

THE FUNDAMENTAL LIMITS OF DATA & METADATA PRIVACY

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30 years ago...

Pre-internet

*Human to
human*



Then came the Internet

Pre-internet

Internet of
content

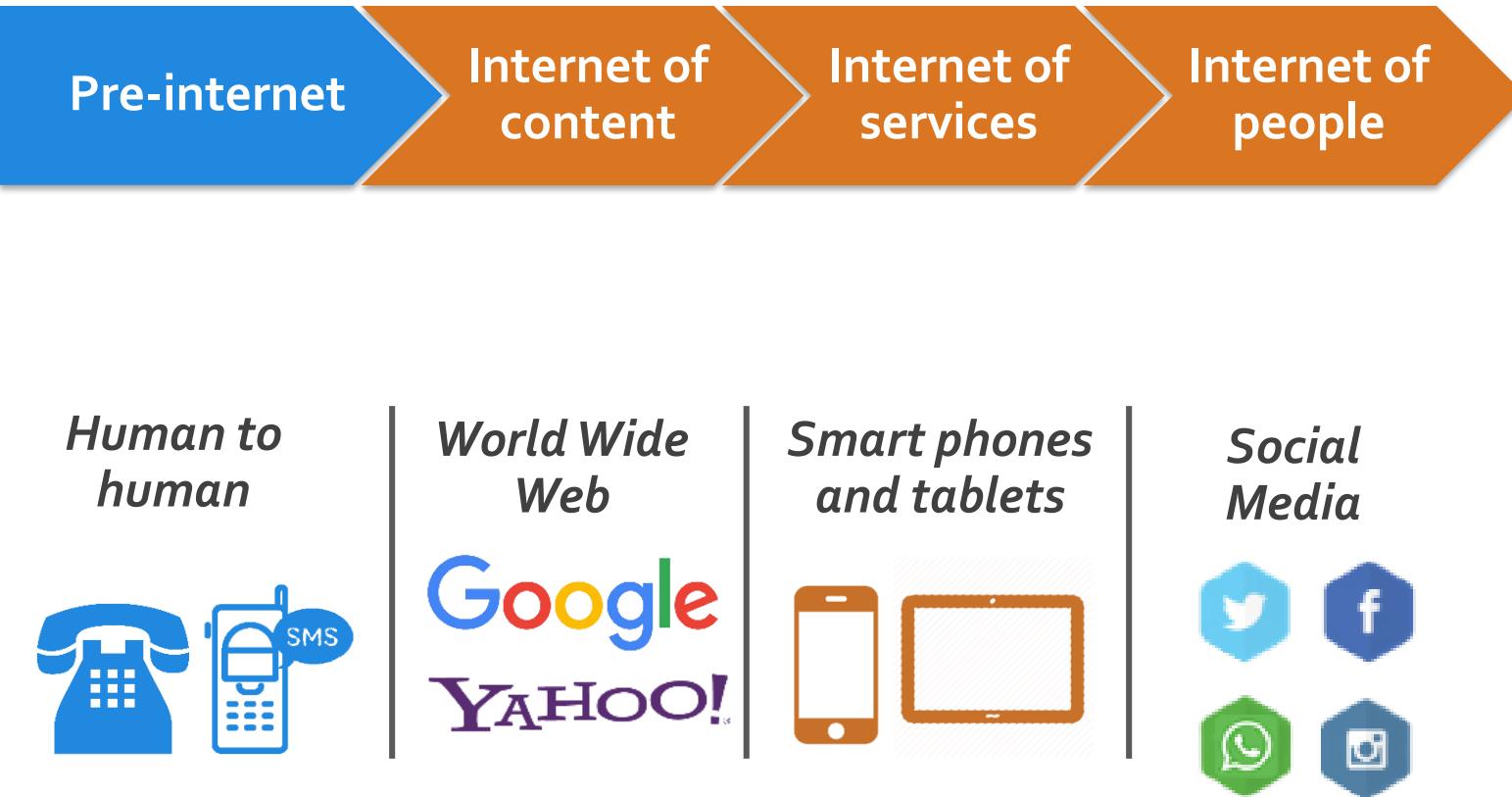
*Human to
human*



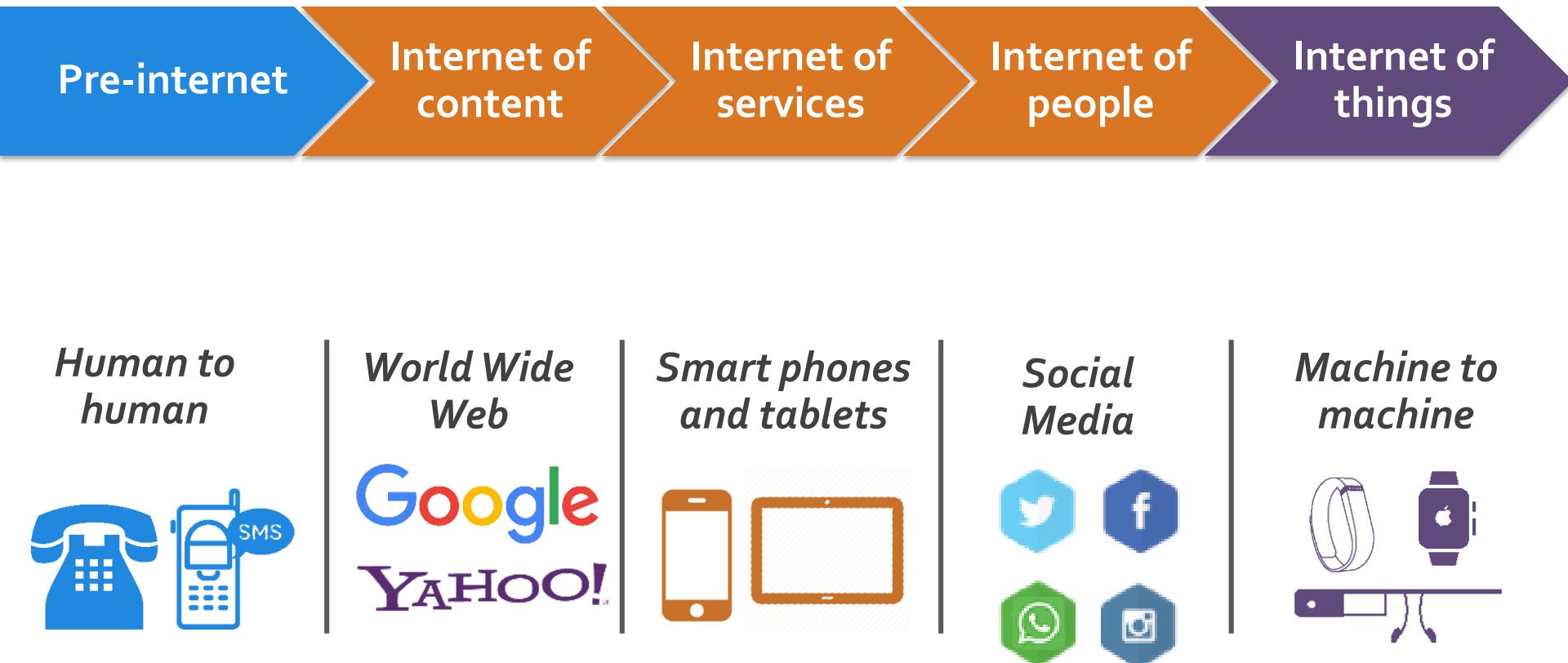
*World Wide
Web*

Google
YAHOO!

And then the Internet became smarter



Unprecedented level of connectivity



WE'RE BEING WATCHED!

Pre-internet

Internet of
content

Internet of
services

Internet of
people

Internet of
things



It's okay, our data is encrypted



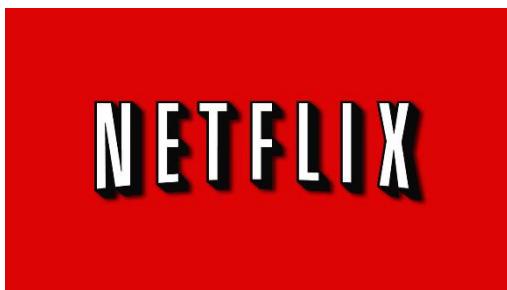
iCloud

ebay

CHASE



National Institutes
of Health



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Data privacy



de-anonymizing Netflix
watch histories



identifying surnames and ages
from anonymized genomes



+ = SSN

Image Credit: Alessandro Acquisti

from anonymous faces to social security numbers

Metadata privacy



Bob
@bob

Follow

I just learned that I'm HIV positive. I'm passing through some tough times and need your support.

7 Jul 12

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Favorite

Jason Rezaian's Year of Imprisonment in Iran

Wednesday marks the one-year anniversary of the *Washington Post* reporter's detention in the Islamic Republic.

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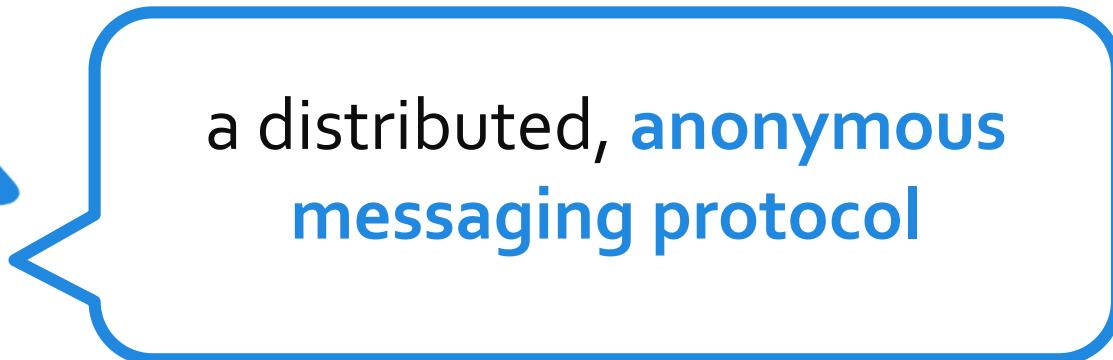
Politics | Fri Nov 23, 2007 4:54pm EST

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DAMASCUS | BY KHALED YACOUB OWEIS

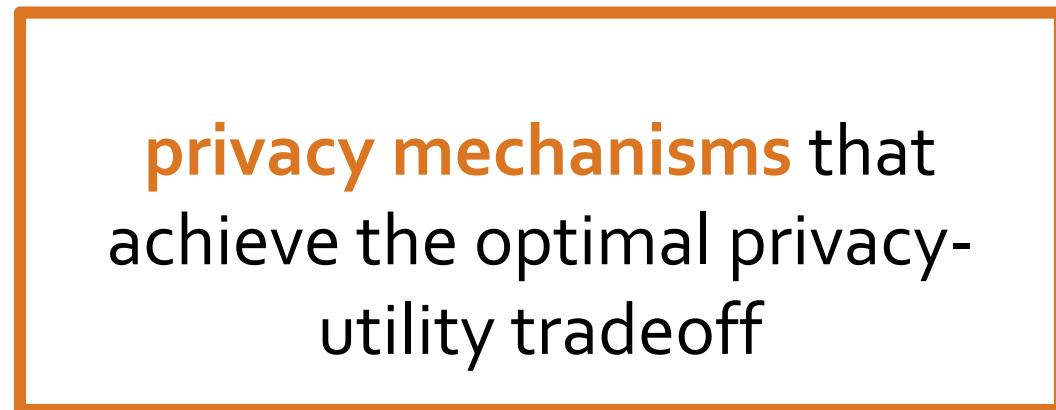
Metadata and data privacy



a distributed, **anonymous**
messaging protocol

[Best Paper Award at SIGMETRICS 15, SIGMETRICS 16]

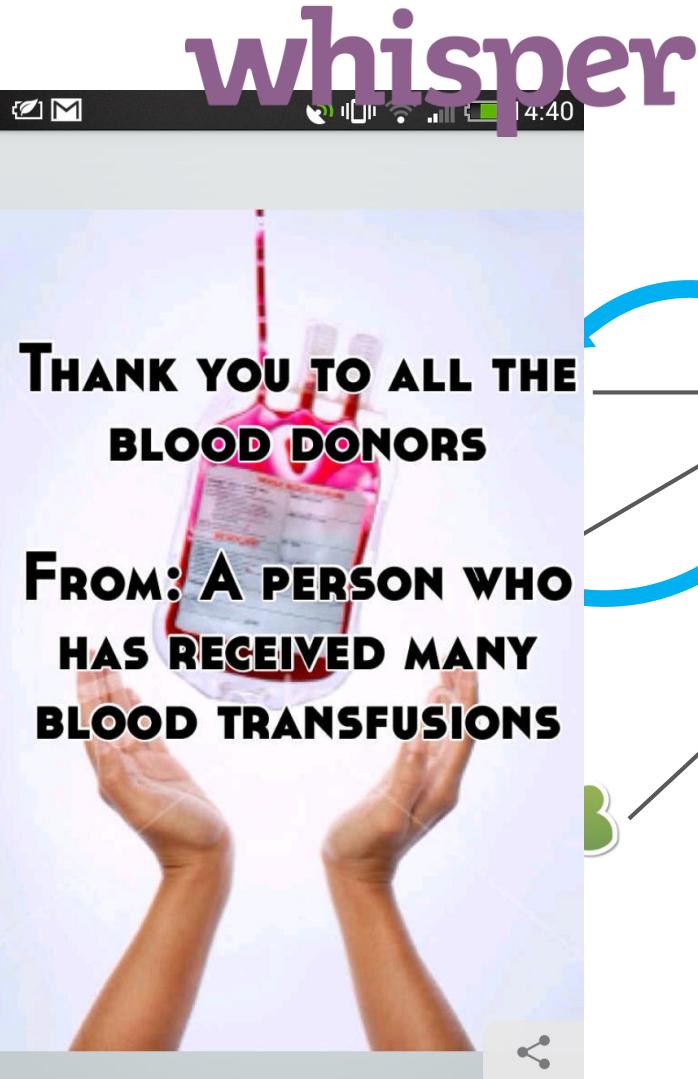
[NIPS 14, NIPS 15, ICML 15, TSTSP 15, CISS 16, JMLR 16, TIT 16]



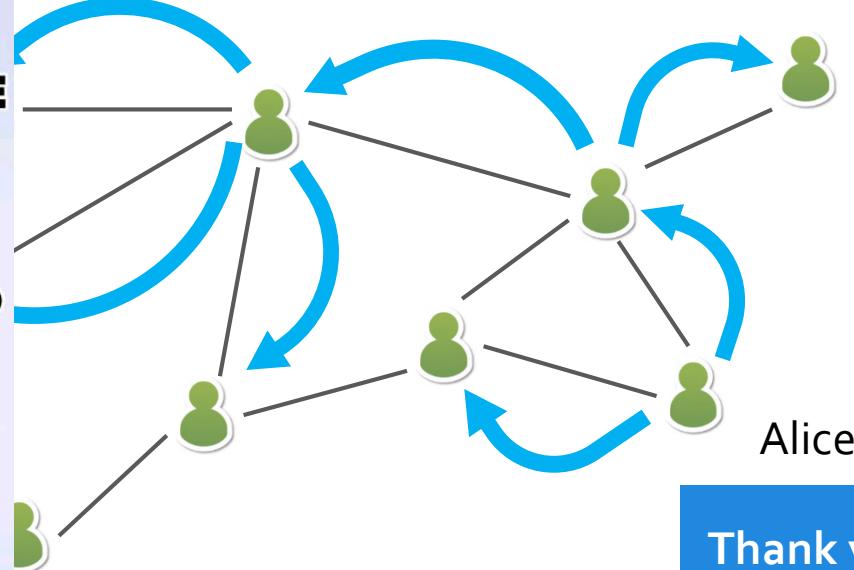
privacy mechanisms that
achieve the optimal privacy-
utility tradeoff

Part 1: Metadata privacy

Anonymous messaging



secret



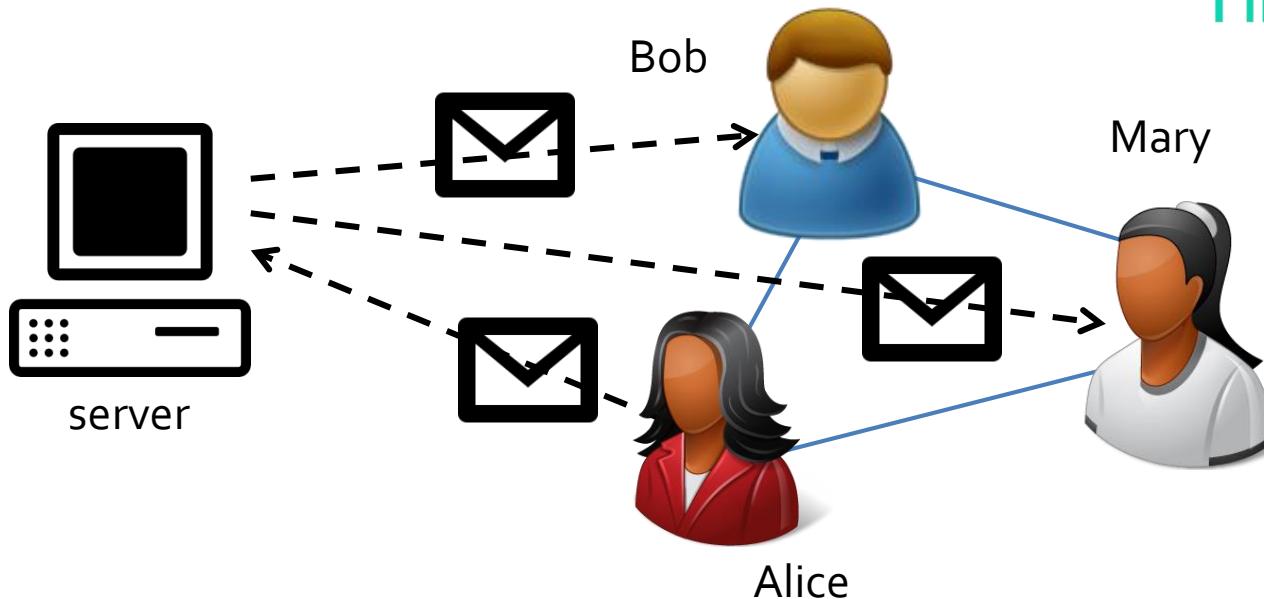
Thank you to all
the blood
donors...

What's wrong with this

whisper



secret



centralized networks **are not** truly anonymous!

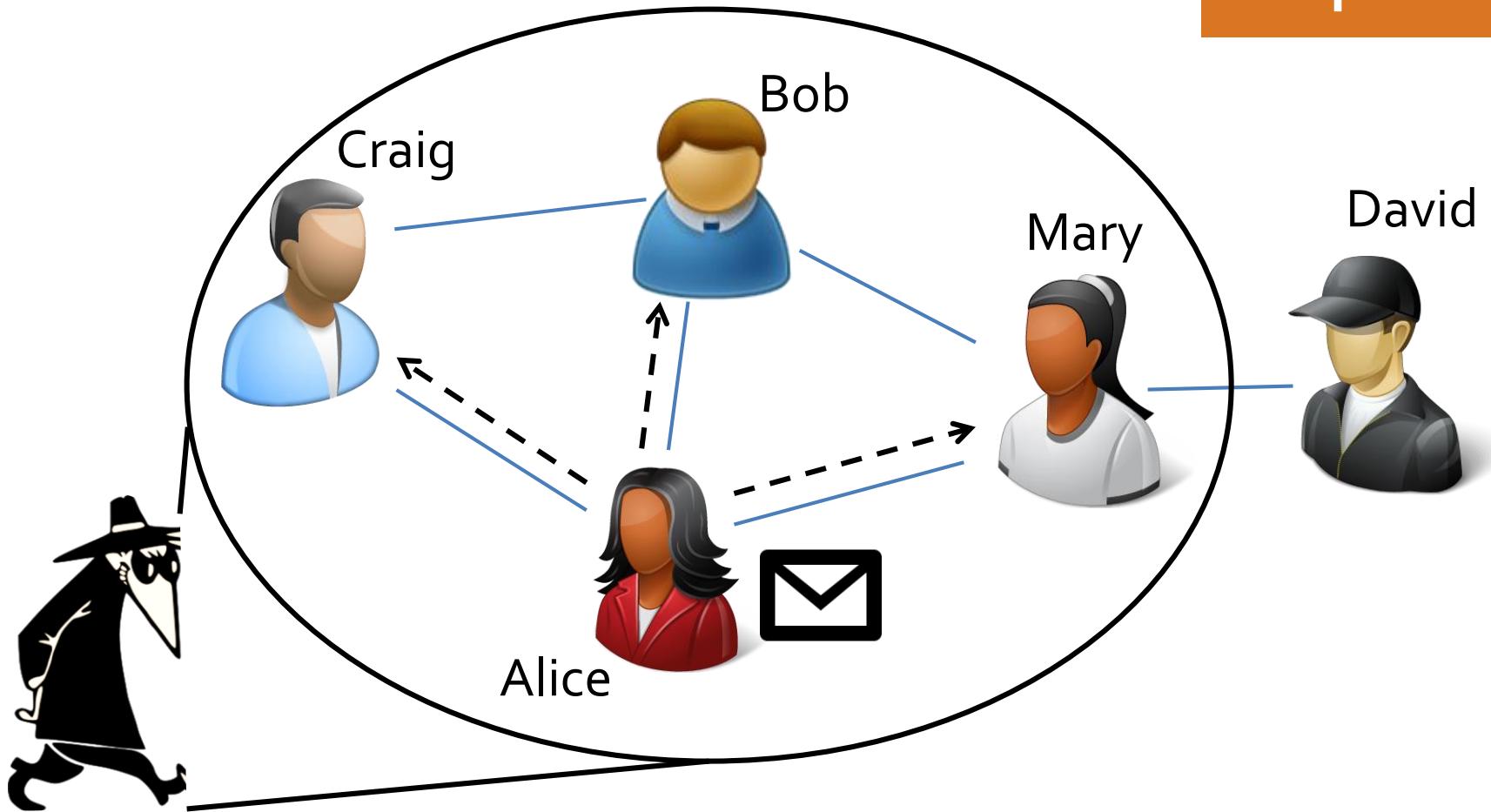
Objective

design a decentralized messaging protocol that:

- (a) spreads message **fast**
- (b) gives authors **anonymity guarantees**

Adversary without timing

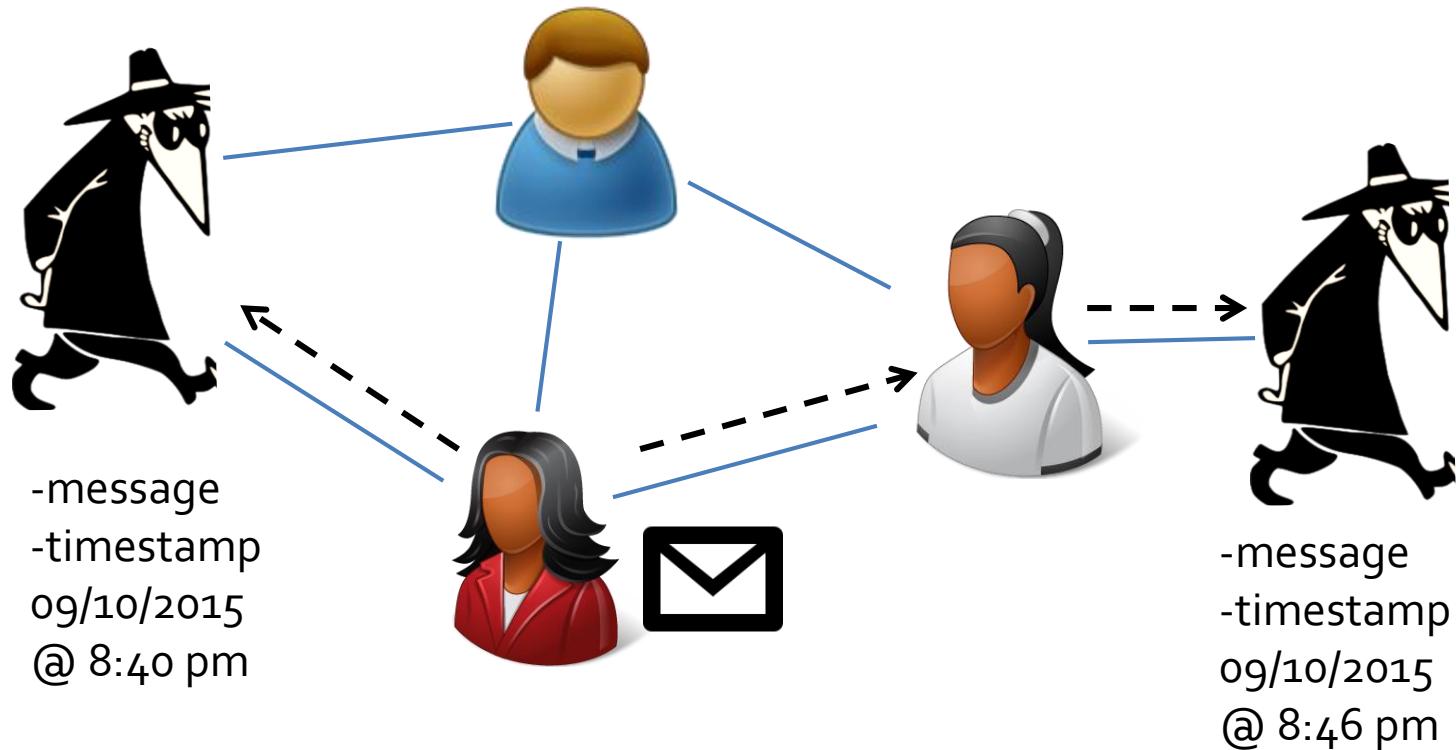
snapshot



adversary can figure out **who got the message**

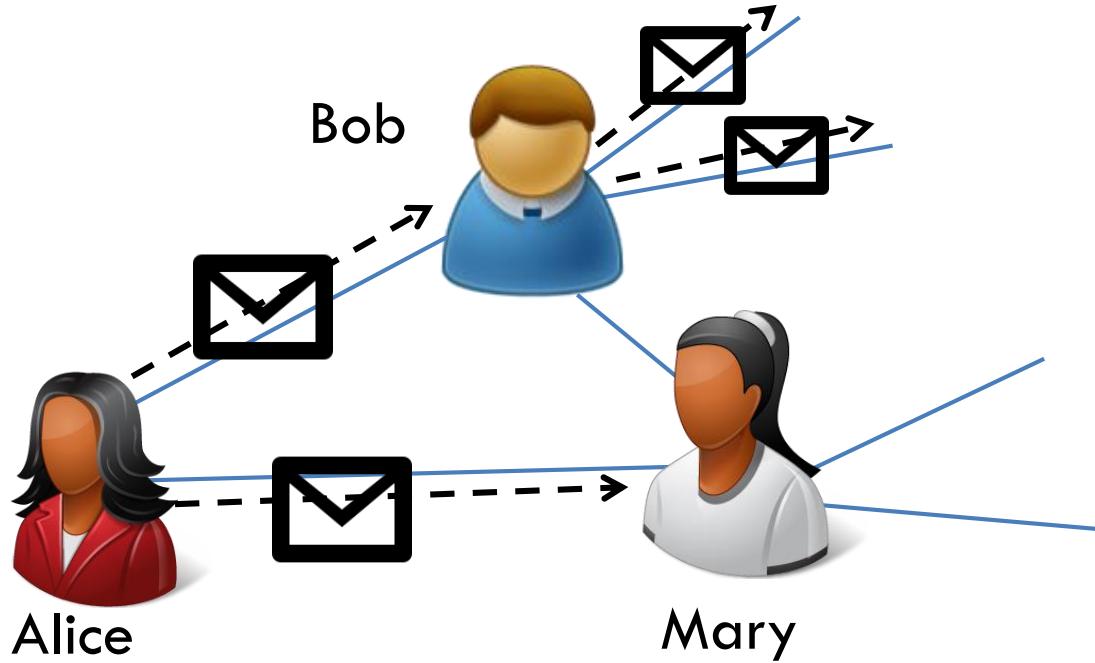
Adversary with timing

spy-based



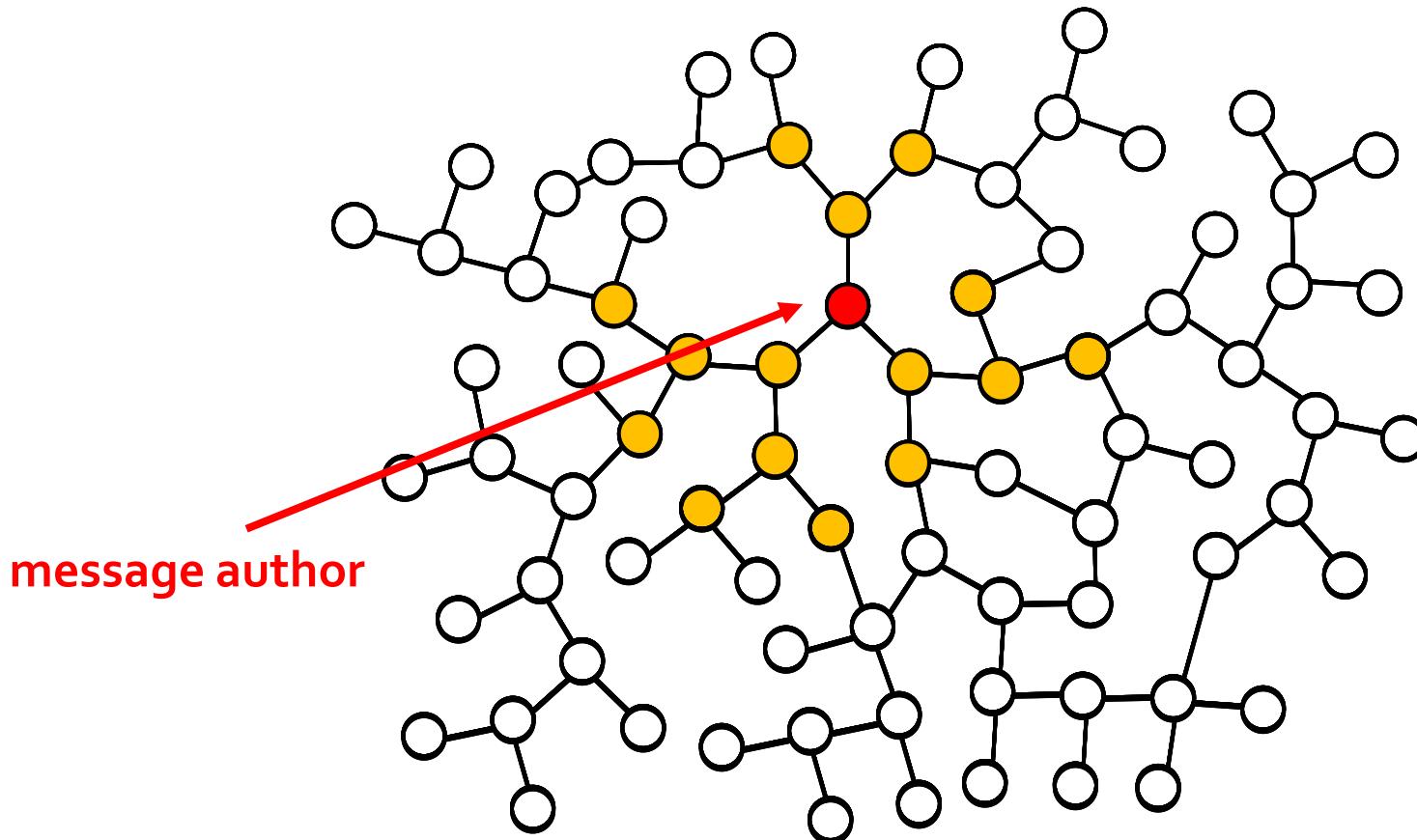
adversary can **collect timing information**

First attempt: distributed networks



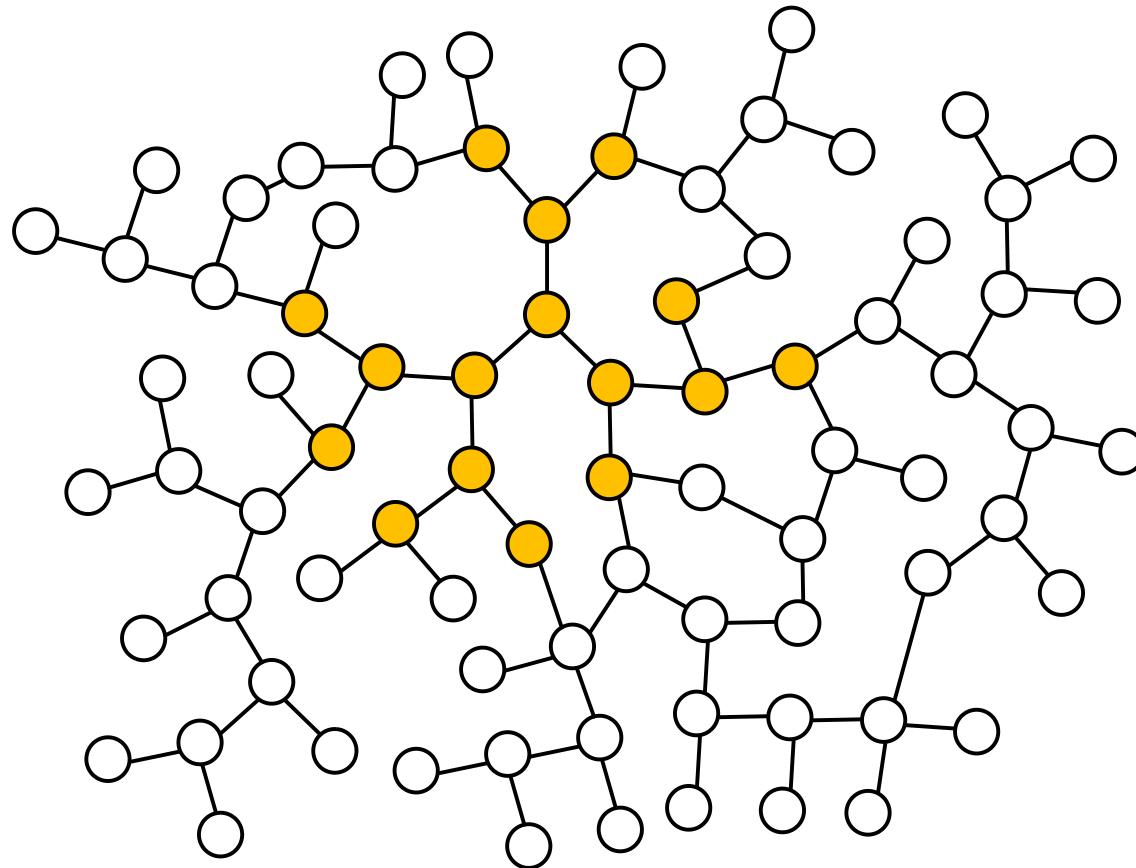
adversary can **still infer the author**

Information flow in social networks

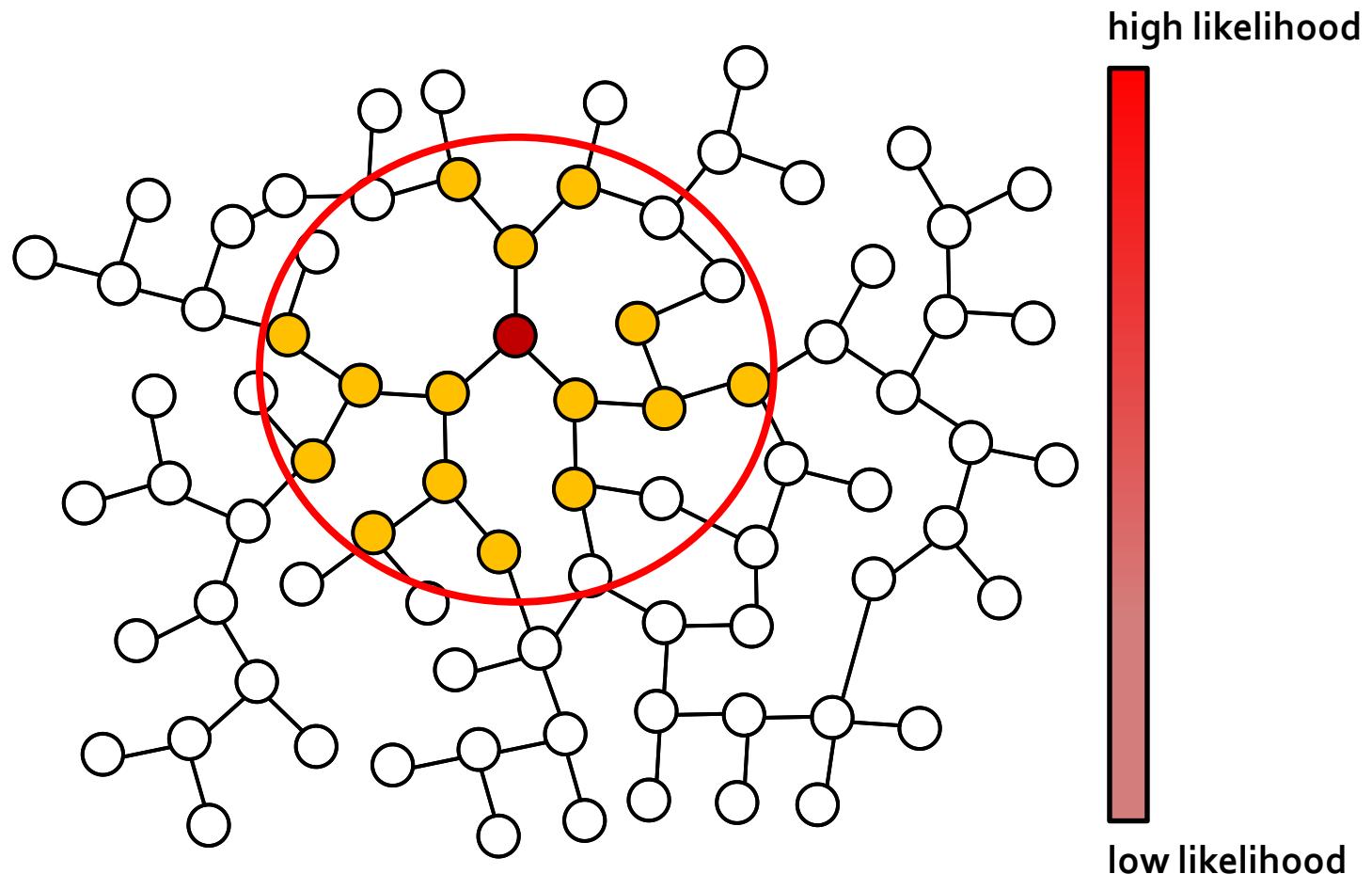


information spreads at the **same rate** in **all direction**

Can you find the source?

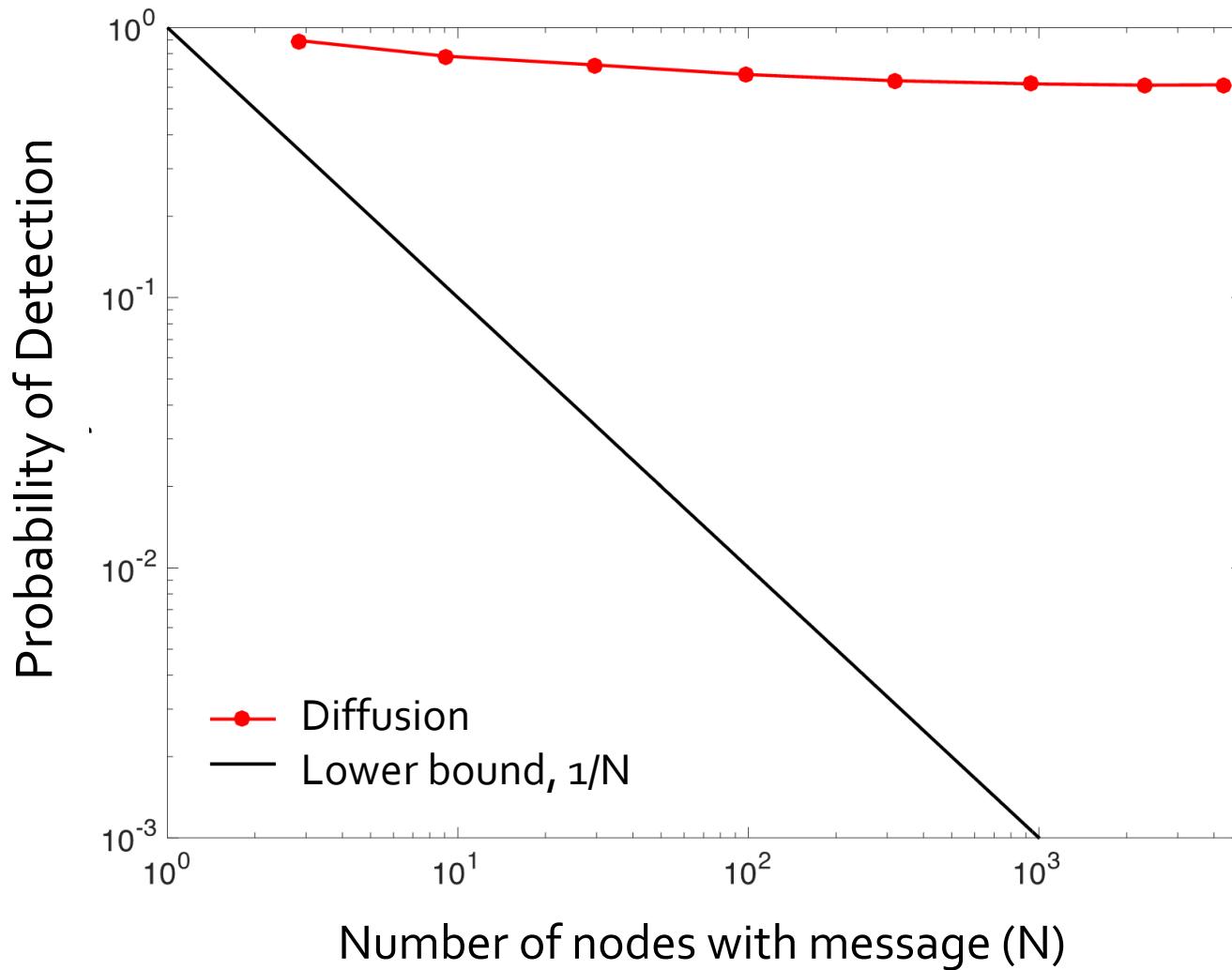


Concentration around the center



diffusion spreading = **de-anonymization**

De-anonymization on social networks



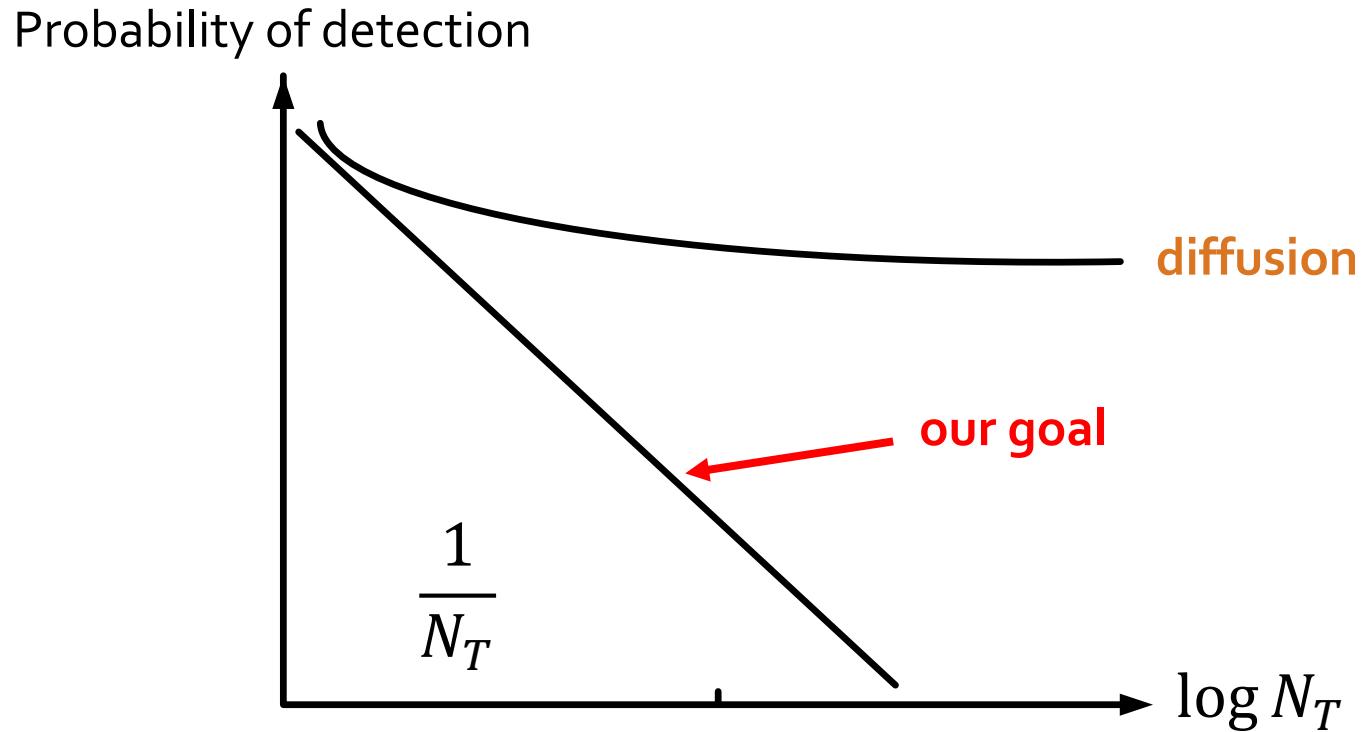
our first attempt failed!

