Detection and Characterization of Stance on Social Media

Part3

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Part 3

Stance Detection Applications & What is next?

@Walid_Magdy

What after detecting users' stance?

- Stance detection applications
  - Analysing discussions in major events
  - Understanding user characteristics/leanings
  - Measuring opinion change
  - Detecting fake news
- Recent trends in stance detection
- Current challenges & possible future directions

Who am I?

- Associate Professor,
  The School of Informatics, University of Edinburgh
- Faculty Fellow,
  The Alan Turing Institute, London
- Director & Founder
  The Social Media Analysis and Support for Humanity (SMASH) group at Edinburgh University (@SMASH_Edin)
- Interests:
  Computational Social Science, Data Mining, and NLP

Part 1

Stance Detection as a Tool

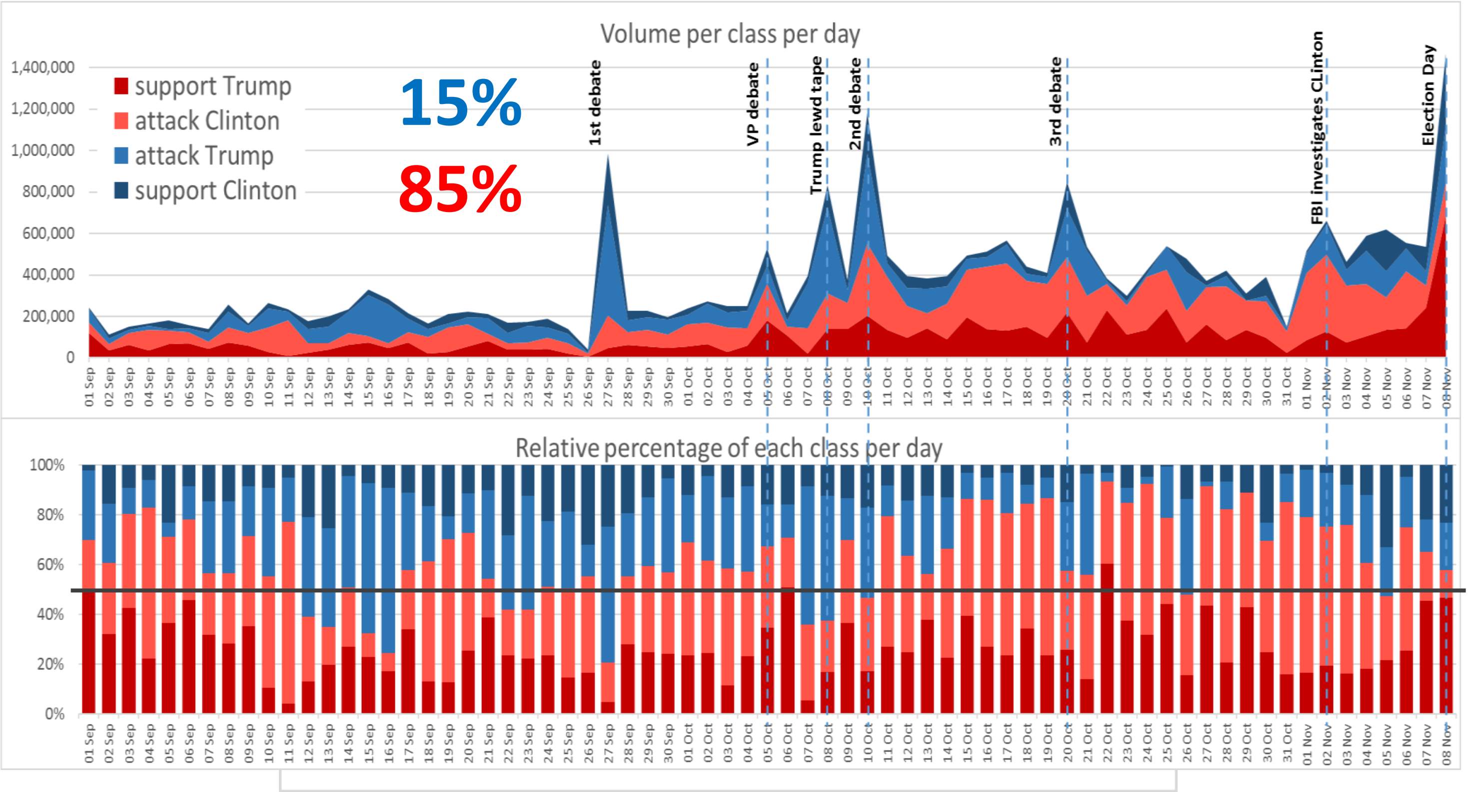
Example 1

What societies are really interested in?

