# Provable Unlinkability Against Traffic Analysis

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ISC'2004

## Anonymous communication

- a valuable information is who is communicating with whom
- hard to hide it in public networks!

Naive solution – all-to-all: send an encrypted message to all participants, keep sending even if no message need to be sent communication overhead!

- generic, scalable technique for distributed systems,
- ► Rackoff and Simon '91, re-invented: BABEL, ONION ROUTING 1996 a kernel of TOR 2004

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- ▶ A chooses at random  $\lambda$  intermediate nodes  $J_1, \ldots, J_{\lambda}$ ;
- A creates an onion:

$$O :=$$

$$\mathsf{Enc}_{J_{\lambda-1}}(\mathsf{Enc}_{J_{\lambda}}(\mathsf{Enc}_{B}(m),B),J_{\lambda})$$

- A chooses at random  $\lambda$  intermediate nodes  $J_1, \ldots, J_{\lambda}$ ;
- A creates an onion:

$$O :=$$

$$\mathsf{Enc}_{J_1}(\dots(\mathsf{Enc}_{J_{\lambda-1}}(\mathsf{Enc}_{J_{\lambda}}(\mathsf{Enc}_{B}(m),B),J_{\lambda}),J_{\lambda-1})\dots,J_2)$$
.

If A wants send a message m encrypted as O to server B

► A sends onion O to J<sub>1</sub>

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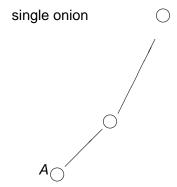
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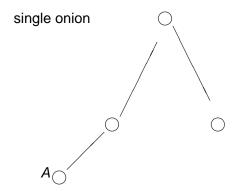
single onion

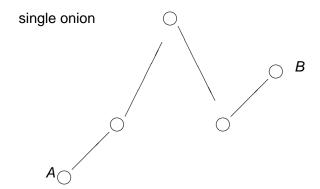


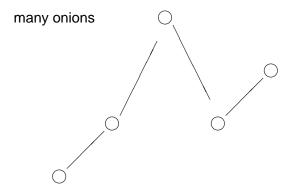
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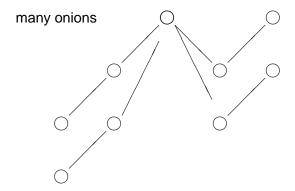


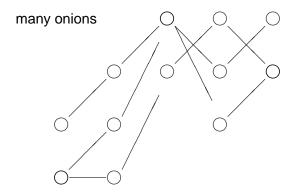


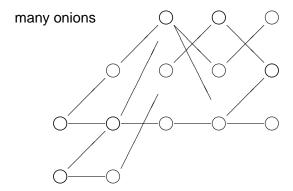


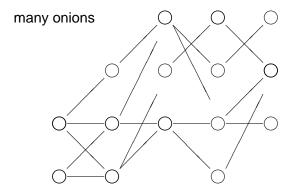


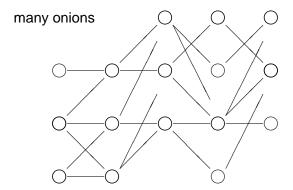


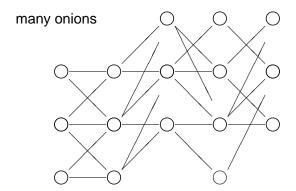


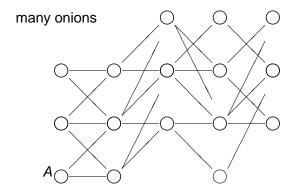












destination of the message starting at A?

## Path length

- intuitively clear: anonymity level grows with growth of λ
- crucial question: how large must be  $\lambda$  in order to guarantee a solid anonymity level?

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- no relationship can be derived between messages entering a node and leaving a node at the same time (probabilistic encryption has to be used)
- but: transmitting a message from a node to another node can be detected

# Traffic analysis

- an adversary tries to determine who is communicating with whom
  - without breaking cryptographic encoding, but
  - with some knowledge about the traffic

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attacks in practice: much smaller probability spaces

but: we would like to show that no statistical analysis can succeed

# Why considering the whole mapping is important?

#### Important case - electronic elections

- ► Eve analyses the votes, and derives probabilities that Alice voted for *X*, for each single *X*
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#### FALSE!

