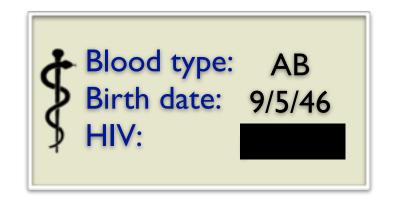
# Quantitative Information Flow

Lecture 6

#### Protection of sensitive information

 This part of the course is dedicated to the problem of protecting secret information when it is collected, stored, processed and communicated by computer systems. This is the central issue in Security

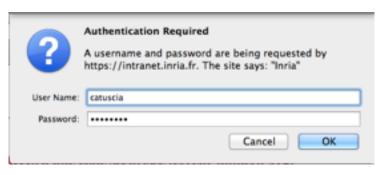




- Typical counter-measures are encryption and access-control.
   However, they are not always sufficient! Systems could leak secret information through correlated observables.
  - The notion of "observable" depends on the adversary
  - Often, secret-leaking observables are public, and therefore available to any adversary

## Leakage through correlated observables

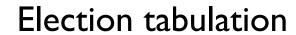
#### Password checking





## Unknown user or password incorrect. Go to the login page





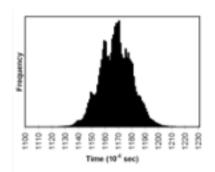






Timings of decryptions





#### Plan of the lecture

- I. Information leakage: motivation for quantitative approaches.
- 2. The information-theoretic approach to quantify the leakage of information:
- 3. Channel matrix
- 4. Prior and posterior probablity

## 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

```
egin{aligned} out &:= \mathsf{OK} \ \mathbf{for} \ i = 1, ..., N \ \mathbf{do} \ \mathbf{if} \ x_i 
eq K_i \ \mathbf{then} \ out &:= \mathsf{FAIL} \end{aligned}
```