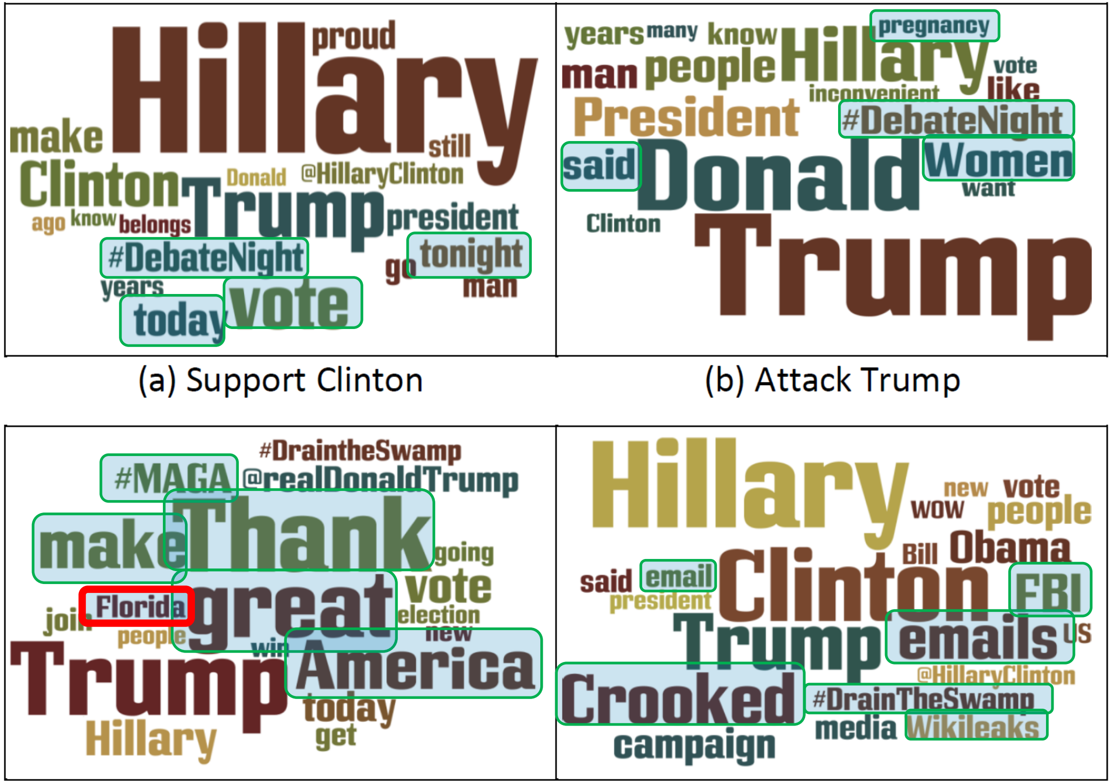
US Election 2016

- Collected tweets on **US Election**
- Study period: 1 Sep 2016 – 8 Nov 2016 (election day)
- Total tweet volume: **66M** tweets/retweets
- Study:
  - Most **50** viral daily tweets
  - **3450** tweets → **26.6M** retweets (**40%** of full volume)
- Label: support/attack Trump/Clinton or neither
- Analyzed:
  top discussed topics, influencers, link sources, state-mentions, … etc.

