#DebateNight: The Role and Influence of **Socialbots** in the Democratic Process

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Two influencers: the 2016 U.S. Presidential elections

60k followers

136k followers

Common traits:

- Pro-republican;
- Highly influential, highly followed and retweeted;
- Opinion leaders;
- ...

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Russian-controlled bots operated by the Internet Research Agency in St. Petersburg

[Forbes, The Guardian, CNN + 50 more]

The political influence of socialbots

SocialBots:

"Software processes that are programmed to appear to be human-generated within the context of social networking sites such as Facebook and Twitter"

(Gehl and Bakardjieva 2016, p.2)

Immediate and long term research questions:

- are socialbots influential in the political discourse?
- did they have political partisanship?
- *(long term)* were they instrumental for the results of the elections?

#DebateNight dataset

- First U.S. Presidential Debate
  (26 sept 2016, 8.45pm to 10.45pm EDT)
- Twitter Firehose

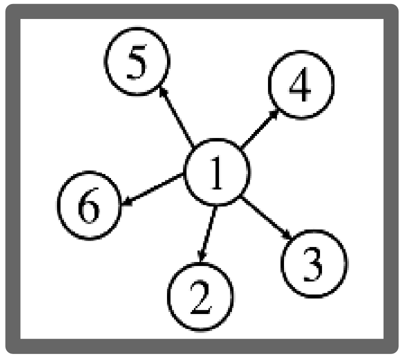
Dataset stats:

- length: **90 minutes**
- #tweets: **6.5M**
- #users: **1.45M**

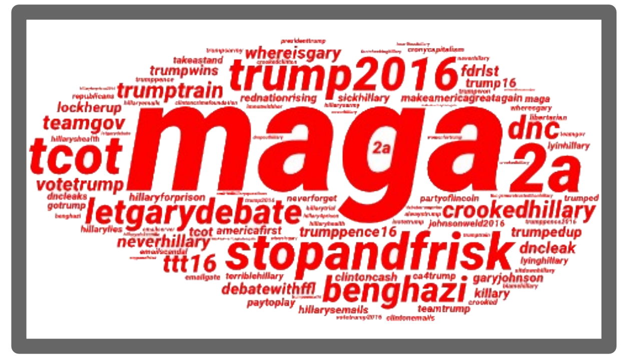
Hashtags:

#DebateNight
#Debates2016
#election2016
#HillaryClinton
#Debates,
#Hillary2016
#DonaldTrump
#Trump2016

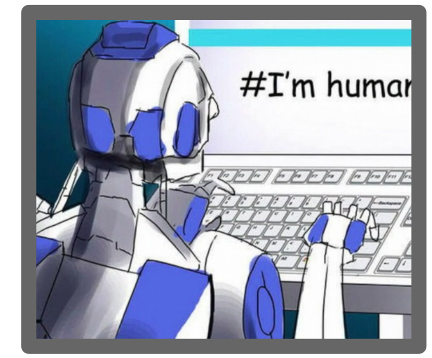
Presentation outline



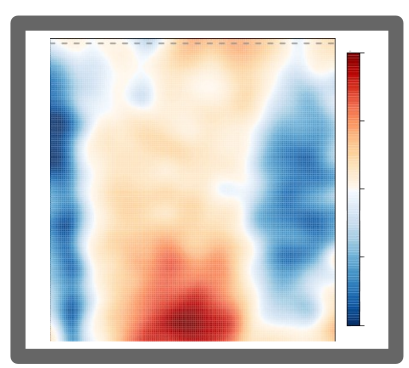
User influence



Political partisanship

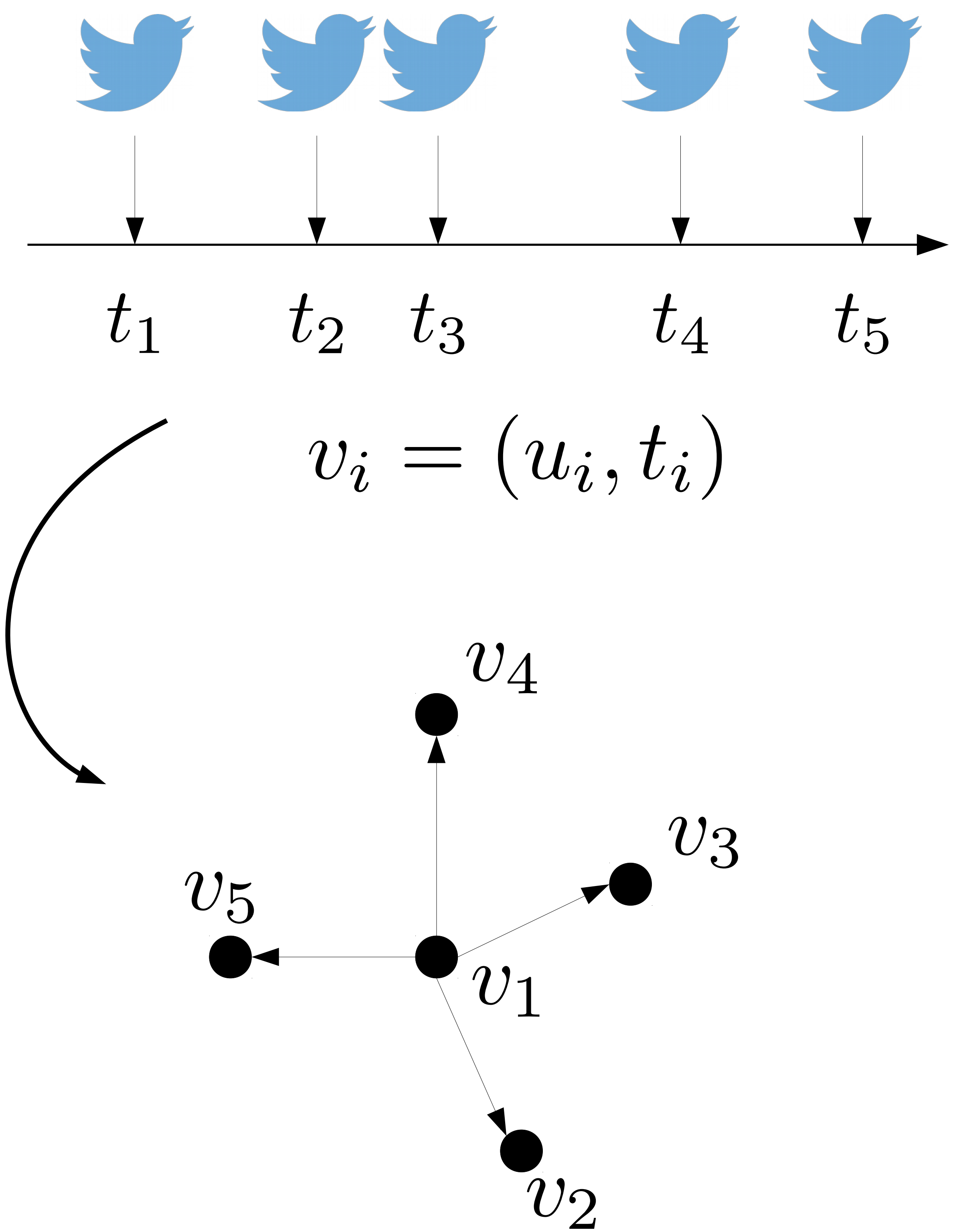


User botness



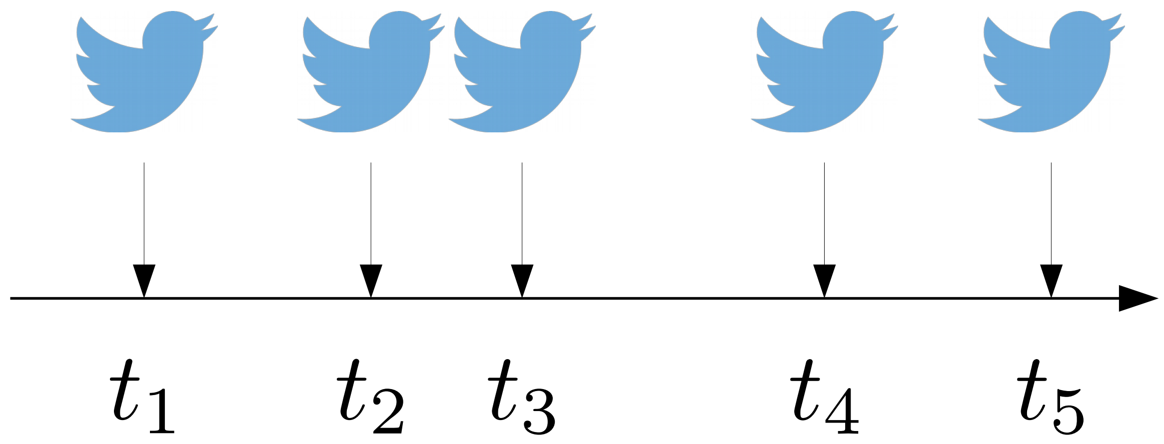
Analyze political behavior of bots

Retweet influence (1)

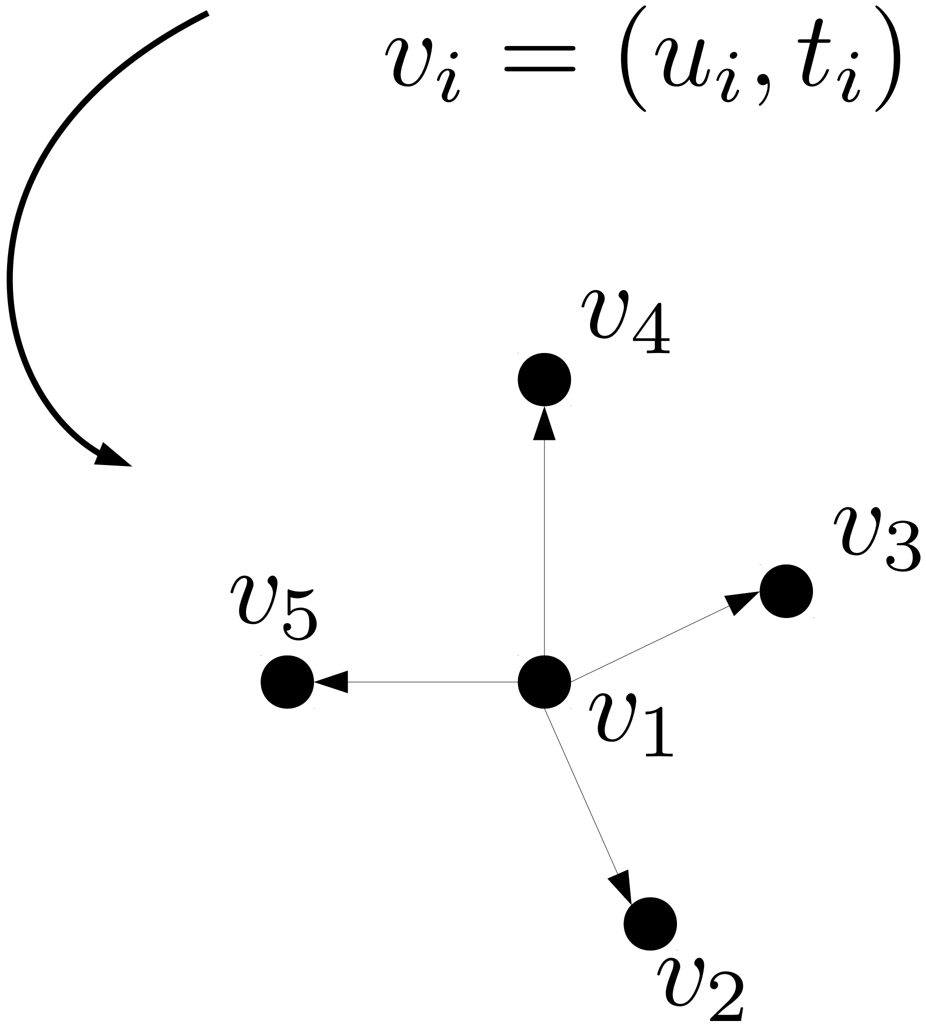


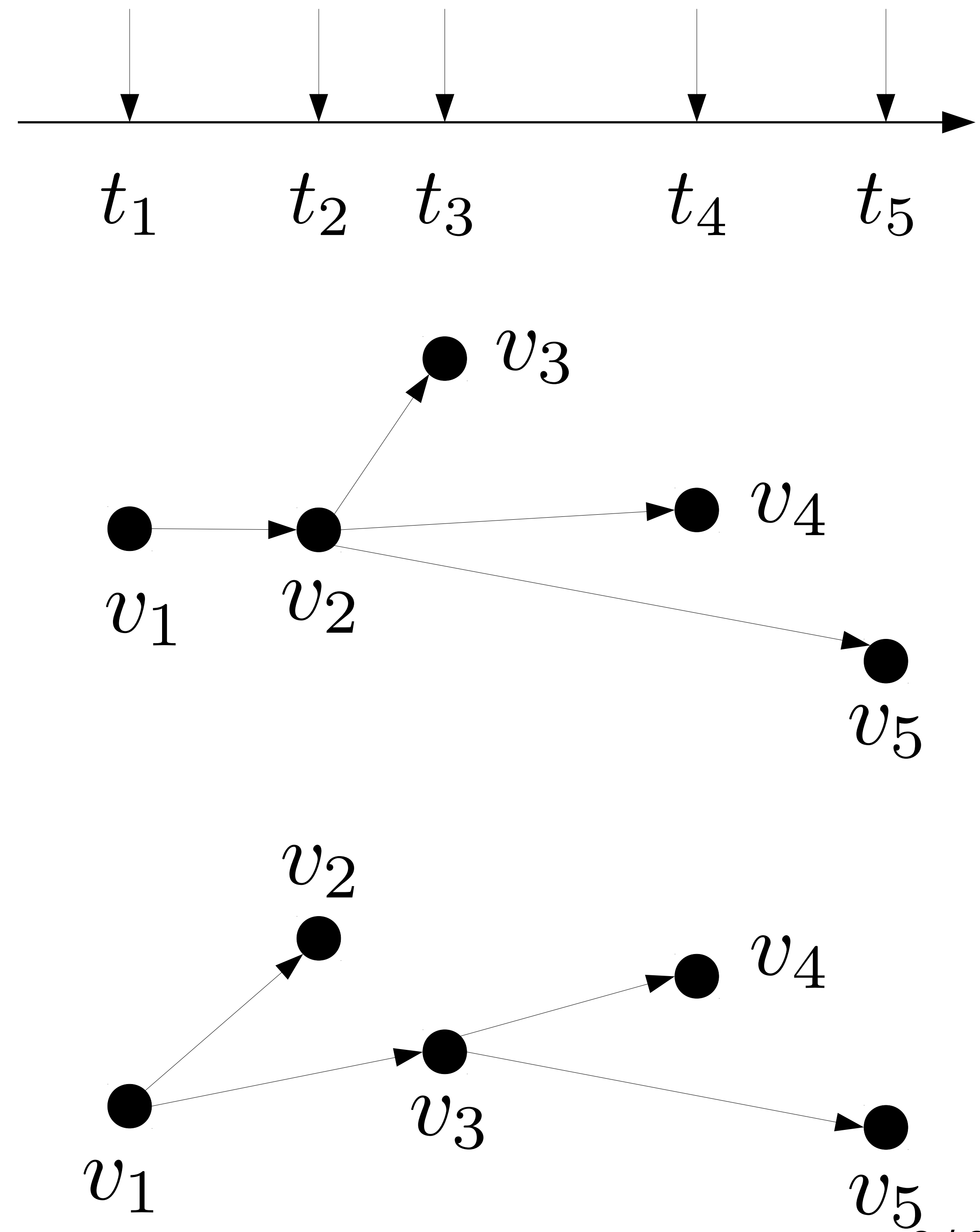
Retweet influence (1)

Diffusion trees and influence



$$v_i = (u_i, t_i)$$





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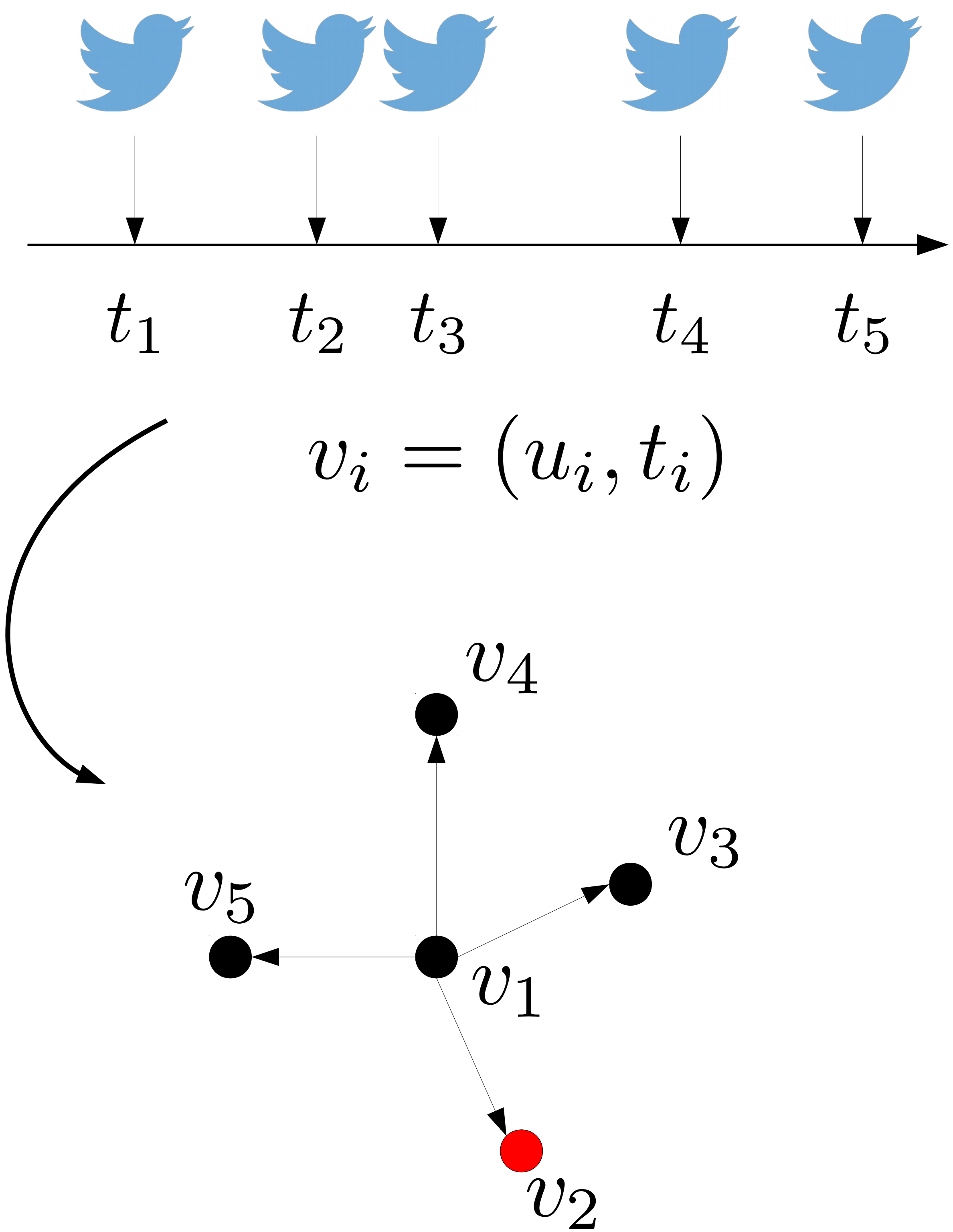

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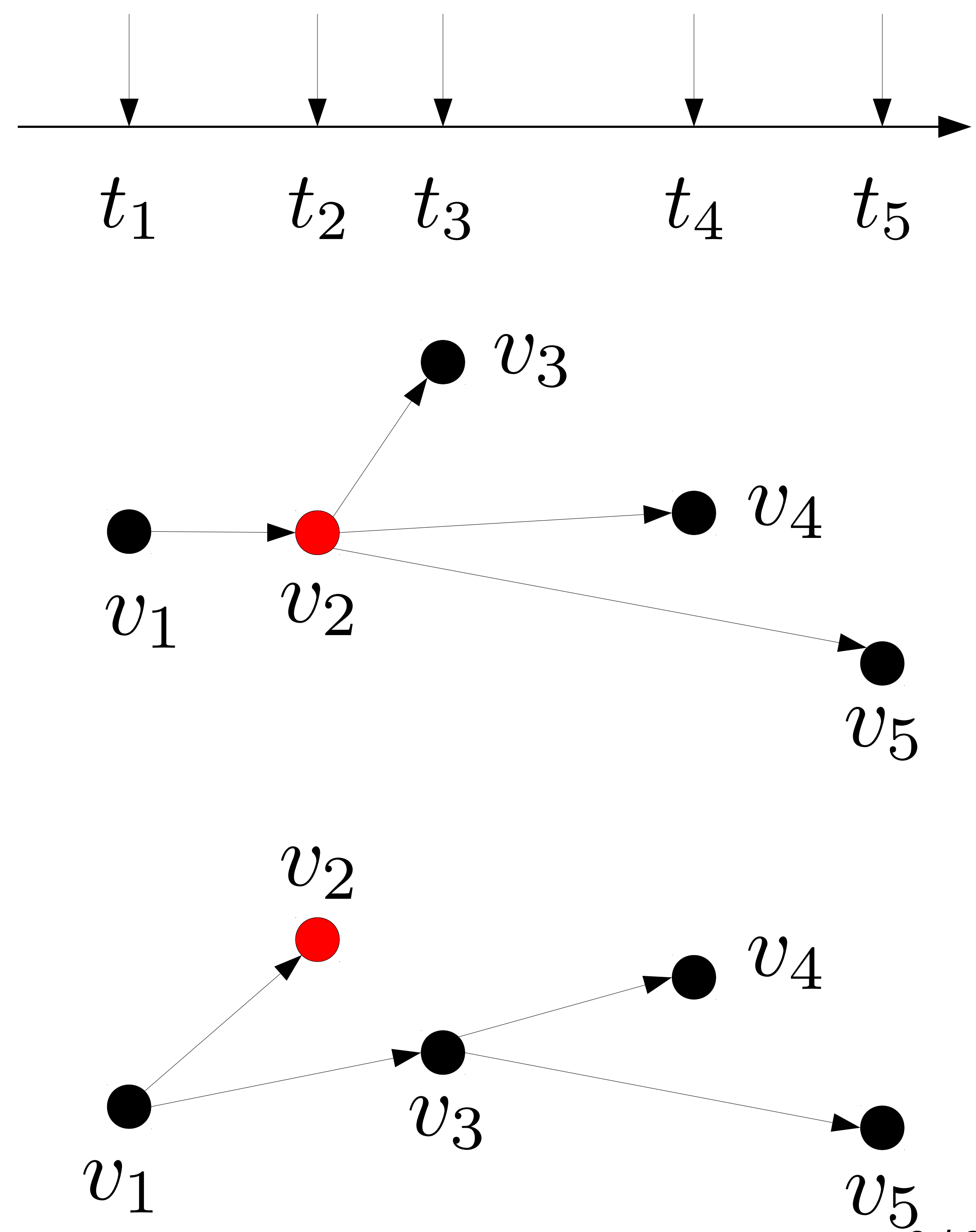

Retweet influence (2)

$$p_{ij} = \frac{m_i e^{-r(t_j - t_i)}}{\sum_{k=1}^{j-1} m_k e^{-r(t_j - t_k)}}$$

branching probability

Retweet influence (2)

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branching probability

- users retweet *fresh content*
  [Hawkes 1971]
  [Wu and Huberman 2007]

Retweet influence (2)

#followers of u_i

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  [Hawkes 1971]
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- preferential attachment
  [Barabási 2005]

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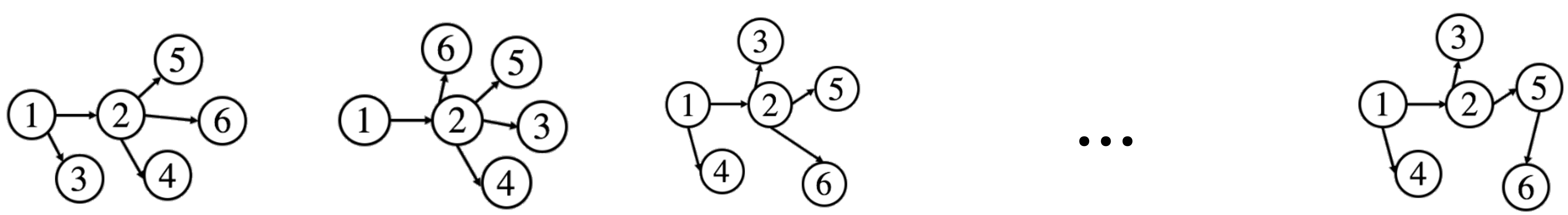
- users retweet *fresh content* [Hawkes 1971] [Wu and Huberman 2007]
- preferential attachment [Barabási 2005]

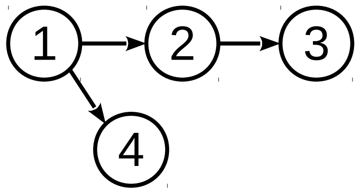
Tweet influence: the expected number of retweets, averaged over all possible trees.

But ... $(n-1)!$ trees 10^{156} trees for 100 tweets



Tractable influence computation

Pair-wise influence score m_{ij}



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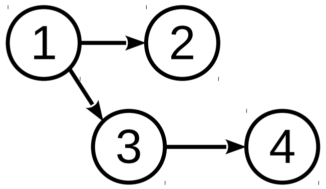
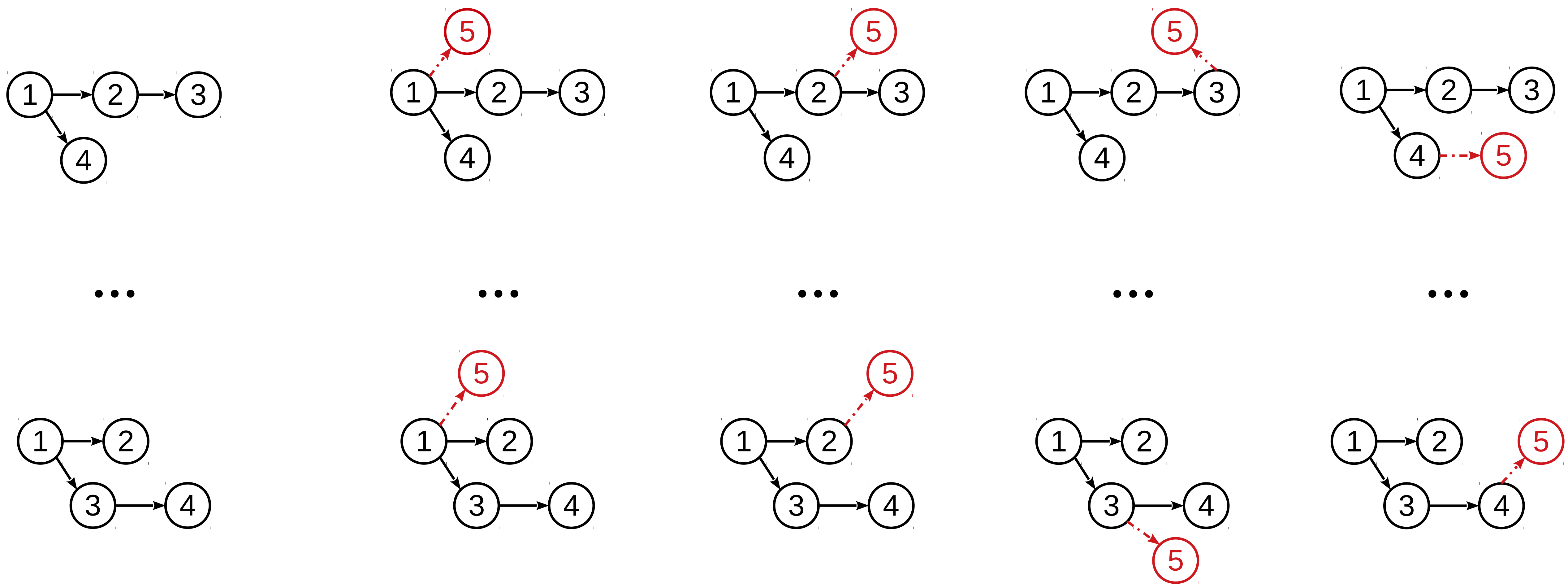


Tractable influence computation

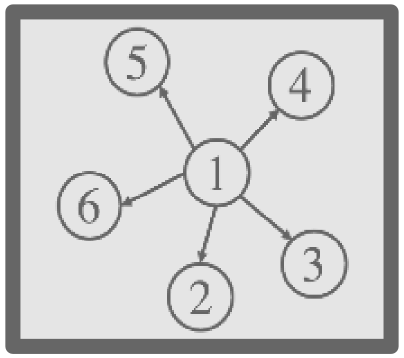
Pair-wise influence score m_{ij}

$$m_{15} = m_{11}p_{15} + m_{12}p_{25} + m_{13}p_{35} + m_{14}p_{45}$$



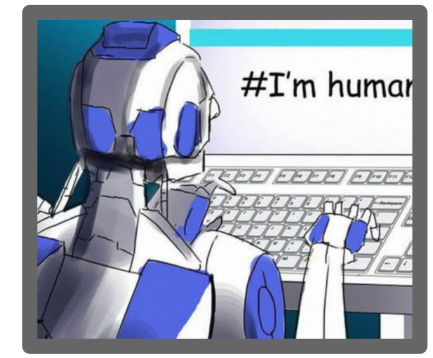
Recursive algorithm $\quad O(n^3)$

Presentation outline

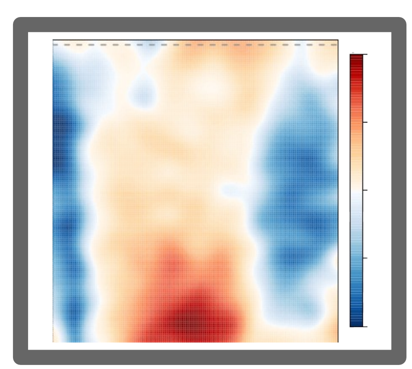


User influence

Political partisanship



User botness

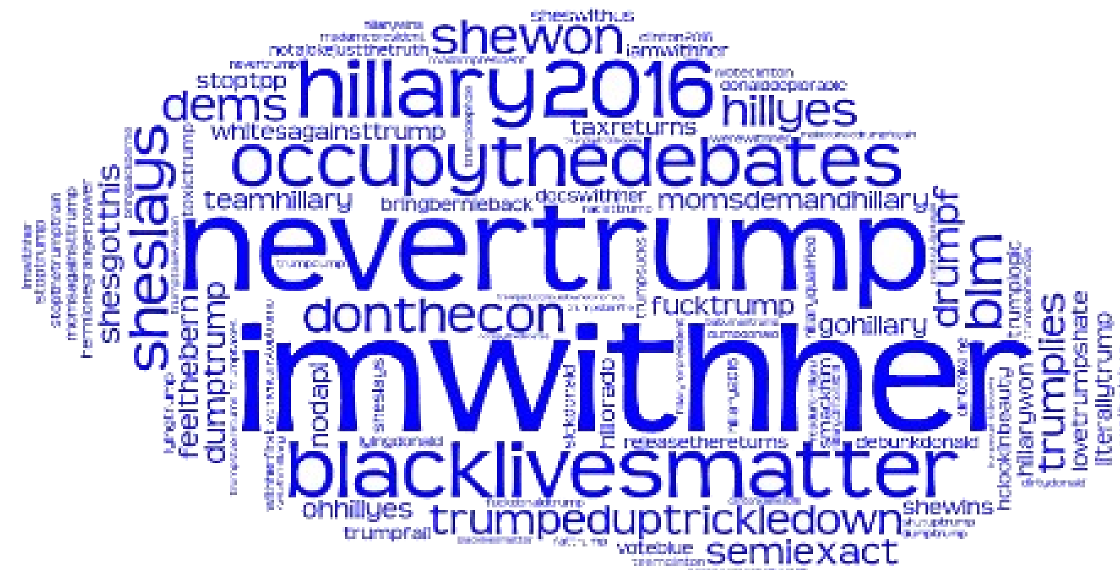


Analyze political behavior of bots

Polarization and engagement (1)

Protocol:

- Top 1000 most frequent hashtags
- Manually labeled as *clearly partisan* pro-democrat or pro-republican



Partisanship stats:

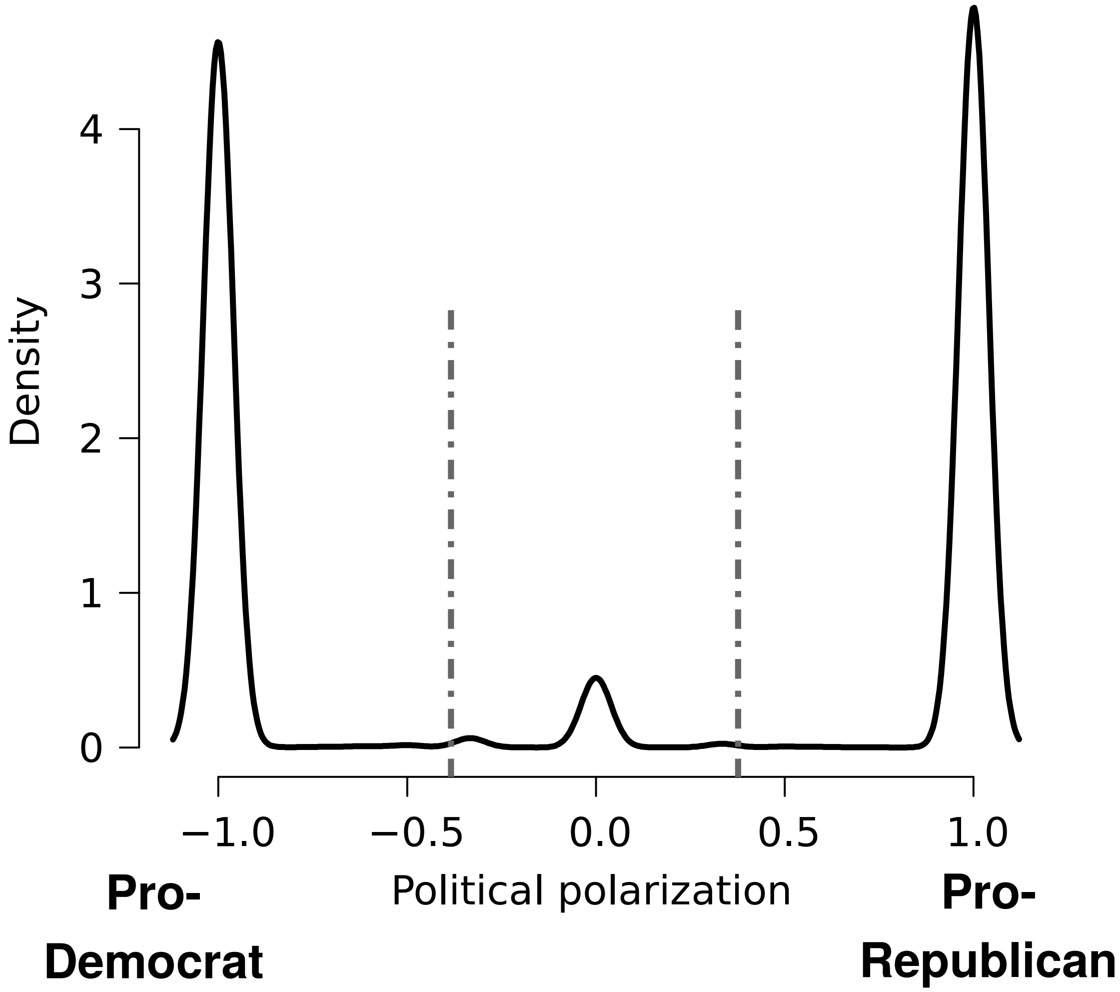
- pro-Democrat hashtags: **93**
- pro-Republican hashtags: **86**
- partisan tweets: **65K**
- partisan users: **47K**

Polarization and engagement (2)

For each user *i*:

- dem_i – #democrat hashtags
- rep_i – #republican hashtags

$$\mathcal{P}(u_i) = \frac{rep_i - dem_i}{rep_i + dem_i}$$



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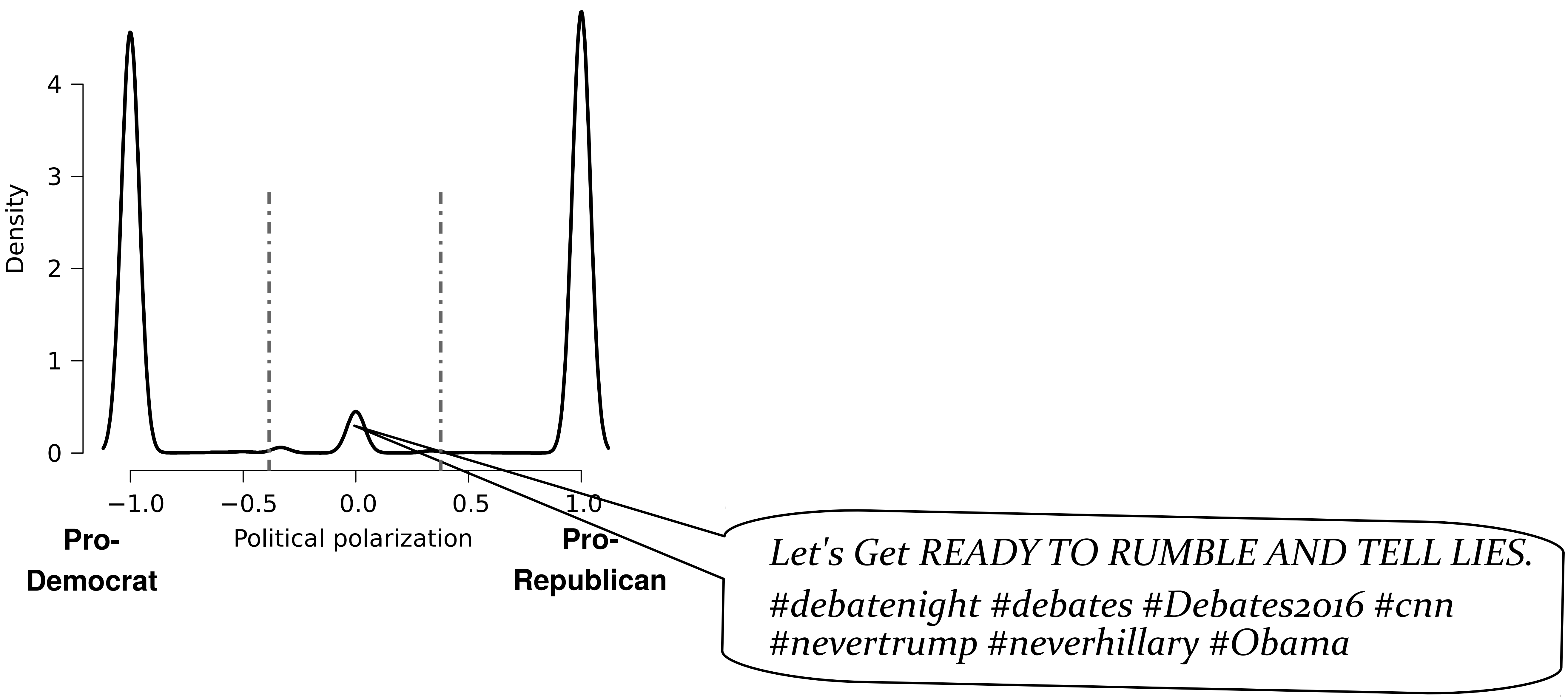

Botness score and bot detection

Bot detection:

- **BotOrNot** [Davis et al, WWW '16] [Varol et al, ICWSM'17]
  - RandomForest classifier
  - more than 1000 features from metadata

