An Algorithmic Framework For Differentially Private Data Analysis on Trusted Processors

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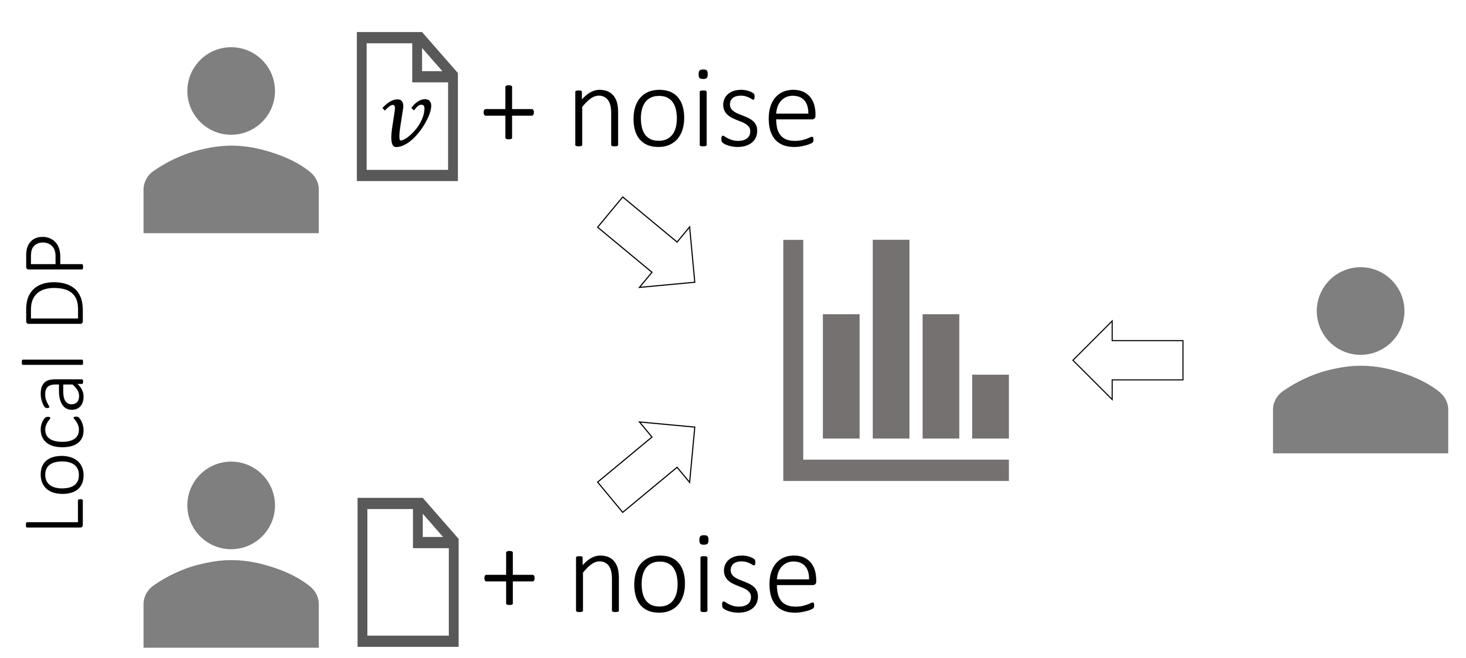
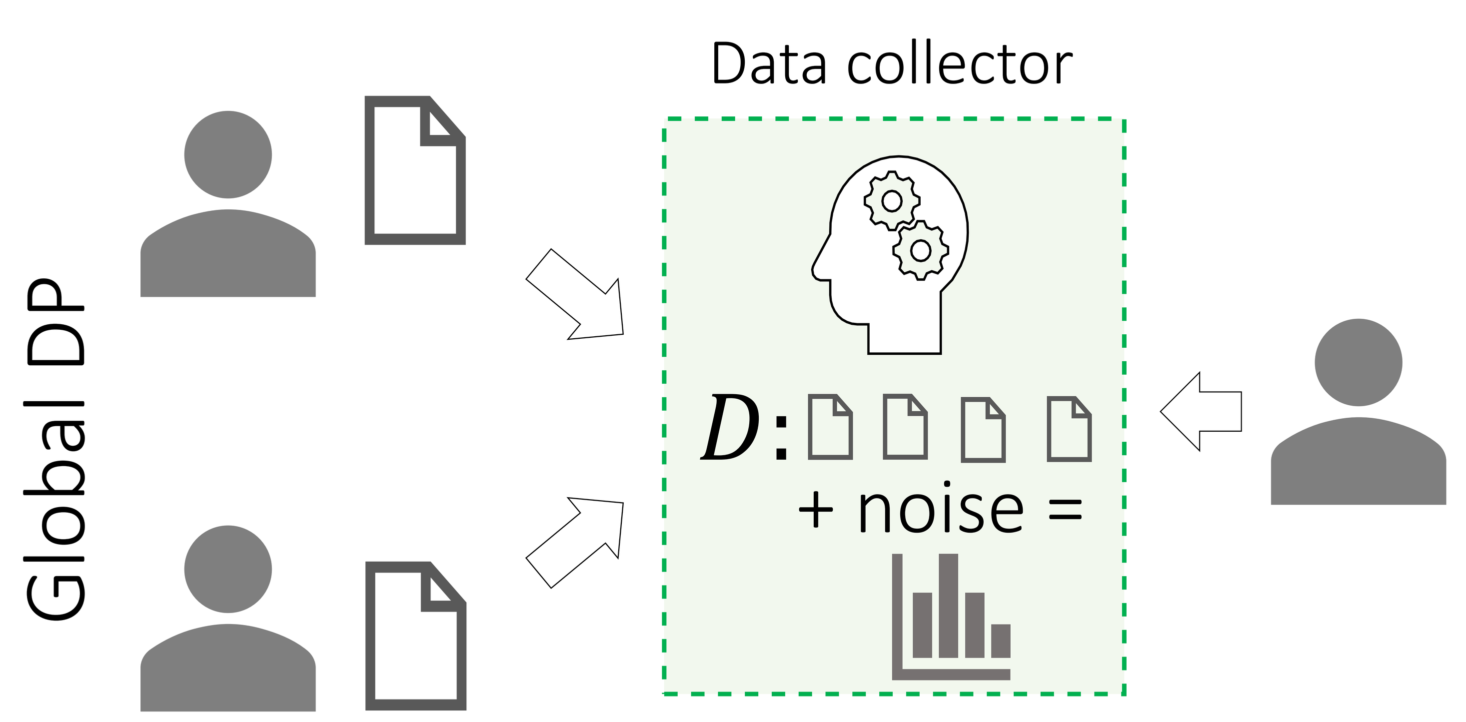
Local vs. Global Differential Privacy (DP)

