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RevOpiD-2018

ACM Hypertext 2018

POLITICS ON TWITTER: A PANORAMA

July 9, 2018

Ophélie FRAISIER

l'Europe s'engage en Occitanie

La Région Occitanie Pyrénées - Méditerranée

PROJET COFINANCÉ PAR LE FONDS EUROPÉEN DE DÉVELOPPEMENT RÉGIONAL

- Context
- Polarisation
- Stance detection
- Election prediction
- Study of political engagement

CONTEXT

TWITTER

- One of the biggest social media worldwide
  - 2018: 336 million monthly active users
  - Majority of data is public and easily accessible

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Twitter Revolution: How the Arab Spring Was Helped By Social Media

By **Saleem Kassim** | July 3, 2012

TWITTER

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In presidential campaign, Twitter was a powerful political tool

Twitter reports 1 billion election-related tweets since August 2015

By Sharon Gaudin

Senior Writer, Computerworld | NOV 8, 2016 11:32 AM PT

TWITTER

- One of the biggest social media worldwide
  - 2018: 336 million monthly active users
  - Majority of data is public and easily accessible

"Twitter has emerged as the single most powerful "socioscope" available to social scientists for collecting fine-grained time-stamped records of human behavior and social interaction at the level of individual events."

(Golder & Macy, 2014)

POLITICAL STANCES?

Social positioning of a person, a thoughtful positioning, justified by a set of values and beliefs, put in relation with the other existing points of view on the given subject.

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How relevant is it to use this data to study complex political topics?

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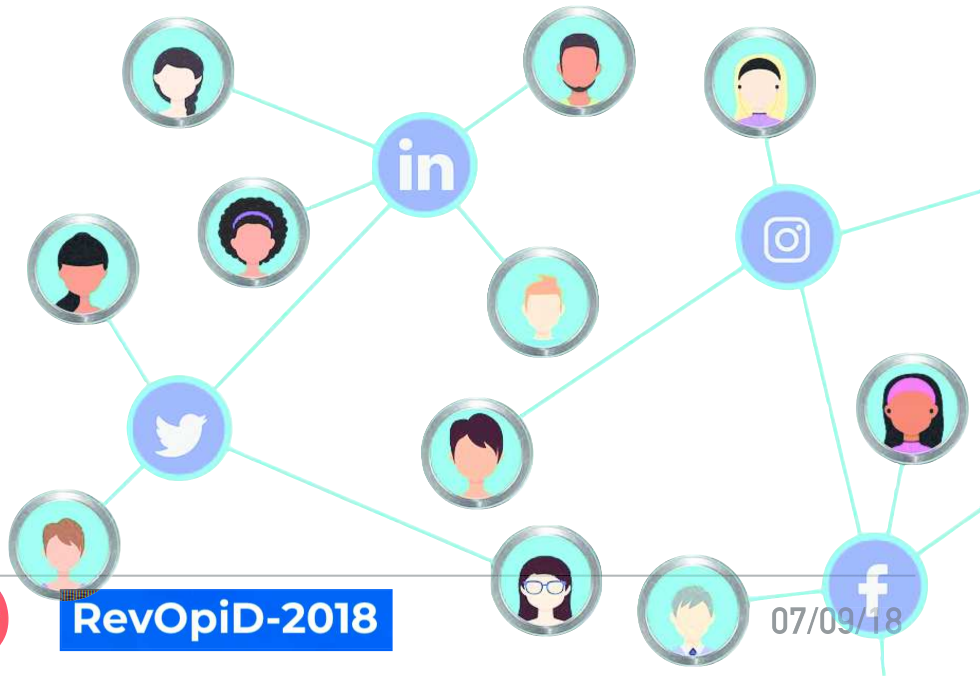
➡ **Twitter can be an useful medium for studying stances**

Polarisation

HOMOPHILY

- *"**Homophily** is the principle that a contact between similar people occurs at a higher rate than among dissimilar people.*
  […]
  *Homophily implies that distance in terms of **social characteristics** translates into **network distance**, the number of relationships through which a piece of information must travel to connect two individuals."*
  (McPherson et al ., 2001)



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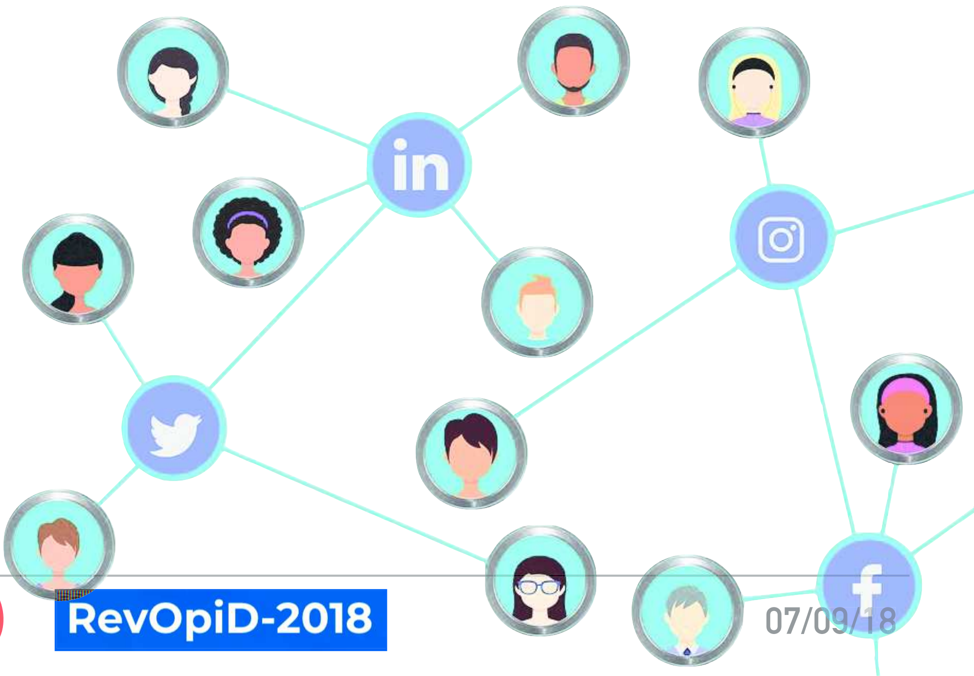
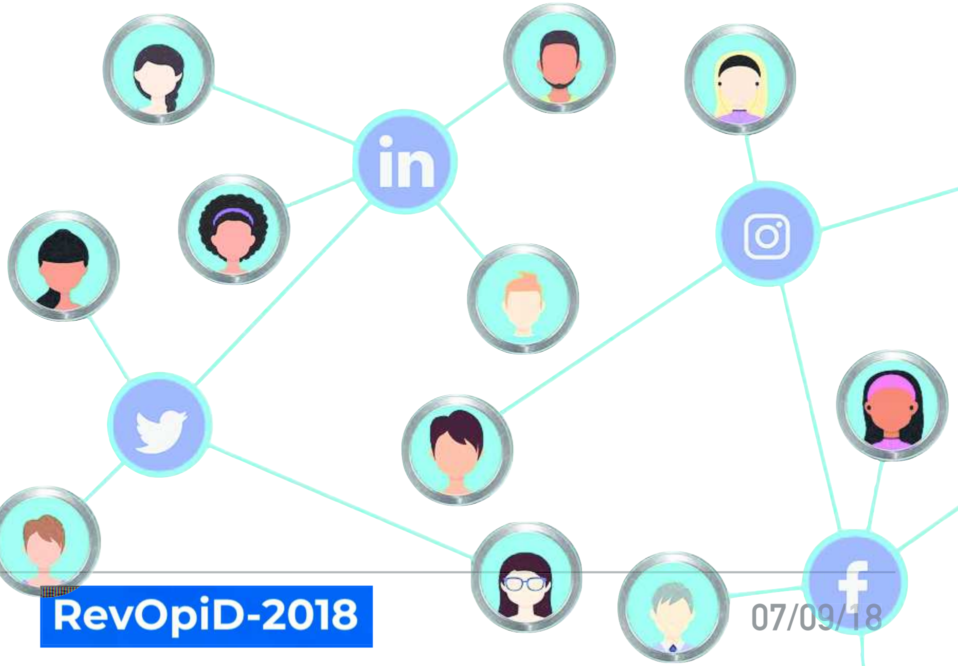
- *Can lead to "**echo chambers**"*
  (Sunstein, 2009)



INFLUENCE OF RETWEETS


European Commission a retweeté
Jean-Claude Juncker @JunckerEU · 3 h
I am convening an informal working meeting on migration and asylum issues in Brussels on Sunday, in order to work with a group of Heads of State or Government of Member States interested in finding European solutions ahead of the upcoming #EUCO. #MigrationEU

- Retweet largely used
  - Action of sharing a tweet
  - One of the most important interaction on the platform



INFLUENCE OF RETWEETS

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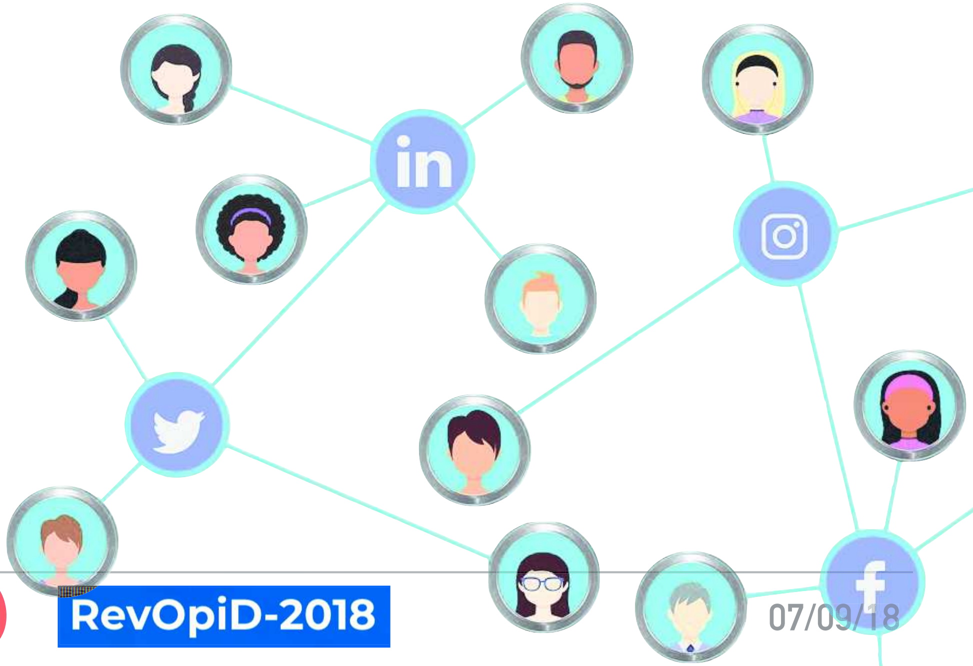
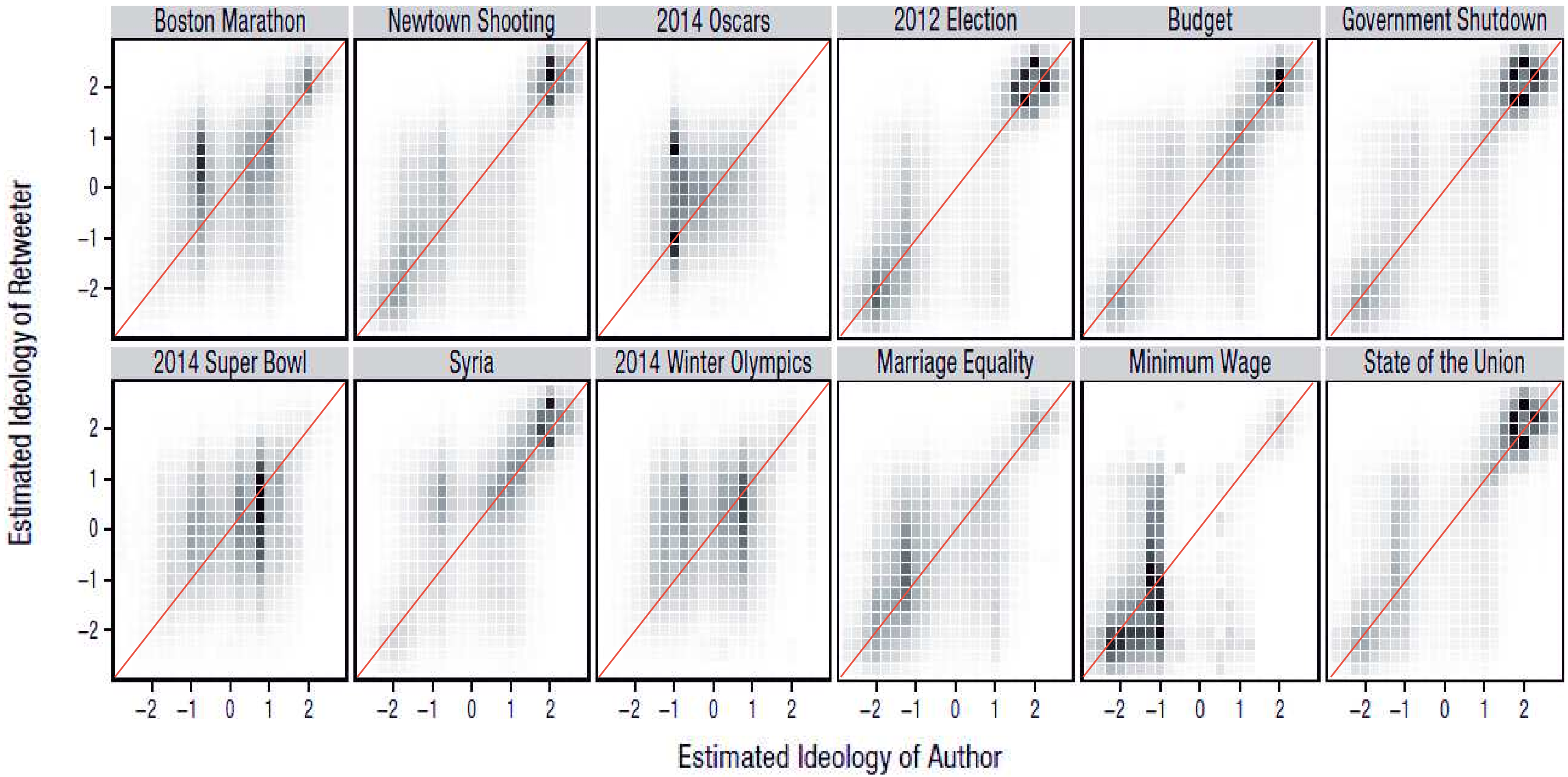
- Motivations for retweeting (boyd et al., 2010):
  - To publicly agree with someone
  - To validate others' thoughts