    0 – very likely human

    1 – very likely bot

  - 94.5% precision

Separating bots from humans

Three populations

Population	Effective
All	1,451,388
Protected	45,316
Suspended	10,162

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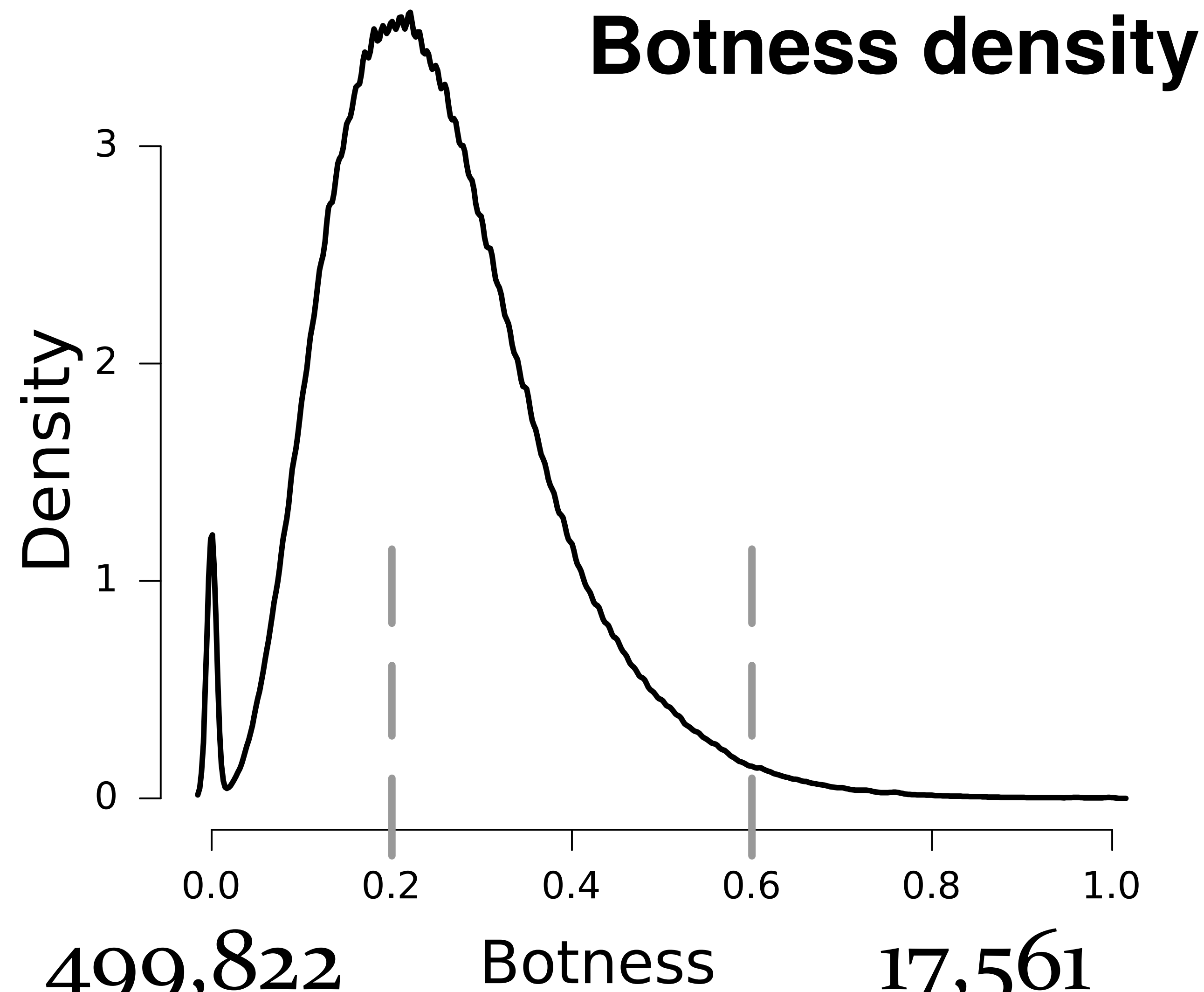
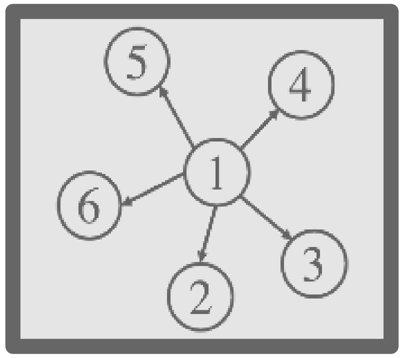


499,822 Humans

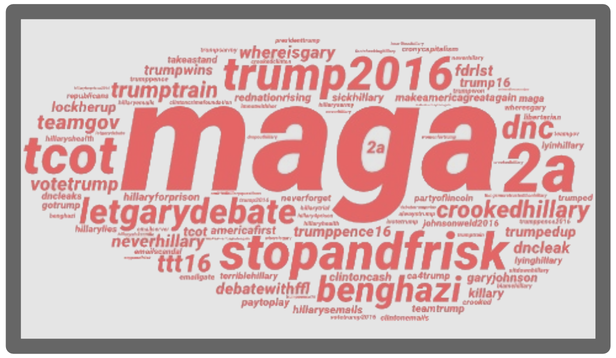
17,561 Bots

[Varol et al, ICWSM'17] use a threshold of 0.5

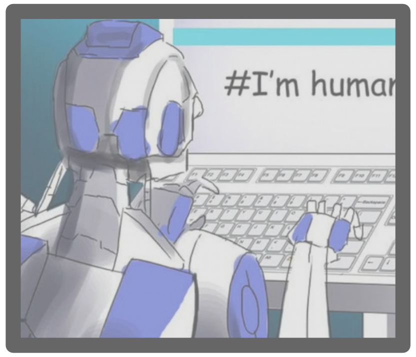
Presentation outline



User influence



Political partisanship



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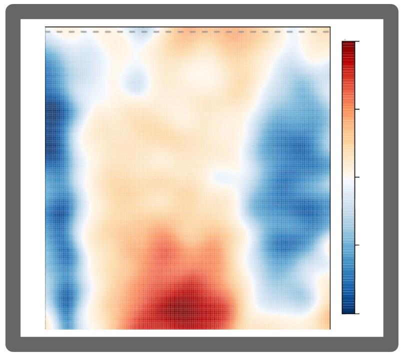
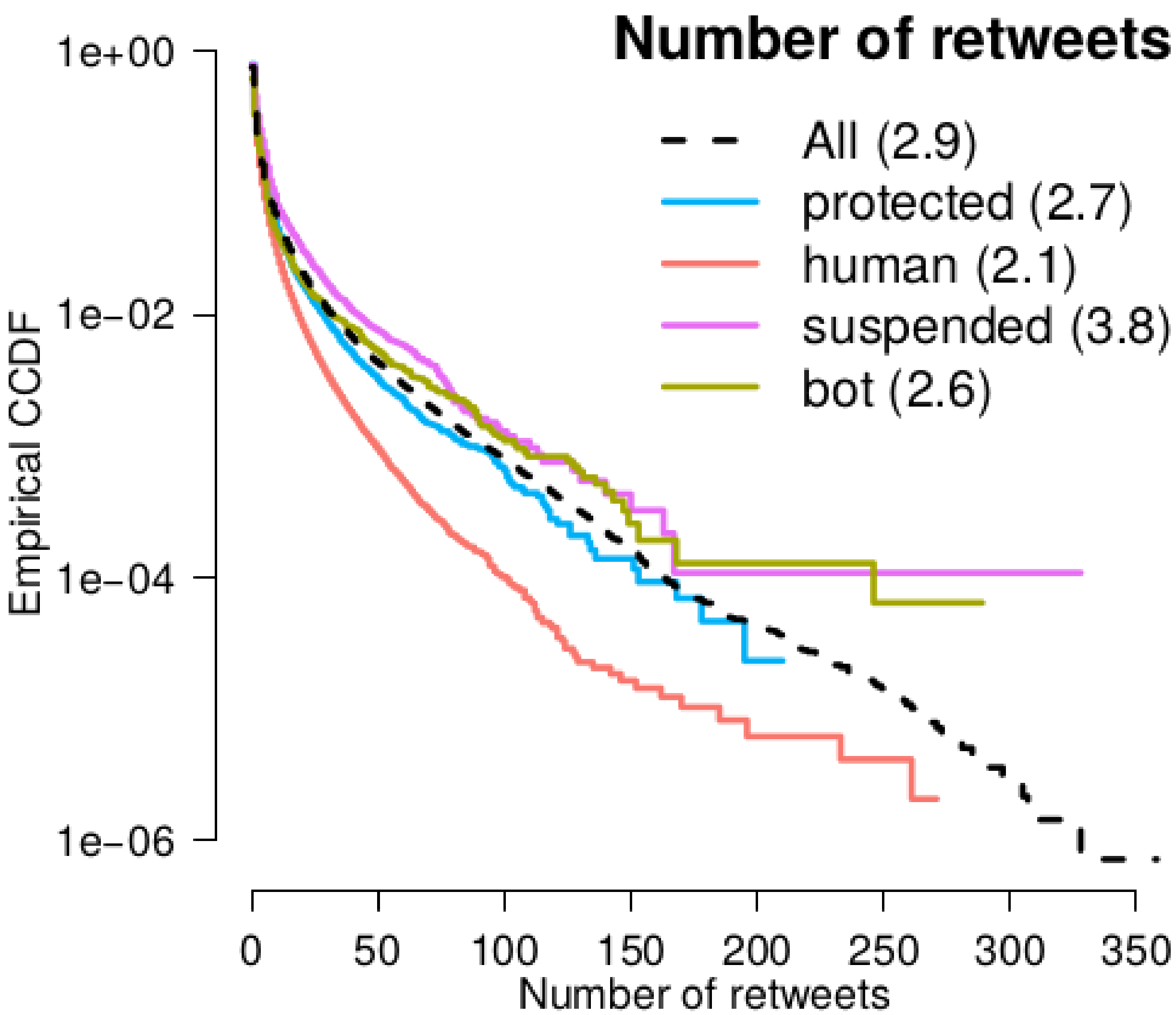
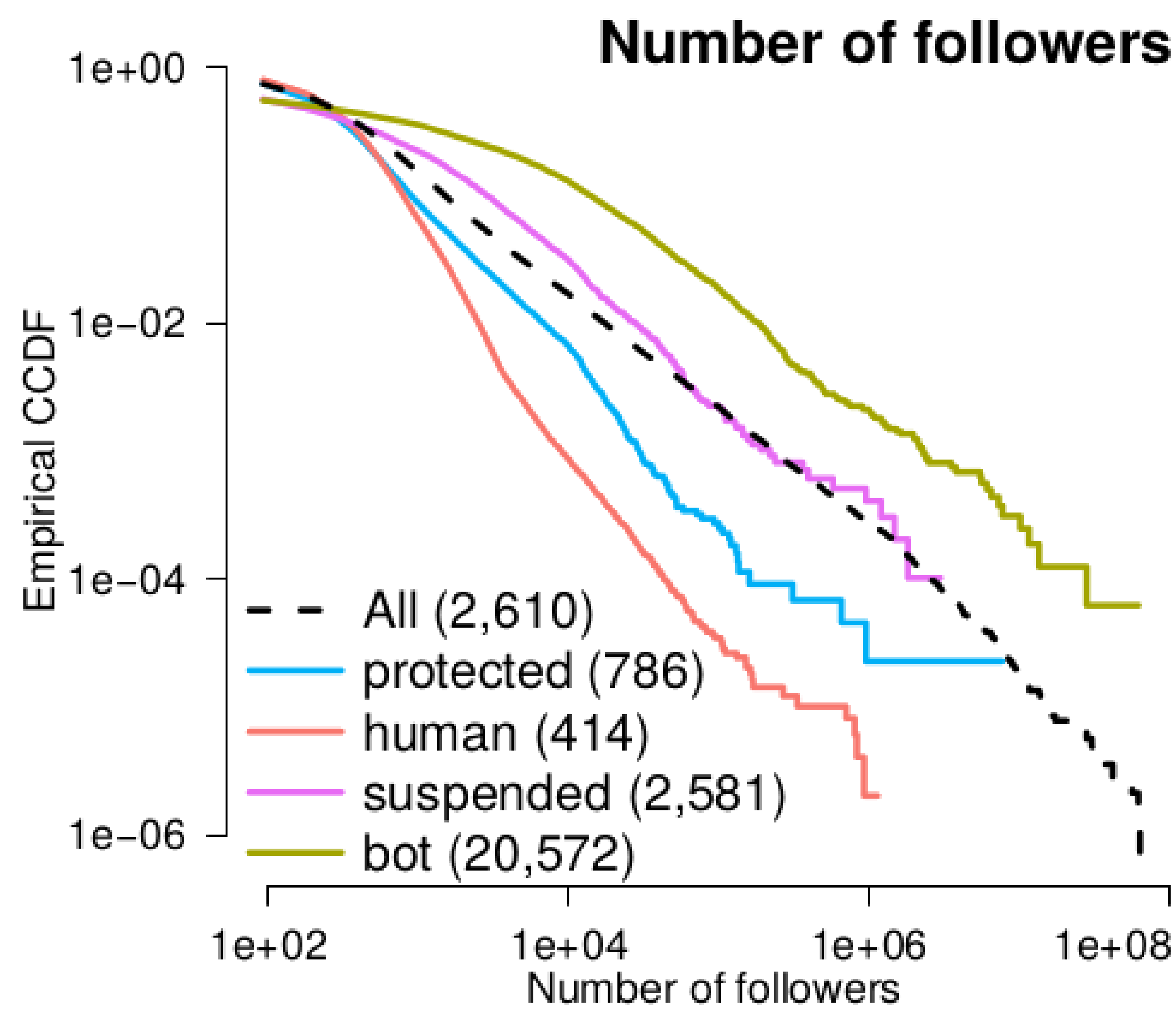


Analyze political behavior of bots

Activity profiling

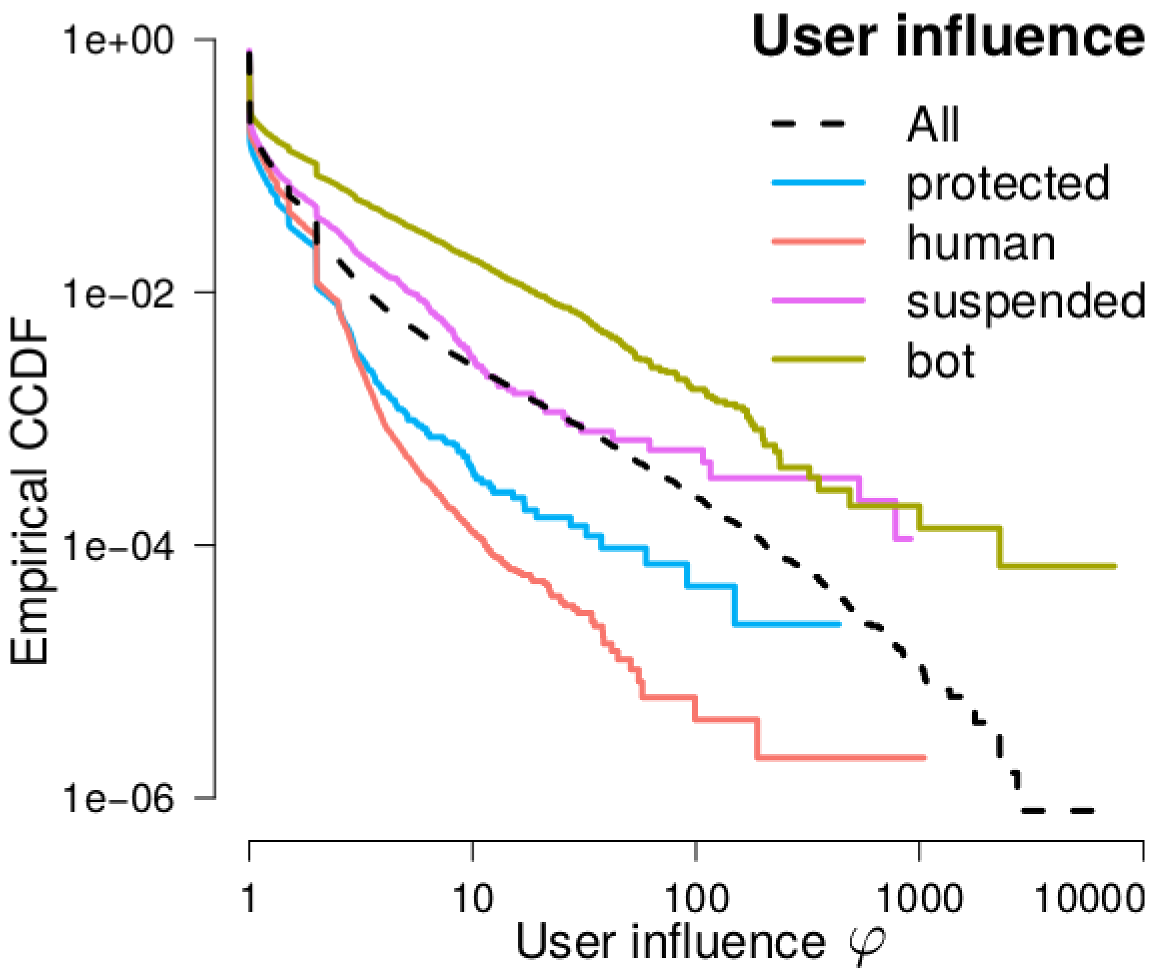


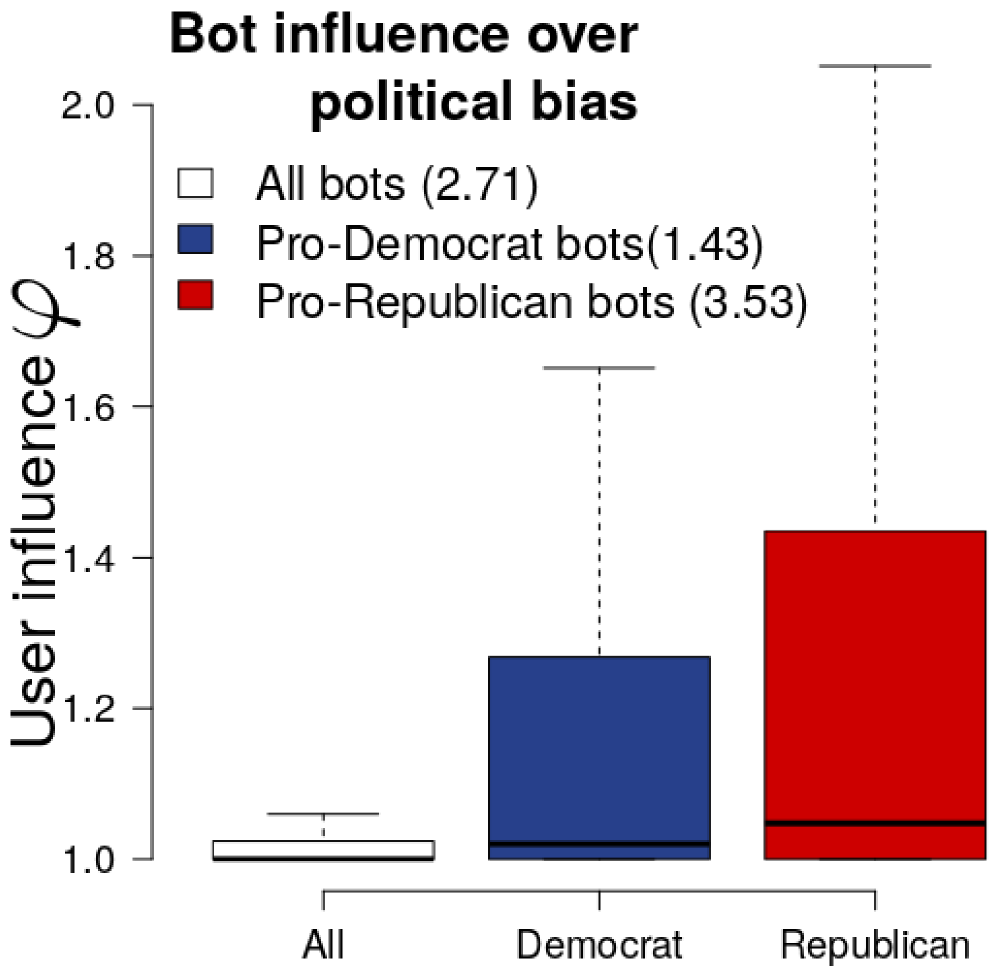


Bots and **Suspended** are more active than **Humans** and **Protected**

Some **Bots** are highly followed, while most are ignored

User influence

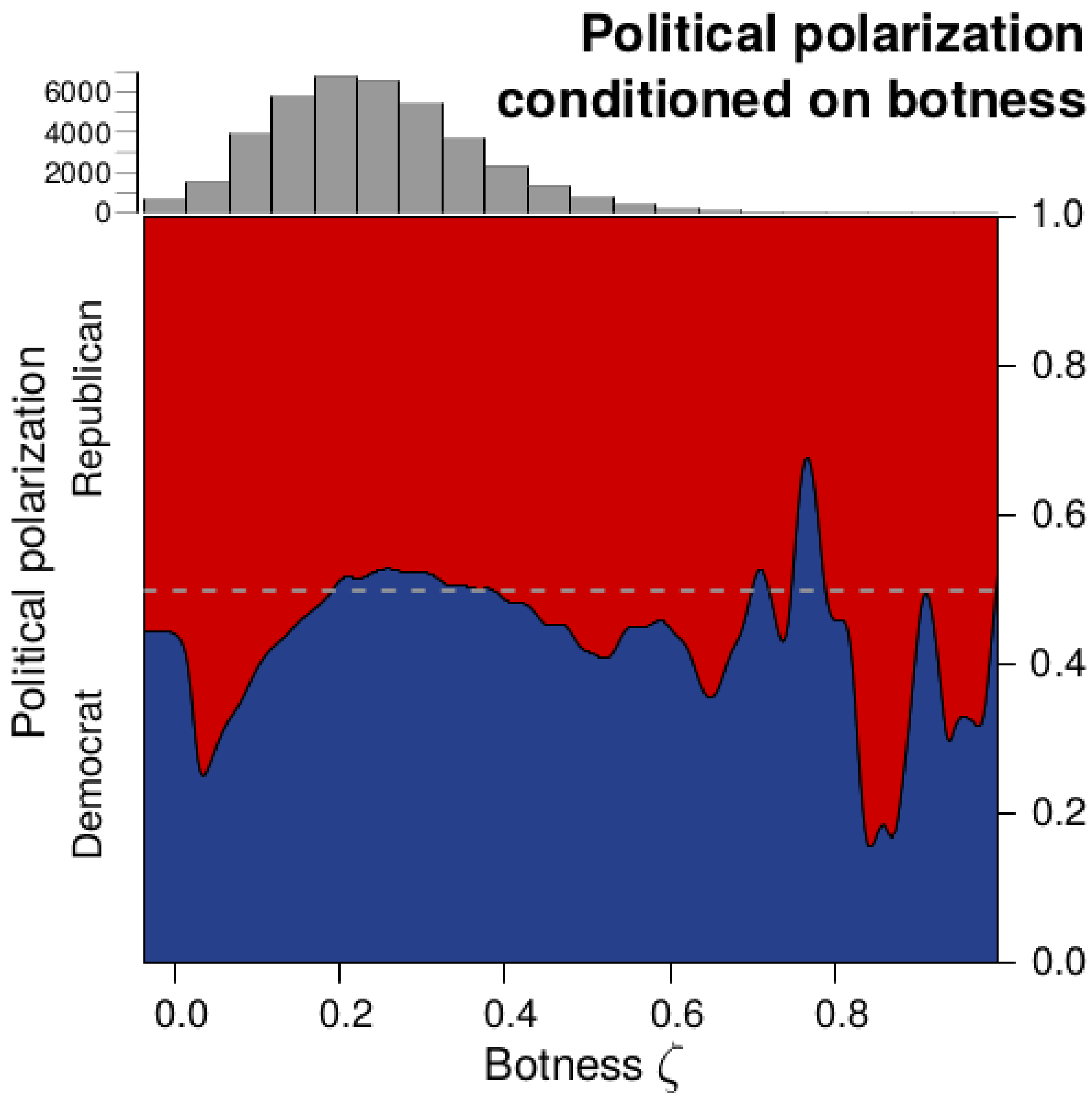


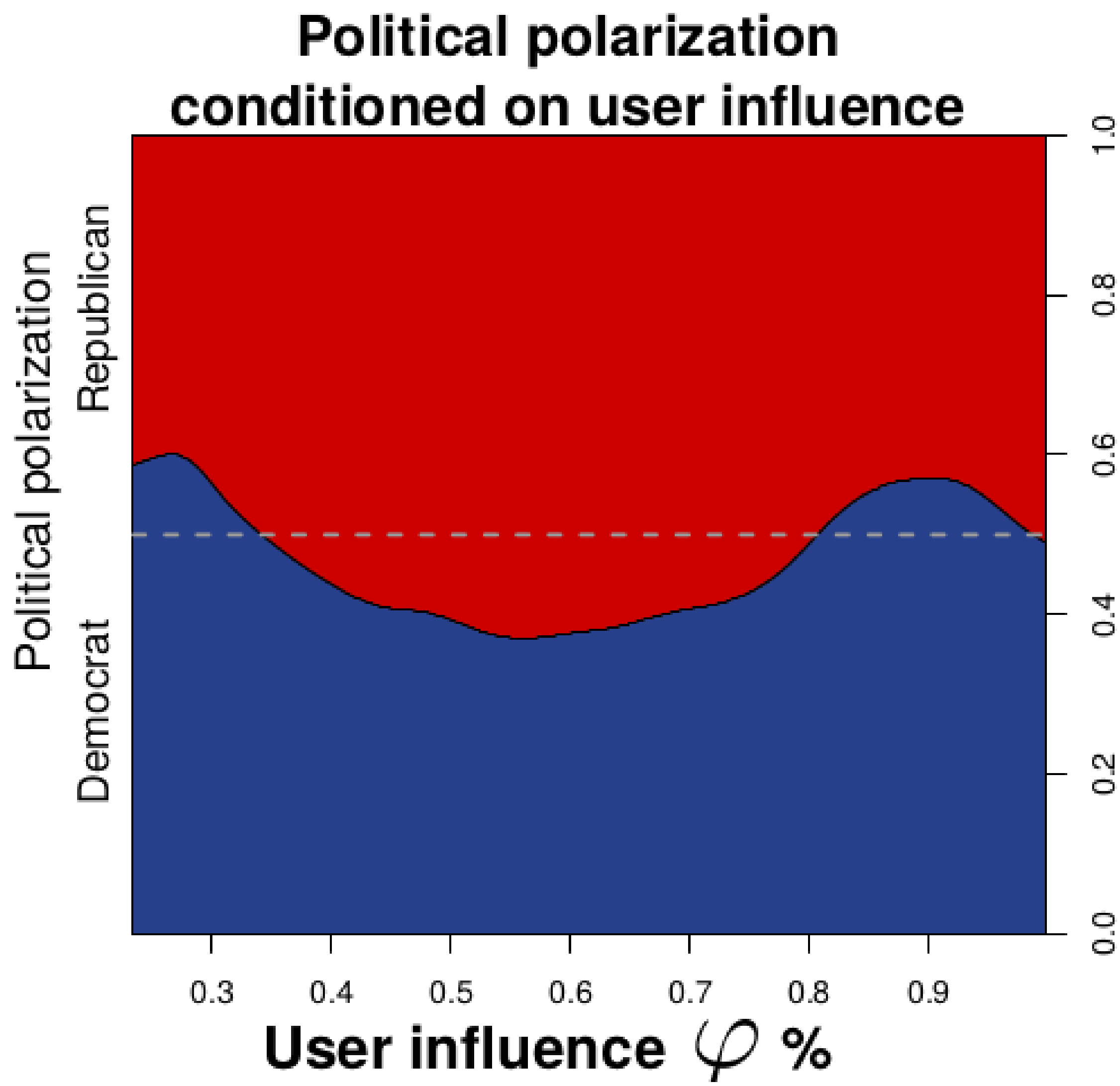


The average **Bot** has 2.5 times more influence than the average **Human**

The average pro-Republican **Bot** is twice as influential as the average pro-Democrat **Bot**