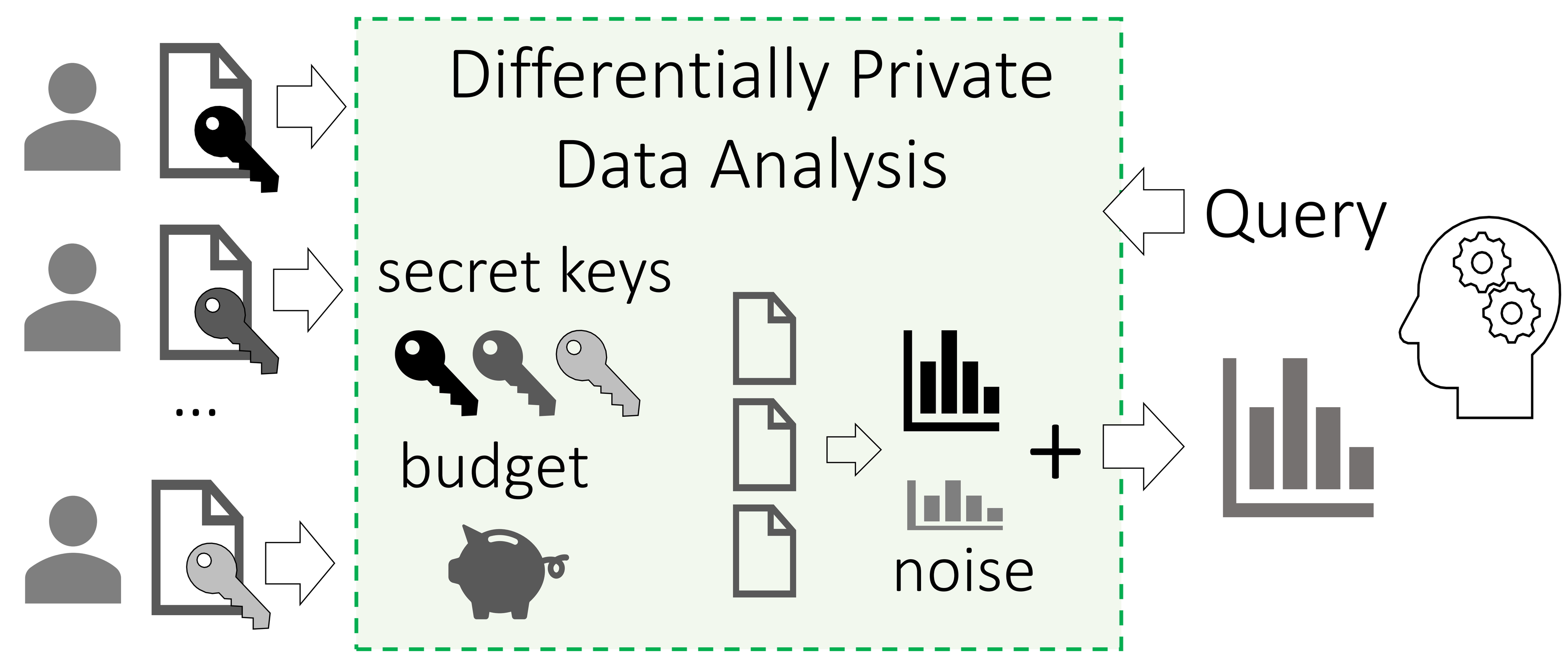


$$\Pr[\mathcal{A}(v) \in S] \leq e^{\epsilon} \Pr[\mathcal{A}(v') \in S]$$



$$\Pr[\mathcal{A}(D_1) \in S] \leq e^{\epsilon} \Pr[\mathcal{A}(D_2) \in S] + \delta$$

