

Vida:

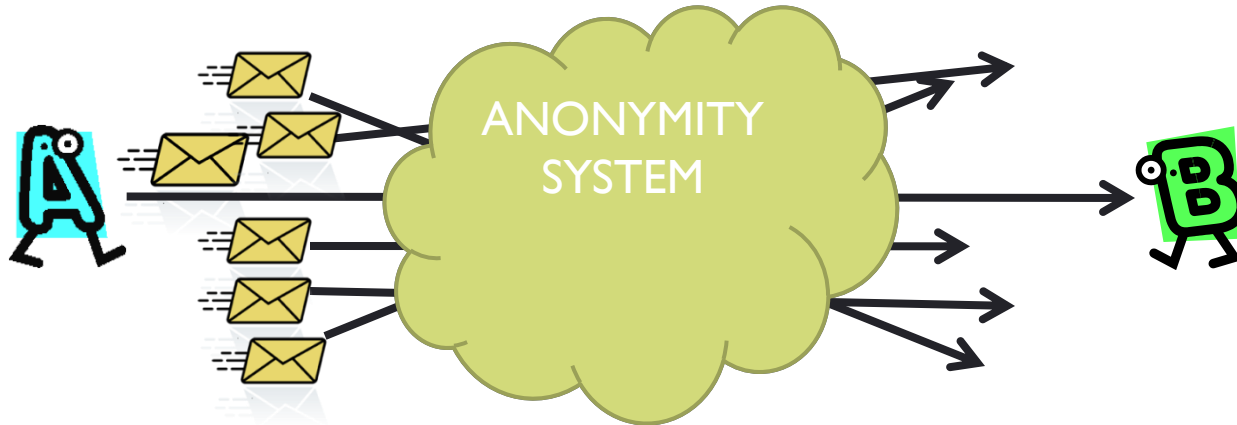
Bayesian Inference to De-Anonymize
communications

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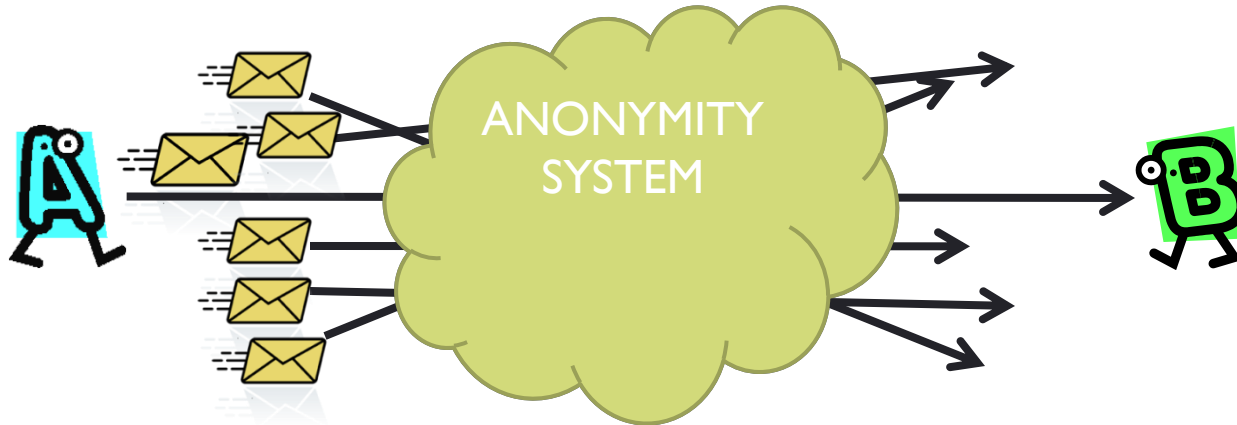
Anonymous communications



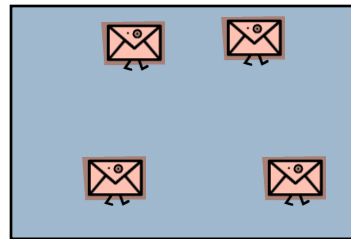
- ▶ Privacy, e-voting, protection of trade secrets, high security military applications
- ▶ The Threshold Mix [Chaum81]



