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Data Confidentiality in Collaborative Computing

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Collaborators

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The most useful data is scattered and hidden

- Data distributed among many parties
- Could be used to compute useful outputs (of benefit to all parties)
- Online collaborative computing looks like a “win-win”, yet …
- Huge potential benefits go unrealized
- Reason: Reluctance to share information

Reluctance to Share Info

- Proprietary info, could help competition
  - Reveal corporate strategy, performance
- Fear of loss of control
  - Further dissemination, misuse
- Fear of embarrassment, lawsuits
- May be illegal to share
- Trusted counterpart but with poor security

Securely Computing f(X,Y)

- Inputs:
  - Data X (with Bob), data Y (with Alice)
- Outputs:
  - Alice or Bob (or both) learn f(X,Y)

Secure Multiparty Computation

- SMC: Protocols for computing with data without learning it
- Computed answers are of same quality as if information had been fully shared
- Nothing is revealed other than the agreed upon computed answers
- No use of trusted third party

SMC (cont'd)

- Yao (1982): {X <= Y}
- Goldwasser, Goldreich, Micali, ...
- General results
  - Deep and elegant, but complex and slow
  - Limited practicality
- Practical solutions for specific problems
- Broaden framework

Potential Benefits ...

- Confidentiality-preserving collaborations
- Use even with trusted counterparts
  - Better security ("defense in depth")
  - Less disastrous if counterpart suffers from break-in, spy-ware, insider misbehavior, ...
  - Lower liability (lower insurance rates)
- May be the only legal way to collaborate
  - Anti-trust, HIPAA, Gramm-Leach-Bliley, ...

… and Difficulties

- Designing practical solutions
  - Specific problems; “moderately untrusted” 3rd party; trade some security; …
- Quality of inputs
  - ZK proofs of well-formedness (e.g., {0,1})
  - Easier to lie with impunity when no one learns the inputs you provide
  - A participant could gain by lying in competitive situations
- Inverse optimization

Quality of Inputs

- The inputs are 3rd-party certified
  - Off-line certification
  - Digital credentials
  - "Usage rules" for credentials
- Participants incentivized to provide truthful inputs
  - Cannot gain by lying

Variant: Outsourcing

- Weak client has all the data
- Powerful server does all the expensive computing
  - Deliberately asymmetric protocols
- Security: Server learns neither input nor output
- Detection of cheating by server
  - E.g., server returns some random values

Models of Participants

- Honest-but-curious
  - Follow protocol
  - Compute all information possible from protocol transcript
- Malicious
  - Can arbitrarily deviate from protocol
- Rational, selfish
  - Deviate if gain (utility function)

Examples of Problems

- Access control, trust negotiations
- Approximate pattern matching & sequence comparisons
- Contract negotiations
- Collaborative benchmarking, forecasting
- Location-dependent query processing
- Credit checking
- Supply chain negotiations
- Data mining (partitioned data)
- Electronic surveillance
- Intrusion detection
- Vulnerability assessment
- Biometric comparisons
- Game theory

Hiding Intermediate Values

- Additive splitting
  - x = x' + x", Alice has x', Bob has x"
- Encoder / Evaluator
  - Alice uses randoms to encode the possible values x can have, Bob learns the random corresponding to x but cannot tell what it encodes

Hiding Intermediate … (cont'd)

- Compute with encrypted data, e.g.
- Homomorphic encryption
  - 2-key (distinct encrypt & decrypt keys)
  - $E_A(x) * E_A(y) = E_A(x+y)$
  - Semantically secure: Having $E_A(x)$ and $E_A(y)$ do not reveal whether x=y

Example: Blind-and-Permute

- Input: $c_1, c_2, \ldots, c_n$ additively split between Alice and Bob: $c_i = a_i + b_i$ where Alice has a_i, Bob has b_i
- Output: A randomly permuted version of the input (still additively split) s.t. neither side knows the random permutation

