Beyond Binary Labels: Political Ideology Prediction of Twitter Users

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Joint work with Ye Liu (NUS), Daniel J Hopkins (Political Science), Lyle Ungar (CS)

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Penn | World Well-Being Project

Motivation

User attribute prediction from text is successful:

- Age (Rao et al. 2010 ACL)
- Gender (Burger et al. 2011 EMNLP)
- Location (Eisenstein et al. 2010 EMNLP)
- Personality (Schwartz et al. 2013 PLoS One)
- Impact (Lampos et al. 2014 EACL)
- Political Orientation (Volkova et al. 2014 ACL)
- Mental Illness (Coppersmith et al. 2014 ACL)
- Occupation (Preoţiuc-Pietro et al. 2015 ACL)
- Income (Preoţiuc-Pietro et al. 2015 PLoS One)

... and useful in many applications.

Political Ideology & Text

Hypothesis:

Political ideology of a user is disclosed through language use

- partisan political mentions or issues

  > @realDonaldTrump your program last night was top notch! You Sir, are a class act! God bless our Vets #MakeAmericaGreatAgain #Trump2016
  >
  > 11:46 PM - 29 Jan 2016

- cultural differences

  > Disappointed today. Either I trust God to "have this" or I don't. I truly do, but still disappointed.
  >
  > 7:58 PM - 15 Jun 2015

Political Ideology & Text

Previous CS/NLP research used data sets with user labels identified through:

1. User descriptions

H1 Users are far more likely to be politically engaged

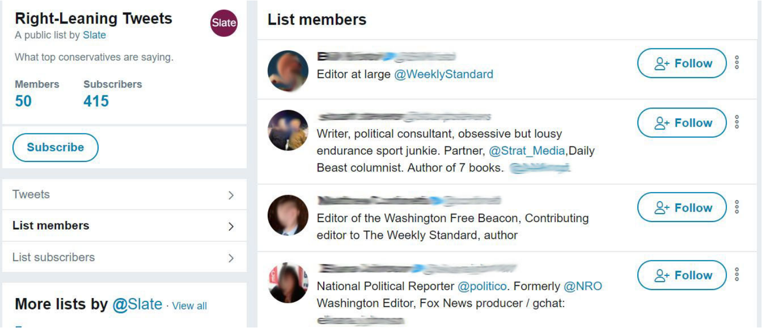
Political Ideology & Text

2. Partisan Hashtags

H2 The prediction problem was so far over-simplified

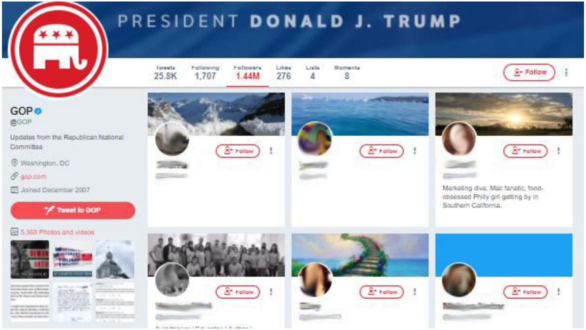
Political Ideology & Text

3. Lists of Conservative/Liberal users



H3 Neutral users

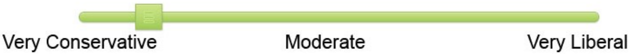
4. Followers of partisan accounts



H4 Differences in language use exist between moderate and extreme users

Data

- Political ideology
  - specific of country and culture
  - our use case is US politics (similar to **all** previous work)
  - the major US ideology spectrum is Conservative – Liberal
  - seven point scale



Data

We collect a new data set:

- 3.938 users (4.8M tweets)
- public Twitter handle with >100 posts

Political ideology is reported through an online survey

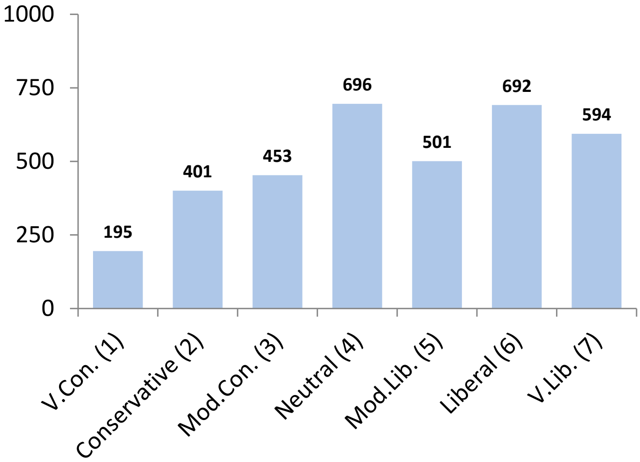
- only way to obtain unbiased ground truth labels (Flekova et al. 2016 ACL, Carpenter et al. 2016 SPPS)
- additionally reported age, gender and other demographics

Data

- Data available at `preotiuc.ro`
  - full data for research purposes
  - aggregate for replicability
- Twitter Developer Agreement & Policy VII.A4

  "**Twitter Content**, and information derived from Twitter Content, **may not be used** by, or knowingly displayed, distributed, or otherwise made available to any entity **to target**, segment, or profile individuals based on [...] **political affiliation** or beliefs"
- Study approved by the Internal Review Board (IRB) of the University of Pennsylvania

Class Distribution



Data

For comparison to previous work, we collect a data set:

- 13.651 users (25.5M tweets)
- follow liberal/conservative politicians on Twitter

Hypotheses

H1 Previous studies used users far more likely to be politically engaged

H2 The prediction problem was so far over-simplified

H3 Neutral users can be identified

H4 Differences in language use exist between moderate and extreme users

Engagement

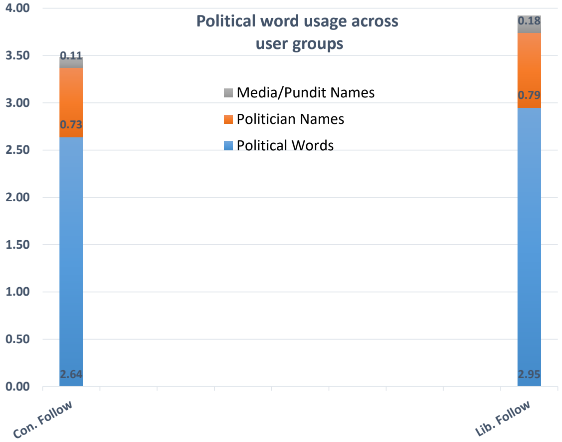
H1 Previous studies used users far more likely to be politically engaged

Manually coded:

- Political words (234)
- Political NEs: mentions of politician proper names (39)
- Media NEs: mentions of political media sources and pundints (20)

Engagement

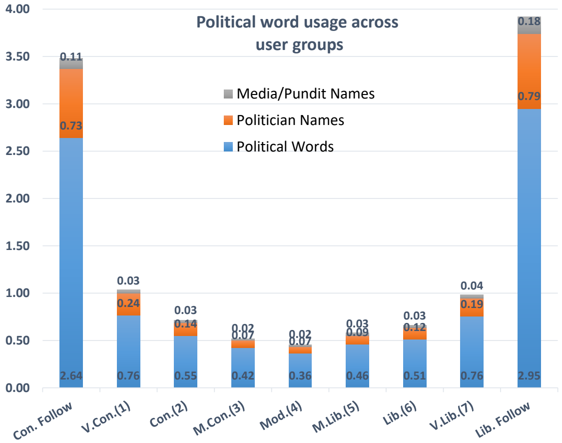
Data set obtained using previous methods



Average percentage of political word usage

Engagement

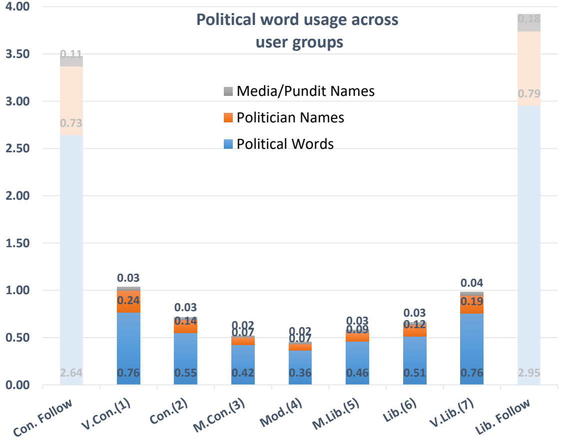
Our data set



Average percentage of political word usage

Engagement

Our data set



Average percentage of political word usage

Engagement

Take aways:

- 3x more political terms for automatically identified users compared to the highest survey-based scores
- almost perfectly symmetrical U-shape across all three types of political terms
- The difference between 1-2/6-7 is larger than 2-3/5-6

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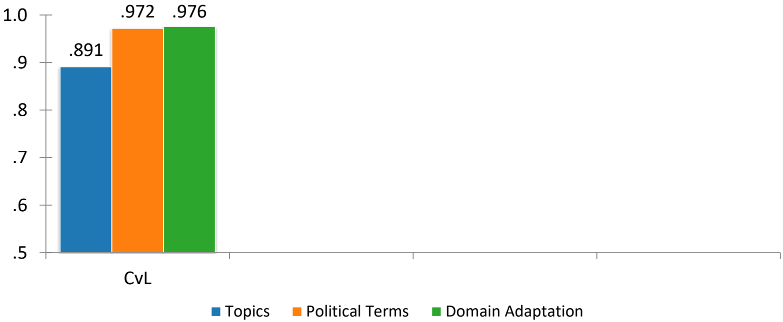
Over-simplification

H2 The prediction problem was so far over-simplified



ROC AUC, Logistic Regression, 10-fold cross-validation

Over-simplification

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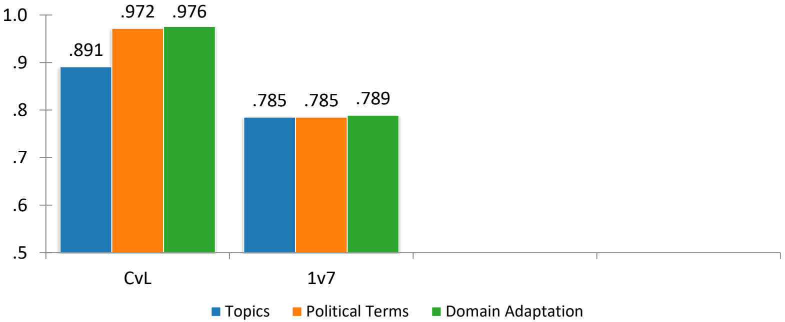

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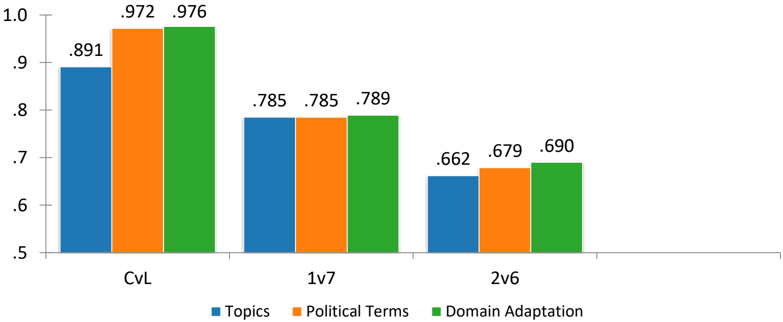