OBSERVED ON VARIOUS POLITICAL LANDSCAPES



Highest level of polarization

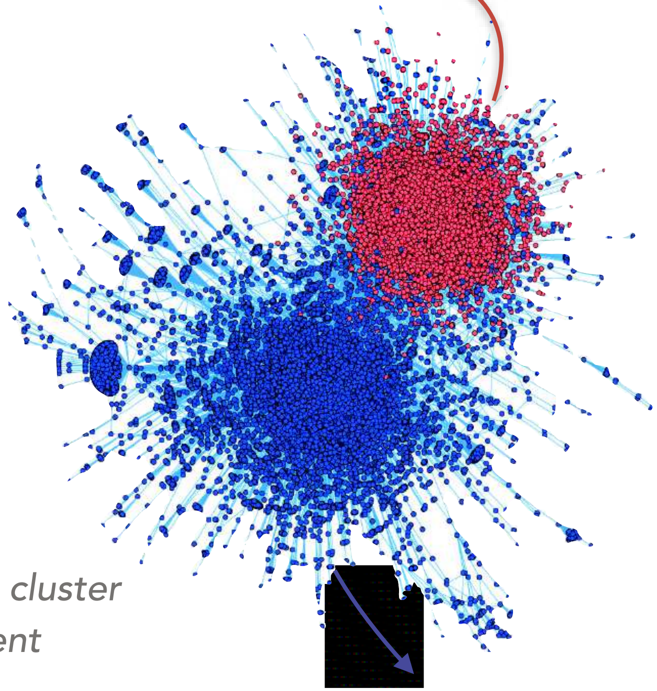
(Barberá et al, 2015)

OBSERVED ON VARIOUS POLITICAL LANDSCAPES

- 2010 US midterm elections
  (Conover et al, 2011)

Retweet network

93% right-leaning profiles

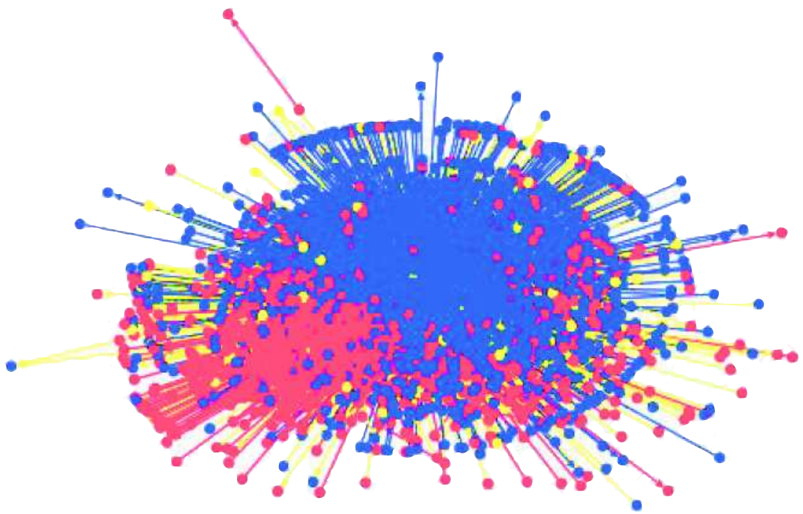


Color = cluster assigment

80% left-leaning profiles

- Secular vs Islamist polarization in Egypt
  (Weber et al, 2013)

Retweet network



Islamists
Secularists
Center

OBSERVED ON VARIOUS POLITICAL LANDSCAPES

- 2017 French presidential election (Fraisier et al, 2018)

Retweet network

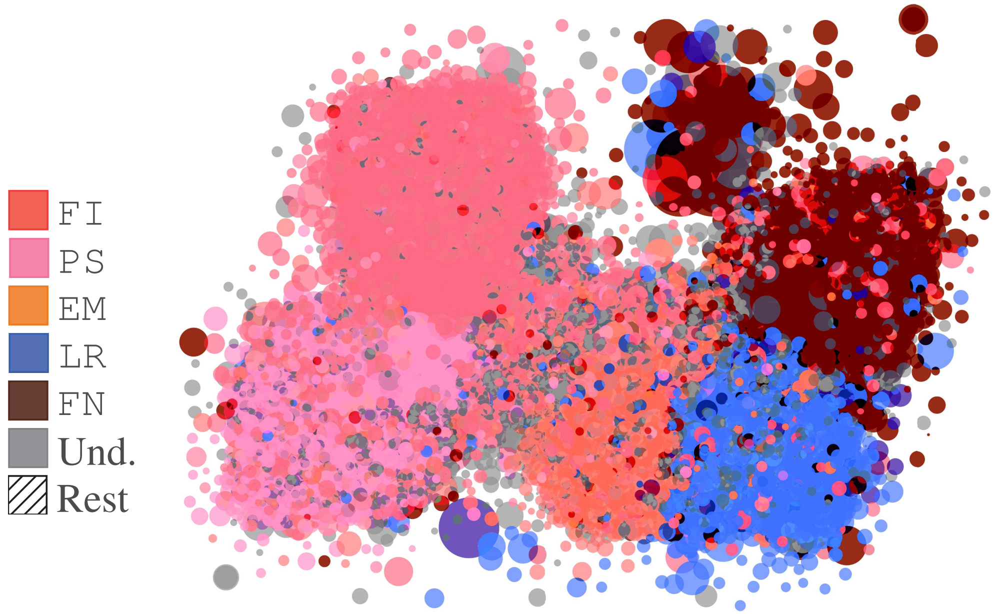
Average number of retweets by profile:

- Intra-party: 149
- Inter-party: 4

Mention network

Average number of mentions by profile:

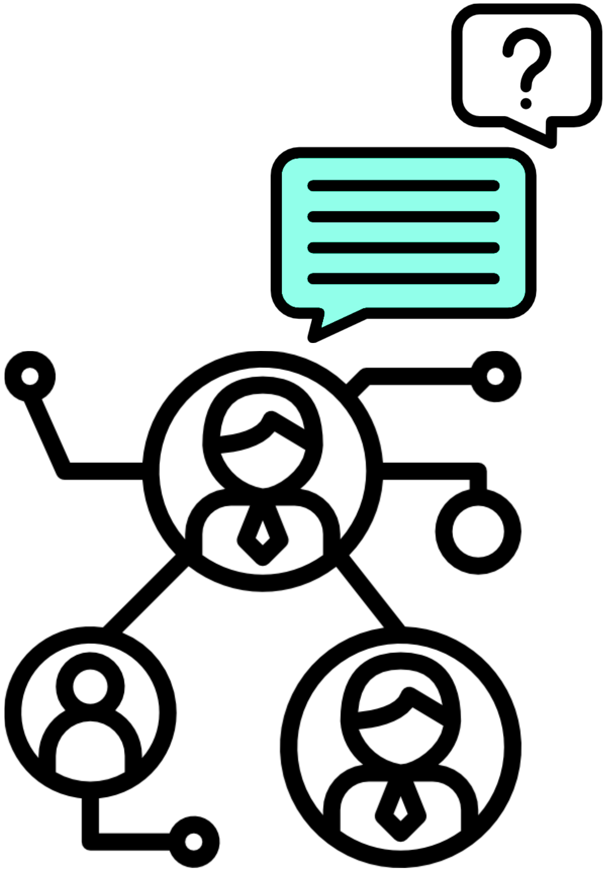
- Intra-party: 281
- Inter-party: 14



Stance Detection

AIM

- Detect profiles' political stance based on their activity



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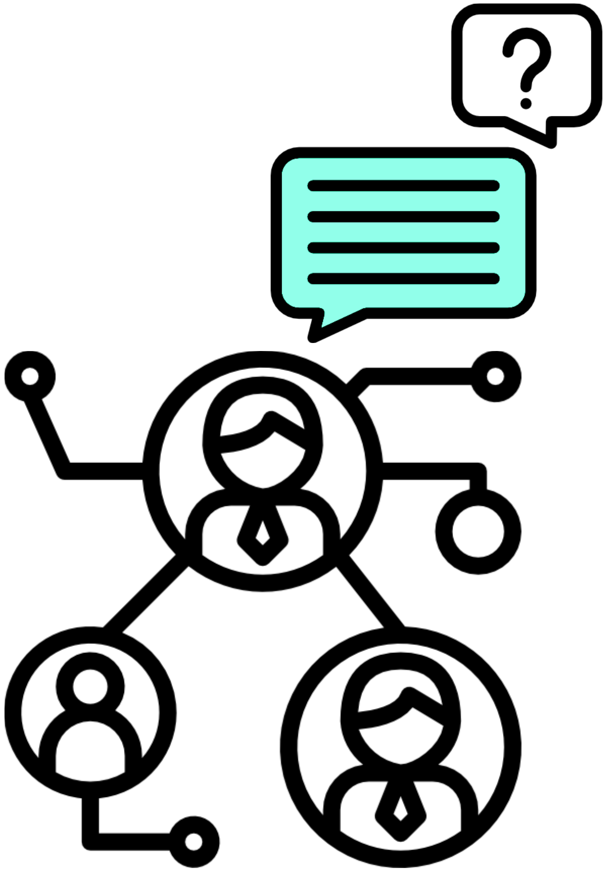

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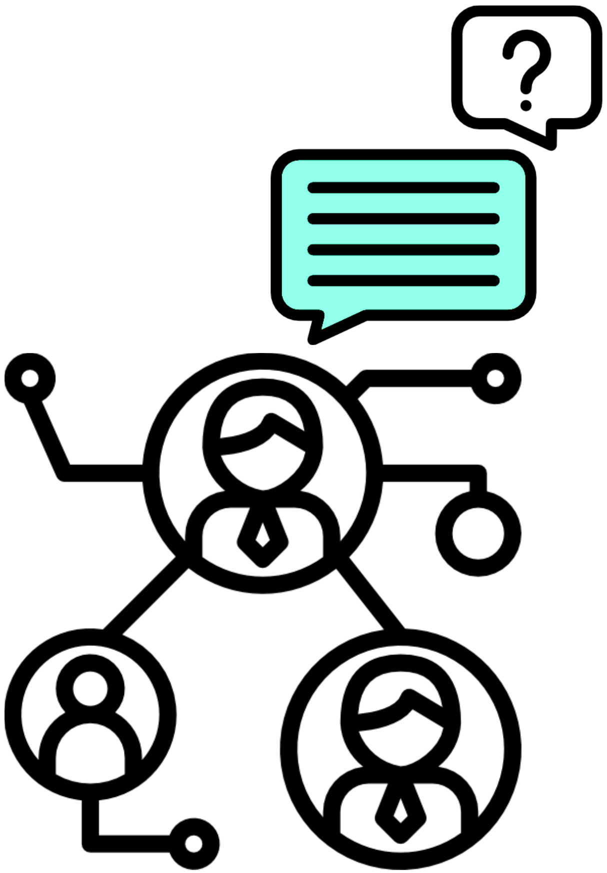

- Global political stance
  - Political parties
  - Conservatives vs Liberals
  - Left vs Right
- Specific political stance
  - Political figure
  - Abortion
  - Climate change
  - Feminism
  - Gun control
  - LGBT rights
  - Immigration
  - Israeli-palestinian conflict

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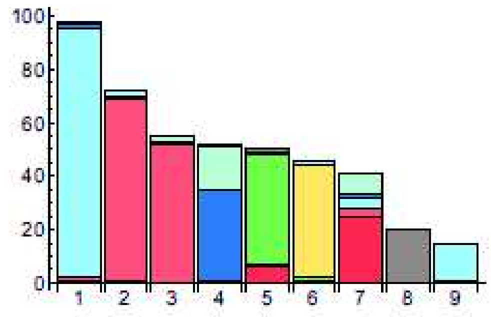

Figure 4. Composition of the 9 communities by political groups in the core network. Different colors indicate the 8 political groups in the EP.

