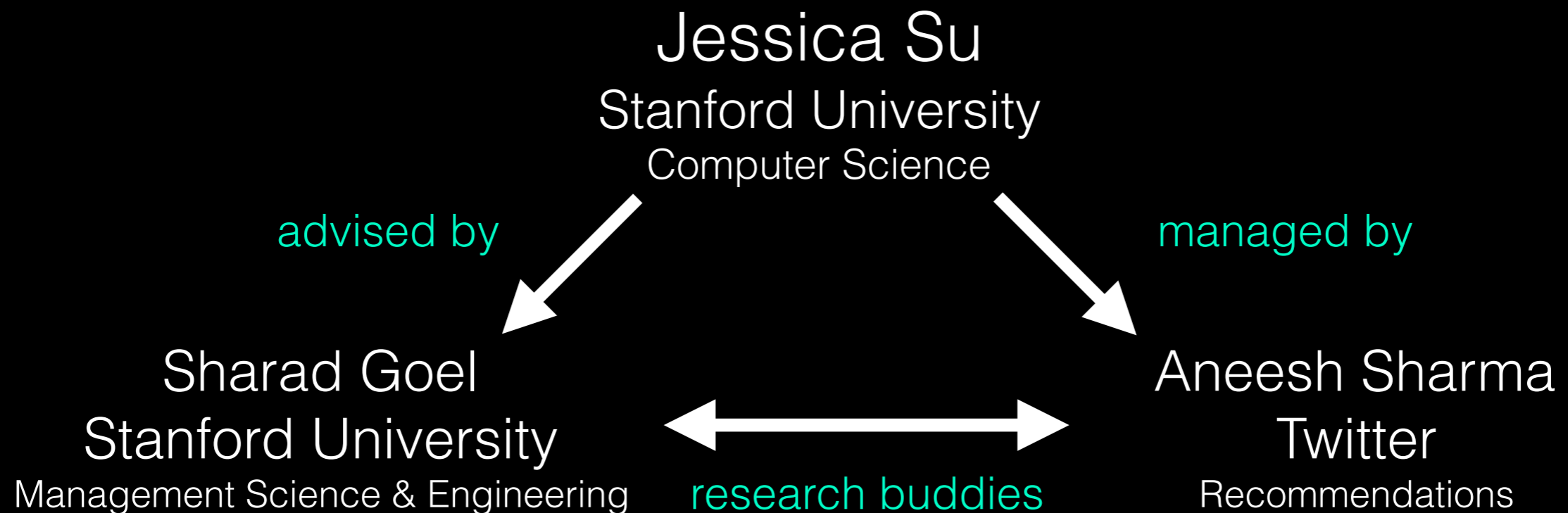


The Effect of Recommendations on Network Structure

[WTF: What Happened To The Twitter Graph?]



Recommendation systems

The Amazon logo, featuring the word "amazon" in a bold, black, lowercase sans-serif font. A yellow curved arrow starts under the letter 'a' and points to the right, ending under the letter 'n'.The Netflix logo, consisting of the word "NETFLIX" in a bold, red, uppercase sans-serif font.The Yelp logo, featuring the word "yelp." in a white, lowercase, rounded sans-serif font with a registered trademark symbol. To the right of the text is a white outline of a six-petaled flower or star shape.

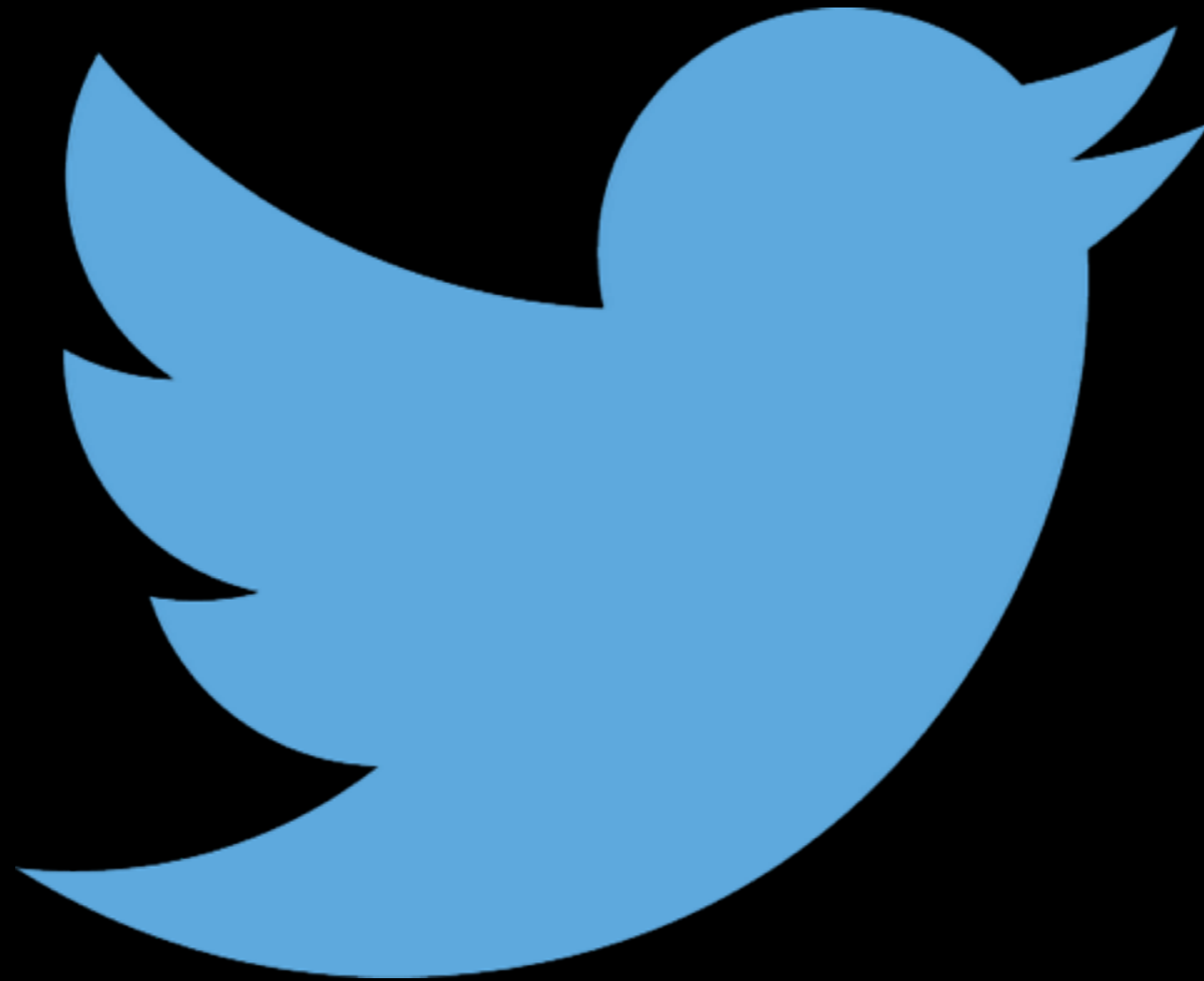
What effect do recommenders have on the overall marketplace?

