

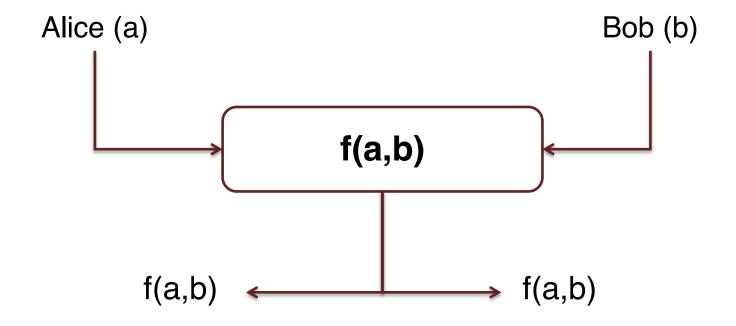
# Cryptographic Protocols for Privacy-Preserving Genomic Testing: Tools and Applications

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# **Secure Multiparty Computation (SMC)**



## **How to Implement SMC?**

#### 1. Garbled Circuits

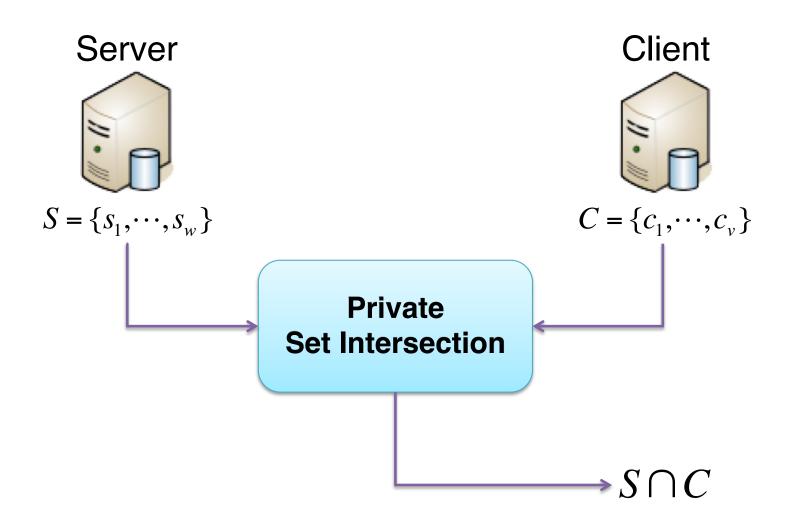
Sender prepares a "garbled" circuit and sends it to the receiver, who obliviously evaluates the circuit, learning the encodings corresponding to both his and the senders output

## 2. Special-Purpose Protocols

Implement one specific function (and only that)

Usually based on public-key crypto properties [Have you ever heard of homomorphic encryption?]

# **Private Set Intersection (PSI)**



## **Private Set Intersection?**

**FBI** (Domestic suspect terrorists) and **CIA** (Foreign suspect terrorists)

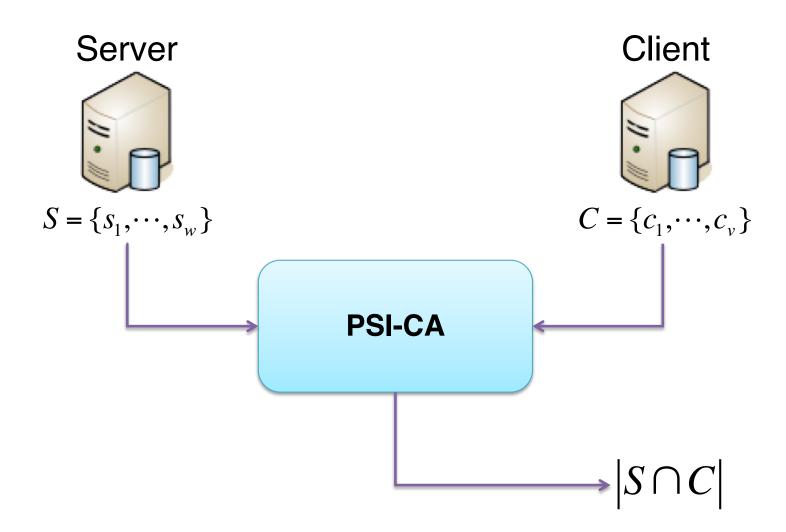
Find out whether any suspect is in common

IRS (Tax Evaders) and Swiss Bank (Customers)