Anonymous communications



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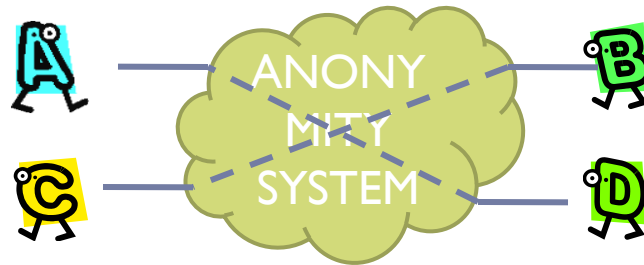


Traffic analysis: Intersection attacks

- ▶ **Exploit persistent patterns for de-anonymization**
 - ▶ Disclosure Attack [Kesdogan et al 02]
 - ▶ Set theory
 - ▶ NP-Problem
 - ▶ Statistical Disclosure Attack [Danezis 03]
 - ▶ Computationally feasible
 - ▶ Inaccurate
 - ▶ Perfect Matching Disclosure Attack [Troncoso et al 08]
 - ▶ Perfect matching
 - ▶ Reuse for profiles
- ▶ **Ad-hoc studies, difficult to estimate errors**
 - ▶ Bayesian inference to de-anonymize and profile systematically

Redefining the traffic analysis problem

- ▶ Find “hidden state” of an anonymity system



$$\Pr(HS | O, C)$$

- ▶ If we apply Bayes theorem...

$$\Pr(HS | O, C) = \frac{\Pr(O | HS, C) \cdot \Pr(HS | C)}{\sum_{HS} \Pr(HS, O | C)}$$

Prior information

Too large to enumerate!!

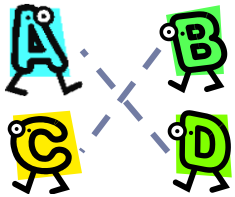
$$HS_1, HS_2, HS_3, \dots \sim \Pr(HS | O, C)$$

- ▶ Markov Chain Monte Carlo methods

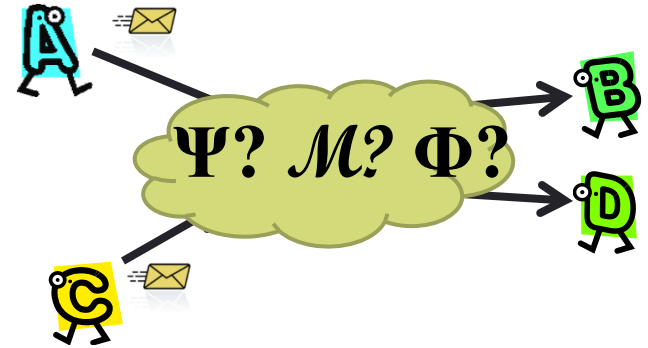
The Vida Black-box model



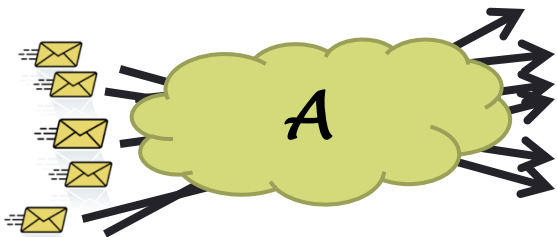
Ψ – User Profiles



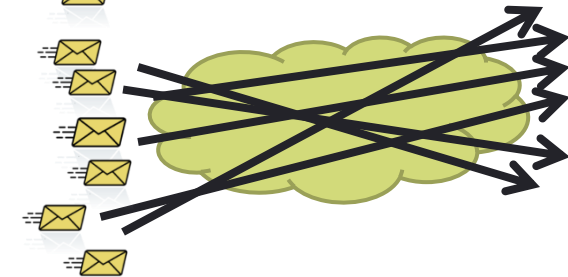
\mathcal{M} – Sender-Receiver match



\mathcal{O} – Observation



\mathcal{A} – Anonymity system



Φ – Assignment

$$\Pr(M, \Phi, \Psi | O, A) = \frac{\Pr(M | \Psi) \cdot \Pr(\Phi | A) \cdot \Pr(\Psi | A)}{\Pr(O | A) \equiv Z}$$

Prior information

(full derivation in the paper)

Markov Chain Monte Carlo Methods

- ▶ Sample from a distribution difficult to sample from directly

$$\Pr(M, \Phi, \Psi | O, A) = \frac{\Pr(M | \Psi) \cdot \Pr(\Phi | A)}{\Pr(O | A) \equiv Z}$$