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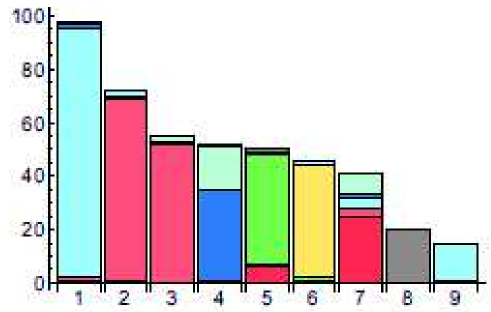

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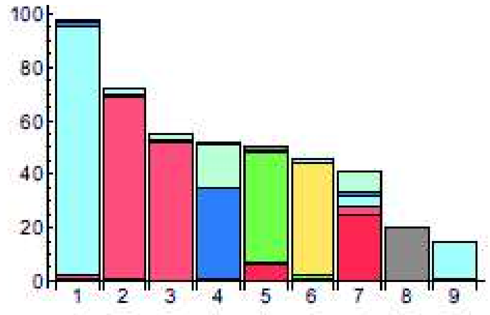

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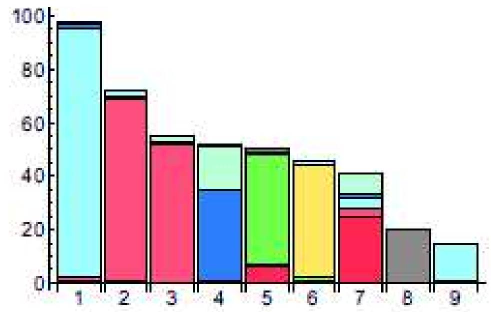

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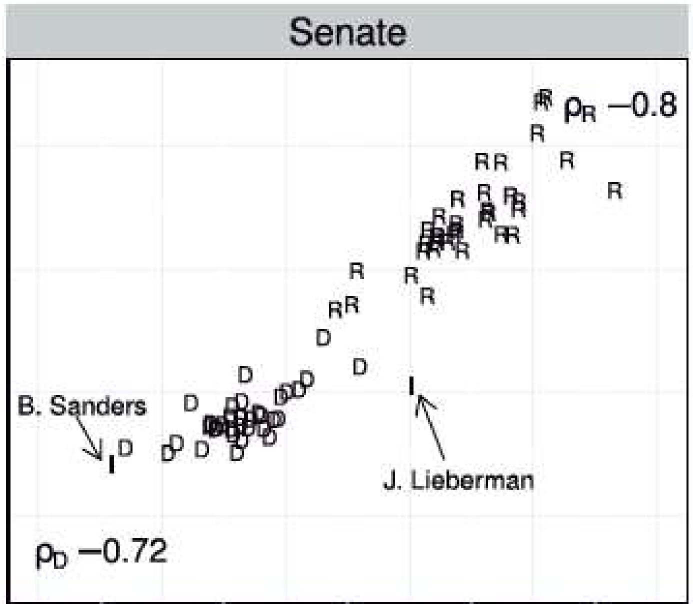

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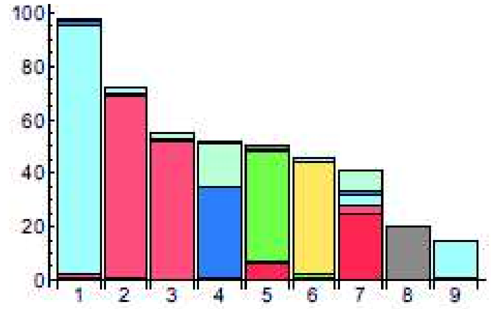

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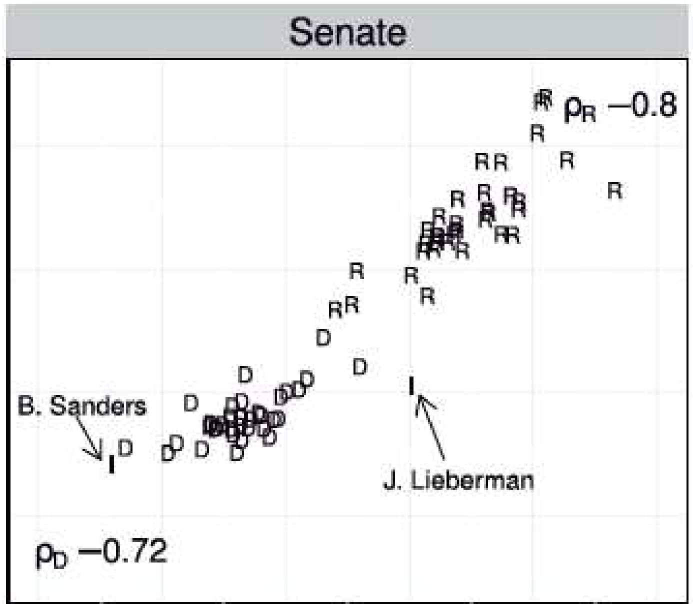

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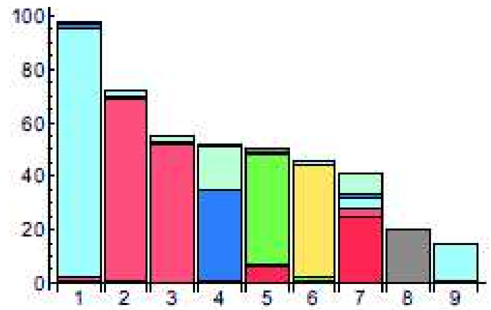

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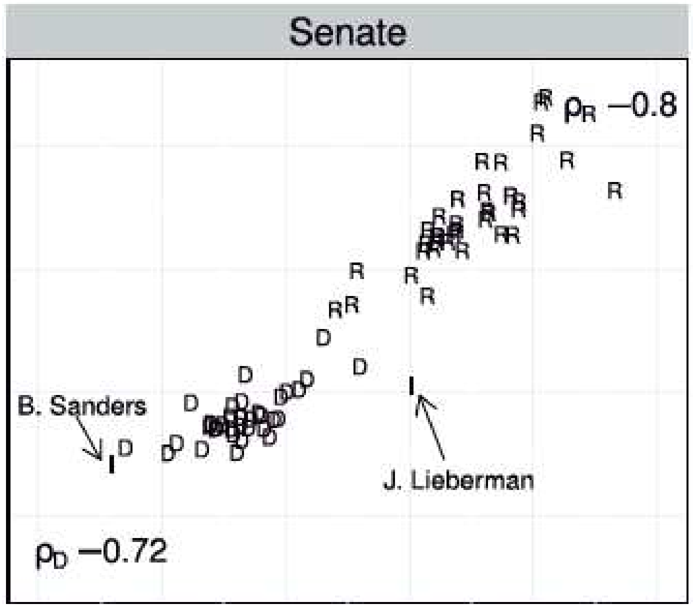

BASED ON TEXT AND SOCIAL INTERACTIONS

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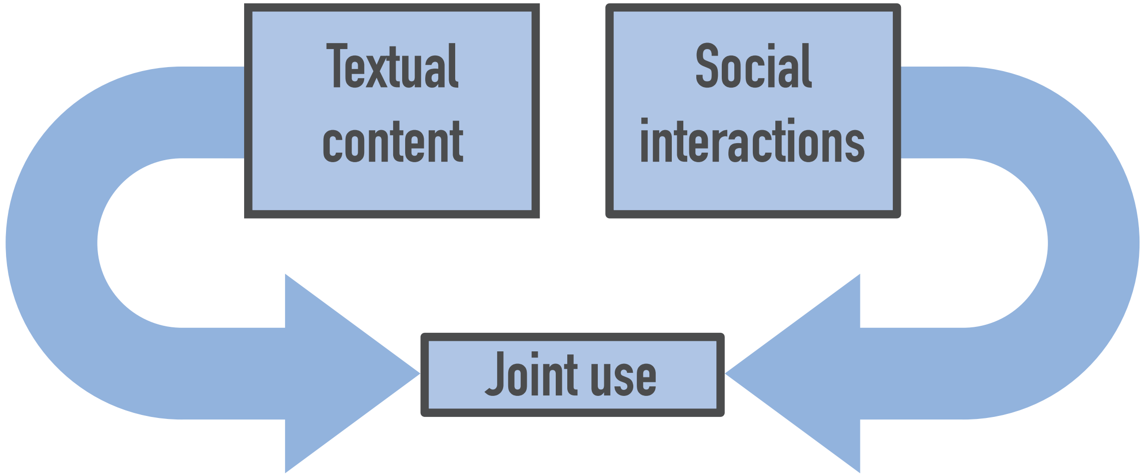

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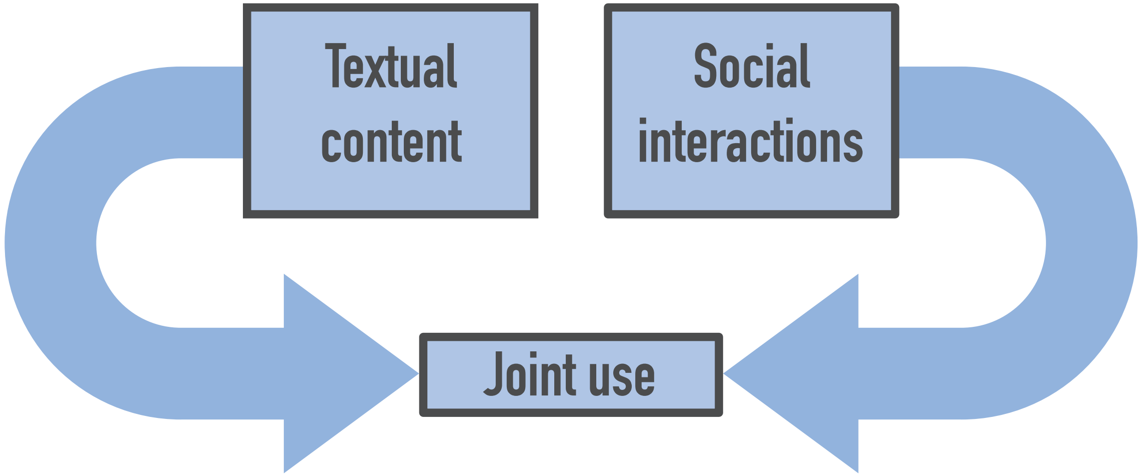

- Topic modeling taking into account tweets and social graph
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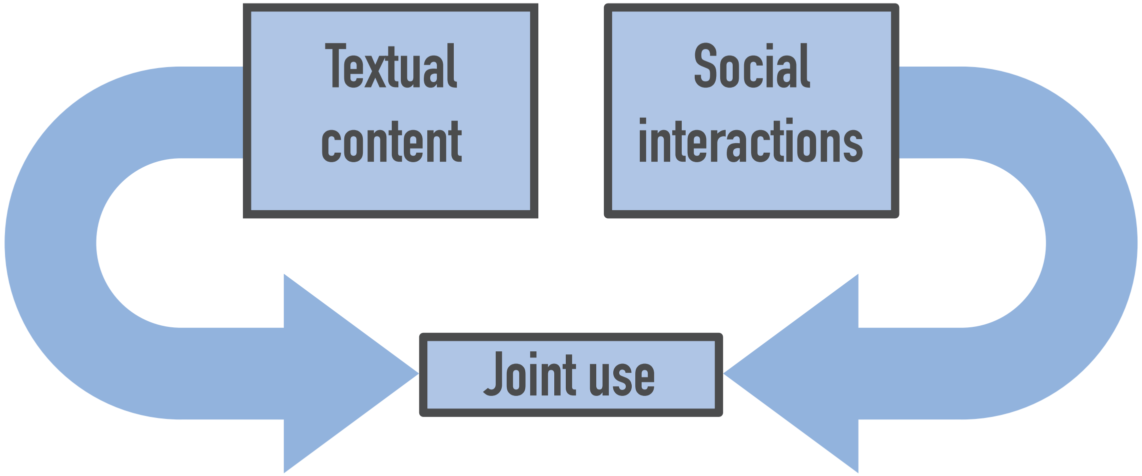