Support/Attack Volume



Most Discussed Topics



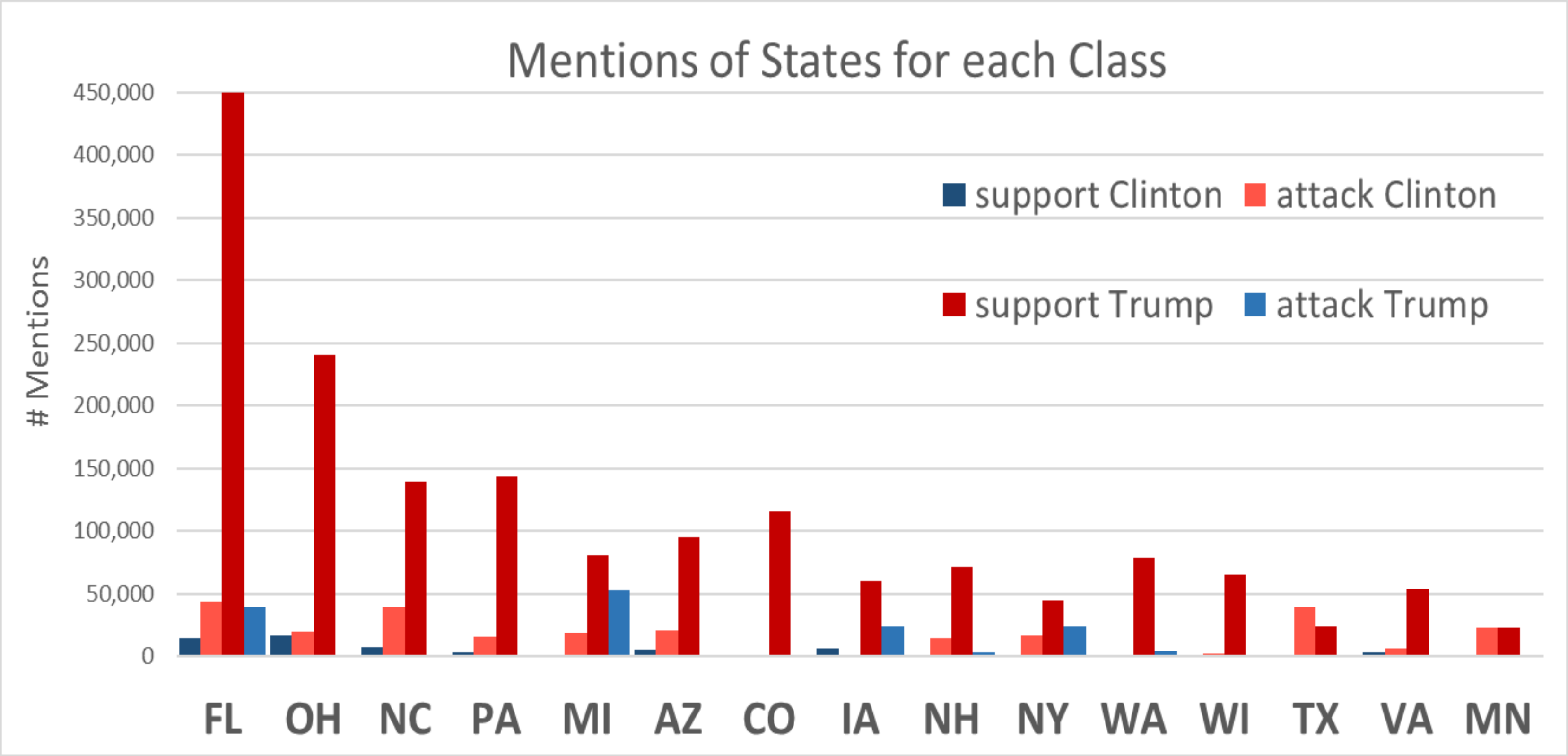
(a) Support Clinton

(b) Attack Trump

(c) Support Trump

(d) Attack Clinton

Mention of States



Most Influential Accounts

support Clinton			attack Trump		
Account	Count	Volume	Account	Count	Volume
Hillary Clinton	331	2,025,821	*Hillary Clinton*	363	2,698,209
President Obama	4	122,947	Bernie Sanders	11	304,860
Senator Tim Kaine	15	84,245	Ozzyonce	1	152,756
Jerry Springer	1	78,872	Bailey Disler	1	124,322
Erin Ruberry	1	72,167	Stephen King	2	121,635
Richard Hine	1	66,817	Kat Combs	1	105,118
Bernie Sanders	7	46,180	Es un racista	1	102,063
CNN	6	41,983	Rob Fee	1	99,401
Funny Or Die	1	27,909	Jerry Springer	1	78,872
Channel 4 News	1	27,409	Master of None	1	67,690