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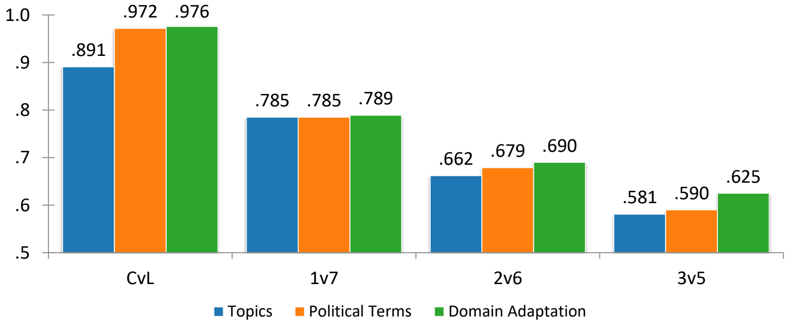
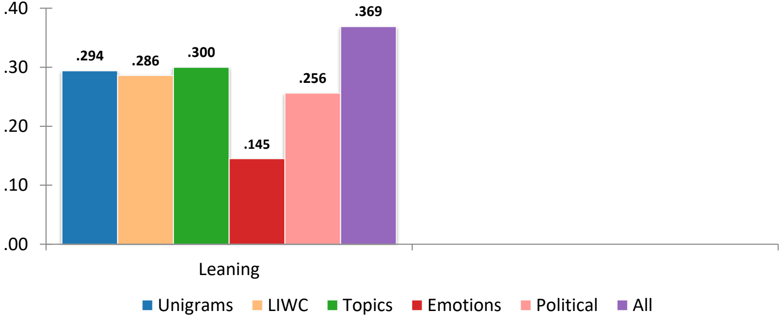


ROC AUC, Logistic Regression, 10 fold-cross validation

Over-simplification

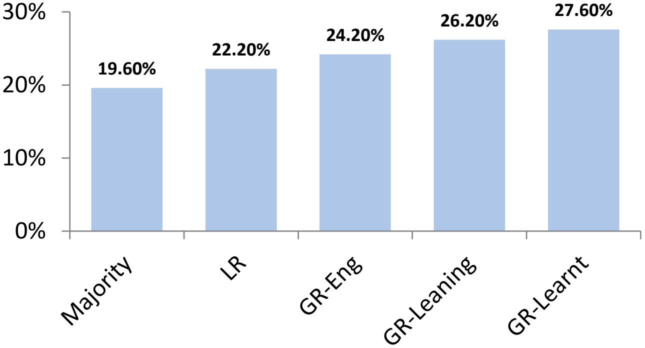
Predicting continuous political leaning (1 – 7)



Pearson R between predictions and true labels, Linear Regression, 10-fold cross-validation

Over-simplification

Seven-class classification



Accuracy, 10-fold cross-validation

GR – Logistic regression with Group Lasso regularisation

Hypotheses

H1 Previous studies used users far more likely to be politically engaged

H2 The prediction problem was so far over-simplified

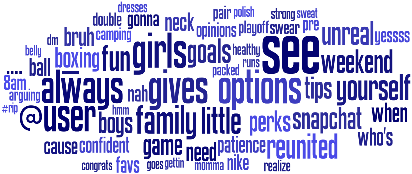
H3 Neutral users can be identified

H4 Differences in language use exist between moderate and extreme users

Neutral Users

H3 Neutral users can be identified

Words associated with either extreme conservative or liberal



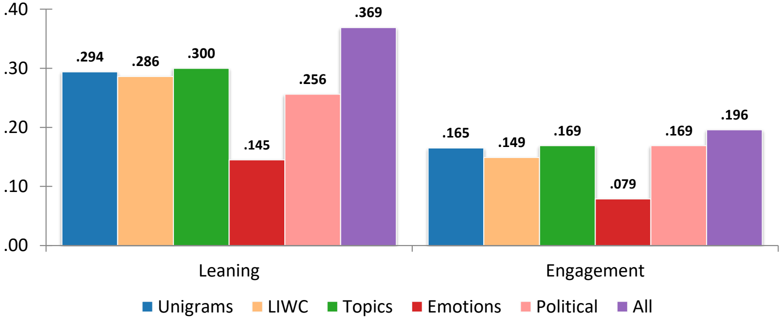
Words associated with neutral users

Correlations are age and gender controlled. Extreme groups are combined using matched age and gender distributions.

Political Engagement

H3a There is a separate dimension of political engagement

Combine the classes into a scale: 4 – 3&5 – 2&6 – 1&7



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Moderate Users

H4 Differences between moderate and extreme users

Words associated with moderate liberals (5 and 6).

Words associated with extreme liberals (7).

Correlations are age and gender controlled

Take Aways

- User-level trait acquisition methodologies can generate non-representative samples
- Political ideology:
  - Goes beyond binary classes
  - The problem was to date over-simplified
  - New data set available for research
  - New model to identify political leaning and engagement

Questions?

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