

## Week 11 Exercises (ECE 598 DA)

**Exercise (Two-Party Sum with Differential Privacy):** Two companies,  $A$  and  $B$ , want to compute the total number of customers they have (combined), without revealing their individual customer counts to each other. Let  $a$  be  $A$ 's customer count and  $b$  be  $B$ 's count. They want the result to satisfy  $\epsilon$ -DP so that neither can infer the other's count too precisely from the output. Describe a simple two-party protocol to solve the problem.

**Exercise (Randomized Response):** Suppose each party in a group of  $n$  uses the randomized response mechanism (with probability  $1/2$  to report truthfully and  $1/2$  to report a random bit) to respond to a sensitive yes/no question, as described earlier. Show that this mechanism satisfies  $\epsilon$ -differential privacy for an appropriate  $\epsilon$ , and determine that  $\epsilon$ .

**Exercise (Privacy Proof for Laplace Mechanism in Multi-Party Setting):** Consider a protocol where  $n$  parties use a secure aggregation to compute the exact sum  $S$  of their inputs, and then one designated party adds Laplace noise  $\text{Lap}(0, b)$  with scale  $b = \frac{\Delta}{\epsilon}$  (where  $\Delta$  is the sensitivity of the sum function) to  $S$  and publishes the result  $Y$ . Formally argue that this protocol is  $\epsilon$ -differentially private for each party's input.

**Exercise (Combining MPC and DP):** Suppose we have an MPC protocol that can compute *any function* exactly with no leakage (except the output). If we want to implement a differentially private function via this MPC, what steps should we take? Specifically, how can we use such an MPC to answer a database query with differential privacy?

**Exercise (Secure AND):** Two parties, Alice and Bob, each have a private input bit ( $x$  and  $y$ , respectively). They want to securely compute the AND of their bits (i.e., output  $z = x \wedge y$  to both) in the *semi-honest model*. Outline a simple protocol for this task and explain why it is secure.

**Exercise (CDP vs. DP Equivalence):** Prove that in the central model, any mechanism that is  $(\epsilon, 0)$ -IND-CDP must also be  $(\epsilon, 0)$ -DP.

**Exercise (PRG-Based Mechanism):** Consider a counting query  $q(\mathbf{x}) = \sum_i x_i$  on a database  $\mathbf{x} = (x_1, \dots, x_n)$  with  $x_i \in \{0, 1\}$ . Define  $M_s(\mathbf{x}) = q(\mathbf{x}) + G(s) \cdot L$ , where  $s \leftarrow \{0, 1\}^k$  is a random seed,  $G : \{0, 1\}^k \rightarrow \mathbb{R}$  outputs a pseudorandom "noise" drawn (say) from a discrete Laplace distribution, and  $L > 0$  is a scale. Show that if  $G$  is a secure PRG, then  $M_s$  is  $\epsilon$ -CDP for  $\epsilon$ -approximate counting (by choosing  $L$  suitably).

**Exercise (Simulation Implies Indistinguishability):** Let  $M_\kappa$  be  $(\epsilon, 0)$ -SIM-CDP via simulator  $S_\kappa$  (where  $S_\kappa$  is an  $\epsilon$ -DP mechanism). Show that  $M_\kappa$  is also  $(\epsilon, \text{neg}(\kappa))$ -IND-CDP.