Using Facebook Data to Predict 2016 US Presidential Election

Keng-Chi Chang  Chun-Fang Chiang  Ming-Jen Lin

Department of Economics
National Taiwan University

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Prepared for Innovations in Political Methodology and China Study International Conference
In This Paper

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  ▸ Are mostly for elites, and uses “following” of a fan page
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  ▸ But people also consume news and process info. through posts

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  ▸ Also account for media, interest groups, parties, etc, and users
  ▸ Pages share similar ideology should share “likes” from similar users
  ▸ Adds time, post content, and region (guessed states) dimensions

• We predict 2016 US presidential election using this measure
  ▸ Derive state level FB support rates based on spatial model
  ▸ Compare with actual vote shares and state polls

• We find under minimal assumptions, Facebook support rates:
  ▸ Predicts election quite well and shares similar trends with polls
  ▸ Overestimates winner’s vote share, but may enhance prediction
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Facebook Data

- Facebook provides fan page data through Graph API

- Specify fan page ideological universe
  - 1475 fan pages of national politicians
    - Members and candidates of Senate, House, and Governors
  - Top 1000 pages related to 2016 presidential election
    - In Aug 2016, find all pages mentioned “Trump” and “Clinton”
    - Weight by likes, comments, shares, find top 1000 pages
    - Includes all major news outlets, interest groups, parties, etc
    - NYT, Fox News, NRA, RNC, Occupy Wall St, Tea Party, 9GAG, ...

- Collect all 24M posts in 2015 and 2016 on these pages
- And user’s 19B reactions (mostly likes) to these posts
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## Data Summary

<table>
<thead>
<tr>
<th>Category</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time Period</strong></td>
<td>2015-01-01 to 2016-11-30</td>
</tr>
<tr>
<td><strong>Total Reactions</strong></td>
<td>19,085,783,534</td>
</tr>
<tr>
<td>US Political User Likes</td>
<td>16,180,488,916</td>
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<tr>
<td><strong>Total Users</strong></td>
<td>366,840,068</td>
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<tr>
<td>US Political Users</td>
<td>29,412,610</td>
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<tr>
<td><strong>Total Posts</strong></td>
<td>24,788,093</td>
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<tr>
<td><strong>Total Pages</strong></td>
<td>2132</td>
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<tr>
<td>Politicians</td>
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<tr>
<td>News Outlets</td>
<td>560</td>
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<tr>
<td>Political Groups</td>
<td>211</td>
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<tr>
<td>Other Public Figures</td>
<td>93</td>
</tr>
<tr>
<td>Others</td>
<td>43</td>
</tr>
</tbody>
</table>
Estimation: Shared Users Matrix

- Measure ideology of pages, then measure those of users
  ~ Similar to Bond and Messing (2015, APSR)
Estimation: Shared Users Matrix

- Measure ideology of pages, then measure those of users
  - Similar to Bond and Messing (2015, APSR)
- First build the page by page affiliation matrix $A$
  - Number of shared users (based on likes) between pages

<table>
<thead>
<tr>
<th></th>
<th>Trump</th>
<th>FoxNews</th>
<th>TeaParty</th>
<th>Clinton</th>
<th>CNN</th>
<th>NYTimes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trump</td>
<td>2243216</td>
<td>1078513</td>
<td>128225</td>
<td>32731</td>
<td>120963</td>
<td>25842</td>
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<td>87084</td>
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<td>1528</td>
<td>10738</td>
<td>2162</td>
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<td>87084</td>
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<td>1768980</td>
<td>351210</td>
<td>367021</td>
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<tr>
<td>CNN</td>
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<td>186850</td>
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<td>351210</td>
<td>1201156</td>
<td>216163</td>
</tr>
<tr>
<td>NYTimes</td>
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<td>63401</td>
<td>2162</td>
<td>367021</td>
<td>216163</td>
<td>986613</td>
</tr>
</tbody>
</table>
Estimation: Transform to Ratios

