Why does Alice follow Bob?

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School of Informatics and Computing
Indiana University, Bloomington

The Role of Information Diffusion in the Evolution of Social Networks

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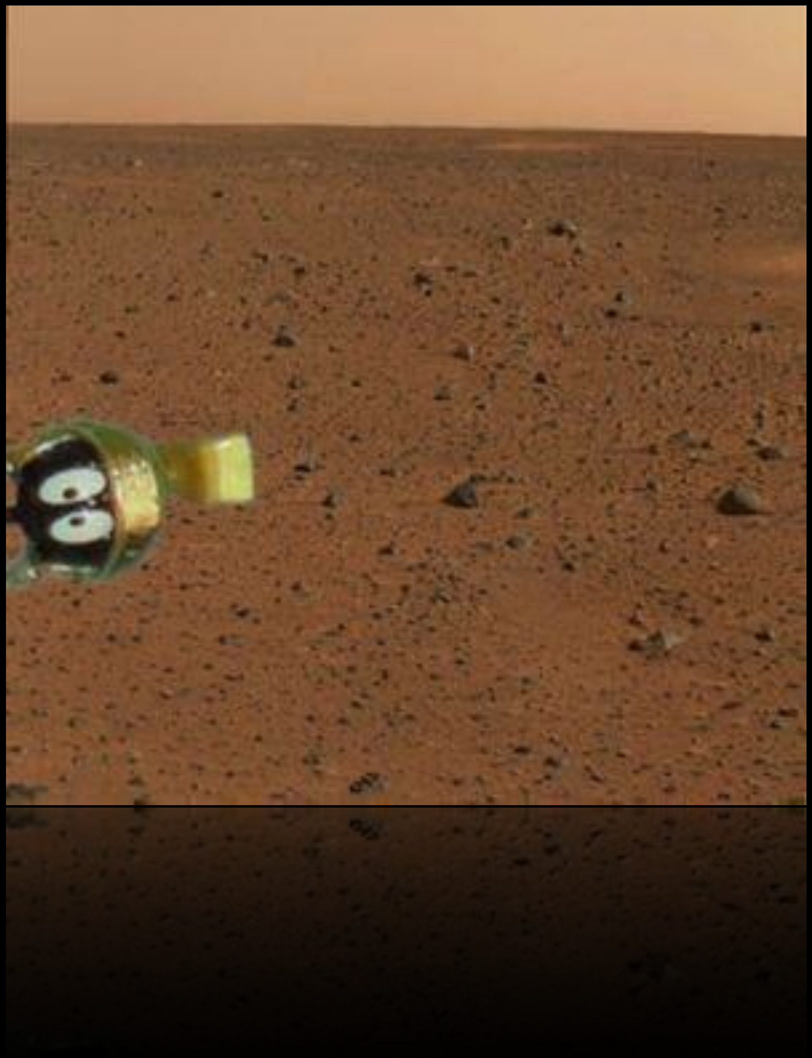
[3]Laboratory for the Modeling of Biological and Socio-technical Systems, Northeastern University, USA
[4]Aix Marseille Université, CNRS, CPT, UMR 7332, Marseille, France
[5]Qatar Computing Research Institute [6]Yahoo! Research Barcelona
[7]Department of Computer Science, University of Torino, Italy



Marvin

2012.08.05 23:05

Stamen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Science News
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Tracking truthiness in the Twitterverse
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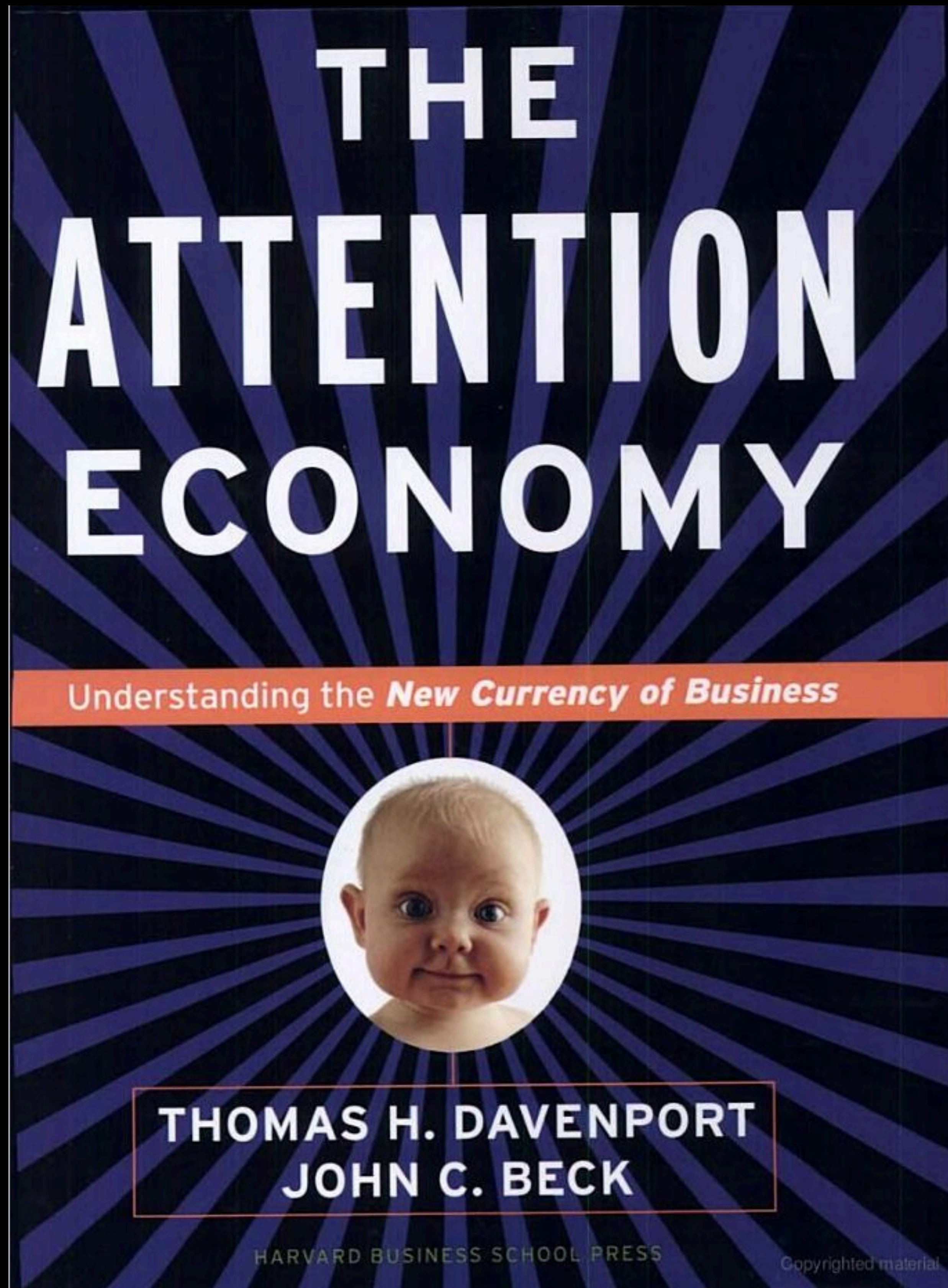
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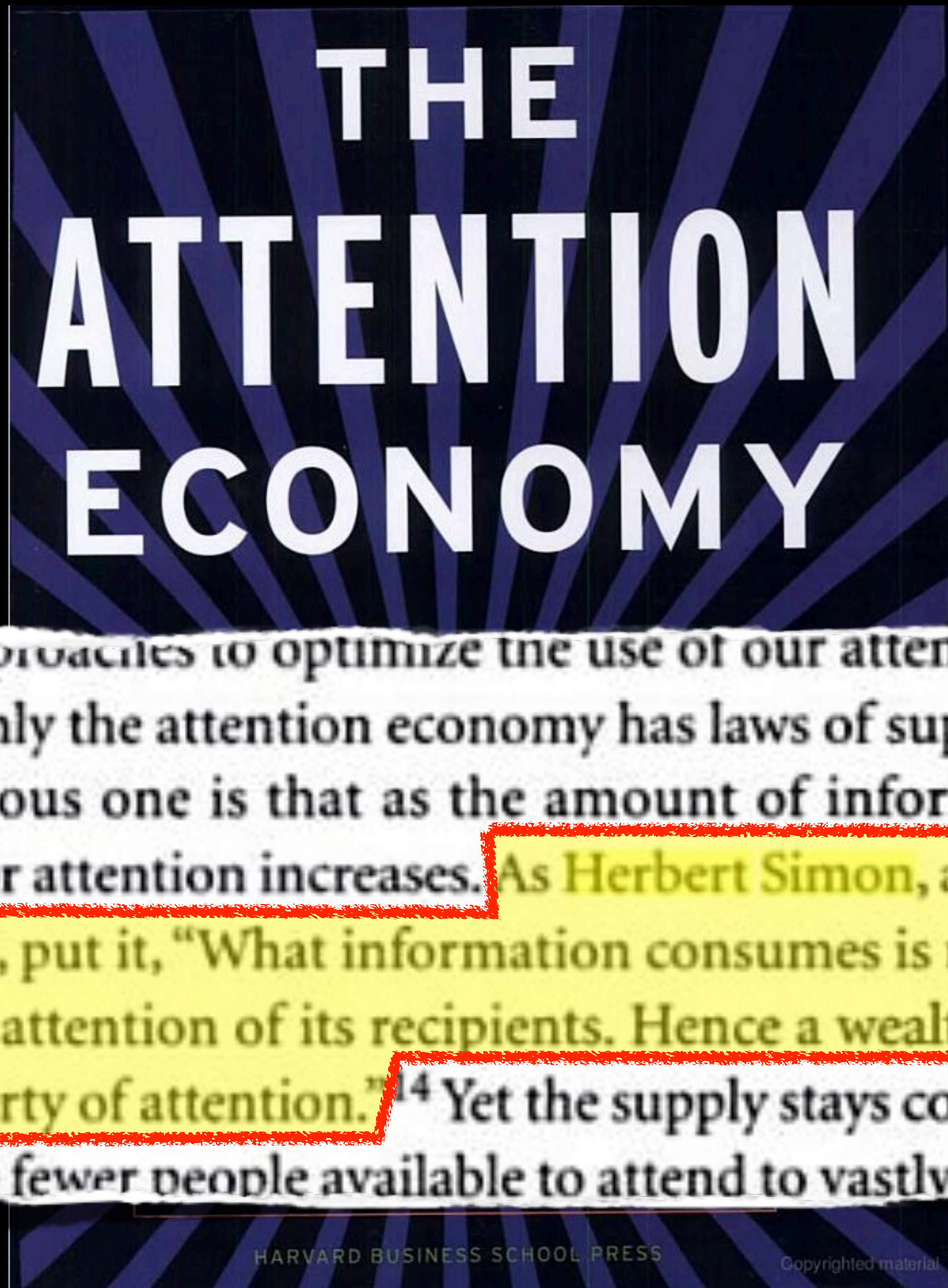
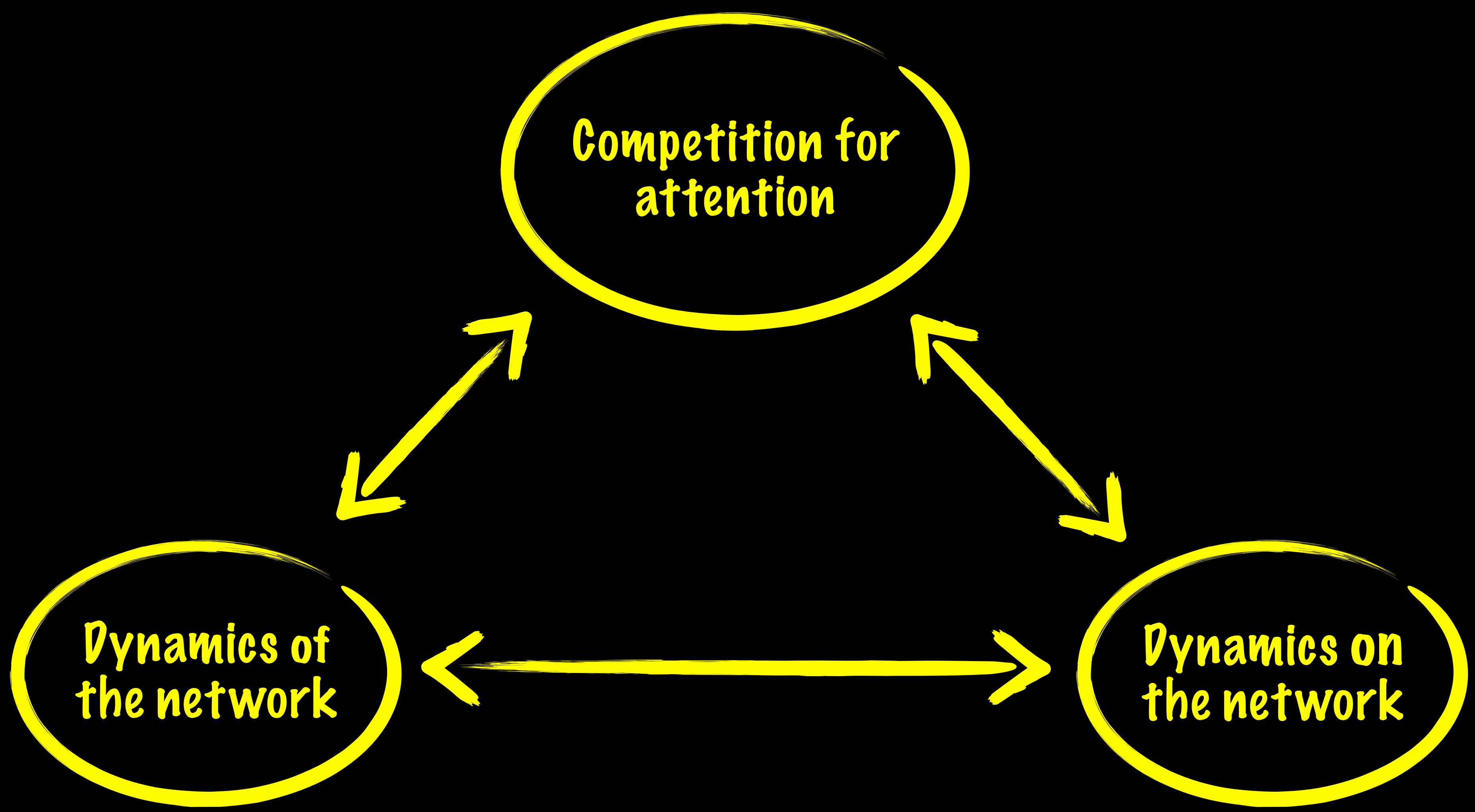
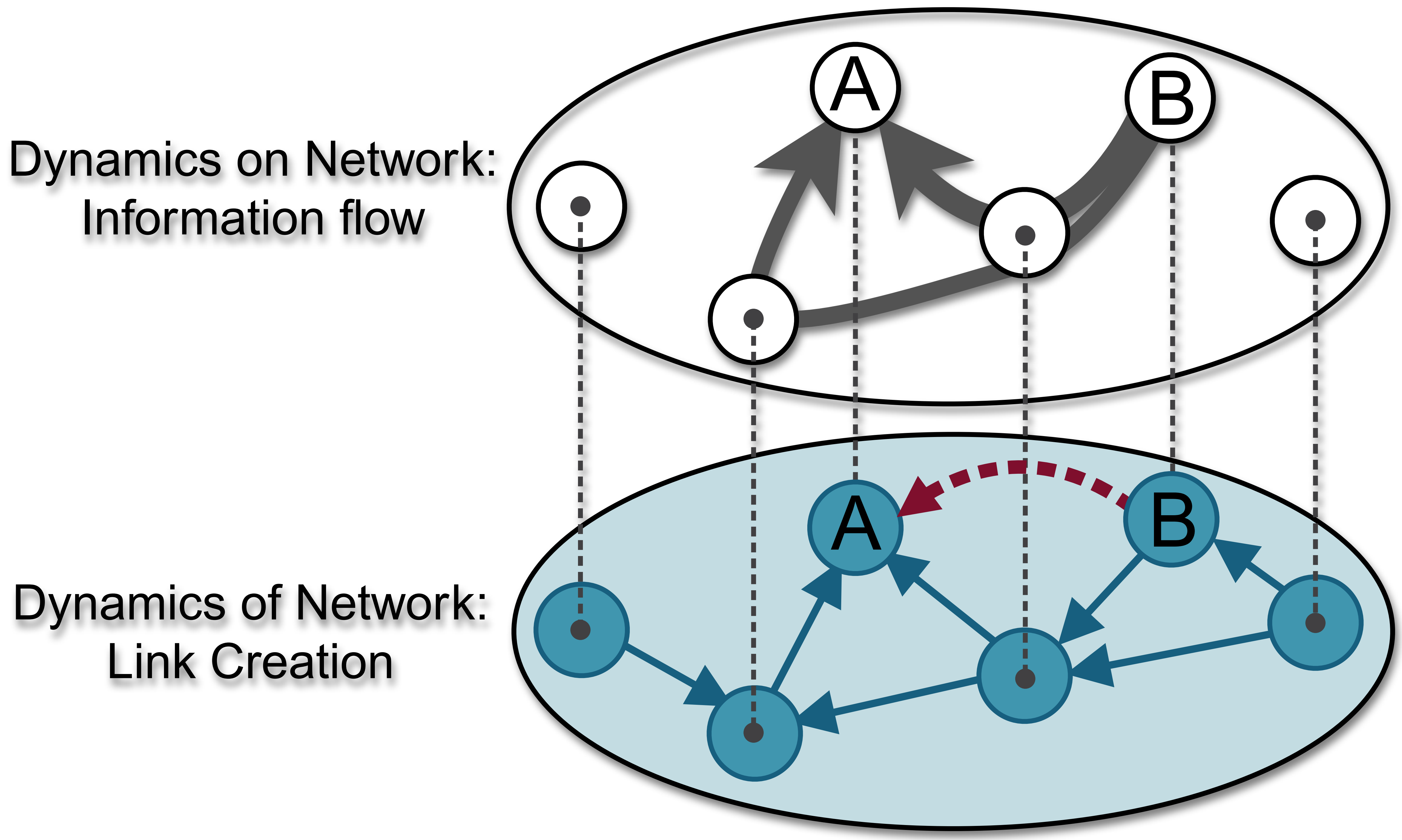
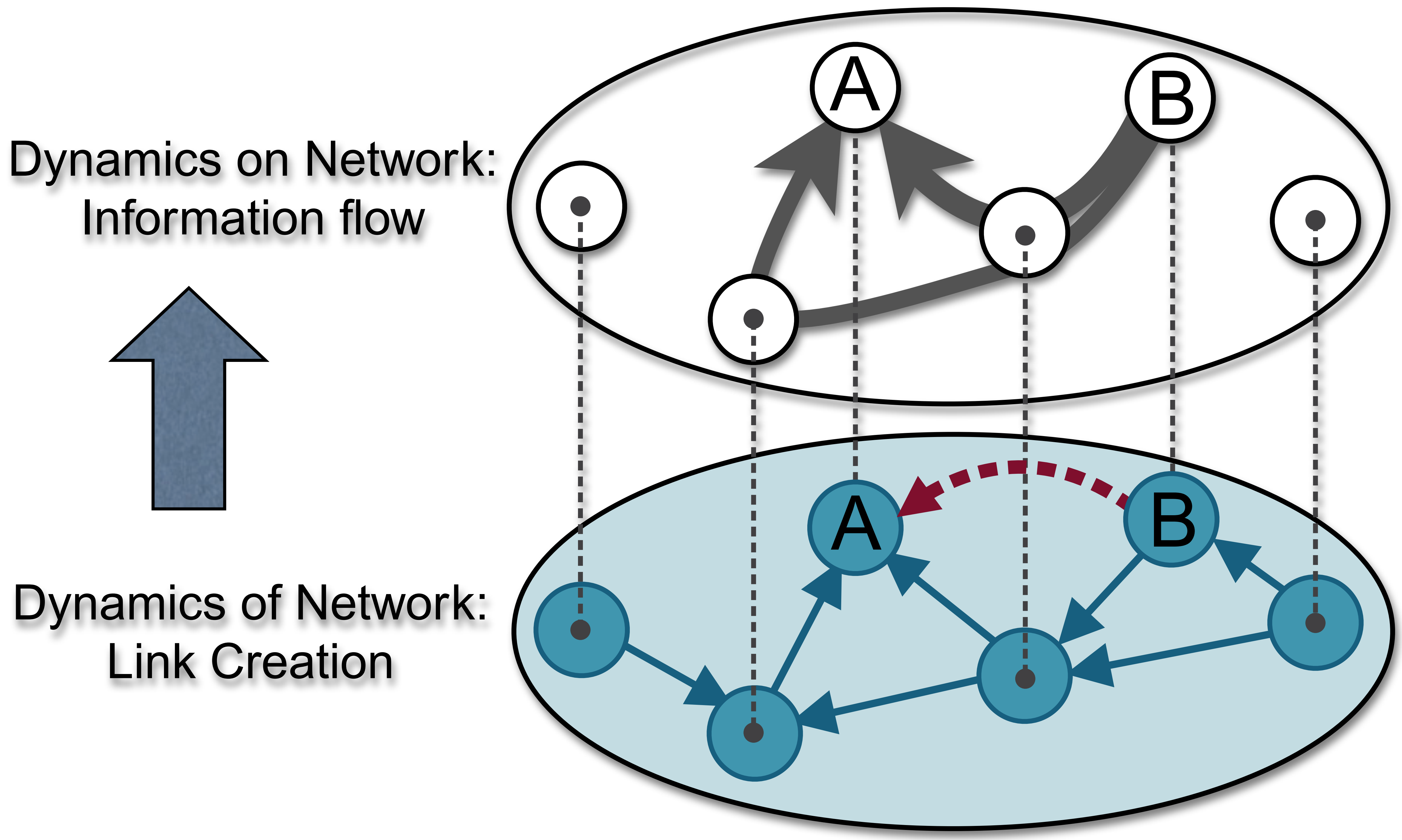