- ▶ Eve may be unable to derive preferences of Alice
- but can deduce that Alice and Bob voted for the same party with probability 90%

#### **Adversaries**

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active adversary: may influence the traffic

non-adaptive an attack cannot be adapted to the traffic observed

adaptive

# Security proofs for onions - results

assumptions: passive adversary, 1 packet messages, onion paths of length  $\lambda$ .

#### An adversary can monitor the whole traffic:

- no security proof for the original protocol
- modified version of the protocol (routing in growing groups) Rackoff, Simon, FOCS'91, for  $\lambda \approx \log^{11} n$ , Czumaj, Kanarek, Kutyłowski, Loryś, SODA'98, for  $\lambda = O(\log^2 n)$

#### Only a fraction of connections may be traced:

▶ Berman, Fiat, Ta-Shma, FC'2004, for  $\lambda = O(\log^4 n)$ 

This presentation: for  $\lambda = \Theta(\log n)$ 

# Traffic analysis - assumptions

- an adversary can see
  - all messages sent at source nodes
  - all messages received by destination nodes
- cryptographic encoding ensures that only the number of messages can be detected, no other information leaked
- an adversary can see the number of messages transmitted at the links (determined by the adversary in advance)
- a constant fraction of links can be traced (not necessarily the same all the time)

# Outcome of Traffic Analysis

- random variable π:
  π(i) = j iff the ith message is delivered at the jth delivery point
- ▶ a priori probability:  $Pr(\pi)$  known by an adversary
- traffic information yields conditioned probabilities:

$$Pr(\pi|C)$$

where C is the observed traffic (for instance a lack of a path may be ray that  $\pi(i) \neq j$  with probability 1)

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▶ probability distributions  $Pr(\pi)$  and  $Pr(\pi|C)$  do not differ substantially

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- ▶ probability distributions  $Pr(\pi)$  and  $Pr(\pi|C)$  do not differ substantially
- ▶ for some C traffic analysis for onion protocol reveals everything: i.e. if the paths of messages are disjoint
- goal: show that

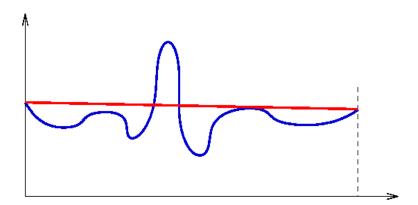
$$Pr(\pi) \approx Pr(\pi|C)$$

for almost all C

#### Variation distance

The total variation distance between probability distributions  $\mu_1$  and  $\mu_2$  defined over space X of elementary events equals

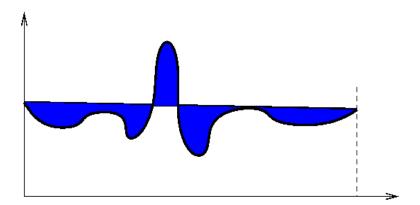
$$\|\mu_1 - \mu_2\| = \frac{1}{2} \sum_{\mathbf{x} \in \mathbf{X}} |\mu_1(\mathbf{x}) - \mu_2(\mathbf{x})|$$
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#### Simplified case

- for each user: uniform probability distribution over destination points
- ▶ Berman, Fiat, Ta-Shma show how to generalize the results to non-uniform distributions (FC'2004)

# Sending messages as a stochastic process

- at each step the messages are sent to next locations at random
- but so that the traffic adheres to the traffic observed by an adversary for simplicity assume that the adversary can see the number of messages at each node

# Stationary distribution

 a probability distribution over the set of states is stationary if applying a single step of the process does not change the probability distribution,

#### Stationary distribution

- a probability distribution over the set of states is stationary if applying a single step of the process does not change the probability distribution,
- ▶ in our case: a uniform distribution of messages 1 through m over m locations holding messages

How many steps are needed until probability distribution becames close to the uniform distribution?