Support Trump			attack Clinton		
Donald J. Trump	446	4,992,845	*Donald J. Trump*	246	3,613,025
Kellyanne Conway	51	199,511	WikiLeaks	141	1,454,903
Mike Pence	36	195,824	*Kellyanne Conway*	92	349,025
Dan Scavino Jr.	40	181,601	Paul Joseph Watson	78	297,273
Official Team Trump	14	141,289	*Official Team Trump*	23	150,932
Donald Trump Jr.	20	112,835	*Donald Trump Jr.*	34	126,744
Eric Trump	8	79,387	Jared Wyand	19	85,742
Immigrants4Trump	4	52,256	Cloyd Rivers	7	84,063
Cloyd Rivers	2	45,493	Juanita Broaddrick	4	83,903
Paul Joseph Watson	10	38,474	James Woods	16	78,719

Most Viral Tweets

Jerry Springer
@jerryspringer

Hillary Clinton belongs in the White House. Donald Trump belongs on my show.

5:55 AM - 27 Sep 2016

163,344 Retweets **321,220** Likes

5.3K 163K 321K

Ozzyoncé
@ozzyetomi

Donald Trump said pregnancy is very inconvenient for businesses, like his mother's pregnancy hasn't been inconvenient for the whole world.

3:52 PM - 15 Sep 2016

149,610 Retweets **183,906** Likes

418 150K 184K

WikiLeaks
@wikileaks

No link between Trump & Russia
No link between Assange & Russia
But Podesta & Clinton involved in selling 20% of US uranium to Russia

4:48 AM - 1 Nov 2016

55,797 Retweets **45,002** Likes

1.6K 56K 45K

Donald J. Trump
@realDonaldTrump

TODAY WE MAKE AMERICA GREAT AGAIN!

2:43 PM - 8 Nov 2016

336,137 Retweets **563,878** Likes

29K 336K 564K

Findings

- Trump had much <u>larger support</u> on Twitter than Clinton
- Clinton (and her supporters) focus was on Attacking Trump
  - Clinton official website was <u>#1</u> referenced in attacking Trump
  - Trump official website was <u>#8</u> referenced in attacking Clinton
- <u>WikiLeaks</u> had strong role in creating content <u>against</u> Clinton
- Trump <u>supporters</u> were significantly <u>more active</u> than Clinton's
- Trump's <u>slogan</u> was well spread, unlike Clinton's

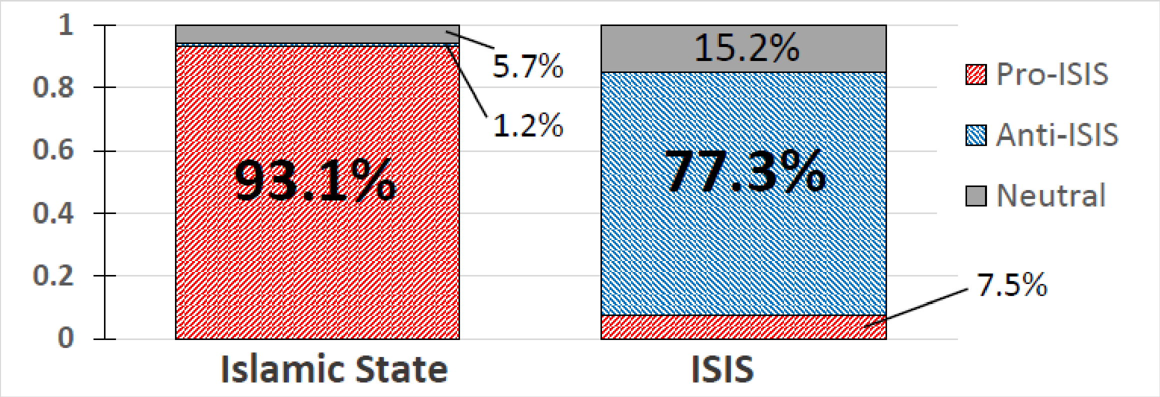
Darwish K., W. Magdy, T. Zanouda. Trump vs. Hillary: What went viral during US Election 2016?. SocInfo 2017

Example 2

Understanding Antecedent of Support

Where ISIS supporters come from?