Blind-and-Permute Protocol

1. A sends to B: E_A and $E_A(a_1),\ldots,E_A(a_n)$
2. B computes $E_A(a_i)*E_A(r_i) = E_A(a_i + r_i)$
3. B applies π_B to $E_A(a_1+r_1), \ldots, E_A(a_n+r_n)$ and sends the result to A
4. B applies π_B to $b_1-r_1, \ldots, b_n-r_n$
5. Repeat the above with the roles of A and B interchanged

Dynamic Programming for Comparing Bio-Sequences

		0	1	2	3	4	...		m
			A	C	T	G	A	T	G
0		0	1	2	3	4	5	6	7
1	A	1	0	1	2	3	4	5	6
2	T	2	1	**2**	**1**	2	3	4	5
3	G	3	2	**3**	**2**				
...	G	4							
	A	5							
n	A	6							

- M(i,j) is the minimum in cost of transform the prefix of X of length i into the prefix of Y of length j

$$M(i,j) = \min \begin{cases} M(i-1, j-1) + S(\lambda_i, \mu_j) \\ M(i-1, j) + D(\lambda_i) \\ M(i, j-1) + I(\mu_j) \end{cases}$$

	I
A	1
C	1
T	1
G	1

Insertion Cost

	D
A	1
C	1
T	1
G	1

Deletion Cost

	A	C	T	G
A	0	∞	∞	∞
C	∞	0	∞	∞
T	∞	∞	0	∞
G	∞	∞	∞	0

Substitution Cost

Correlated Action Selection

- (p_1,a_1,b_1), … , (p_n,a_n,b_n)
- Prob p_j of choosing index j
- A (resp., B) learns only a_j (b_j)
- Correlated equilibrium
- Implemention with third-party mediator
- Question: Is mediator needed?

Correlated Action Selection (cont'd)

- Protocols without mediator exist
- Dodis et al. (Crypto '00)
  - Uniform distribution
- Teague (FC '04)
  - Arbitrary distribution, exponential complexity
- Our result: Arbitrary distribution with polynomial complexity

Correlated Action Selection (cont'd)

- A sends to B: E_A and a permutation of the n triplets $E_A(p_j), E_A(a_j), E_A(b_j)$
- B permutes the n triplets and computes $E_A(Q_j)=E_A(p_1)*\ldots* E_A(p_j)=E_A(p_1+\ldots+p_j)$
- B computes $E_A(Q_j-r_j), E_A(a_j-r'_j), E_A(b_j-r''_j)$, then permutes and sends to A the n triplets so obtained
- A and B select an additively split random r ($=r_A+r_B$) and "locate" r in the additively split list of Q_js