similar approaches to optimize the use of our attention.

Certainly the attention economy has laws of supply and demand. The most obvious one is that as the amount of information increases, the demand for attention increases. As Herbert Simon, a Nobel prize–winning economist, put it, "What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention."[14] Yet the supply stays constant or even shrinks if there are fewer people available to attend to vastly more information. As

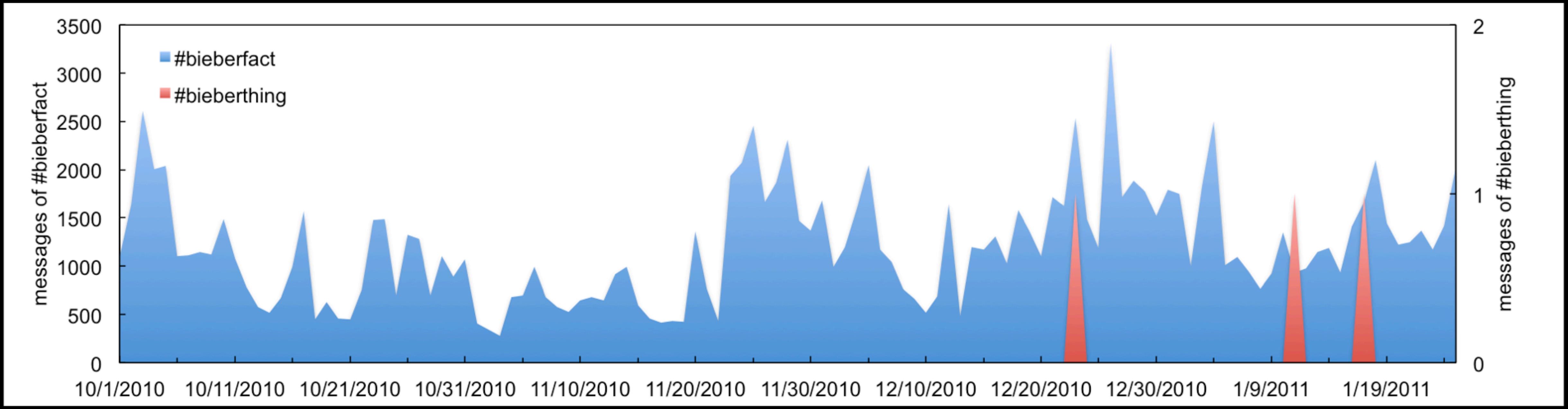

Competition for attention
Dynamics of the network
Dynamics on the network


Dynamics on Network:
Information flow
A
B
Dynamics of Network:
Link Creation
A
B

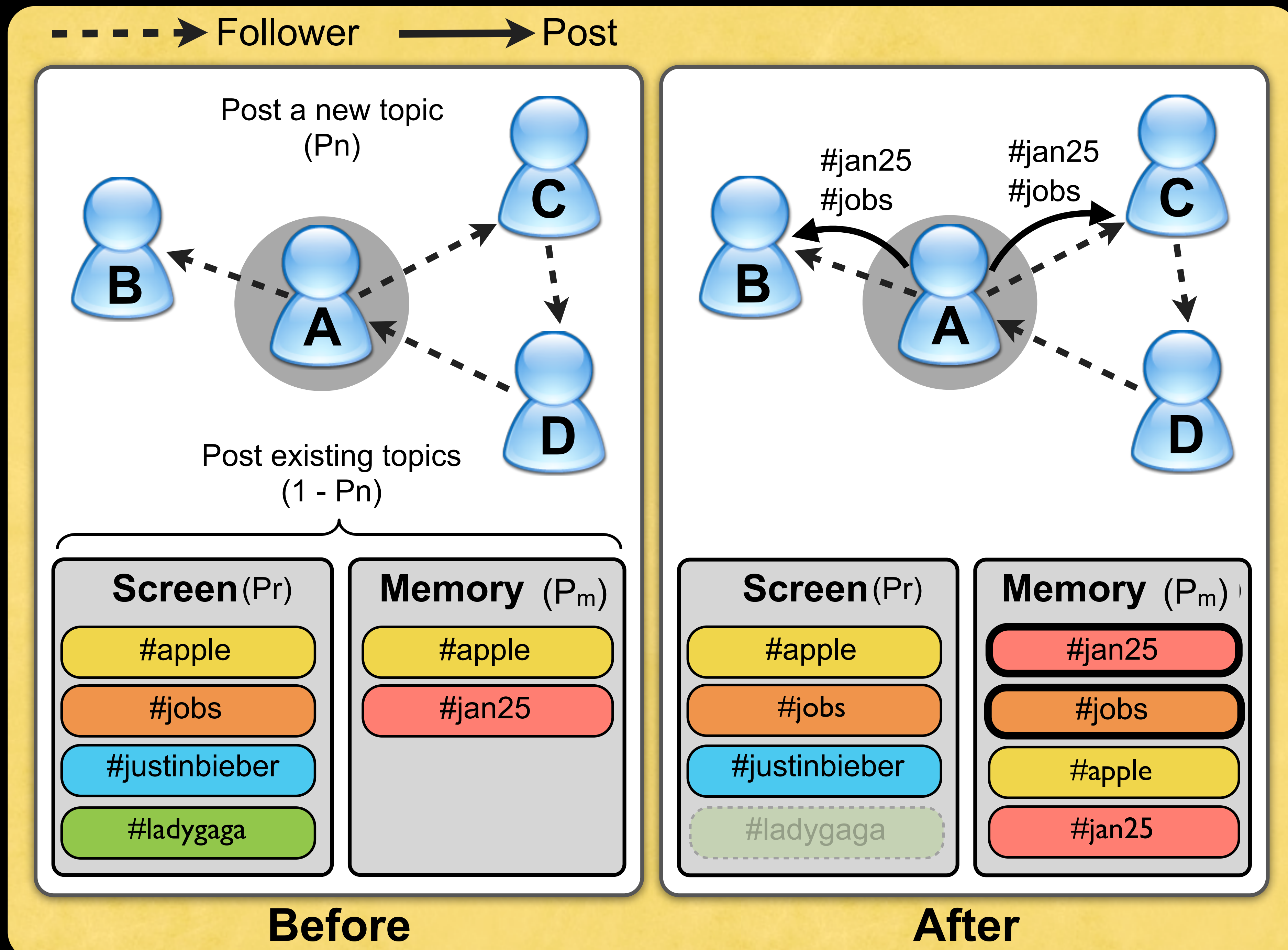


Dynamics on Network:
Information flow
A
B
Dynamics of Network:
Link Creation
A
B

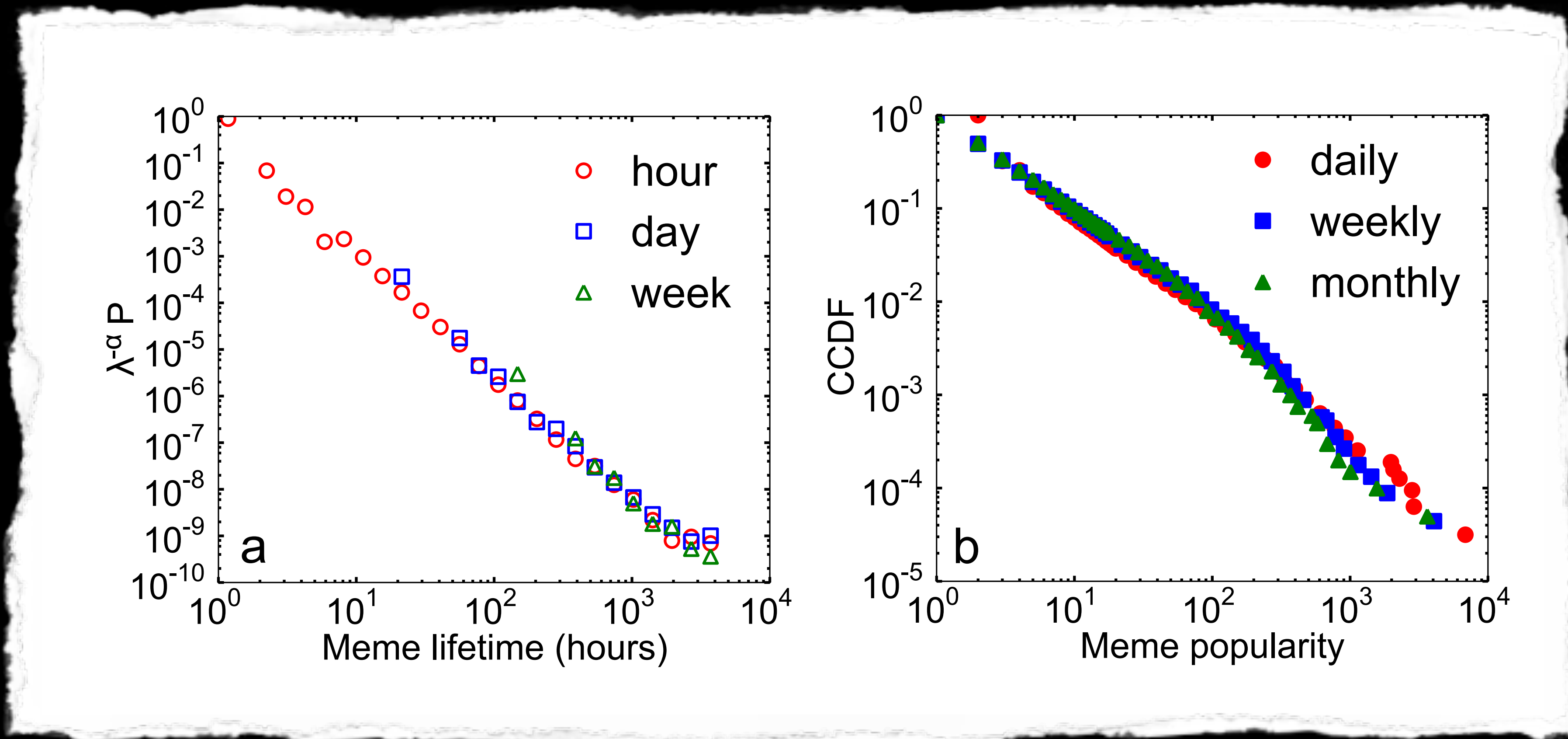
meme	popularity (number of messages)	lifetime (longest consecutive number of days)
#bieberfact	139760	145
#bieberthing	3	1