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- SVM trained on tweets and social graph (Magdy et al., 2016)

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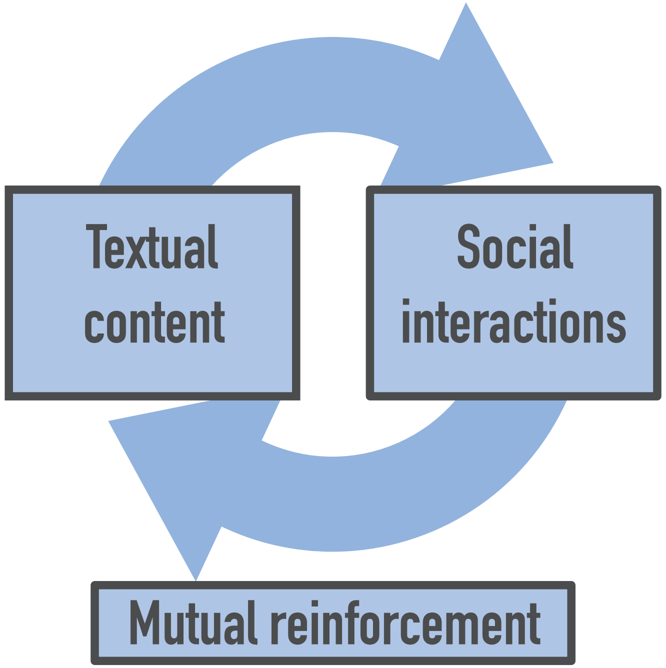

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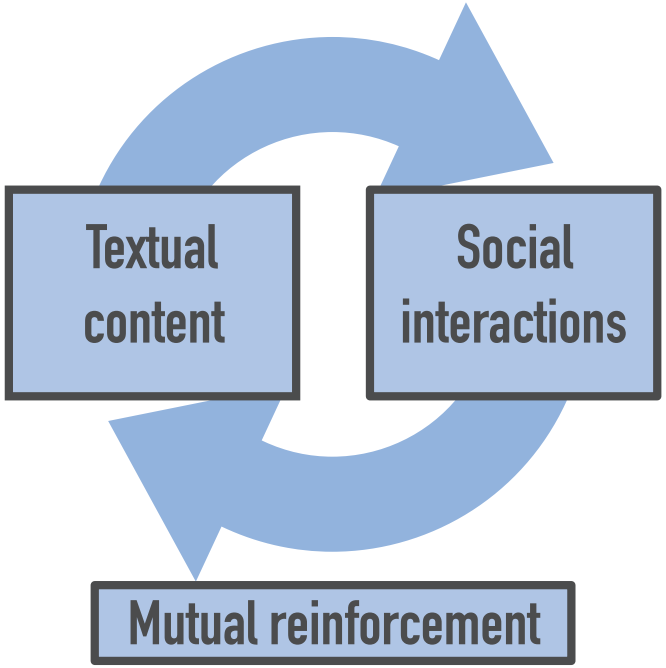

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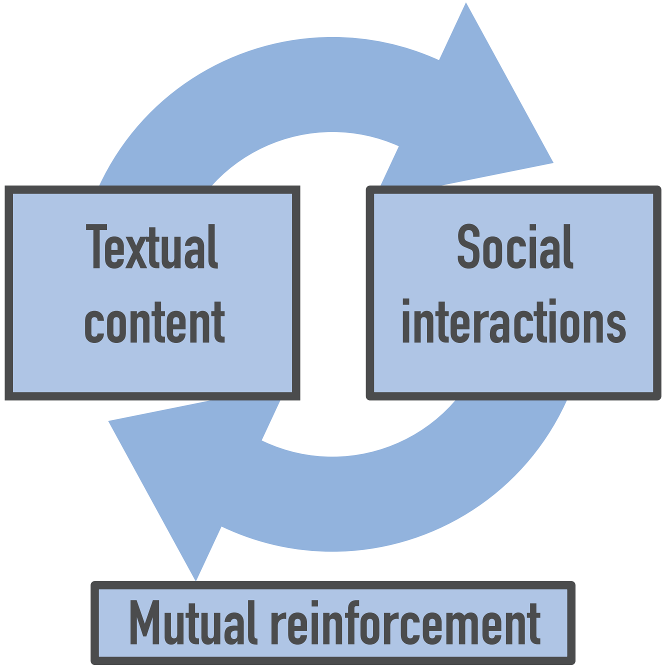

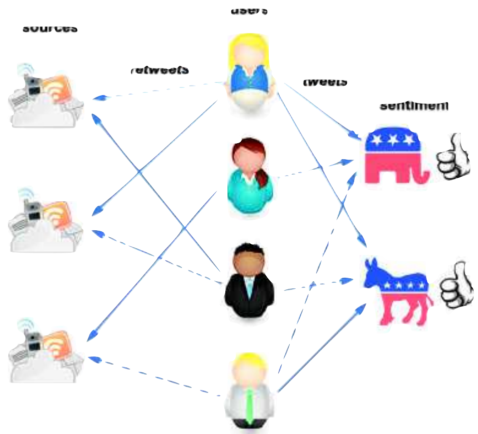

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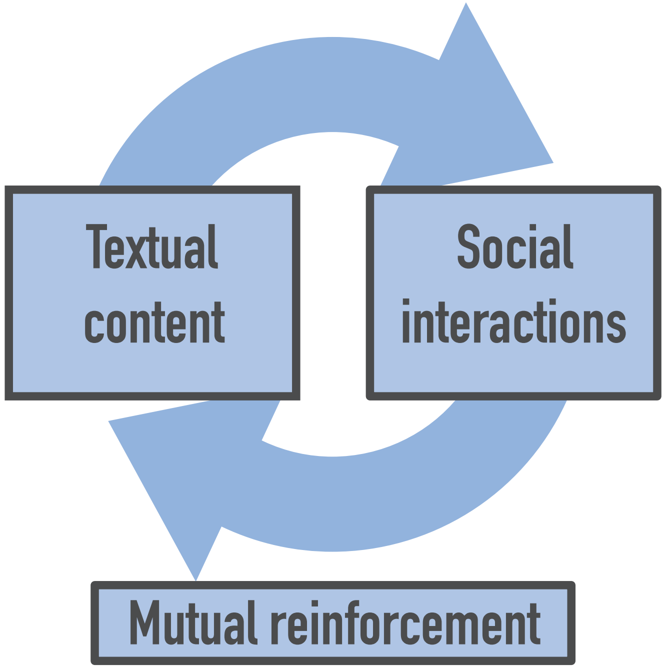

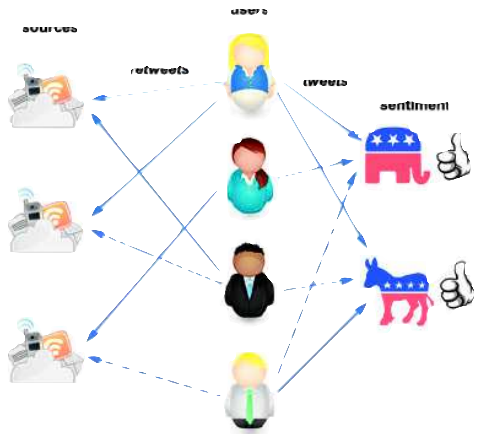

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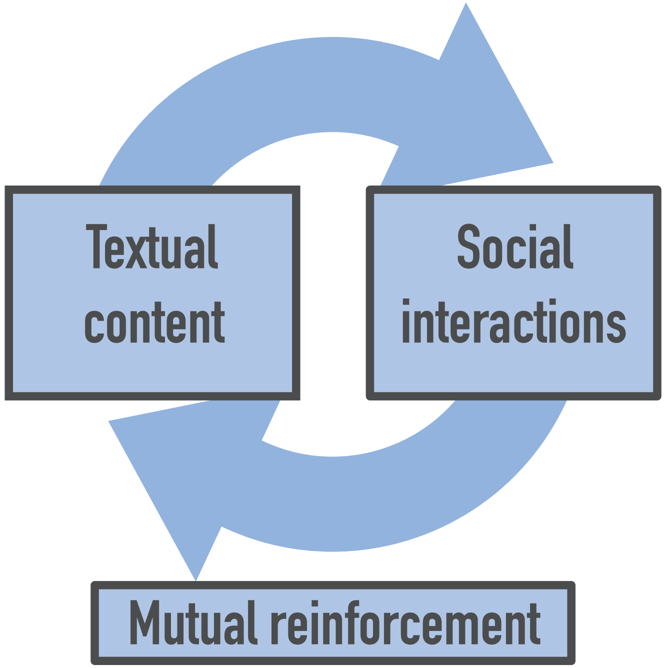

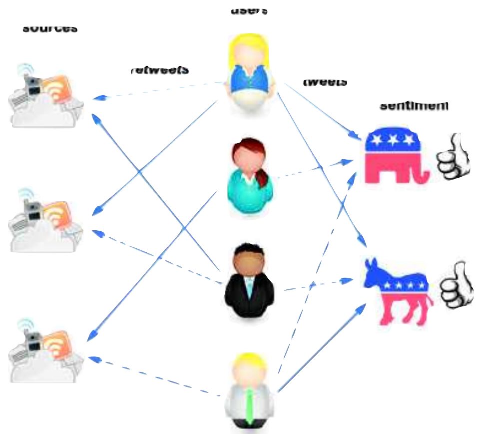

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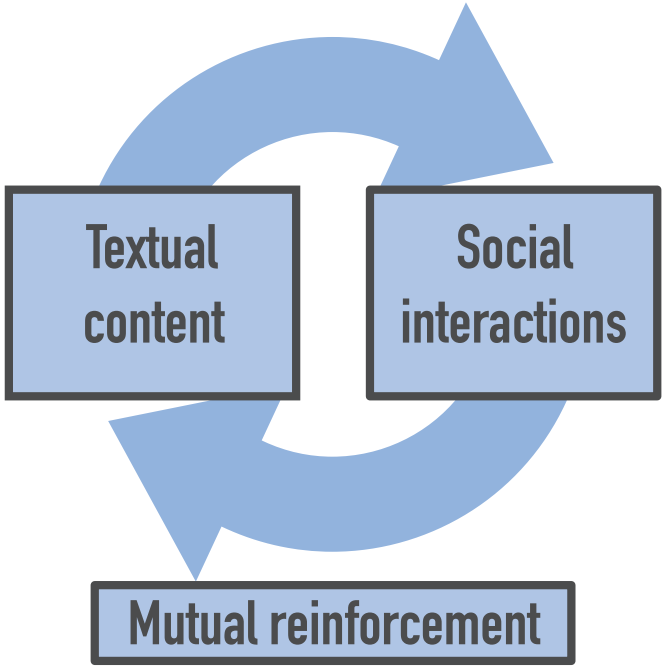
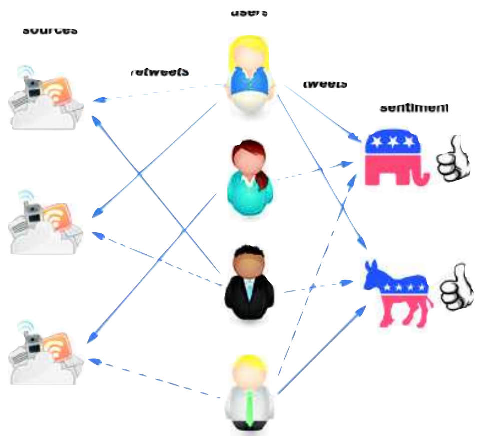
BASED ON TEXT AND SOCIAL INTERACTIONS





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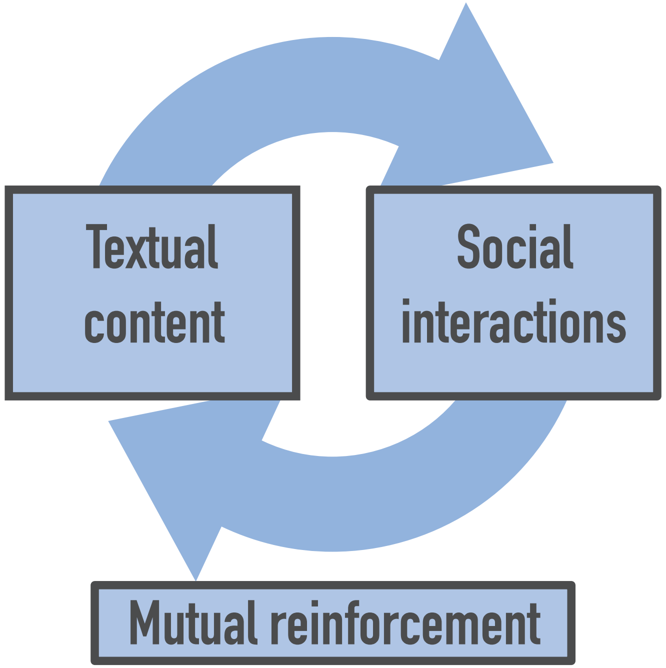

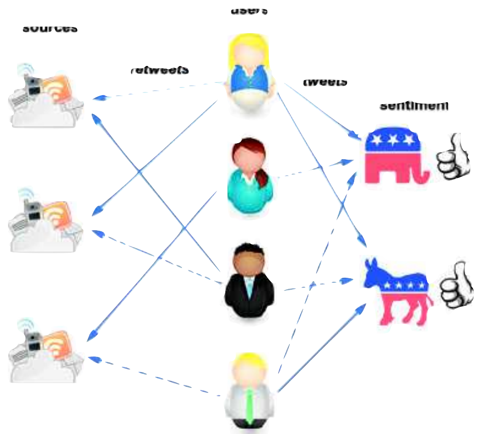

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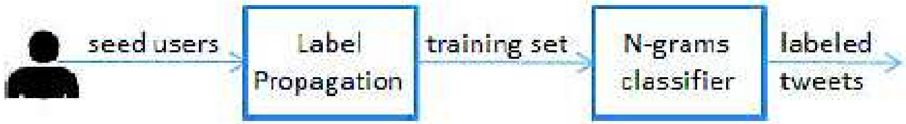

ELECTION PREDICTION

MULTIPLES ATTEMPTS

2008	US presidential election	(O'Connor et al. 2010)	(Gayo-Avello 2011)
2009	German federal election	(Tumasjan et al. 2010)	(Jungherr et al. 2011)
2010	US elections in various states	(Metaxas et al. 2011)	(Livne et al. 2011)
2011	Irish general election	(Bermingham & Smeaton, 2011)	
2011	Singaporean general election	(Skoric et al., 2012)	
2011	Dutch senate election	(Sang & Bos, 2012)	
2013	Pakistani general election	(Razzaq et al., 2014)	
2015	Venezuelan parliamentary election	(Castro et al., 2017)	

MULTIPLES ATTEMPTS

Good predictions & better than traditional polls

Year	Election	Study	Volume of tweets	Sentiment analysis	Other
2008	US presidential election	(O'Connor et al. 2010)			
		(Gayo-Avello 2011)			
2009	German federal election	(Tumasjan et al. 2010)			
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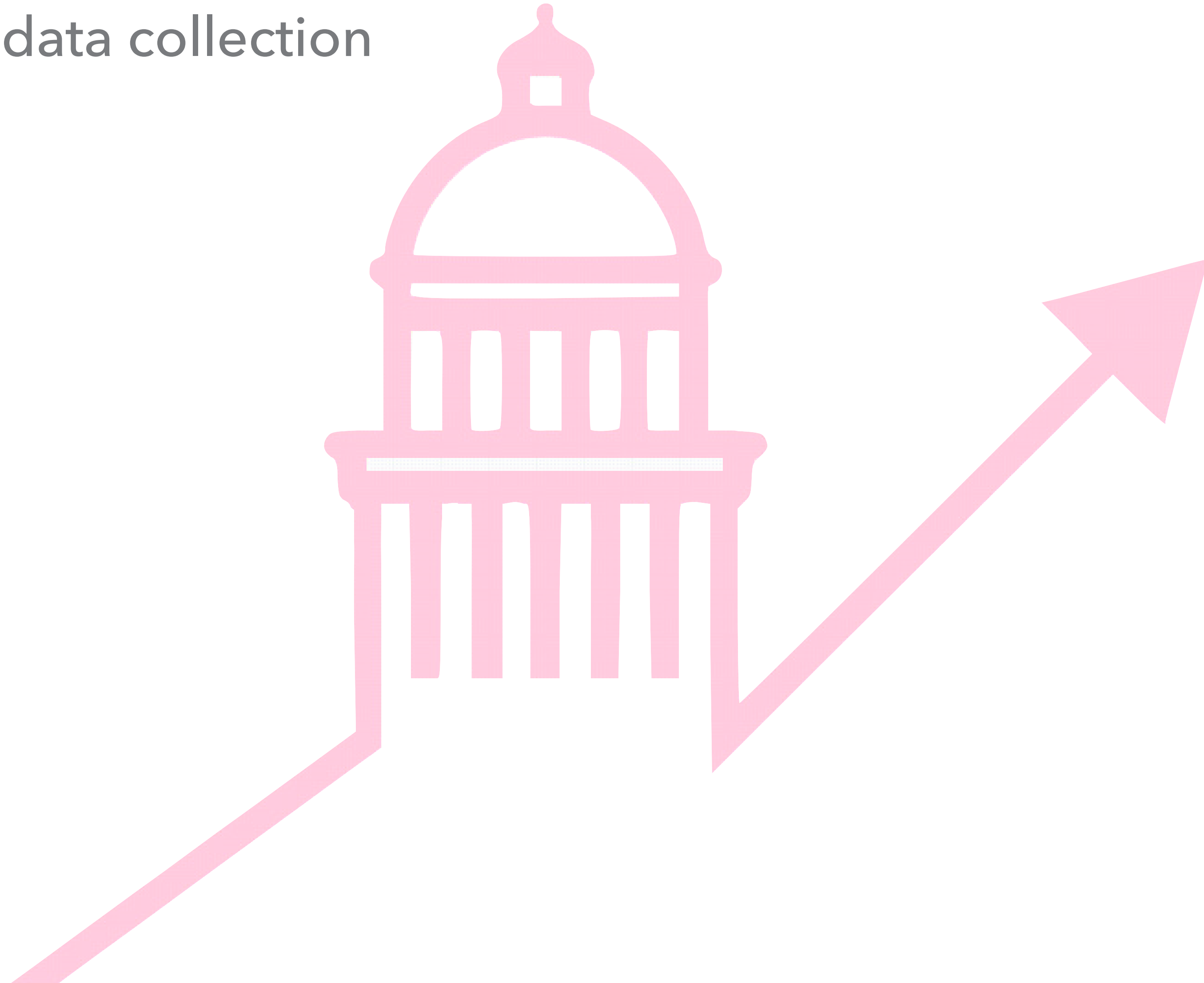
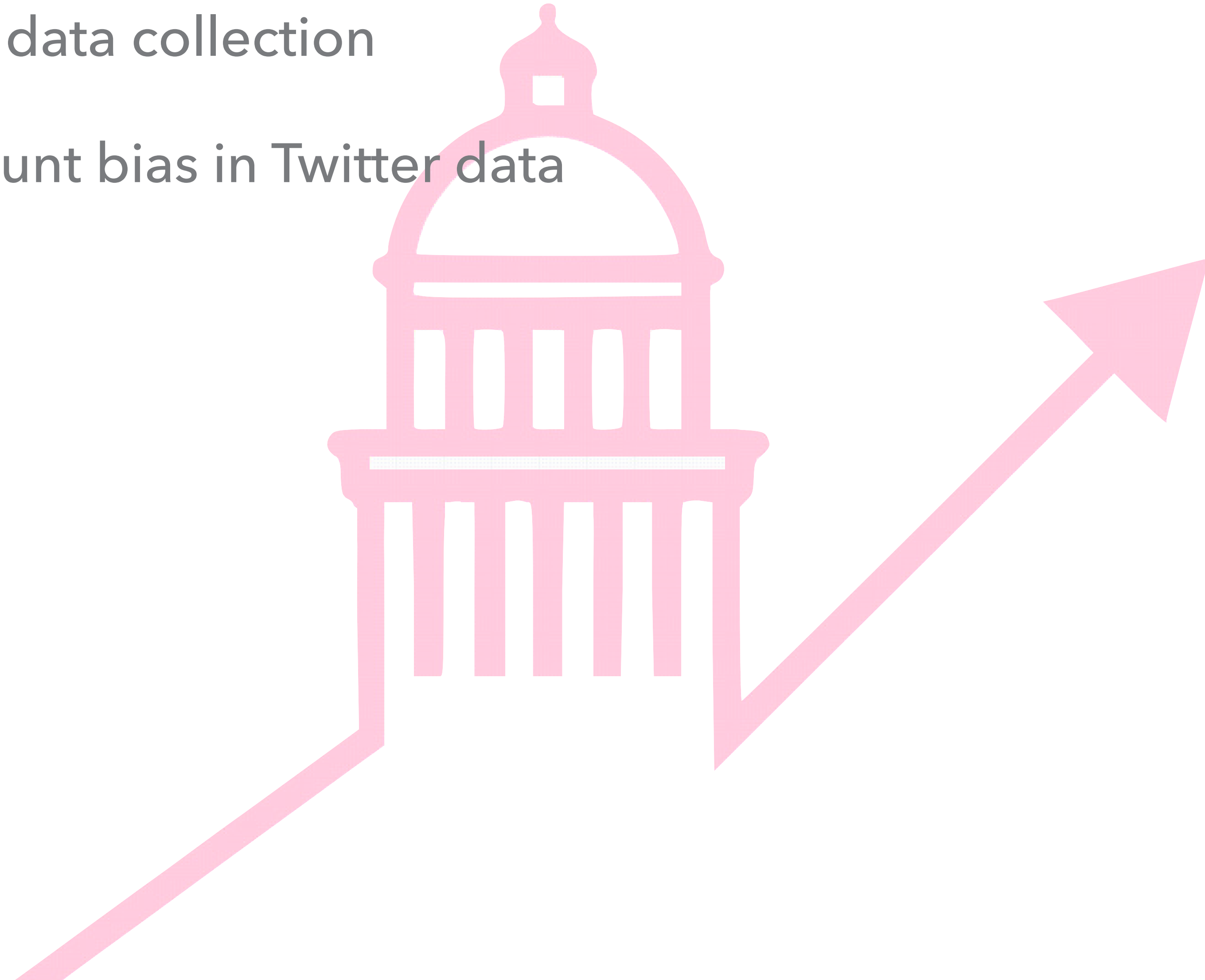
BUT...

- Highly dependant on data collection



BUT...

- Highly dependant on data collection
- Rarely takes into account bias in Twitter data



BUT…

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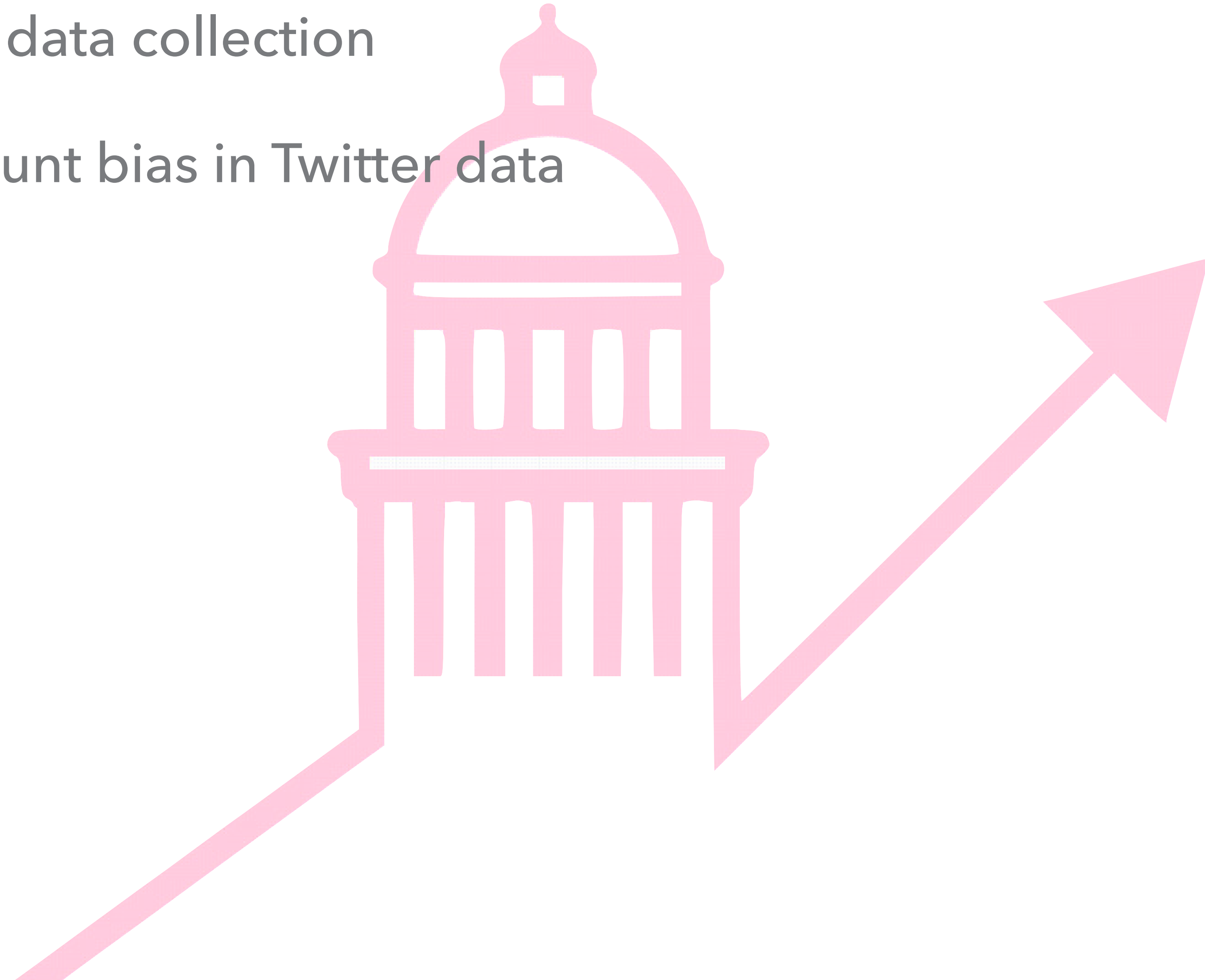
- Rarely takes into account bias in Twitter data
  - Demographics bias