- Signals of ISIS support is frequently noticed on Twitter in 2014
- Collected 3 million tweets mentioning ISIS
- Labeling:



- 57K (11K + 46K) users talking about ISIS (10 tweets at least)

Modeling Users

- **Data Collection:**
  - Collect tweets timeline for **57K** users → **123 million** tweets
  - Identify tweets of users before even mention ISIS
- **Stance Classifier:**
  - Train classifier with Pre-ISIS tweets → Pro/Anti ISIS
  - Accuracy → **87%**
- **Analysis:**
  - Find most distinguishing feats for Pro-ISIS
    (before being supporters to ISIS)

Findings

- Most distinguishing features:
  - Related to Arab spring (Egypt, Syria, Libya)
  - Related to protesting against Arab regimes (SA, Kuwait, Iraq)
- Qualitative

Date	Tweet (translated)
May 25, 2012	Don't be surprised if it rains today ... martyrs are spitting on us
Nov. 9, 2014	Preliminary schizophrenia: I like ISIS, but I want to watch Chris Nolan's new movie
Nov. 17, 2014	Check the gazes of Bashar's soldiers before slaughter by #Islamic_State in #despite_the_disbelivers

- Support of ISIS is <u>not ideological</u>, but for <u>revenge</u>

Magdy W., K. Darwish, and I. Weber. #FailedRevolutions: Using Twitter to Study the Antecedents of ISIS Support. First Monday, 2016

Example 3

Factors Influencing our Leanings

Stance towards Muslims after #ParisAttacks

- Paris Attacks
  → Worldwide support (#Pray4Paris)
  → ISIS announce responsibility
  → Campaign against Muslims (#MuslimsAreTerrorists)
  → Campaign defending Muslims (#ISISisNotIslam)
- Collected: **8.4 million** tweets about **#ParisAttacks** in **50hrs**
- **900K** tweets mentioning something about Islam
- Sampling + label propagation → **336K** tweets
  Attacking Muslims / Defending Muslims / Neutral

Top Hashtags about Muslims

Positive	Count	Negative	Count
#MuslimsAreNotTerrorist	34,925	#IslamIsTheProblem	3,154
#MuslimAreNotTerrorist	17,759	#RadicalIslam	1,618
#NotInMyName	4,728	#StopIslam	1,598
#MuslimsStandWithParis	1,228	#BanIslam	460
#MuslimsAreNotTerrorists	1,106	#StopIslamicImmigration	333
#ThisisNotIslam	781	#IslamIsEvil	290
#NothingToDoWithIslam	619	#IslamAttacksParis	280
#ISISareNotMuslim	316	#ImpeachTheMuslim	215
#ExtremistsAreNotMuslim	306	#KillAllMuslims	206
#ISISisNotIslam	243	#DeportAllMuslims	186

Can we predict stance before it happens?

- Identified **44K US-based** polarized users towards **Muslims**
  - Mentioned Islam before (10.5K → 6.6K+4K)
  - Never mentioned Islam (33.5K → 27.5K+6K)
- Collected latest **400** tweets/user <u>before</u> attacks
  - **12.6M** tweets + Network interactions + Profile info
- Tested several features for predicting user stance towards Muslims:
  - User’s **tweets content**, **network interactions**, and **profile**
- Prediction Accuracy: **88%**
  - Using <u>**network interaction**</u> features only

Feature Analysis

Defending Muslims

THE HUFFINGTON POST

THE NEW YORKER

BLACK LIVES MATTER

LOVE WINS

NRA

EDM ELECTRONIC DANCE MUSIC

Acabella

Attacking Muslims

FOX NEWS

NFL

NHL

b theblaze

NASCAR

DRUDGE REPORT

#TCOT

Findings

- People’s unspoken views are predictable
- Unrelated events/hobbies can tell us a lot
- Humans tend to group into homophily, even on social media

Ref:

- Magdy W., K. Darwish, A. Rahimi, N. Abukhodair, T. Balswin. #ISISisNotIslam or #DeportAllMuslims? Predicting Unspoken Views. *Web Science 2016*
- Darwish K., W. Magdy, A. Rahimi, N. Abukhodair, T. Baldwin. Predicting Online Islamophopic Behavior after #ParisAttacks. *Journal of Web Science 2017*

Example 4

People Changing Opinion?

