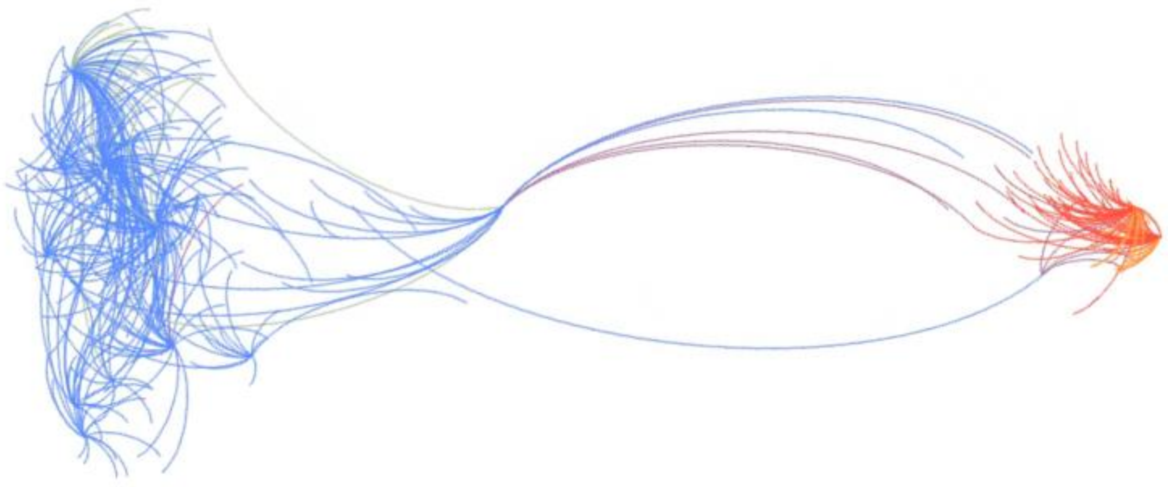
Measuring the Impact of Bot Accounts on Political Network Polarization

Mert Ozer
Arizona State University

Random Walk Controversy Score



$$RWC = P_{LL^+}P_{RR^+} - P_{LR^+}P_{RL^+}$$

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"Quantifying controversy in social media,"
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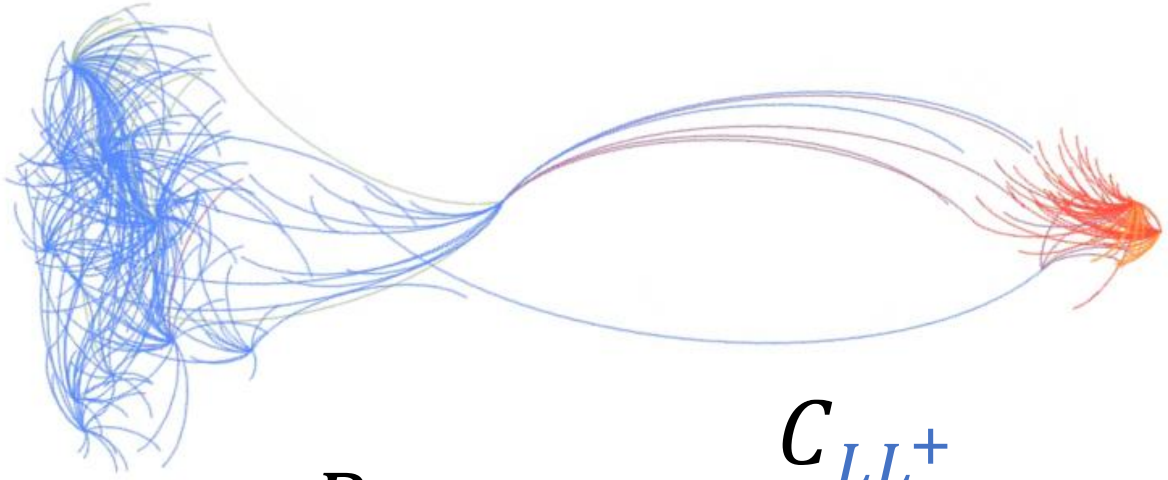

$$P_{LL^+} = \frac{C_{LL^+}}{C_{LL^+} + C_{LR^+}}$$

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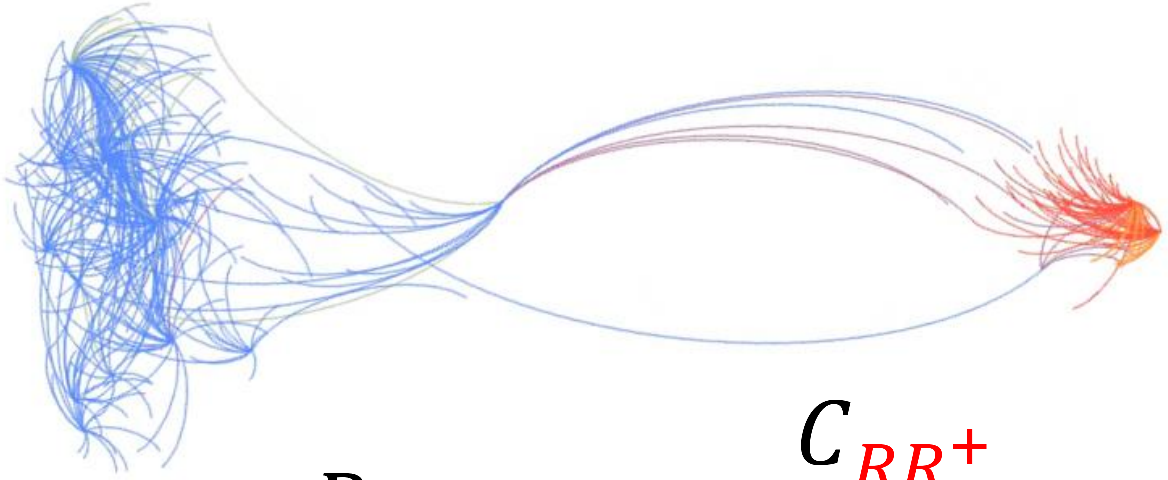

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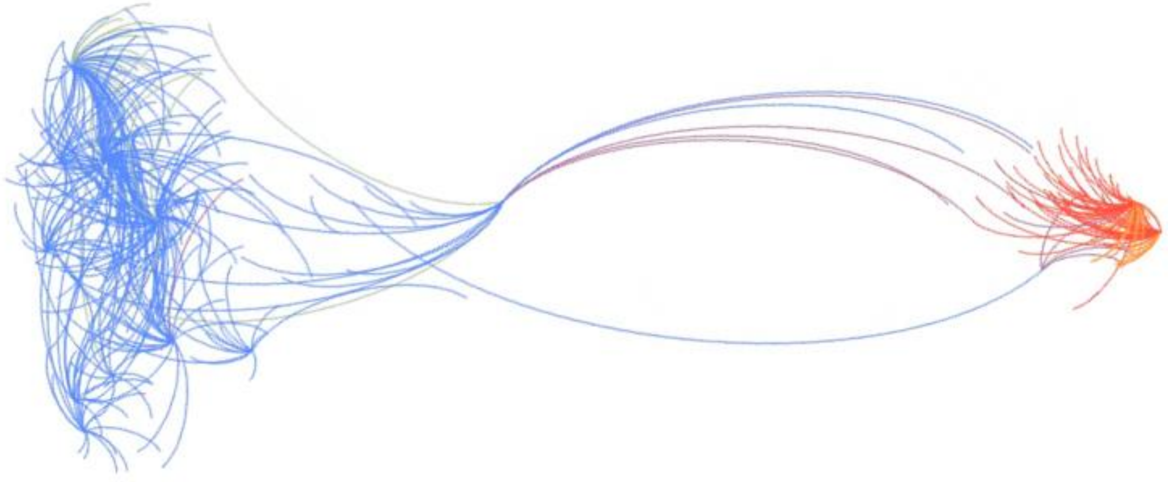

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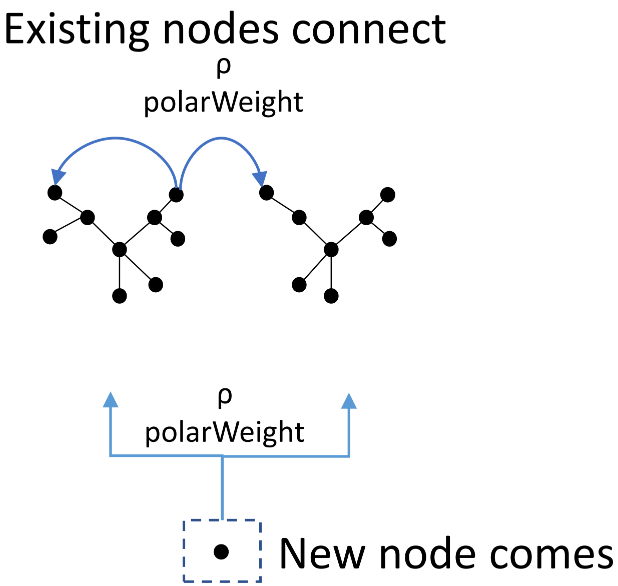

BOLLOBAS´ , B., BORGS, C., CHAYES, J. T., AND RIORDAN, O. 2003.
Directed scale-free graphs.
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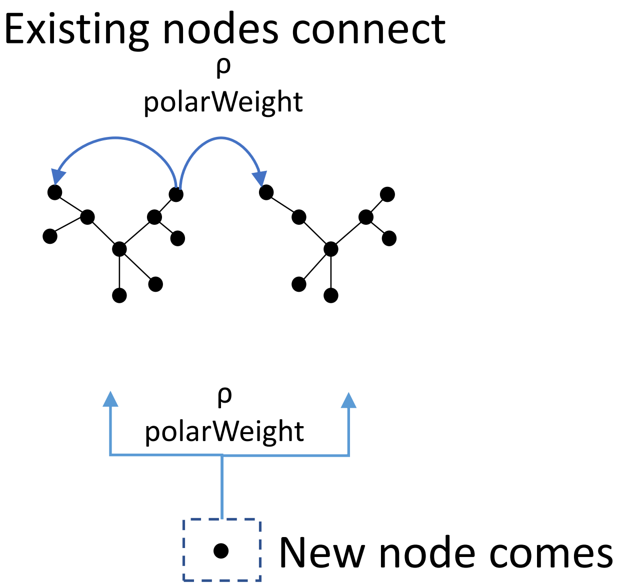

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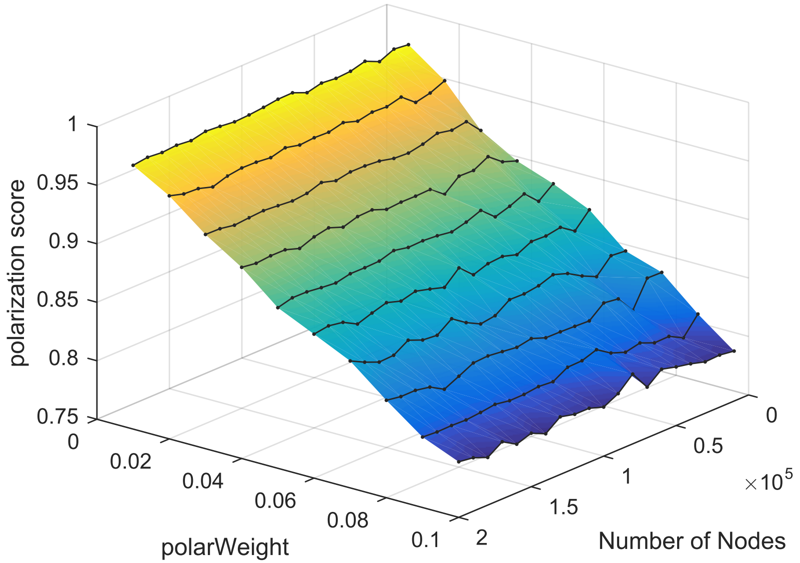