“Yelp helps me find hole-in-the-wall restaurants that I’d never have seen otherwise”





“Yelp just boosts traffic for popular restaurants, making life harder for everyone else”

My project



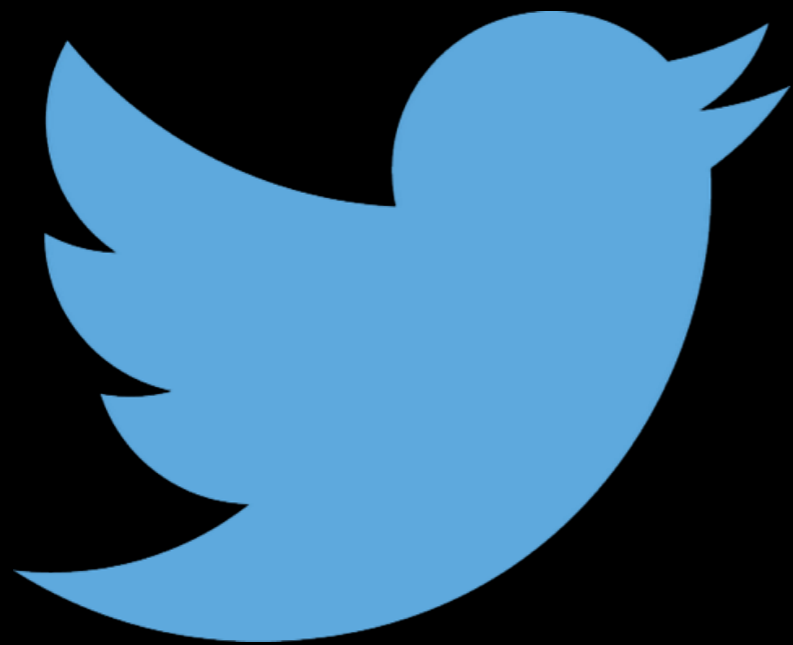
My project

Who to follow · [Refresh](#) · [View all](#)

-  **Vinay Mahagaokar** @vinay... ×
[+ Follow](#)
-  **Aneesh Sharma** @aneeshs ×
[+ Follow](#)
-  **Praveen B.** @praveenbom ×
[+ Follow](#)

What effect do recommenders have on the structure of the Twitter graph?

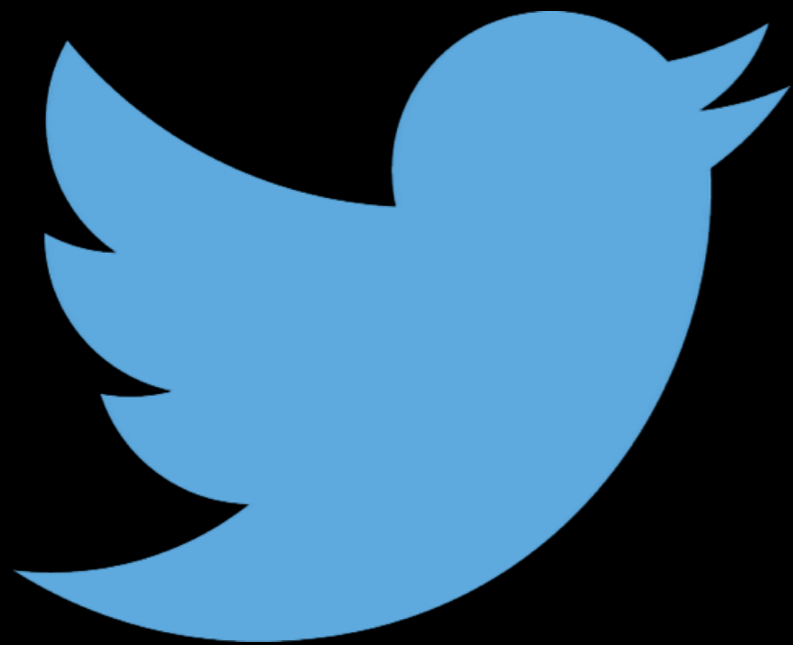
“I’m so glad Who To Follow exists, because before I never got followers, and now I do!”



“Who To Follow is okay and all, but it always shows me people like Justin Bieber, who I already knew about”

What effect do recommenders have on the structure of the Twitter graph?

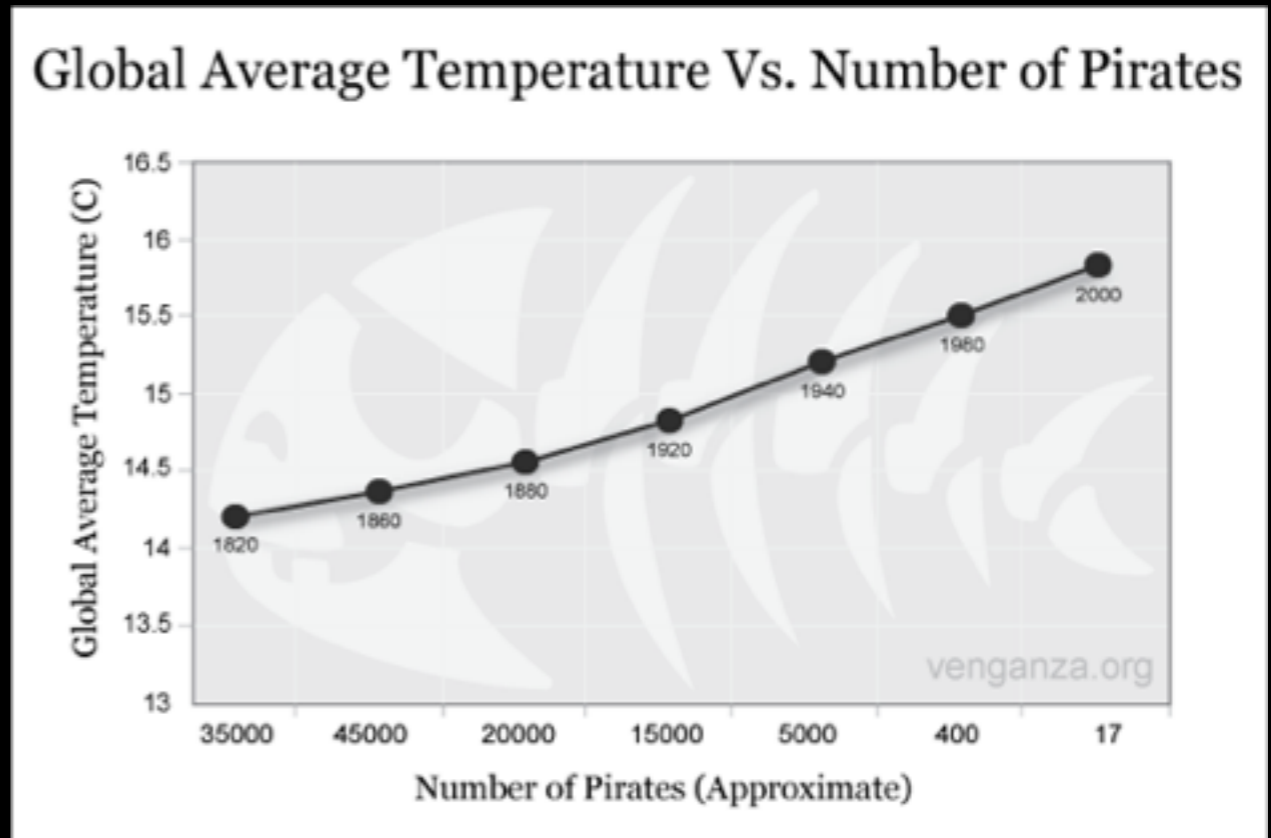
“I’ve made so many friends on Twitter! Who To Follow was where I met my first wife.”



“I’ve been following all these people in Who To Follow, and none of them follow me back”

Causality

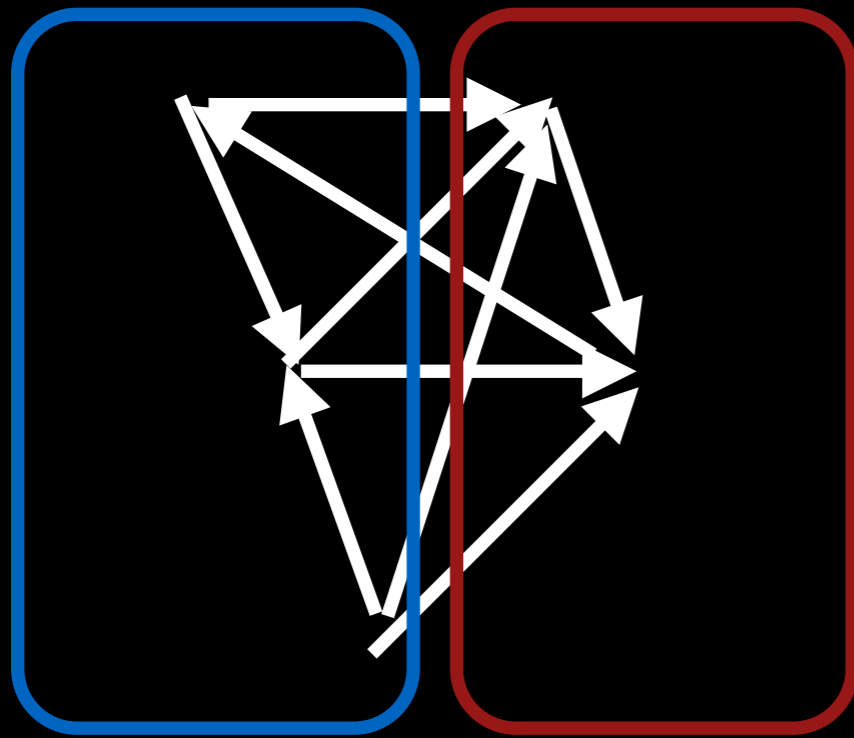
Correlational analyses
are okay and all...