The Egyptian Military Intervention 2013

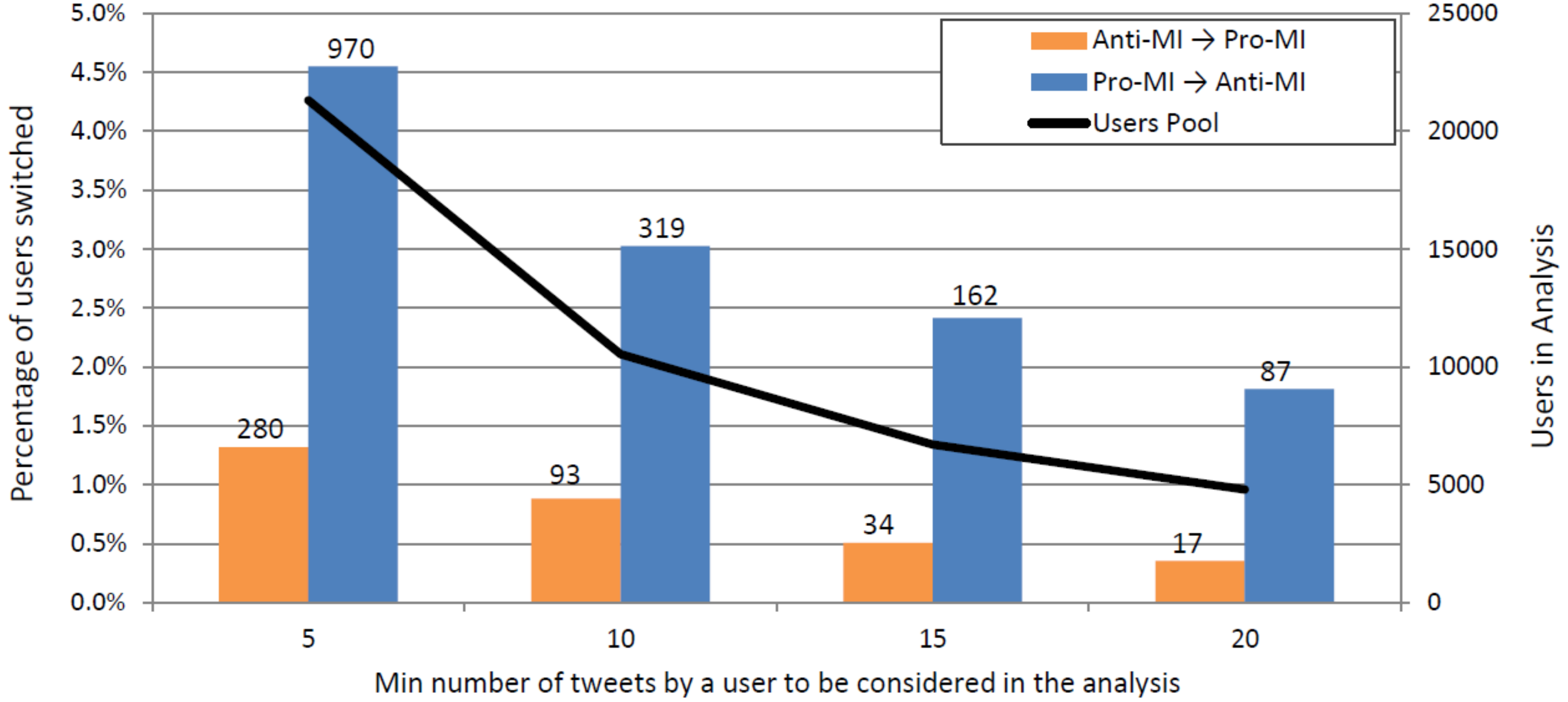
- 30 June 2013: large demonstration in Egypt against Morsi
- 3 July 2013: Military ousted Morsi
- 5 July-13 Aug: Large Sit-in against military coup
- 14 Aug: Army ends Sit-in by force, while hundreds killed

- **RQ: Did these major events led anyone to change his/her opinion about the military intervention?**

Study

- **Data Collection:**
  - 6M tweets on Egypt → 21 July 2013 – 30 Sep 2013
  - 22K Twitter users with >5 tweets on topic
- **<u>Tweet-level</u> Stance Classifier:**
  - Trained stance classifier → Pro/Anti military intervention
  - Accuracy: 85% (on the tweet level)
  - Label all tweets on topic using the classifier
- **Analysis:**
  - Global/User-level analysis
  - Observe change in support pattern over time (at least 5, 10, 20 tweets)