Spreads fast



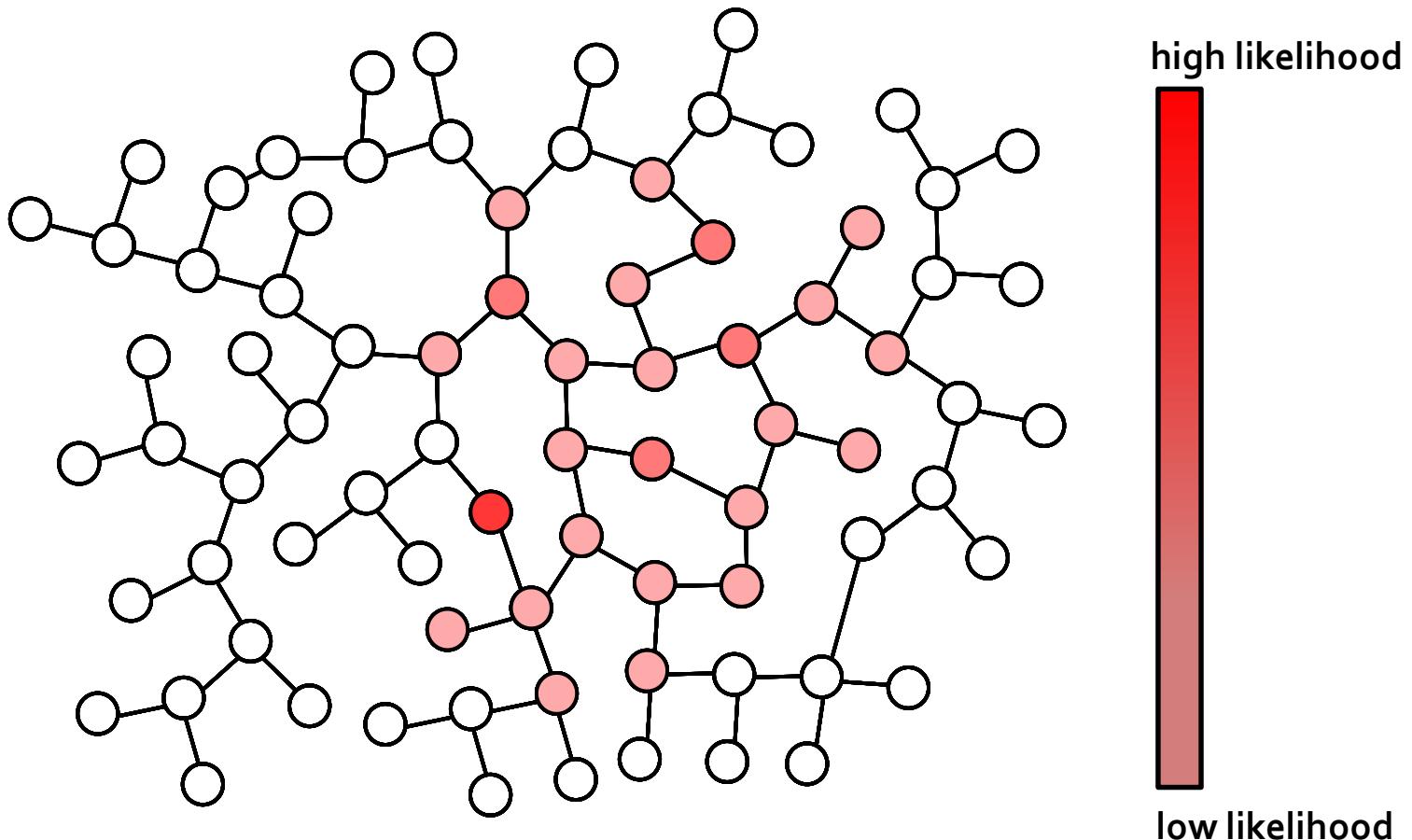
Bad anonymity
properties ☹

Objectives



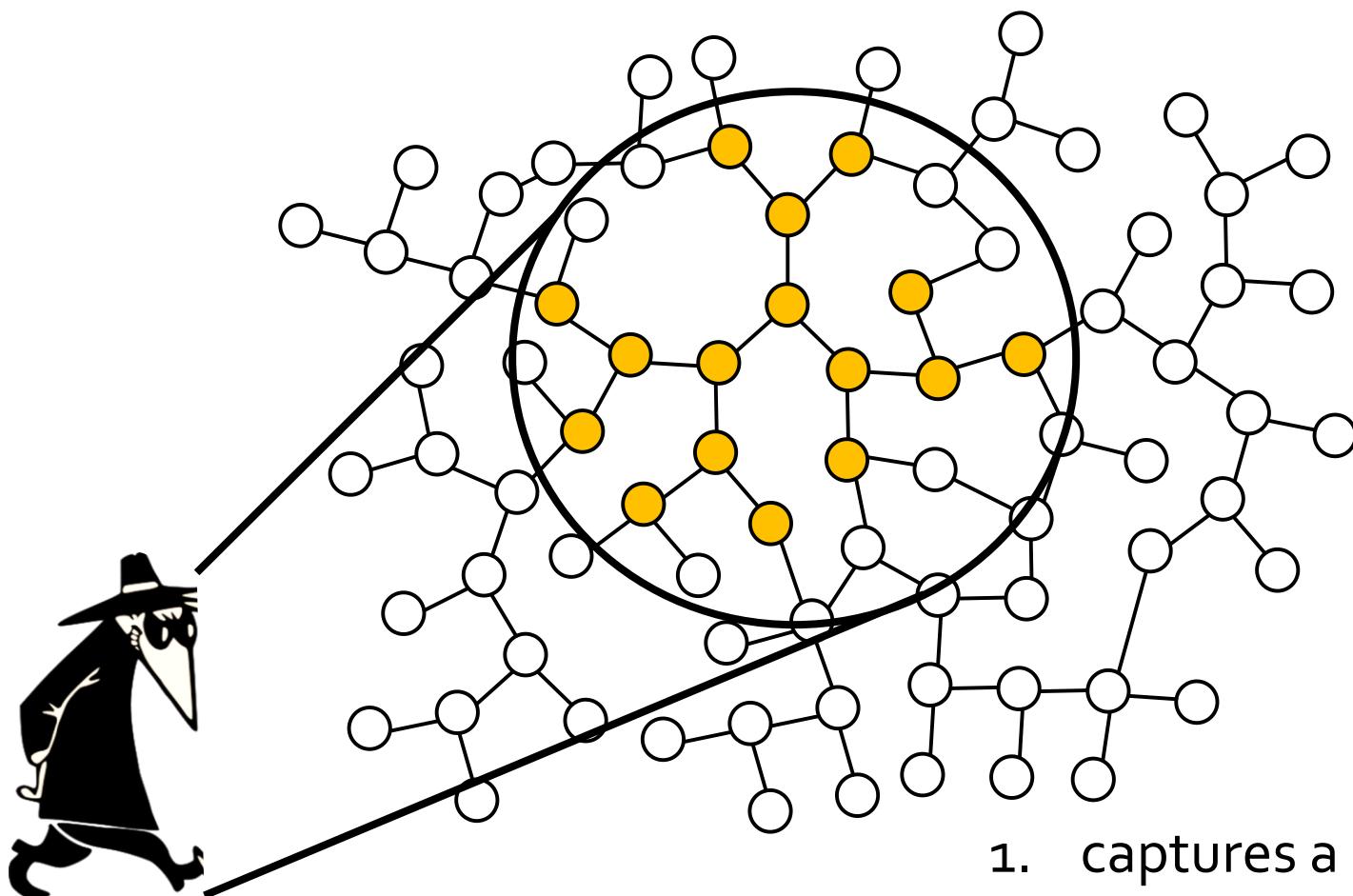
N_T = number of nodes with the message at time T

Adaptive diffusion



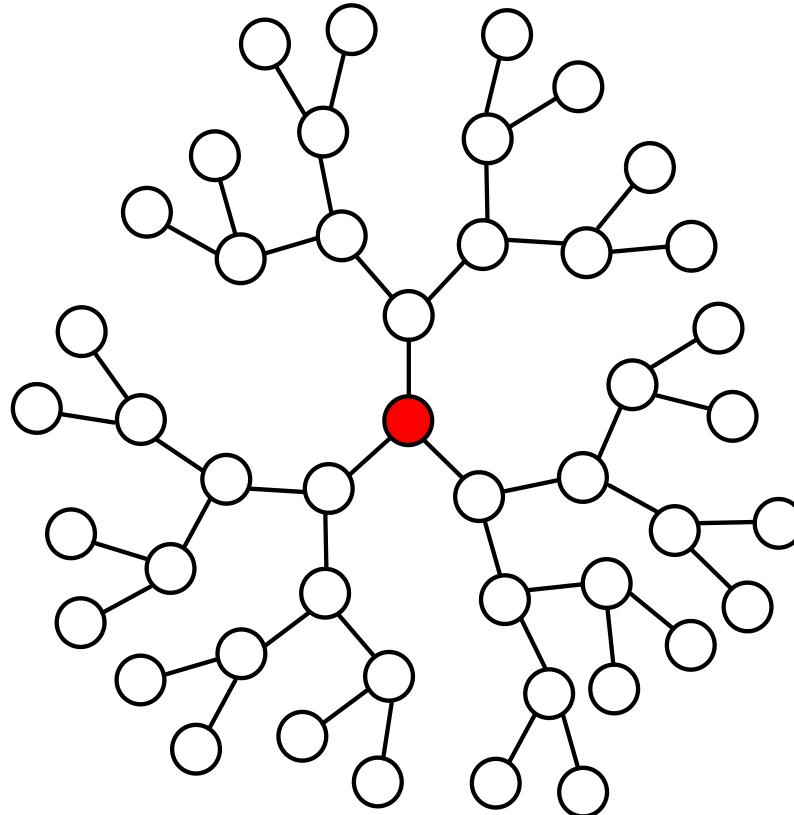
provides provable anonymity guarantees

Snapshot adversary



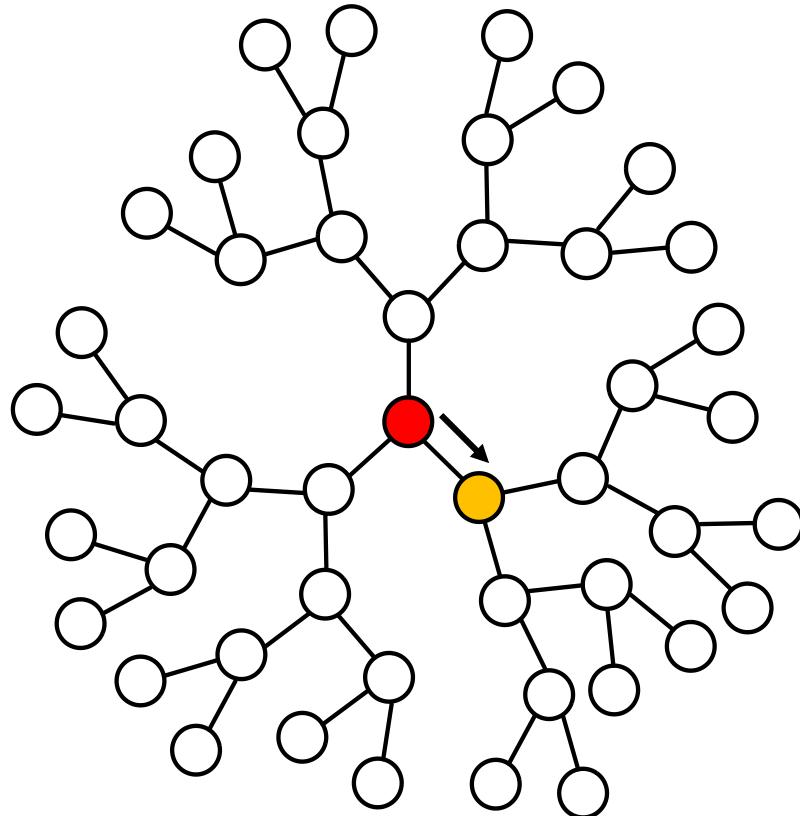
1. captures a snapshot
2. has access to underlying graph
3. knows the spreading protocol
4. is computationally unbounded

d -regular trees: adaptive diffusion



initially, the author is also the “virtual source”

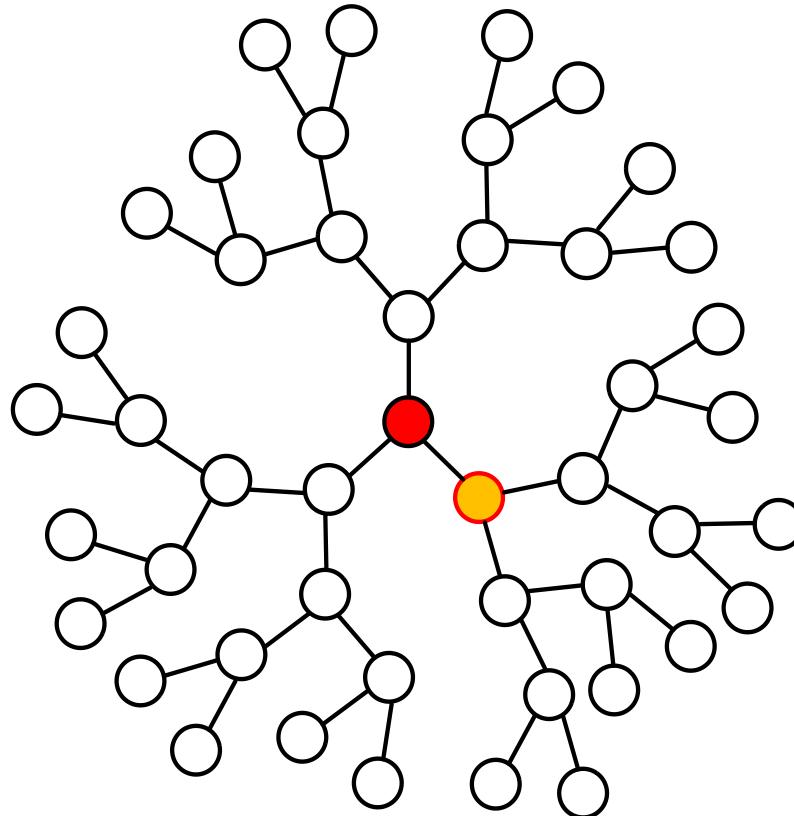
d -regular trees: adaptive diffusion



break
directional
symmetry

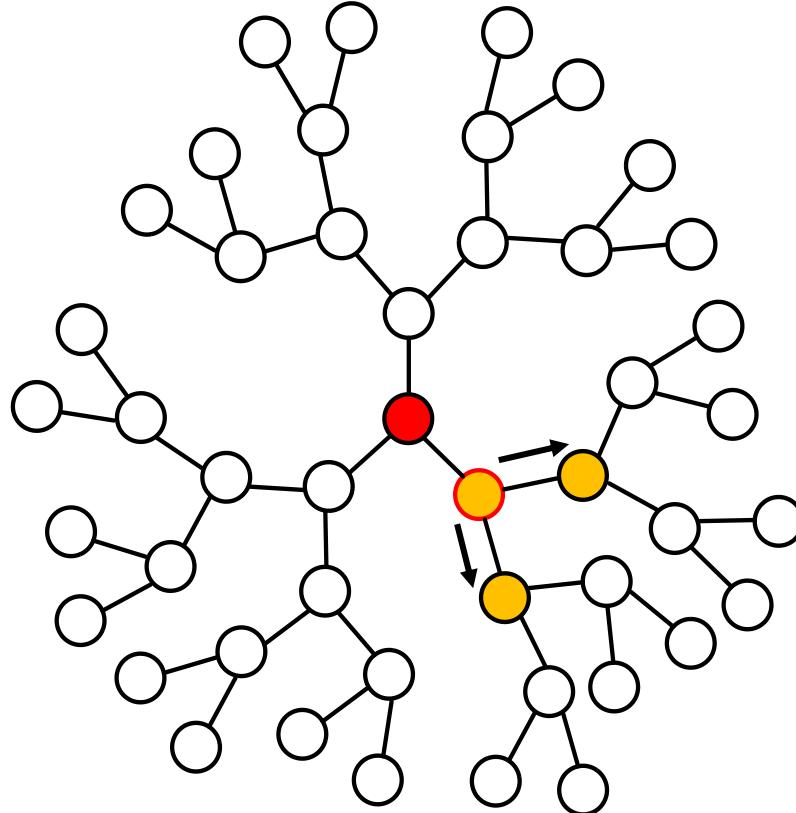
$T = 1$, the author selects one neighbor at random

