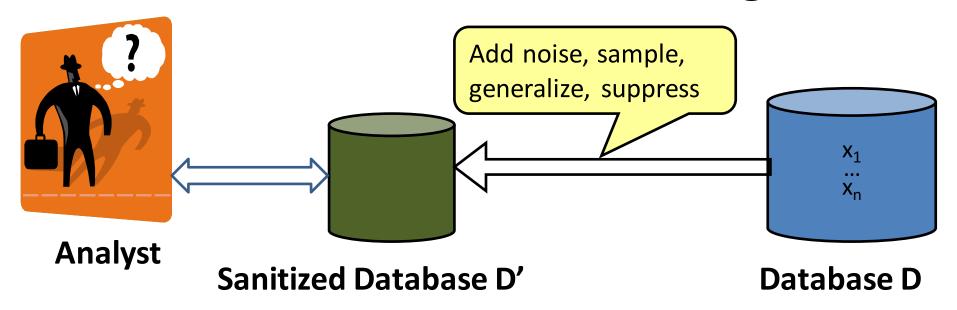
Differential Privacy: The Non-Interactive Setting

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Privacy-Preserving Statistics: Non-Interactive Setting



Goals:

- Release sanitized database that answers all queries from a class accurately
- Preserve differential privacy

Example Class: Interval Queries

- Database D of n points in [0,1] discretized to b bits of precision
- Interval indicator function

$$I_{a_1,a_2}(x) = \begin{cases} 1, & a_1 \le x \le a_2; \\ 0, & \text{otherwise.} \end{cases}$$

Interval query

$$Q_{[a_1,a_2]}(D) = \sum_{x \in D} \frac{I_{a_1,a_2}(x)}{|D|}.$$

Example: grade distribution in a course

Goal

- Design efficient mechanism to release sanitized dataset D' from D s.t. it is
 - Useful, i.e. answers all interval queries accurately with high probability
 - Preserves differential privacy

DEFINITION 2.6 (USEFULNESS DEFINITION 1). A database mechanism A is (ϵ, δ) -useful for queries in class C if with probability $1 - \delta$, for every $Q \in C$ and every database D, for $\widehat{D} = A(D)$, $|Q(\widehat{D}) - Q(D)| \le \epsilon$.

Mechanism(roughly)

• Given D, perform a number of α' -differentially private interval queries to partition [0, 1] into sub-intervals containing probability mass in the range $[\epsilon_1/2 - \epsilon_2, \epsilon_1/2 + \epsilon_2]$.

• Output dataset that has $(\epsilon_1/2) \cdot n$ points in each of these intervals

Theorem

THEOREM 4.2. With $\alpha' = (\epsilon \alpha)/4b$, $\epsilon_1 = (\epsilon/2)$ and $\epsilon_2 = (\epsilon^2/8)$, the above mechanism preserves α -differential privacy while being (ϵ, δ) -useful for the class of interval queries given a database of size:

$$|D| \ge O\left(\frac{b(\log b + \log(1/\epsilon\delta))}{\alpha\epsilon^3}\right)$$

More general results

 A Learning Theory Approach to Non-Interactive Database Privacy. Avrim Blum, Katrina Ligett, Aaron Roth. In the proceedings of STOC 2008: The 40th ACM Symposium on the Theory of Computing.