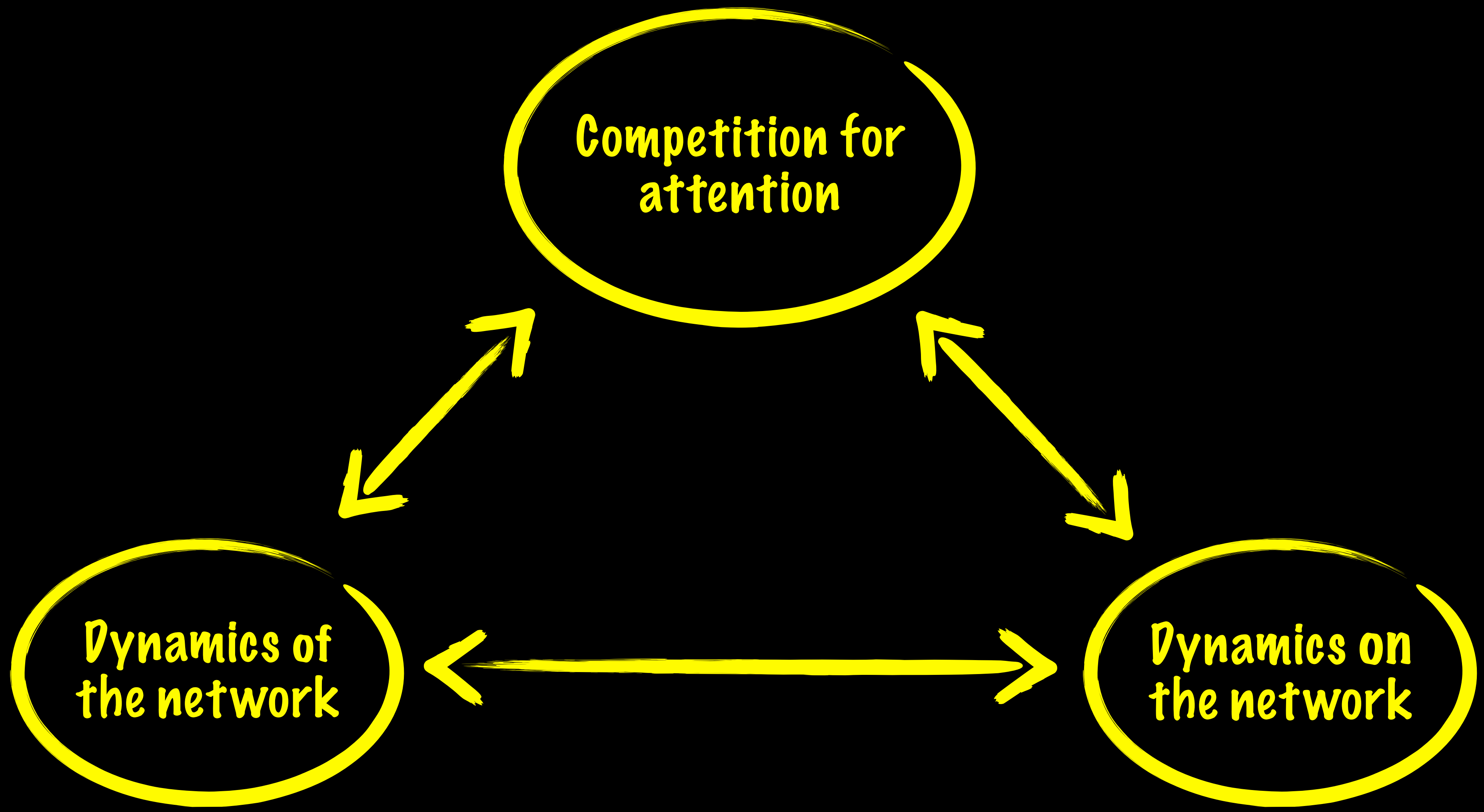
Two key ingredients

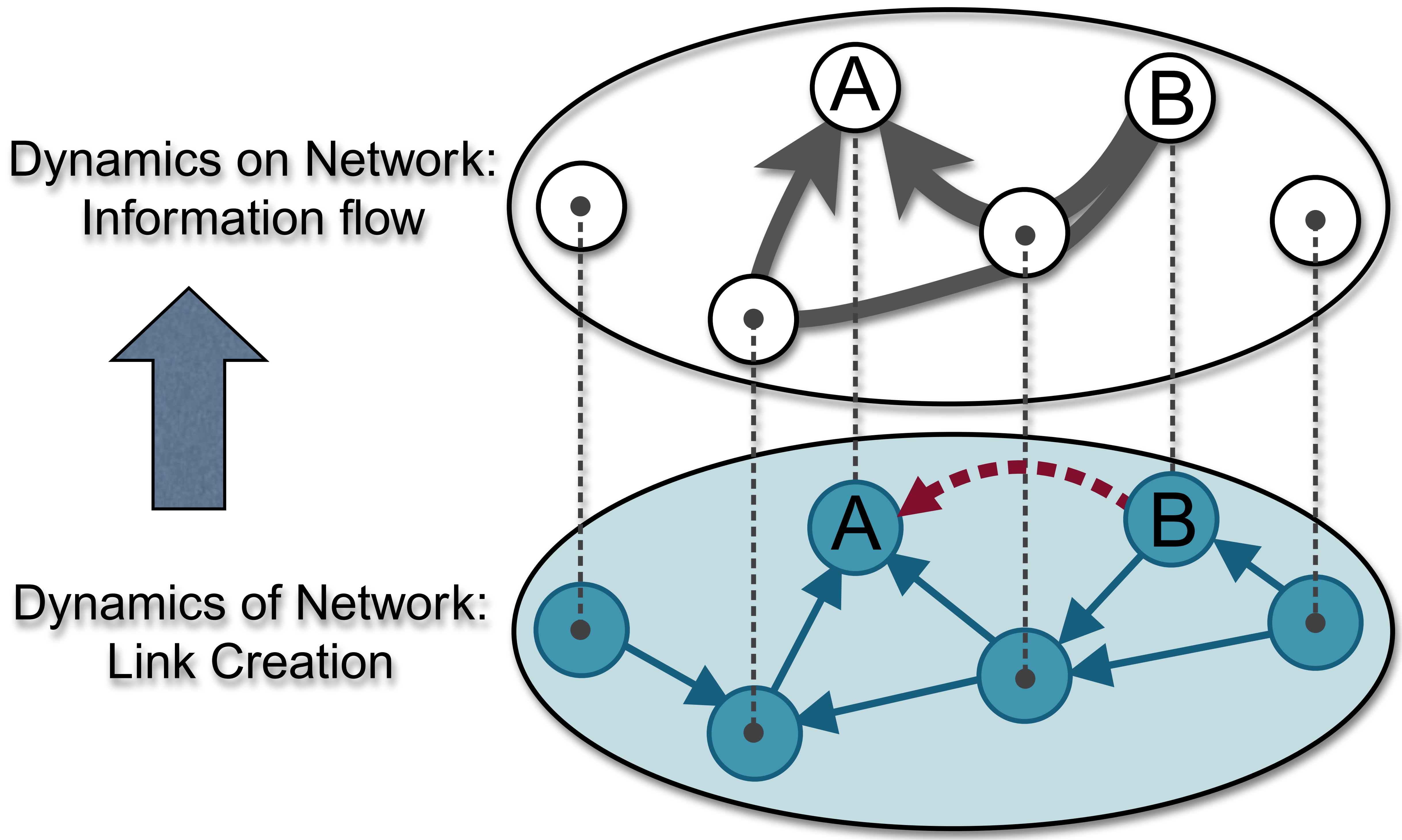


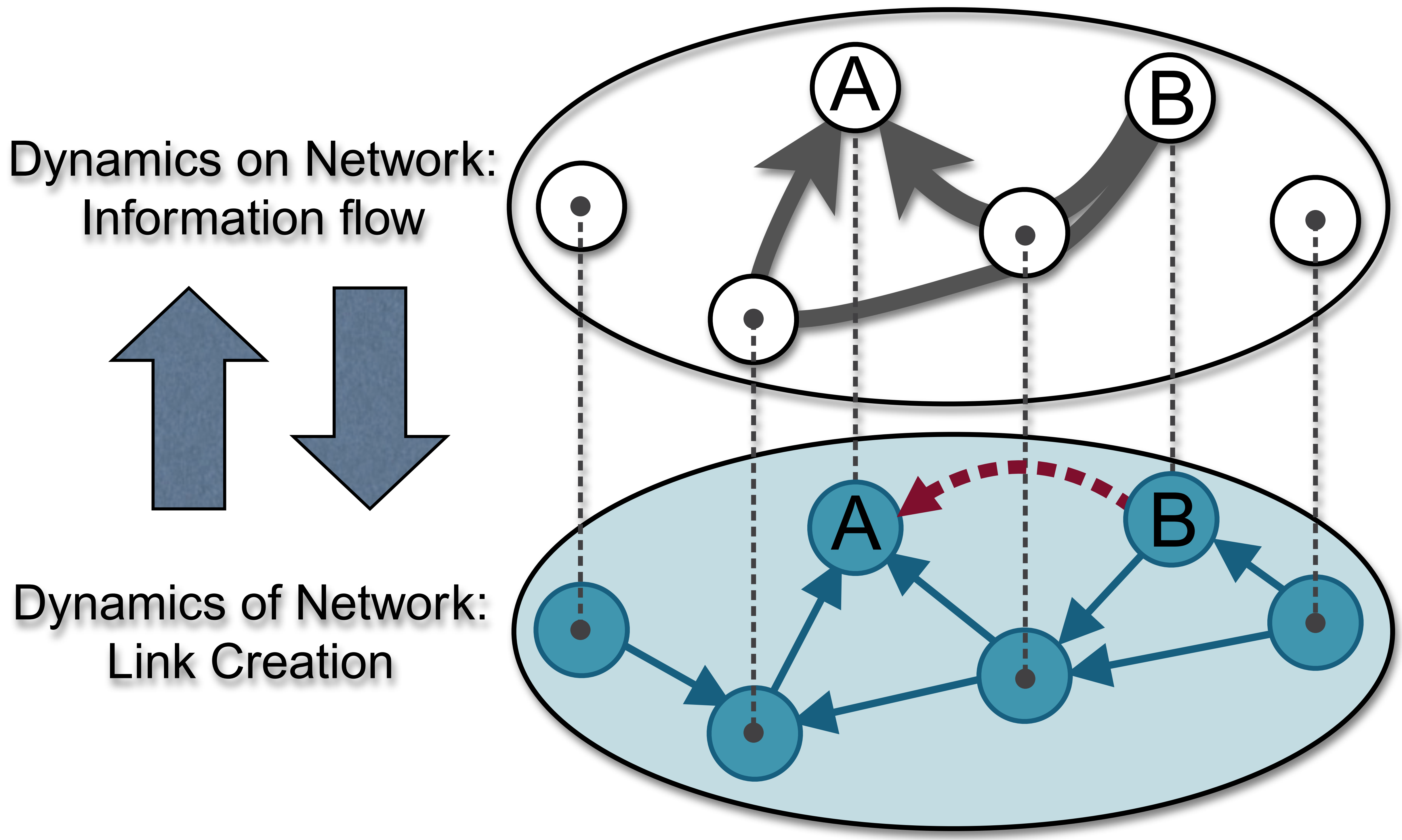
Weng *et al.* *Nature Sci. Rep.* 2012

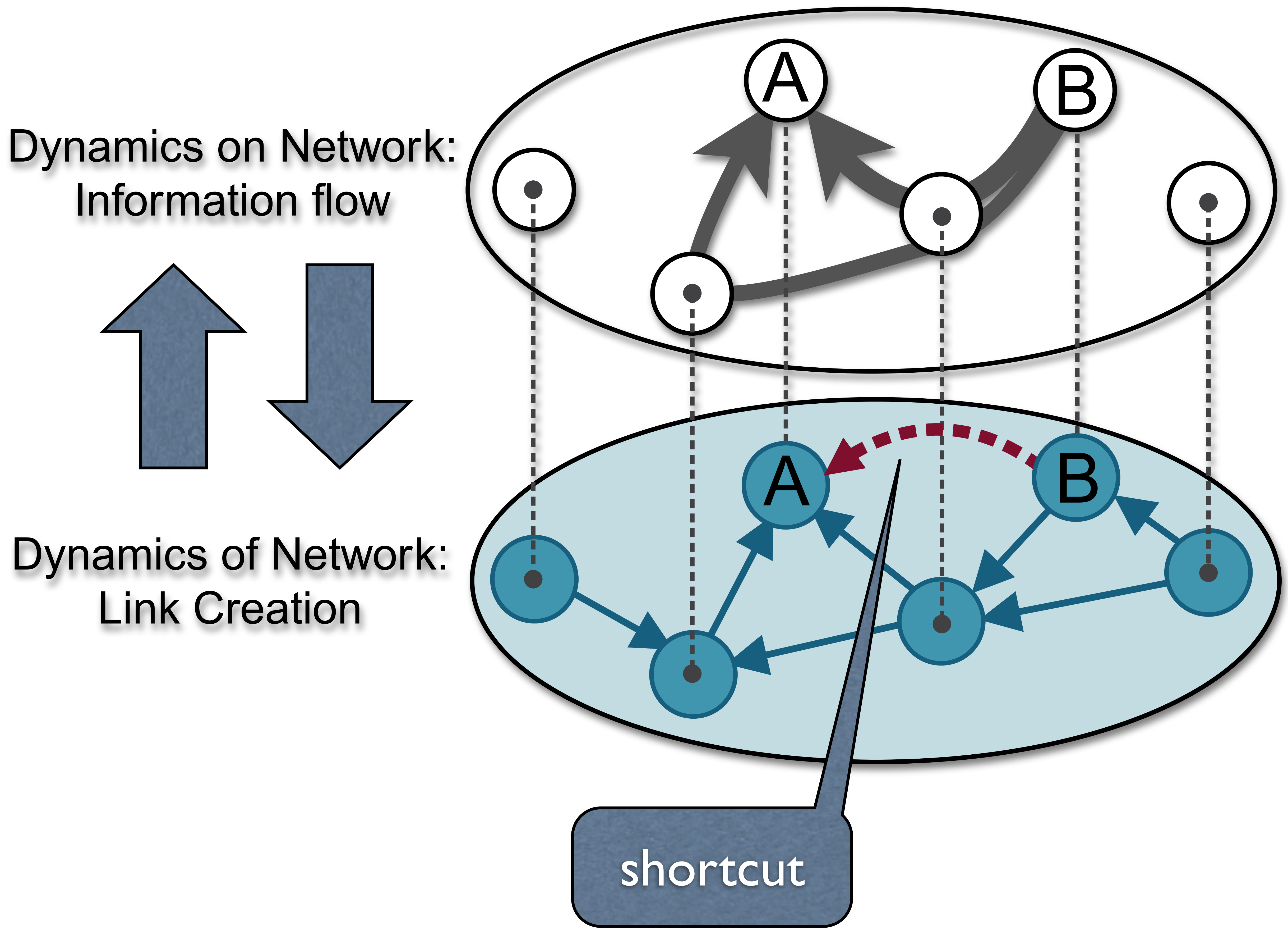


Dataset: Twitter 10% sample
October 2010 – January 2011
~12.5M users, ~1.3M hashtags

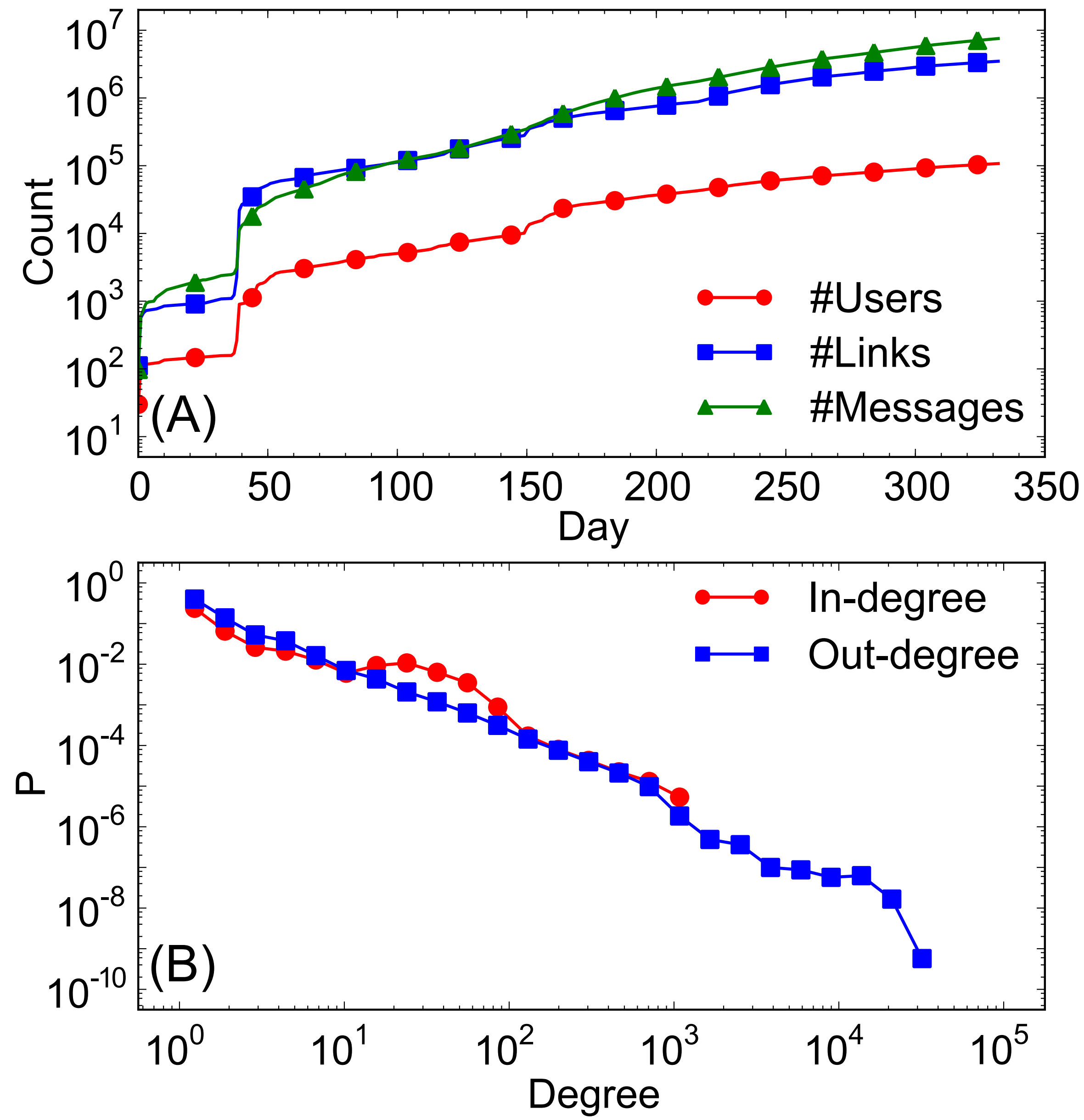

Competition for attention
Dynamics of the network
Dynamics on the network


Dynamics on Network:
Information flow
Dynamics of Network:
Link Creation
A
B
A
B


Dynamics on Network:
Information flow
Dynamics of Network:
Link Creation
A
B
A
B

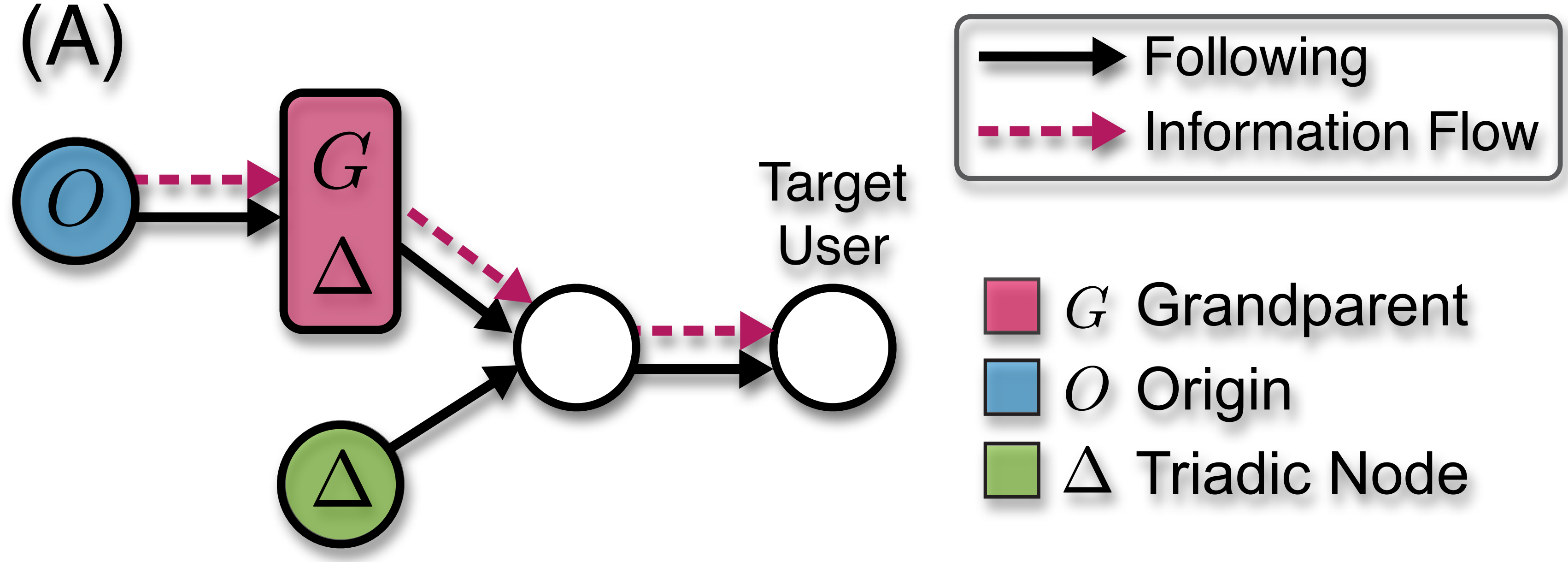

Dynamics on Network:
Information flow
A
B
Dynamics of Network:
Link Creation
A
B
shortcut

Dataset: Yahoo! Meme
April 2009 – March 2010

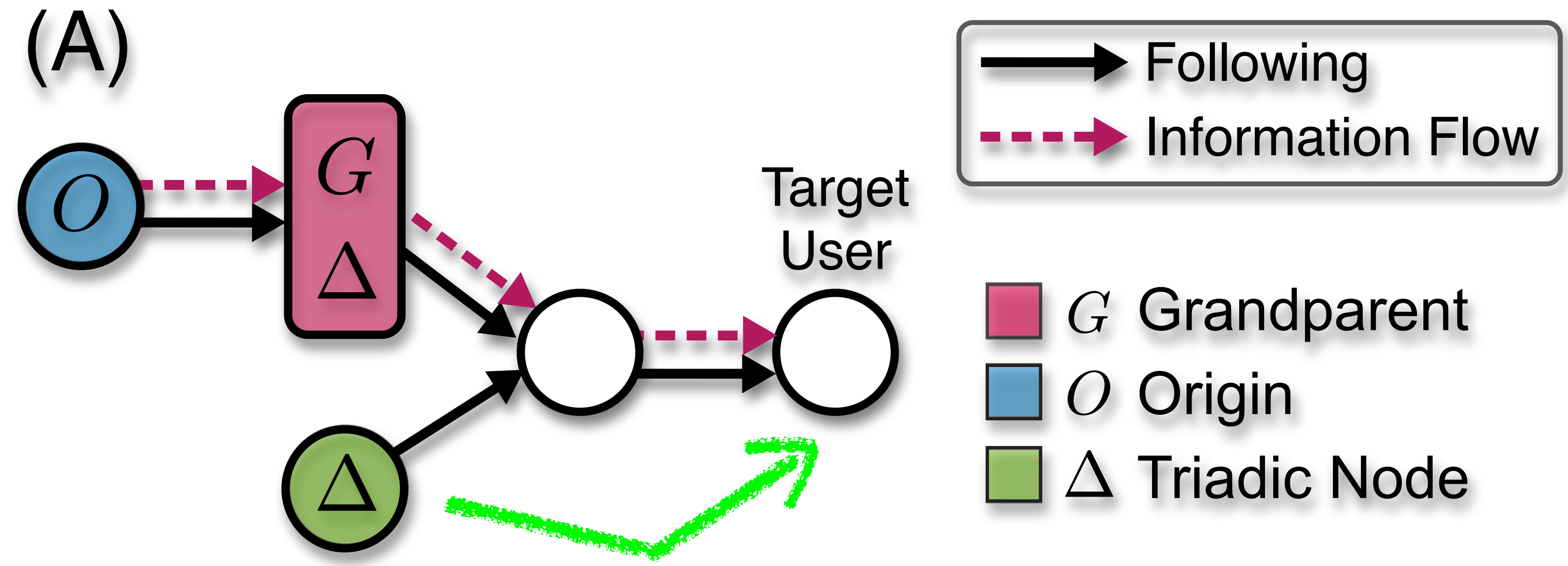


~128k users, ~3.5M links, ~7M posts

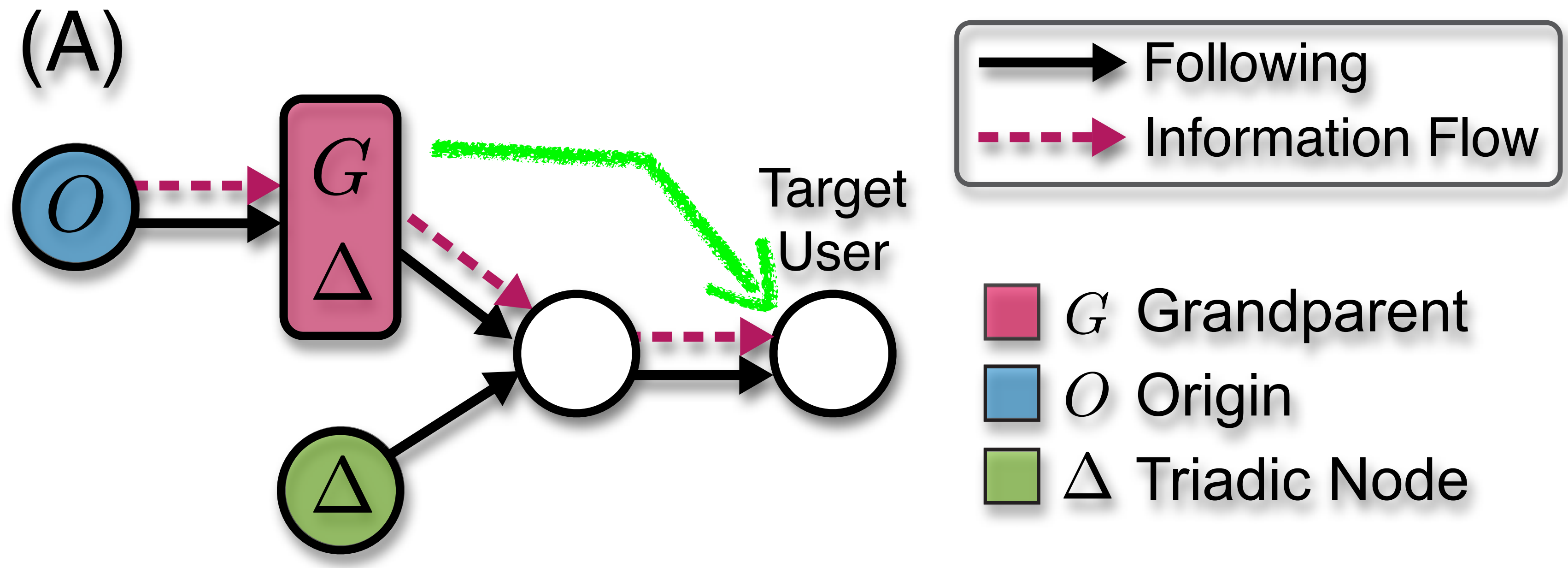
(A)

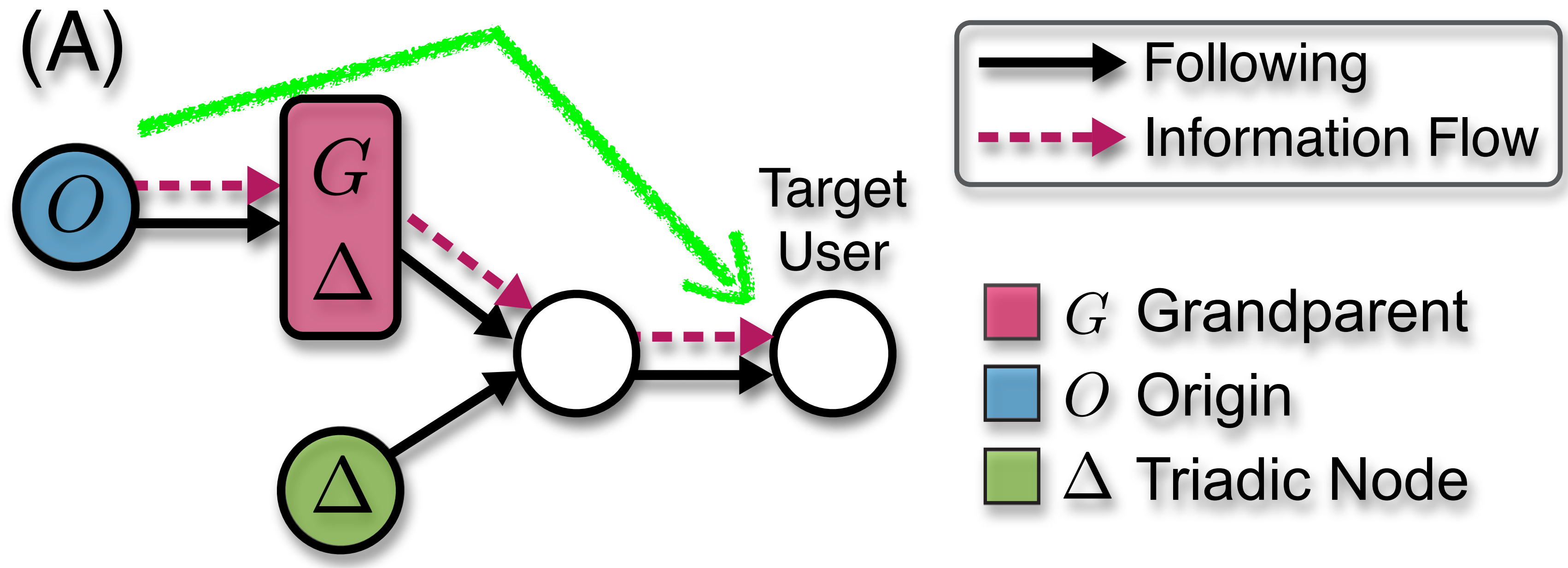


G
Δ
O
Δ
Target User
Following
Information Flow
G Grandparent
O Origin
Δ Triadic Node