...but to really determine causation,
you need to run an experiment

Running experiments on networks is tricky

“Stable unit treatment value assumption”:
experimenting on one person doesn't
change what happens to the others



If you encourage a user to follow someone, it affects other users too, making it hard to divide users into treatment and control groups

Control?

Treatment?

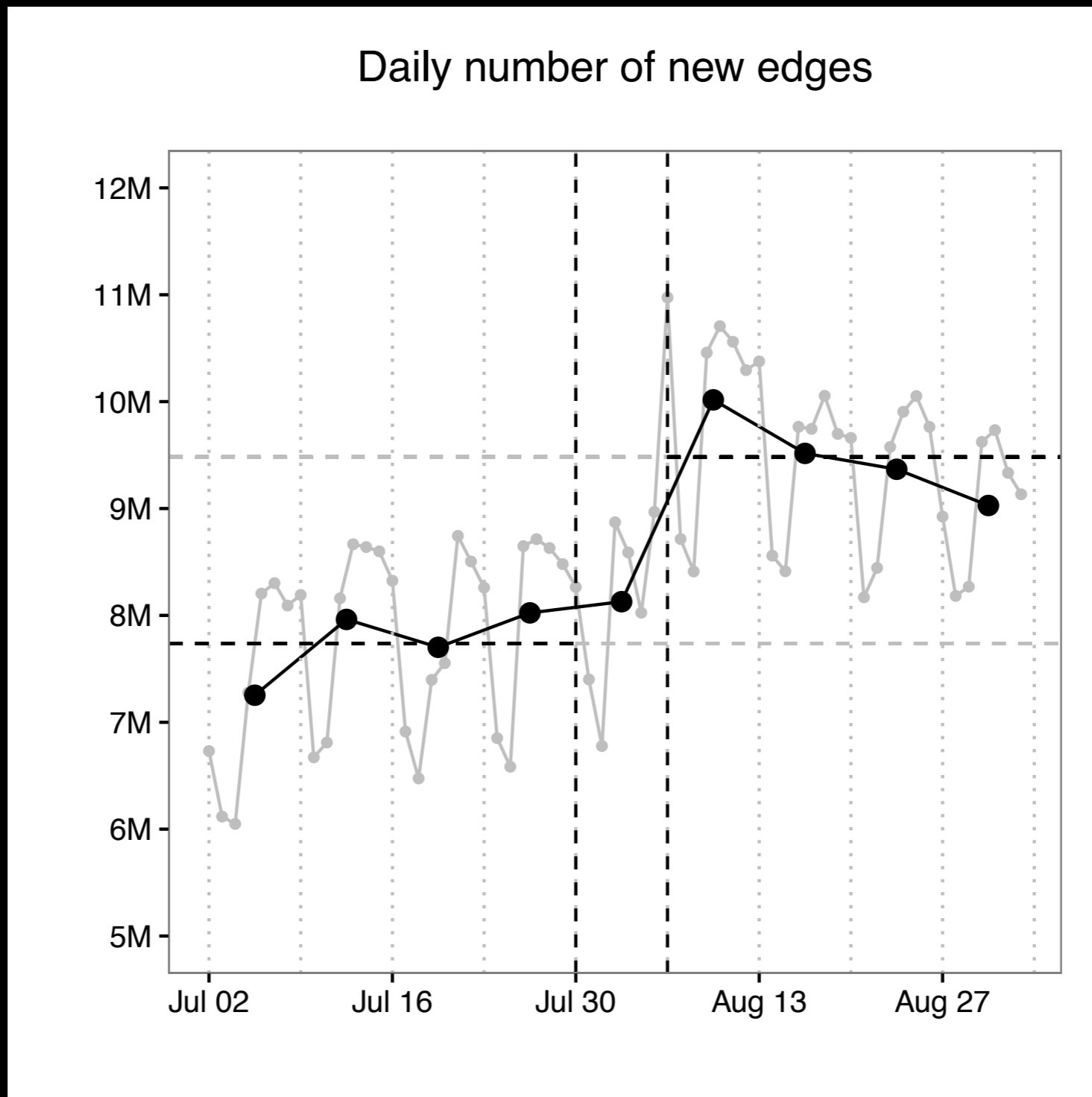
Effect of Who To Follow recommendations on the global structure of the Twitter graph

Look at the network at two points in time: (1) right before Who To Follow was introduced, and (2) right after.

Due to the short time window, any differences in network structure should be random, **except** for ones caused by Who To Follow.

Results

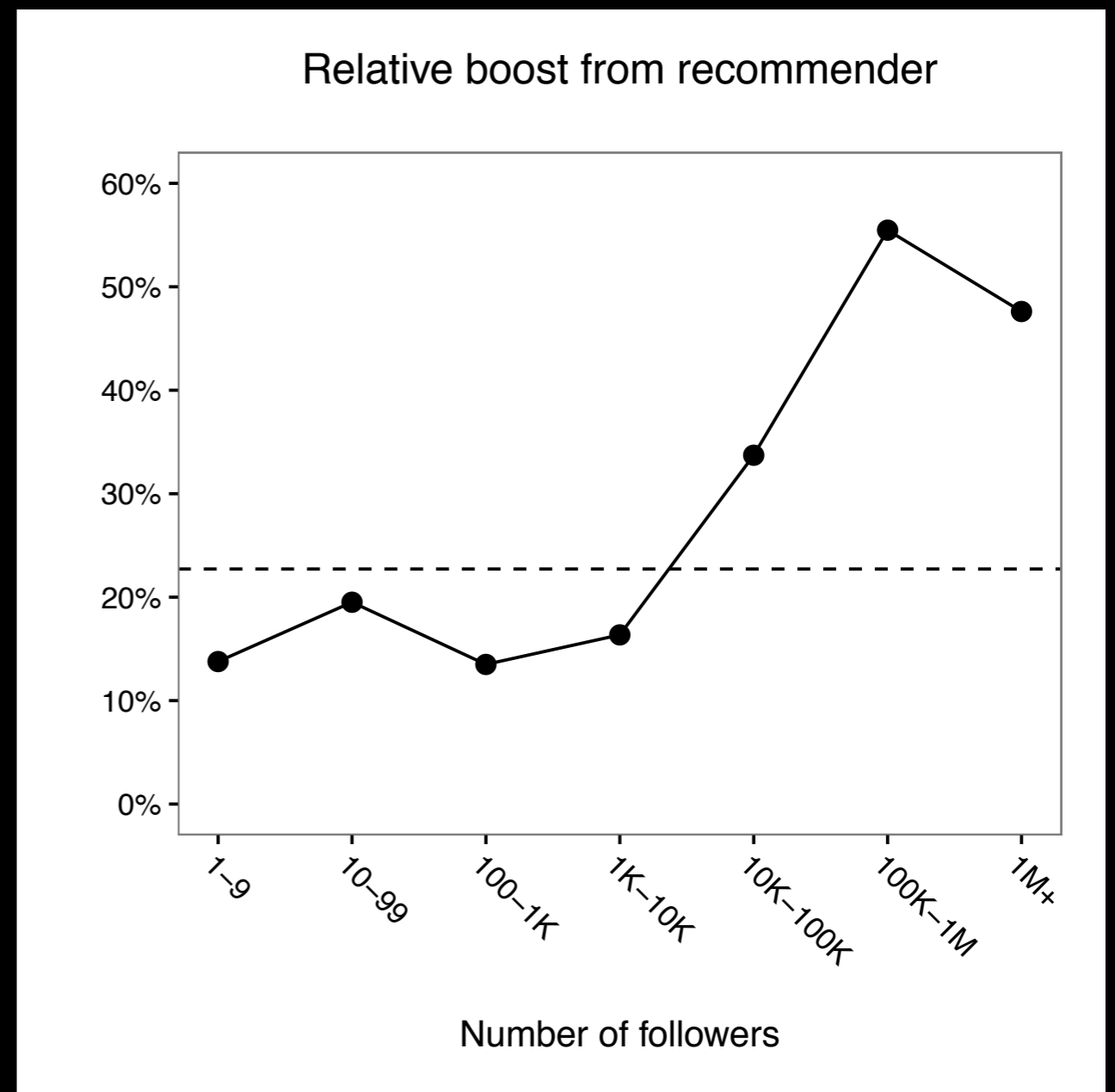
There is an effect



The rich get richer

(but a rising tide lifts all boats)

