Detection and Characterization of Stance on Social Media

Part 3
Detection and Characterization of Stance on Social Media

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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

15%  85%
Most Discussed Topics

(a) Support Clinton

(b) Attack Trump

(c) Support Trump

(d) Attack Clinton
Mention of States

Mentions of States for each Class

- Support Clinton
- Attack Clinton
- Support Trump
- Attack Trump
# Most Influential Accounts

<table>
<thead>
<tr>
<th>Account</th>
<th>support Clinton</th>
<th>attack Trump</th>
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<tbody>
<tr>
<td></td>
<td>Count</td>
<td>Volume</td>
</tr>
<tr>
<td>Hillary Clinton</td>
<td>331</td>
<td>2,025,821</td>
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<td>President Obama</td>
<td>4</td>
<td>122,947</td>
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<td>Senator Tim Kaine</td>
<td>15</td>
<td>84,245</td>
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<td>Jerry Springer</td>
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<td>78,872</td>
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<tr>
<td>Erin Ruberry</td>
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<td>72,167</td>
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<tr>
<td>Richard Hine</td>
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<td>66,817</td>
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<td>Bernie Sanders</td>
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<td>CNN</td>
<td>6</td>
<td>41,983</td>
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<tr>
<td>Funny Or Die</td>
<td>1</td>
<td>27,909</td>
</tr>
<tr>
<td>Channel 4 News</td>
<td>1</td>
<td>27,409</td>
</tr>
</tbody>
</table>

| Support Trump         | 446    | 4,992,845  | Donald J. Trump    | 246    | 3,613,025  |
|                       |        |            | Kellyanne Conway   | 141    | 1,454,903  |
|                       |        |            | Mike Pence         | 92     | 349,025    |
|                       |        |            | Dan Scavino Jr.    | 78     | 297,273    |
|                       |        |            | Official Team Trump| 23     | 150,932    |
|                       |        |            | Donald Trump Jr.   | 34     | 126,744    |
|                       |        |            | Eric Trump         | 19     | 85,742     |
|                       |        |            | Immigrants4Trump   | 7      | 84,063     |
|                       |        |            | Cloyd Rivers       | 4      | 83,903     |
|                       |        |            | Juanita Broaddrick | 4      | 83,903     |
|                       |        |            | James Woods        | 16     | 78,719     |
Most Viral Tweets

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

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

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

TODAY WE MAKE AMERICA GREAT AGAIN!
2:43 PM - 8 Nov 2016
336,137 Retweets 563,878 Likes
Findings

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

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:

![Bar chart showing the distribution of users discussing ISIS. 93.1% are pro-ISIS, 77.3% are anti-ISIS, and 1.2% are neutral.]

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

- **Data Collection:**
  - Collect tweets timeline for 57K users $\rightarrow$ 123 million tweets
  - Identify tweets of users before even mention ISIS

- **Stance Classifier:**
  - Train classifier with Pre-ISIS tweets $\rightarrow$ Pro/Anti ISIS
  - Accuracy $\rightarrow$ 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

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

- Support of ISIS is not ideological, but for revenge

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

<table>
<thead>
<tr>
<th>Positive</th>
<th>Count</th>
<th>Negative</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>#MuslimsAreNotTerrorist</td>
<td>34,925</td>
<td>#IslamIsTheProblem</td>
<td>3,154</td>
</tr>
<tr>
<td>#MuslimAreNotTerrorist</td>
<td>17,759</td>
<td>#RadicalIslam</td>
<td>1,618</td>
</tr>
<tr>
<td>#NotInMyName</td>
<td>4,728</td>
<td>#StopIslam</td>
<td>1,598</td>
</tr>
<tr>
<td>#MuslimsStandWithParis</td>
<td>1,228</td>
<td>#BanIslam</td>
<td>460</td>
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<tr>
<td>#MuslimsAreNotTerrorists</td>
<td>1,106</td>
<td>#StopIslamicImmigration</td>
<td>333</td>
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<tr>
<td>#ThisisNotIslam</td>
<td>781</td>
<td>#IslamIsEvil</td>
<td>290</td>
</tr>
<tr>
<td>#NothingToDoWithIslam</td>
<td>619</td>
<td>#IslamAttacksParis</td>
<td>280</td>
</tr>
<tr>
<td>#ISISareNotMuslim</td>
<td>316</td>
<td>#ImpeachTheMuslim</td>
<td>215</td>
</tr>
<tr>
<td>#ExtremistsAreNotMuslim</td>
<td>306</td>
<td>#KillAllMuslims</td>
<td>206</td>
</tr>
<tr>
<td>#ISISisNotIslam</td>
<td>243</td>
<td>#DeportAllMuslims</td>
<td>186</td>
</tr>
</tbody>
</table>
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 before 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 **network interaction** features only
Feature Analysis

Defending Muslims

Attacking Muslims
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:
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

- **Tweet-level 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

- **Anti-MI → Pro-MI**
- **Pro-MI → Anti-MI**
- **Users Pool**

Percentage of users switched vs. Min number of tweets by a user to be considered in the analysis.
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:
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

→ **User2:** Apparently a hoax. Best to take Tweet down
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:
Part 2
Recent Trends
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.
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 $\rightarrow$ 59%
  - 150 photo/member classification $\rightarrow$ 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
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:
- Bowen Zhang, Min Yang, Xutao Li, Yunming Ye, Xiaofei Xu, Kuai Dai. Enhancing Cross-target Stance Detection with Transferable Semantic-Emotion Knowledge. ACL 2020
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:
# Characterizing News Media Leaning

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<th>Bias</th>
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Part 3
Challenges & Future Directions
Technical Challenges

- Spams/Bots
  - How our data samples are free of spams?
  - Are the accounts we classify 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 models 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 represent all users of a given stance?
  - Can we sample users with limited activity online (silent users)?

- Correlation vs Causality

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:
