### MPRI 2.3.2 - Foundations of privacy

#### Lecture 1

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### Plan of the course

#### Overview of applications

Quantitative Information Flow

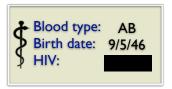
- Vulnerability and entropy operational interpretation
- Information-theoretic approaches
- Relation with differential privacy
- Decision-theoretic approaches: g-leakage
- Comparing systems, the lattice of information

Location privacy

- Optimal Bayesian approaches
- Geo-indistinguishability

### Protection of sensitive information

 Protecting the confidentiality of sensitive information is a fundamental issue in computer security





- Access control and encryption are not sufficient! Systems could leak secret information through correlated observables.
  - The notion of "observable" depends on the adversary
  - Often, secret-leaking observables are public, and therefore available to the adversary

### Leakage through correlated observables

#### Password checking

	Authentication Required		
	A username and password are being requested https://intranet.inria.fr. The site says: "Inria"	by	ERROR
			Unknown user or password incorrect.
User Name Password			Go to the login page
Password	Cancel	ОК	
		Election tabulation	
	A CO	Timings of decryptions	400 The (100

## Quantitative Information Flow

Information Flow: Leakage of secret information via correlated observables

Ideally: No leak

• No interference [Goguen & Meseguer'82]

In practice: There is almost always some leak

- Intrinsic to the system (public observables, part of the design)
- Side channels

⇒ need quantitative ways to measure the leak

### Example I

#### Password checker I

Password:  $K_1K_2...K_N$ Input by the user:  $x_1x_2...x_N$ Output: *out* (Fail or OK)

#### Intrinsic leakage

By learning the result of the check the adversary learns something about the secret

out := OKfor i = 1, ..., N do if  $x_i \neq K_i$  then out := FAIL

end if end for

### Example I

#### Password checker 2

Password:  $K_1K_2...K_N$ Input by the user:  $x_1x_2...x_N$ Output: *out* (Fail or OK)

More efficient, but what about security?

 $out := \mathsf{OK}$ for i = 1, ..., N do if  $x_i \neq K_i$  then  $\begin{cases} out := \mathsf{FAIL} \\ exit() \\ end \text{ if} \\ end \text{ for} \end{cases}$ 

### Example I

#### Password checker 2

Password:  $K_1K_2...K_N$ Input by the user:  $x_1x_2...x_N$ Output: *out* (Fail or OK)

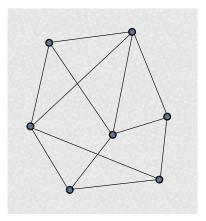
#### Side channel attack

If the adversary can measure the execution time, then he can also learn the longest correct prefix of the password out := OKfor i = 1, ..., N do if  $x_i \neq K_i$  then  $\begin{cases} out := FAIL\\ exit() \\ end if \\ end for \end{cases}$ 

## Example 2

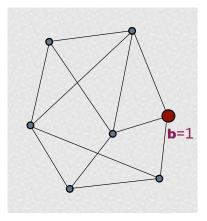
Example of Anonymity Protocol: DC Nets [Chaum'88]

- A set of nodes with some communication channels (edges).
- One of the nodes (source) wants to broadcast one bit **b** of information
- The source (broadcaster) must remain anonymous

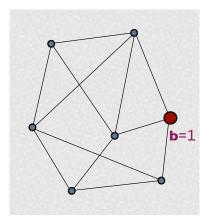


Example of Anonymity Protocol: DC Nets [Chaum'88]

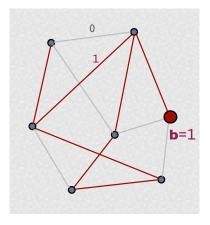
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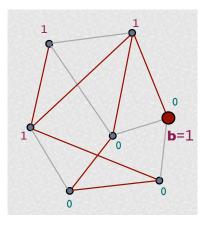
• Associate to each edge a fair binary coin



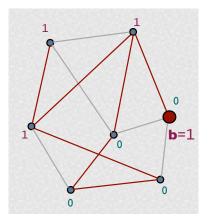
- Associate to each edge a fair binary coin
- Toss the coins



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- Each node computes the binary sum of the incident edges. The source adds **b**. They all broadcast their results



- Associate to each edge a fair binary coin
- Toss the coins
- Each node computes the binary sum of the incident edges. The source adds b. They all broadcast their results
- Achievement of the goal: Compute the total binary sum: it coincides with **b**



## Anonymity of DC Nets

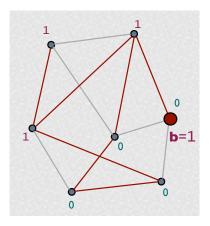
- **Observables:** An (external) attacker can only see the declarations of the nodes
- **Question:** Does the protocol protects the anonymity of the source?