d -regular trees: adaptive diffusion



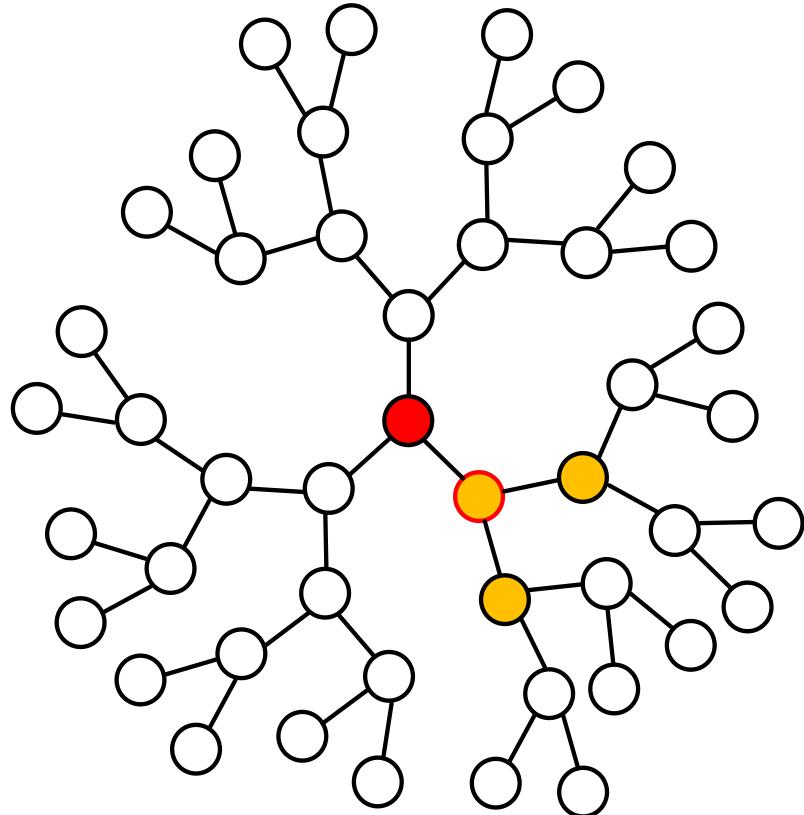
chosen neighbor = new virtual source

d -regular trees: adaptive diffusion



$T = 2$, virtual source passes the message to all its neighbors

d -regular trees: adaptive diffusion

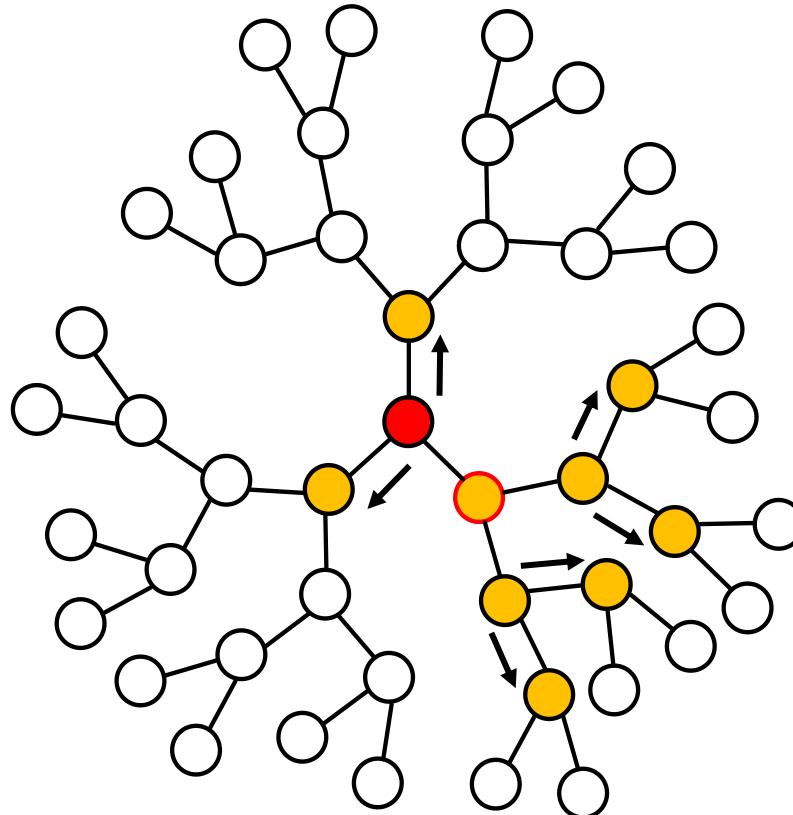


break
temporal
symmetry

keep the virtual source token

pass the virtual source token

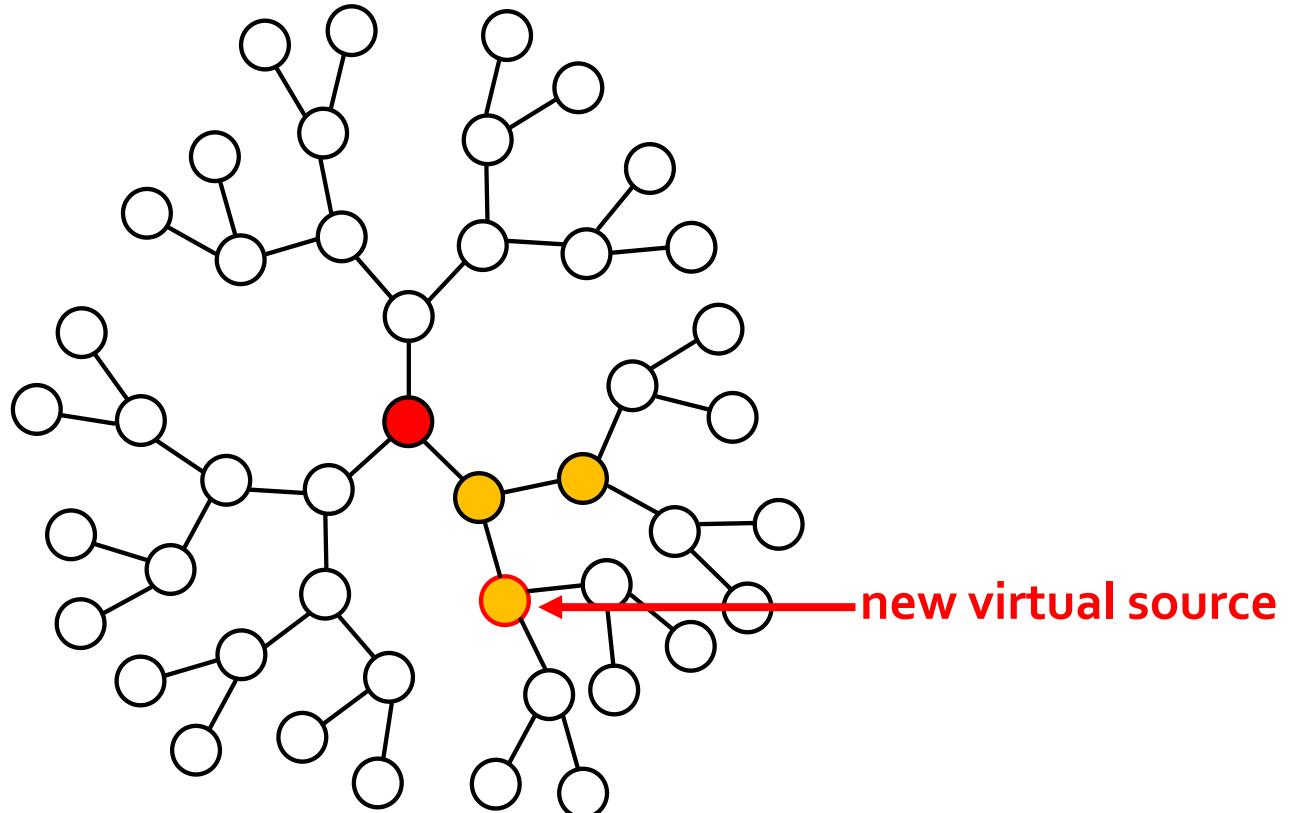
keep the virtual source token



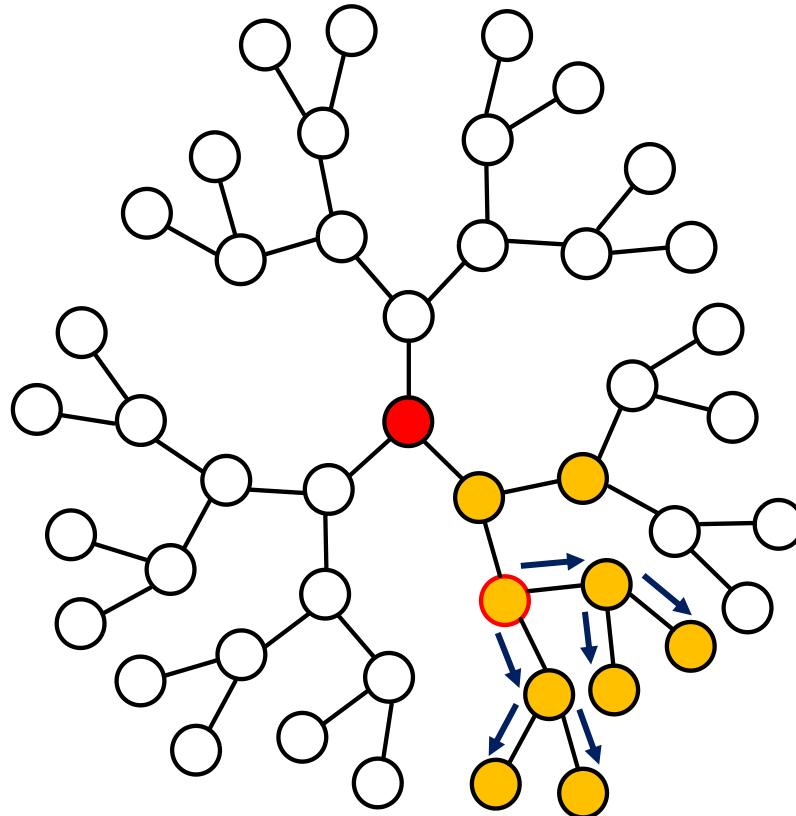
happens in
 $T = 3$ and
 $T = 4$

spread the message in all directions

pass the virtual source token



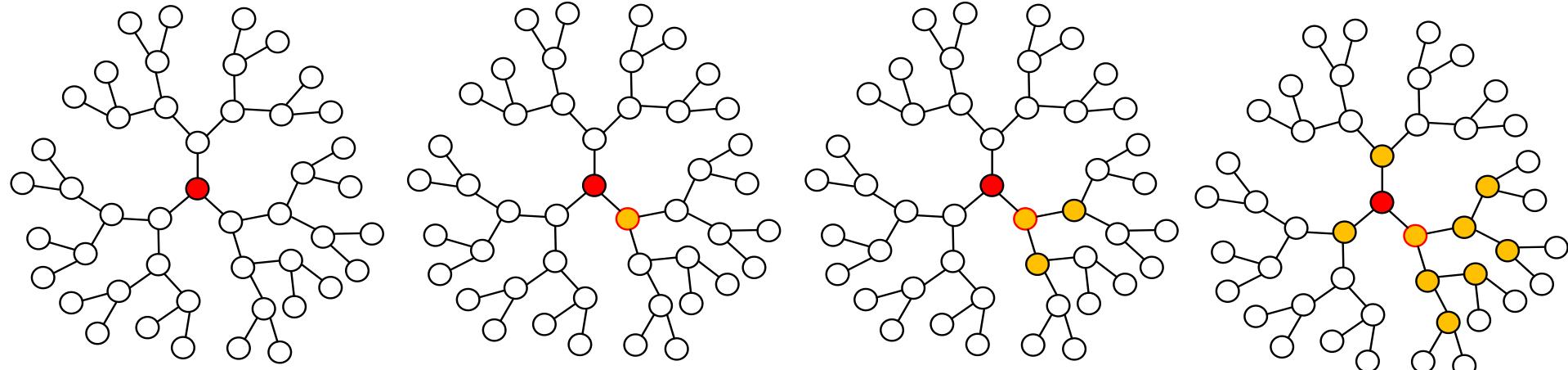
pass the virtual source token



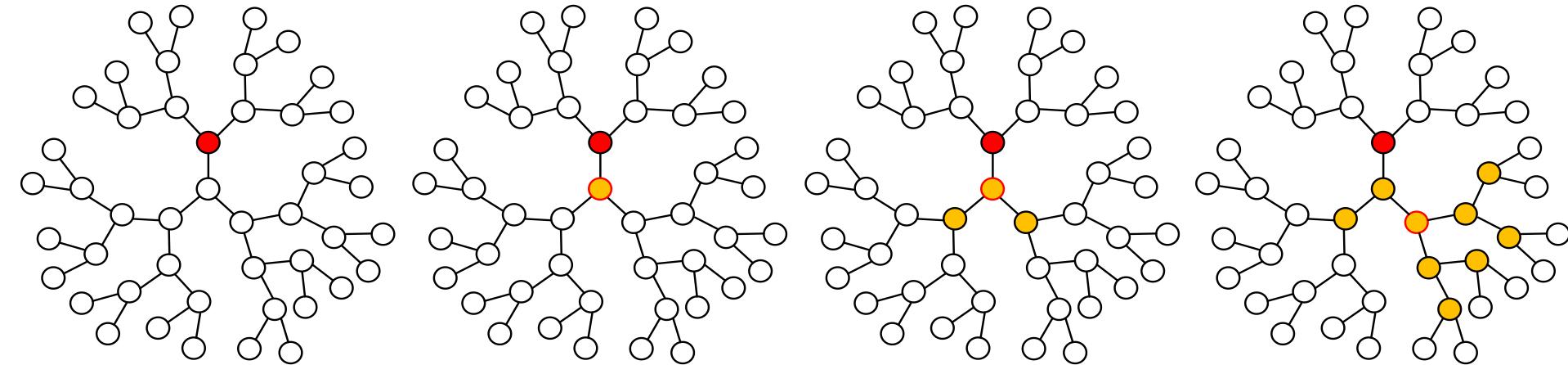
happens in
 $T = 3$ and
 $T = 4$

spread the message in the direction of: old → new virtual source

Sample paths

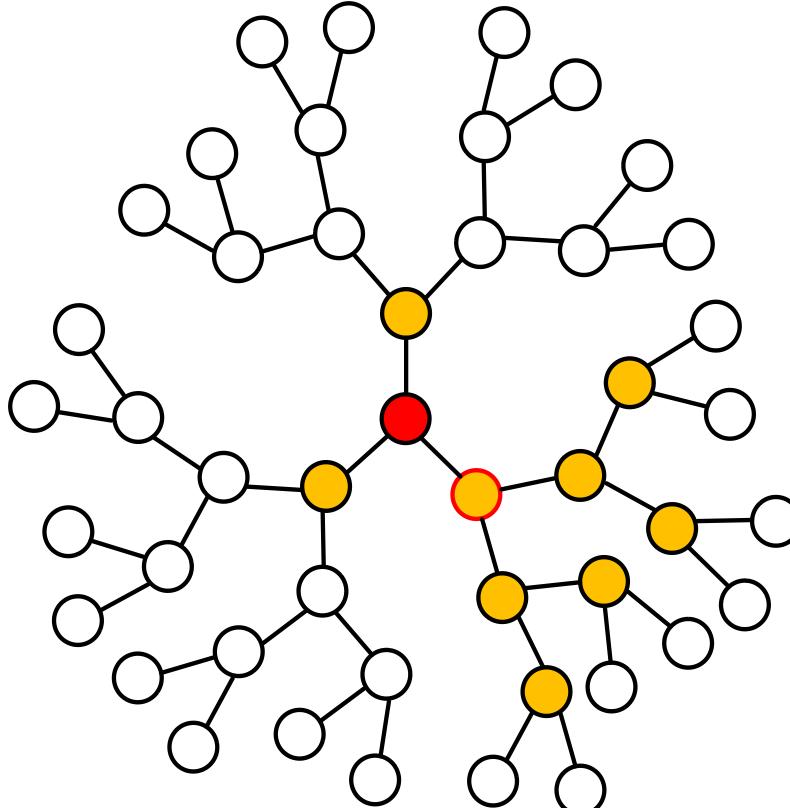


choose a neighbor at random → keep the virtual source token



choose a neighbor at random → pass the virtual source token

When to keep the virtual source



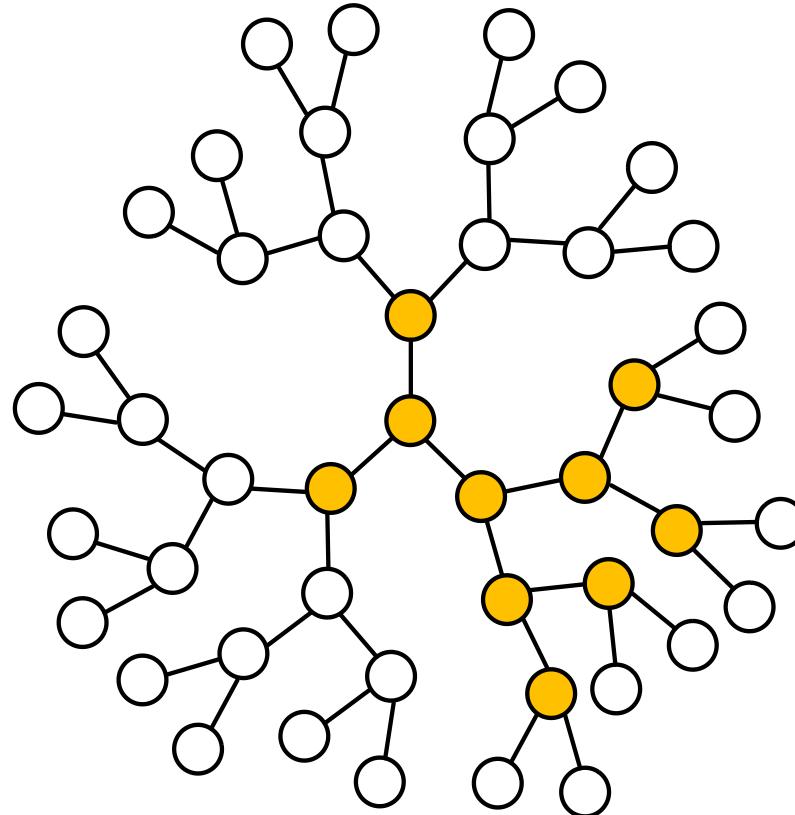
node degree

time index

distance to source

virtual source token is kept w.p. $\alpha = \frac{(d-1)^{\frac{T}{2}-h+1}-1}{(d-1)^{\frac{T}{2}+1}-1}$

Adversary with a snapshot



can the adversary locate the source of the message?

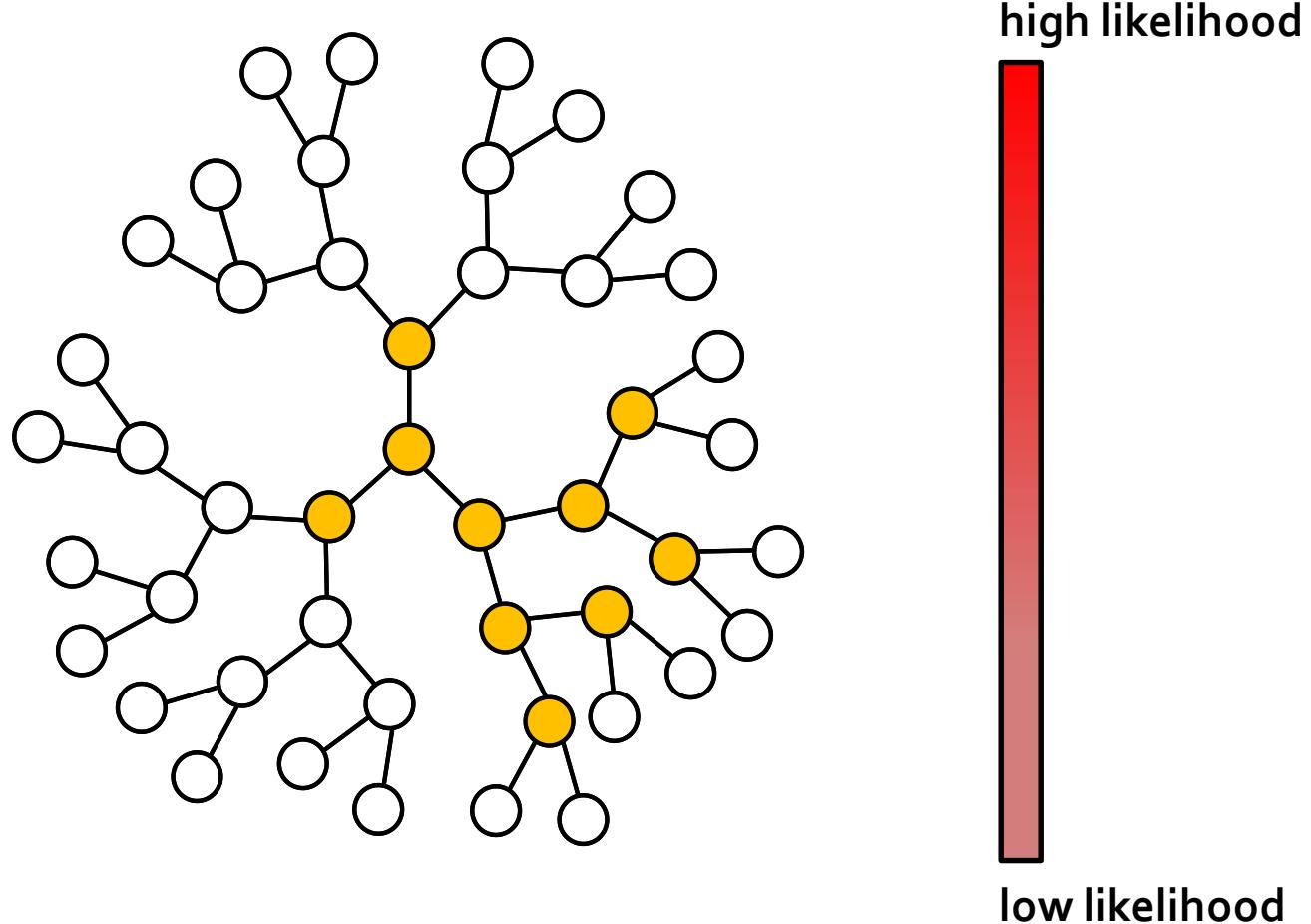
THEOREM

1. We spread fast: $N_T \approx (d - 1)^{\frac{T}{2}}$.
2. Probability of source detection under maximum likelihood detection is given by

$$P(\hat{v}_{ML} = v^*) = \frac{1}{N_T - 1}.$$

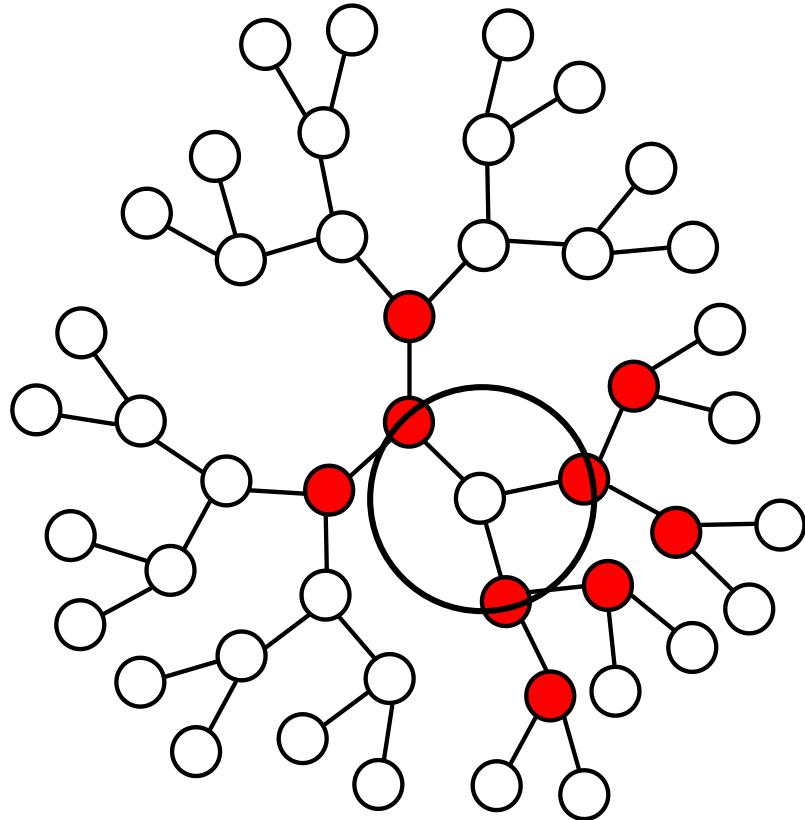
3. The expected distance between the estimated and true source is at least $\frac{T}{2}$.