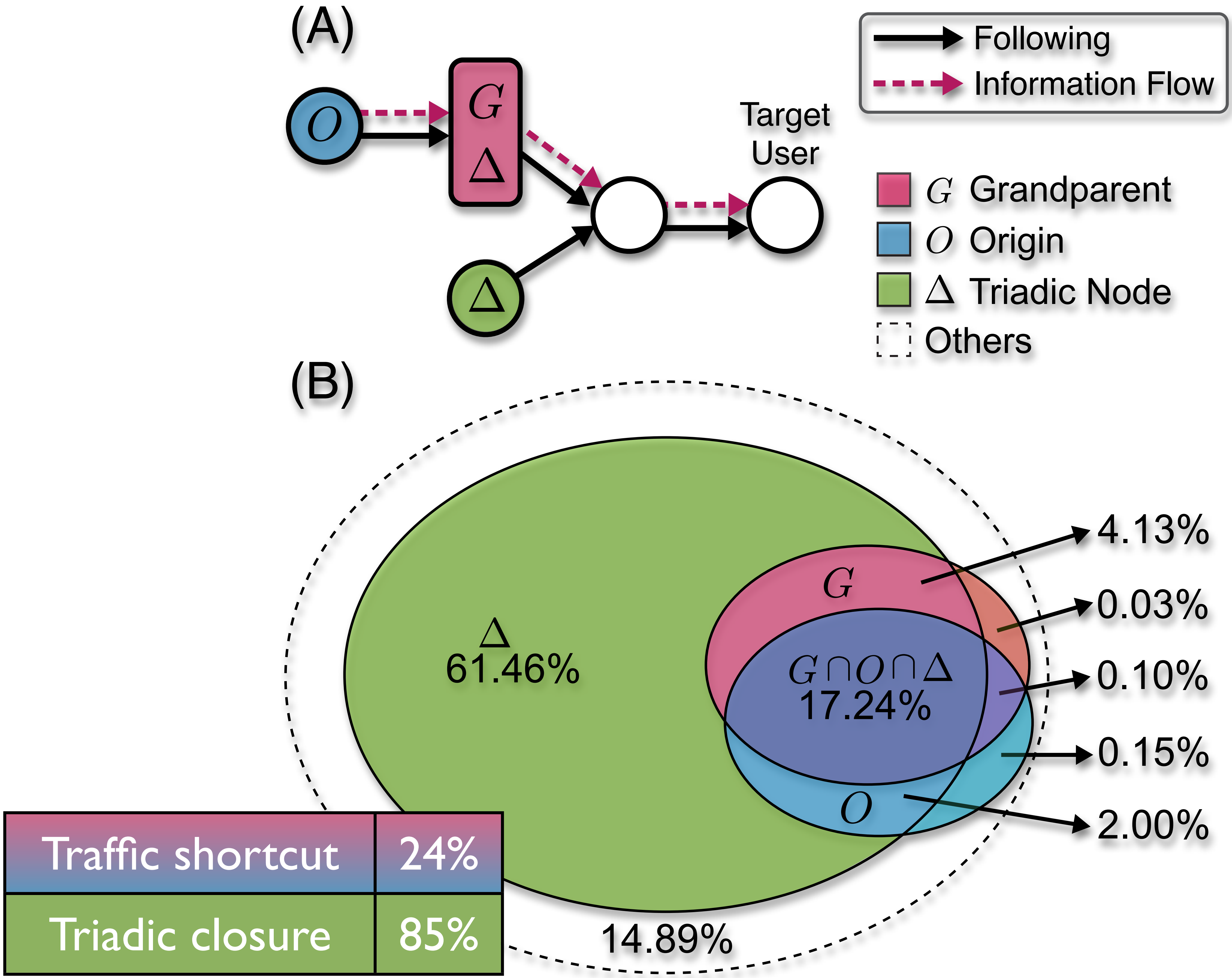


(A)
O
G
Δ
Δ
Target
User
Following
Information Flow
G Grandparent
O Origin
Δ Triadic Node


(A)
G
Δ
O
Δ
Target User
Following
Information Flow
G Grandparent
O Origin
Δ Triadic Node



(A)
O
G
Δ
Δ
Target User
Following
Information Flow
G Grandparent
O Origin
Δ Triadic Node


(A)
O
G
Δ
Δ
Target User
Following
Information Flow
G Grandparent
O Origin
Δ Triadic Node
Others
(B)
Δ
61.46%
G
G∩O∩Δ
17.24%
O
4.13%
0.03%
0.10%
0.15%
2.00%
14.89%
Traffic shortcut
24%
Triadic closure
85%

Could this happen by chance?

$$z = \frac{S - E}{\sigma} \in \aleph(0,1)$$

Could this happen by chance?

Actual number of links of that type in the data

Expected number of links of a certain type according to the null hypothesis (by chance). E.g., links to grandparents:

$$E_G = \sum_{\ell}^{L} \frac{N_G(\ell)}{N(\ell) - k(\ell) - 1}$$

$$z = \frac{S - E}{\sigma} \in \aleph(0,1)$$

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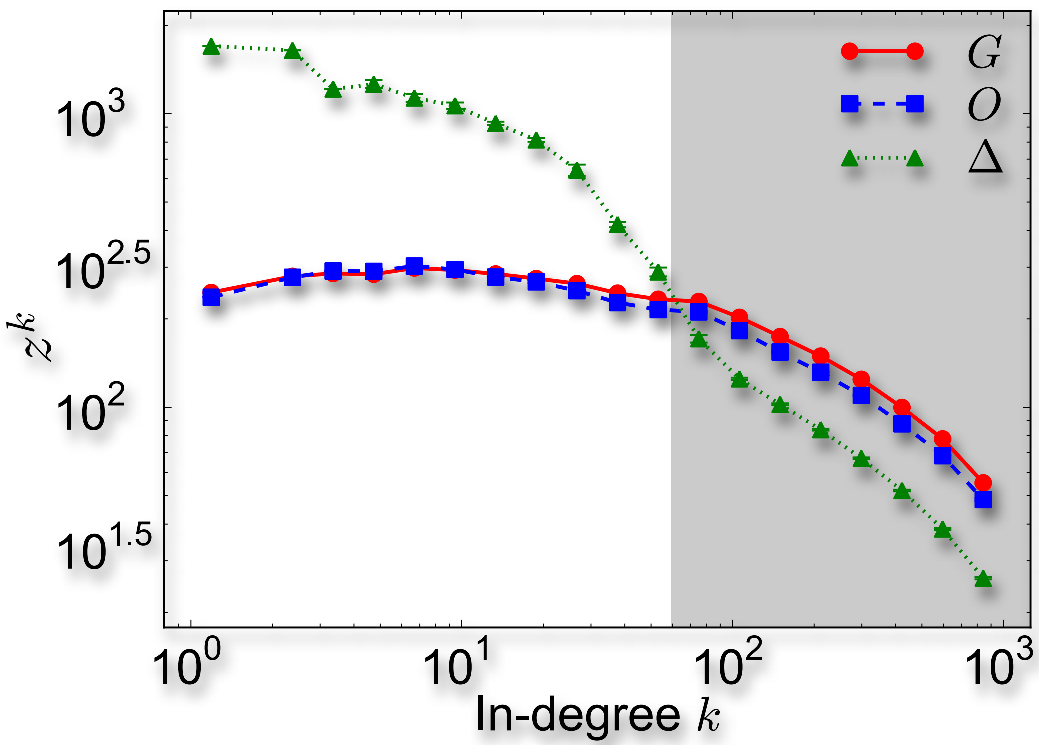
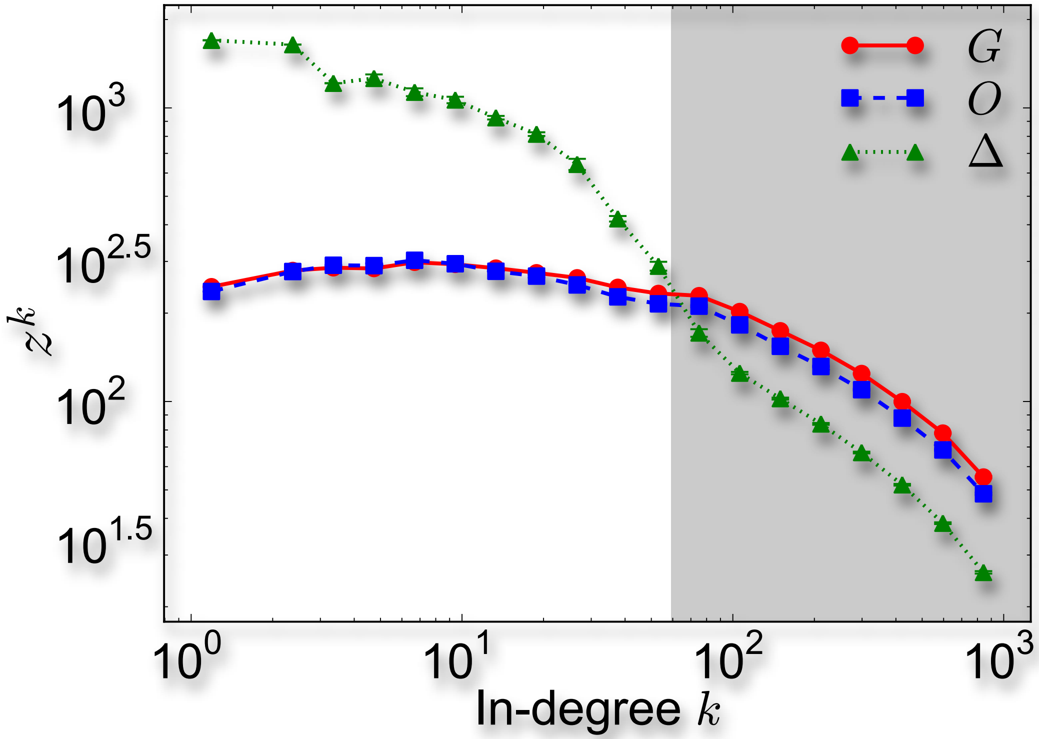
$$z = \frac{S - E}{\sigma} \in \aleph(0,1)$$

z_{Δ}, z_G, z_O very large ⇒ reject null hypothesis:

links are <u>not</u> created randomly

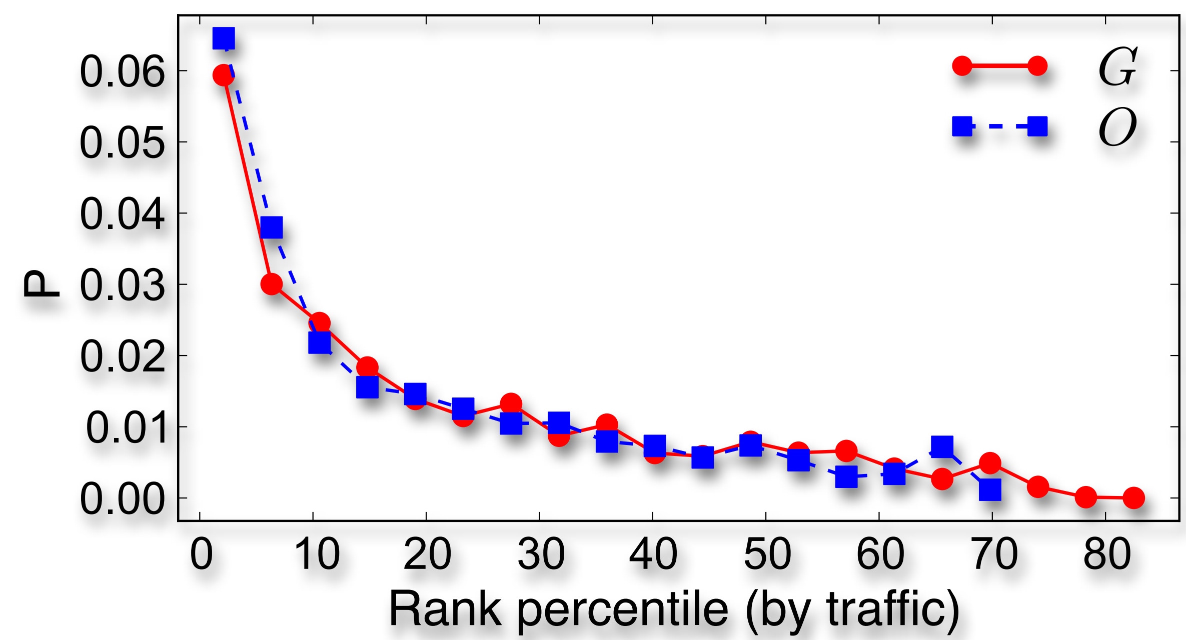


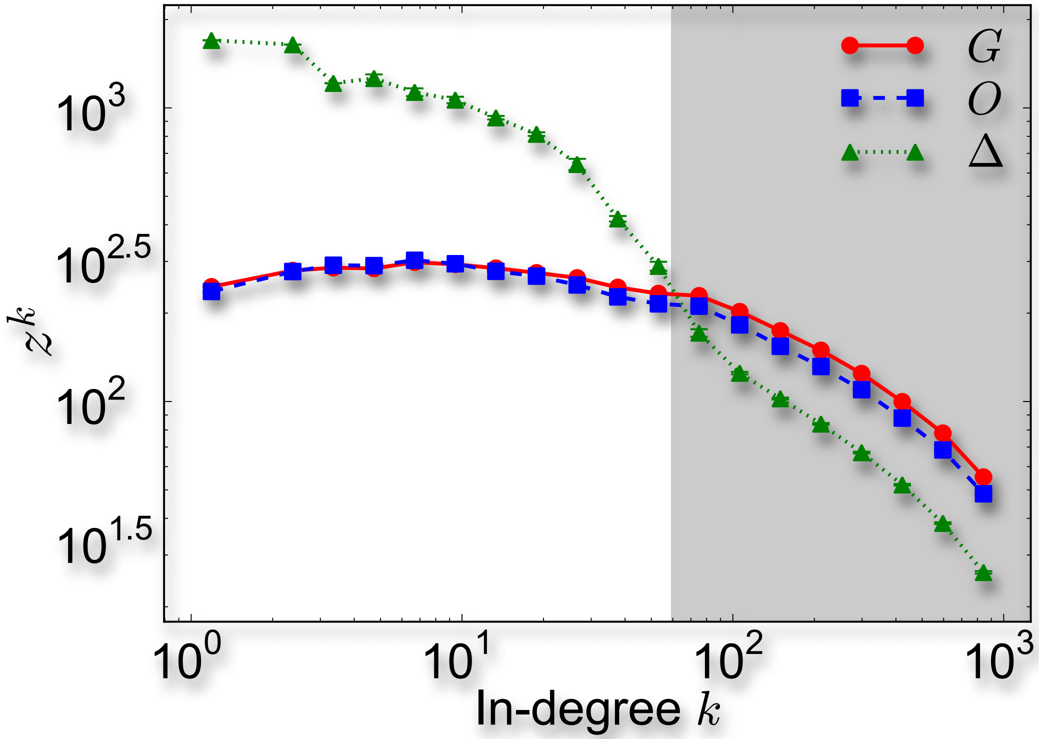
Preference for traffic-based shortcuts as users become more active