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 out := \mathsf{FAIL} exit() end if end for
```

## Example I

#### Password checker 2

Password:  $K_1K_2 \dots K_N$ 

Input by the user:  $x_1x_2...x_N$ 

Output: out (Fail or OK)

#### Side channel attack

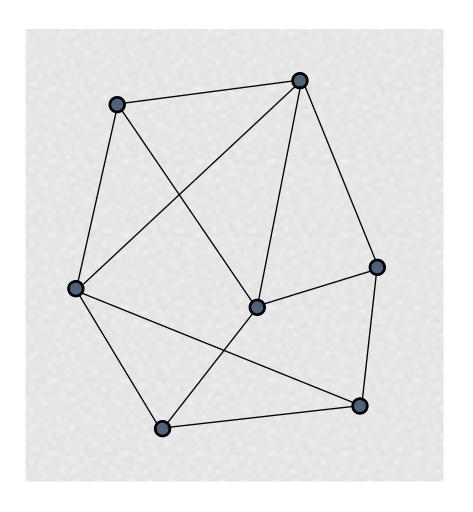
If the adversary can measure the execution time, then he can also learn the longest correct prefix of the password

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

## Example 2

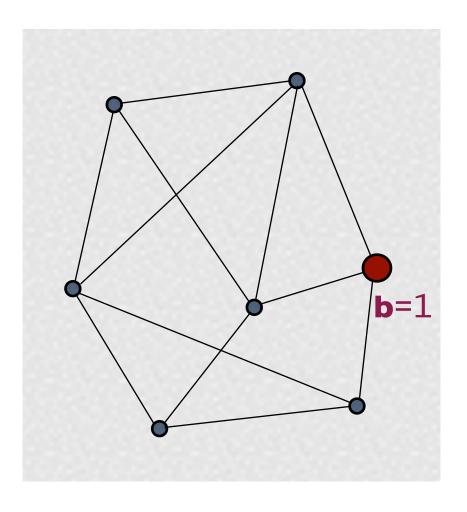
## Example of Anonymity Protocol: DC Nets [Chaum'88]

- 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

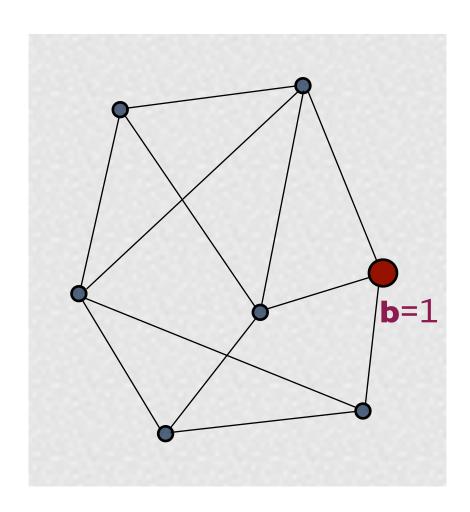


## Example of Anonymity Protocol: DC Nets [Chaum'88]

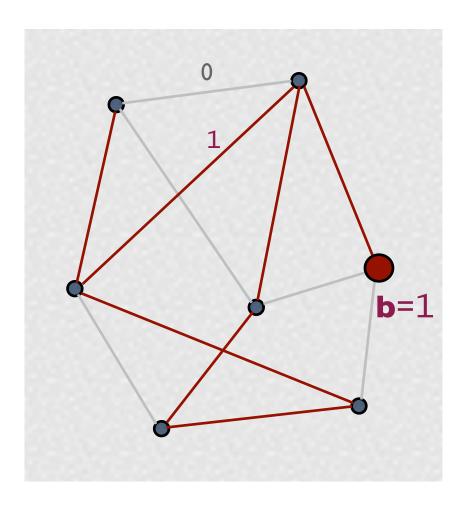
- A set of nodes with some communication channels (edges).
- One of the nodes (source) wants to broadcast one bit b of information
- The source (broadcaster) must remain anonymous



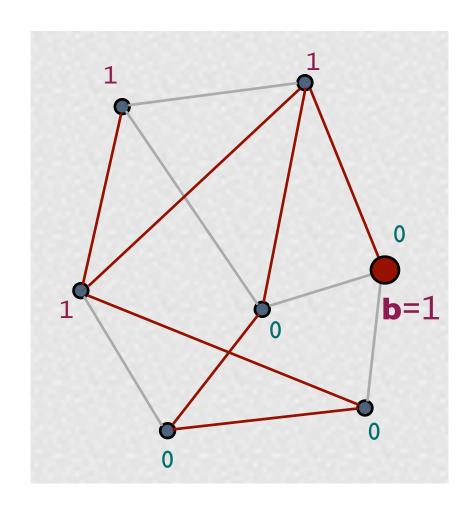
Associate to each edge a fair binary coin



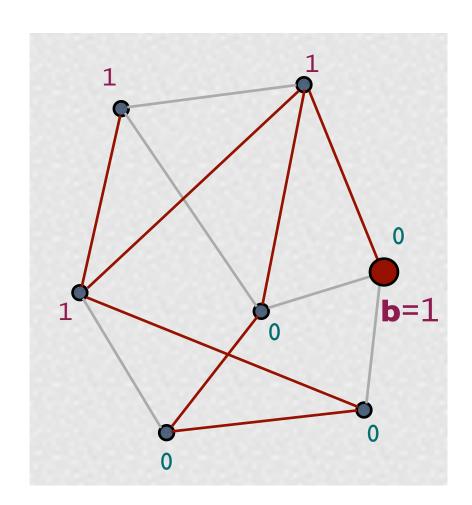
- Associate to each edge a fair binary coin
- Toss the coins



- 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



- 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

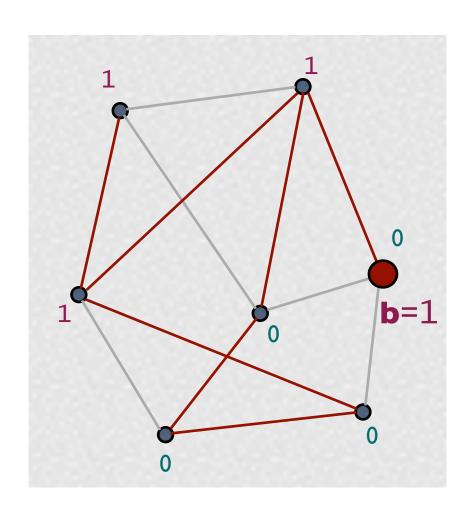