Political partisanship

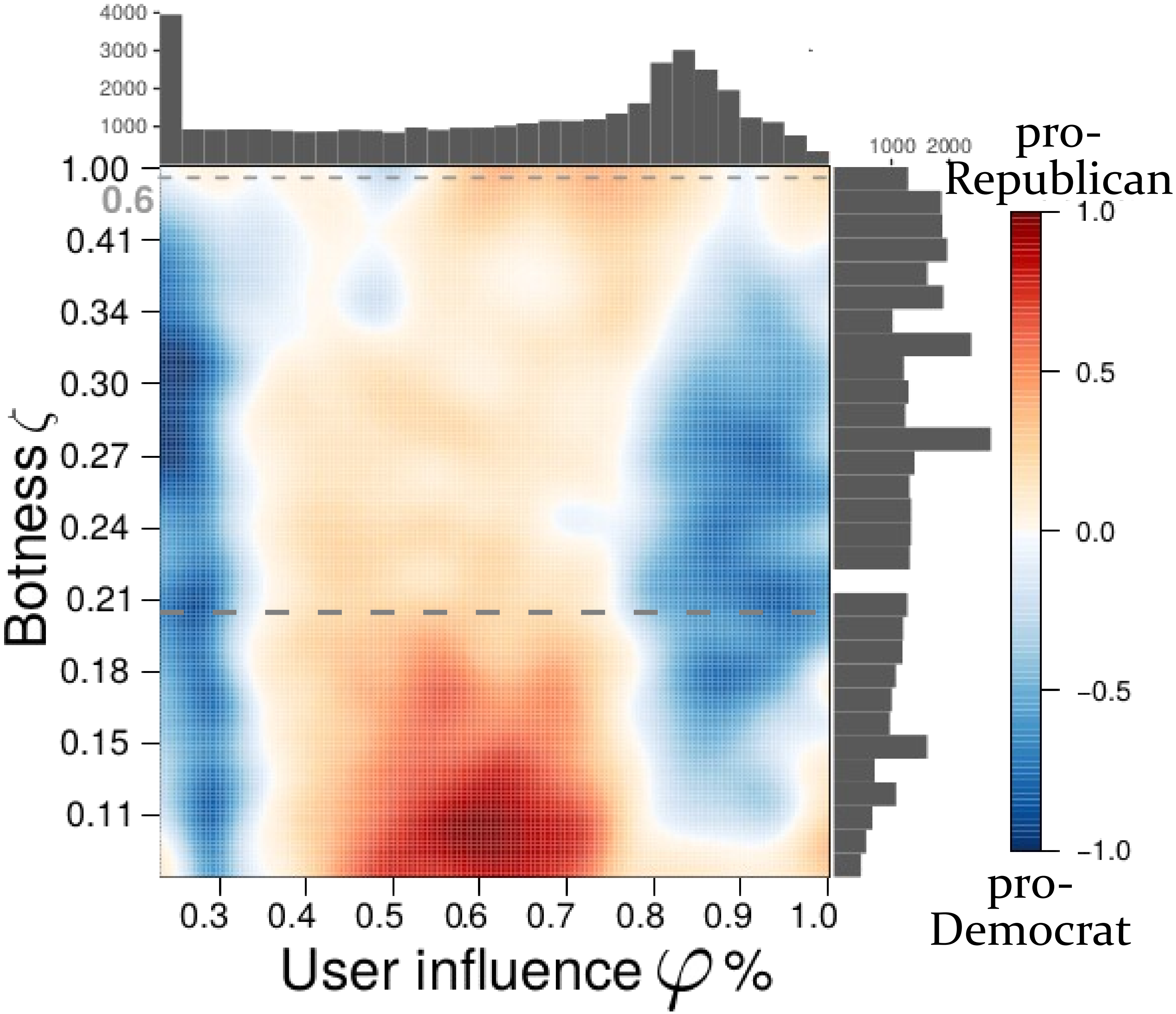




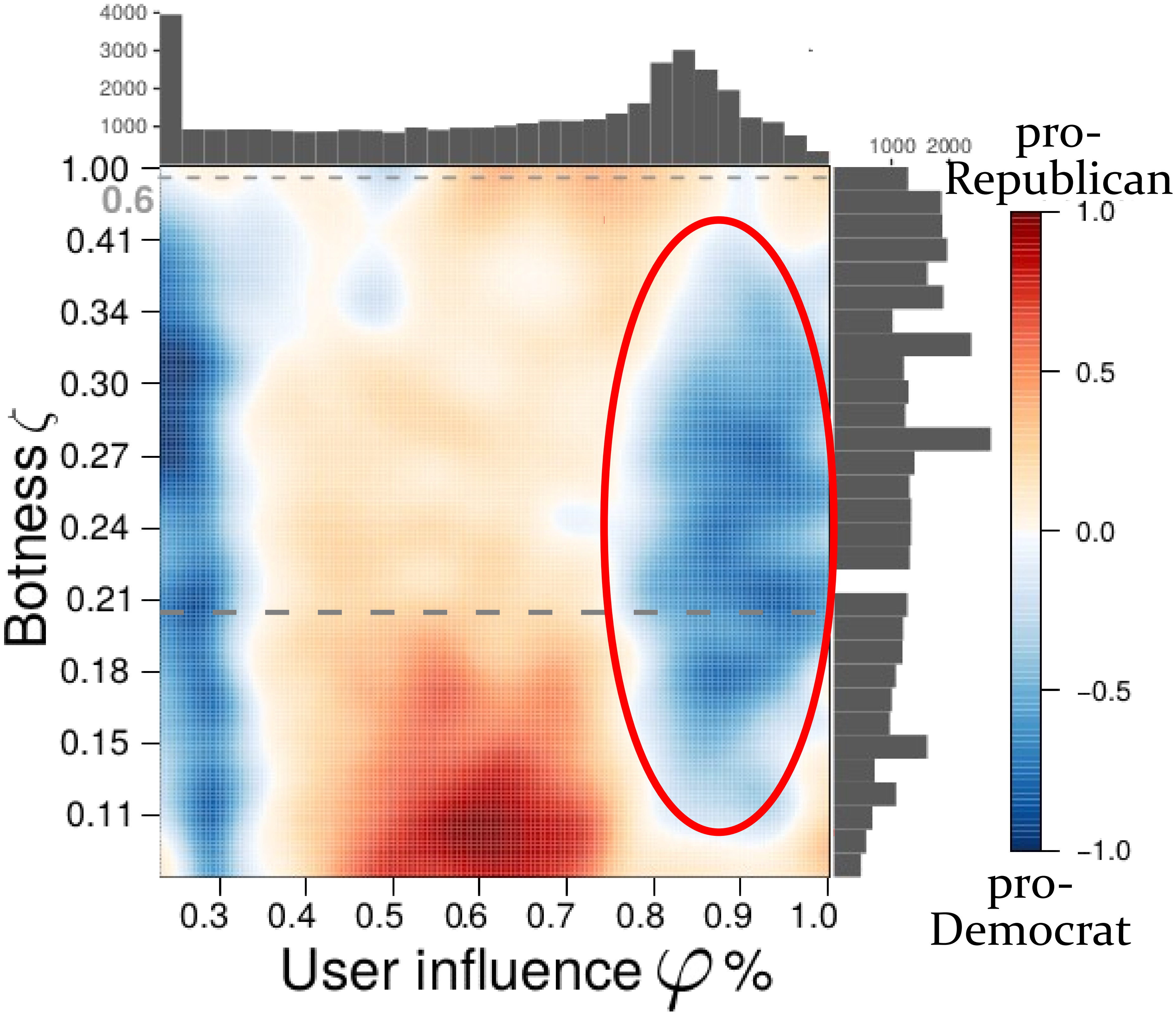
Bots are more likely to be pro-Republican (than pro-Democrat)

Very highly influential users are more likely to be pro-Democrat

Polarization map



Polarization map



Very highly influential users are pro-Democrat (D: 7201, R: 5736)

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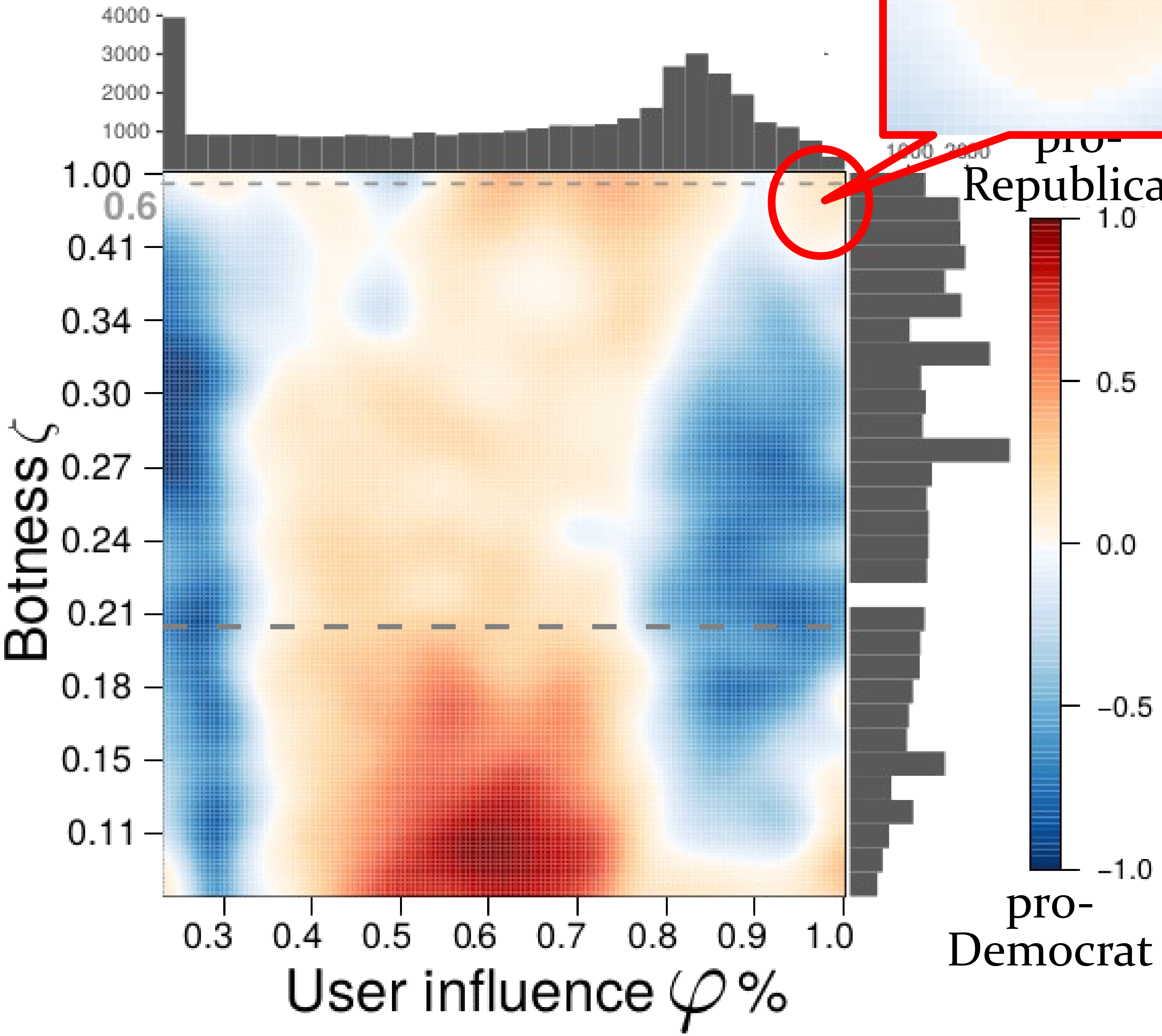
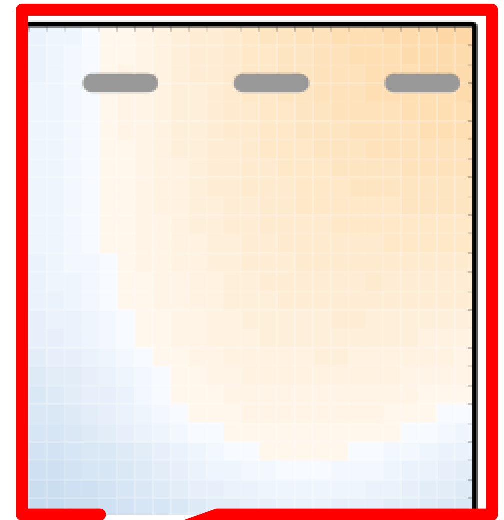
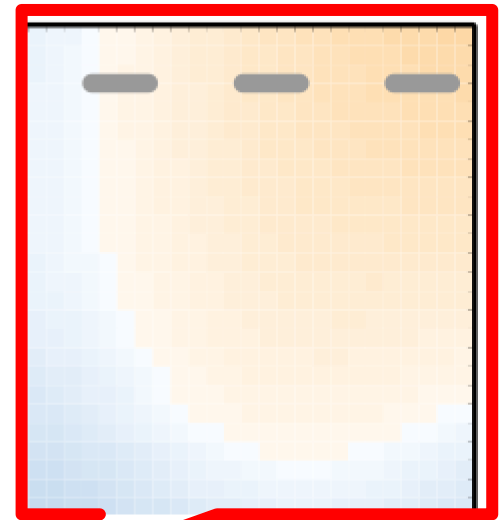