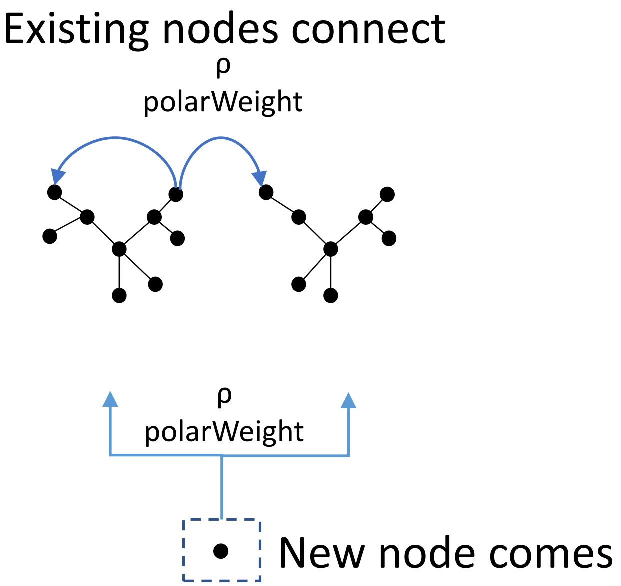

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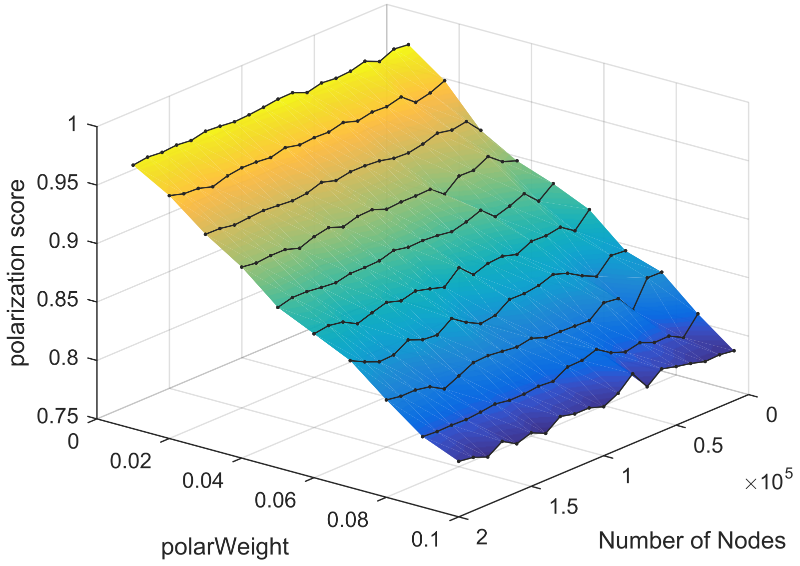
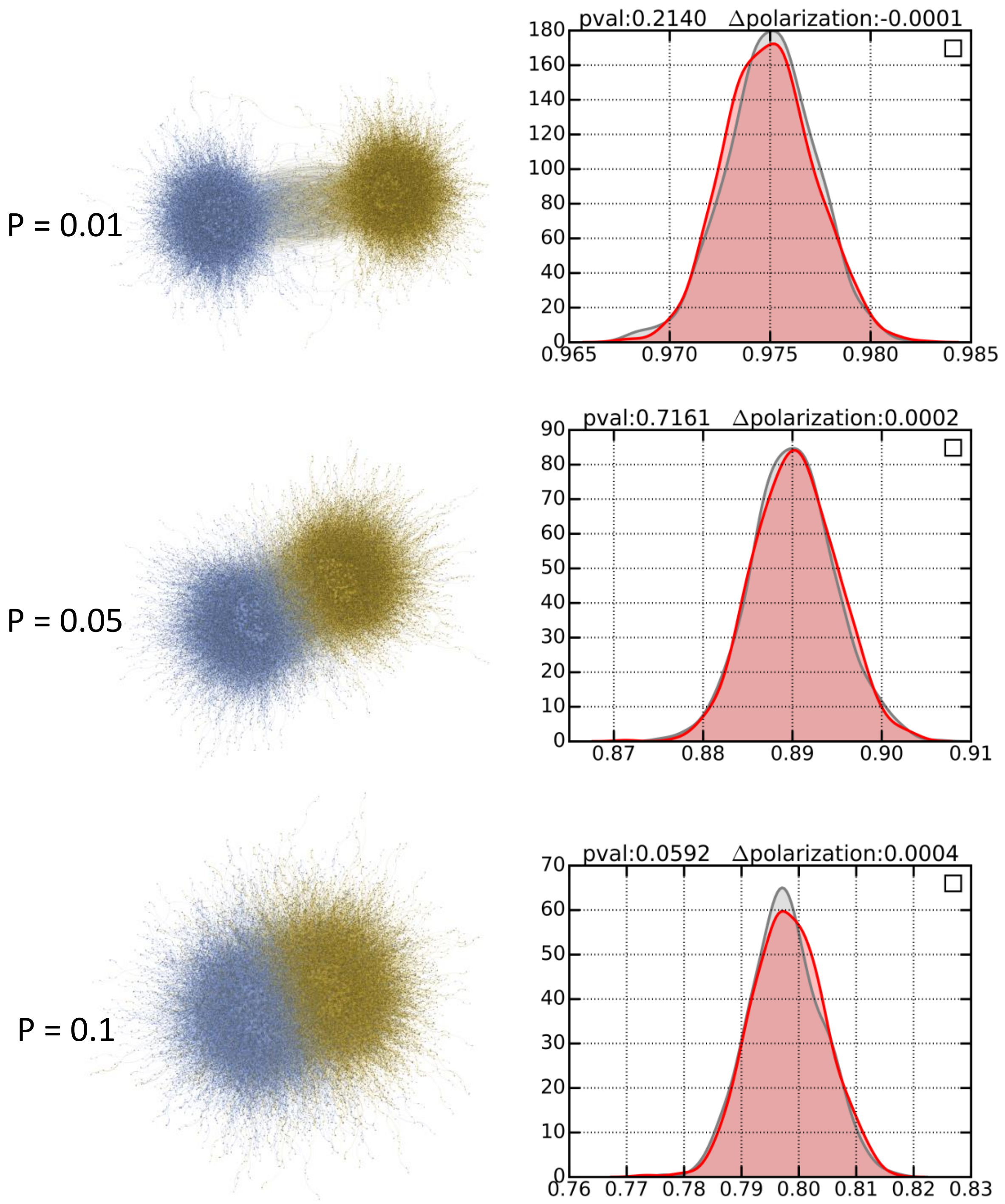


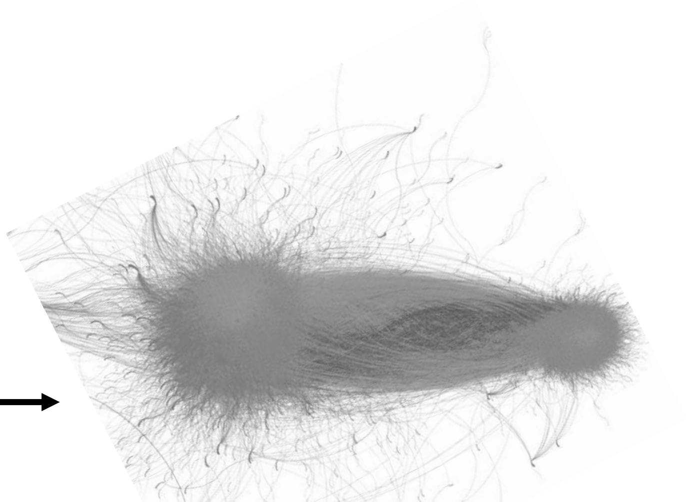


NRA
=
BLOODSHED
357 GUNS
Million
73 KIDS
MILLION
GUNS
more
than my
BOOKs
not
BULLet