Question: Does the protocol protects the anonymity of the source?

### Strong anonymity (Chaum)

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

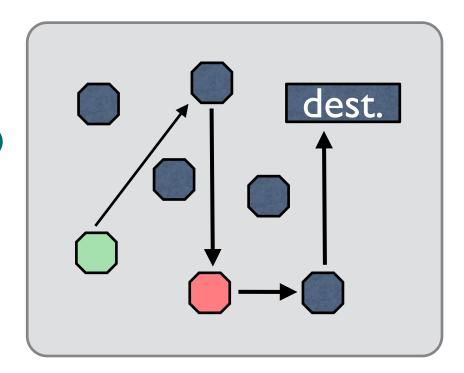
the *a posteriori* probability that a certain node is the source is equal to its *a priori* probability

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



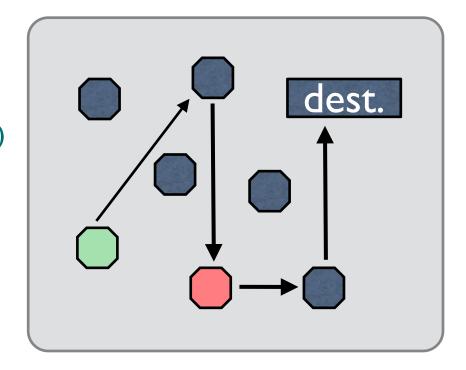
## Example 3: Crowds [Rubin and Reiter'98]

- Problem: A user (initiator) wants to send a message anonymously to another user (dest.)
- Crowds: A group of n users who agree to participate in the protocol.
- The initiator selects randomly another user (forwarder) and forwards the request to her
- A forwarder randomly decides whether to send the message to another forwarder or to dest.
- ... and so on



### Example 3: Crowds [Rubin and Reiter'98]

- Problem: A user (initiator) wants to send a message anonymously to another user (dest.)
- Crowds: A group of n users who agree to participate in the protocol.
- The initiator selects randomly another user (forwarder) and forwards the request to her
- A forwarder randomly decides whether to send the message to another forwarder or to dest.
- ... and so on



**Probable innocence:** under certain conditions, an attacker who intercepts the message from x cannot attribute more than 0.5 probability to x to be the initiator

#### Common features

#### Secret information

- Password checker: The password
