

Membership Inference Attacks, Part II

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① Exercise on means + variances.

from in-class exercises ≈ 2 weeks ago.

② Worst-case mechanism? similar to exercise, but leaves mechanism uncertain about μ .

$$\mu \sim N(0, I_k)$$

$$X_1, \dots, X_n \sim_{\text{iid}} N(\mu, I_k)$$

$$\mathcal{M}(X) = \bar{x} + e \quad \text{where } \|e\|_2 \leq \alpha \sqrt{k} \text{ (RMSE } \alpha)$$

$$T(a, y) = \langle a - \mu, y - \mu \rangle$$

OUT: $\mathbb{E}(T | \text{OUT}) = \mathbb{E} \langle X - \mu, \bar{x} + e - \mu \rangle$

$$= \mathbb{E} \langle X - \mu, \bar{x} - \mu \rangle + \mathbb{E} \langle X - \mu, e \rangle$$

$\uparrow$ indep, mean 0 $\uparrow$ mean 0, indep of e .

$$\text{Var}(T | \text{OUT}) = \text{Var}(X(i) - \mu(i)) + \text{Var}(N(0, \|e\|^2))$$

Use the fact that $\text{Var}(A+B) \leq 2(\text{Var}(A) + \text{Var}(B))$ same as case of Gauss noise with $\rho \propto \alpha$.

$$\leq 2\left(\frac{k}{n} + \alpha^2 d\right)$$

if A, B indep with mean 0
Then $\text{Var}(AB) = \mathbb{E}(A^2 B^2)$
 $= \mathbb{E}(A^2) \mathbb{E}(B^2)$
 $= \text{Var}(A) \text{Var}(B)$

IN: $\mathbb{E}(T | \text{IN}) = \mathbb{E}_i \langle X_i - \mu, \mathcal{M}(X) - \mu \rangle$

$$= \langle \bar{x} - \mu, \mathcal{M}(X) - \mu \rangle$$

$$= \langle \bar{x} - \mu, \bar{x} - \mu \rangle + \langle \bar{x} - \mu, e \rangle$$

• Now condition on $\bar{x}$ and e (where $\|e\|_2 \leq \alpha \sqrt{k}$)

• What is distrib of $\mu \mid \bar{X} = \bar{x}$?

Claim

- From analyst's pov (that is, conditioned on $X_1, \dots, X_n$)
$$\mu \sim \frac{n}{n+1} \bar{X} + \frac{1}{n+1} Z \quad \text{where } Z \sim N(0, I_d) \text{ indep of } \bar{X}$$

Proof:

- $\text{Cov}(\mu, \bar{X}) = \begin{pmatrix} I & I \\ I & (1+\frac{1}{n})I \end{pmatrix}$
- Suppose that $\mu = a\bar{X} + bZ$ where $Z \sim N(0, I_d)$
Then $\text{Cov}(\mu, \bar{X}) = \begin{pmatrix} a^2 \Sigma_{\bar{X}} + b^2 I & a \Sigma_{\bar{X}} \\ a \Sigma_{\bar{X}} & \Sigma_{\bar{X}} \end{pmatrix} \stackrel{!}{=} \begin{pmatrix} I & I \\ I & (1+\frac{1}{n})I \end{pmatrix}$
$$\begin{aligned} b^2 &= \frac{1}{n+1} \\ a^2 &= \frac{1}{1+\frac{1}{n}} = \frac{n}{n+1} \end{aligned}$$

• So $\mu = \frac{n}{n+1} \bar{X} + bZ$.

- Furthermore, all the info about μ in $X_1, \dots, X_n$ is contained in $\bar{X}$.
(that is, $\bar{X}$ is a "sufficient statistic" for μ)

→ To see why, note that

$$\begin{aligned} p(X_1, \dots, X_n | \mu) &\propto \prod \exp\left(-\frac{1}{2} \|x_i - \mu\|^2\right) \\ &= \exp\left(-\frac{1}{2} \sum \|x_i - \mu\|^2\right) \\ &= \exp\left(-\frac{1}{2} \sum_i \left(\|x_i - \bar{X}\|^2 + \|\bar{X} - \mu\|^2 + 2\langle x_i - \bar{X}, \bar{X} - \mu \rangle\right)\right) \\ &= \exp\left(-\frac{1}{2} \left(n\|\bar{X} - \mu\|^2 + \sum_i \|x_i - \bar{X}\|^2 + 2\langle 0, \bar{X} - \mu \rangle\right)\right) \\ &= \underbrace{\exp\left(-\frac{1}{2} n\|\bar{X} - \mu\|^2\right)}_{\propto P(\bar{X} | \mu)} \cdot \underbrace{\exp\left(-\frac{1}{2} \sum \|x_i - \bar{X}\|^2\right)}_{\propto P(X_1, \dots, X_n | \bar{X}, \mu)} \end{aligned}$$

QED

• We can now use the claim

$$\begin{aligned}\mathbb{E}(T | \mathcal{I}_N) &= \mathbb{E}(\|\bar{x} - \mu\|^2 + \langle \bar{x} - \mu, e \rangle) \\ &= d/n + \mathbb{E} \langle \bar{x} - \mu, e \rangle\end{aligned}$$

• Conditioning on $\bar{x}$ and e , we get:

$$= \frac{d}{n} + \mathbb{E}_{\bar{x}, e} \mathbb{E} \langle \bar{x} - \frac{n}{n+1} \bar{x} + \frac{1}{n+1} z, e \rangle$$

$$= \frac{d}{n} + \mathbb{E}_{\bar{x}, e} \frac{1}{n+1} \langle \bar{x}, e \rangle$$

$$\geq \frac{d}{n} - \frac{1}{n+1} \underbrace{\|\bar{x}\|}_{\approx \sqrt{d}} \cdot \underbrace{\|e\|}_{\leq \alpha \sqrt{d}}$$

$$\geq \frac{d}{n} (1 - \alpha)$$

which is less than $\frac{d}{n}$ for $\alpha \leq \frac{1}{2}$.