- Transform $A$ to matrix of ratios $G$, where $g_{ij} = \frac{a_{ij}}{a_{ii}}$

$$\sim 0.44 = \frac{\Pr(\text{Trump} \cap \text{FoxNews})}{\Pr(\text{FoxNews})} = \Pr(\text{Trump} | \text{FoxNews})$$

- Can interpret columns as features and rows as observations

  $\sim$ Col 1 is how each row similar to “Trump” feature

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<tr>
<td>Trump</td>
<td>1.00</td>
<td>0.48</td>
<td>0.06</td>
<td>0.01</td>
<td>0.05</td>
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<td>FoxNews</td>
<td>0.44</td>
<td>1.00</td>
<td>0.06</td>
<td>0.04</td>
<td>0.08</td>
<td>0.03</td>
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<td>0.61</td>
<td>1.00</td>
<td>0.01</td>
<td>0.04</td>
<td>0.01</td>
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<tr>
<td>Clinton</td>
<td>0.02</td>
<td>0.05</td>
<td>0.00</td>
<td>1.00</td>
<td>0.20</td>
<td>0.21</td>
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<td>CNN</td>
<td>0.10</td>
<td>0.16</td>
<td>0.01</td>
<td>0.29</td>
<td>1.00</td>
<td>0.18</td>
</tr>
<tr>
<td>NYTimes</td>
<td>0.03</td>
<td>0.06</td>
<td>0.00</td>
<td>0.37</td>
<td>0.22</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Estimation: Dimension Reduction

- Compute the principal components of $G$ after standardizing

**Diagram:**
- **Original Data Space:**
  - Gene 1
  - Gene 2
  - Gene 3
- **Component Space:**
  - PC 1
  - PC 2
  - PC 3
Estimation: Dimension Reduction

- Compute the principal components of $G$ after standardizing

  - PC1 is the dimension explains the largest variation
    - Unsupervised $\Rightarrow$ Guess and verify PC1 is related to “ideology”

  - PC1 = mean ideology of pages user liked
  - Guess user’s state residence by their likes on national politicians
    - Like more politicians from NY $\Rightarrow$ More likely from NY
Estimation: Dimension Reduction

• Compute the principal components of $G$ after standardizing

• PC1 is the dimension explains the largest variation
  $\Rightarrow$ Unsupervised $\Rightarrow$ Guess and verify PC1 is related to “ideology”

• User ideology = mean ideology of pages user liked

• Guess user’s state residence by their likes on national politicians
  $\Rightarrow$ Like more politicians from NY $\Rightarrow$ More likely from NY
Scree Plot for Principal Component Analysis

Proportion of Variance Explained vs. k-th Principal Component
PC1 Density of TV, Radio, Website Pages

PC1 (First Principal Component)

Density

type_sub
radio
tv
website

The Rachel Maddow Fan Page
MSNBC
PBS
CNN
ABC News
Fox News
Breitbart
The Federalist Papers
NRA News
Fox News Opinion

PC1 Density of TV, Radio, Website Pages
Validation for Congressional Politicians

\[ \rho = 0.92 \]

\[ \rho_R = 0.50 \]

\[ \rho_D = 0.22 \]

Estimated Facebook Page Ideology Score, 2015-01 to 2016-11
Using politician and top 1000 page matrix
User Ideology Density by States

- Massachusetts
- Washington
- Michigan
- Pennsylvania
- Texas
- Wyoming
User Ideology Density by States

Politician-Only Method (Bond and Messing 2015)
Politician Ideology Dynamics

Estimated Facebook Ideology Score


Cruz
Rubio
Trump
Johnson
Sanders
Clinton
Warren
Ryan

-1.0
-0.5
0.0
0.5
1.0


Cruz
Rubio
Trump
Johnson
Sanders
Clinton
Warren
Ryan

-1.0
-0.5
0.0
0.5
1.0
Apply the Hotelling-Downs spatial model for voting: Voters support candidates closer to their own ideological location.
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In each state, we compare:
- FB support rate: Share of user’s ideology closer to Trump or Clinton.
- Polls: State polling averages calculated by FiveThirtyEight.
- Actual vote shares in the 2016 election.
FB Support Rates, Polls, and Vote Shares