Data Collection & Preprocessing

25M tweets
3.7M users

Retweet Activity



Retweet Network

Data Collection & Preprocessing

25M tweets
3.7M users

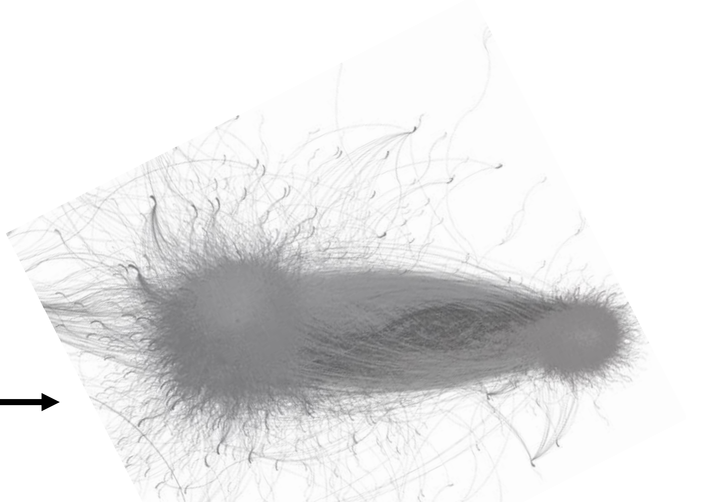
.news .news

50K labeled accounts

Label Propagation

	Precision	Recall	F-1
Left	0.98	0.99	0.98
Right	0.96	0.90	0.93

Retweet Activity



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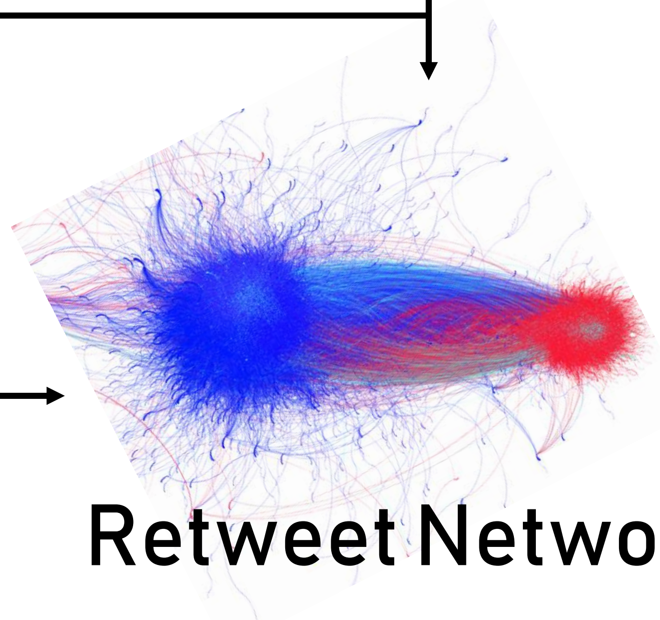
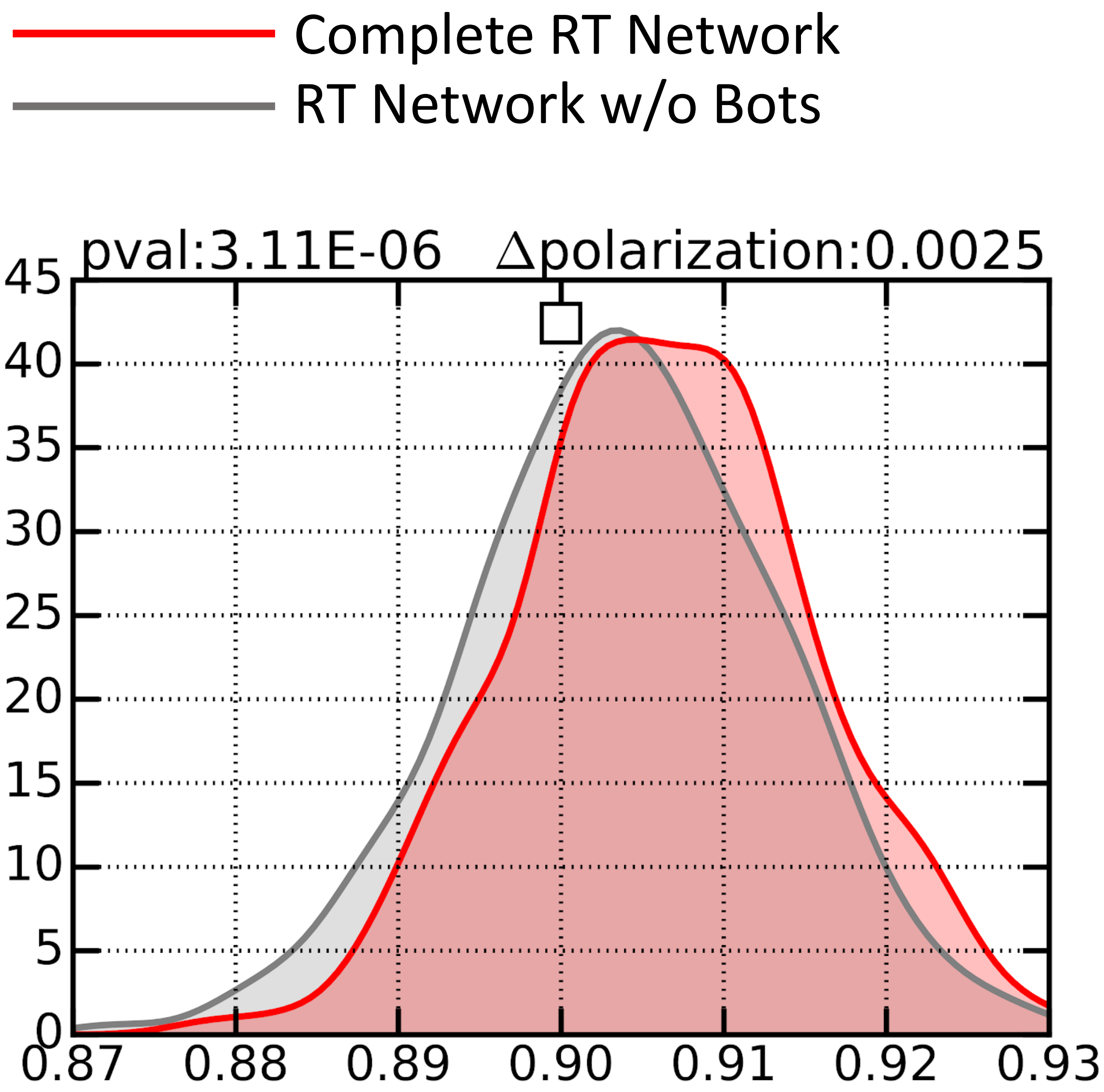
Botometer®
An OSoMe project (bot•o•meter)

Retweet Activity

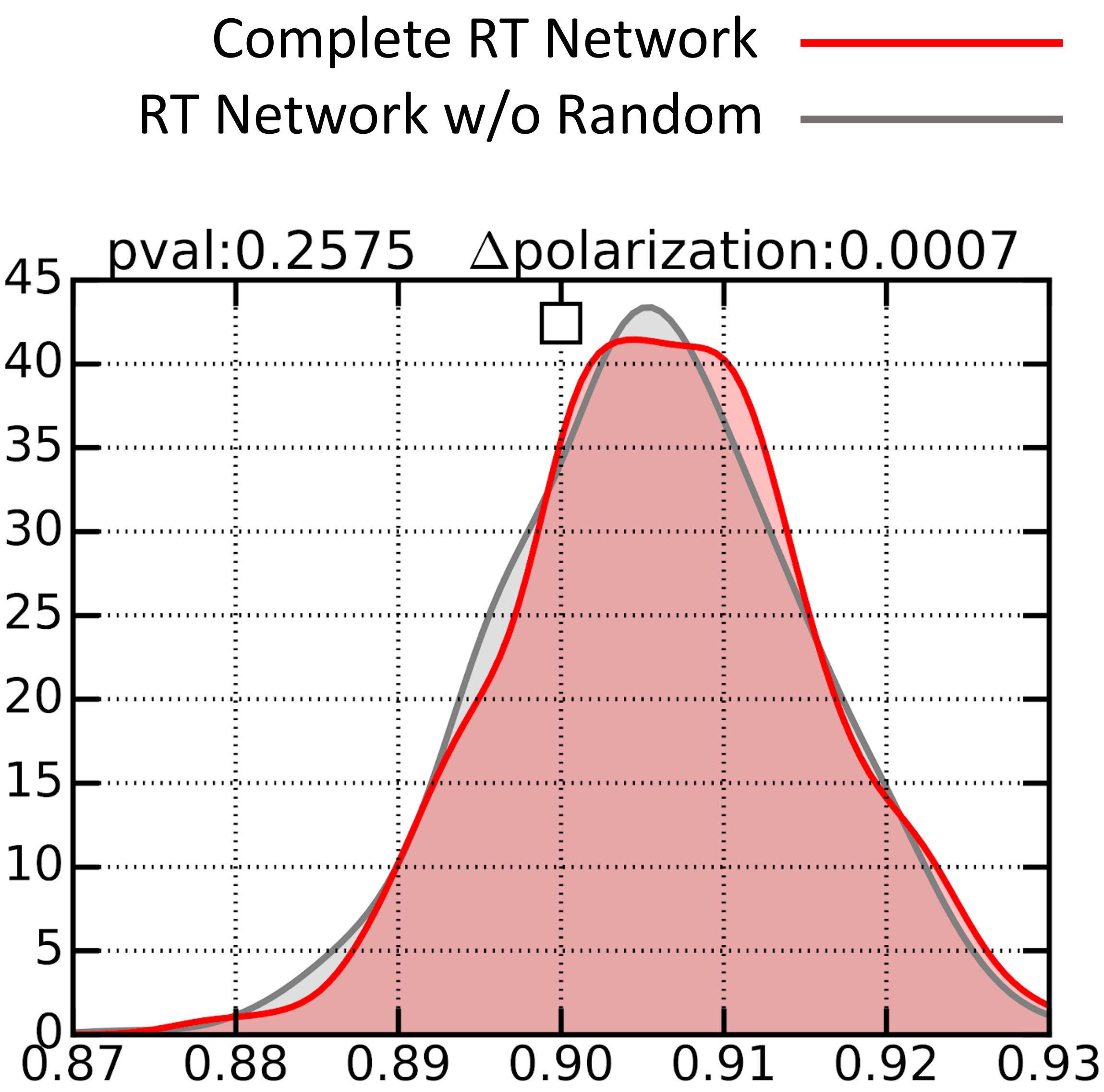


Retweet Network

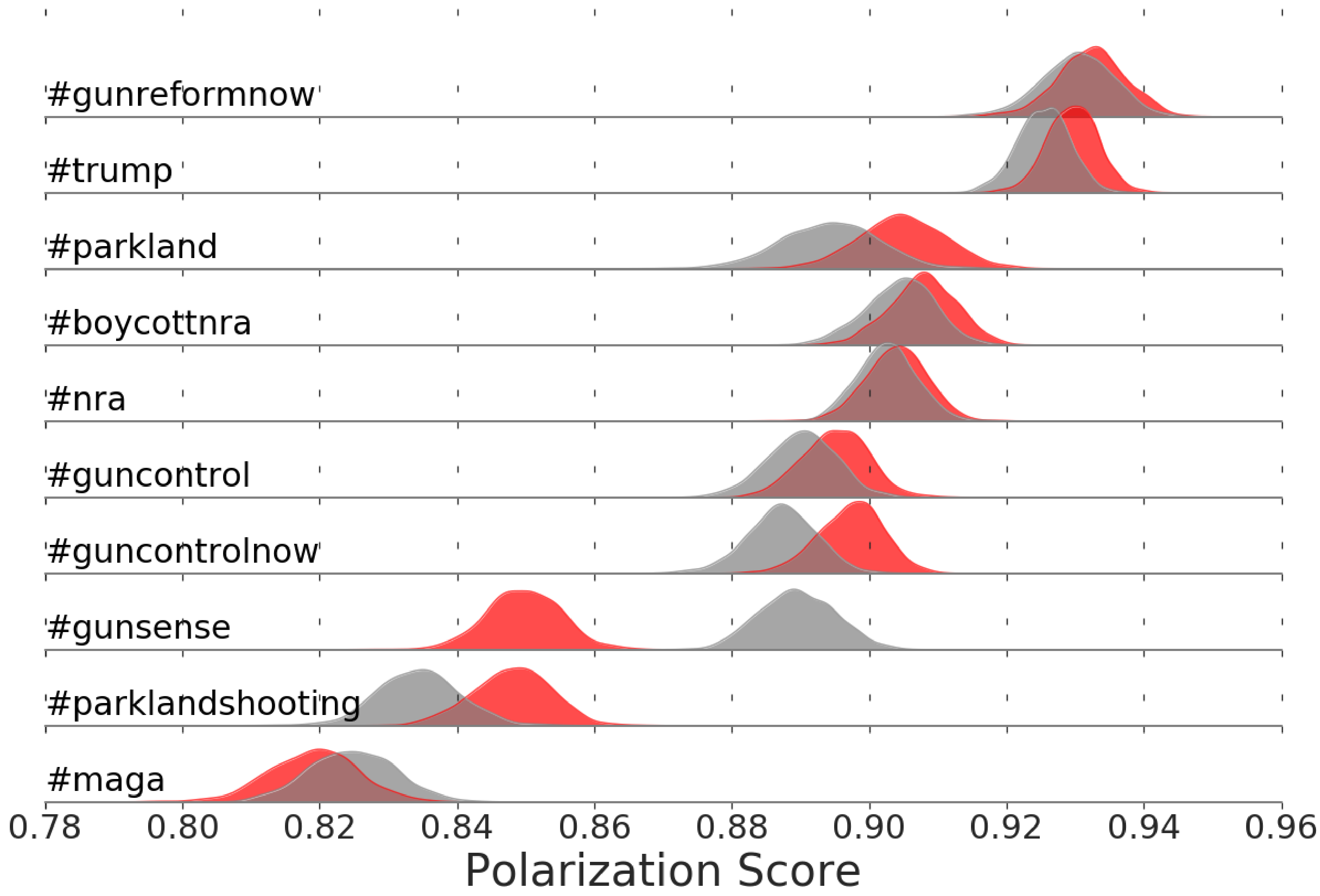
Bot Accounts' Effect



Random Removal Effect



Bot Accounts' Effect on Hashtags

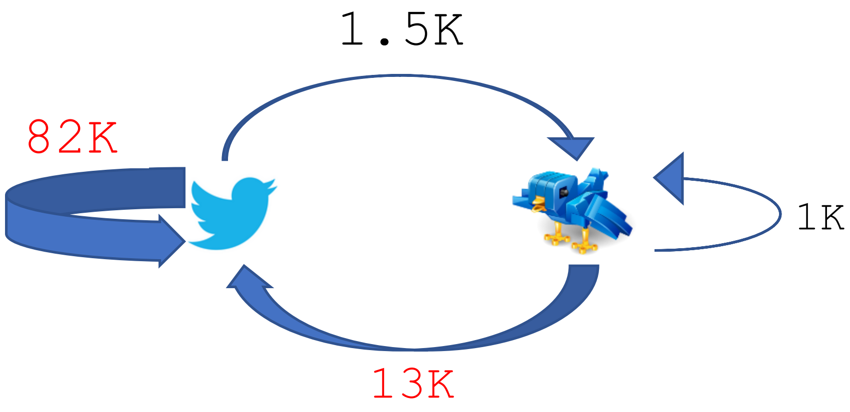


Out of top 100 hashtags;

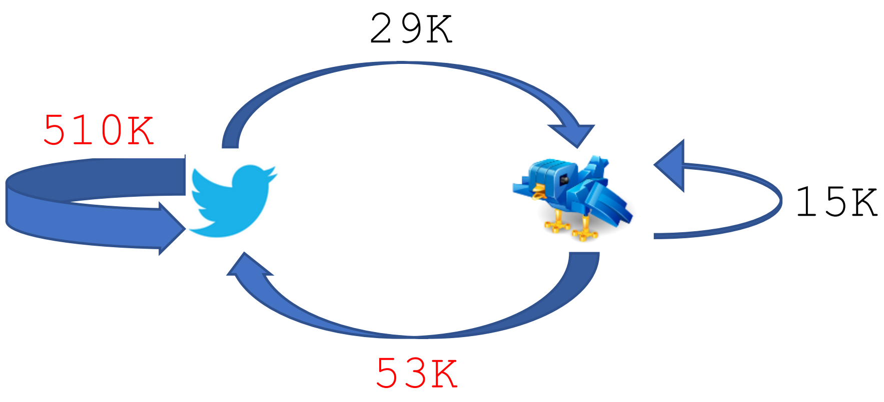
- 63 increase
- 10 no difference
- 27 decrease

Non-Bot and Bot Interactions

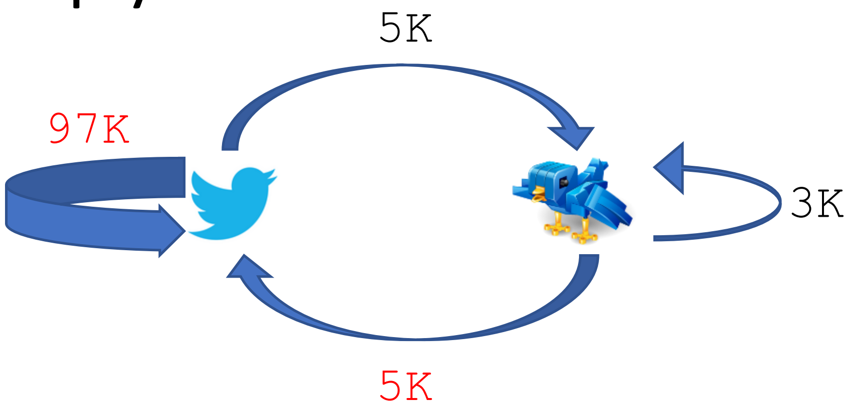
User Mention:



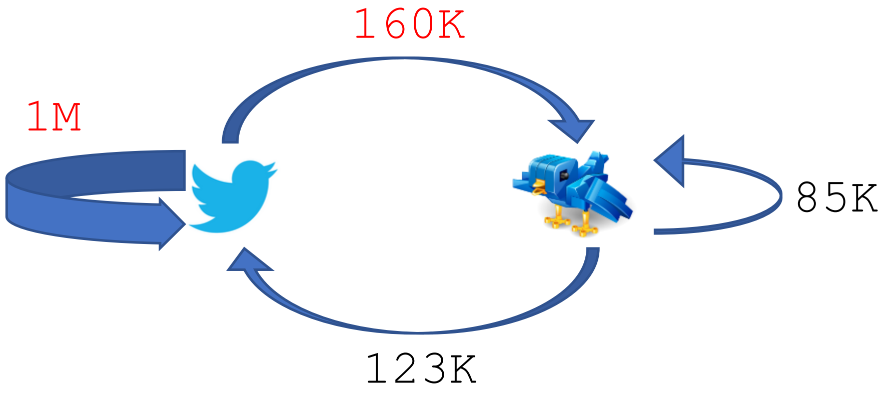
Quote:



Reply:



Retweet:



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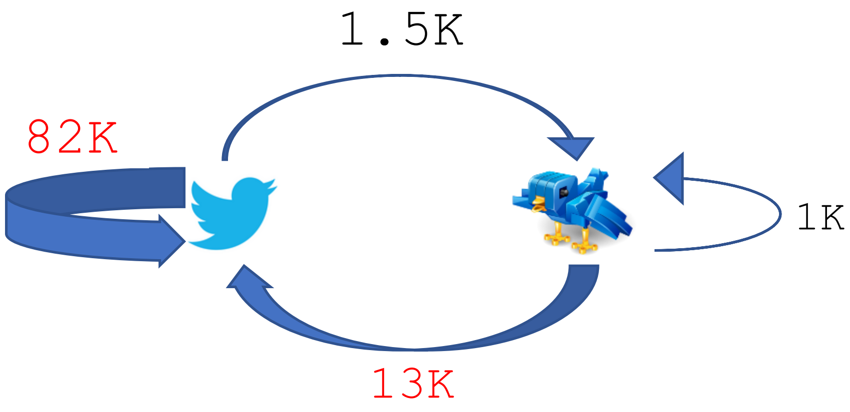

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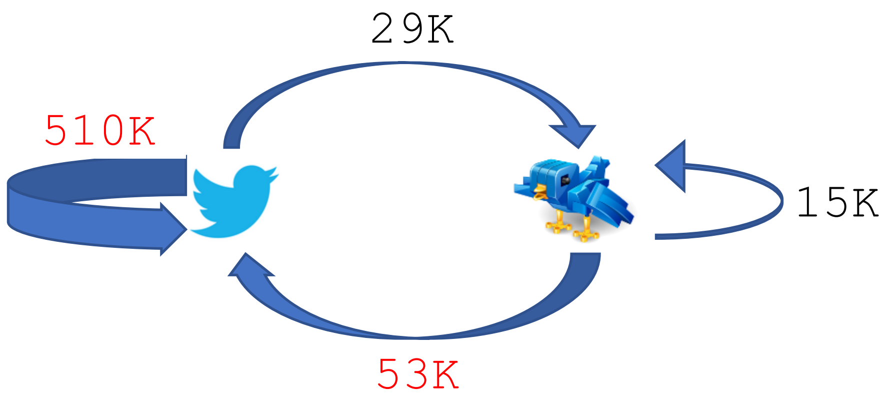

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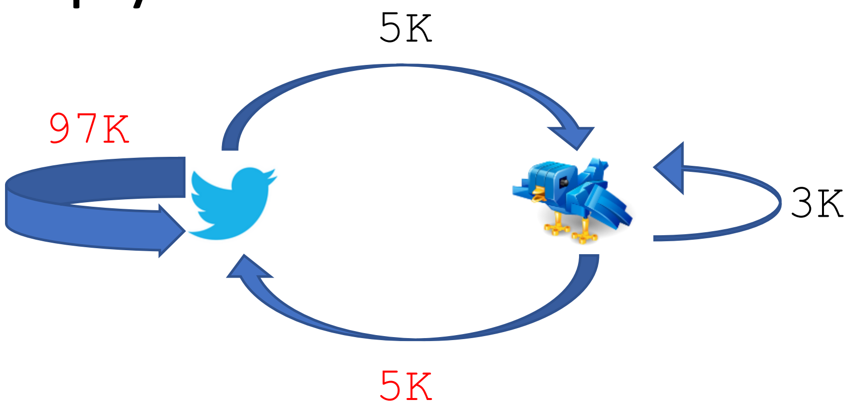

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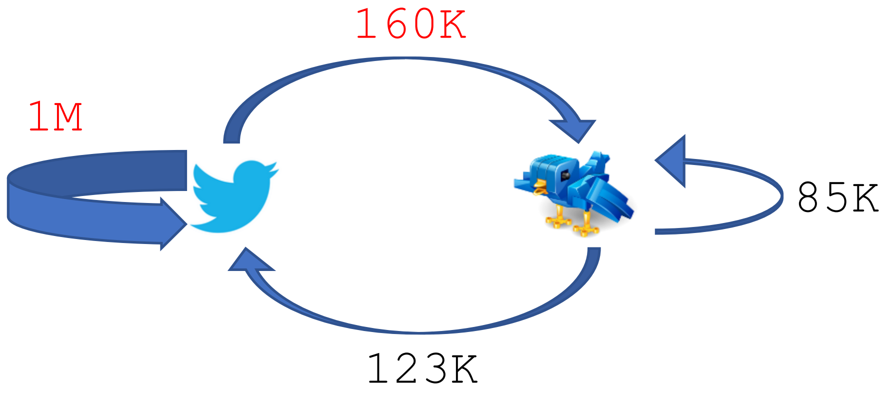

What type of posts of bot accounts achieve higher RT engagement?

ZI Negative Binomial Regression On 100K Bot Generated Tweets	Incident Rate Ratios		
Dependent Variables *(***p < 0.0001)*	IRR	Lower 95%	Upper 95%
*url_count****	0.5522044	0.5350116	0.5699496
*mention_count****	0.9830683	0.9776805	0.9884858
*followers_count****	1.0000667	1.0000653	1.0000681
*Emotional Only****	1.0762037	1.0588882	1.0938023
*Moral-Emotional****	1.1104801	1.0741481	1.148041
*Moral Only****	0.951206	0.9312959	0.9715419
*media_count****	1.5962573	1.538831	1.6558266
we	1.0027852	0.9726296	1.0338758
*they****	1.1832946	1.1430972	1.2249056

Brady, W. J., Wills, J. A., Jost, J. T., Tucker, J. A. & Bavel, J. J. V. Emotion shapes the diffusion of moralized content in social networks PNAS (2017).
Suh, B., Hong, L., Pirolli, P., & Chi, E. Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network. SocialCom (2010).

When Self-Identified

@screen_name
Account Name

*_bot	*_robot	*_chatbot
* bot	* robot	* chatbot
bot_*	robot_*	chatbot_*
bot *	Robot *	chatbot *
[a-z]+Bot	[a-z]+Robot	[a-z]+Chatbot

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Account Name

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bot_*	robot_*	chatbot_*
bot *	Robot *	chatbot *
[a-z]+Bot	[a-z]+Robot	[a-z]+Chatbot

LoserBot @loser__bot · 24 Sep 2018

What a loser.