- DC: the identity of the source
- Crowds: the identity of the initiator

#### Public information (Observables)

- Password checker: The result (OK / Fail) and the execution time
- DC: the declarations of the nodes
- Crowds: the identity of the agent forwarding to a corrupted user

#### The system may be probabilistic

- Often the system uses randomization to obfuscate the relation between secrets and observables
- DC: coin tossing
- Crowds: random forwarding to another user

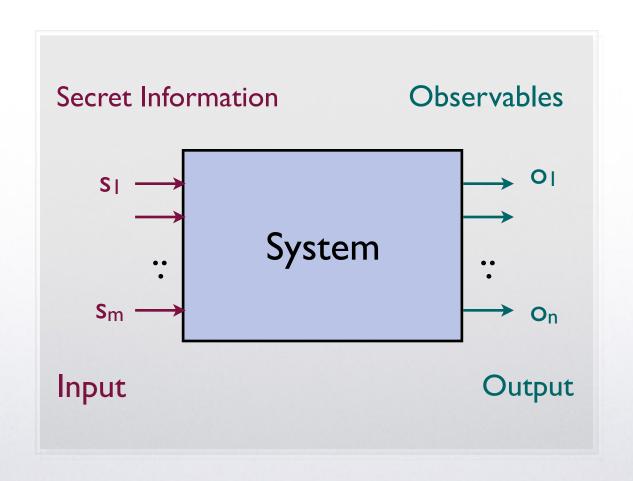
## Simplifying assumptions

#### In this course we assume:

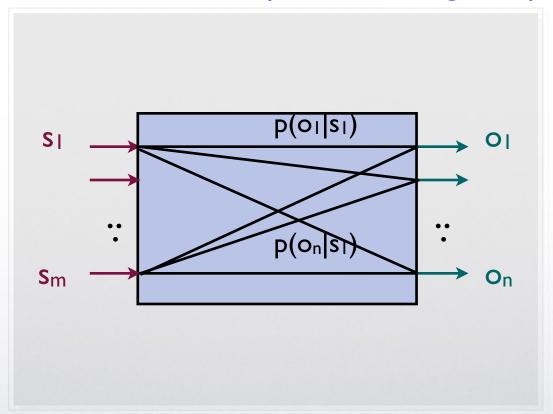
- Secrets: elements of a random variable
- Observables: elements of a random variable O
- For each secret s, the probability that we obtain an observable o is given by p(o | s)
- No feedback: the secret is not influenced by the observables
- No nondeterminism: everything is (either deterministic or) probabilistic, although we may not know the distribution

#### The basic model:

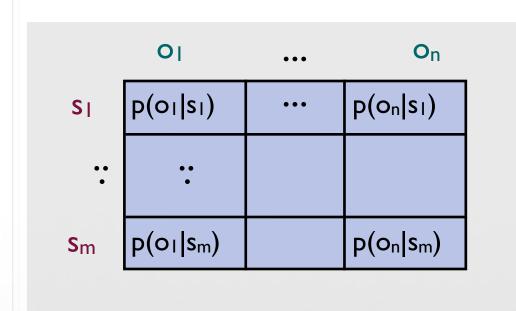
#### Systems = Information-Theoretic channels



Probabilistic systems are **noisy** channels: an output can correspond to different inputs, and an input can generate different outputs, according to a prob. distribution