Everyone sees an increase
in follower growth, but the
popular people benefit
the most

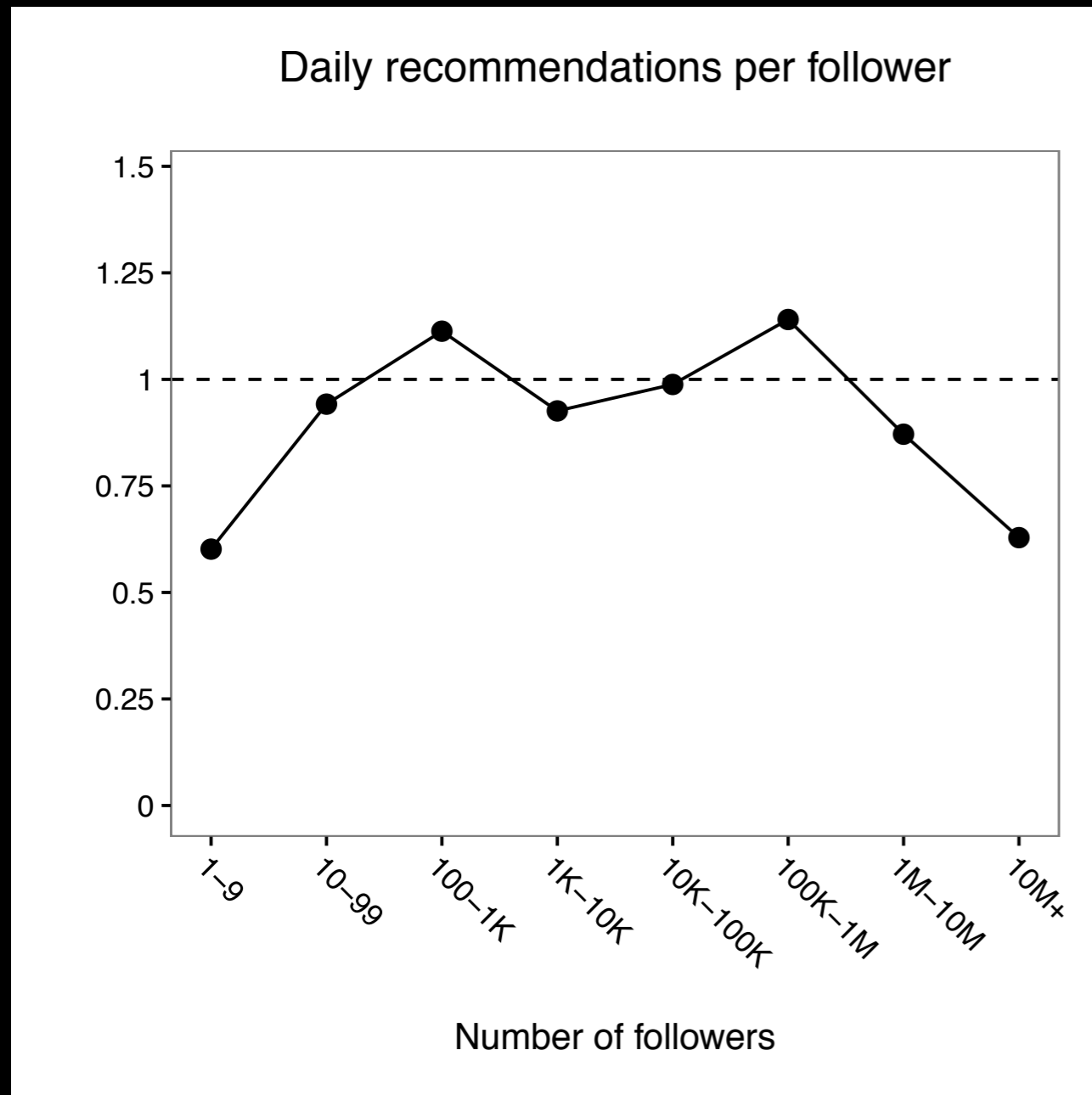


Why do the rich get
richer?

Why do the rich get richer?

1. Mismatch between the dynamics of the recommender and the natural evolution of the network
2. Users respond better to popular users

Linear recommender boost



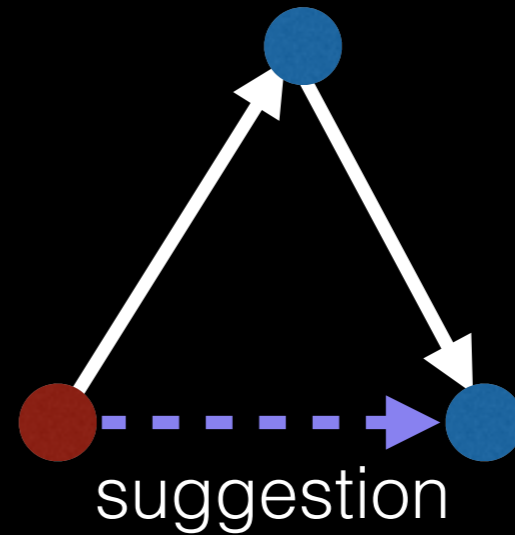
The recommender displays users in a way that is directly proportional to their popularity

Under certain models, we can actually prove this

(y-axis obscured to protect confidentiality;
1 denotes the overall average)

Linear recommender boost

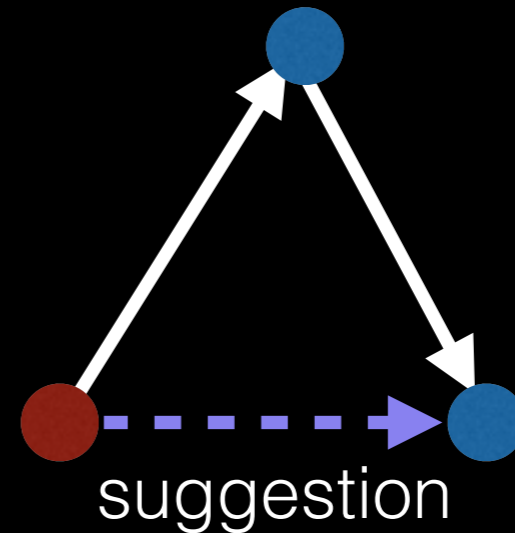
Assume a “friend-of-friend” recommender, where suggestions come from people who your friends are following



To create a recommendation, choose a friend at random, then choose one of their friends at random

Linear recommender boost

Assume a “friend-of-friend” recommender, where suggestions come from people who your friends are following



Theorem 1: If you run this friend-of-friend recommender on a random graph generated using the configuration model, then users are recommended in proportion to how many followers they have

Why the boost?

