(pretend after the fact that my input was really x_i')

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$e^{-\epsilon} \le \Pr(A(S)=v)/\Pr(A(S')=v) \le e^{\epsilon}$

$\approx 1-\epsilon$ | probability over randomness in A | $\approx 1+\epsilon$

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Differential Privacy: Methods

It's a property of a protocol A which you run on some dataset X producing some output A(X).

- Can we achieve it?
- Sure, just have A(X) always output 0.
- This is perfectly private, but also completely useless.
- Can we achieve it while still providing useful information?

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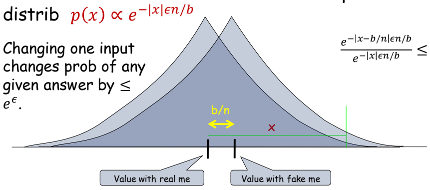
Laplace Mechanism

Say have n inputs in range [0,b]. Want to release average while preserving privacy.

- Changing one input can affect average by $\le$ b/n.
- Idea: take answer and add noise from Laplace distrib $p(x) \propto e^{-|x|\epsilon n/b}$
- Changing one input changes prob of any given answer by $\le e^{\epsilon}$.

$\frac{e^{-|x-b/n|\epsilon n/b}}{e^{-|x|\epsilon n/b}} \le e^{\epsilon}$.



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- Idea: take answer and add noise from Laplace distrib $p(x) \propto e^{-|x|\epsilon n/b}$
- Amount of noise added will be $\approx \pm b/(n\epsilon)$.
- To get an overall error of $\pm\gamma$, you need a sample size $n = \frac{b}{\gamma\epsilon}$.
- Get a utility/privacy/database-size tradeoff.
- If want to estimate mean of a distribution up to $\pm\gamma$ and the database is an iid sample, then for $\gamma < \epsilon$ you can get privacy "for free".

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Laplace mechanism more generally

f

f(X) + noise

- E.g., f = standard deviation of income
- E.g., f = result of some fancy computation.

Global Sensitivity of f:
$GS_f = \max_{\text{neighbors } X,X'} |f(X) - f(X')|$

- Just add noise Lap(GS_f / ϵ).

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What can we do with this?

f

f(X) + noise

- Interface to ask questions
- Run learning algorithms by breaking down interaction into series of queries with noisy answers.
- *But, each answer leaks some privacy:*
  - If k questions and want total privacy loss of ϵ, better answer each with ϵ/k.

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Can run SQ algorithms

- Anything learnable via Statistical Queries is learnable differentially privately using Laplace mechanism.
- Statistical query model:

X

q(x,l)

$\Pr_D[q(x,f(x))=1] \pm\gamma$.

- What is the error rate of my current rule?
- What is the correlation of x_1 with f when x_2=0? ...

- Many algorithms can be re-written to interface via such statistical estimates.

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- Statistical query model:

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$\Pr_D[q(x,f(x))=1] \pm\gamma$.

- What is the error rate of my current rule?

  - Really tailor-made for DP.
  - In fact, for a single query, Laplace mechanism adds noise $1/(\epsilon n)$. Less than $1/n^{1/2}$ due to sampling if $\epsilon \geq 1/n^{1/2}$.
  - Privacy "for free" unless q's from space of low VC-dim...

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Privately learnable = SQ-learnable?

- [KLNRS08]: Actually, anything learnable is learnable in principle with DP.
  - Exponential mechanism for general classes.
    - *Assign score to each f $\in$ C, exponentially decaying in its suboptimality.*
    - *Choose from this distrib over C.*
  - Efficient algorithm for C = {parity functions}.
    - Interesting since not known to be efficiently learnable with noise, and *provably not SQ-learnable.*
  - SQ-learnable = learnable with local privacy, where no centralized database at all.

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Local Sensitivity

f

f(X) + noise

- Consider f = median income
  - On some databases, f could be *very* sensitive. E.g., 3 people at salary=0, 3 people at salary=b, and you.
  - But on many databases, it's not.
  - If f is not very sensitive on the actual input X, does that mean we don't need to add much noise?

$LS_f(X) = \max_{\text{nbrs } X'} |f(X)-f(X')|$

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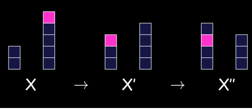
Local Sensitivity

f

f(X) + noise

- Consider f = median income
  - If f is not very sensitive on the actual input X, does that mean we don't need to add much noise?
- Be careful: what if sensitivity itself is sensitive?



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Smooth Sensitivity

f

f(X) + noise

- [NRS07] prove can instead use (roughly) the following smooth bound instead:

  $Max_Y \, [\, LS_f(Y) e^{-\epsilon d(X,Y)} \,]$

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Smooth Sensitivity

Alg

Alg(X) + noise

- In principle, could apply sensitivity idea to any learning algorithm (say) that you'd like to run on your data.
- But might be hard to figure out

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Objective perturbation [CMS08]

Alg* = Alg + noise

Alg*(X)

- Idea: add noise to the objective function used by the learning algorithm.
- Natural for algorithms like SVMs that have regularization term.
- [CMS] show how to do this, if use a smooth loss function. Also show nice experimental results.