 $p(o_j|s_i)$ : the conditional probability to observe  $o_j$  given the secret  $s_i$ 



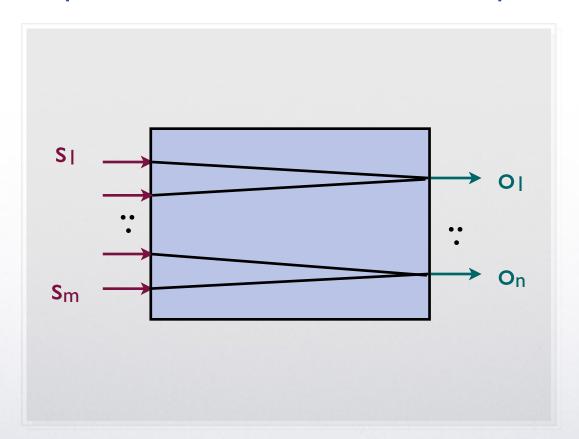
$$p(o|s) = \frac{p(o \ and \ s)}{p(s)}$$

A channel is characterized by its matrix: the array of conditional probabilities

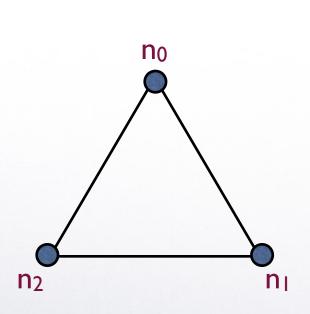
In a information-theoretic channel these conditional probabilities are independent from the input distribution

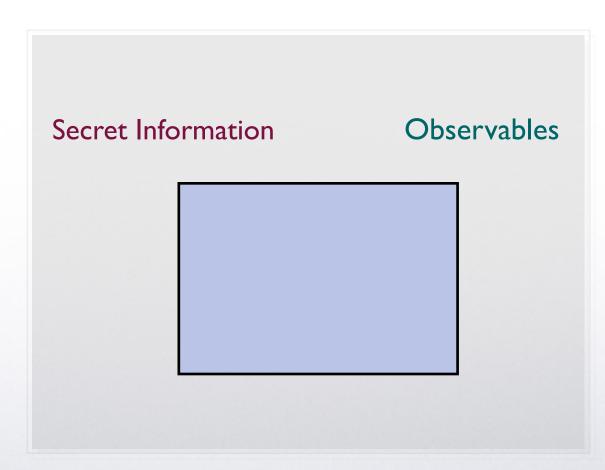
This means that we can model systems abstracting from the input distribution

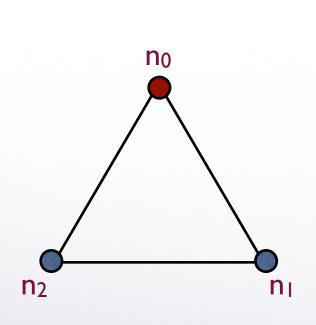
## Particular case: **Deterministic systems**In these systems an input generates only one output Still interesting: the problem is how to retrieve the input from the output

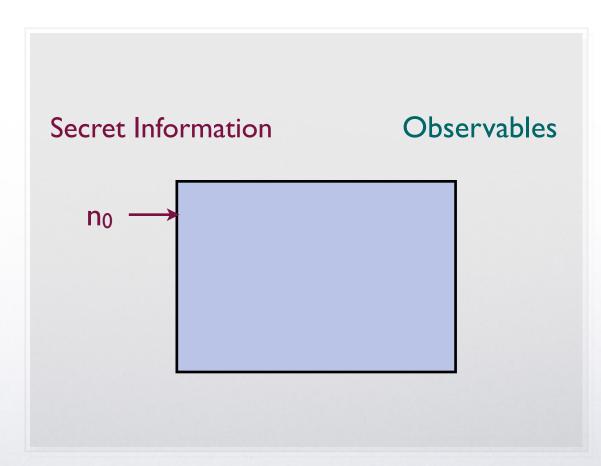


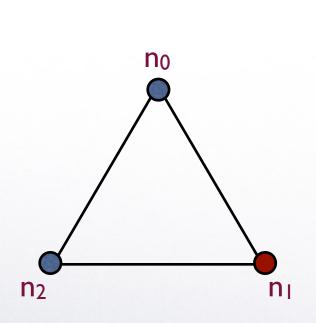
The entries of the channel matrix can be only 0 or 1

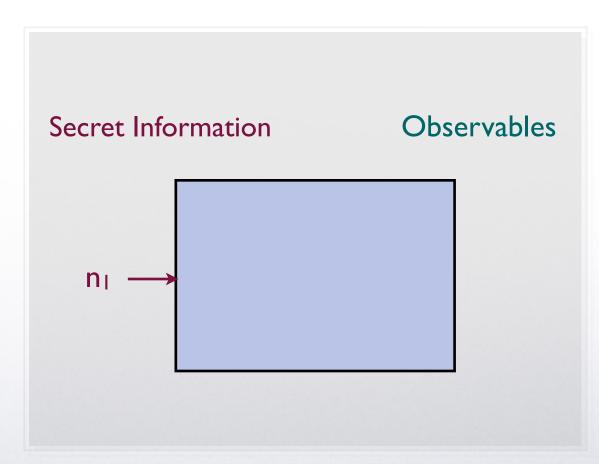


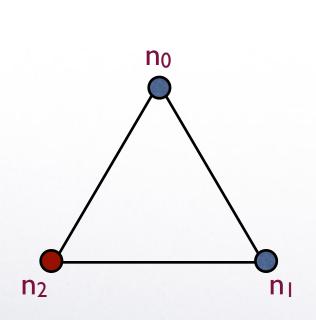


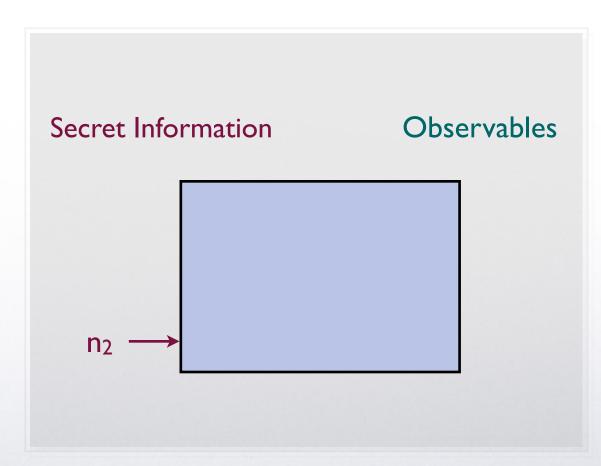


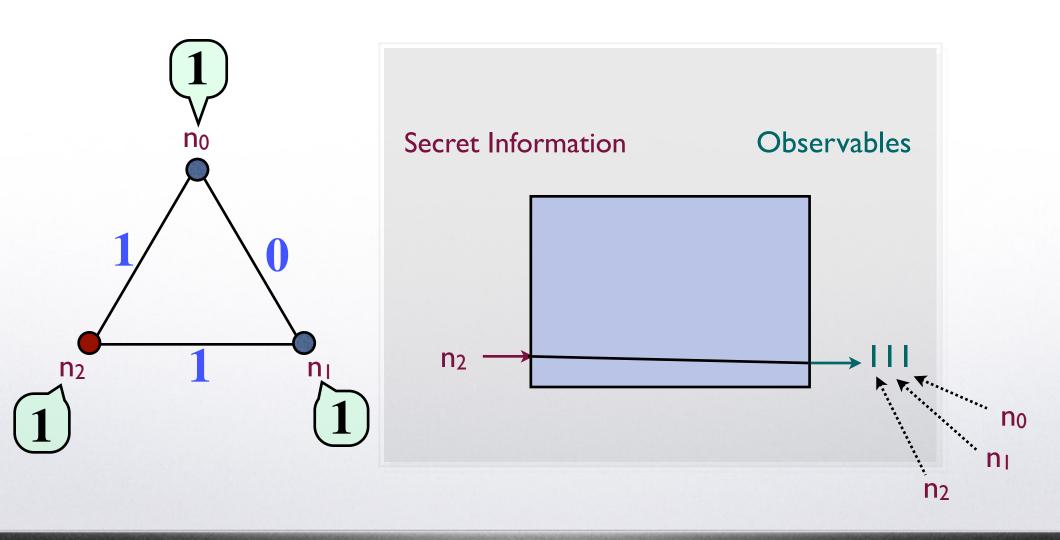


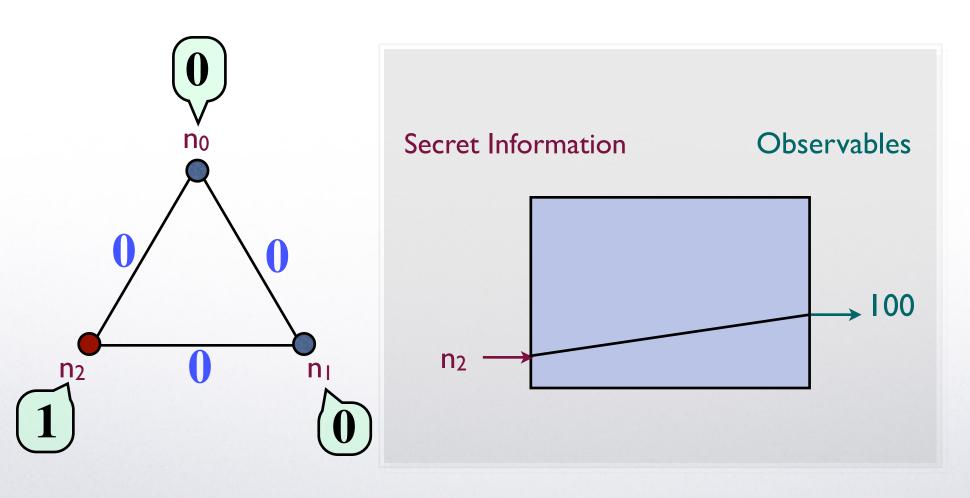


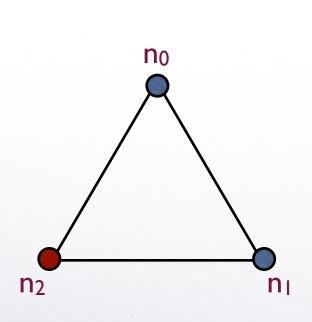


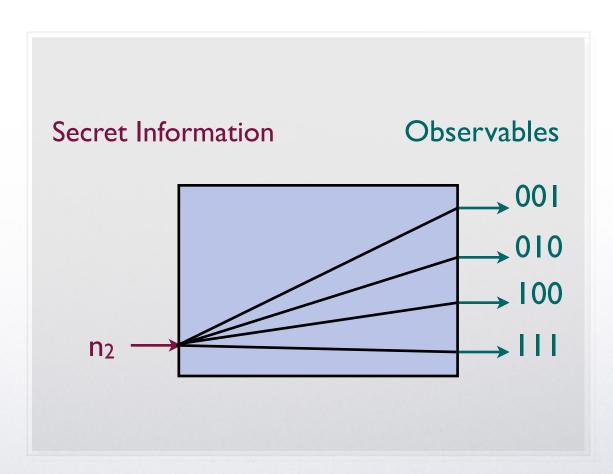


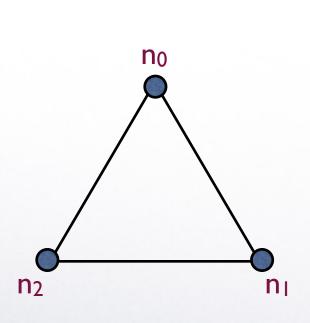


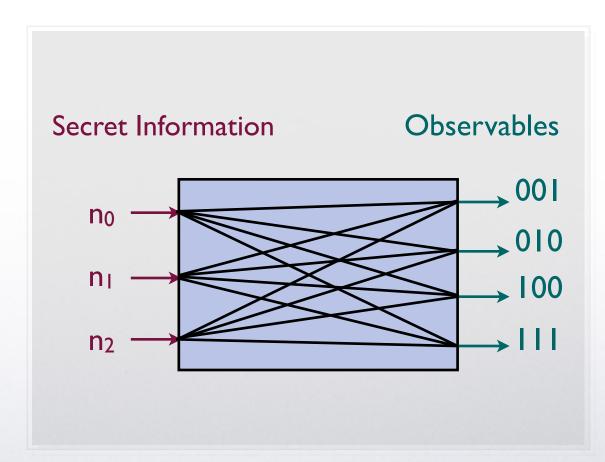