The recommender displays users in a way that is directly proportional to their popularity



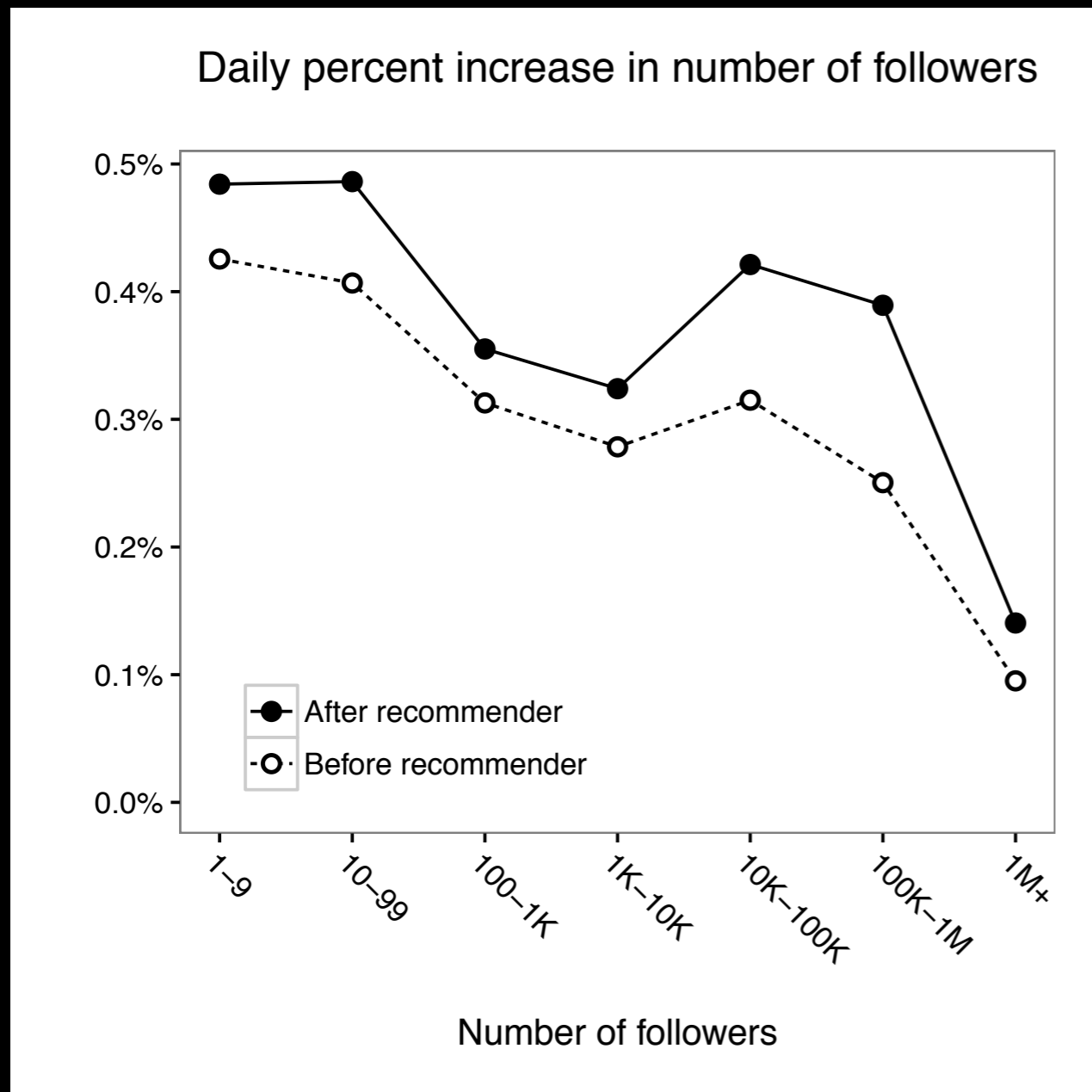
Standard models of network growth predict that people gain followers at a rate proportional to their current follower count, so in theory the recommender shouldn't really change things

Sublinear growth

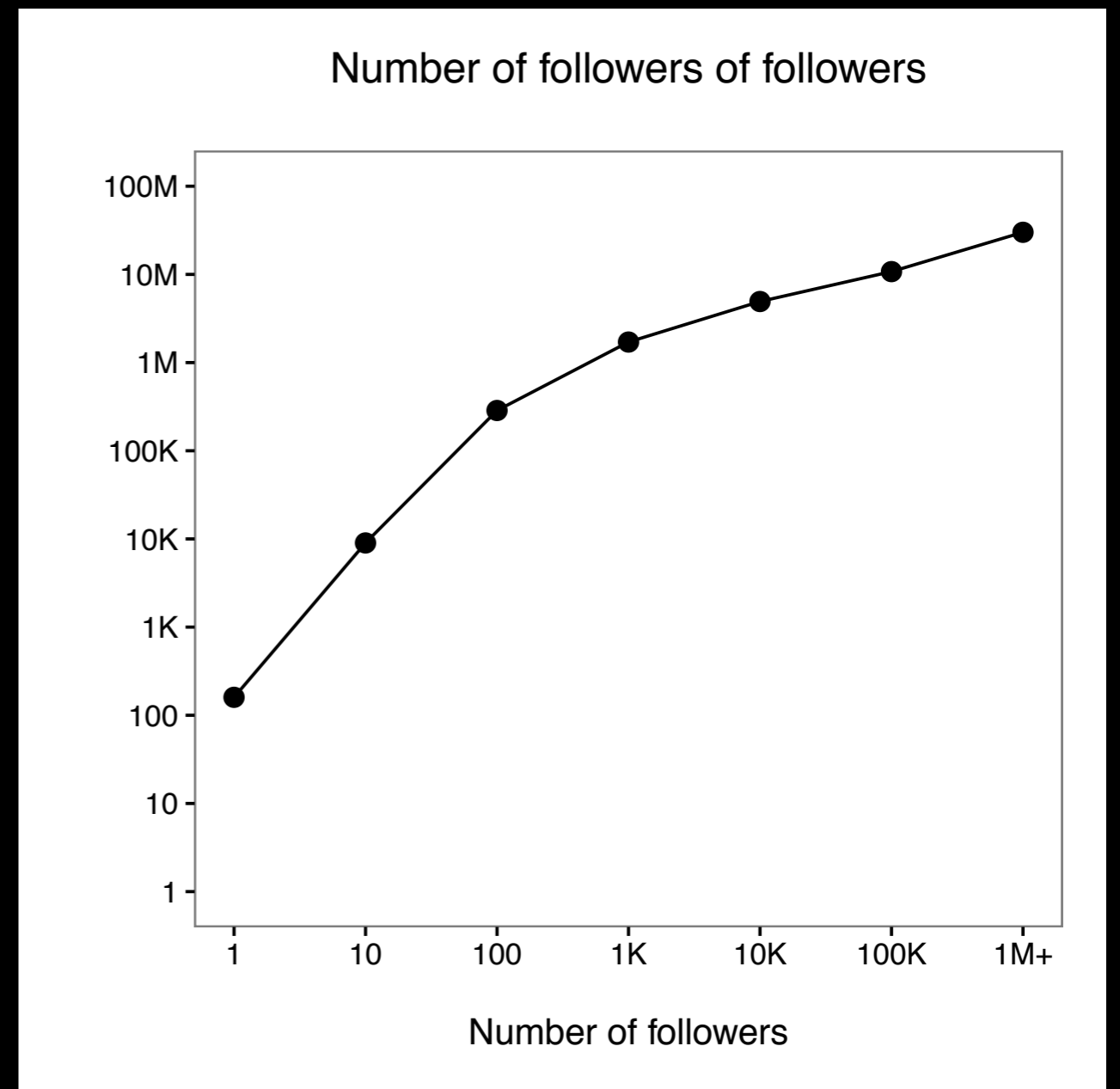
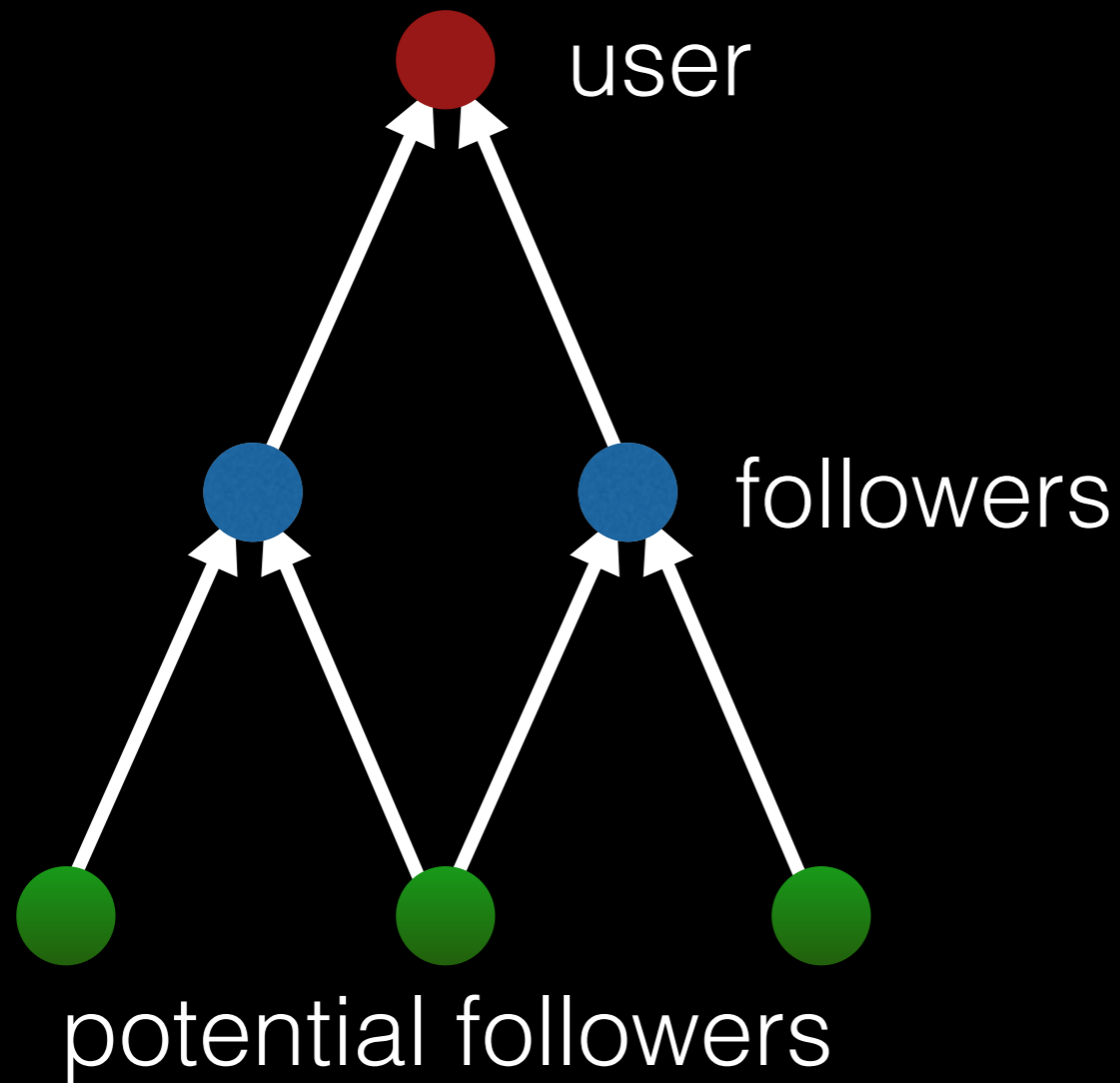
But people **don't** gain followers at a rate proportional to their current follower count