BUT…

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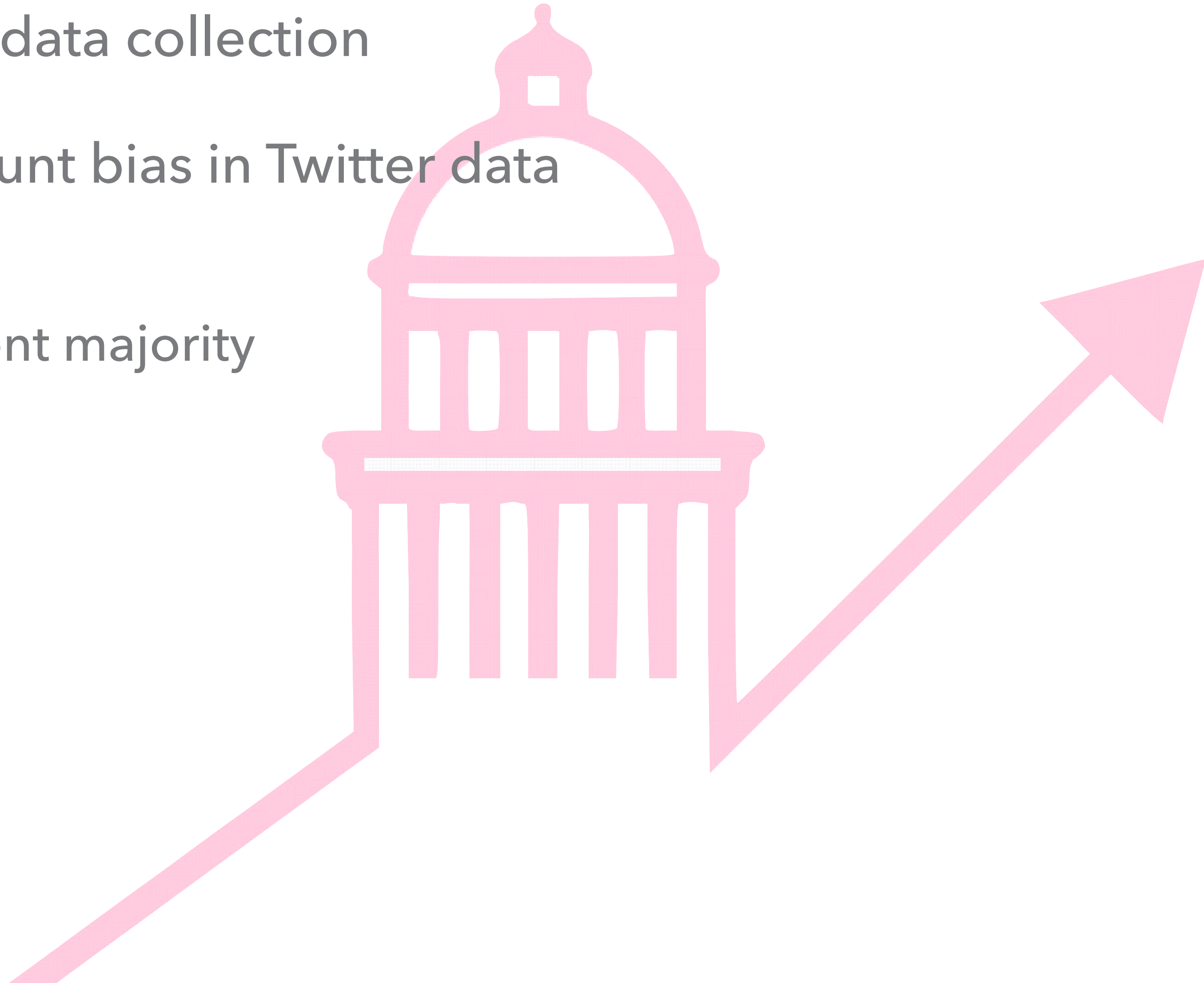
  - Vocal minority vs silent majority



BUT…

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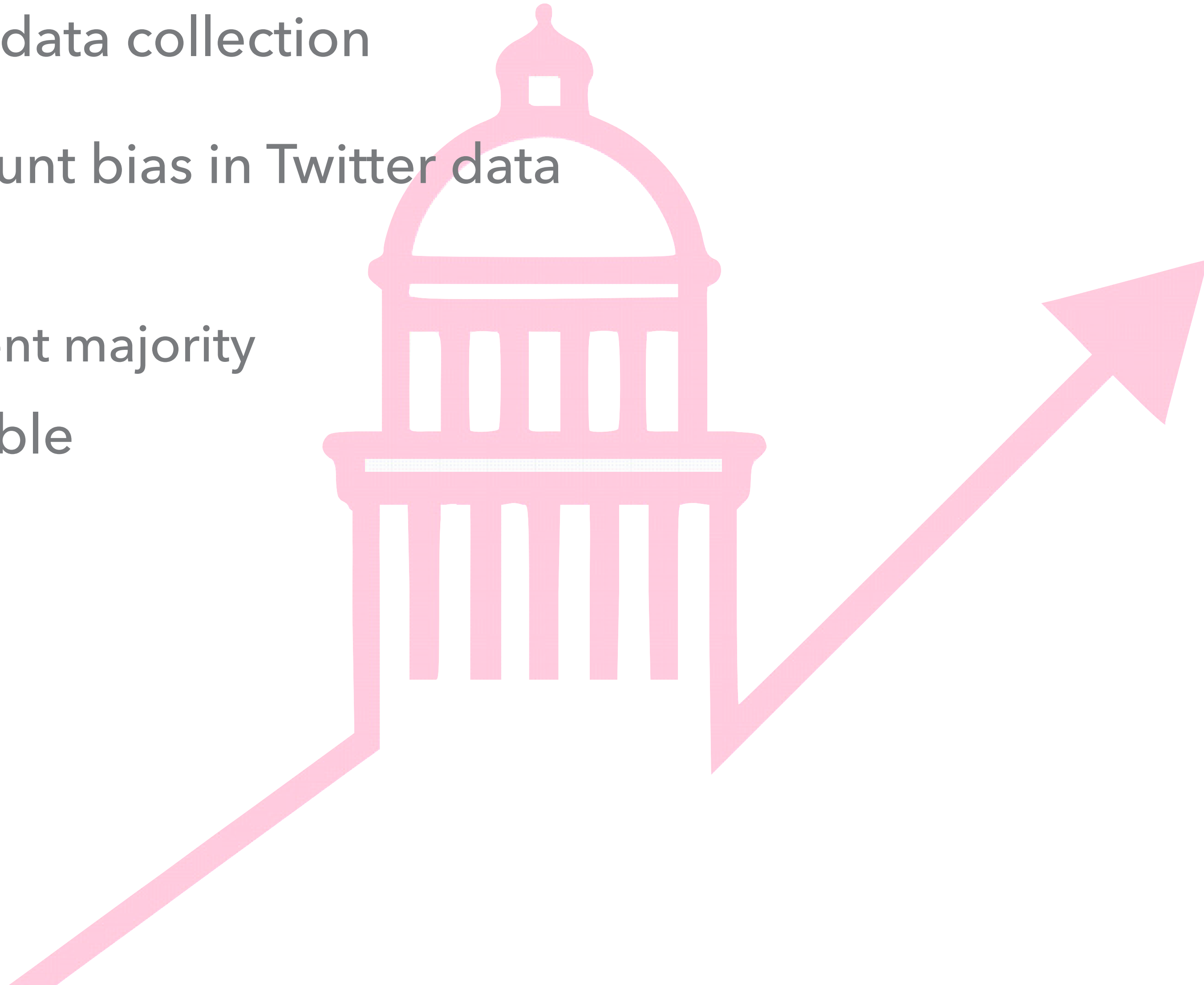
  - Demographics bias
  - Vocal minority vs silent majority
- Data purity questionable



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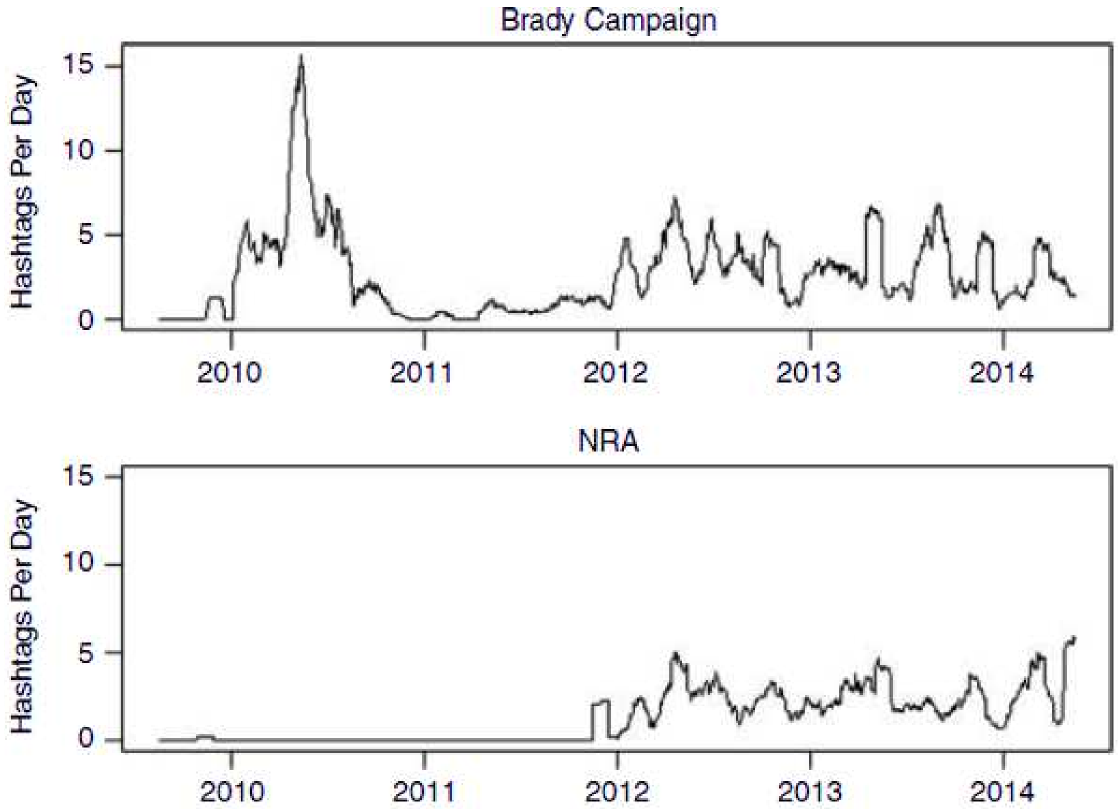
- Highly dependant on data collection
- Rarely takes into account bias in Twitter data
  - Demographics bias
  - Vocal minority vs silent majority
- Data purity questionable
  - Not all collected profiles eligible to vote
- For the time being, not better than traditional polls