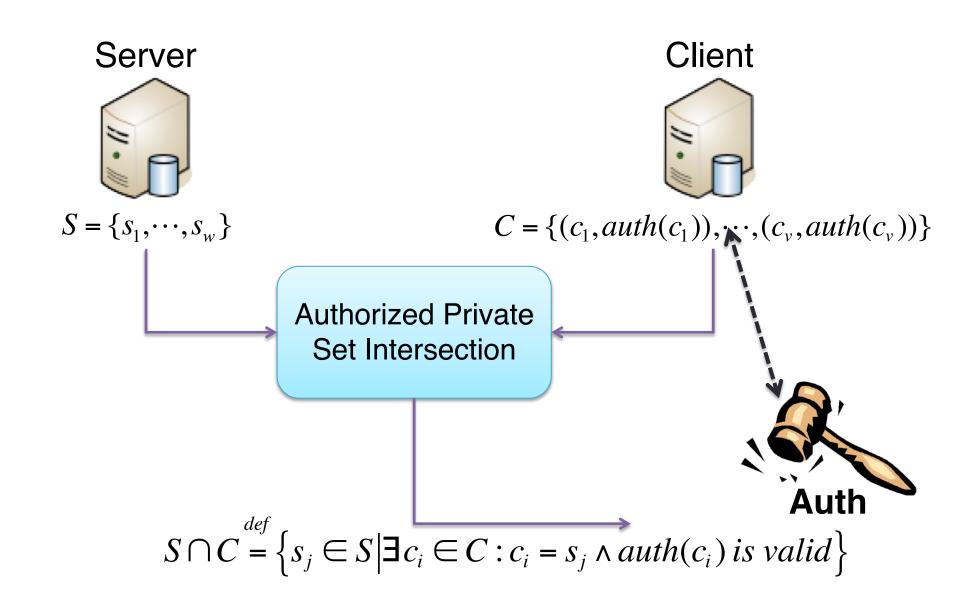
Discover if tax evaders have accounts at foreign banks

#### And more!

## **Private Set Intersection Cardinality (PSI-CA)**



## **Authorized Private Set Intersection (APSI)**



## **Private Personal Genomic Tests**

## Individuals retain control of their sequenced genome

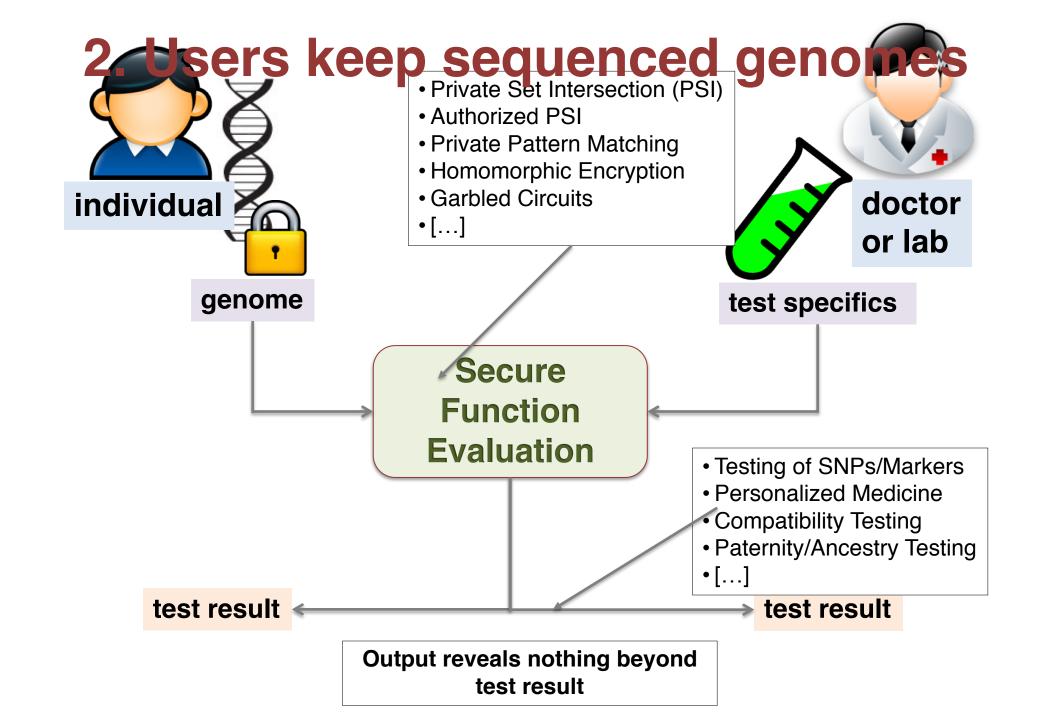
#### Allow doctors/labs to run genetics tests, but:

- 1. Genome never disclosed, only test output is
- 2. Pharmas can keep test specifics confidential

... two main approaches ...

## 1. Using Semi-Trusted Parties

**STORAGE AND CERTIFIED** PROCESSING UNIT (SPU) **INSTITUTION (CI)** (ii) Encrypted SNPs (i) Encrypted clinical and length on the length of the len omputation (iii) Disease (i) DNA sample Risk (i) Clinical and **Environmental MEDICAL PATIENT** data **UNIT (MU) (P)** 



# 2. Users keep sequenced genomes

#### Baldi et al. (CCS'11)

Privacy-preserving version of a few genetic tests, based on private set operations

Paternity test, Personalized Medicine, Compatibility Tests (First work to consider fully sequenced genomes)

#### De Cristofaro et al. (WPES'12), extends the above

Framework and prototype deployment on **Android**Adds Ancestry/Genealogy Testing

# **Genetic Paternity Test**

### A Strawman Approach for Paternity Test:

On average, ~99.5% of any two human genomes are identical

Parents and children have even more similar genomes

Compare candidate's genome with that of the alleged child:

Test positive if percentage of matching nucleotides is  $> 99.5 + \tau$ 

## **First-Attempt Privacy-Preserving Protocol:**

Use an appropriate secure two-party protocol for the comparison

PROs: High-accuracy and error resilience

CONs: Performance not promising (3 billion symbols in input)

In our experiments, computation takes a few days

# **Genetic Paternity Test**

#### Wait a minute!

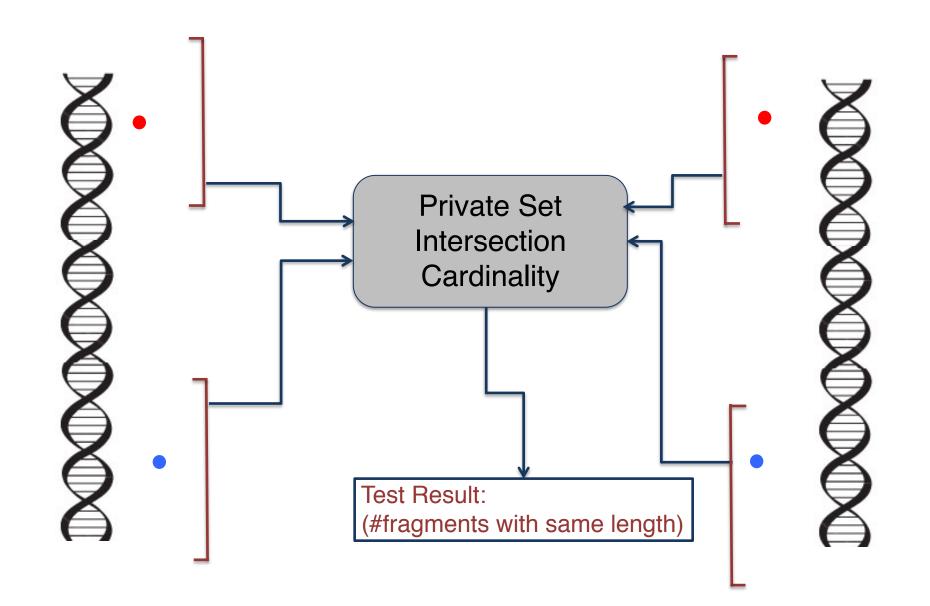
~99.5% of any two human genomes are identical

Why don't we compare *only* the remaining 0.5%?

We can compare by counting how many

But... We don't know (yet) where exactly this 0.5% occur!

# **Private RFLP-based Paternity Test**



# Personalized Medicine (PM)

#### Drugs designed for patients' genetic features

Associating drugs with a unique genetic fingerprint

Max effectiveness for patients with matching genome

Test drug's "genetic fingerprint" against patient's genome

#### **Examples:**

*tmpt* gene – relevant to leukemia

(1) G->C mutation in pos. 238 of gene's c-DNA, or (2) G->A mutation in pos. 460 and one A->G is pos. 419 cause the *tpmt* disorder (relevant for leukemia patients)

*hla-B* gene – relevant to HIV treatment

One G->T mutation (known as *hla-B\*5701* allelic variant) is associated with extreme sensitivity to abacavir (HIV drug)

# Reducing P<sup>3</sup>MT to APSI

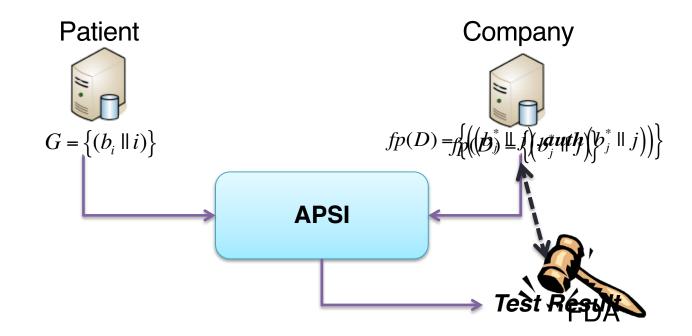
#### Intuition:

FDA = Court, Pharma = *Client*, Patient = *Server* 

Patient's private input set:  $G = \{(b_i \parallel i) | b_i \in \{A, C, G, T\}\}_{i=1}^{3\cdot 10^9}$ 

Pharmaceutical company's input set:  $fp(D) = \{(b_j^* \parallel j)\}$ 

Each item in fp(D) needs to be authorized by FDA



## Other Areas 1/

Secure computation for data sharing

Homomorphic encryption for computation outsourcing

Honey encryption for long-term storage

# **Beyond Crypto**

#### **Differential privacy**

Adding noise to a dataset with the goal of supporting statistical queries while preserving the privacy of the users whose information is contained in the dataset

#### **Examples:**

Computing number/location of SNPs associated to disease Significance/correlation between a SNP and a disease

## **Open Problems**

#### Where do we store genomes?

Encryption can't guarantee security past 30-50 yrs

Reliability and availability issues?

## **Challenges with Crypto**

Efficiency overhead

Dealing with sequencing errors

How much understanding required from users?







# Thank you!

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