Who will RT this?

Automatically Identifying and Engaging Strangers on Twitter to Spread Information

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@jwnichls
Public Social Media Contains a Wealth of Information about Individuals...

Tweets

- **Jeffrey Nichols @jwnichls · 10h**
  @woobrockjo thoughts would appear and then be replaced with "wrong" and then disappear many times before something meaningful came out
  View conversation

- **Jeffrey Nichols @jwnichls · 16h**
  @woobrockjo if I could control computers at the speed of thought, then I'd be spending even more time pressing "delete" than I do now
  View conversation

- **Leo Mutukur @C_Leo_patra · Feb 24**
  What Happens after the Olympics Leave Town? resilientcities...rientcities.rockefellerfoundation.org/blog/entry/wh...
  Expand

- **Chris Dixon @cdixon · Feb 24**
  In fact, one of the main advantages entrepreneurs have is a 5+ year time horizon vs big companies beholden to short term Wall Street types.
  Expand

- **Jeffrey Nichols @jwnichls · Feb 23**
  I wonder if @netflix struck and leaked a deal to encourage backlash so net neutrality is reinstated ...
  Expand

- **Chris Dixon @cdixon · Feb 23**
  Innovation means running experiments. Some of the best will look silly at first. More parties who can block experiments = less innovation.
  Expand

- **Jeffrey Nichols @jwnichls · Feb 14**
  The Beer Board looks awesome. courtesy of @Thal. inno.ShareSD
Public Social Media Contains a Wealth of Information about Individuals...

Can we harness this information for something useful?

- Identify people to recruit to do various tasks
- Collect Information
- Spread Information
Today: Information Spreading

- Relevant marketing campaign messages
- Alerts and SOS messages in an emergency
- Etc.
Today: Information Spreading

Challenge: Low percentage of people respond to this task
• Can we predict who will retweet and direct requests only to them?
• Can we predict who will retweet more quickly?
Our Process

1. Data Collection
2. Feature Extraction
3. Feature Selection
4. Model Building
5. Evaluation
Ground-Truth Data Collection

**Public Safety** (location-based)

- Randomly selected users who tweeted from the San Francisco bay area (via geo-tags)
- Contacted 1,902 users
- 52 (2.8%) retweeted our message
- Message reached a total of 18,670 followers

**Bird Flu** (topic-based)

- Randomly selected users who posted one of the following words in at least one tweet: “bird flu”, “H5N1” and “avian influenza”
- Contacted 1,859 users
- 155 (8.4%) retweeted our message
- Message reached a total of 184,325 followers
Resulting Data

In total:
- Contacted 3,761 strangers
- 207 positive examples, 3,554 negative examples

For each user we contacted, we collected:
- Twitter profile (screen name, tweet count, etc.)
- People they followed, followers,
- Up to 200 recent messages
- Ground truth (“retweeter” or “non-retweeter”)
Feature Extraction

Feature Categories

• Profile Features
• Social Network Features
• Personality Features
• Activity Features
• Past Retweeting Features
• Readiness Features
Feature Extraction

Feature Categories

- Profile Features
- Social Network Features
- Personality Features
- Activity Features
- Past Retweeting Features
- Readiness Features

Profile Features
- longevity (age) of an account
- length of screen name
- whether the user profile has a description
- length of the description
- whether the user profile has a URL

Social Network Features
- number of users following (friends)
- number of followers
- and the ratio of number of friends to number of followers
Feature Extraction

Feature Categories

• Profile Features
• Social Network Features
• **Personality Features**
• Activity Features
• Past Retweeting Features
• Readiness Features

Users’ word usage has been found to predict their personality

• Linguistic Inquiry and Word Count (LIWC) dictionary
• Personality features derived from LIWC categories [Yarkoni 2010, Mahmud 2013]

<table>
<thead>
<tr>
<th>Personality Features</th>
<th>Total Number</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIWC</td>
<td>68</td>
<td>Sadness, 1st Person Plural, Anxiety</td>
</tr>
<tr>
<td>Big Five</td>
<td>5</td>
<td>Agreeableness, Conscientiousness</td>
</tr>
<tr>
<td>Big Five Sub-Facets</td>
<td>30</td>
<td>Friendliness, Anxiety</td>
</tr>
</tbody>
</table>
Feature Extraction

Feature Categories

- Profile Features
- Social Network Features
- Personality Features
- Activity Features
- Past Retweeting Features
- Readiness Features

- Number of status messages
- Number of direct mentions (e.g., @johny) per status message
- Number of URLs per status message
- Number of hashtags per status message
- Number of status messages per day during her entire
- Account life (= total number of posted status messages / longevity)
- Number of status messages per day during last one month
- Number of direct mentions per day during last one month
- Number of URLs per day during last one month
- Number of hashtags per day during last one month
Feature Extraction

Feature Categories

• Profile Features
• Social Network Features
• Personality Features
• Activity Features
• Past Retweeting Features
• Readiness Features

Past Retweeting Behavior

• Number of retweets per status message: R/N
• Average number of retweets per day
• Fraction of retweets for which original messages are posted by strangers who are not in her social network

Readiness Based on Previous Activity

• Tweeting Likelihood (Day)
• Tweeting Likelihood (Hour)
• Entropy of Tweeting Likelihood (Day)
• Entropy of Tweeting Likelihood (Hour)
• Tweeting Steadiness
• Tweeting Inactivity
Predicting Retweeters