Study of Political Engagement

COMMUNICATIONS OF GUN POLICY ORGANIZATIONS

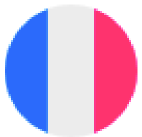
- (Merry, 2016)

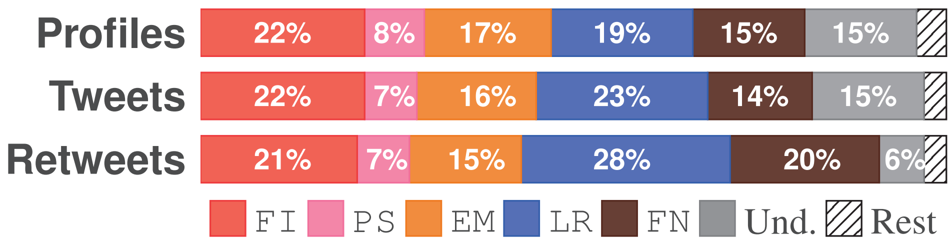


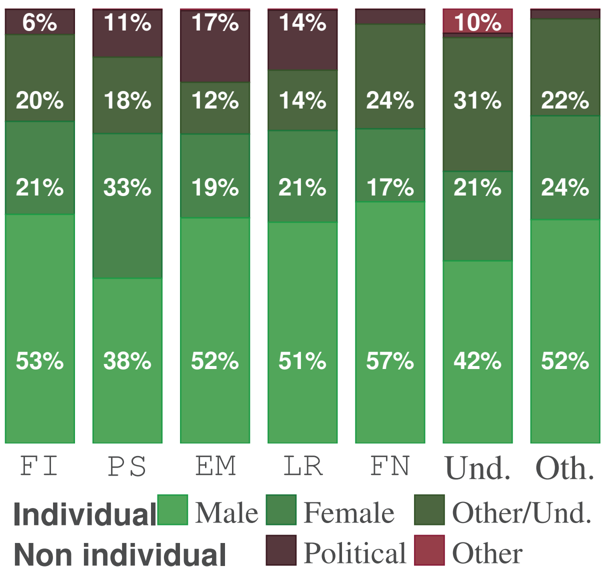
		Tweets containing character	% of tweets with Twitter handle
Brady campaign	Ally	492	5.7
	Hero	800	30.0
	Opponent	25	4.0
	Villain	730	9.0
NRA	Ally	289	10.4
	Hero	519	30.3
	Opponent	259	3.9
	Villain	508	5.1

2017 FRENCH PRESIDENTIAL CAMPAIGN

- (Fraisier et al., 2018)

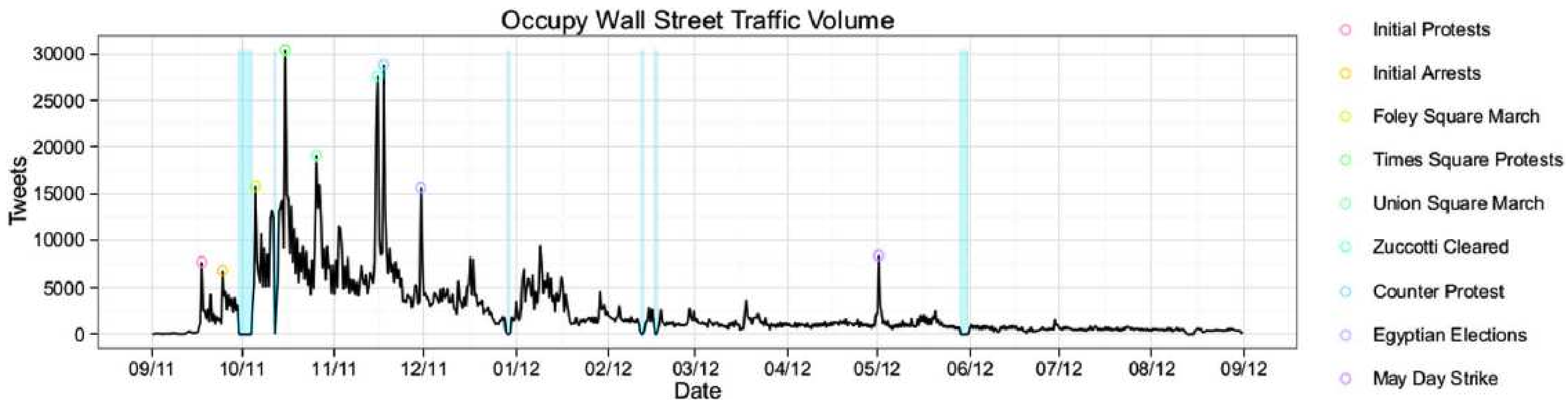


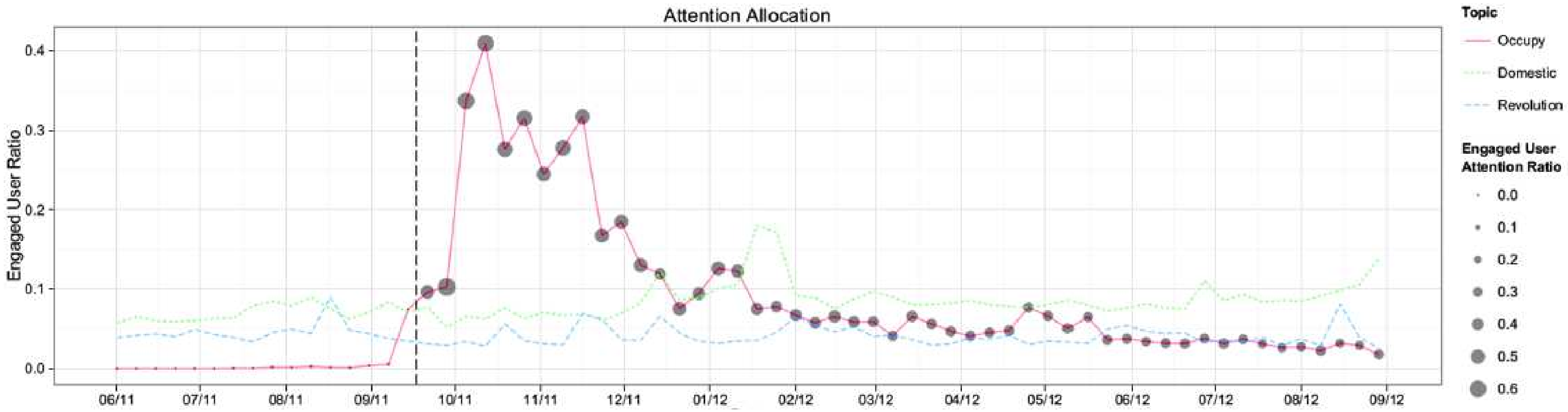




INVOLVEMENT IN OCCUPY WALL STREET

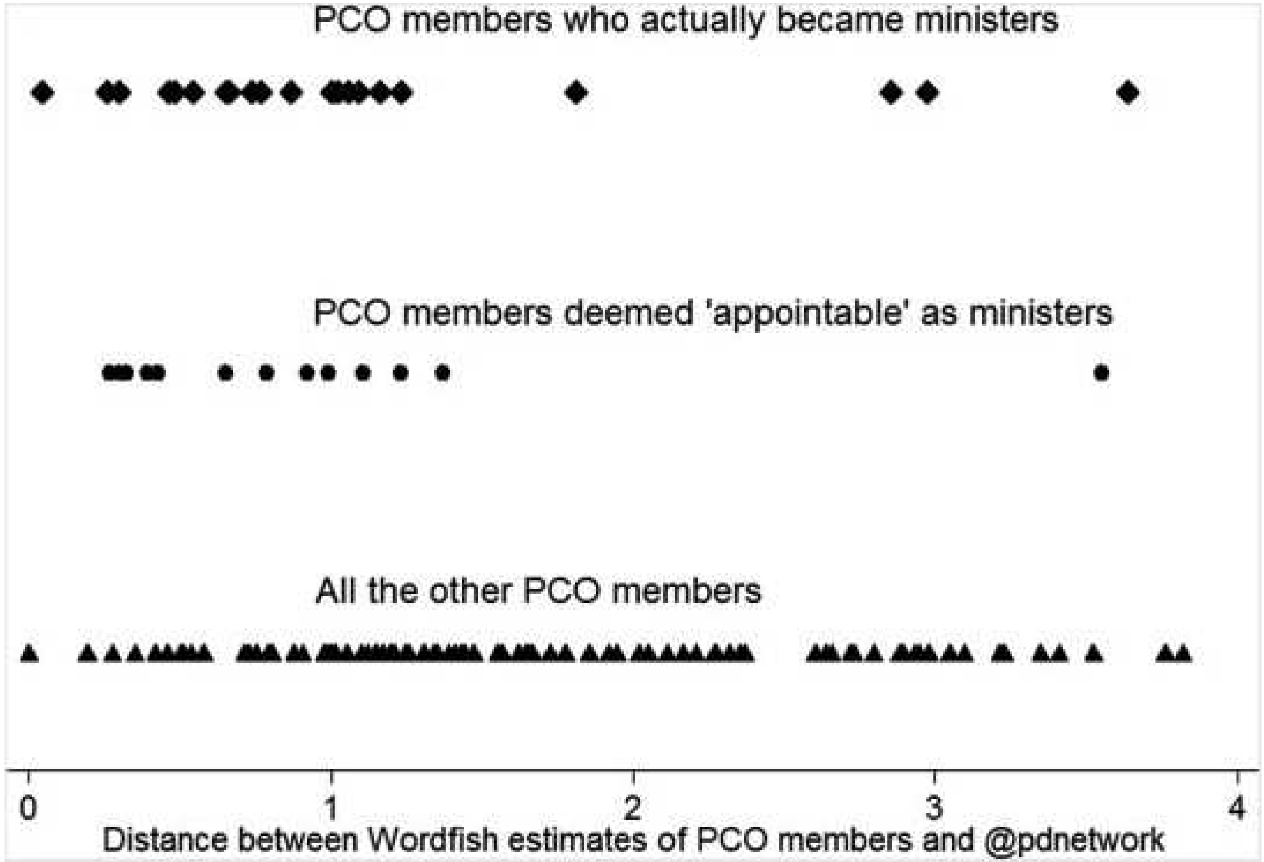
- (Conover et al., 2013)





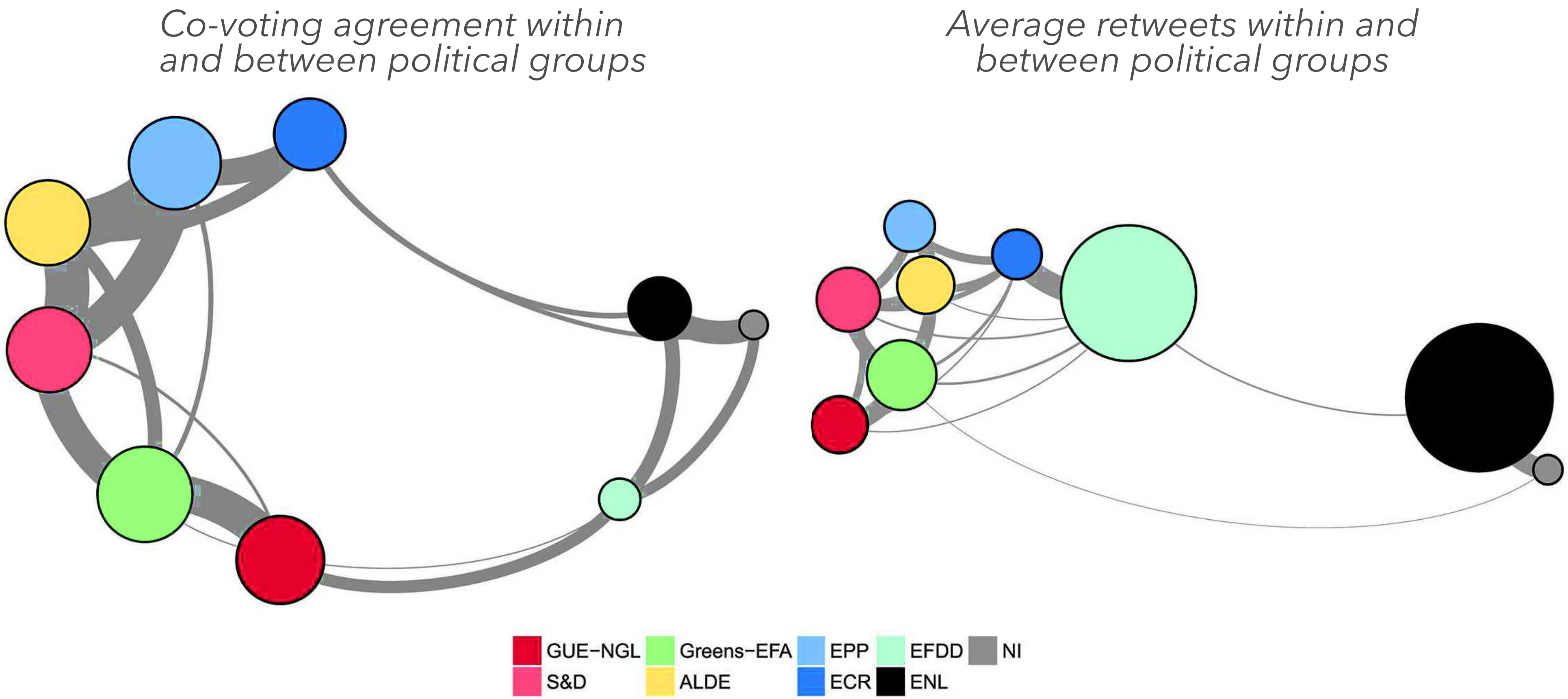
ITALIAN INTRA-PARTY POLITICS

- (Ceron, 2017)