- ▶ Constructs a Markov Chain with stationary distribution equal to the target distribution
- ▶ Gibbs sampling
 - ▶ Efficient for sampling joint distributions
 - ▶ Eliminate the need to compute Z

Gibbs sampling for Vida

$$\Pr(M, \Phi, \Psi \mid O, A)$$

- ▶ Iteratively draw samples from the marginal distributions

$$\Phi_j, M_j \sim \Pr(\Phi, M \mid \Psi_{j-1}, O, A)$$

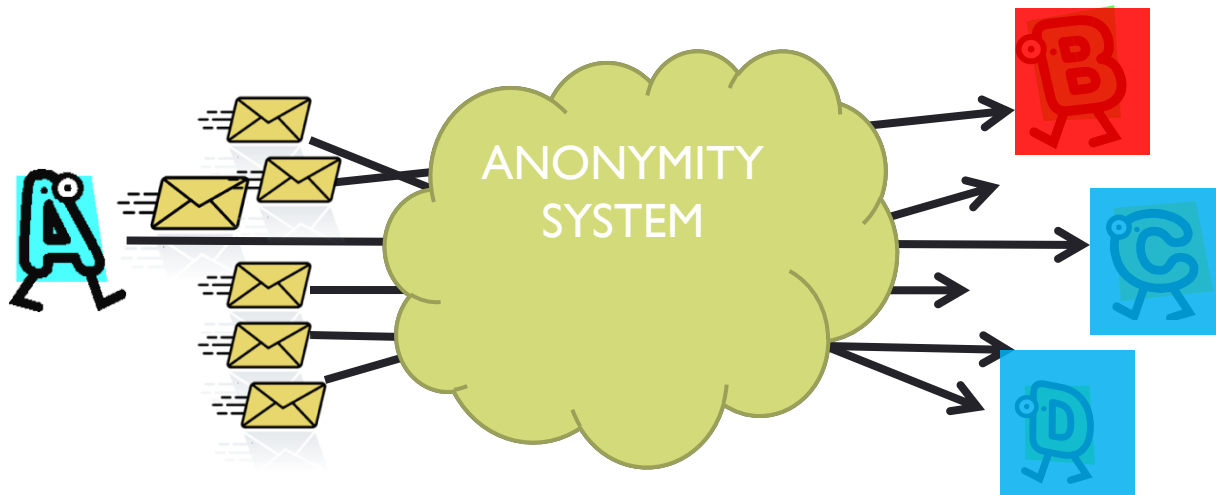
$$\Psi_j \sim \Pr(\Psi \mid \Phi_j, M_j, O, A)$$

- ▶ Φ, \mathcal{M} – Find perfect matching (reject if not valid)
- ▶ Ψ – Use the dirichlet distribution (prior of multinomial)

$$\Psi_A \sim \text{Dirichlet}(Ct_M(A \rightarrow B) + 1, Ct_M(A \rightarrow C) + 1, \dots, Ct_M(A \rightarrow Z) + 1)$$

Simple Vida: Red-Blue Model

- ▶ Do we actually want to know to whom every user speaks?
 - ▶ Who sent a message to Bob?
 - ▶ Who is friends with receiver Bob?



- ▶ Profiles become binomial (Red or Blue)
- ▶ Blue receivers are equivalent when making assignments \mathcal{M}