n <sub>0</sub> 1/ <sub>4</sub> 1/ <sub>4</sub> 1/ <sub>4</sub> 1/ <sub>4</sub> 1/ <sub>4</sub> n <sub>1</sub> 1/ <sub>4</sub>		001	010	100	111
	n <sub>0</sub>	1/4	1/4	1/4	1/4
	nı	1/4	1/4	1/4	1/4
$n_2   \frac{1}{4}   \frac{1}{4}   \frac{1}{4}   \frac{1}{4}$	n <sub>2</sub>	1/4	1/4	1/4	1/4

	001	010	100	111
n <sub>0</sub>	1/3	2/9	2/9	2/9
nı	2/9	1/3	2/9	2/9
n <sub>2</sub>	2/9	2/9	1/3	2/9

fair coins: 
$$Pr(0) = Pr(1) = \frac{1}{2}$$
  
strong anonymity

biased coins: 
$$Pr(0) = \frac{2}{3}$$
,  $Pr(1) = \frac{1}{3}$ 

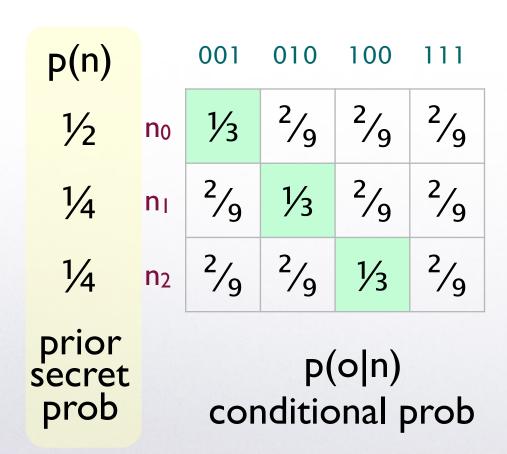
The source is more likely to declare 1 than 0

## Quantitative Information Flow

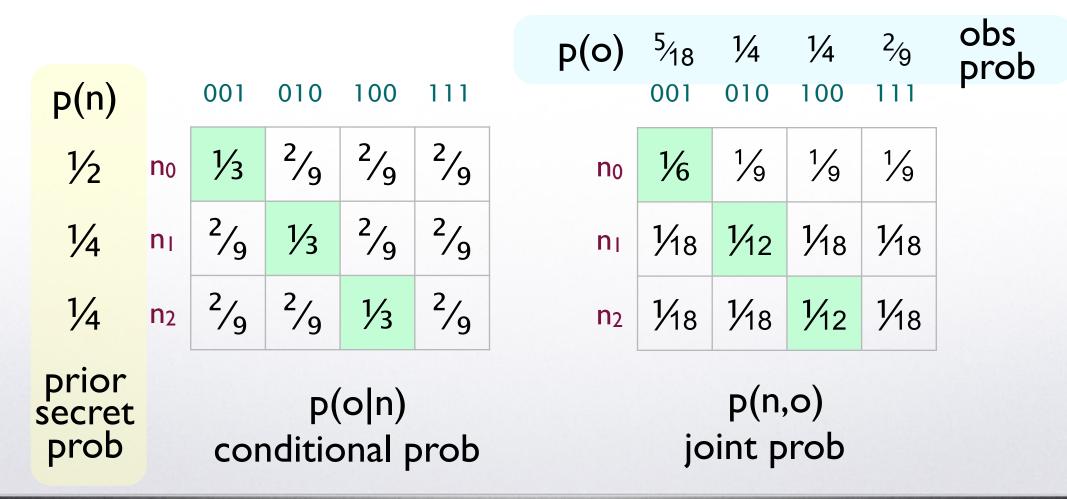
 Intuitively, the leakage is the (probabilistic) information that the adversary gains about the secret through the observables

 Each observable changes the prior probability distribution on the secret values into a posterior probability distribution according to the Bayes theorem

• In the average, the posterior probability distribution gives a **better hint** about the actual secret value



p(n)		001	010	100	111		001	010	100	111
1/2	n <sub>0</sub>	1/3	2/9	2/9	2/9	n <sub>0</sub>	1/6	1/9	1/9	1/9
1/4	nı	2/9	1/3	2/9	2/9	nı	1/18	1/12	1/18	1/18
1/4	n <sub>2</sub>	2/9	2/9	1/3	2/9	n <sub>2</sub>	1/18	1/18	1/12	1/18