Differential Privacy with Trusted Processors

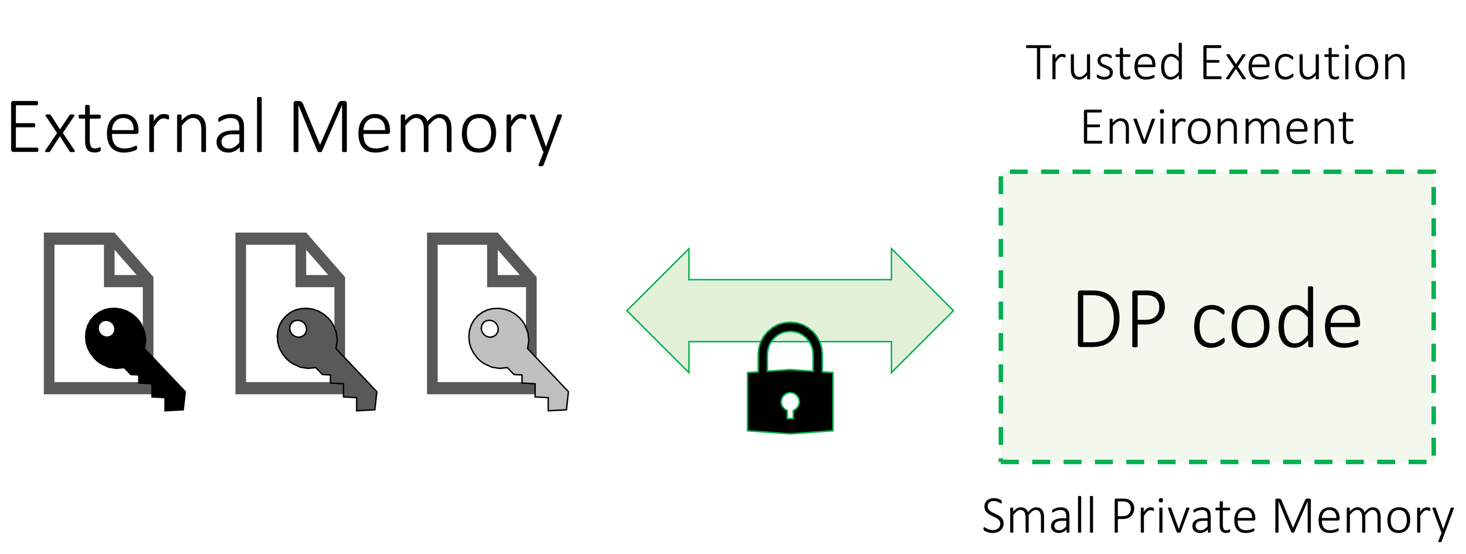


Trusted Execution Environment:

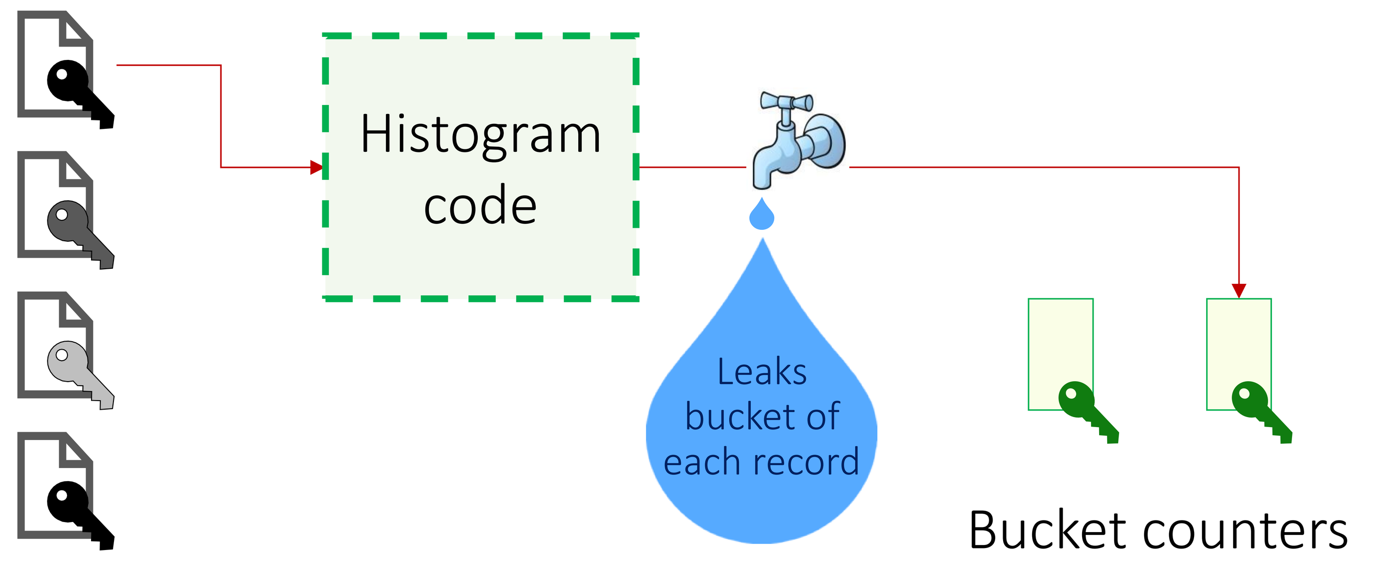
- containers for code and data
- isolated from the rest of the system (hypervisor, OS)
- data always encrypted in RAM
- remote attestation

Intel SGX

Information is Leaked via Side-Channels



Memory access patterns to external memory compromise differential privacy guarantees