Donald J. Trump @realDonaldTrump

Today, we commit to fighting the drug epidemic together! #UNGA

LoserBot @loser__bot · 24 Sep 2018

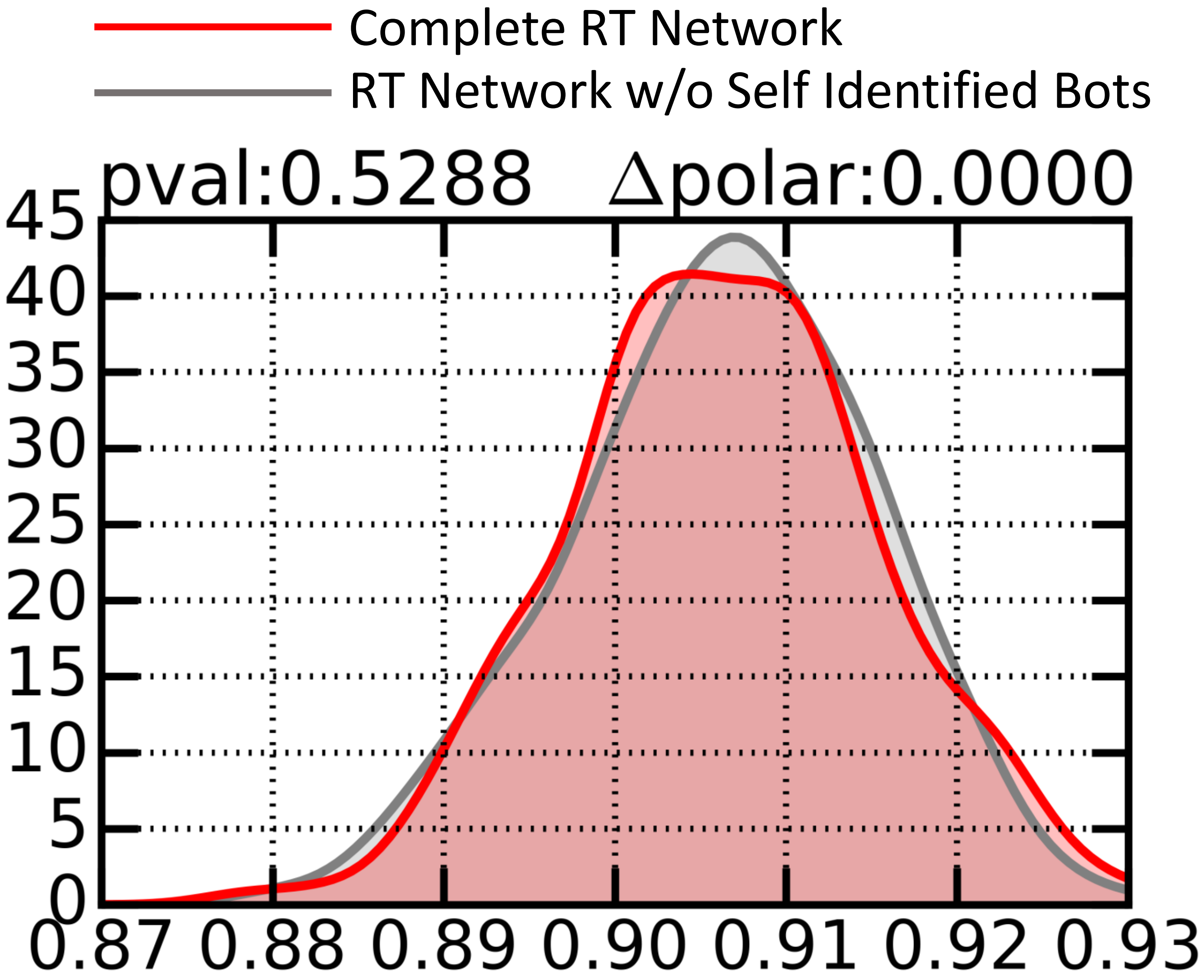
Such a loser.

Donald J. Trump @realDonaldTrump

"Remarks by President Trump at 'Global Call to Action on the World Drug Problem' Event" #UNGA

➡️45.wh.gov/FaDM6c

When Self-Identified



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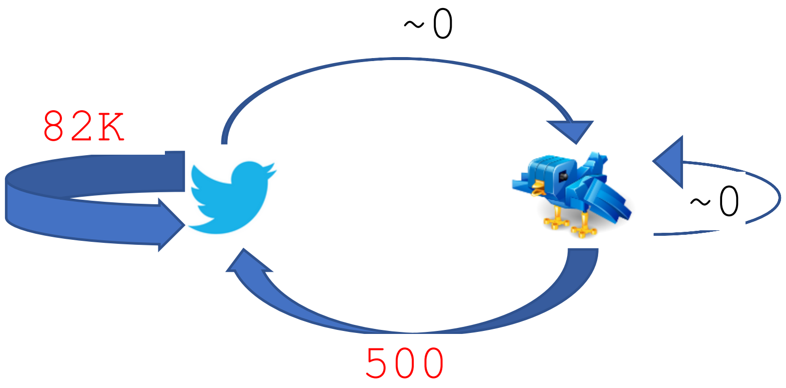

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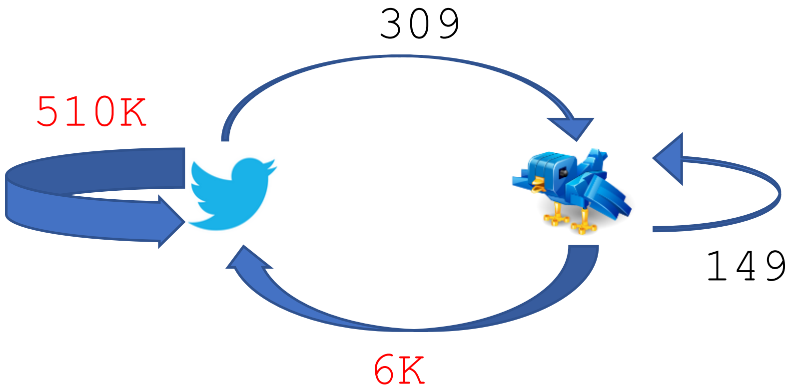

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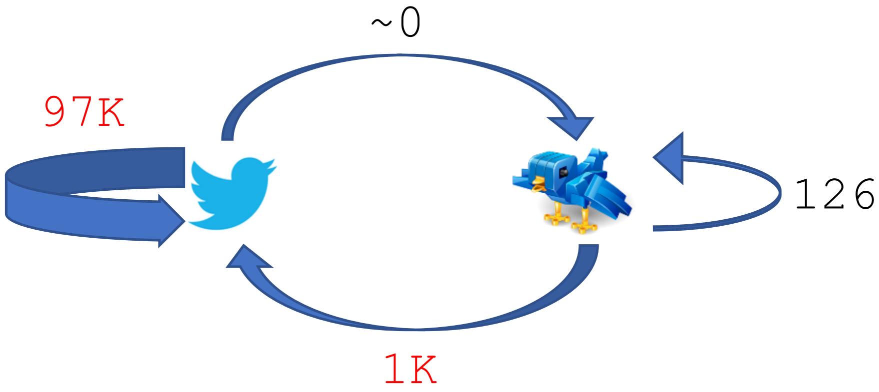

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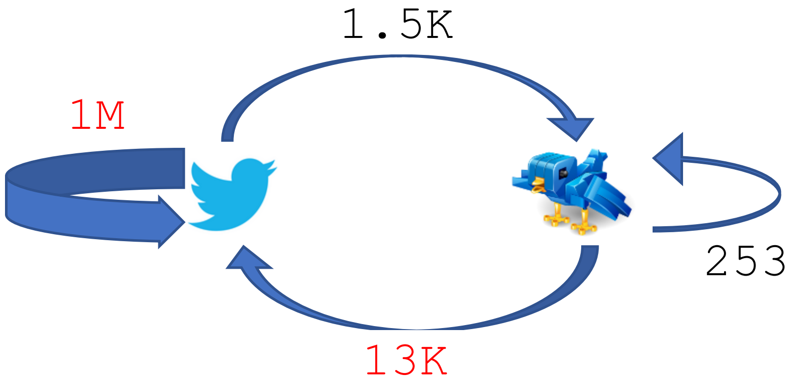

Discussion & Future Steps

[D] Bot accounts appear to **have contributed to the polarization of endorsement networks** during the unfolding of Parkland Shooting incident **more than** randomly selected samples.
[D] Analysis of engaging content generated by bot accounts overlap with previous studies of general engaging content on social media.
[D] When a bot is self identified, the effect seems to be not measurable given the data;

- Can a simple indicator (such as tick for verified accounts) alleviate the impact?

[F] May Botometer classifier be picking up correlates of polarizing accounts?
[F] Analyzing polarizing bot generated content against bridging ones.

Thank you!