Proof sketch

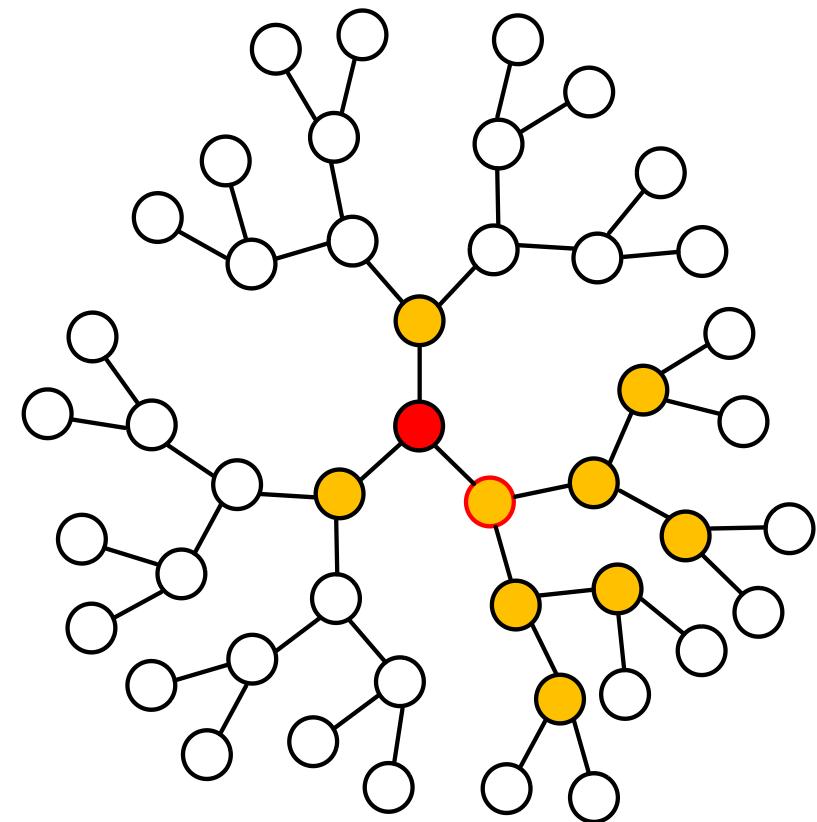


all nodes except for the final virtual source are equally likely

Proof sketch



nodes at the same hop distance from the virtual source are
equally likely



Markov chain over the hop distance between the true source and final virtual source

$$h_t = d(v^*, vs_t)$$

After every 2 time steps

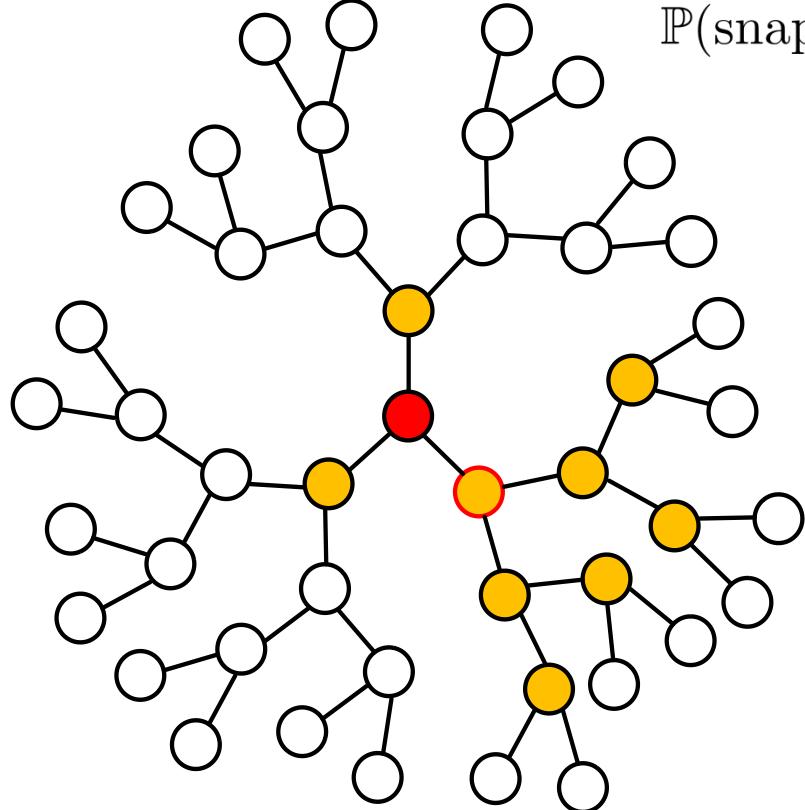
$$h_{t+2} = h_t \text{ or } h_{t+2} = h_t + 1$$

Probability of keeping token

$$\alpha_d(t, h) = \mathbb{P}(h_{t+2} = h_t | h_t = h)$$

Probability state vector

$$p^{(t)} = [\mathbb{P}(h_t = h)]_{h \in \{1, \dots, t/2\}}$$



State transition matrix

$$\begin{aligned} \mathbb{P}(\text{snapshot} | v, d(v, vs_t) = h) &= \frac{1}{d(d-1)^{h-1}} p_h^{(t)} \\ &= \frac{d-2}{d((d-1)^{t/2} - 1)} \end{aligned}$$



$$p^{(t)} = \frac{d-2}{(d-1)^{t/2} - 1} \begin{bmatrix} 1 \\ (d-1) \\ \vdots \\ (d-1)^{t/2-1} \end{bmatrix}$$

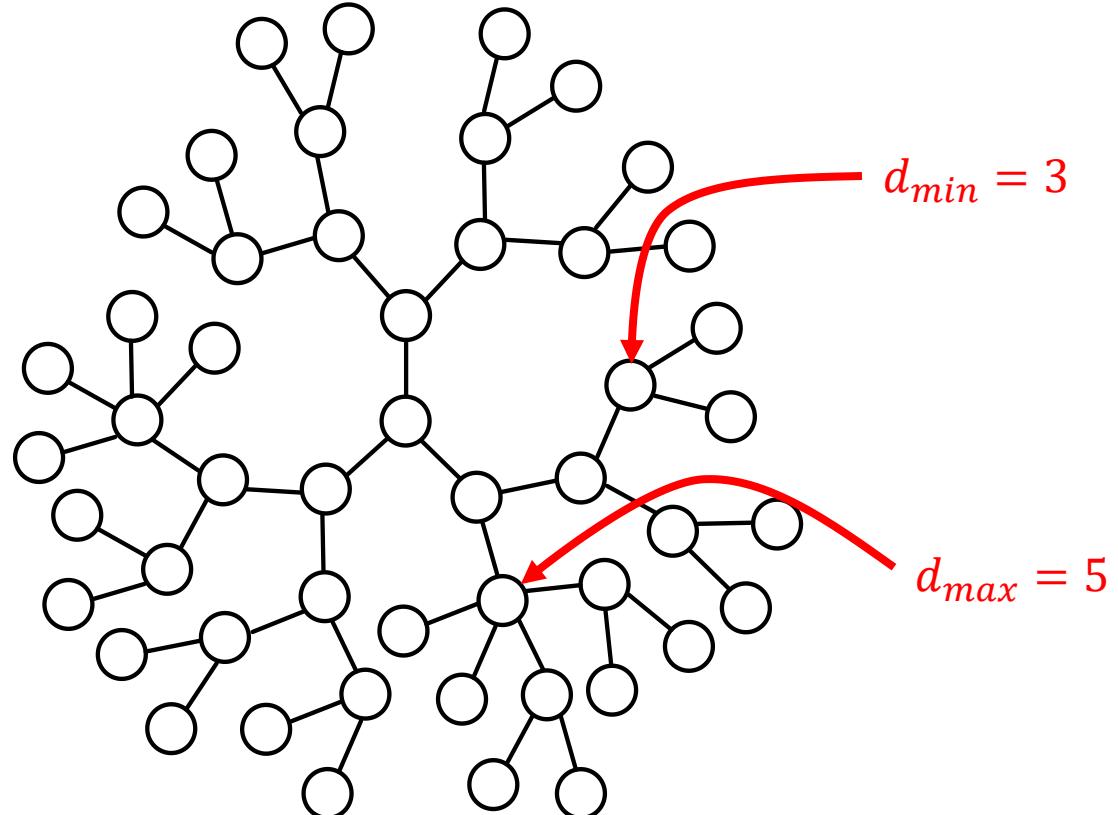


$$\alpha_d(t, h) = \frac{(d-1)^{t/2-h+1}-1}{(d-1)^{t/2+1}-1}$$

$$p^{(t+2)} = \begin{bmatrix} \alpha_d(t, 1) & & & \\ 1 - \alpha_d(t, 1) & \alpha_d(t, 2) & & \\ & & 1 - \alpha_d(t, 2) & \ddots \\ & & & \ddots & \alpha_d(t, t/2) \\ & & & & 1 - \alpha_d(t, t/2) \end{bmatrix} p^{(t)}$$

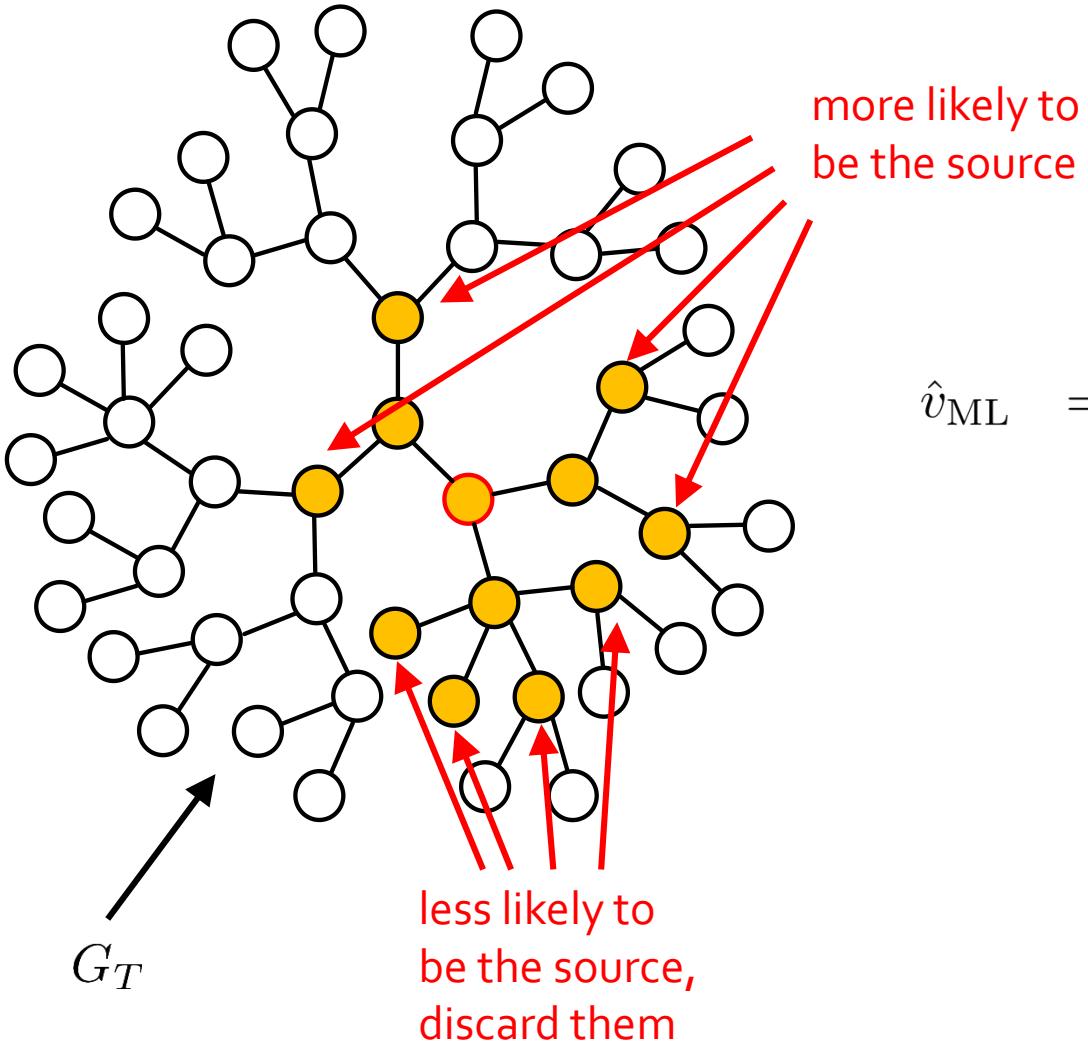
What about irregular trees?

$$d_v = \begin{cases} 3 & w.p. \quad 0.8 \\ 5 & w.p. \quad 0.2 \end{cases}$$



virtual source is moved with probability 1 ($\alpha = 0$)

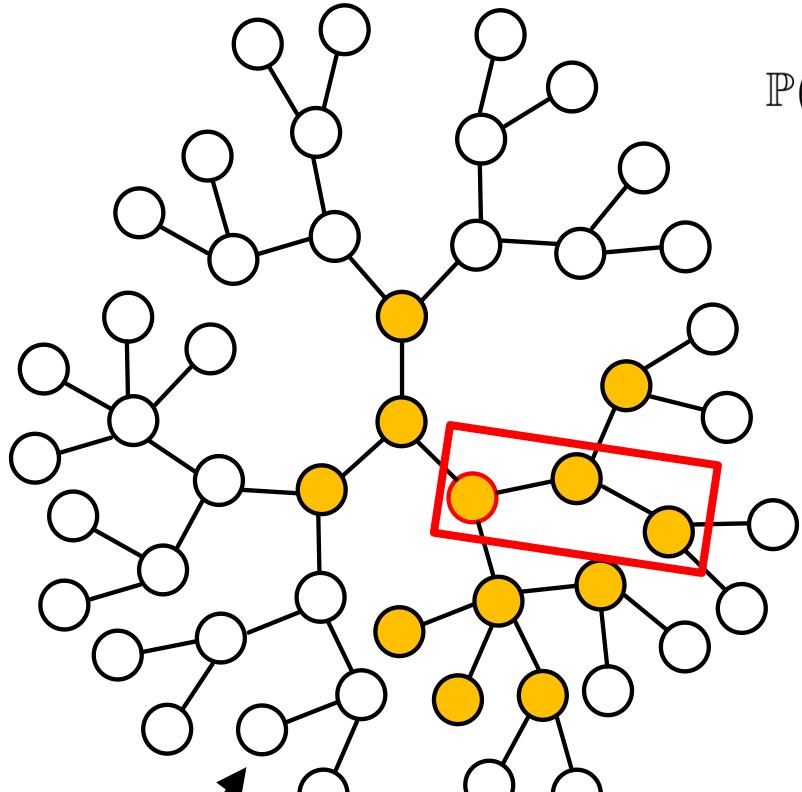
Maximum likelihood detection



$$\hat{v}_{\text{ML}} = \arg \min_{v \in \partial G_T} \prod_{w \in \phi(v, vs) \setminus \{vs, v\}} (d_w - 1)$$

path from leaf node v to virtual source

Performance of ML detection



$$d_v = \begin{cases} d_{min} & w.p. p_{min} \\ d_{max} & w.p. p_{max} \end{cases}$$

$$\mathbb{P}(\hat{v}_{\text{ML}} = v^* | G_T) = \frac{1}{d_{v_s} \min_{v \in \partial G_T} \prod_{\substack{w \in \phi(v, v_s) \\ \setminus \{v_s, v\}}} (d_w - 1)}$$

path from leaf
node v to
virtual source

degree of
node w

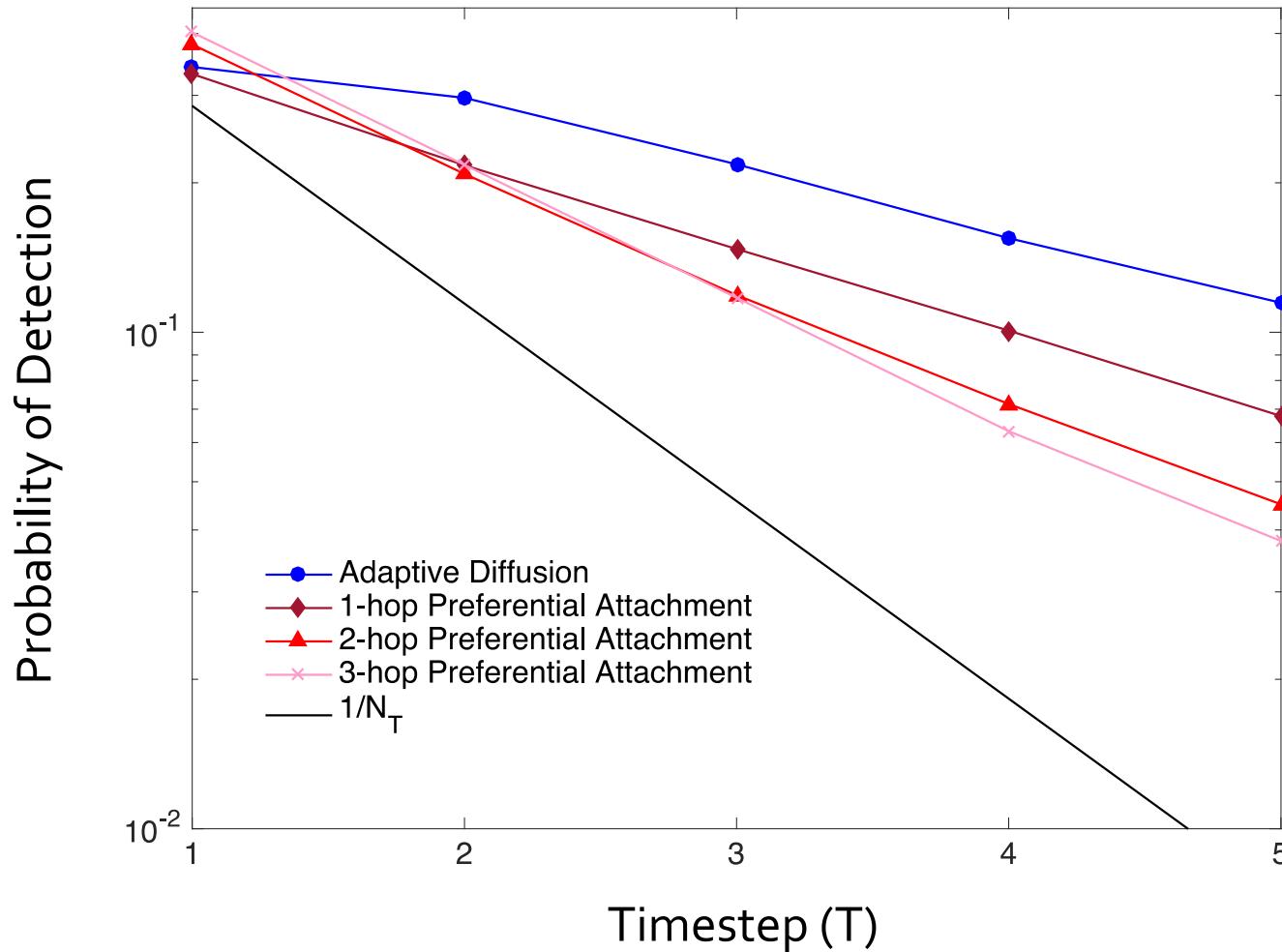
$$\mathbb{P}(\hat{v}_{\text{ML}} = v^*) = \mathbb{E}_{G_T} [\mathbb{P}(\hat{v}_{\text{ML}} = v^* | G_T)]$$

$$\frac{1}{9} \text{ If } p_{min}(d_{min} - 1) > 1$$

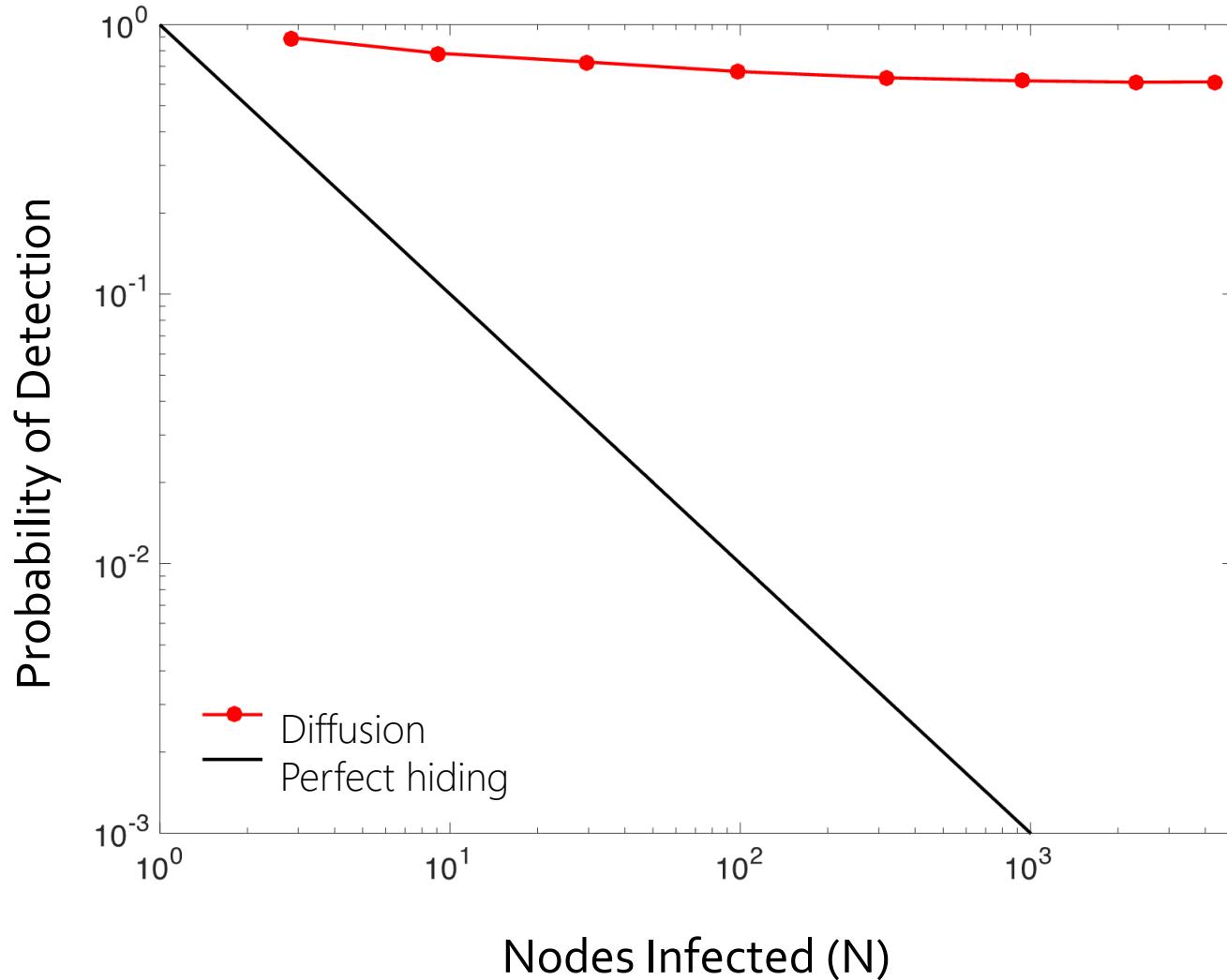
$$\mathbb{P}(\hat{v}_{\text{ML}} = v^* | G_T) \approx (d_{min} - 1)^{-T/2}$$

G_T
THEOREM: probability of detection $\approx \frac{1}{(d_{min}-1)^{T/2}}$

Preferential attachment protocol



Facebook graph



Lessons for snapshot adversary

- 1) Diffusion = de-anonymization
- 2) For anonymity, break symmetry.
- 3) For *more* anonymity, hide in a crowd.

