POLITICS ON TWITTER: A PANORAMA

July 9, 2018

Ophélie FRAISIER
• 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

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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 6, 2016 11:32 AM PT
"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)
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.
POLITICAL STANCES?

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博物学的著作：拉斐尔·拉斐尔

07/09/18

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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 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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(Sunstein, 2009)

Can lead to "echo chambers"

(Sunstein, 2009)
INFLUENCE OF RETWEETS

- Retweet largely used
  - Action of sharing a tweet
  - One of the most important interaction on the platform
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- Motivations for retweeting (boyd et al., 2010):
  - To publicly agree with someone
  - To validate others’ thoughts
POLITICS ON TWITTER: A PANORAMA

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

- **Secular vs Islamist polarization in Egypt**
  (Weber et al, 2013)
  
  Retweet network
  
  Color = cluster assignment
  
  80% left-leaning profiles
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
AIM

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  - Global political stance
    - Political parties
    - Conservatives vs Liberals
    - Left vs Right
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  - Global political stance
    - Political parties
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  - Specific political stance
    - Political figure
    - Abortion
    - Climate change
    - Feminism
    - Gun control
    - LGBT rights
    - Immigration
    - Israeli-palestinian conflict
BASED ON TWEETS' TEXTUAL CONTENT
POLITICS ON TWITTER: A PANORAMA

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- Supervised models (Naive Bayes & SVM) (Mohammad et al., 2017; Conover et al, 2011)
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Based on tweets' textual content

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  - Poisson's law modeling of the discourse (Boireau, 2014)
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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.
Based on Profiles' Social Interactions

- Retweet network
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Based on text and social interactions

- Topic modeling taking into account tweets and social graph
  (Thonet et al., 2017)
Based on text and social interactions

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- SVM trained on tweets and social graph (Magdy et al., 2016)
BASED ON TEXT AND SOCIAL INTERACTIONS
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Textual content

Social interactions

Mutual reinforcement
BASED ON TEXT AND SOCIAL INTERACTIONS

- Consistence between tweets and retweets
  (Wong et al., 2016)
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Election Prediction
## MULTIPLES ATTEMPTS

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<thead>
<tr>
<th>Year</th>
<th>Event</th>
<th>Authors</th>
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<tbody>
<tr>
<td>2008</td>
<td>US presidential election</td>
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## Politics on Twitter: A Panorama

### Multiples Attempts

**Good predictions & better than traditional polls**

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  - 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)

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<th>Tweets containing character</th>
<th>% of tweets with Twitter handle</th>
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<tr>
<td>Ally</td>
<td>492</td>
<td>5.7</td>
</tr>
<tr>
<td>Hero</td>
<td>800</td>
<td>30.0</td>
</tr>
<tr>
<td>Opponent</td>
<td>25</td>
<td>4.0</td>
</tr>
<tr>
<td>Villain</td>
<td>730</td>
<td>9.0</td>
</tr>
<tr>
<td>Ally</td>
<td>289</td>
<td>10.4</td>
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<tr>
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<tr>
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<td>3.9</td>
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<tr>
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<td>508</td>
<td>5.1</td>
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2017 FRENCH PRESIDENTIAL CAMPAIGN

(Fraisier et al., 2018)
IN Volvement IN OCCUPY WALL STREET

(Conover et al., 2013)
ITALIAN INTRA-PARTY POLITICS

(Ceron, 2017)
COALITIONS IN THE EUROPEAN PARLIAMENT

(Cherepnalkosk, 2016)

Co-voting agreement within and between political groups

Average retweets within and between political groups
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)
• 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
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- 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


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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#.UiQDiH4f


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