Preference for traffic-based shortcuts as users become more active

The more posts we see from someone, the more we are likely to follow them





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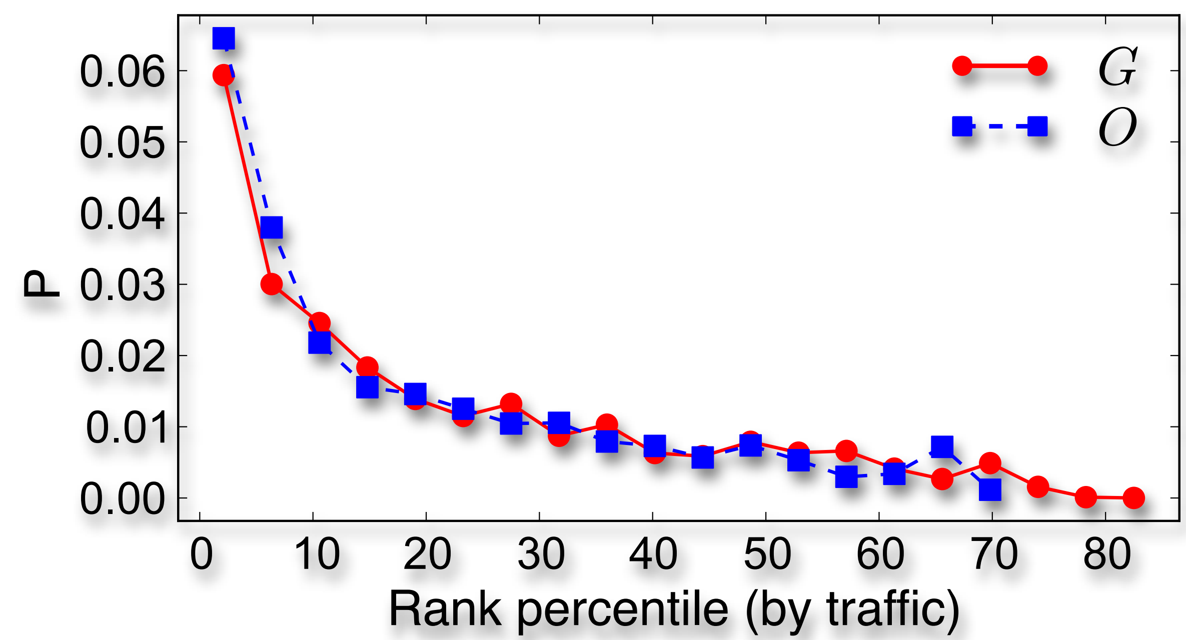

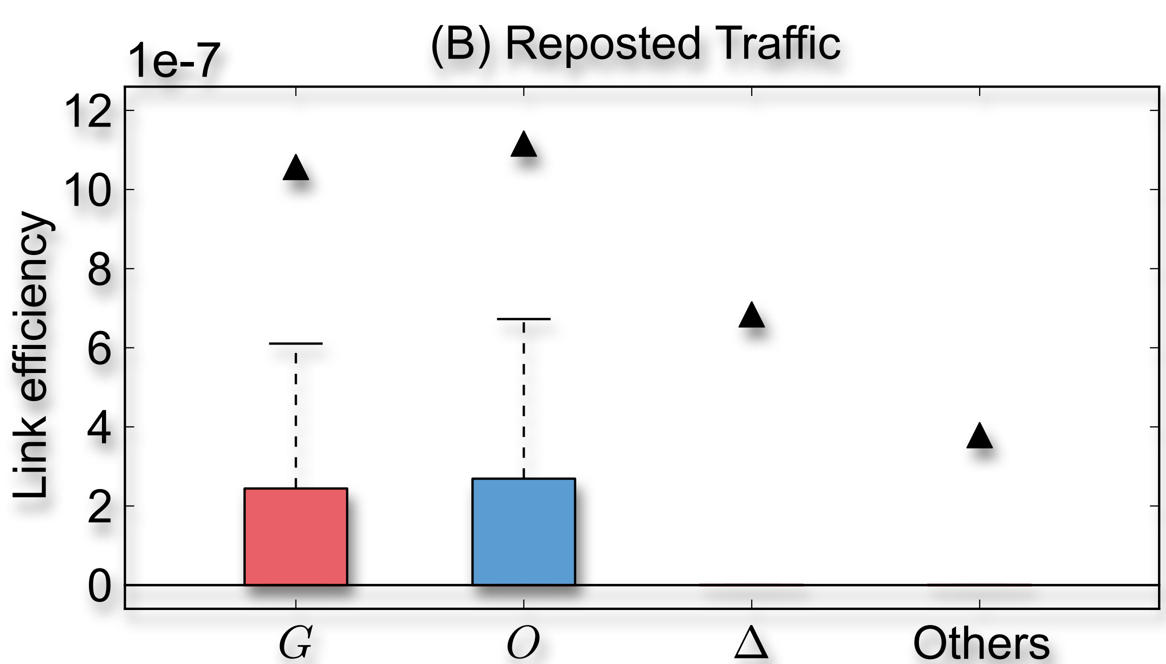

Shortcuts are more efficient at carrying messages we see and report

Maximum Likelihood Estimation

Maximum Likelihood Estimation

$\forall$ link ℓ, compute:

$f(\ell \mid \Gamma, \Theta)$ = likelihood of the target being followed by the creator according to a particular strategy Γ, given the network configuration Θ at the time when ℓ is created.

Maximum Likelihood Estimation

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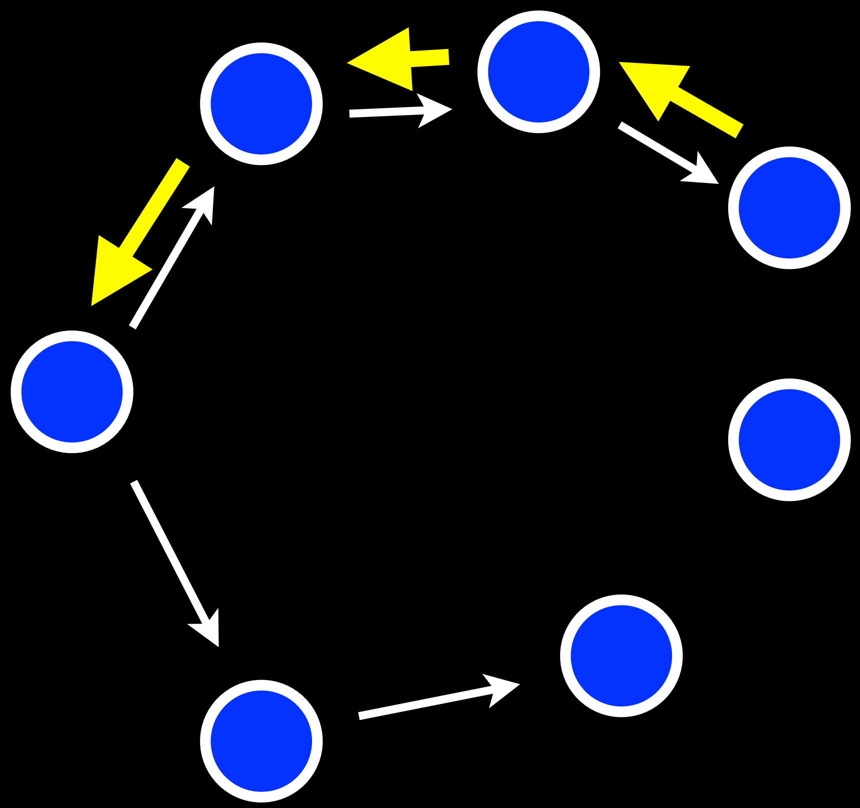
Single strategy

Combined strategy

Individual strategy

MLE single strategies

- Random
- Triadic closure (**Δ**)
- Grandparent (**G**)
- Origin (**O**)
- Traffic shortcut (**G** ∪ **O**)



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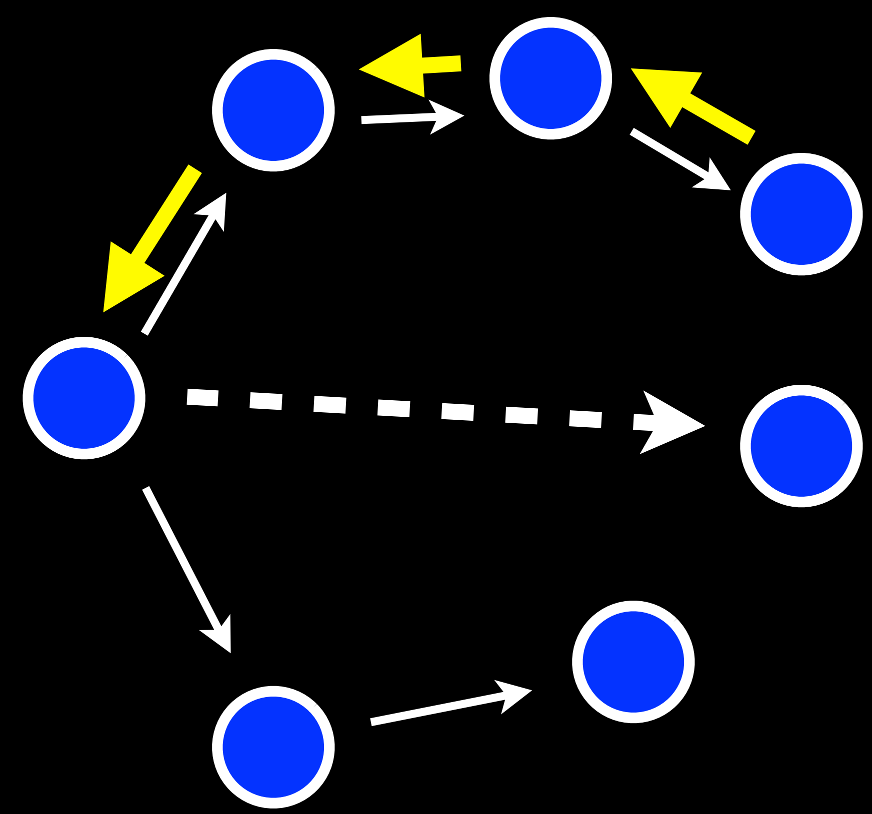
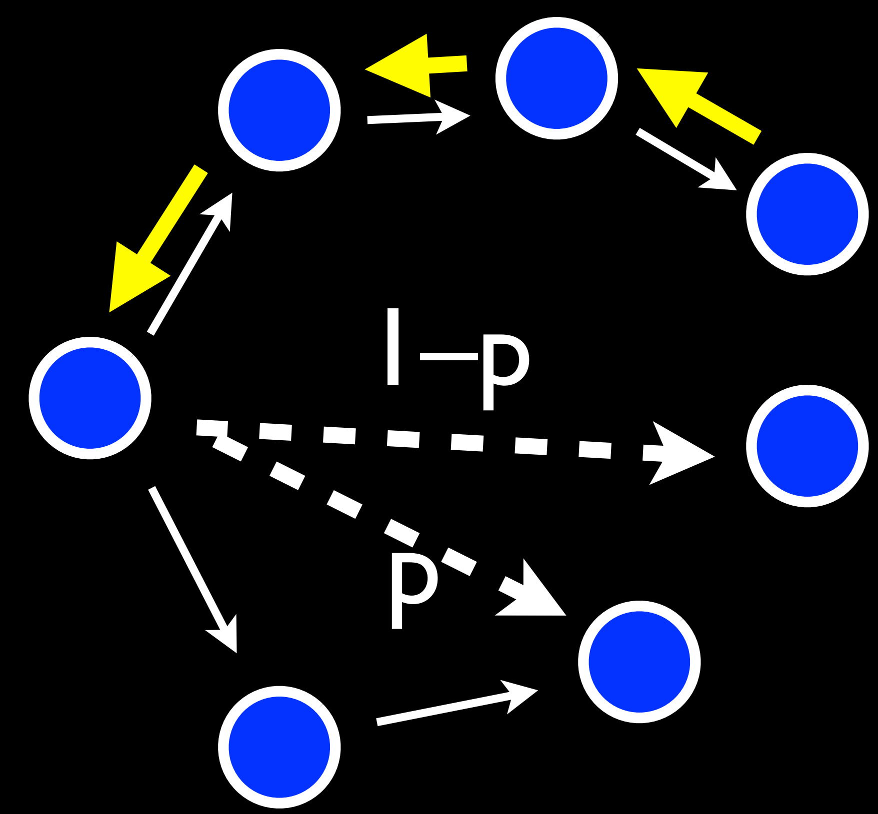


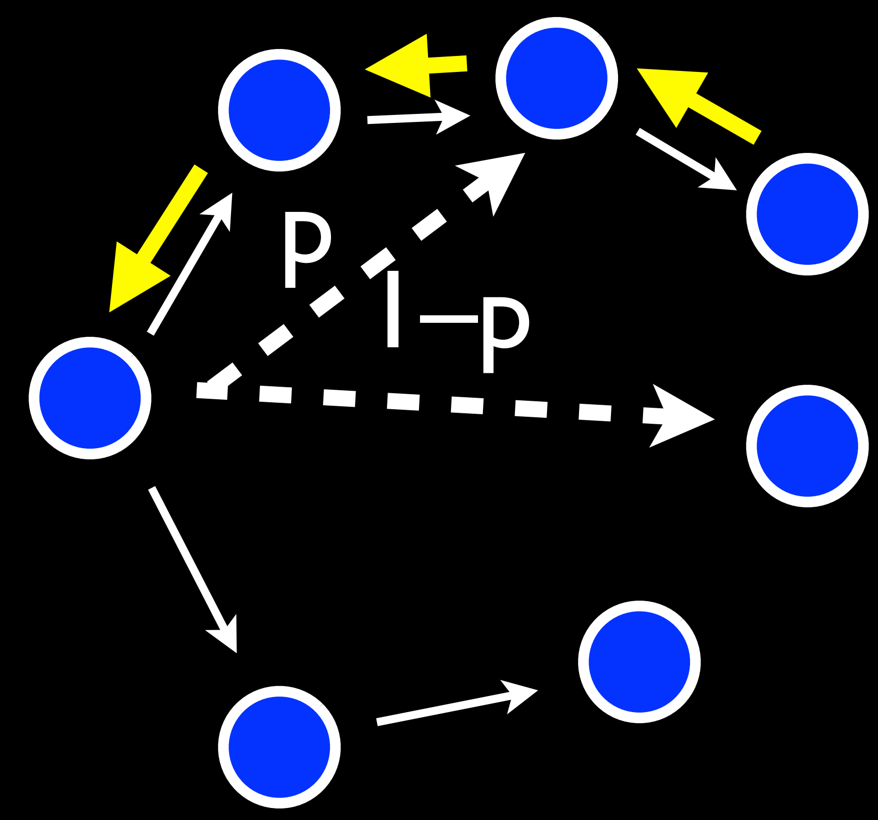
MLE single strategies

- Random
- Triadic closure (Δ)



