

# Lecture 11 Packing Lower Bounds

## Settings

One-way marginals:  $\mathcal{X} = \{0, 1\}^d$   
 $f_j(x) = \frac{1}{n} \sum_{i=1}^n x_i^{(j)}$

Histograms:  $\mathcal{X} = [k]$   
 $f_j(x) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}\{X_i = j\}$

Pure DP:  
 $n \geq \Omega\left(\frac{\log k}{\alpha \epsilon}\right)$   
Approx DP:  
 $n \geq \Omega\left(\frac{\log(1/\delta)}{\alpha \epsilon}\right)$

Pure DP:  
Given  $n \geq \Omega\left(\frac{d \log d}{\alpha \epsilon}\right)$ ,  
 $\text{err} \leq \alpha \forall$  o.w.m g's  
 $\text{w.p.} \geq \frac{1}{2}$ .  
Approx:  $n \geq \Omega\left(\frac{\sqrt{d \log(1/\delta)}}{\alpha \epsilon}\right)$

"Packing" Lower bound

M: both private + accurate

# Example 1: Mode of a dataset

$X = [k]$

Want  $M$ : -  $\epsilon$ -DP

- Output mode of  $X$  w.p.  $\geq \frac{1}{2}$

$D_1, \dots, D_k: D_j = \{j\}^n$

Fix  $j$ . Dist of  $M(D_j)$ .

$\exists l \in [k], \text{st. } \Pr[M(D_j) = l] \leq \frac{1}{k}$

Acc.  $\rightarrow \Pr[M(D_l) = l] \geq \frac{1}{2}$

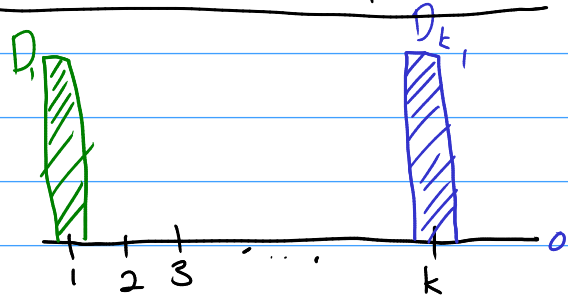
Group privacy

$$\frac{1}{2} \leq \Pr[M(D_l) = l] \leq e^{\epsilon n} \Pr[M(D_j) = l] \leq \frac{e^{\epsilon n}}{k}$$

$\uparrow$   
acc

$$e^{\epsilon n} \geq \frac{k}{2} \rightarrow \epsilon n \geq \log(k/2)$$

$$\hookrightarrow n \geq \frac{\log(k/2)}{\epsilon} = \Omega\left(\frac{\log k}{\epsilon}\right)$$



$$p = \frac{1}{2}, t = n$$

$$m \leq 2e^{n\varepsilon}$$

# Key Packing Theorem

**Theorem 1.** Let  $D_1, \dots, D_m \in \mathcal{X}^n$  be a set of  $m$  datasets, which are at Hamming distance at most  $t$  from some fixed dataset  $D \in \mathcal{X}^n$ . Let  $Y_1, \dots, Y_m \in \mathcal{Y}$  be a set of  $m$  disjoint subsets of the space  $\mathcal{Y}$ . If there is an  $\varepsilon$ -DP mechanism  $M: \mathcal{X}^n \rightarrow \mathcal{Y}$  such that  $\Pr[M(D_\ell) \in Y_\ell] \geq p$  for every  $\ell \in [m]$ , then

$$\frac{1}{m} \geq pe^{-t\varepsilon}.$$

$$\Pr[M(D_\ell) \in Y_\ell] \geq p.$$

$$\Pr[M(D_\ell) \in Y_\ell] \leq e^{t\varepsilon} \Pr[M(D) \in Y_\ell]$$

$$\Pr[M(D) \in Y_\ell] \geq pe^{-t\varepsilon} \quad \leftarrow \text{Group privacy}$$

$$\underbrace{mpe^{-t\varepsilon}}_{\text{circled}} \leq \sum_{\ell \in [m]} \Pr[M(D) \in Y_\ell] = \Pr[M(D) \in \underbrace{\bigcup_{\ell \in [m]} Y_\ell}_{\text{Disjoint}}] \leq \underbrace{1}_{\text{circled}} \quad \square$$

## Example 2: One-Way Marginals

Approx  
 $n = O(\sqrt{d}/\epsilon)$

**Theorem 2.** Any  $\epsilon$ -DP algorithm  $M : \{0, 1\}^{d \times n} \rightarrow [0, 1]^d$  which simultaneously answers all one-way marginals to accuracy  $< 1/2$  with probability  $\geq 1/2$  requires  $n = \Omega(d/\epsilon)$ .