Follower gains grow as a sublinear function of user popularity

(If it were linear, the dotted line would be flat)



Sublinear growth



Popular people are penalized by network “overlap”

Sublinear growth / linear boost

How often the recommender displays users is linearly related to how many followers they have

Since the original rate of follower growth was sublinear as a function of follower count, a linear boost disproportionately favors people with more followers

Sublinear growth / linear boost

$$df/dt = \text{sqrt}(f)$$

$$f = 100 \quad df/dt = 10$$

$$f = 10000 \quad df/dt = 100$$

$$df/dt = \text{sqrt}(f) + f / 10$$

$$f = 100 \quad df/dt = 20$$

$$f = 10000 \quad df/dt = 1100$$

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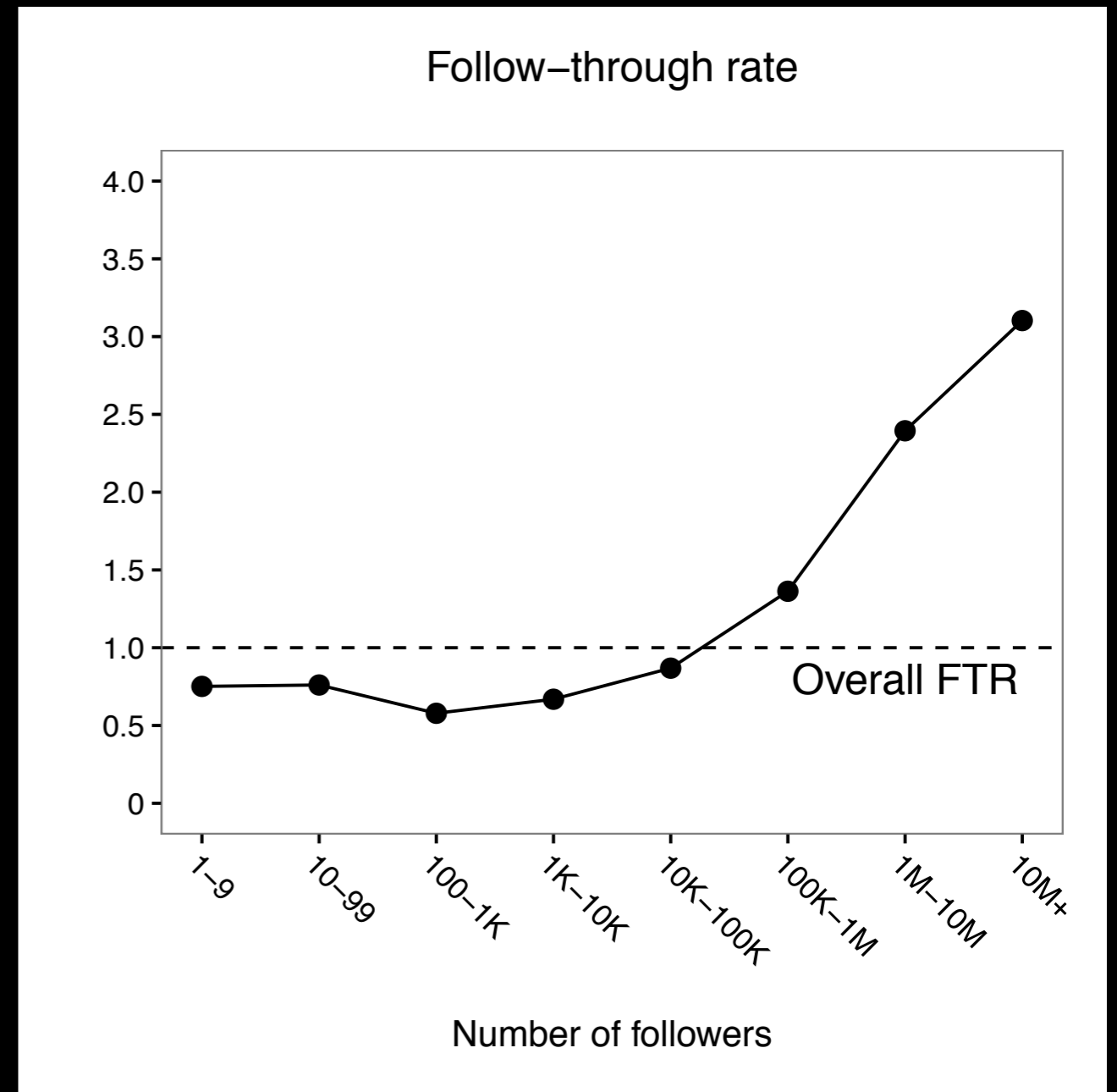
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Since the original rate of follower growth was sublinear as a function of follower count, a linear boost disproportionately favors people with more followers

User response

People are more likely to click
“Follow” for more popular
users



(y-axis obscured to protect confidentiality;
1 denotes the overall average)

Other structural
changes

What kind of connections are being formed?