MLE single strategies

- Random
- Triadic closure (**Δ**)
- Grandparent (**G**)



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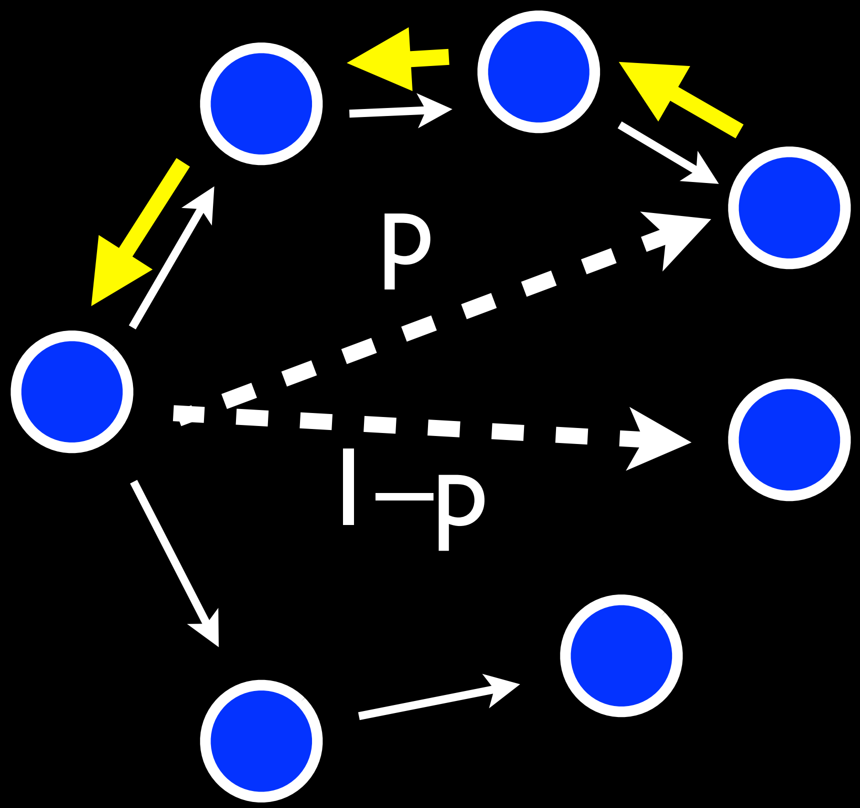

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- Triadic closure (**Δ**)
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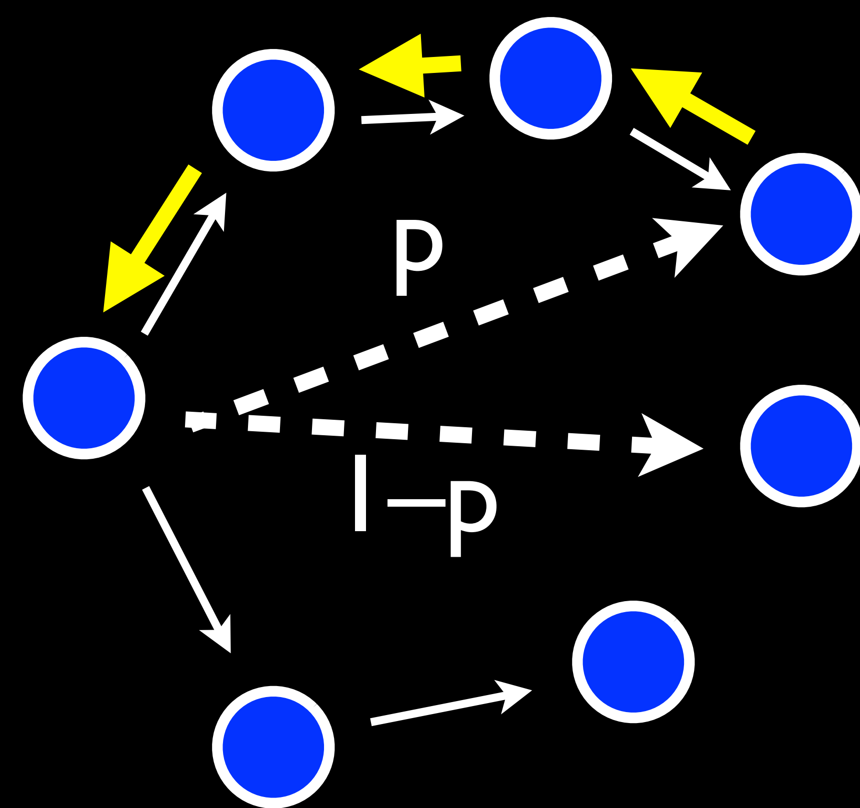
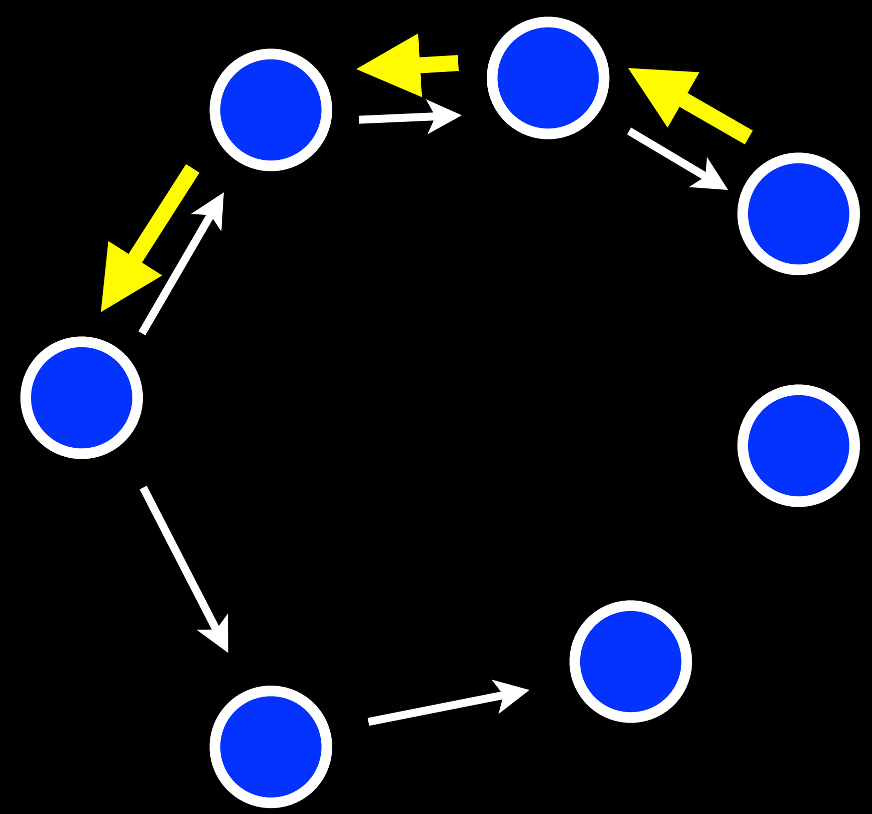


Example:

$$\log \mathcal{L}_G(p) = \sum_{\mathbf{1}_G(\ell)=1} \ln\left(\frac{p}{N_G(\ell)} + \frac{1-p}{N(\ell)-k(\ell)-1}\right) + \sum_{\mathbf{1}_G(\ell)=0} \ln \frac{1-p}{N(\ell)-k(\ell)-1}.$$

MLE combined strategies

- Grandparent or triadic closure (**G + Δ**)
- Origin or triadic closure (**O + Δ**)
- Traffic shortcut or triadic closure (**G** ∪ **O + Δ**)



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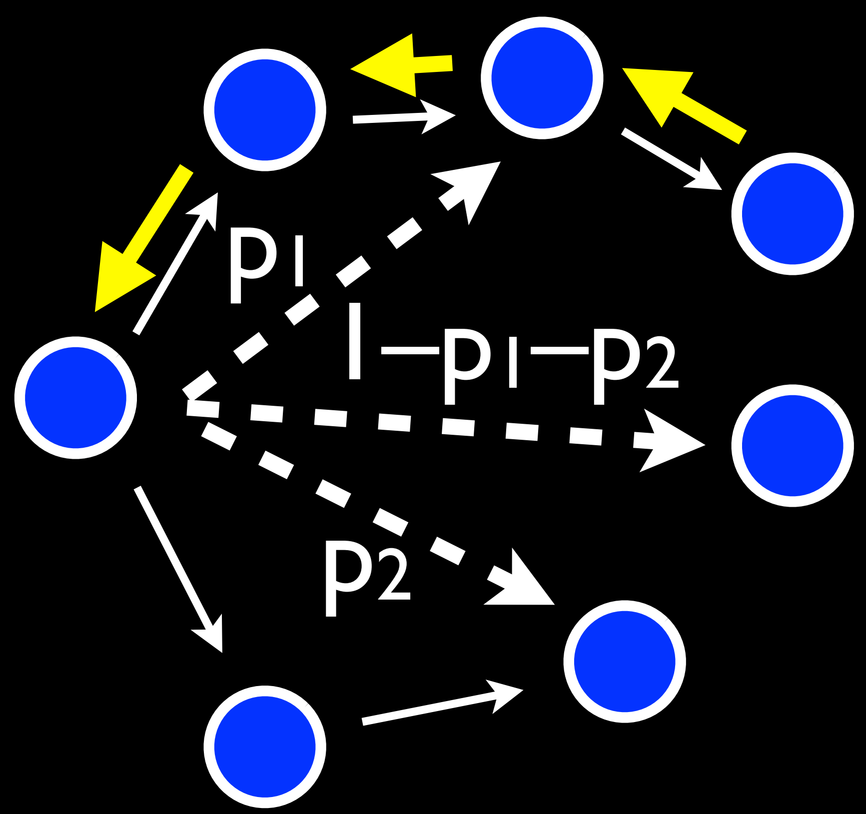

MLE combined strategies

Example:

$$
\begin{aligned}
&\log \mathcal{L}_{G+\Delta}(p_1, p_2) \\
&= \log \prod_{\ell=1}^{L} [p_1 f(\ell|G,\Theta) + p_2 f(\ell|\Delta,\Theta) \\
&\quad + (1 - p_1 - p_2) f(\ell|\mathrm{Rand},\Theta)] \\
&= \sum_{\substack{\mathbf{1}_G(\ell)=1 \\ \mathbf{1}_\Delta(\ell)=1}} \log\left(\frac{p_1}{N_G(\ell)} + \frac{p_2}{N_\Delta(\ell)} + \frac{1-p_1-p_2}{N(\ell)-k(\ell)-1}\right) \\
&\quad + \sum_{\substack{\mathbf{1}_G(\ell)=1 \\ \mathbf{1}_\Delta(\ell)=0}} \log\left(\frac{p_1}{N_G(\ell)} + \frac{1-p_1-p_2}{N(\ell)-k(\ell)-1}\right) \\
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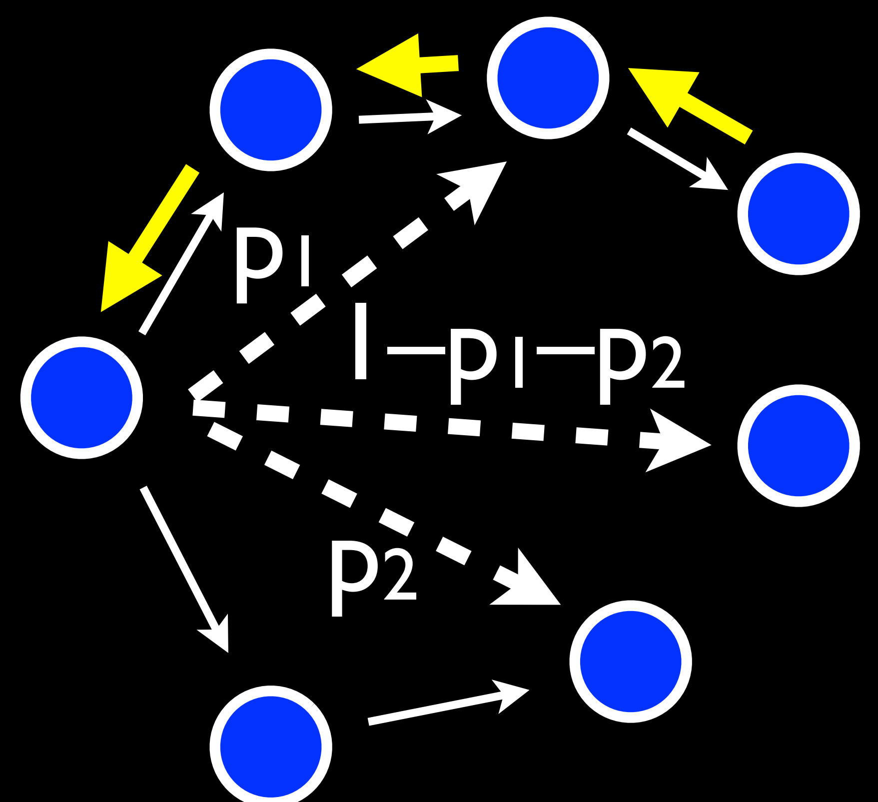
\end{aligned}
$$

- Grandparent or triadic closure (**G + Δ**)
- Origin or triadic closure (**O + Δ**)
- Traffic shortcut or triadic closure (**G ∪ O + Δ**)