Opinion Change over 3+ Months



Findings

- Observed global change in trends does not mean change on the individual levels
- Groups feeling unjust tend to be more vocal
- It is really **not easy** to get someone **change opinion**

Ref:

Borge-Holthoefer J., W. Magdy, K. Darwish, and I. Weber. Content and Network Dynamics Behind Egyptian Political Polarization on Twitter. *CSCW 2015*

Example 5

Detecting Fake News

Claim-based Stance detection

Breaking911
@Breaking911

BREAKING: @TMZ reporting Kim Jong Un is dead or "on his death bed with no hope for recuperation"

7:16 pm · 25 Apr 2020 · Twitter for iPhone

- **User1:** Great, the world is now one dictator less. Hope other dictators will follow — **Support**
- **User2:** Apparently a hoax. Best to take Tweet down — **Deny**

Claim-based Stance detection

- A full line of research uses stance detection to label replies/comments on news to be either supporting/denying it.
- Proven to be an effective feature for measuring the truthfulness of a piece of news
- Several shared tasks: RumourEval 2017/2019

Ref:

Derczynski, L., Bontcheva, K., Liakata, M., Procter, R., Hoi, G. W. S., & Zubiaga, A. (2017). SemEval-2017 Task 8: RumourEval: Determining rumour veracity and support for rumours.

Gorrell, G., Kochkina, E., Liakata, M., Aker, A., Zubiaga, A., Bontcheva, K., & Derczynski, L. (2019). SemEval-2019 task 7: RumourEval, determining rumour veracity and support for rumours.

Quanzhi Li, Qiong Zhang, and Luo Si. 2019. Rumor Detection by Exploiting User Credibility Information, Attention and Multitask Learning. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics.

Part 2

Recent Trends

Ideology Detection by Images

Person 1: How do you like my new profile pic?

Person 2: Oh man, you look too republican here ☺

- **Question**:
  Is it possible to predict ideology of politicians solely from their images and the photos they share online?

- **Task**:
  Classify 319 US congress members to democrat/republican from their images only.

Image src: http://clipart-library.com/clipart/240595.htm

Study

- **Data Collection:**
  - 296,461 images for 319 Members of Congress from their FB.
  - For each member, test classification using one photo vs 150 photos
- **Ideology Classifier:**
  - CNN
  - Use 10-fold cross-validation for training and testing
- **Results:**
  - 1 photo/member classification → 59%
  - 150 photo/member classification → 82%

Findings

- Not just our words and network expose our leanings, but also the photos we share as well.
- Is it homophily again? Or life-style?

Ref:

Nan Xi, Di Ma, Marcus Liou, Zachary Steinert-Threlkeld, Lefteris Anastasopoulos, Jungseock Joo. Understanding the Political Ideology of Legislators from Social Media Images. ICWSM 2020

Stance detection beyond politics

- Costanza Conforti, Jakob Berndt, Mohammad Taher Pilehvar, Chryssi Giannitsarou, Flavio Toxvaerd and Nigel Collier. **Will-They-Won't-They: A Very Large Dataset for Stance Detection on Twitter**. *ACL 2020*
- **WT-WT stance dataset:**
  - 51,284 tweets
  - Financial domain
  - 5 topics on M&A of companies in two domains: entertainment and healthcare.
  - Labels: support/refute/comment/unrelated

Transfer-learning / Cross-target SD

- Train on Topic X and classify topic Y
- Train on Topics T1, T2, T3 … Tn, and classify any topic Tx
- Most studies experimented SemEval dataset
- Results are still much lower compared to supervised

- Ref:

- Javid Ebrahimi, Dejing Dou, and Daniel Lowd. A Joint Sentiment-Target-Stance Model for Stance Classification inTweets.. In COLING 2016
- Bowen Zhang, Min Yang, Xutao Li, Yunming Ye, Xiaofei Xu, Kuai Dai. Enhancing Cross-target Stance Detection with Transferable Semantic-Emotion Knowledge. *ACL 2020*
- *Penghui Wei, Wenji Mao, and Guandan Chen. 2019. A Topic-Aware Reinforced Model for Weakly Supervised Stance Detection. AAAI 2019*

Characterizing News Media Leaning

- Premise: Users cite news media that align with their stance
- Procedure:
  - Automatically split users based on stance on different topics
  - Compute correlation between media and users with different stances (valence)
  - Assign a score to media based correlation across topics:
    - (far-left, left, neutral, right, far-right)
- Ref:

- Peter Stefanov, Kareem Darwish, Atanas Atanasov, and Preslav Nakov. 2020. Predicting the Topical Stance of Media and Popular Twitter Users. ACL 2020.

