Secure Multiparty Computation

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Outline

Secure Multiparty Computation

Context

- n parties
- each party i has a private input, x_i
- collaboratively compute a function, $f(x_1, ..., x_n)$

SMC Proprieties

- Privacy
- Correctness

Main SMC primitives

- Homomorphic Encryption
- Oblivious transfer
- Garbled Circuits

Homomorphic Encryption

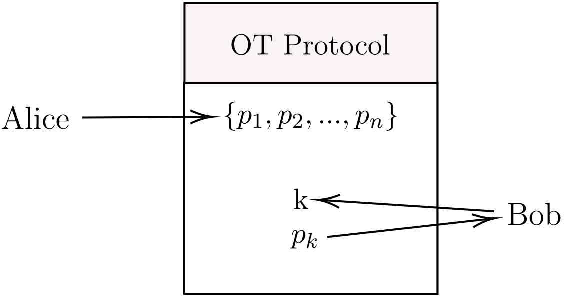
$$E(x_1) \bullet E(x_2) = E(x_1 \bullet x_2)$$

RSA :

$$E(x_1) \bullet E(x_2) = x_1^e x_2^e \bmod n = (x_1 x_2)^e \bmod n = E(x_1 x_2)$$

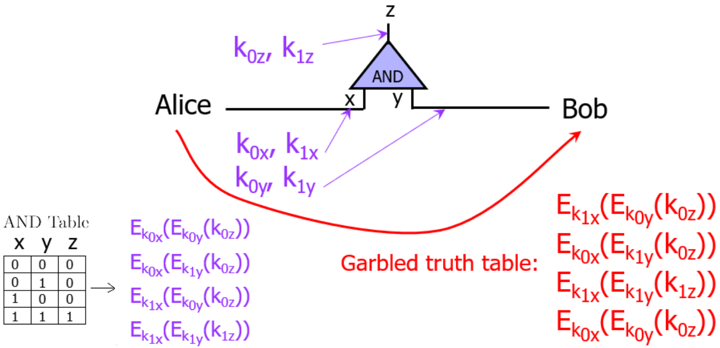
Oblivious Transfer

FIGURE – 1-out-of-n Oblivious Transfer

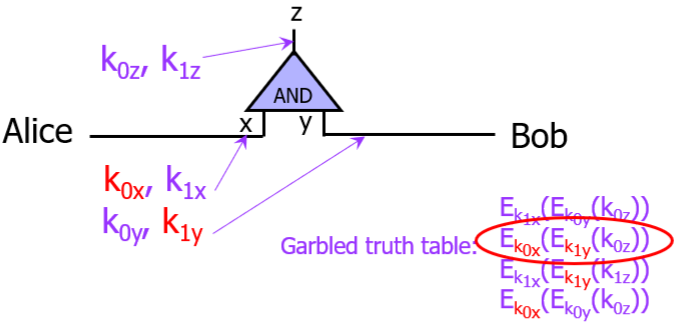


- Alice should not know the value of k
- Bob should not know more than the value he requested, p_k

Garbled Circuits Construction



Garbled Circuits Construction



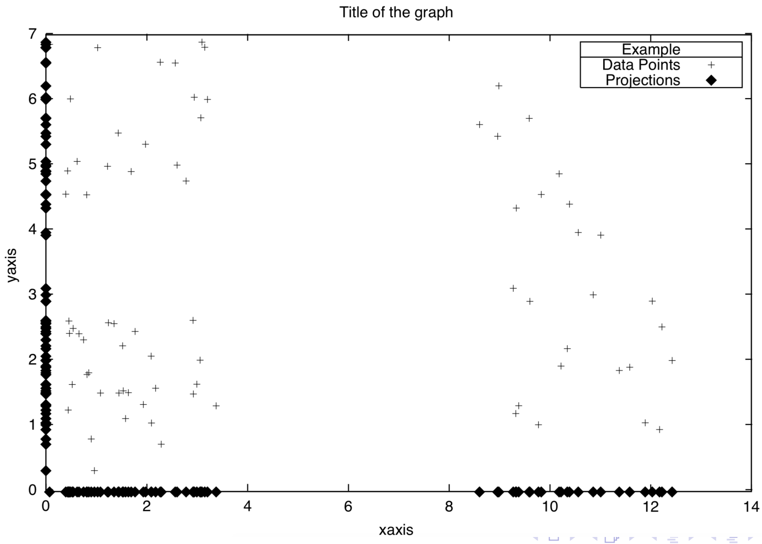
Vitaly Shmatikov, University of Texas, Austin, CS 380S
`www.cs.utexas.edu/~shmat/courses/cs380s_fall09/17yao.ppt`