**Theorem 1.** Let  $D_1, \dots, D_m \in \mathcal{X}^n$  be a set of  $m$  datasets, which are at Hamming distance at most  $t$  from some fixed dataset  $D \in \mathcal{X}^n$ . Let  $Y_1, \dots, Y_m \in \mathcal{Y}$  be a set of  $m$  disjoint subsets of the space  $\mathcal{Y}$ . If there is an  $\epsilon$ -DP mechanism  $M : \mathcal{X}^n \rightarrow \mathcal{Y}$  such that  $\Pr[M(D_\ell) \in Y_\ell] \geq p$  for every  $\ell \in [m]$ , then

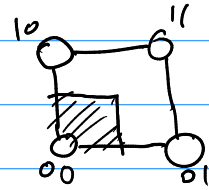
$$\frac{1}{m} \geq pe^{-\epsilon}.$$

$m = 2^d$  databases

$\forall w \in \{0, 1\}^d, D_w = n$  copies of  $w$ .

$$Y_w = \{x \in [0, 1]^d : |x_j - w_j| < 1/2, \forall j \in [d]\}$$

$Y_w = l_{\infty}$ -ball of radius  $1/2$  around  $w$ .



$$\Pr[M(D_w) \in Y_w] \geq \frac{1}{2}.$$

$$p = 1/2, t = n, m = 2^d$$

$$2^{-d} \geq \frac{1}{2} e^{-n\epsilon} \Rightarrow n = \Omega(d/\epsilon) \quad \square$$

**Theorem 1.** Let  $D_1, \dots, D_m \in \mathcal{X}^n$  be a set of  $m$  datasets, which are at Hamming distance at most  $t$  from some fixed dataset  $D \in \mathcal{X}^n$ . Let  $Y_1, \dots, Y_m \in \mathcal{Y}$  be a set of  $m$  disjoint subsets of the space  $\mathcal{Y}$ . If there is an  $\epsilon$ -DP mechanism  $M: \mathcal{X}^n \rightarrow \mathcal{Y}$  such that  $\Pr[M(D_\ell) \in Y_\ell] \geq p$  for every  $\ell \in [m]$ , then

$$\frac{1}{m} \geq pe^{-t\epsilon}.$$

## Example 3: Histograms

**Theorem 3.** Any  $\epsilon$ -DP algorithm  $M: [k]^n \rightarrow [0, 1]^k$  which estimates all histogram counts to accuracy  $\leq \alpha$  with probability  $\geq 1/2$  requires  $n = \Omega\left(\frac{\log k}{\alpha\epsilon}\right)$ .

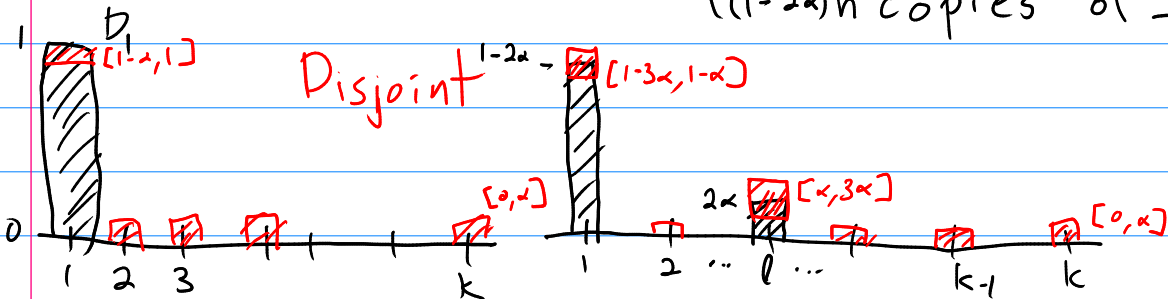
Proof:  $X \in [k]^n \rightarrow h(X) \in [0, 1]^k$ .  $h_i(X) = \frac{1}{n} \sum \mathbb{1}\{X_i = j\}$

$$y(X) \subseteq [0, 1]^k$$

=  $\ell_\infty$ -ball of radius  $\alpha$  around  $h(X)$

$$y_j(X) = h_j(X) \pm \alpha \quad D_1, \dots, D_k \text{ (} m=k \text{ databases)}$$

$$\Pr[M(X) \in y(X)] \geq \frac{1}{2} \quad D_\ell = \begin{cases} t=2\alpha n \text{ copies of } \ell \\ (1-2\alpha)n \text{ copies of } 1 \end{cases}$$



$Y_\ell = y(D_\ell) \rightarrow Y_\ell$ 's are disjoint

$$\frac{1}{k} \geq \frac{1}{2} \exp(-2\alpha n \epsilon)$$

$$k \leq 2 \exp(2\alpha n \epsilon)$$

$$\log(k/2) \leq 2\alpha n \epsilon$$

$$n \geq \frac{\log(k/2)}{2\alpha \epsilon} = \Omega\left(\frac{\log k}{\alpha \epsilon}\right) \quad \square$$