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Predicting Vote Shares and Outcomes

- **Purple circles**: Swings from Obama to Trump
- **Blue squares**: Dem wins 2016 & 2012

**Graph**
- 2016 Clinton Vote Share vs. Share of Facebook User Closer to Clinton (10-01 to 11-07)
- 95% CI [0.56, 0.84]
- $\rho = 0.73$

**Legend**
- **GA**: Georgia
- **AZ**: Arizona
- **WI**: Wisconsin
- **NC**: North Carolina
- **FL**: Florida
- **ME**: Maine
- **PA**: Pennsylvania
- **OH**: Ohio
- **MI**: Michigan
- **NH**: New Hampshire
- **VT**: Vermont
- **MA**: Massachusetts
- **MD**: Maryland
- **VA**: Virginia
- **TN**: Tennessee
- **KS**: Kansas
- **LA**: Louisiana
- **MO**: Missouri
- **NE**: Nebraska
- **SD**: South Dakota
- **ND**: North Dakota
- **WY**: Wyoming

**Additional Notes**
- Rep wins 2016 & 2012
- Swings from Obama to Trump
- Dem wins 2016 & 2012
## Compare with Major Forecasters

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<td>Trump</td>
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<td>Iowa</td>
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<td>Montana</td>
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<td></td>
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<tr>
<td>Alaska</td>
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<td>Clinton</td>
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<tr>
<td>Maine</td>
<td>2</td>
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Trump's Electoral Vote: 306

†Electoral Votes.

*Princeton Election Consortium.
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<td>Florida</td>
<td>29</td>
<td>Trump</td>
<td>○</td>
<td>×</td>
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<td>○</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Wisconsin</td>
<td>10</td>
<td>Trump</td>
<td>○</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Michigan</td>
<td>16</td>
<td>Trump</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Ohio</td>
<td>18</td>
<td>Trump</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Iowa</td>
<td>6</td>
<td>Trump</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Montana</td>
<td>3</td>
<td>Trump</td>
<td>×</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Alaska</td>
<td>3</td>
<td>Clinton</td>
<td>×</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Maine</td>
<td>2</td>
<td>Clinton</td>
<td>×</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
</tbody>
</table>

| Trump’s Electoral Vote | 306 | 292 | 235 | 216 | 215 |

† Electoral Votes.  
* Princeton Election Consortium.
Predicting Electoral Votes

Predicted Electoral Votes for Trump

Actual

Even

Facebook

FiveThirtyEight

03-01 2016 05-01 2016 07-01 2016 09-01 2016 11-01 2016
Trump: FB (Dotted), Polls, and Vote Shares

Pennsylvania

Ohio

Nevada

Maine

New Hampshire

Florida

Michigan

Wisconsin

Iowa
Clinton: FB (Dotted), Polls, and Vote Shares

Alabama

West Virginia

Kentucky

Tennessee

Kansas

Arkansas

Idaho

Missouri

North Dakota
Polls Overestimates Clinton in Red and Swing States

Dem wins 2016 & 2012
Rep wins 2016 & 2012
Swings from Obama to Trump
FB Overestimates Trump in Red and Swing States

- Trump: Facebook Support - Actual Vote Share
- 2016 & 2012

Dem wins 2016 & 2012
Rep wins 2016 & 2012
Swings from Obama to Trump
Discussions

• Strengths of Facebook based prediction:
  ▸ Revealed preference instead of self-report
  ▸ Low cost and almost in real time
  ▸ Trace individuals repeatedly over time
  ▸ Overestimation for winners can help to make predictions
Discussions

• Strengths of Facebook based prediction:
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• Weaknesses, compared to polls or surveys:
  ▸ Not representative
    ~ Can reweight if more social-demographic information is known
  ▸ Hard to link with offline behaviors
    ~ Ex. “Strong supporter” vs. “Likely voter”
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    ↘ Ex. “Strong supporter” vs. “Likely voter”

• Can complement each other if more research try to link the two
Working on: Effect of Fake News

