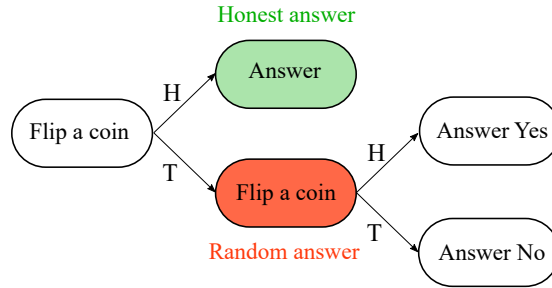


# Privacy - Homework

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## 1 Plausible deniability example

A sensitive "yes-no" question is asked to the participants of a survey. The following protocol is implemented.



**Definition 1 (Hamming's distance)** Let  $D_1$  and  $D_2$  be two datasets of the same size, the Hamming's distance is define as the number of entries on which they differ.

$$d(D_1, D_2) = \# \{i : (D_1)_i \neq (D_2)_i\}$$

**Definition 2** For all  $\epsilon > 0$ , a randomized algorithm  $A$  is  $\epsilon$ -differentially private if, for all  $S \in \text{Im}(A)$  and for all  $D_1$  and  $D_2$  datasets such as  $d(D_1, D_2) = 1$ , we have

$$\frac{\mathbb{P}(A(D_1) \in S)}{\mathbb{P}(A(D_2) \in S)} \leq e^\epsilon$$

1. Let  $D_1$  and  $D_2$  be two sets of answers of size  $n$ , differing in their last entry:  $(D_1)_n = \text{Yes}$  and  $(D_2)_n = \text{No}$ . Show that the protocol is  $\ln(3)$ -differentially private.
2. Still in the case of a "yes-no" question, propose an  $\epsilon$ -differentially private protocol.
3. How can you extend this protocol if the question has  $K$  possible outcomes?

## 2 Mecanisms

**Definition 3 ( $p$ -sensitivity)**  $\Delta_p(A) = \max_{d(D_1, D_2)=1} \|A(D_1) - A(D_2)\|_p$

**Theorem 1 (Laplace mechanism)** *Let  $\epsilon > 0$ ,  $A$  be an algorithm with values in  $\mathbb{R}^d$  and  $D$  a dataset. Then,  $\mathcal{M}_{Lap}(A, D, \epsilon) = A(D) + \mathbf{Z}$  with  $\mathbf{Z} \sim \text{Lap}(\frac{\Delta_1(A)}{\epsilon})^{\otimes d}$  is  $\epsilon$ -DP.*

**Theorem 2 (Gaussian mechanism)** *Let  $\epsilon, \delta > 0$ ,  $A$  be an algorithm with values in  $\mathbb{R}^d$  and  $D$  a dataset. Then,  $\mathcal{M}_{Gauss}(A, D, \epsilon, \delta) = A(D) + \mathbf{Z}$  with  $\mathbf{Z} \sim \mathcal{N}(0, \frac{\sqrt{2 \ln \frac{2}{\delta}} \Delta_2(A)}{\epsilon})^{\otimes d}$  is  $(\epsilon, \delta)$ -DP.*

**Definition 4 ( $(\alpha, \beta)$ -accuracy)** *A mechanism  $\mathcal{M}$  is  $(\alpha, \beta)$ -accurate w.r.t an algorithm  $A$  if for all dataset  $D$  and with probability at least  $1 - \beta$ , we have*

$$\|\mathcal{M}(A, D, \epsilon) - A(D)\|_{\infty} \leq \alpha(\epsilon)$$

1. Recalling that the p.d.f. of a random variable sampled according to  $\text{Lap}(a)$  is equal to  $f(x) = \frac{1}{2a} e^{-\frac{|x|}{a}}$ , prove Theorem 1.
2. Explain why the definition of differential privacy is a "worst case" definition. How can we relax it?
3. Compute  $\mathbb{E}[\|\mathcal{M}_{Lap}(A, D, \epsilon) - A(D)\|_1]$
4. For a fixed  $\beta$ , find  $\alpha$  such that the Laplace mechanism is  $(\alpha, \beta)$ -accurate.
5. For a fixed  $\beta$ , find  $\alpha$  such that the Gaussian mechanism is  $(\alpha, \beta)$ -accurate.
6. When  $k$  is big, which mechanism seems to be more appropriate?