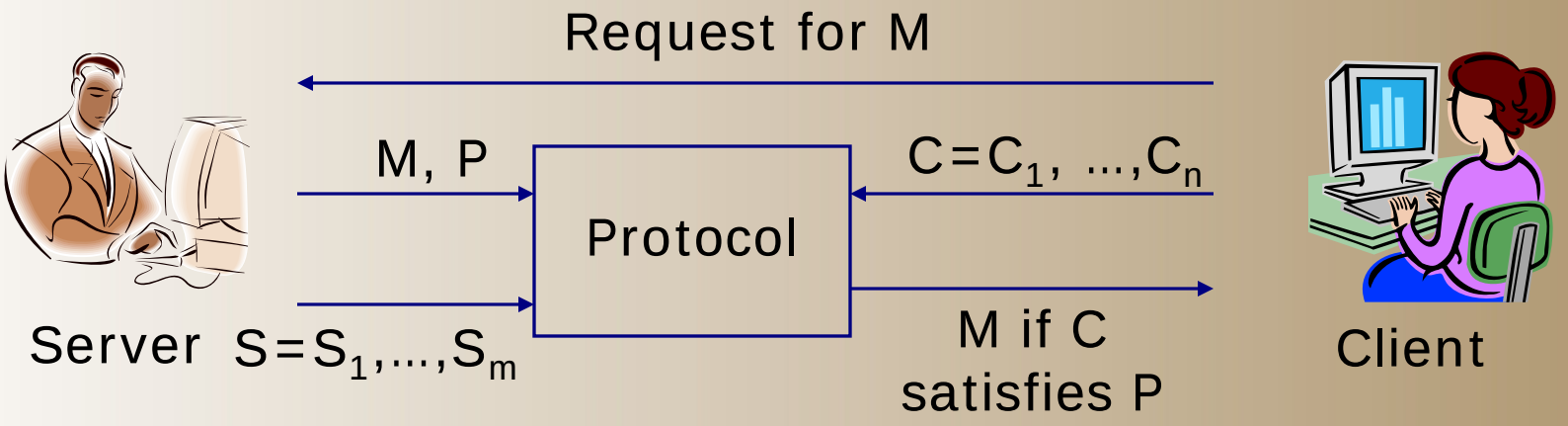
Access Control

- Access control decisions are often based on requester *characteristics* rather than identity
  - Access policy stated in terms of attributes
- Digital credentials, e.g.,
  - Citizenship, age, physical condition (disabilities), employment (government, healthcare, FEMA, etc), credit status, group membership (AAA, AARP, ...), security clearance, ...

Access Control (cont'd)

- Treat credentials as sensitive
  - Better individual privacy
  - Better security
- Treat access policies as sensitive
  - Hide business strategy (fewer unwelcome imitators)
  - Less "gaming"

Model



- M = message ; P = Policy ; C, S = credentials
  - Credential sets C and S are issued off-line, *and can have their own "use policies"*
- Client gets M iff usable C_j's satisfy policy P
- Cannot use a trusted third party

Solution Requirements

- Server does not learn whether client got access or not
- Server does not learn anything about client's credentials, and vice-versa
- Client learns neither server's policy structure nor which credentials caused her to gain access
- No off-line probing (e.g., by requesting an M once and then trying various subsets of credentials)

Credentials

- Generated by certificate authority (CA), using Identity Based Encryption
- E.g., issuing Alice a student credential:
  - Use Identity Based Encryption with ID = Alice||student
  - Credential = private key corresponding to ID
- Simple example of credential usage:
  - Send Alice M encrypted with public key for ID
  - Alice can decrypt only with a student credential
  - Server does not learn whether Alice is a student or not

Policy

- A Boolean function $p_M(x_1, \ldots, x_n)$
  - x_i corresponds to attribute $attr_i$
- Policy is satisfied iff
  - $p_M(x_1, \ldots, x_n) = 1$ where x_i is 1 iff there is a usable credential in C for attribute $attr_i$
- E.g.,
  - Alice is a senior citizen and has low income
  - Policy = (disability $\vee$ senior-citizen) $\wedge$ low-income
  - Policy = $(x_1 \vee x_2) \wedge x_3 = (0 \vee 1) \wedge 1 = 1$

Ideas in Solution

- Phase 1: Credential and Attribute Hiding
  - For each $attr_i$ server generates 2 randoms $r_i[0]$, $r_i[1]$
  - Client learns n values $k_1, k_2, \ldots, k_n$ s.t. $k_i = r_i[1]$ if she has a credential for $attr_i$, otherwise $k_i = r_i[0]$
- Phase 2: Blinded Policy Evaluation
  - Client's inputs are the above $k_1, k_2, \ldots, k_n$
  - Server's input now includes the n pairs $r_i[0]$, $r_i[1]$
  - Client obtains M if and only if $p_M(x_1, \ldots, x_n) = 1$

Concluding Remarks

- Promising area (both research and potential practical impact)
- Need more implementations and software tools
  - FAIRPLAY (Malkhi et.al.)
- Currently impractical solutions will become practical