COALITIONS IN THE EUROPEAN PARLIAMENT

- (Cherepnalkosk, 2016)

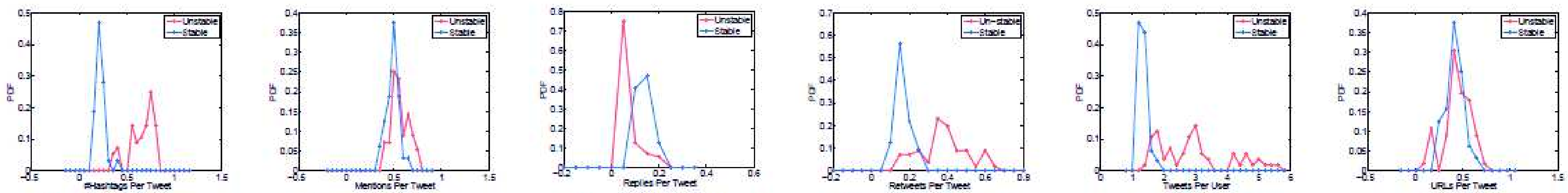


DETECTION OF SOCIAL UNREST

- Social unrest: public expression of discontent, including public protest that does not threaten the regime's hold on power, and/or sporadic but low-level violence.

➡ Identifying tweets relevant to social unrest (Mishler et al., 2017)

➡ Identifying *unstable* countries based on tweets (Raja et al., 2016)



(a) Hashtags Per Tweet (b) Mentions Per Tweet (c) Replies Per Tweet (d) Retweets Per User (e) Tweets Per User (f) URLs Per User

- Large body of work on Twitter and politics
  - Various tasks
  - Diversity of subjects, after being focused on US politics for some time
- Known limits
  - Need for caution when extrapolating
- Importance of quantitative & qualitative analysis

THANK YOU
FOR YOUR ATTENTION

- Abbasi, M. A., Zafarani, R., Tang, J., & Liu, H. (2014). Am i more similar to my followers or followees?: analyzing homophily effect in directed social networks. In Proceedings of the 25th ACM Conference on Hypertext and Social Media (p. 200–205). ACM Press. https://doi.org/10.1145/2631775.2631828
- Barberá, P. (2015). Birds of the Same Feather Tweet Together: Bayesian Ideal Point Estimation Using Twitter Data. Political Analysis, 23(01), 76–91. https://doi.org/10.1093/pan/mpu011
- Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A., & Bonneau, R. (2015). Tweeting From Left to Right: Is Online Political Communication More Than an Echo Chamber? Psychological Science, 26(10), 1531–1542. https://doi.org/10.1177/0956797615594620
- Bermingham, A., & Smeaton, A. F. (2011). On using Twitter to monitor political sentiment and predict election results. In Sentiment Analysis where AI meets Psychology (SAAIP) Workshop at the International Joint Conference for Natural Language Processing (IJCNLP). Chiang Mai, Thailand.
- Boireau, M. (2014). Determining Political Stances from Twitter Timelines: The Belgian Parliament Case. In Proceedings of the 2014 Conference on Electronic Governance and Open Society: Challenges in Eurasia (p. 145–151). St. Petersburg, Russian Federation: ACM Press. https://doi.org/10.1145/2729104.2729114
- Castro, R., Kuffo, L., & Vaca, C. (2017). Back to #6D: Predicting Venezuelan states political election results through Twitter (p. 148–153). IEEE. https://doi.org/10.1109/ICEDEG.2017.7962525
- Castro, R., & Vaca, C. (2017). National Leaders' Twitter Speech to Infer Political Leaning and Election Results in 2015 Venezuelan Parliamentary Elections (p. 866–871). IEEE. https://doi.org/10.1109/ICDMW.2017.118
- Ceron, A. (2017). Intra-party politics in 140 characters. Party Politics, 23(1), 7–17. https://doi.org/10.1177/1354068816654325
- Cherepnalkoski, D., Karpf, A., Mozetič, I., & Grčar, M. (2016). Cohesion and Coalition Formation in the European Parliament: Roll-Call Votes and Twitter Activities. PLOS ONE, 11(11), e0166586. https://doi.org/10.1371/journal.pone.0166586
- Cherepnalkoski, D., & Mozetic, I. (2015). A Retweet Network Analysis of the European Parliament (p. 350–357). IEEE. https://doi.org/10.1109/SITIS.2015.8
- Conover, M. D., Ratkiewicz, J., Francisco, M., Gonçalves, B., Flammini, A., & Menczer, F. (2011). Political Polarization on Twitter. In Proceedings of the 5th International AAAI Conference on Weblogs and Social Media (p. 89--96). Barcelona, Spain: AAAI Press. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/viewFile/2847/3275
- Conover, Michael D., Ferrara, E., Menczer, F., & Flammini, A. (2013). The Digital Evolution of Occupy Wall Street. PLoS ONE, 8(5), e64679. https://doi.org/10.1371/journal.pone.0064679
- Conover, Michael D., Goncalves, B., Ratkiewicz, J., Flammini, A., & Menczer, F. (2011). Predicting the Political Alignment of Twitter Users (p. 192–199). IEEE. https://doi.org/10.1109/PASSAT/SocialCom.2011.34
- Fang, A., Ounis, I., Habel, P., Macdonald, C., & Limsopatham, N. (2015). Topic-centric Classification of Twitter User's Political Orientation. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (p. 791-794). New York, NY, USA: ACM. https://doi.org/10.1145/2766462.2767833
- Fraisier, O., Cabanac, G., Pitarch, Y., Besancon, R., & Boughanem, M. (2018). #Élysée2017fr: The 2017 French Presidential Campaign on Twitter. In Proceedings of the 12th International AAAI Conference on Weblogs and Social Media. Stanford, California, USA: AAAI Press. https://www.irit.fr/publis/IRIS/2018_ICWSM_FCPBB.pdf
- Gaudin, S. (2016, novembre 8). In presidential campaign, Twitter was a powerful political tool. https://www.computerworld.com/article/3137261/social-media/in-presidential-campaign-twitter-was-a-powerful-political-tool.html
- Gayo-Avello, D. (2011). Don't turn social media into another « Literary Digest » poll. Communications of the ACM, 54(10), 121. https://doi.org/10.1145/2001269.2001297
- Gayo-Avello, D. (2013). A Meta-Analysis of State-of-the-Art Electoral Prediction From Twitter Data. Social Science Computer Review, 31(6), 649–679. https://doi.org/10.1177/0894439313493979
- Golder, S., & Macy, M. (2015). Opportunities and Challenges for Online Social Research. In Y. Mejova, I. Weber, & M. Macy (Ed.), Twitter: A Digital Socioscope (p. 1–20). Cambridge University Press.

- Guerrero-Solé, F. (2017). Community Detection in Political Discussions on Twitter: An Application of the Retweet Overlap Network Method to the Catalan Process Toward Independence. Social Science Computer Review, 35(2), 244–261. https://doi.org/10.1177/0894439315617254
- Kassim, S. (2012, juillet 3). Twitter Revolution: How the Arab Spring was helped by Social Media. https://mic.com/articles/10642/twitter-revolution-how-the-arab-spring-was-helped-by-social-media#.UiQDIpH4f
- Livne, A., Simmons, M. P., Adar, E., & Adamic, L. A. (2011). The Party is Over Here: Structure and Content in the 2010 Election. Presented at ICWSM.
- Magdy, W., Darwish, K., Abokhodair, N., Rahimi, A., & Baldwin, T. (2016). #ISISisNotIslam or #DeportAllMuslims?: predicting unspoken views. In Proceedings of the 8th ACM Conference on Web Science (p. 95–106). Hannover, Germany: ACM Press. https://doi.org/10.1145/2908131.2908150
- Merry, M. (2016). Making friends and enemies on social media: the case of gun policy organizations. Online Information Review, 40(5), 624–642. https://doi.org/10.1108/OIR-10-2015-0333
- Metaxas, P. T., Mustafaraj, E., & Gayo-Avello, D. (2011). How (Not) to Predict Elections. Presented at IEEE SocialCom Conference, Boston, MA.
- Mishler, A., Wonus, K., Chambers, W., & Bloodgood, M. (2017). Filtering Tweets for Social Unrest (p. 17–23). IEEE. https://doi.org/10.1109/ICSC.2017.75
- Mohammad, S. M., Sobhani, P., & Kiritchenko, S. (2017). Stance and Sentiment in Tweets. ACM Transactions on Internet Technology, 17(3), 1–23. https://doi.org/10.1145/3003433
- O'Connor, B., Balasubramanya, R., Routledge, B. R., & Smith, N. A. (2010). From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In Proceedings of the International AAAI Conference on Weblogs and Social Media. Washington, DC.
- Pennacchiotti, M., & Popescu, A.-M. (2011). Democrats, republicans and starbucks afficionados: user classification in twitter. In Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining (p. 430). ACM Press. https://doi.org/10.1145/2020408.2020477
- Rabelo, J., Prudencio, R. B. C., & Barros, F. (2012). Collective Classification for Sentiment Analysis in Social Networks (p. 958–963). IEEE. https://doi.org/10.1109/ICTAI.2012.135
- Raja, H., Ilyas, M. U., Saleh, S., Liu, A. X., & Radha, H. (2016). Detecting national political unrest on Twitter (p. 1–7). IEEE. https://doi.org/10.1109/ICC.2016.7511393
- Rajadesingan, A., & Liu, H. (2014). Identifying Users with Opposing Opinions in Twitter Debates. In W. G. Kennedy, N. Agarwal, & S. J. Yang (Ed.), Social Computing, Behavioral-Cultural Modeling and Prediction (Vol. 8393, p. 153–160). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-05579-4_19
- Razzaq, M. A., Qamar, A. M., & Hafiz Syed Muhammad Bilal. (2014). Prediction and analysis of Pakistan election 2013 based on sentiment analysis (p. 700–703). IEEE. https://doi.org/10.1109/ASONAM.2014.6921662
- Skoric, M., Poor, N., Achananuparp, P., Lim, E.-P., & Jiang, J. (2012). Tweets and Votes: A Study of the 2011 Singapore General Election (p. 2583–2591). IEEE. https://doi.org/10.1109/HICSS.2012.607
- Smith, L. M., Zhu, L., Lerman, K., & Kozareva, Z. (2013). The Role of Social Media in the Discussion of Controversial Topics (p. 236–243). IEEE. https://doi.org/10.1109/SocialCom.2013.41
- Thonet, T., Cabanac, G., Boughanem, M., & Pinel-Sauvagnat, K. (2017). Users Are Known by the Company They Keep: Topic Models for Viewpoint Discovery in Social Networks. In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management (p. 87–96). Singapore, Singapore: ACM Press. https://doi.org/10.1145/3132847.3132897
- Volkova, S., Bachrach, Y., & Durme, B. V. (2016). Mining User Interests to Predict Perceived Psycho-Demographic Traits on Twitter (p. 36–43). IEEE. https://doi.org/10.1109/BigDataService.2016.28
- Weber, I., Garimella, V. R. K., & Batayneh, A. (2013). Secular vs. Islamist polarization in Egypt on Twitter. In Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (p. 290–297). ACM Press. https://doi.org/10.1145/2492517.2492557
- Wong, F. M. F., Tan, C. W., Sen, S., & Chiang, M. (2016). Quantifying Political Leaning from Tweets, Retweets, and Retweeters. IEEE Transactions on Knowledge and Data Engineering, 28(8), 2158–2172. https://doi.org/10.1109/TKDE.2016.2553667