

Modern Secure Multi-Party Computation Techniques

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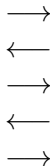
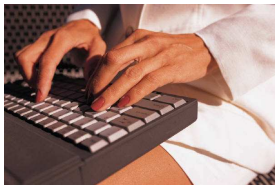
Secure Computation

- **Secure multi-party computation** enables parties to jointly evaluate a function on their private inputs without disclosing them
 - each participant holds their own private data
 - participants jointly perform the computation on cryptographically protected private data
 - private data can only leave the owner after applying proper cryptographic protection
 - only the outcome is revealed to the intended output recipients

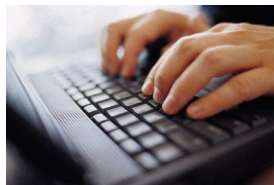
The Famous Millionaires Problem

- Alice and Bob would like to determine who is richer without revealing their worth to each other

Alice
private x



Bob
private y



output $x < y$

Secure Computation

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 - obtain access to private data and promise to comply with data usage requirements
 - or private data is accessible to software, but the software doesn't let users to “see” the data

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 - obtain access to private data and promise to comply with data usage requirements
 - or private data is accessible to software, but the software doesn't let users to “see” the data
- Contrast this with **secure computation**:
 - nothing about private data is recoverable by others throughout the computation
 - observed information is the same as if the computation was performed by a **trusted third party**

Secure Multi-Party Computation

- Secure computation can take many forms

- secure **two-party computation**

- e.g., evaluating predisposition to a genetic disease



- secure **multi-party computation**

- e.g., determining the best treatment for a rare condition by multiple hospitals

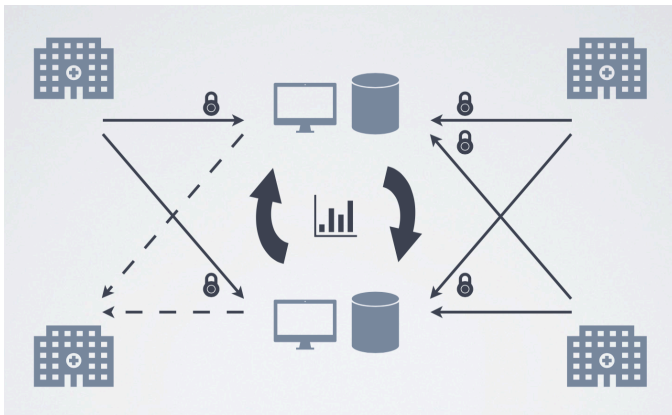


- secure **computation outsourcing**

- e.g., offloading image processing to a cloud



Secure Multi-Party Computation



Data Protection Techniques

- There are different ways to protect private values in a way that we can **compute with protected data**
 - garbled circuit evaluation
 - secret sharing
 - homomorphic encryption

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- With **(n, t) secret sharing**
 - a secret s is divided into n shares s_1, s_2, \dots, s_n
 - access to $\leq t$ shares reveals nothing about s
 - access to $\geq t + 1$ shares allows for s to be reconstructed

Secret Sharing

- **Example: Additive secret sharing**
 - $t = n - 1$, i.e., all n shares are required for reconstruction
 - let $n = 2$ and our secret be $0 \leq x < N$
 - choose random r from \mathbb{Z}_N and set the first share $x_1 = r$
 - compute the second share $x_2 = (x - r) \bmod N$
 - to **reconstruct**, compute $x = (x_1 + x_2) \bmod N$
 - for example
 - let $N = 10$ and $x = 3$
 - suppose we choose random $x_1 = 5$
 - we compute $x_2 = 3 - 5 \bmod 10 = 8$

Security of Secret Sharing

- Unlike encryption, secret sharing is unbreakable
 - secret sharing enjoys information theoretic security and achieves perfect secrecy
 - intuitively, in this example, x_1 is uniformly random and is independent of the secret
 - similarly, x_2 is uniform and there is not enough information to guess the secret
- More interesting and useful are threshold secret sharing with flexible t
 - honest majority setting with $t < n/2$ and
 - dishonest majority setting $t < n$

Threshold Secret Sharing

- One example is **Shamir secret sharing**
 - a secret is encoded as a **polynomial of degree t** with random coefficients
 - each share corresponds to the evaluation of the polynomial on a new point
 - secret reconstruction uses **polynomial interpolation** with $\geq t + 1$ points
- Another example is **replicated secret sharing**
 - additive secret sharing where a party stores > 1 share
 - a new share is created for **each set of parties of size t** and is given to the parties not in the set

Computing on Shares

- Computing on shares can often be expressed as evaluating an **arithmetic circuit**
 - evaluation of **addition gates** is performed locally on the shares
 - all of the above secret sharing schemes are **linear**
 - given secret-shared $[a_1], \dots, [a_k]$, the parties can locally evaluate a linear combination $c_1[a_1] + \dots + c_k[a_k]$
 - evaluation of **multiplication gates** $[a] \cdot [b]$ requires communication
 - typical logic is to compute a partial product locally and re-share
 - the goal is to minimize communication and local work
 - different types of secret sharing offer performance tradeoffs

General-Purpose Computation

- Any functionality can be expressed as an arithmetic circuit
 - this doesn't mean that we can evaluate general-purpose programs efficiently
- In practice, we
 - extend the set of elementary operations with additional gates, most importantly, random value generation
 - design custom efficient protocols for non-arithmetic operations such as comparisons
 - minimize multiplicative depth or round complexity

Security Notions

- There are two standard **threat models**:
 - **passive (or semi-honest) security**
 - the computational parties follow the protocol but attempt to gather unauthorized information
 - communication channels are publically observable
 - **active (or malicious) security**
 - the computational parties can arbitrarily deviate from the prescribed protocol
 - detection of protocol deviation incurs additional cost
 - one example is dual execution on $[x]$ and $[r \cdot x]$ values and checking the branches for consistency

Real-World Uses

- **Danish sugar beet auction**
 - country-wide sealed bid auction that cryptographically protected farmer's bids
- **Tax fraud detection in Estonia**
 - citizens pay taxes on goods acquired abroad
 - the government can compute taxes without access to purchases
- **Correlation between student employment and college graduation**
 - employment information was extracted from tax records
 - it was combined with university records

Real-World Uses

- **City of Boston gender wage gap study**
 - analysis of wages by gender and race in the Greater Boston area
 - significantly larger participation the second year
 - provided valuable insights for decision makers
- **Effectiveness of Google ads**
 - Google knows on what ads a user clicked
 - the store knows how much a user spent at the store
 - this allows for determining effectiveness of ads
- **Improving effectiveness of public transport**
 - trip records were privately analyzed to improve public transport utilization

Current Research Directions

- Secure computation with **certified inputs**
 - security definitions place no constraints on inputs
 - some applications require authentic inputs
 - current **research project**: compliance with sustainability policies
- Understanding **information disclosure** from the output
 - security definitions require no information disclosure during the computation
 - but they don't impose constraints on disclosure from the output
 - current **research project**: we measure this for different statistical functions
- **Performance optimizations**