prior secret prob	p(o n) conditional prob			jo	p(n, int p					



$$p(n|o) = \frac{p(n,o)}{p(o)} \quad \text{Bayes theorem}$$

$$p(n|oo1) \quad 001 \quad 010 \quad 100 \quad 111 \quad 001 \quad 010 \quad 010 \quad 100 \quad 111 \quad 001 \quad 010 \quad 010 \quad 010 \quad 100 \quad 111 \quad 001 \quad 010 \quad 0$$

### Password-checker 1

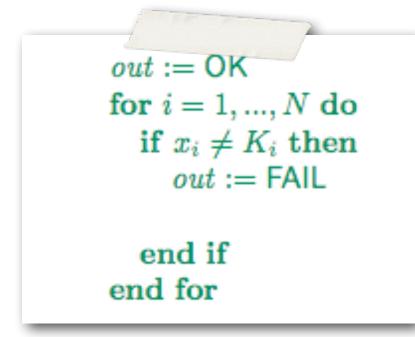
```
egin{aligned} out := \mathsf{OK} \ & \mathbf{for} \ i = 1, ..., N \ & \mathbf{do} \ & \mathbf{if} \ x_i 
eq K_i \ & \mathbf{then} \ & out := \mathsf{FAIL} \end{aligned} end if end for
```

Let us construct the channel matrix

Note: The string  $x_1x_2x_3$  typed by the user is a parameter, and  $K_1K_2K_3$  is the channel input

The standard view is that the input represents the secret. Hence we should take  $K_1K_2K_3$  as the channel input

### Password-checker 1

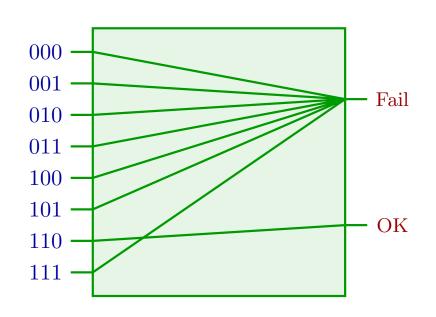


Assume the user string is  $x_1x_2x_3 = 110$ 

#### Let us construct the channel matrix

Input:  $K_1K_2K_3 \in \{000, 001, \dots, 111\}$ 

Output:  $out \in \{\mathsf{OK}, \mathsf{FAIL}\}$ 



	Fail	OK
000	1	0
001	1	0
010	1	0
011	1	0
100	1	0
101	1	0
110	0	1
111	1	0

Different values of  $x_1x_2x_3$  give different channel matrices, but they all have this kind of shape (seven inputs map to Fail, one maps to OK)

## Password-checker 2