Our results

	d -Regular trees	Irregular trees	Facebook graph
snapshot	[1]	[1, 2]	[1]
spy-based	[3]	[3]	[3]

[1] Spy vs. Spy: Rumor Source Obfuscation, SIGMETRICS 2015

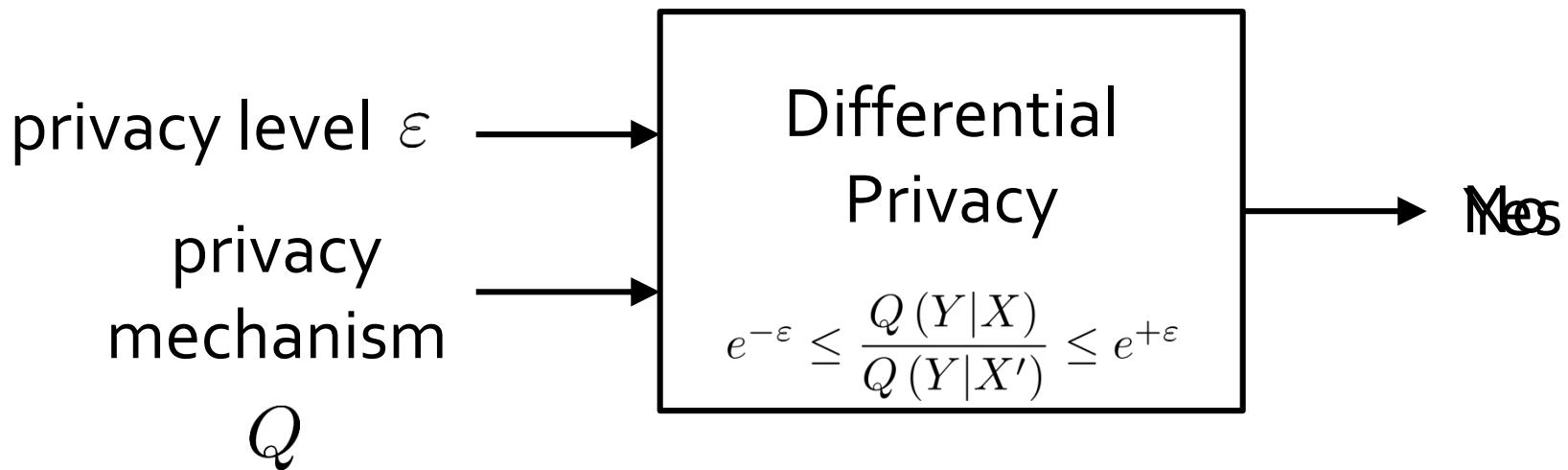
[2] Rumor Source Obfuscation on Irregular Trees, to appear in SIGMETRICS 2016

[3] Under review

Part 2: Data Privacy

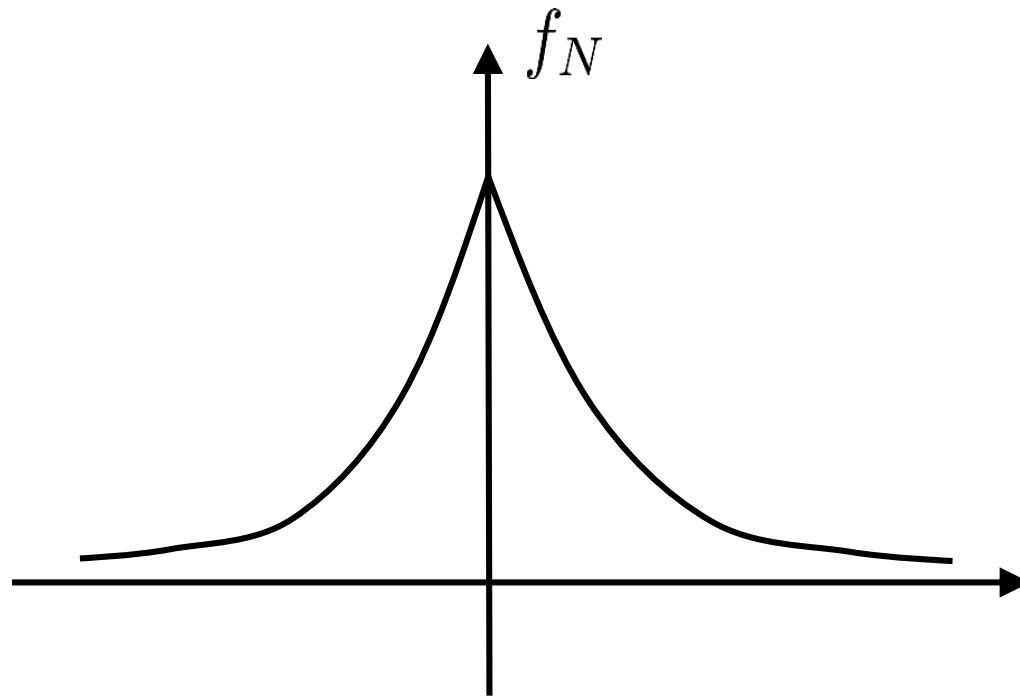
Differential privacy

we need **context free** privacy guarantees



Differential privacy

Laplace Mechanism



standard deviation proportional to privacy level

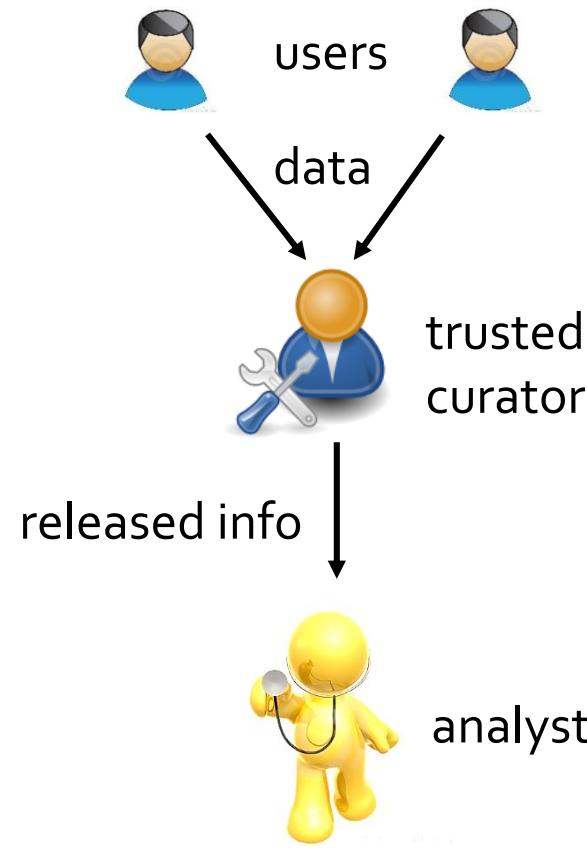
Privacy vs. utility

given a **privacy level**

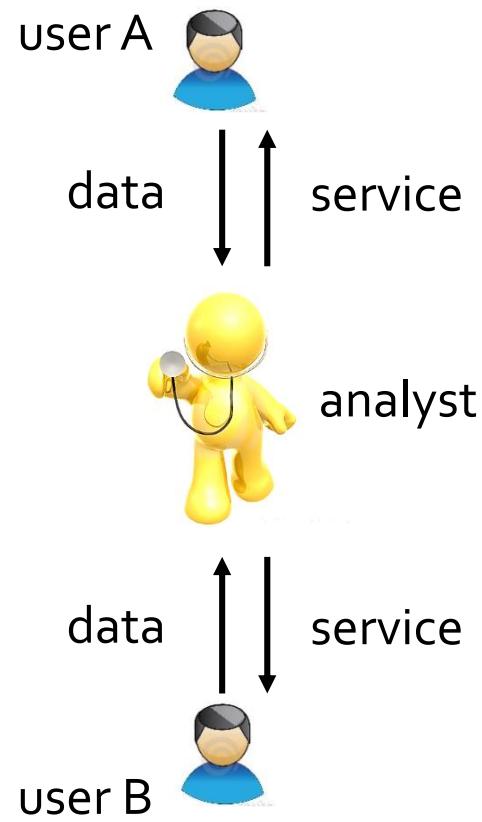
find the **privacy mechanism** that
maximizes utility

Three main settings

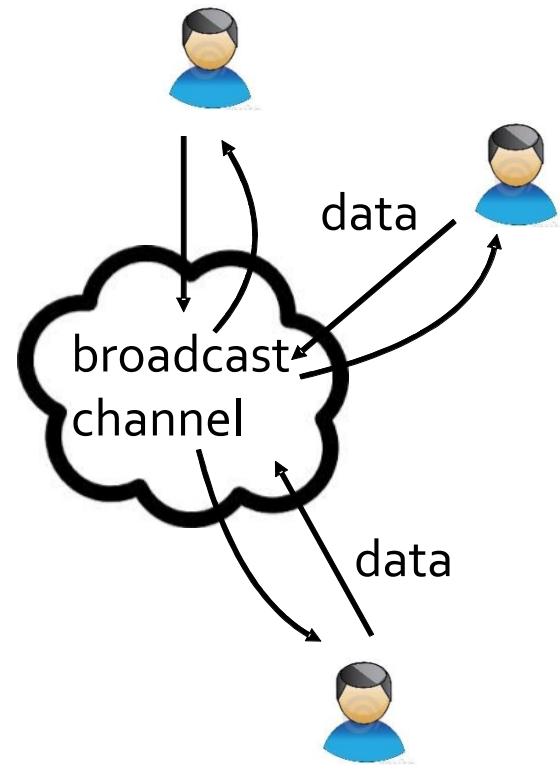
Global Privacy



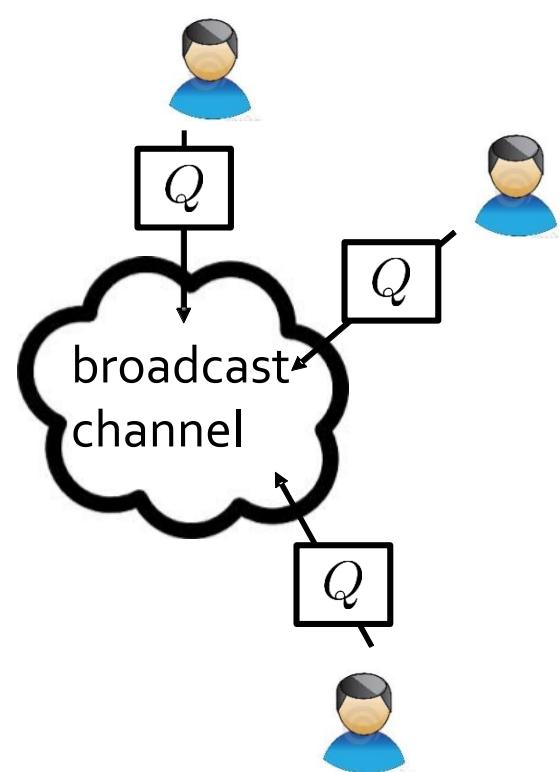
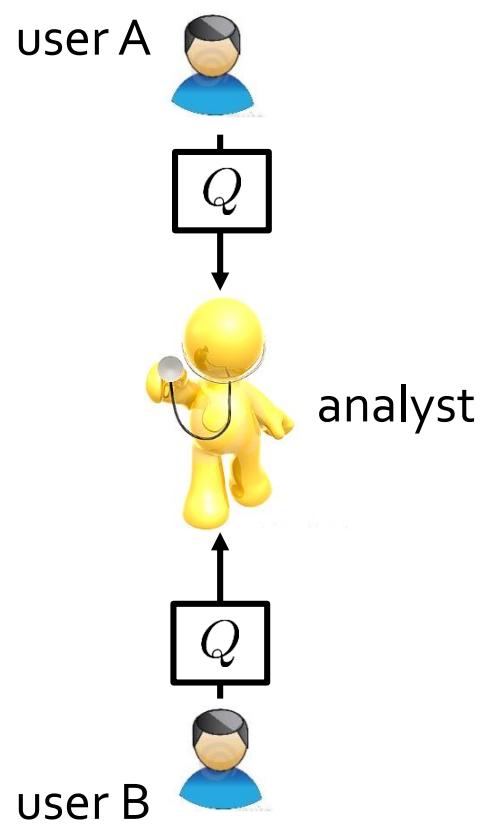
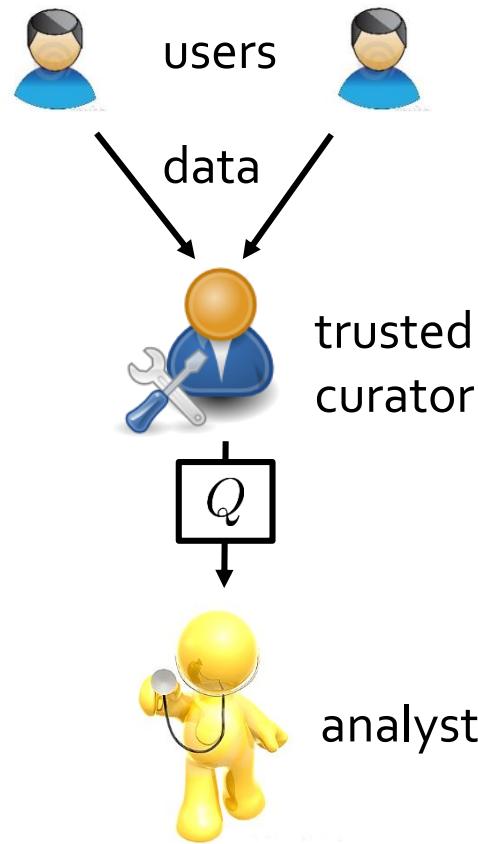
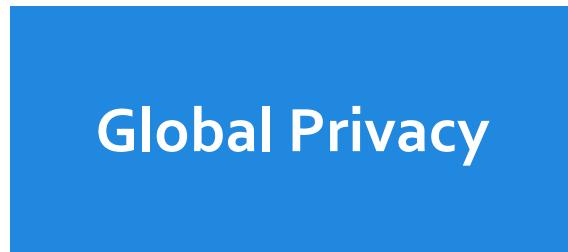
Local Privacy



Multi-Party Privacy



Three main settings



Our results

Global Privacy

Local Privacy

Multi-Party
Privacy

privacy mechanisms that achieve the best
privacy-utility tradeoff

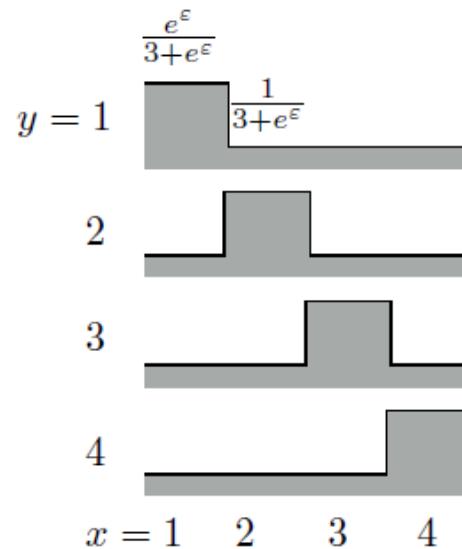
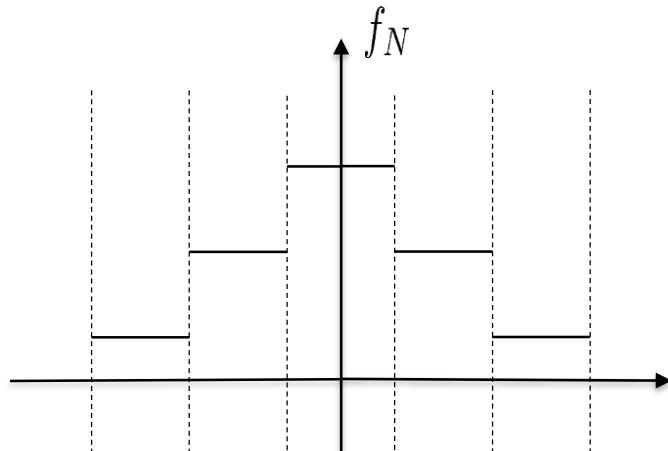
Our results

Global Privacy

Local Privacy

Multi-Party
Privacy

the optimal mechanisms in all three settings have a **staircase shape**

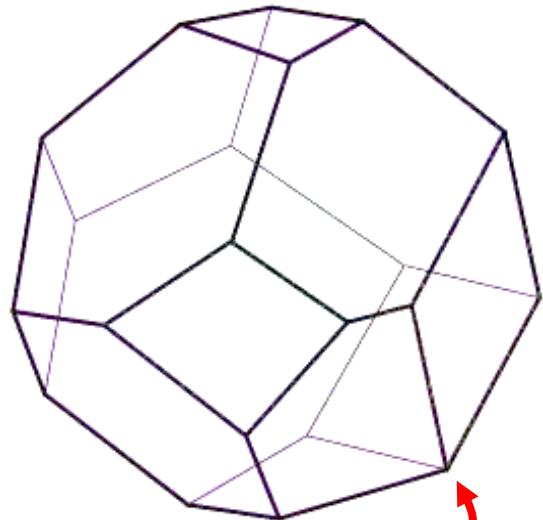


Main tools used

Geometry of differential privacy

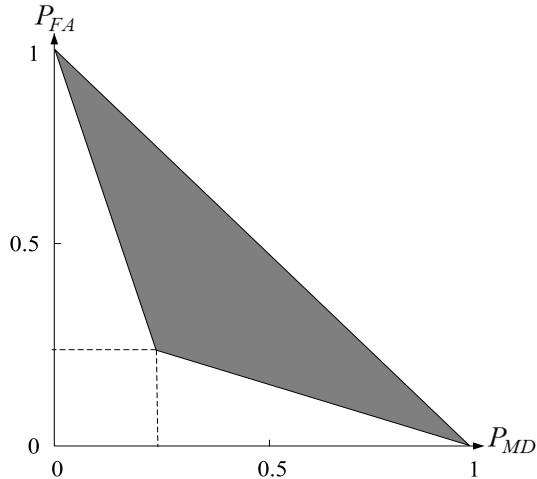
maximize utility

subject to differential privacy



$$\frac{Q(Y|X)}{Q(Y|X')} \in \{e^{-\varepsilon}, 1, e^{+\varepsilon}\}$$

Privacy as a region

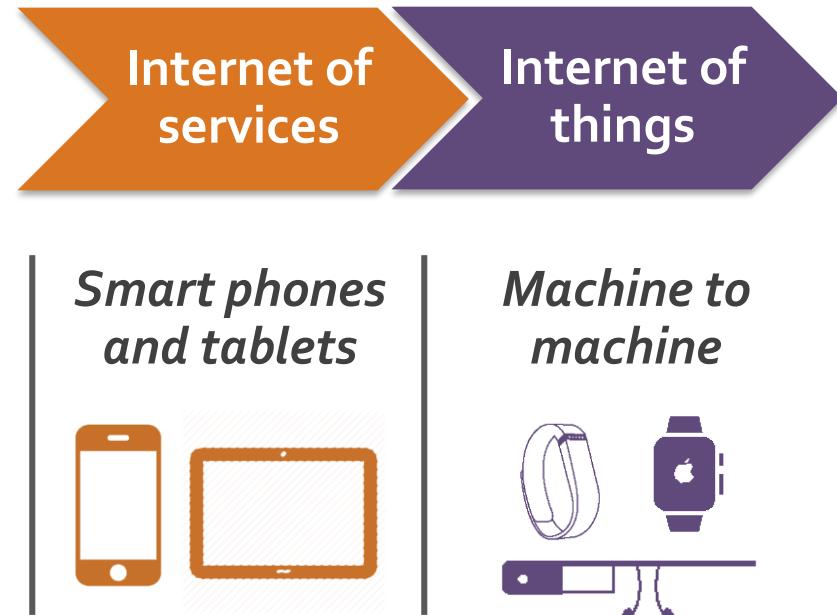
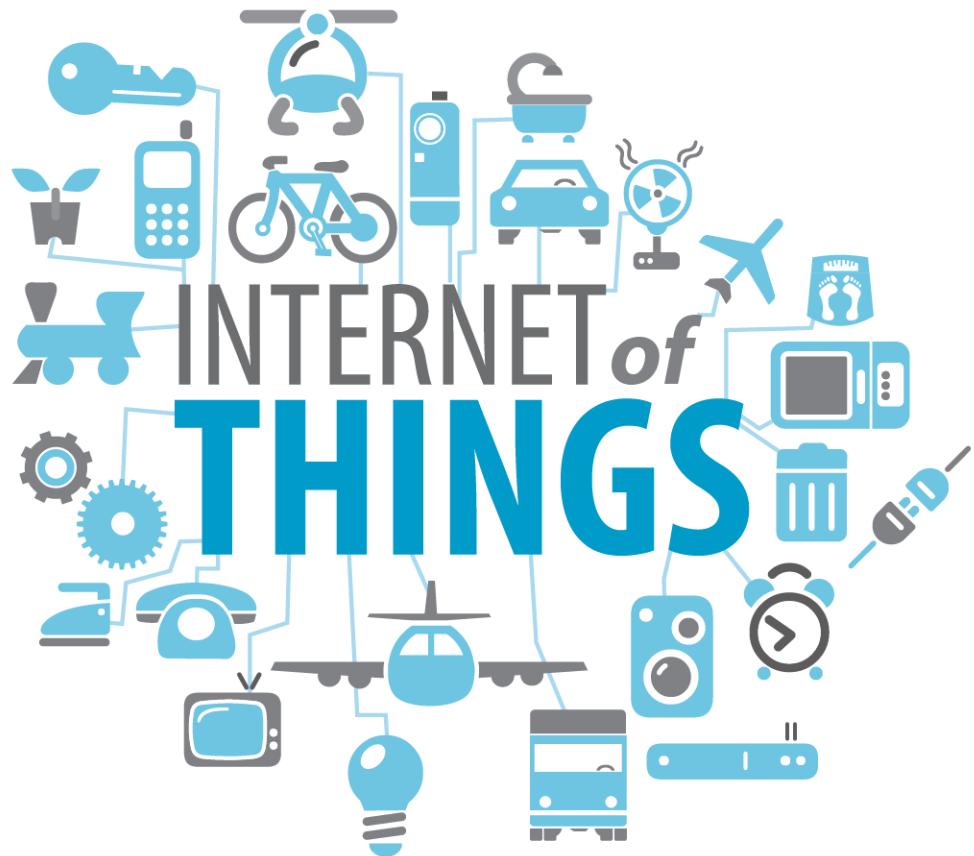


leads to **optimal** results in

- [1] Composition
- [2] Local Differential Privacy
- [3] Multi-party differential privacy