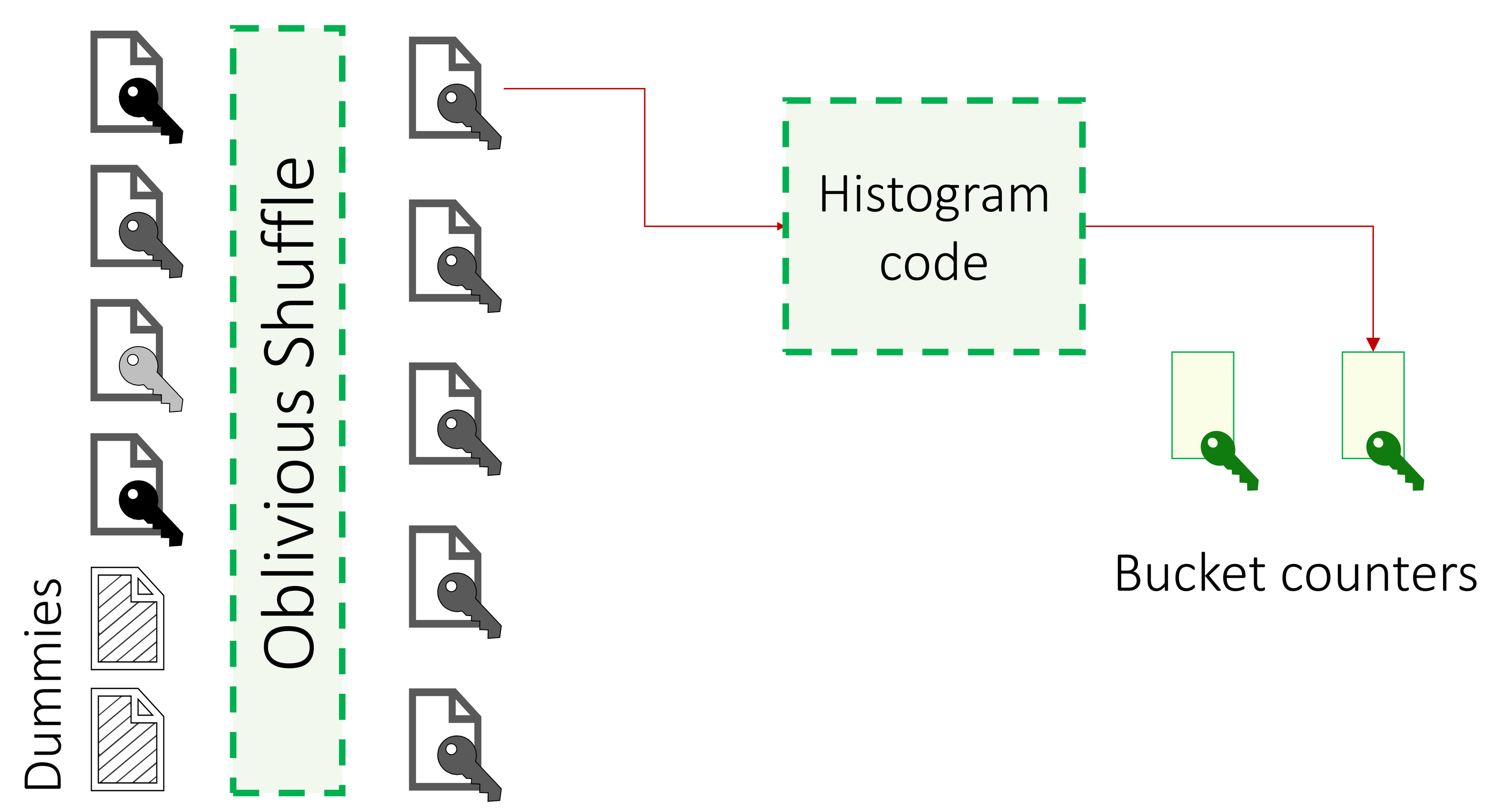


Oblivious Differential Privacy

$$\Pr[\mathcal{A}(D_1) \in (O, S)] \leq e^{\epsilon} \Pr[\mathcal{A}(D_2) \in (O, S)] + \delta$$

where O is a subset of outputs and S is a subset of memory access patters produced by $\mathcal{A}$

Oblivious Differentially Private Histogram Algorithm:



Microsoft