Do people follow outsiders,
or people who are already
“in their network?”

Do people make friends, or do
they follow people who don't
reciprocate their interest?

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Do new edges
close triangles?

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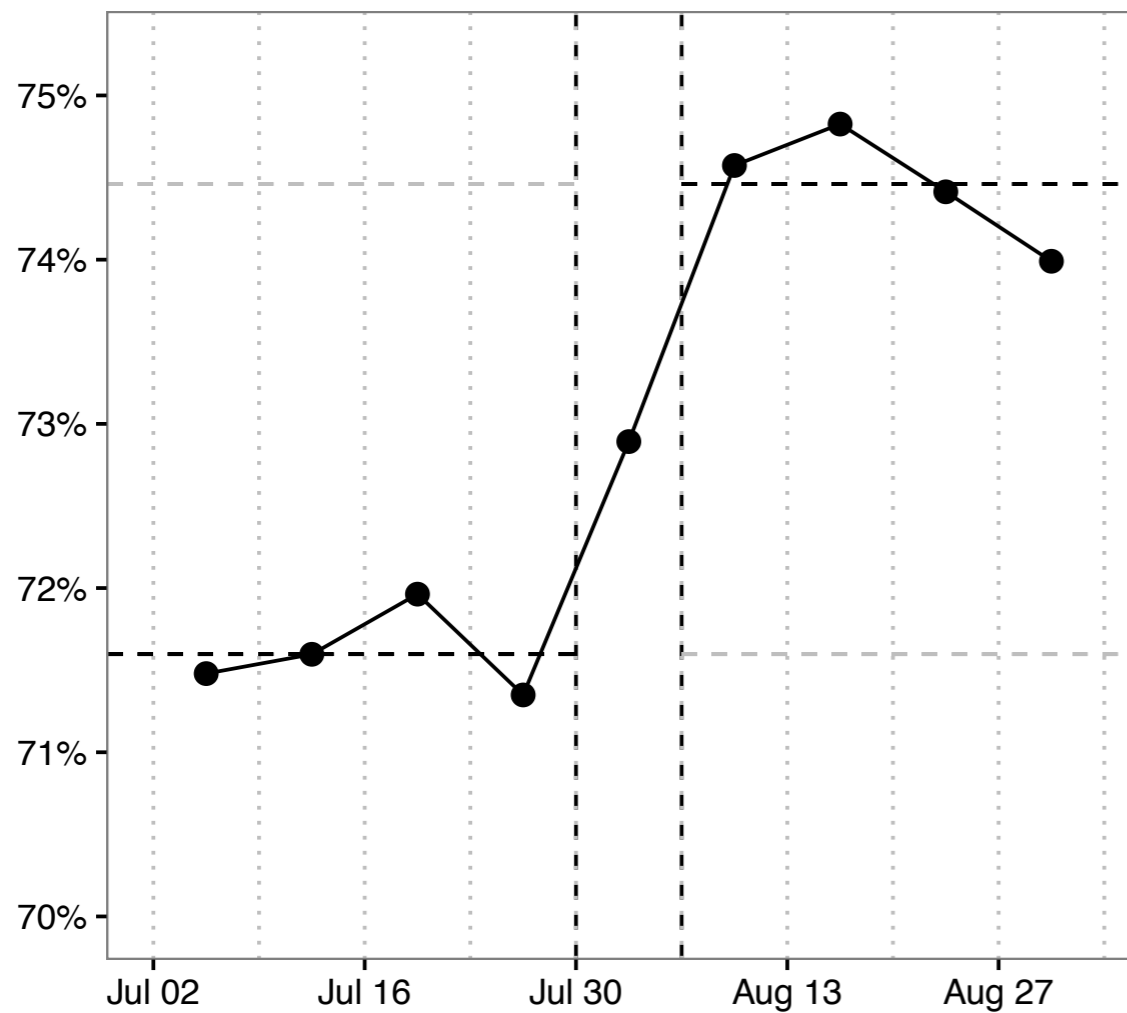
Are new edges reciprocated?

Do new edges close triangles?

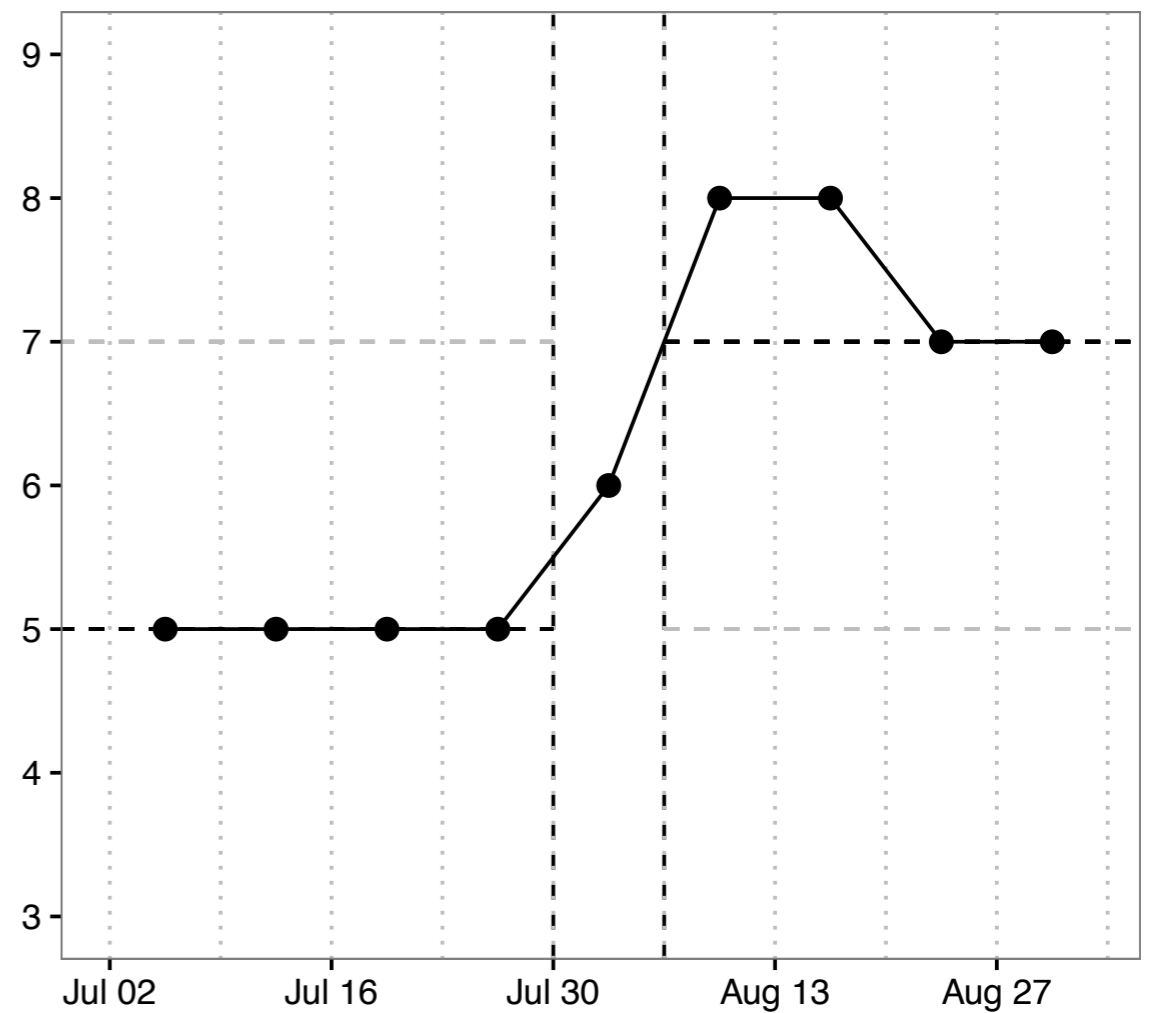
Do people make friends, or do they follow people who don't reciprocate their interest?