### Strong anonymity (Chaum)

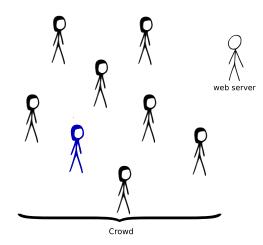
 If the graph is connected and the coins are fair, then for an external observer, the protocol satisfies strong anonymity:

the *a* posteriori probability that a certain node is the source is equal to its *a* priori probability

 A priori / a posteriori = before / after observing the declarations

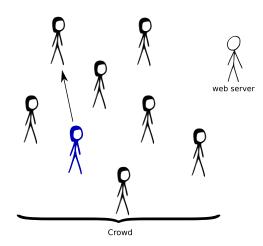


- DC is not practical for a large number of users
- ► In practice we might want to trade anonymity for efficiency
- Crowds offers a weaker notion of anonymity called probable innocence
- Designed for anonymous web surfing



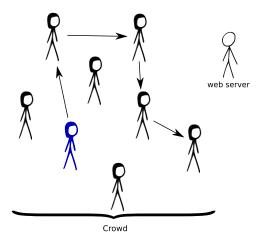
The Crowds protocol The initiator:

Forwards the message

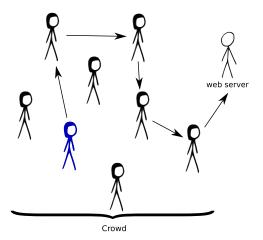


The Crowds protocol The initiator:

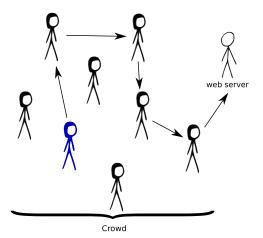
- Forwards the message
- A forwarder:
  - ▶ With pb *p<sub>f</sub>* forwards



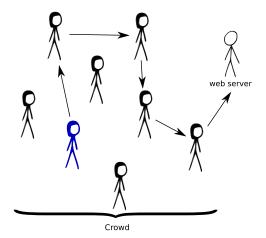
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  - The path is used in the opposite direction for the reply

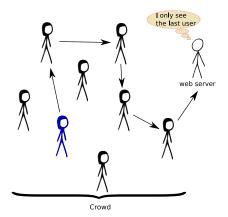


- Forwards the message
- A forwarder:
  - With pb p<sub>f</sub> forwards
  - ► With pb 1 − p<sub>f</sub> delivers
  - The path is used in the opposite direction for the reply
  - The same path is used in future requests



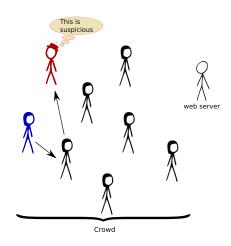
### The Crowds protocol: anonymity

- We consider sender anonymity
- Attacker model
  - Cannot see the whole network
  - Only messages sent to him
- The server:
  - only sees the last user
  - Strong anonymity is satisfied



# The Crowds protocol: anonymity

- They can see forwarding requests and "detect" a user i
- User *i* can still claim that he was forwading the message for user *j*
- Is strong anonymity satisfied?
- Compare the probability to detect *i*:
  - when i is the payer
  - when j is the payer
- They are different: strong anonymity is violated



# Location-Based Systems

A **location-based system** is a system that uses geographical information in order to provide a service.

- Retrieval of Points of Interest (POIs).
- Mapping Applications.
- Deals and discounts applications.
- Location-Aware Social Networks.



## Location-Based Systems

- Location information is sensitive. (it can be linked to home, work, religion, political views, etc).
- Ideally: we want to **hide our true location**.
- Reality: we need to **disclose some information**.

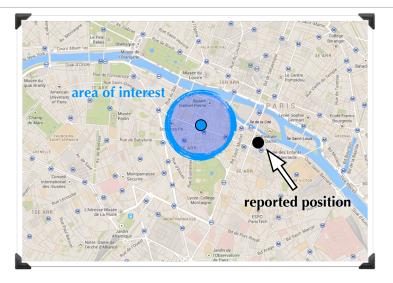


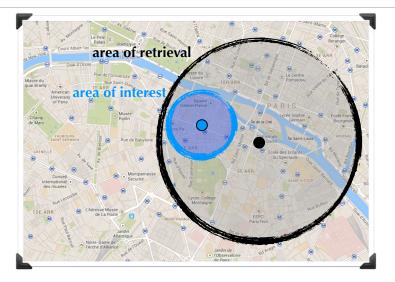
# Example

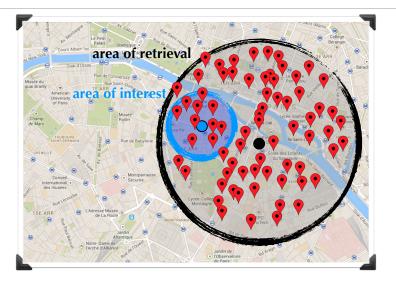
- Find restaurants within 300 meters.
- Hide location, not identity.
- Provide approximate location.













How can get we generate the noise?

What kind of formal privacy guarantees do we get?

Which mechanism gives optimal utility?

What if we use the service repeatedly?