# Rapid mixing techniques

#### Goal:

- ightharpoonup given a stochastic process  $\mathcal{P}$  with a stationary distribution u
- ▶ show that after *t* steps the probability distribution of the process started in an arbitrary state is close to *u*

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How to construct such a proof?

# Coupling techniques

- define two processes  $\mathcal{P}_A, \mathcal{P}_B$
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- define two processes  $\mathcal{P}_A, \mathcal{P}_B$
- ▶ both are the copies of P,
- but the choices of the first process may influence the second process

# Coupling goal

- define dependencies so that the processes "converge"
  - (with probabilities growing with the number of steps) they reach the same state

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- define dependencies so that the processes "converge"
  (with probabilities growing with the number of steps) they reach the same state
- key property coupling lemma:

variation distance after t steps

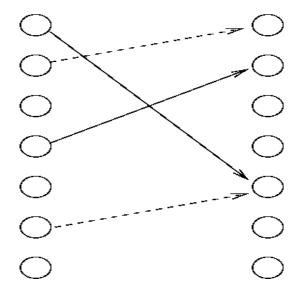
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 $Pr[\mathcal{P}_A \text{ and } \mathcal{P}_B \text{ differ after } t \text{ steps}].$ 

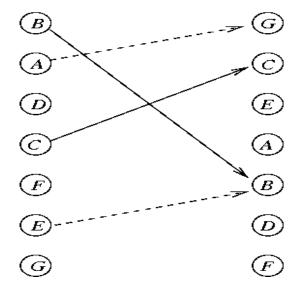
#### Path coupling

- it suffices to consider processes that are almost in the same state
  - distance function between process states; values 1,2,..., for each pair of states a "path" where neighbors are at distance 1,
  - it suffices to consider pair of processes at distance 1

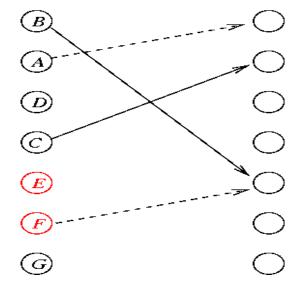
#### Coupling rule - traffic information



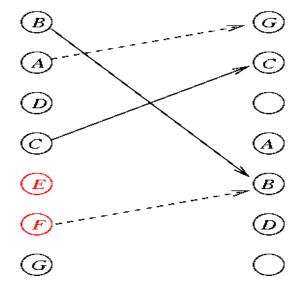
#### Coupling rule - transition of process I



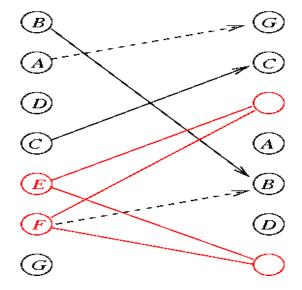
# Coupling rule - state of process II



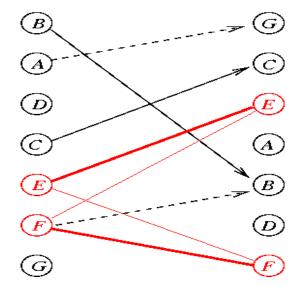
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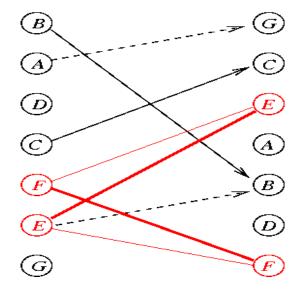
#### Coupling rule - crossover



#### Coupling rule - transition of process II



#### Coupling rule - transition of process I



#### Path coupling

- large number of crossovers regardless of the strategy of an adversary (Lemma of Noga Alon)
- 2 steps processes couple with probability > const

#### Remarks and Conclusions

- somewhat strange technique but: strong and easy to use
- coupling proofs also work well for "limited anonymity" targets
- other results:
  - on Chaum's electronic voting scheme (2003)
  - on networks of mixes (2004?)

**Provable Unlinkability Against Traffic Analysis** 

Thanks for your attention!