Research Vision

Unprecedented level of connectivity



Privacy preserving
technologies

On-device
intelligence

Ultra-low power
communication

Collaborations



Pramod
Viswanath



Sewoong
Oh



Kannan
Ramchandran



Pavan
Hanumolu



Songbin
Gong



Giulia
Fanti



Keith
Bonawitz



Brendan
McMahan



Daniel
Ramage

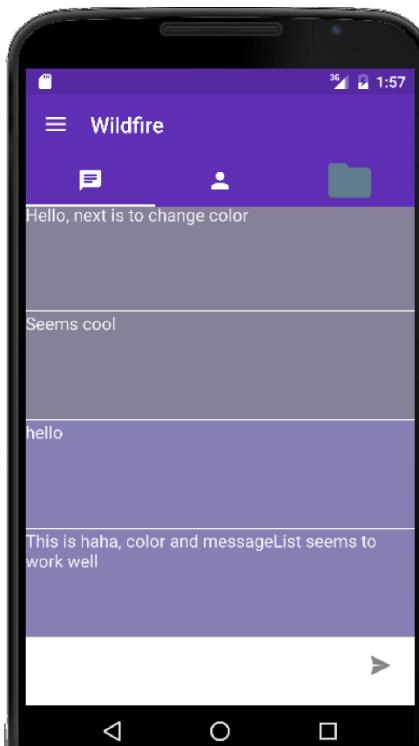
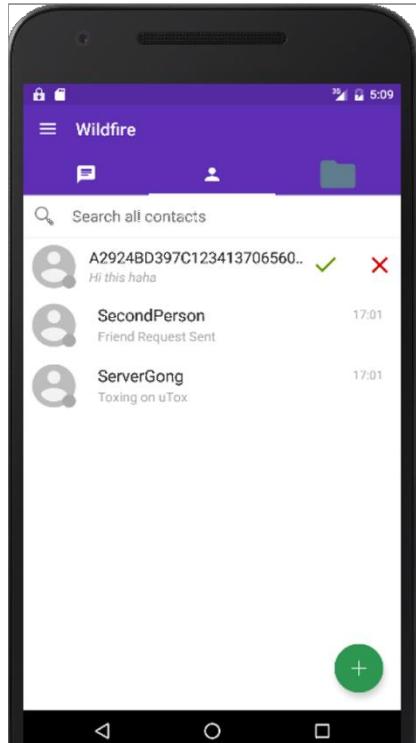


Haitham
Hassanieh

THANK YOU!

BACK UP SLIDES

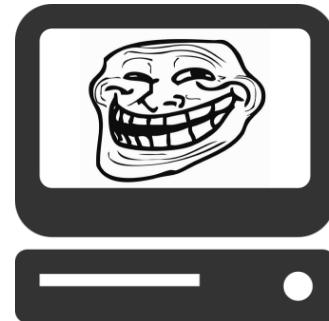
Wildfire: P2P anonymous messaging



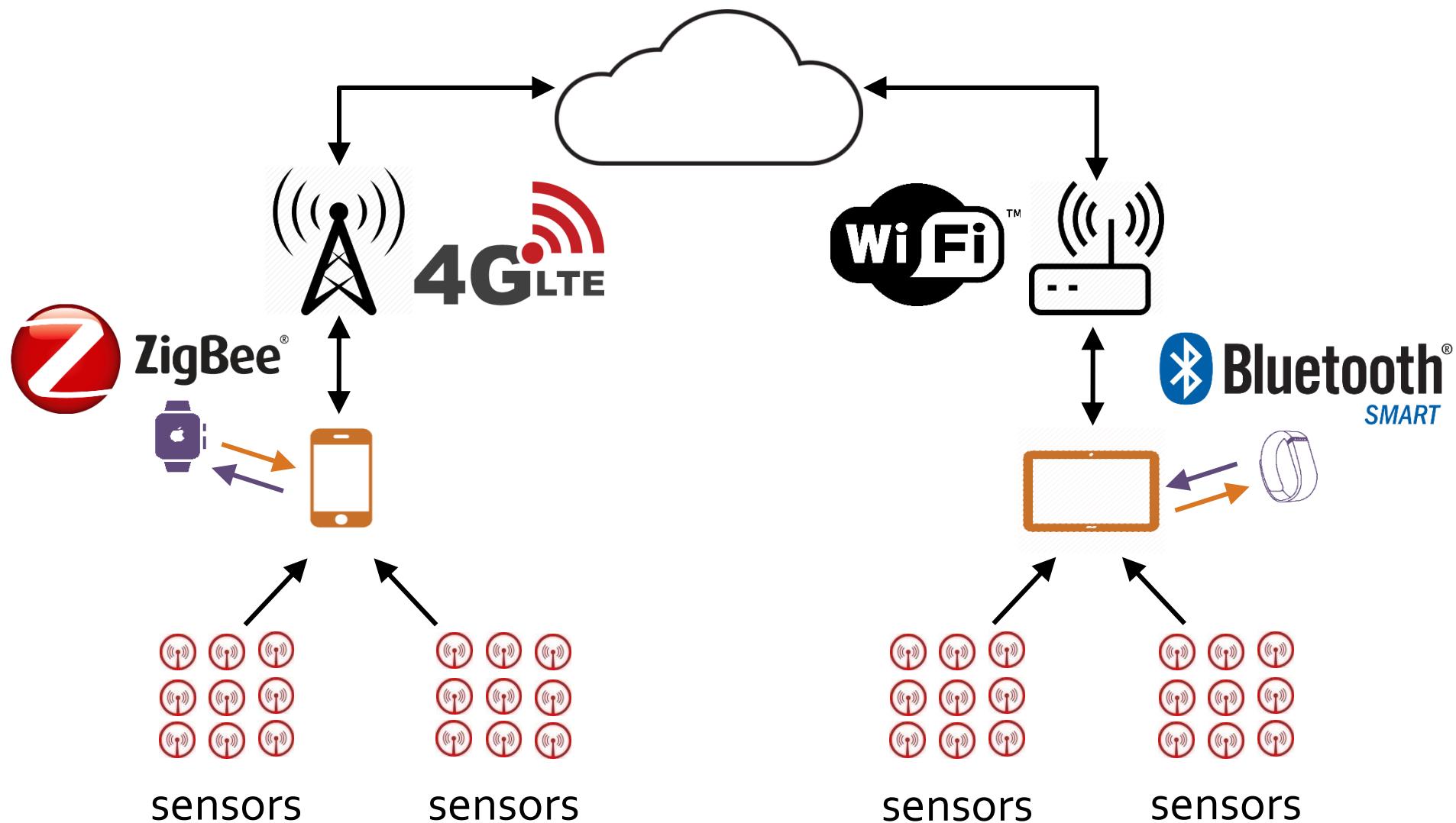
Namespace resolution



Cyberbullying



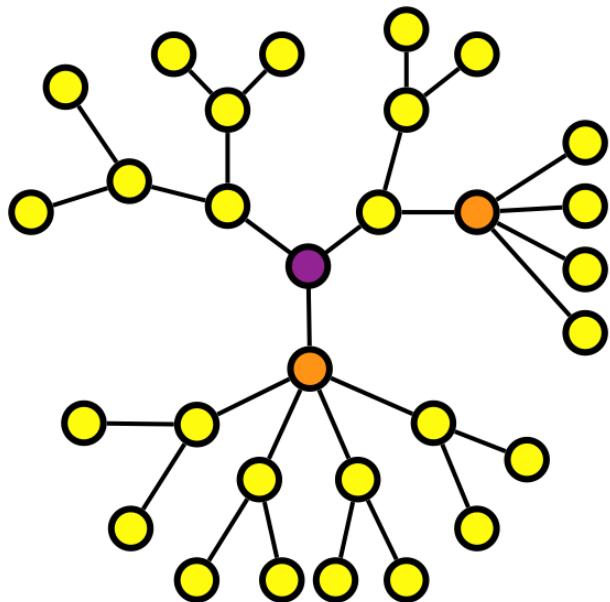
Ultra-low power communication



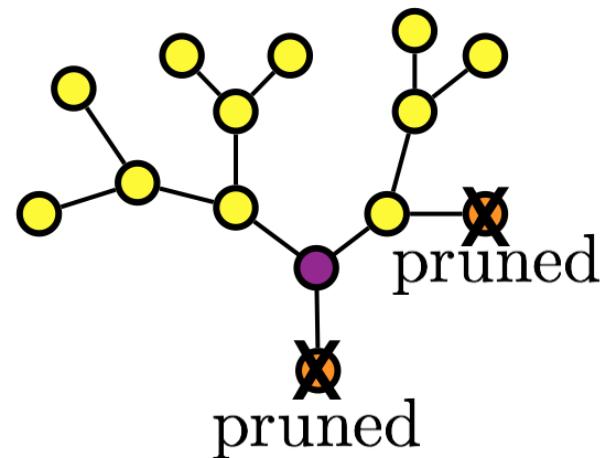
one-way, event driven, asynchronous communication

$$\min_{v \in \text{leaves}} \prod_{v \in P(v, v_T)} d_v \approx (d_{\min} - 1)^{T/2}$$

$$d_v = \begin{cases} 3 & \text{w.p. } 0.7 \\ 5 & \text{w.p. } 0.3 \end{cases}$$



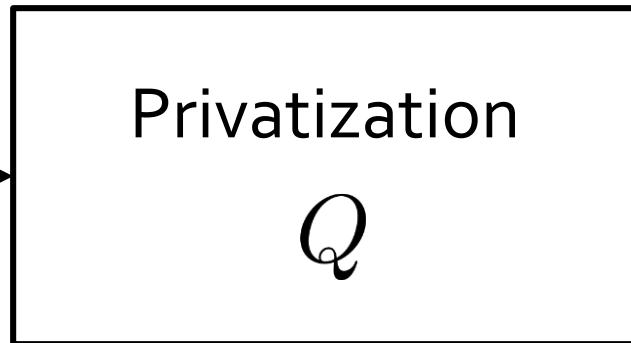
$$d_v = \begin{cases} 3 & \text{w.p. } 0.7 \\ 1 & \text{w.p. } 0.3 \end{cases}$$



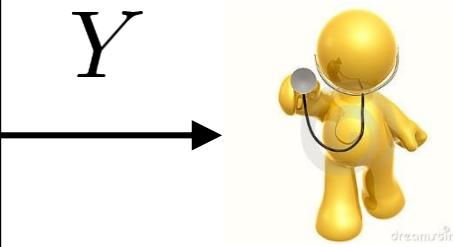
$\downarrow 0.7$ $\downarrow 3$
 If $p_{\min}(d_{\min} - 1) > 1$ then the pruned process survives.

Binary data

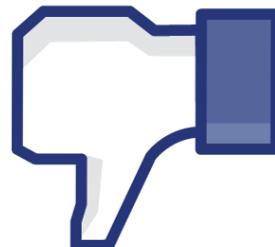
$X \in \{0, 1\}$



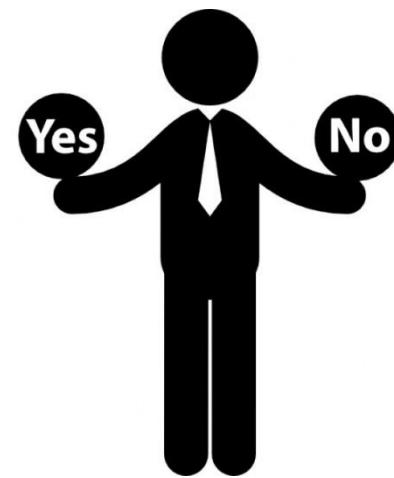
Y



malicious
analyst

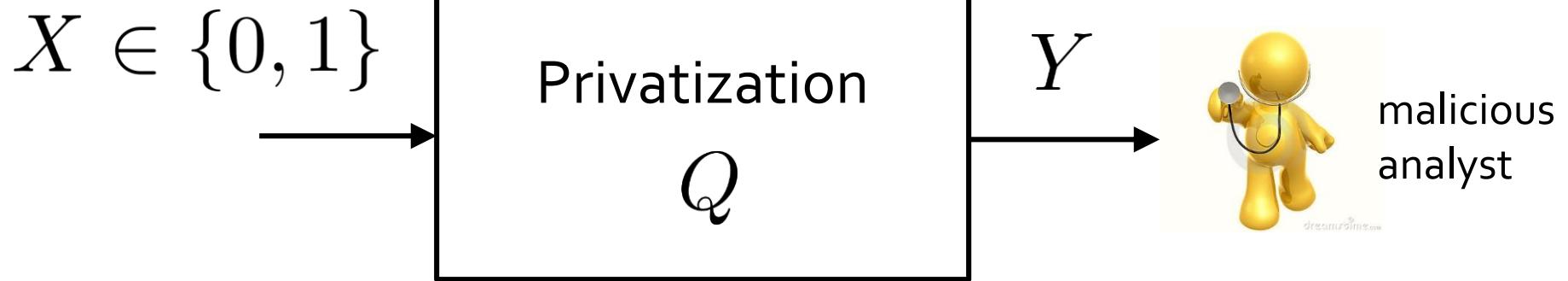


thumbs up
thumbs down



Yes/No
questions

Differential privacy



$$e^{-\varepsilon} \leq \frac{\mathbb{P}(Y|X=1)}{\mathbb{P}(Y|X=0)} \leq e^{+\varepsilon}$$

ε controls the level of privacy
large ε , low privacy
small ε , high privacy

Randomized response



answer truthfully



answer wrongly

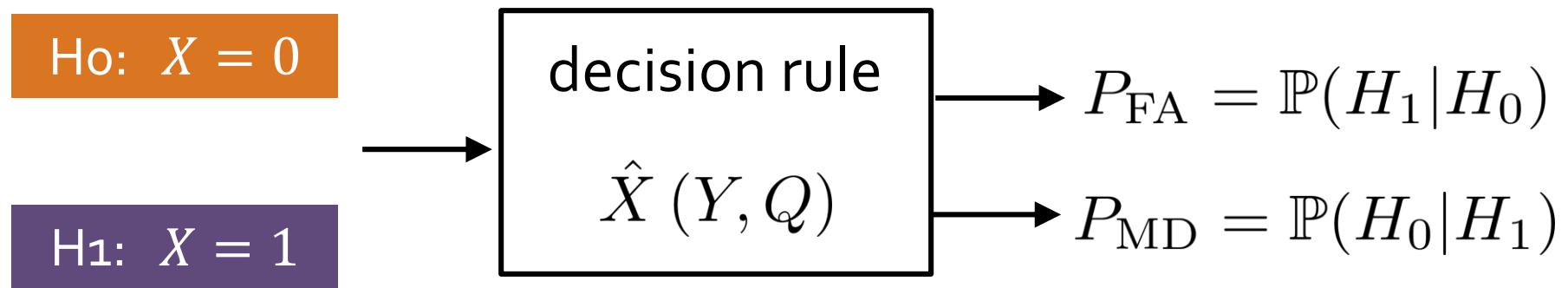
$$\frac{e^\varepsilon}{e^\varepsilon + 1}$$

$$\frac{1}{e^\varepsilon + 1}$$

False alarm, missed detection tradeoff

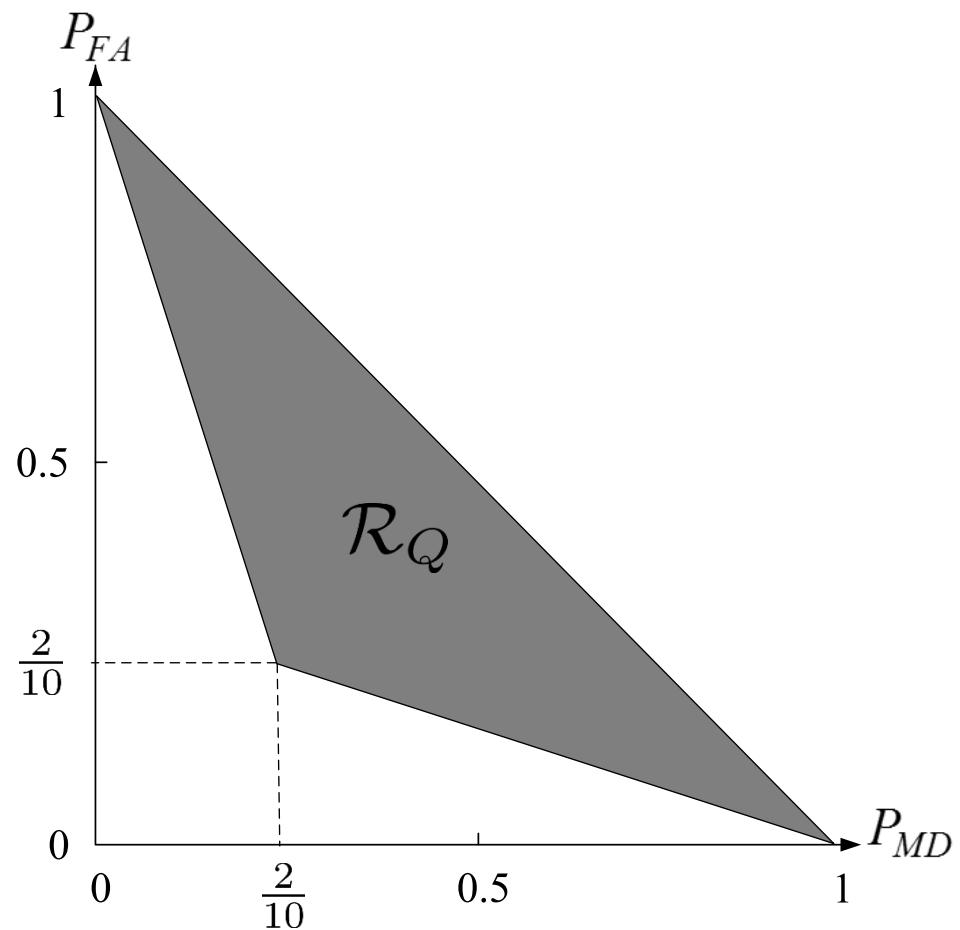
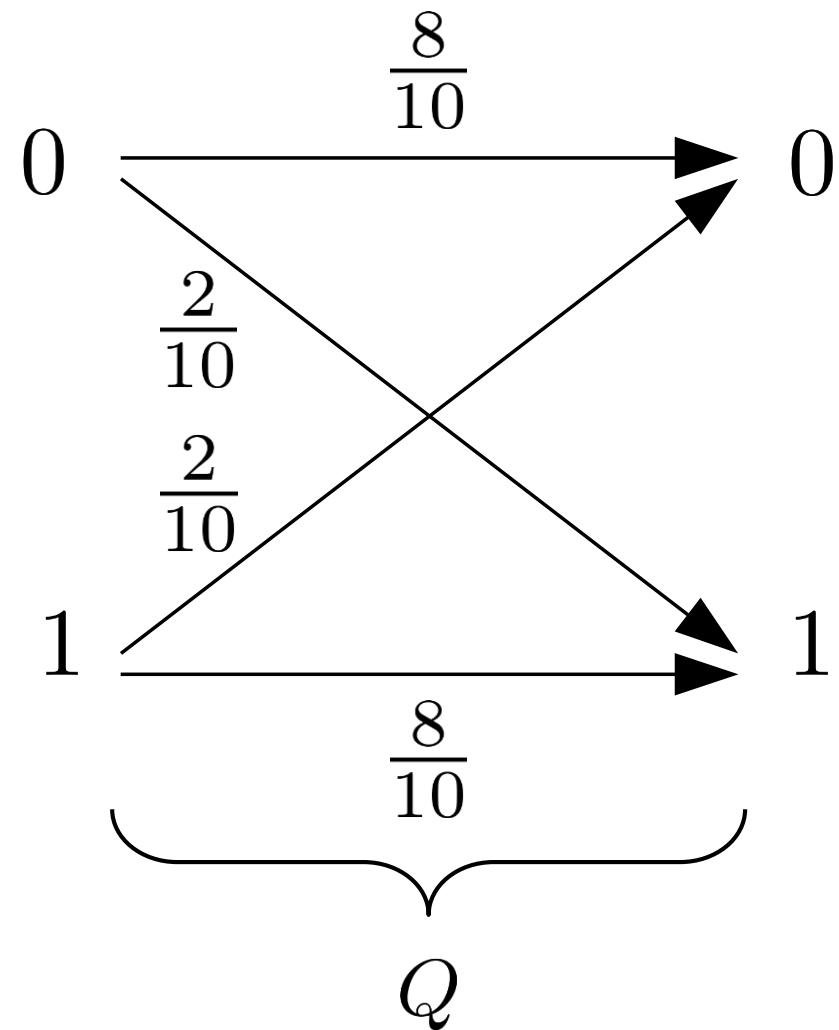