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So far: learning as goal, privacy as constraint

Now: learning as tool for achieving stronger privacy

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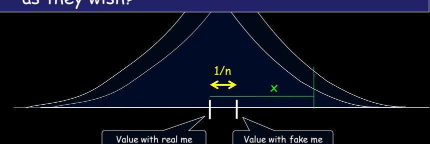
Answering more questions

"Add iid noise" approach can only answer a limited number of questions before it has to shut down.

- Fundamental limit: #questions $|S|^2$ to preserve this kind of privacy?
- Output "sanitized database" people can examine as they wish?



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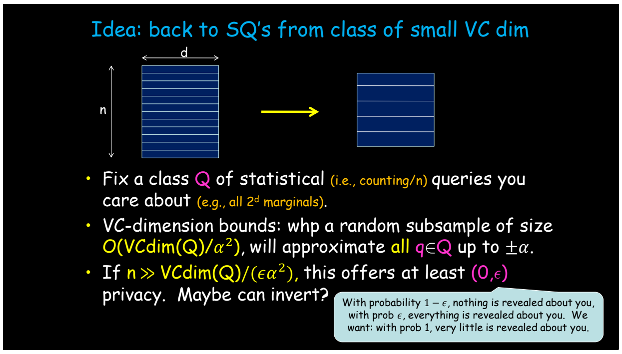
Idea: back to SQ's from class of small VC dim
d
n
• Fix a class Q of statistical (i.e., counting/n) queries you care about (e.g., all 2^d marginals).
• VC-dimension bounds: whp a random subsample of size $O(\mathrm{VCdim}(Q)/\alpha^2)$, will approximate all $q \in Q$ up to $\pm\alpha$.
• If $n \gg \mathrm{VCdim}(Q)/(\epsilon\alpha^2)$, this offers at least $(0,\epsilon)$ privacy. Maybe can invert?
With probability $1-\epsilon$, nothing is revealed about you, with prob ϵ, everything is revealed about you. We want: with prob 1, very little is revealed about you.

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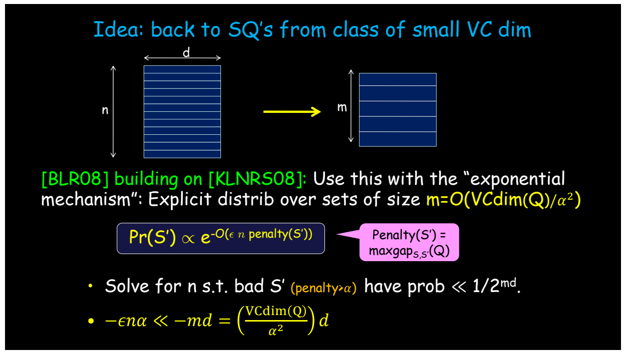
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[BLR08] building on [KLNRS08]: Use this with the "exponential mechanism": Explicit distrib over sets of size $m = O(\mathrm{VCdim}(Q)/\alpha^2)$
$\Pr(S') \propto e^{-O(\epsilon\, n\ \mathrm{penalty}(S'))}$
Penalty(S') = $\mathrm{maxgap}_{S,S'}(Q)$
• Solve for n s.t. bad S' (penalty>α) have prob $\ll 1/2^{md}$.
• $-\epsilon n\alpha \ll -md = \left(\frac{\mathrm{VCdim}(Q)}{\alpha^2}\right) d$

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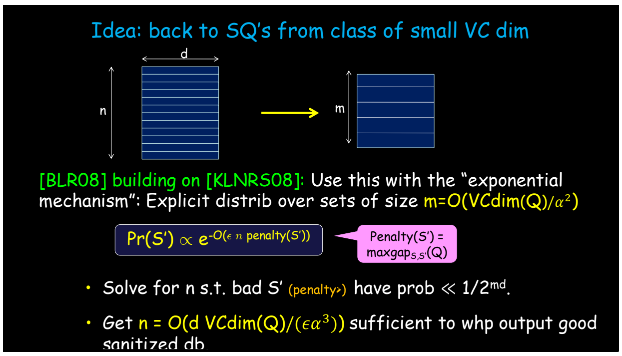
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Penalty(S') = $\mathrm{maxgap}_{S,S'}(Q)$
• Solve for n s.t. bad S' (penalty>) have prob $\ll 1/2^{md}$.
• Get $n = O(d\ \mathrm{VCdim}(Q)/(\epsilon\alpha^3))$ sufficient to whp output good sanitized db

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