Privacy-Preserving KMeans Clustering

classic approach

- Initialize the k means $\mu_1 ... \mu_k$ to 0.
- Arbitrarily select k starting points $\mu'_1 ... \mu'_k$
- **repeat**
  - Assign $\mu'_1 ... \mu'_k$ to $\mu_1 ... \mu_k$ respectively
  - **for all** *points* i
    - put point i in the *closest cluster* (given a distance function)
  - **end for**
  - Calculate new means $\mu_1 ... \mu_k$
- **until** the difference between $\mu'_1 ... \mu'_k$ and $\mu_1 ... \mu_k <$ an arbitrary threshold

Vertically partitioned data and clustering



Privacy-Preserving KMeans Clustering

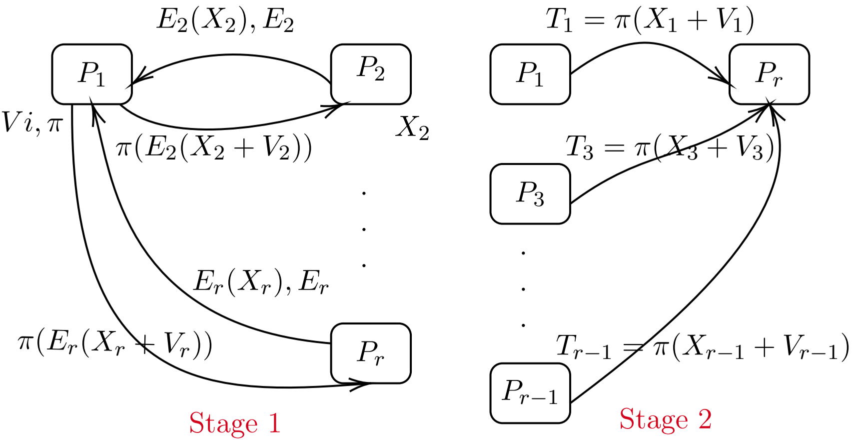
secure approach

$$P_1 \text{ has } X_1 = \begin{bmatrix} x_{11} \\ x_{21} \\ \vdots \\ x_{k1} \end{bmatrix}, P_2 \text{ has } X_2 = \begin{bmatrix} x_{12} \\ x_{22} \\ \vdots \\ x_{k2} \end{bmatrix} \ldots P_r \text{ has } X_r = \begin{bmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{kr} \end{bmatrix}$$

$$\underset{i=1..k}{\operatorname{argmin}}\Big(\sum_{j=1..r} x_{ij} \Big)$$

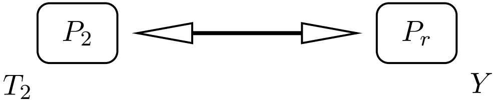
- Disguise the components of the distance with random values that cancel out when combined.
- Compare distances so only the comparison result is learned.
- Permute the order of clusters.

closest cluster



with $V_{k \times r}$ such that $\sum_{i=1}^{r} \vec{V_i} = \vec{0}$

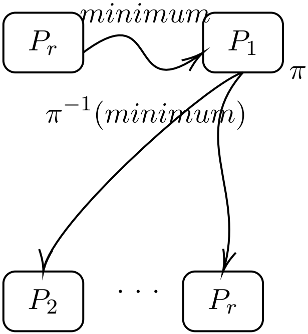
closest cluster
retrieving the minimum



$$secureAddAndCompare$$
$$(\mathbf{Y_j} + T_{2j}\ , \mathbf{Y_{minimum}} + T_{2minimum})$$

$$update\ minimum\ accordingly$$

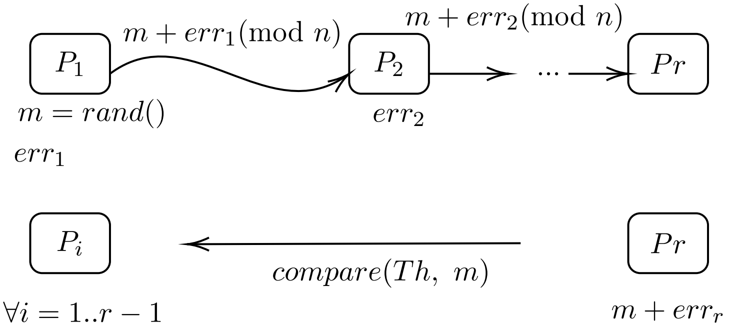
Stage 3



Stage 4

$$Y = T_1 + \sum_{i=3}^{r} T_i$$

check termination threshold



$$err_i = 0$$
$$for\ each\ j\ in\ \{1...k\}:$$
$$err_i = err_i + dist(\mu_j,\ \mu'_j)$$

`Jaideep Vaidya, Privacy – preserving kmeans clustering over vertically partitioned data`

Future work

Directions for further study :

- Reduce computational and communication cost
- Other clustering solutions with the privacy-preserving property