hypothesis test

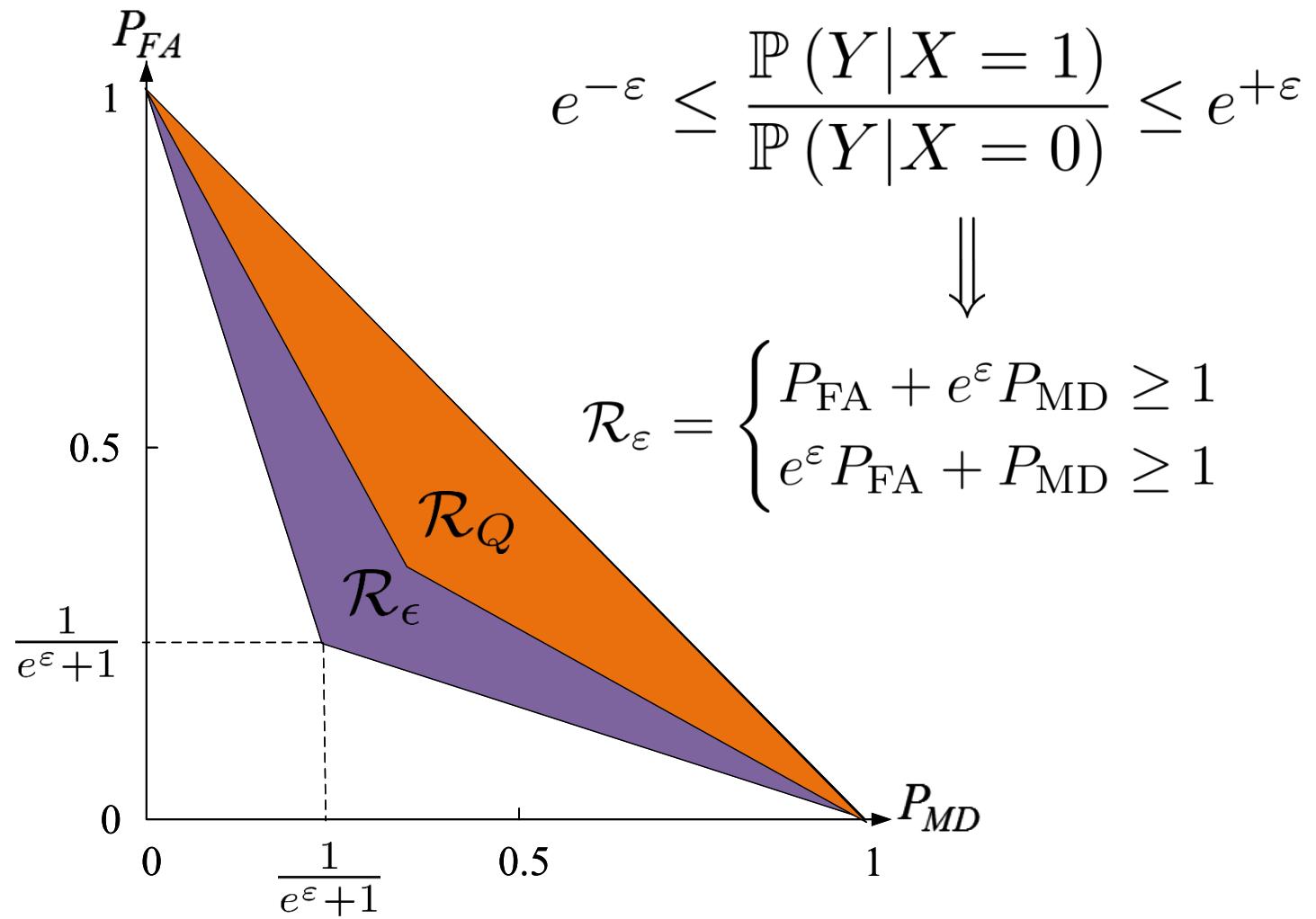


$$\mathcal{R}_Q = \text{all achievable pairs of } (P_{\text{FA}}, P_{\text{MD}})$$

False alarm, missed detection region

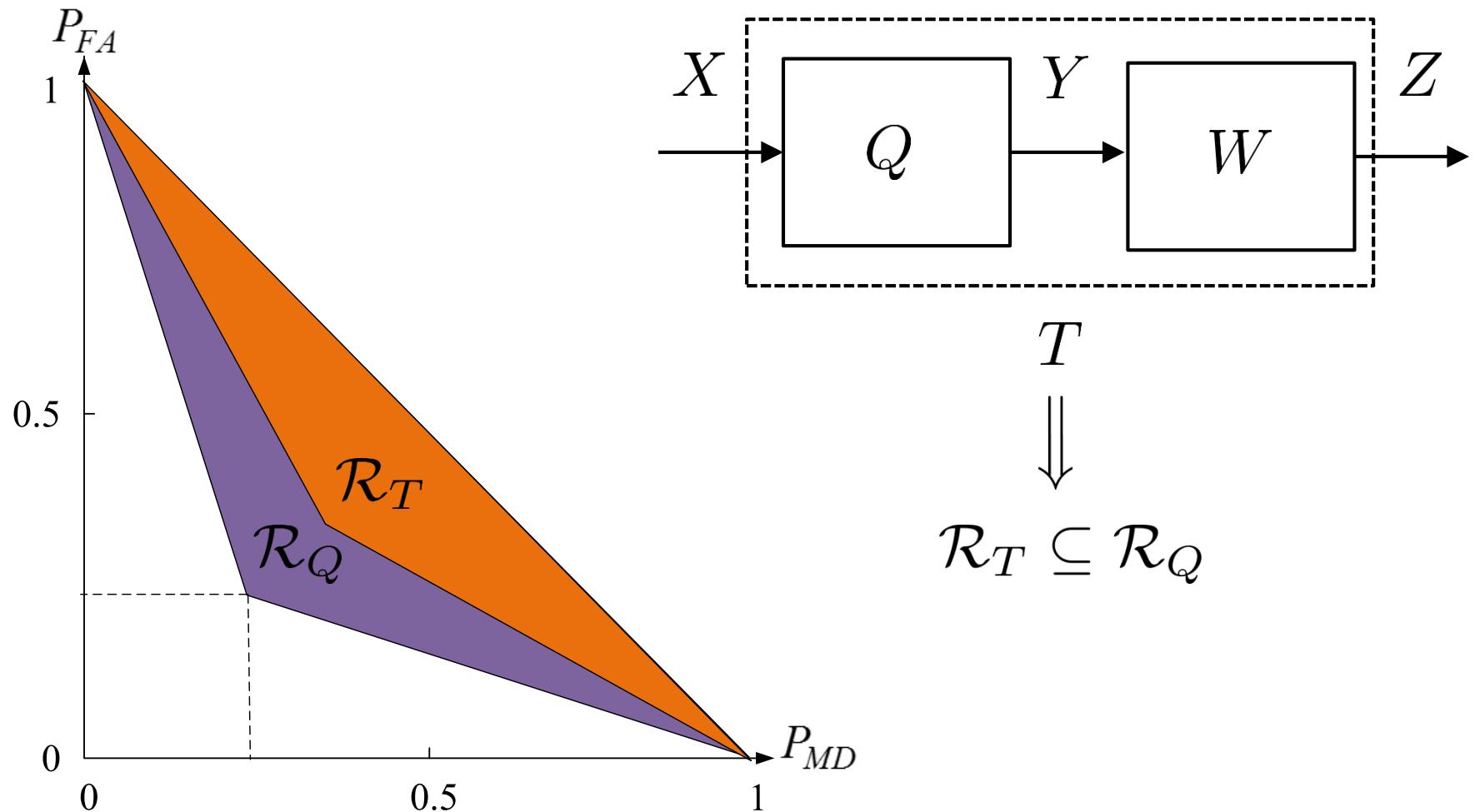


Differential privacy as a privacy region



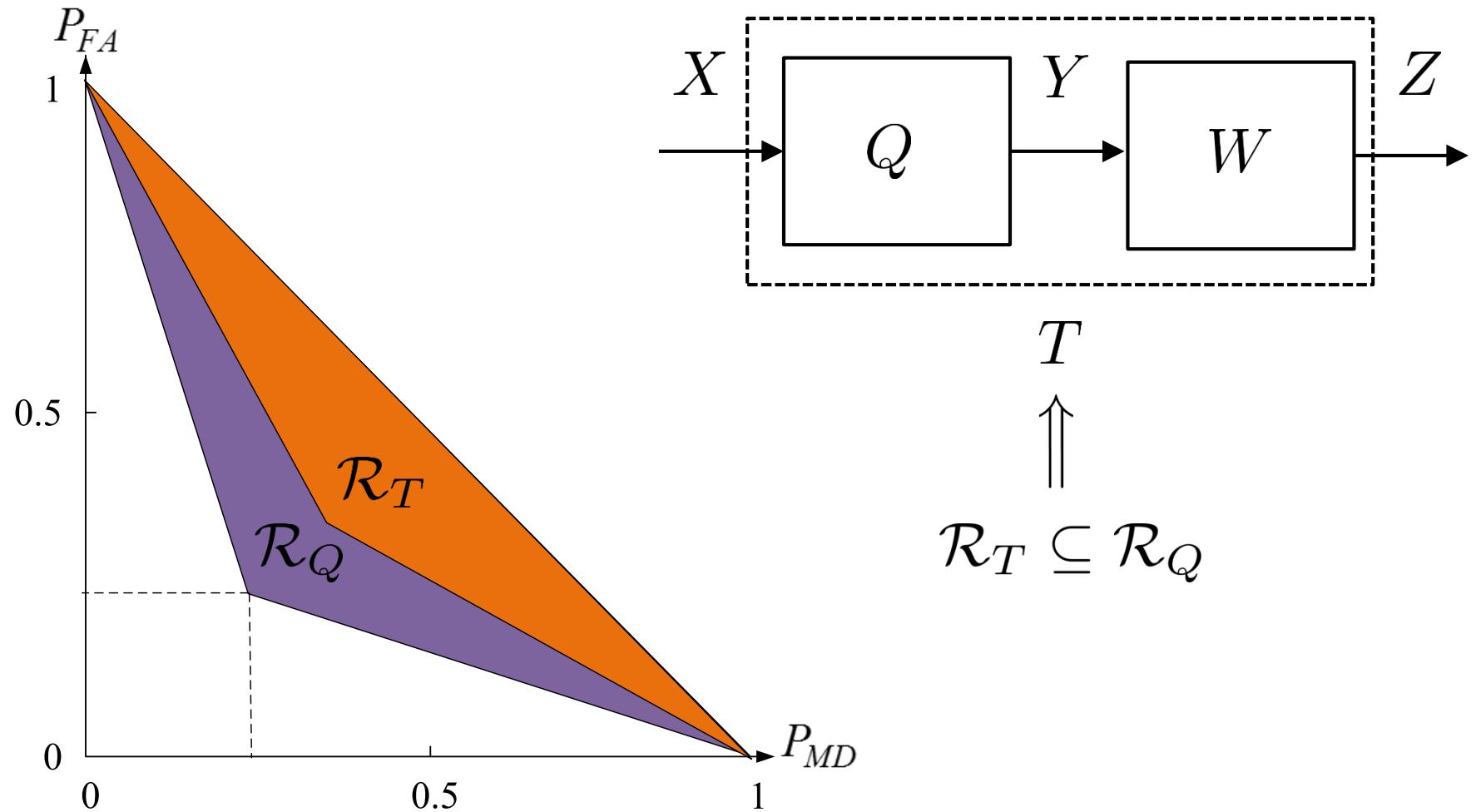
Q is differentially private if and only if $\mathcal{R}_Q \subseteq \mathcal{R}_\varepsilon$

Data processing inequality (DPI)



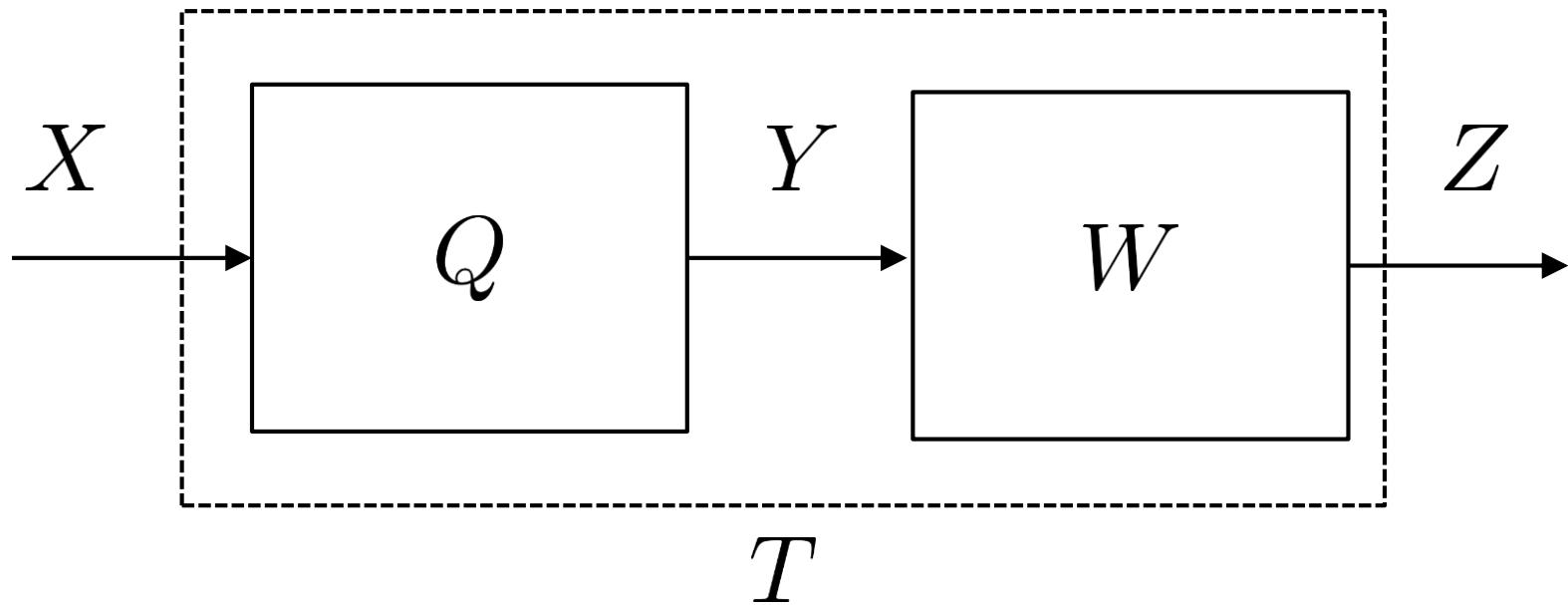
if Q is differentially private then T is differentially private

Converse to DPI [Blackwell 1953]



if $\mathcal{R}_T \subseteq \mathcal{R}_Q$ then there exists a W such that $T = Q \circ W$

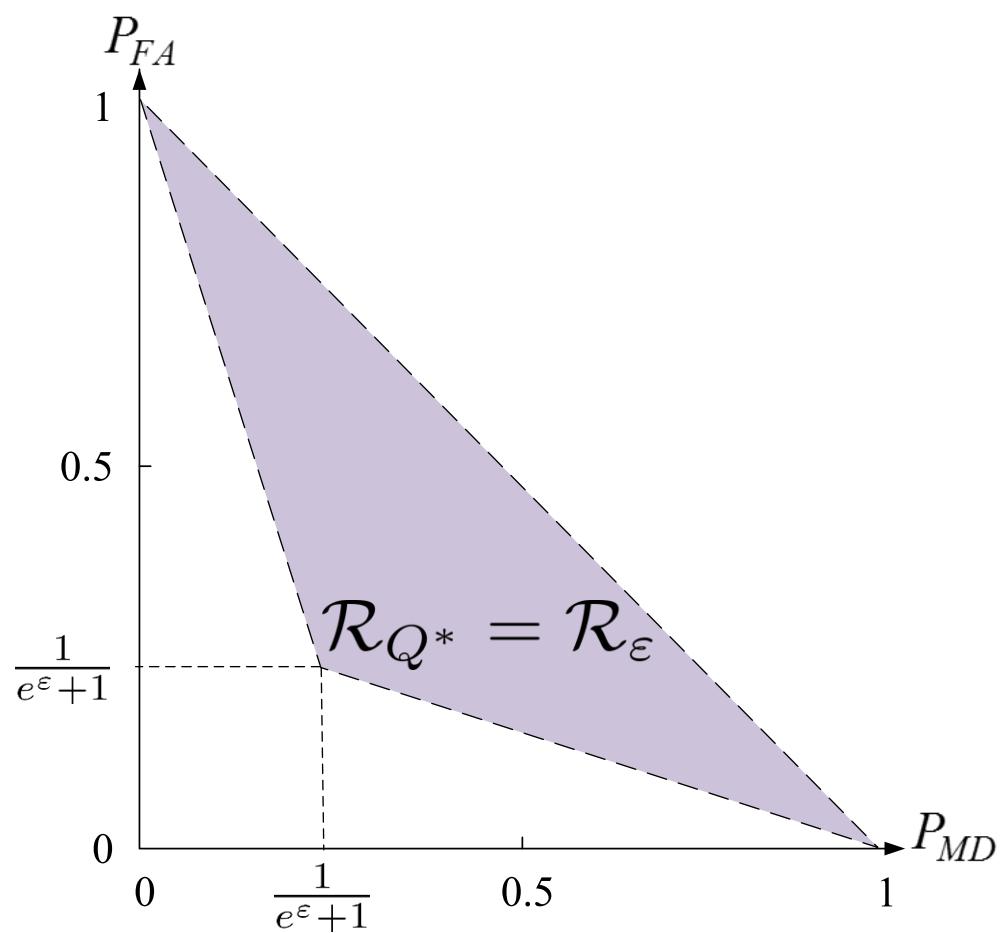
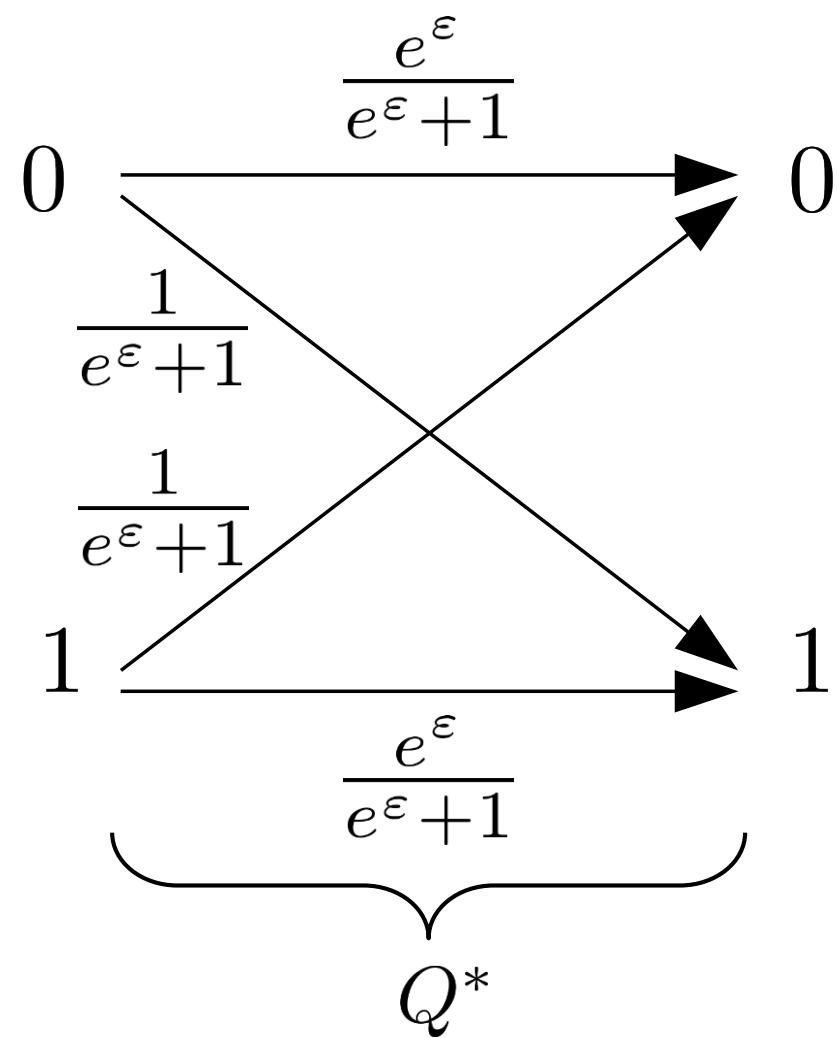
Utility functions obeying DPI



$$U(Q) \geq U(T)$$

further randomization can only reduce utility

Dominant mechanism for DP



optimal for all privacy levels & all utilities obeying DPI