Characterizing News Media Leaning

media	factuality	bias	Average	climate change	gun control	ilhan	immigration	midterm	police & racism	SCOTUS	vaccine
thehill.com	H	L-C	**+**	0	++	+	+	+	+	++	++
theguardian.com	H	L-C	**++**	++	++	++	++	++	++	++	++
washingtonpost.com	H	L-C	**++**	++	++	++	++	++	++	++	++
breitbart.com	VL	Far R	**−−**	−−	−−	−−	−−	−−	−−	−−	−−
foxnews.com	M	R	**−−**	−−	−−	−−	−−	−−	−−	−−	
nytimes.com	H	L-C	**++**	+	++	+	+	+	++	++	++
cnn.com	M	L	**+**	+	++	+	++	+	+	++	+
apple.news			**+**	0	0	+	0	0	+	+	++
dailycaller.com	M	R	**−−**	−−	−−	−−	−−	−−	−−	−−	
rawstory.com	M	L	**++**	++	++	++	++	++	++	++	++
huffingtonpost.com	H	L	**++**	++	++	++	++	+	++	++	++
truepundit.com	L		**−−**	−−	−−	−−	−−	−−	−−	−−	−−
nbcnews.com	H	L-C	**+**	−−	++	+	++	+	+	++	++
westernjournal.com	M	R	**−−**	−−	−−	−−	−−	−−	−−	−−	

Peter Stefanov, Kareem Darwish, Atanas Atanasov, and Preslav Nakov. 2020. Predicting the Topical Stance of Media and Popular Twitter Users. ACL 2020.

Part 3

Challenges & Future Directions

Technical Challenges

- Spams/Bots
  - How our data samples are free of spams?
  - Are the accounts we classify are for real people or bots?
- Two or Three stance classes?
  - Is using Support/Oppose the optimal choice?
  - Is there anything called “neutral” stance for a user?

Ethical Challenges

- Are stance detection model racist?
  - Create stereotypes for users with specific leanings
  - Even with homophily, outliers are misclassified
  - Isn’t this true for all demographic classifiers? (gender, race … etc)

- Data Bias
  - Does our sample data representative to all users of a given stance?
  - Can we sample users with limited activity online (silent users)?
  - Correlation vs Causality

Olteanu, A., Castillo, C., Diaz, F., & Kiciman, E. (2019). Social data: Biases, methodological pitfalls, and ethical boundaries. *Frontiers in Big Data*, *2*, 13.

Ethical Challenges

- User’s privacy
  - With stance model, we can classify users’ leaning even if never discussed the topic. Is this a violation to user’s privacy?
  - What about sensitive topics? Is it ethical to create such tools? “Is user X with or against their government?”
  - Can we help users to protect their privacy from these models?

What should be next?

- A better stance detection model? Possibly!
  - especially semi/un-supervised ones
  - new features (e.g. photos)
- New datasets covering other domains
  e.g. sports, science, finance
- New methods to counter stance detection models
  protect user’s privacy
- New ethical procedure for data usage
- New applications
  using stance detection to measure bots impact on user’s opinion

Final Takeaways

- Stance ≠ Sentiment
- Different features for detecting stance: text, network, and images
- Network features show significant performance over others
- Most work used supervised learning. Recent work explores semi-supervised, unsupervised, and transfer learning
- Many applications of stance: events analysis, understanding people's interest, fake news detection … etc.
- Challenges need addressing: technical, ethical, and privacy
- Future: new less-supervised methods, datasets, applications.

Two References:

- Two references sum it all:

1. Dilek Küçük and Fazli Can. 2019.
   Stance Detection: *A Survey.*
   ACM Computing Surveys (CSUR) 53, 1 (2020), 1–37

2. Aldayel A. and Walid Magdy. 2020.
   Stance Detection on Social Media : State of the Art and Trends.
   Pre-print (link)