MLE combined strategies

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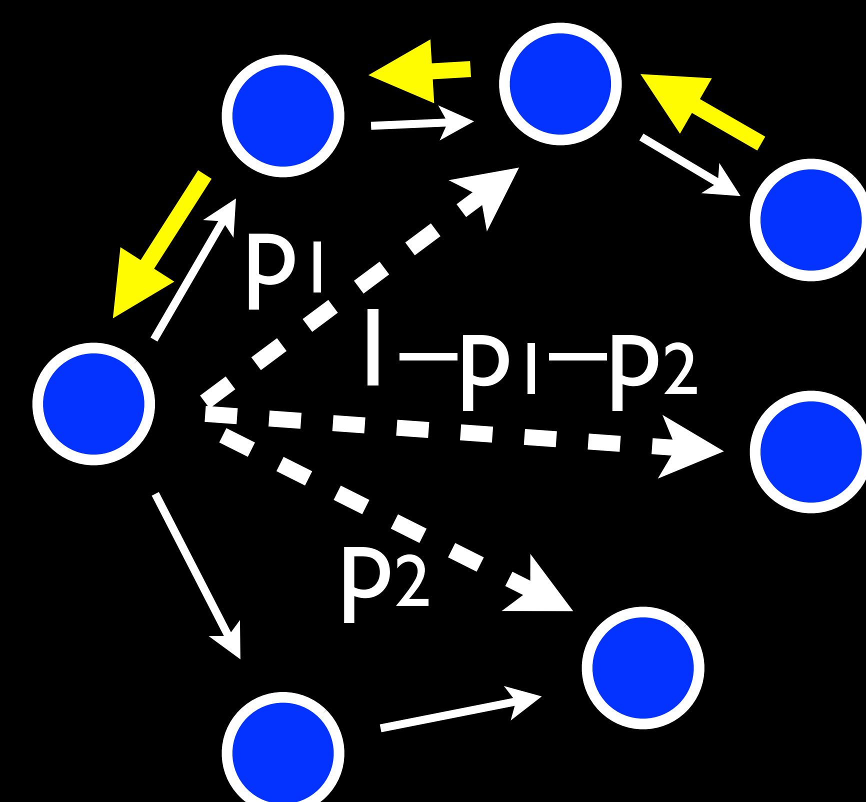
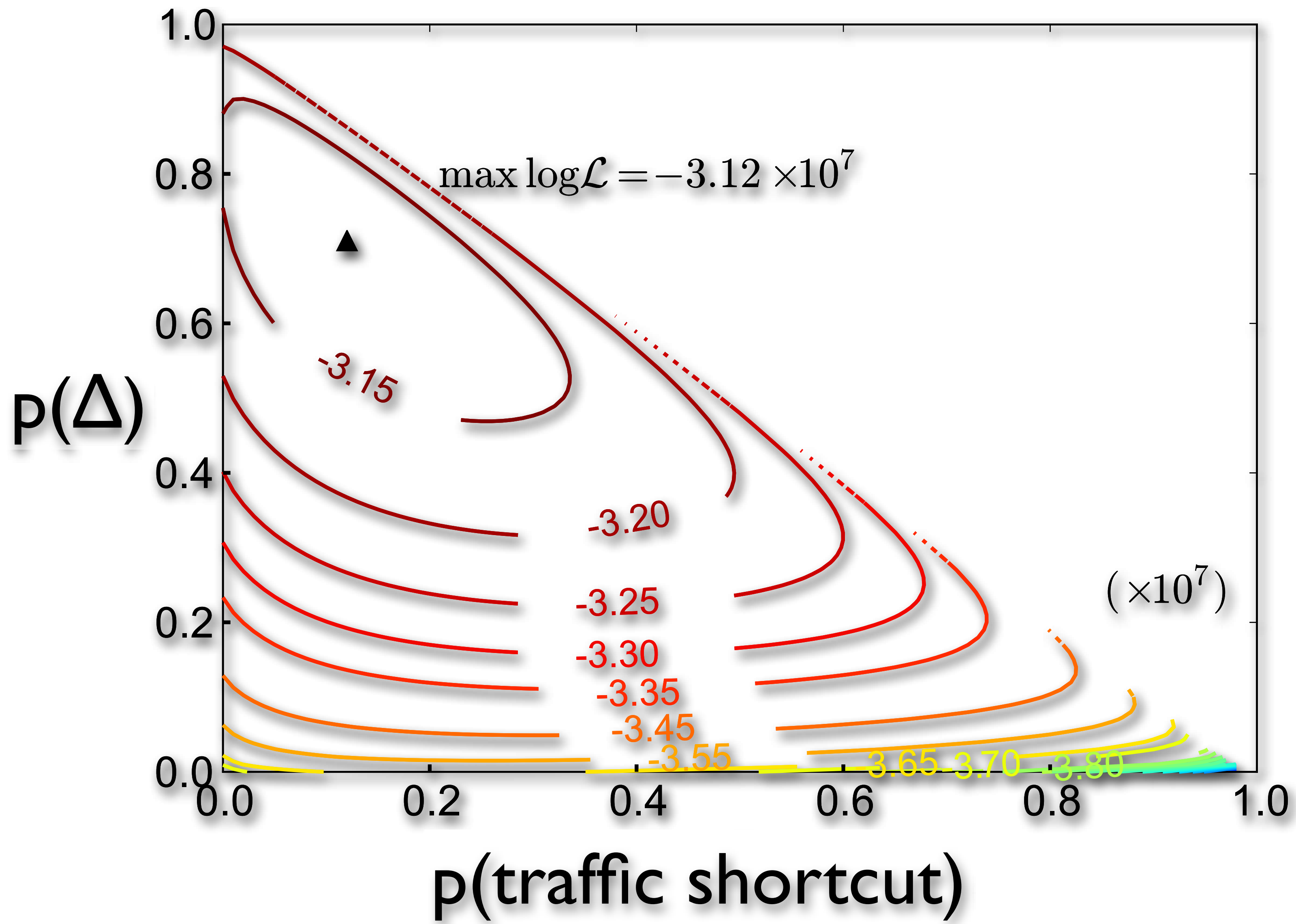


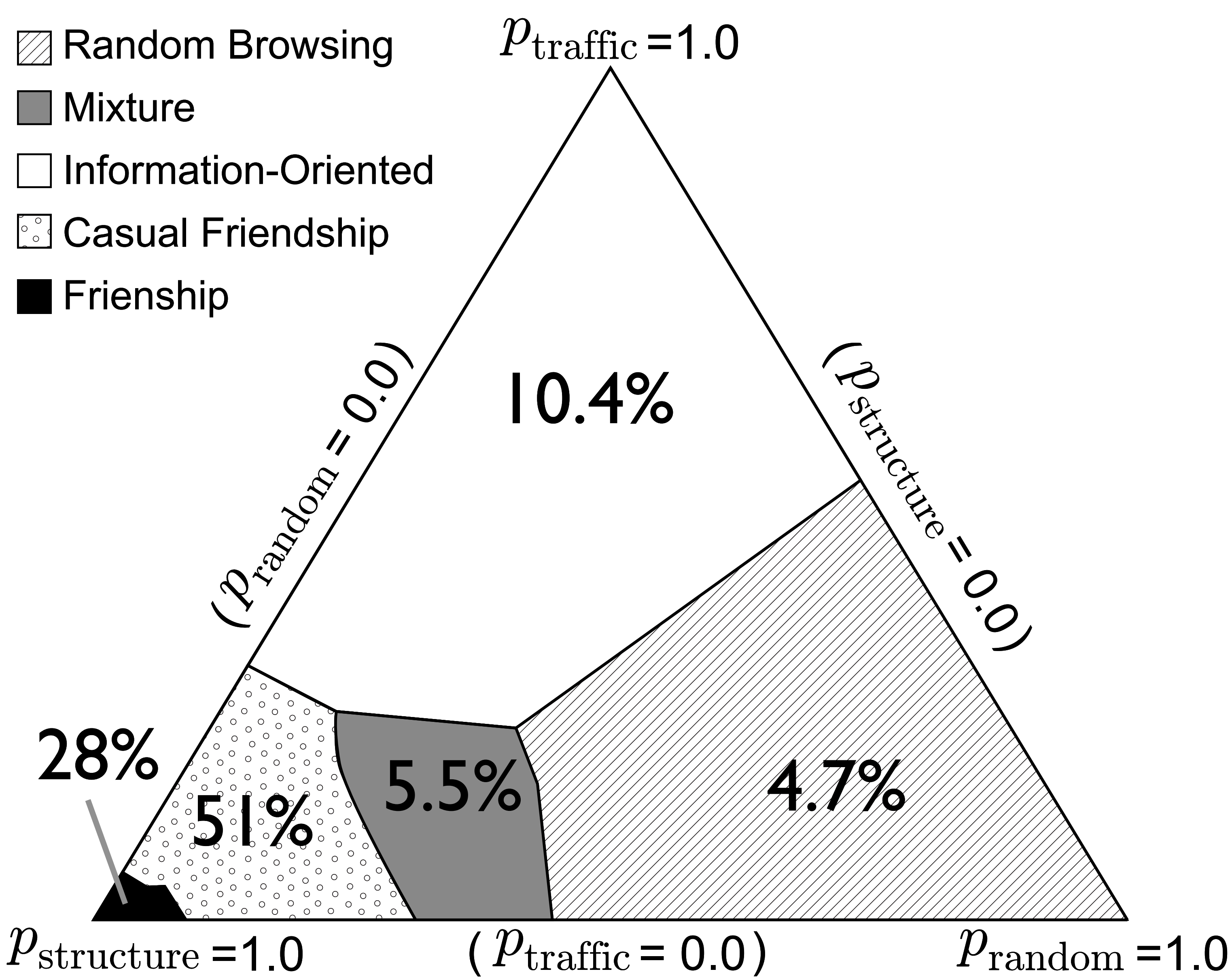
Maximum Likelihood

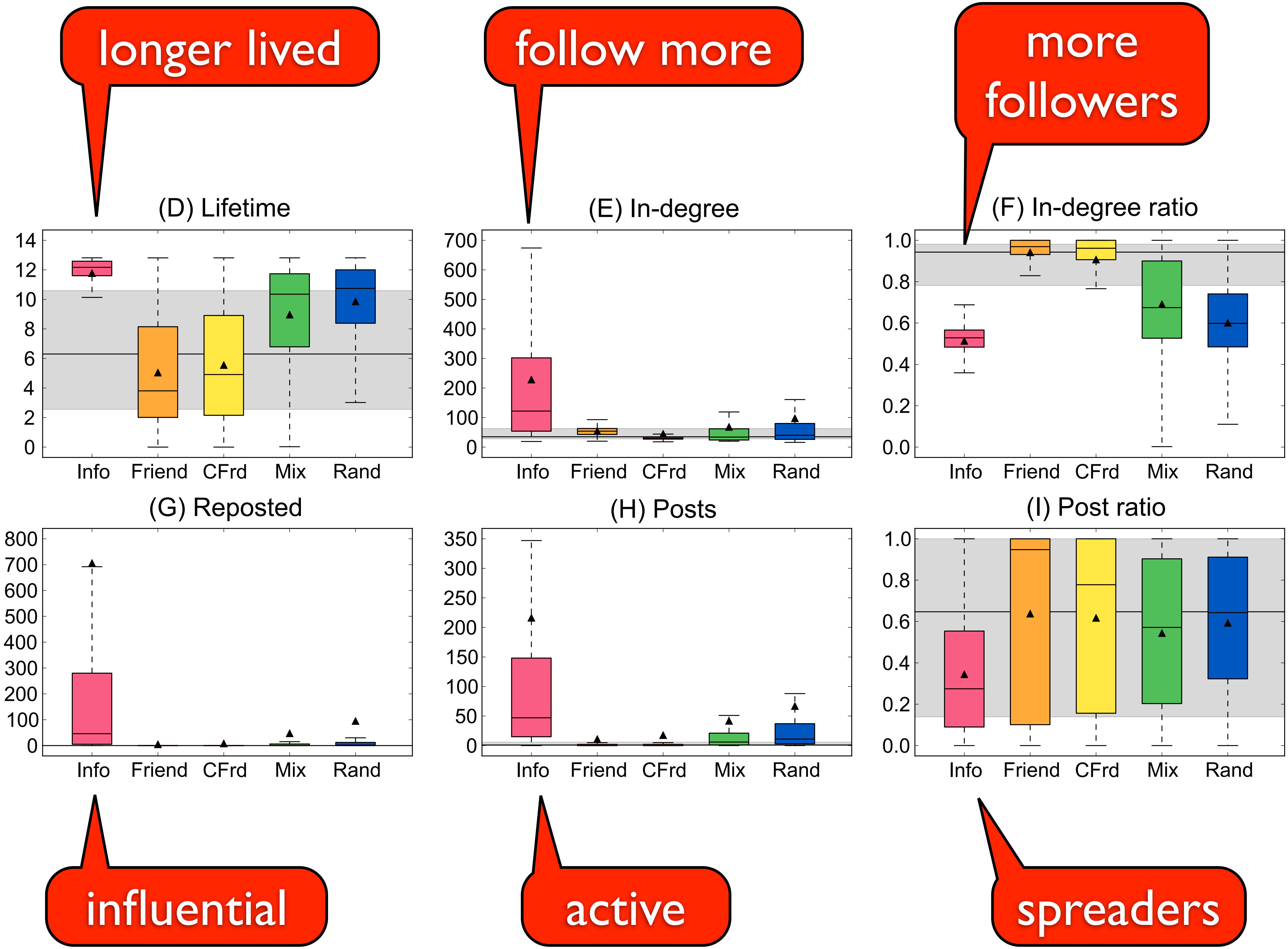
(**G** ∪ **O** + **Δ**)



Maximum Likelihood

($\mathbf{G} \cup \mathbf{O} + \boldsymbol{\Delta}$)




longer lived
follow more
more followers
(D) Lifetime
(E) In-degree
(F) In-degree ratio
Info
Friend
CFrd
Mix
Rand
(G) Reposted
(H) Posts
(I) Post ratio
influential
active
spreaders

As users become more active, more popular, and more influential, they make the network more "efficient" by shortening the distance between producers and consumers of information.

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[5]Qatar Computing Research Institute [6]Yahoo! Research Barcelona

[7]Department of Computer Science, University of Torino, Italy

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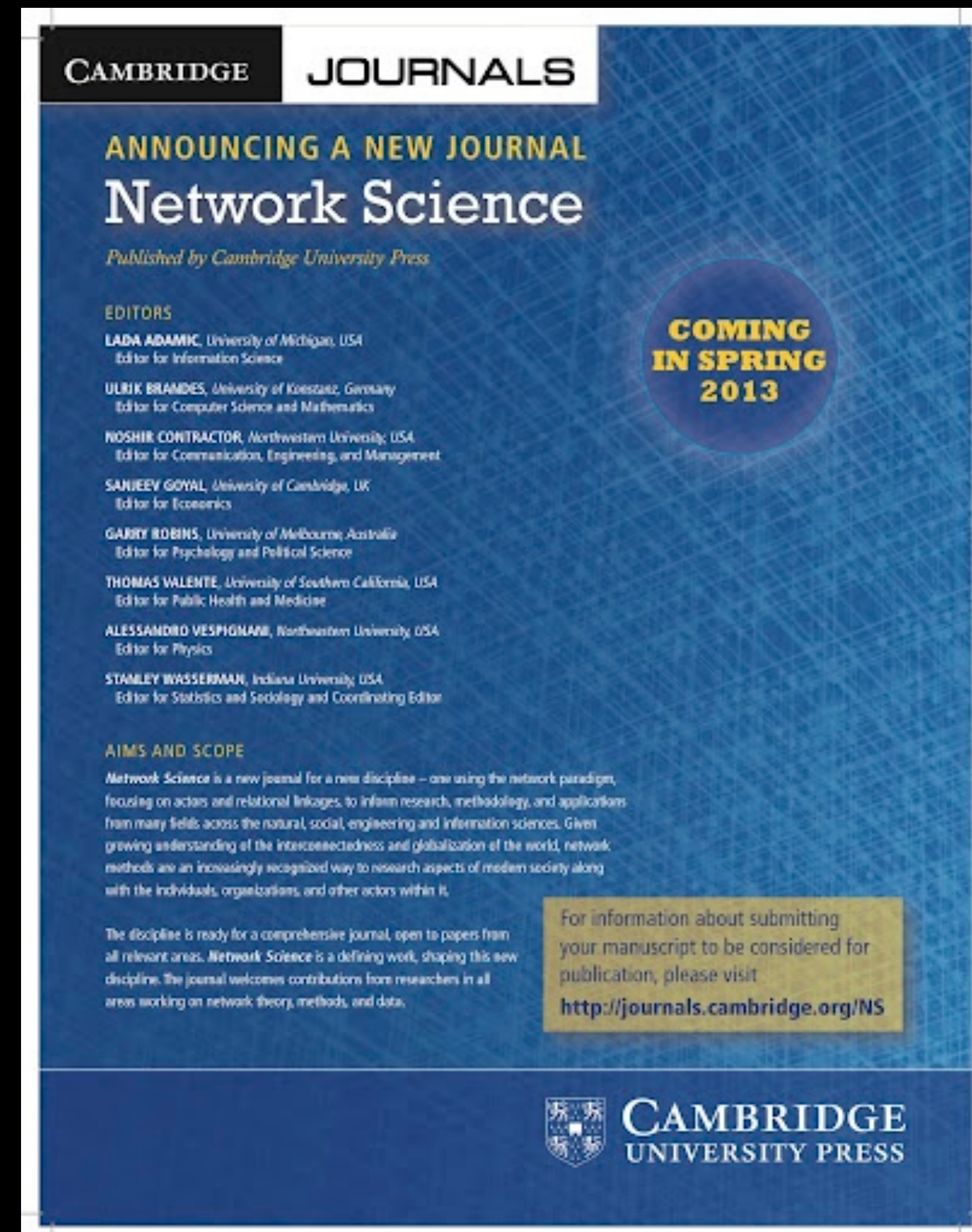
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