- Joint with Chun-Fang Chiang, Brian Knight, and Ming-Jen Lin
- Would consuming fake news change people’s ideology or information consumption?
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• Would consuming fake news change people’s ideology or information consumption?
• If so, what kind of fake stories have larger effect, and why?
Working on: Effect of Fake News

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• Would consuming fake news change people’s ideology or information consumption?
• If so, what kind of fake stories have larger effect, and why?
• Fake news pool on Facebook:
  ▶ Top 40 fake stories, 536 posts, 130 pages
  ▶ Posts link to fake domains, 139,074 posts, 177 pages
Individual Ideology

Users Do Not Like Fake Post

Users Like Fake Post

Ideology (2016 Jan to Apr)

Density

27 / 32
Individual Ideology Difference

- Users Do Not Like Fake Post
- Users Like Fake Post

Ideology Difference (2016 Jul to Nov - 2016 Jan to Apr)
Density

Users Do Not Like Fake Post
Users Like Fake Post

Individual Ideology Difference

28 / 32
Strategies for Identification

• Challenges:
  ▪ People “like” fake post may be very different
  ▪ Pages posting fake posts may attract very different users
  ▪ Some stories may be “too fake” for people to believe, even backfire
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  ▸ Find nonfake pages very similar to fake page through different
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Strategies for Identification

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  - Find nonfake pages very similar to fake page through different matching methods as control
  - Find potential *followers* of these pages, instead of “likes”
Strategies for Identification

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• For each fake post, we:
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  ▶ Compare the ideology of these fake and nonfake followers before and after fake page unexpectedly started posting fake story
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  ▸ Compare the ideology of these fake and nonfake followers before and after fake page unexpectedly started posting fake story

\[
\text{Ideology}_{it} = \alpha \mathbb{1} (\text{After}_t) + \gamma \mathbb{1} (\text{FollowFake}_i) \\
+ \beta \mathbb{1} (\text{FollowFake}_i) \mathbb{1} (\text{After}_t) + \varepsilon_{it}
\]
"BREAKING: Official Set to Testify Against Hillary Found Dead" by Western Journalism

Users Follow Fake Page
(Treatment)

Users Not Follow Fake Page
(Control)

Parallel Line

Week After Post

Mean Follower Ideology
Story Level Ideology Change for Following Pages Sharing Pro–Trump Fake News
Week +1 to −1, DiD Estimates with Individual Fixed Effects and 99.9% CI

- Pentagon furious Clinton nuclear response time
- Clinton financial connection to Saudi Arabia
- Wikileaks: Clinton sold weapons to ISIS
- Pope Francis endorses Trump
- Trump sends own plane to transport marines
- Obama refuses to leave office if Trump elected
- Clinton HIV secret revealed
- Clinton goes to Texas Muslim fundraiser
- Associate to testify against Clinton dead
- Stanford University: Dem election fraud
- Trump protester: I was paid to protest
- Official to testify against Clinton dead
- Uncounted Sanders ballots on Clinton server
- Clinton ISIS email leaked
- ISIS leader calls voters support Clinton
- Clinton disqualified holding Federal office
- Clinton tells nuclear launch response time
- Bill Clinton 2000 sex partners, Hillary lesbian
- Billy Graham STUNNING statement on Trump
- Putin: Emails reveal Clinton threatens Sanders
- Graham: Christians must support Trump
- Clinton email reopens, Comey asks immunity
- Clinton to be indicted, prayers answered
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- Palin to become Trump VP
- Rupaul: Trump touched me inappropriately
- Trump critical condition choking own bullshit
- Ireland accepts Trump refugees
- Rage Against the Machine anti Trump album
- Trump: Giving Canada independence mistake
- Trump U offers Palin honorary climate degree
- Mexico will close border if Trump elected
- Trump: I will overtern shocking gay marriage
- Trump picks Stacey Dash as VP
- Pence: Michelle Obama most vulgar FLOTUS
- Palin endorses Cruz
- Sauron endorses Trump
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5−NN Matching  10−NN Matching  5−Nearest PS Matching  10−Nearest PS Matching
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