Evaluation

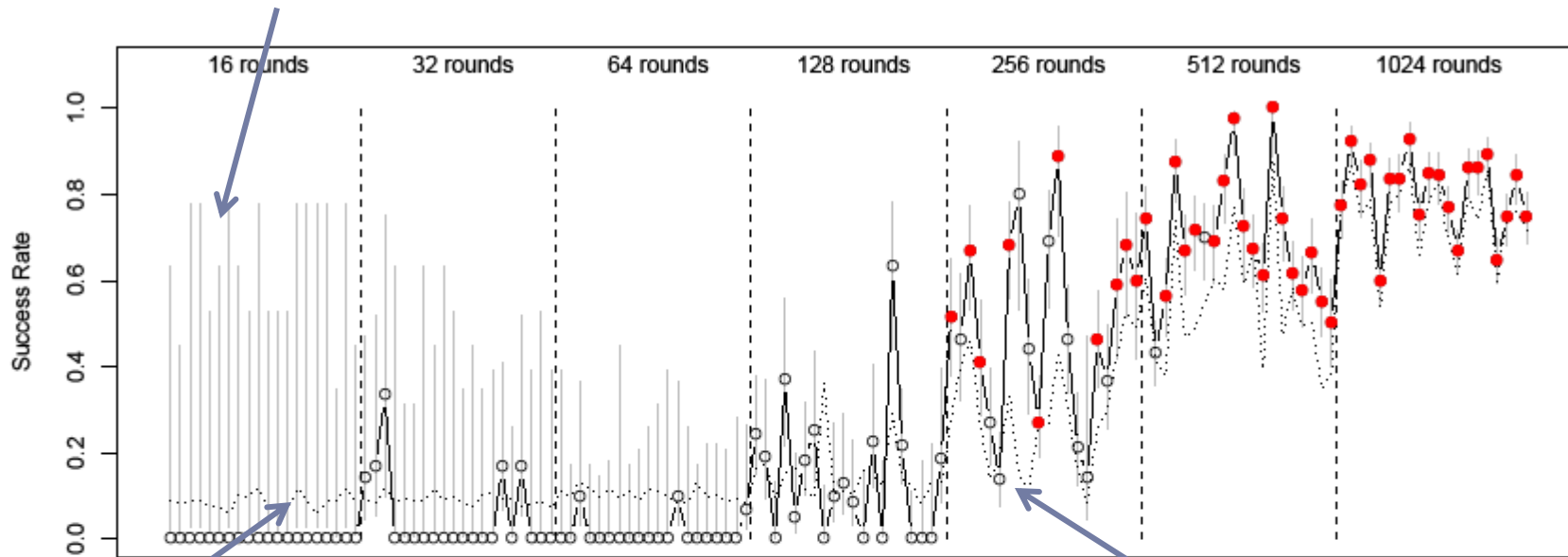
- ▶ Synthetic anonymized traces

Users	1000
Friends	5
Threshold	100

- ▶ Target sender in 20% of the rounds
 - ▶ Friend of Red receiver
 - ▶ Allow profiling of other users
- ▶ Use Gibbs sampler to guess receiver (200 samples)
 - ▶ Prior belief $\Pr(\Psi | A)$ Beta(0.01,0.01)
 - ▶ Bayes optimal criterion

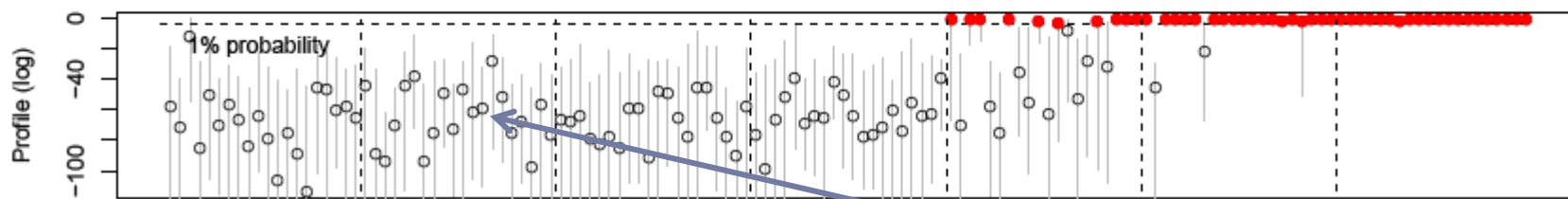
Success rate

90% confidence interval



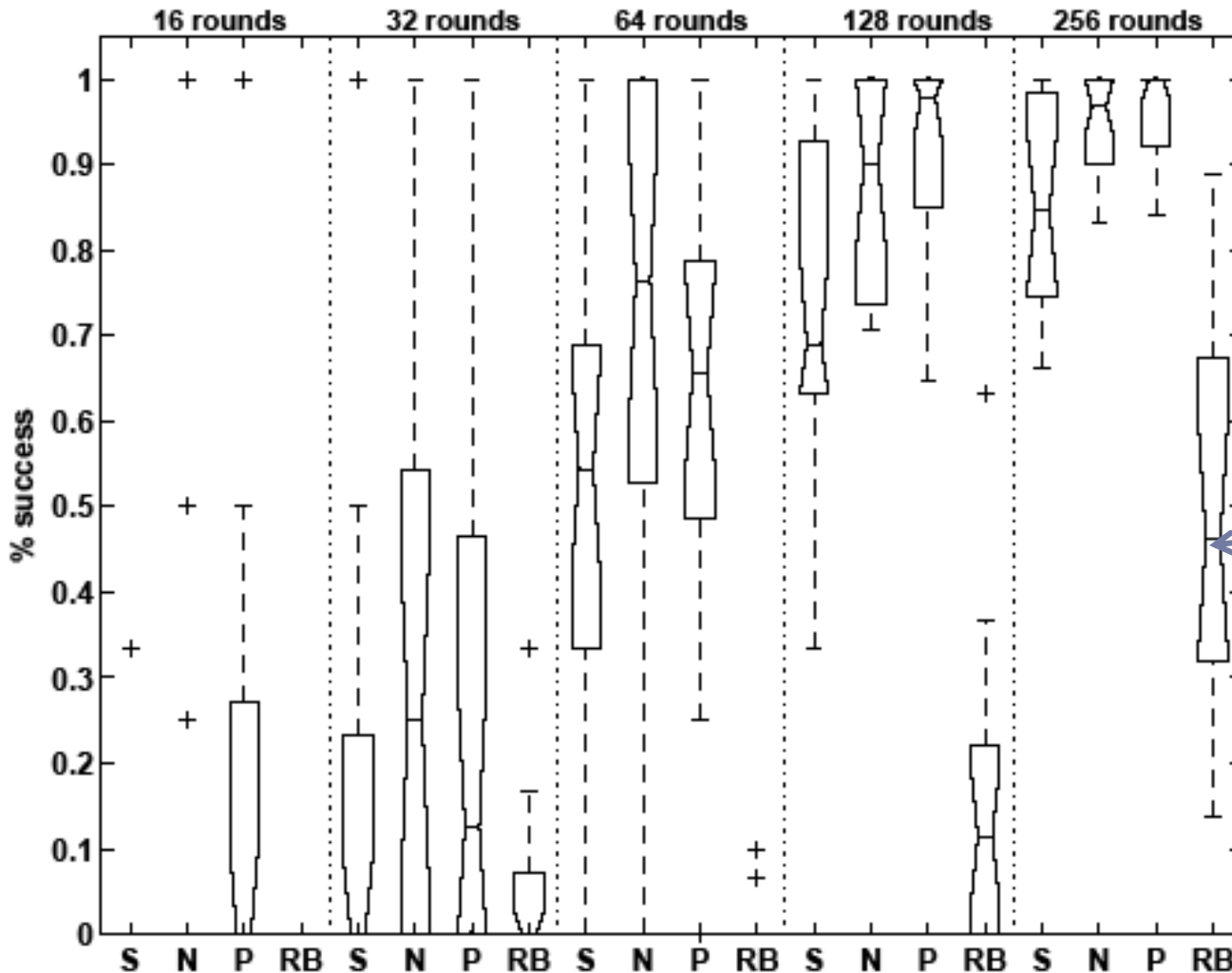
Prediction of success

Success



Profile quality

Comparison with previous work



- ▶ S-SDA
- ▶ N-NSDA
- ▶ P-PMDA
- ▶ RB-Vida

Bayes optimal criterion does not guarantee a perfect matching!

Good error estimates

Full distribution

Lots to do...

- ▶ **Weighted incomplete Bipartite graph**
 - ▶ Threshold mix is easy to compute
 - ▶ What about networks?
 - ▶ **The Bayesian Traffic Analysis of Mix Networks.** Carmela Troncoso and George Danezis. CCS 09
- ▶ **Increase constraints on the profiling**
 - ▶ Modeling more difficult but better results
- ▶ **Social Networks inference**
 - ▶ Prior information can be easily added to the model
- ▶ **Beyond communications**
 - ▶ Location privacy, Database de-anonymization

Conclusions

- ▶ **Vida Black-Box model**
 - ▶ Generic
 - ▶ Accommodates any anonymity system
 - ▶ No need to know number of friends
- ▶ **Vida Red-Blue model**
 - ▶ Efficiently de-anonymizes targeted senders/receivers
- ▶ **Markov Chain Monte Carlo as basis for traffic analysis**
 - ▶ 3 Key advantages:
 - ▶ Requires generative model
 - ▶ Good estimation of errors
 - ▶ Systematic

Questions?

Thanks for your attention!!

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