Graph becomes more “tightly connected”

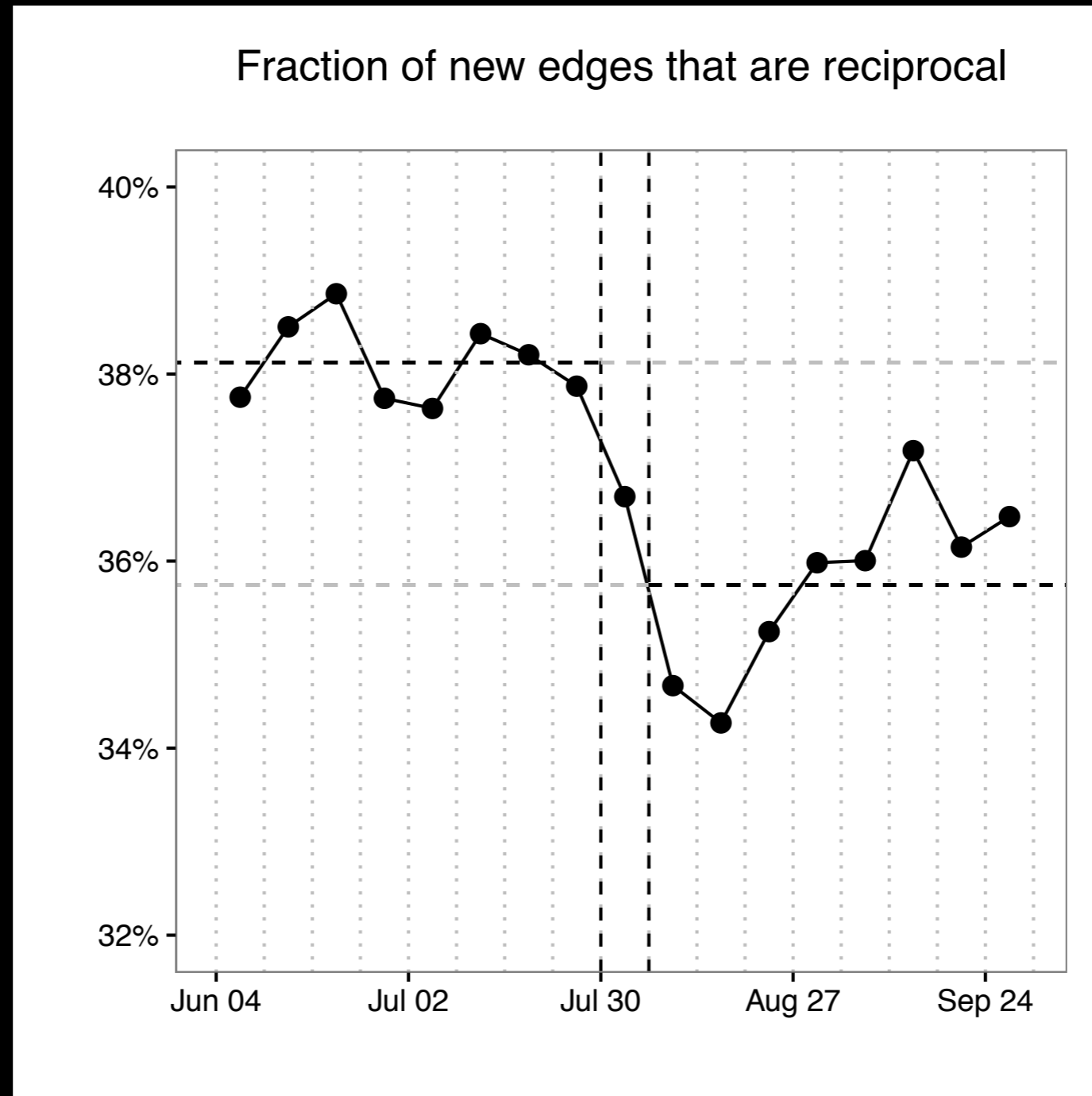
Percent of edges that close a triangle



Median number of triangles closed

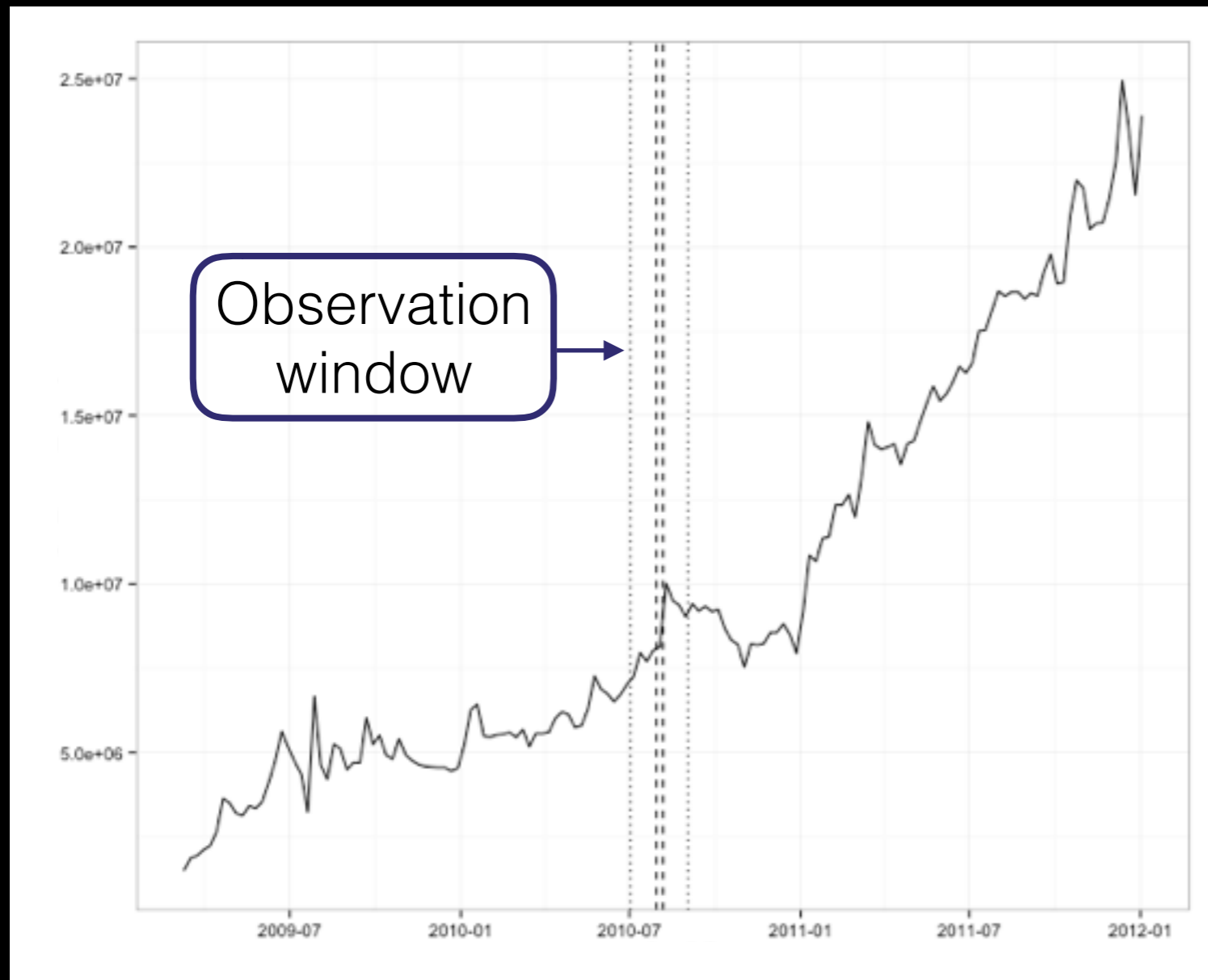


But people aren't really making friends



Thanks for listening

FAQ #1: What happens outside the window of observation?



Misleading

Natural experiment
breaks down

Changes may no
longer be caused by
the recommendation
system

Number of edges added each day