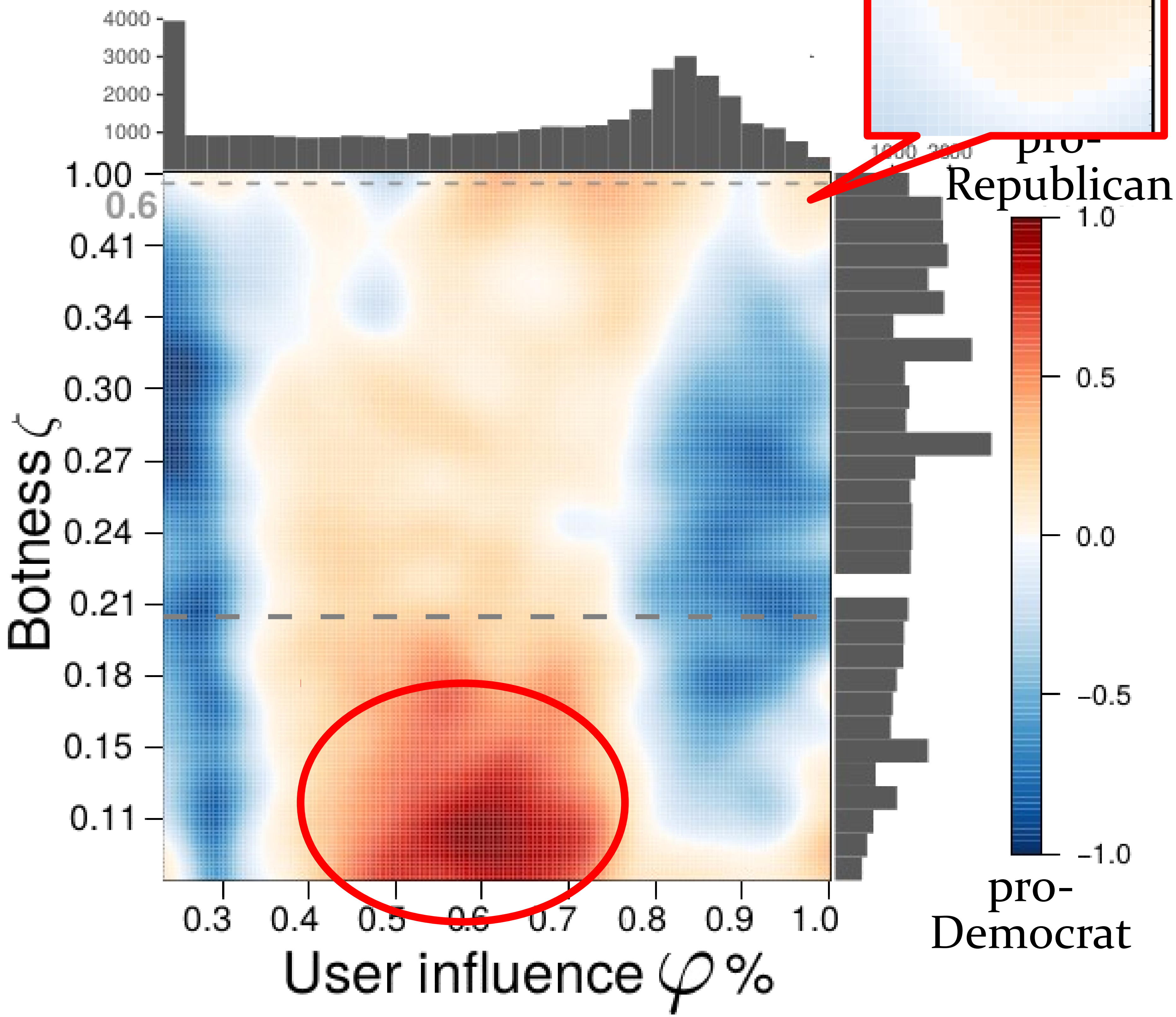


Very highly influential users are pro-Democrat (**D: 7201**, **R: 5736**)

Highly influential **Bots** are pro-Republican (**D: 24**, **R: 45**)

Polarization map





Very highly influential users are pro-Democrat

(**D: 7201**, **R: 5736**)

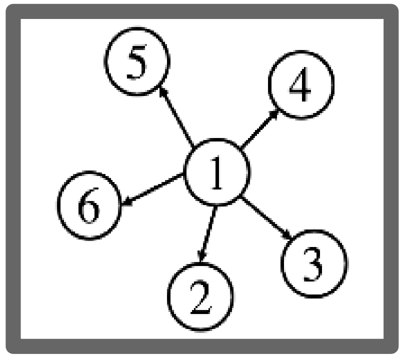
Highly influential **Bots** are pro-Republican

(**D: 24**, **R: 45**)

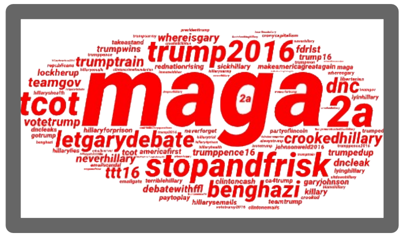
Mid-influential humans are pro-Republican

(**D: 1530**, **R: 3311**)

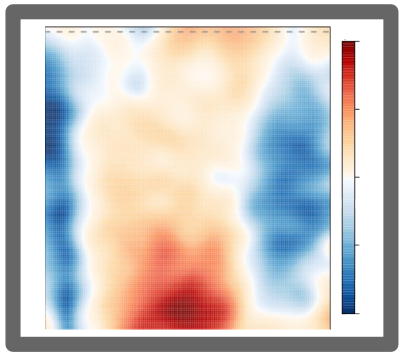
Summary



A scalable algorithm to estimate user influence from latent network structures



Three measures to quantify the influence, the political partisanship and botness of Twitter users



A detailed analysis of the role and influence of socialbots during the first U.S. Presidential debate.

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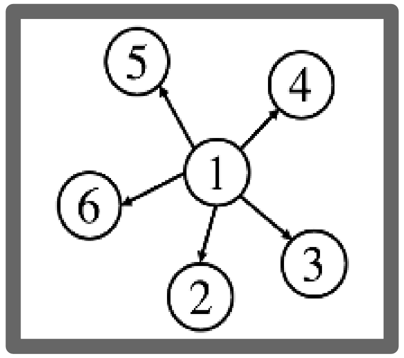

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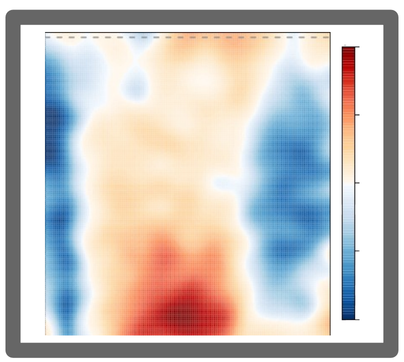

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Limitations: Organizational accounts appear as **Bots**; binary partisanship characterization (e.g. independent voters)

Were Bots instrumental for the results of the elections?

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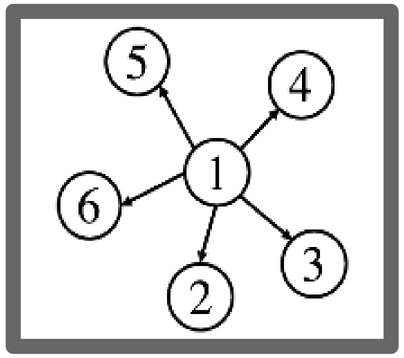
https://github.com/computationalmedia/cascade-influence



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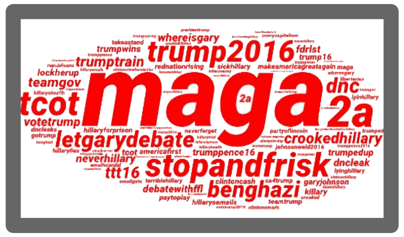

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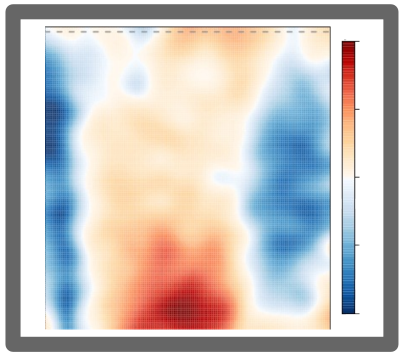

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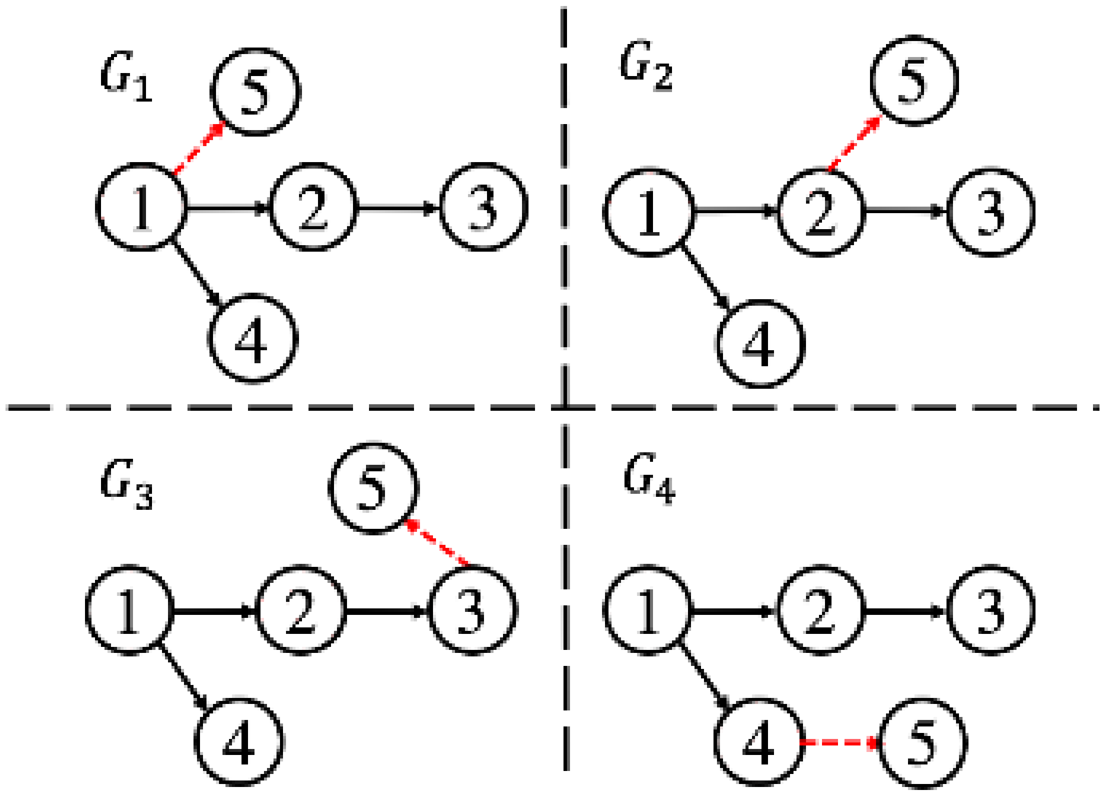
Tractable influence computation

Pair-wise influence score:

$$m_{ij} = \begin{cases} \sum_{k=i}^{j-1} m_{ik} p_{kj} & , i < j \\ 1 & , i = j \\ 0 & , i > j. \end{cases}$$



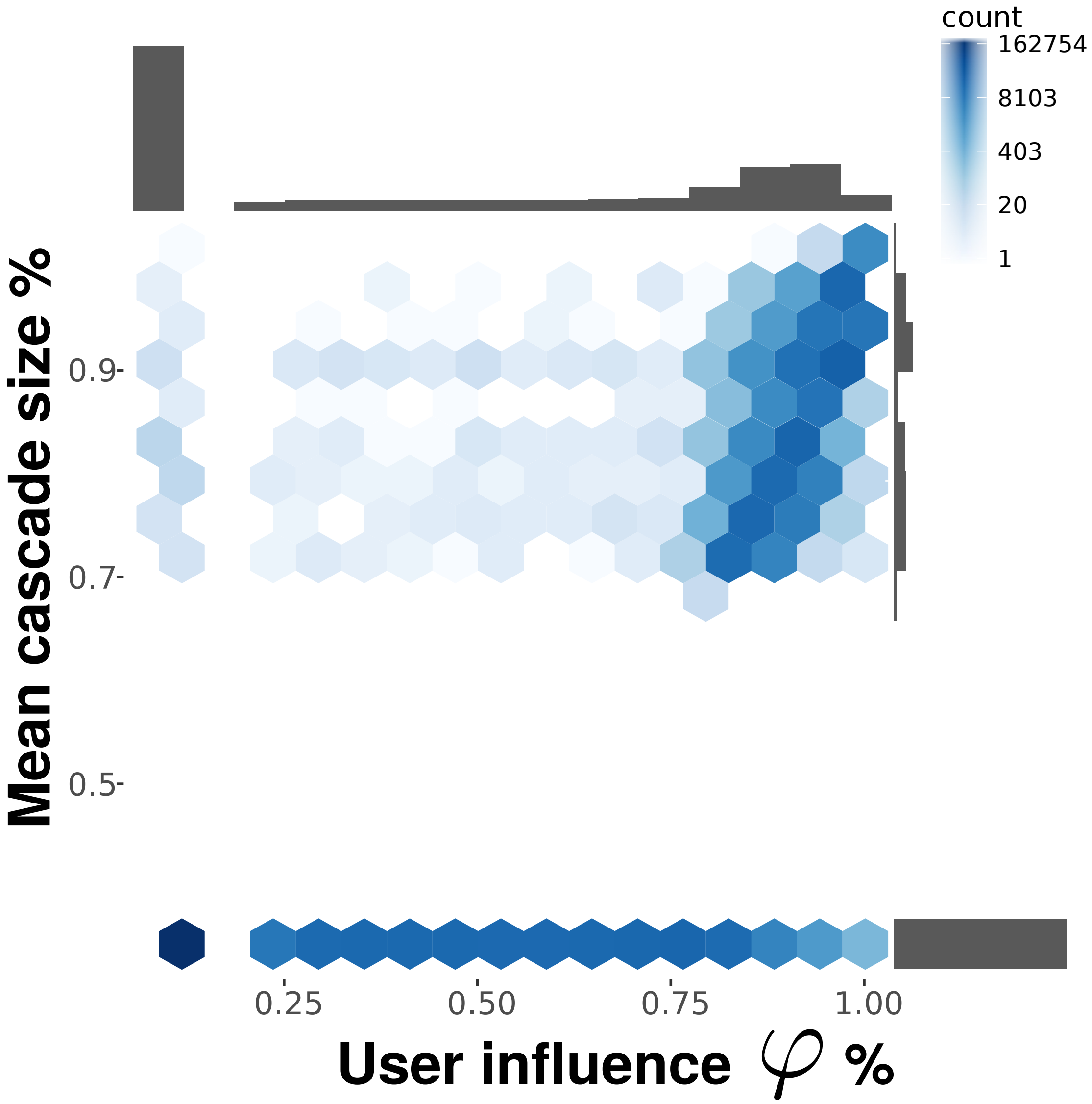
Influence of a tweet:

$$\varphi(v_i) = \sum_{j=1}^{k} m_{ij}.$$

Influence of a user:

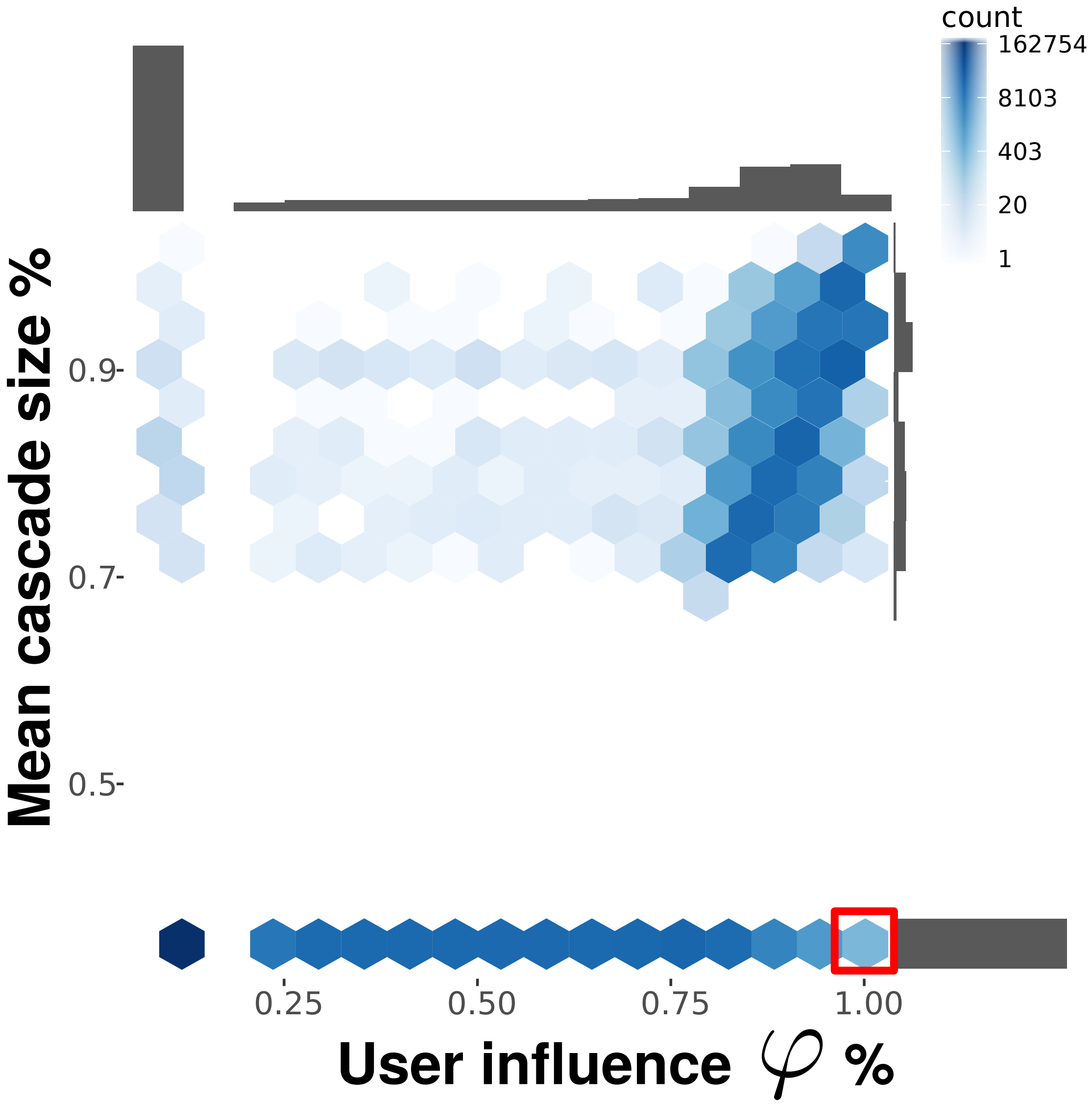
$$\varphi(u) = \frac{\sum_{v \in \mathcal{T}(u)} \varphi(v)}{|\mathcal{T}(u)|}, \mathcal{T}(u) = \{v | u_v = u\}$$

Supp: Influence vs. cascade size



Density plot for 653K users
(45% users start a cascade)

Supp: Influence vs. cascade size



Density plot for 653K users
(45% users start a cascade)

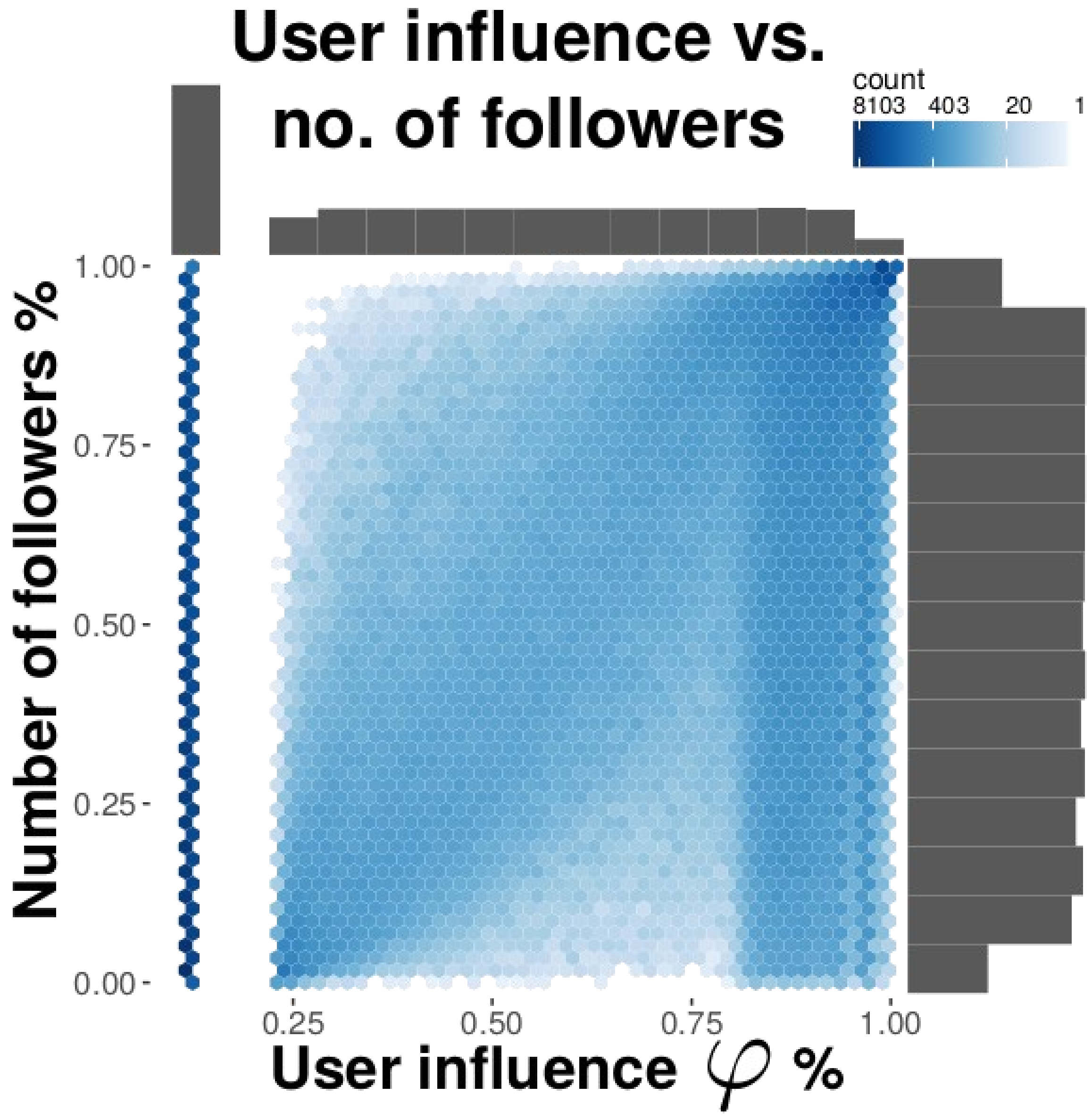
actor and filmmaker

10.8 million followers

comedian

2.1 million followers

Supp: Influence vs. number of followers



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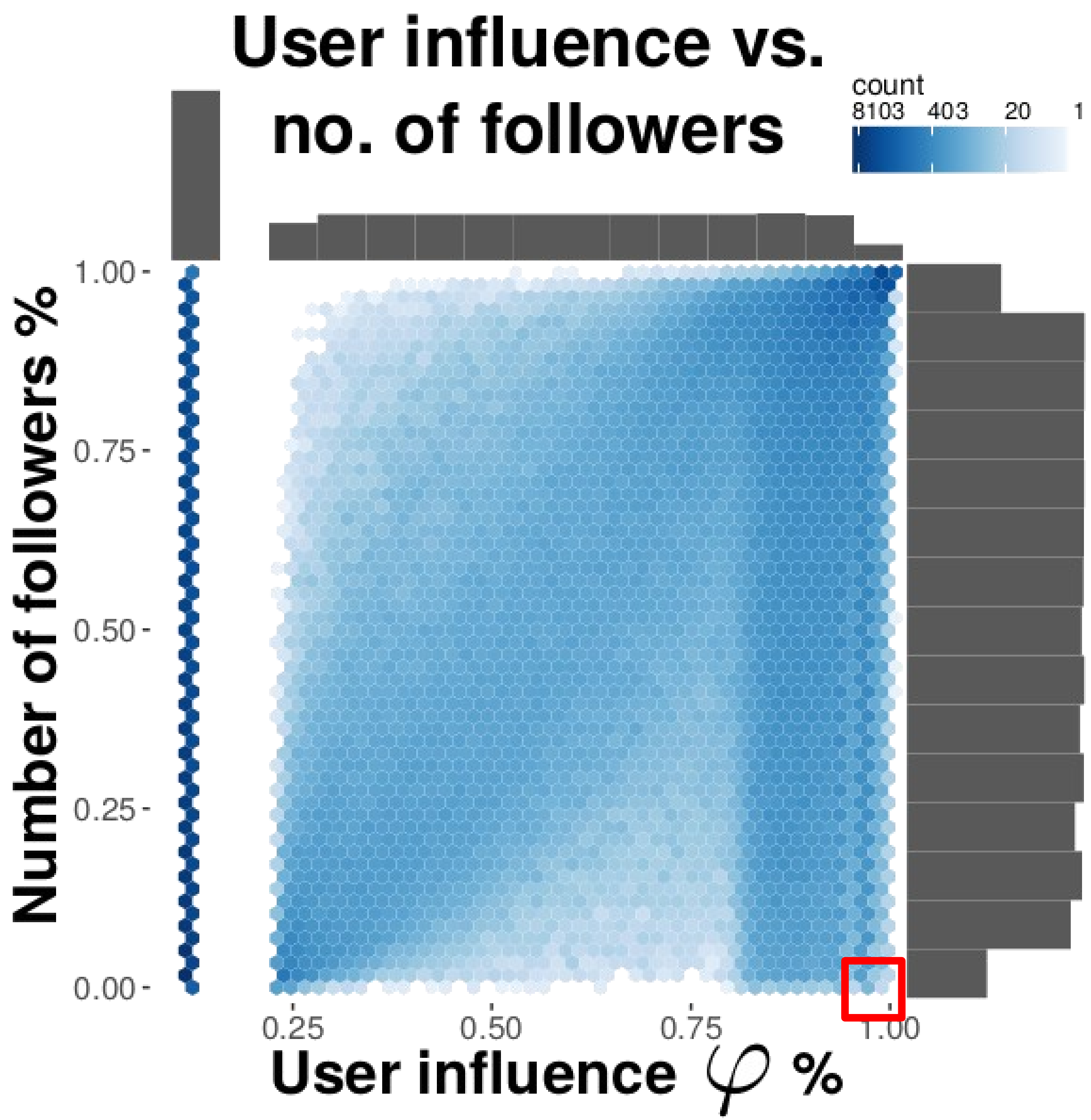

now suspended

2 followers

1 follower

Initiated a big cascade

Initiated a big cascade