```
egin{aligned} out := \mathsf{OK} \ & \mathbf{for} \ i = 1,...,N \ & \mathbf{do} \ & \mathbf{if} \ x_i 
eq K_i \ & \mathbf{then} \ & out := \mathsf{FAIL} \ & \mathbf{exit}() \ & \mathbf{end} \ & \mathbf{for} \ & \mathbf{end} \ & \mathbf{for} \ \end{aligned}
```

Assume the user string is  $x_1x_2x_3 = 110$ 

## Assume the adversary can measure the execution time

#### Let us construct the channel matrix

Input:  $K_1K_2K_3 \in \{000, 001, ..., 111\}$ Output:  $out \in \{OK, (FAIL, 1), (FAIL, 2), (FAIL, 3)\}$ 

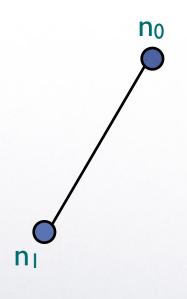
	ı
000 —	— (Fail,1)
001 —	(1 an, 1)
010 —	— (Fail,2)
011 —	( ) )
100 —	— (Fail,3)
101 <b>—</b>	
110 — 111 —	— OK
111	

	(Fail, 1)	(Fail, 2)	(Fail, 3)	OK
000	1	0	0	0
001	1	0	0	0
010	1	0	0	0
011	1	0	0	0
100	0	1	0	0
101	0	1	0	0
110	0	0	0	1
111	0	0	1	0

## Exercise I

 Assuming that the possible passwords have uniform prior distribution, compute the matrix of the joint probabilities, and the posterior probabilities, for the two passwordchecker programs

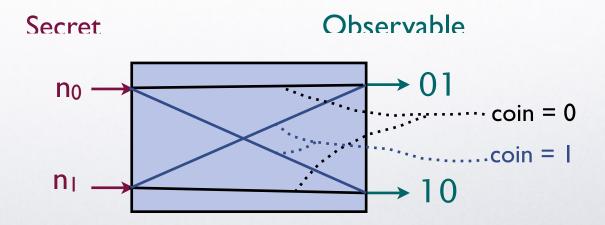
#### **Example:** DC nets. Ring of 2 nodes, and assume b = I



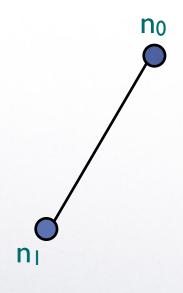
Let us construct the channel matrix

Input:  $n_0$ ,  $n_1$ 

Output: the declarations of  $n_1$  and  $n_0$ :  $d_1d_0 \in \{01,10\}$ 



#### **Example:** DC nets. Ring of 2 nodes, and assume b = 1



#### Let us construct the channel matrix

Input:  $n_0$ ,  $n_1$ 

Output: the declarations of  $n_1$  and  $n_0$ :  $d_1d_0 \in \{01,10\}$ 

	01	10
n <sub>0</sub>	1/2	1/2
nı	1/2	1/2

Fair coin:  $p(0) = p(1) = \frac{1}{2}$  Biased coin:  $p(0) = \frac{2}{3}$   $p(1) = \frac{1}{3}$ 

	01	10
n <sub>0</sub>	2/3	1/3
nı	1/3	2/3

## Exercise 2

• DC nets: Assuming that n<sub>0</sub> and n<sub>1</sub> have uniform prior distribution, compute the matrix of the joint probabilities, and the posterior probabilities, in the two cases of fair coins, and of biased coins

 Same exercise, but now assume that the prior distribution is 2/3 for n<sub>0</sub> and 1/3 for n<sub>1</sub>