Training and Test Sets:
- Each dataset (public safety and bird flu) was randomly split to training set (2/3 data) and testing set (1/3 data)

5 Predictive Models
- Random Forest, Naïve Bayes, Logistic Regression, SMO (SVM) and AdaboostM1

Handling Class Imbalance
- Used both over-sampling (SMOTE) and weighting approaches (cost-sensitive approach)
# Feature Selection

Computed $\chi^2$ value for each feature in training

<table>
<thead>
<tr>
<th>Feature Group</th>
<th>Significant Features (bolded is common to both data sets)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profile</td>
<td>the longevity of the account</td>
</tr>
</tbody>
</table>
| Social-network  | [following]
|                 | ratio of number of friends to number of followers                                                                      |
| Activity        | [URLs] per day 
|                 | [direct mentions] per day 
|                 | [hashtags] per day 
|                 | [status messages]
|                 | [status messages] per day during entire account life
|                 | [status messages] per day during last one month                                                                       |
| Past Retweeting | [retweets] per status message
|                 | [retweets] per day                                                                                                      |
| Readiness       | Tweeting Likelihood of the Day
|                 | Tweeting Likelihood of the Day (Entropy)                                                                                |
| Personality     | 7 LIWC features: Inclusive, Achievement, Humans, Time, Sadness, Articles, Nonfluencies
|                 | 1 Facet feature: Modesty                                                                                               |

21 Features Selected by $\chi^2$ in Publish Safety Dataset

<table>
<thead>
<tr>
<th>Feature Group</th>
<th>Significant Features (bolded is common to both data sets)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profile</td>
<td>the length of description has description in profile</td>
</tr>
</tbody>
</table>
| Activity        | [URLs] per day 
|                 | [direct mentions] per day 
|                 | [hashtags] per day 
|                 | [status messages]
|                 | [direct mentions] per status message
|                 | [hashtags] per status message
|                 | [URLs] per status message                                                                                              |
| Past Retweeting | [retweets] per status message
|                 | [retweets] per day                                                                                                      |
| Readiness       | Tweeting Likelihood of the Hour (Entropy)                                                                                |
| Personality     | 34 LIWC features: Inclusive, Total Pronouns, 1st Person Plural, 2nd Person, 3rd Person, Social Processes, Positive Emotions, Numbers, Other References, Occupation, Affect, School, Anxiety, Hearing, Certainty, Szensoy Processes, Death, Body States, Positive Feelings, Leisure, Optimism, Negation, Physical States, Communication
|                 | 8 Facet features: Liberalism, Assertiveness, Achievement Striving, Self-Discipline, Gregariousness, Chearelulness, Activity Level, Intellect
|                 | 2 Big5 features: Conscientiousness, Openness                                                                            |

46 Features Selected by $\chi^2$ in Bird Flu Dataset

Activity, personality, readiness and past retweeting feature groups have more significant power.
Six significant features (bolded names) are common to both sets.
Evaluating Retweeter Prediction
Only the significant features are used for prediction

<table>
<thead>
<tr>
<th>Classifier</th>
<th>AUC</th>
<th>F1</th>
<th>F1 of Retweeter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Basic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.638</td>
<td>0.958</td>
<td>0</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.619</td>
<td>0.939</td>
<td>0.172</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.640</td>
<td>0.958</td>
<td>0</td>
</tr>
<tr>
<td>SMO</td>
<td>0.500</td>
<td>0.96</td>
<td>0</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>0.548</td>
<td>0.962</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>SMOTE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.606</td>
<td>0.916</td>
<td>0.119</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.637</td>
<td>0.923</td>
<td>0.132</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.664</td>
<td>0.833</td>
<td>0.091</td>
</tr>
<tr>
<td>SMO</td>
<td>0.626</td>
<td>0.813</td>
<td>0.091</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>0.633</td>
<td>0.933</td>
<td>0.129</td>
</tr>
<tr>
<td></td>
<td>Cost-Sensitive (Weighting, showing the best results in each model)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td><strong>0.692</strong></td>
<td><strong>0.954</strong></td>
<td><strong>0.125</strong></td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.619</td>
<td>0.93</td>
<td>0.147</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.623</td>
<td>0.938</td>
<td>0.042</td>
</tr>
<tr>
<td>SMO</td>
<td>0.633</td>
<td>0.892</td>
<td>0.123</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>0.678</td>
<td>0.956</td>
<td>0.133</td>
</tr>
</tbody>
</table>

Prediction accuracy (Public Safety)

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>AUC</th>
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<tr>
<td></td>
<td>Basic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.707</td>
<td>0.877</td>
<td>0.066</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.670</td>
<td>0.834</td>
<td>0.222</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.751</td>
<td>0.878</td>
<td>0.067</td>
</tr>
<tr>
<td>SMO</td>
<td>0.500</td>
<td>0.876</td>
<td>0</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>0.627</td>
<td>0.878</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>SMOTE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.707</td>
<td>0.819</td>
<td>0.236</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.679</td>
<td>0.724</td>
<td>0.231</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.76</td>
<td>0.733</td>
<td>0.258</td>
</tr>
<tr>
<td>SMO</td>
<td>0.729</td>
<td>0.712</td>
<td>0.278</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>0.709</td>
<td>0.837</td>
<td>0.292</td>
</tr>
<tr>
<td></td>
<td>Cost-Sensitive (Weighting, showing the best results in each model)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td><strong>0.785</strong></td>
<td><strong>0.815</strong></td>
<td><strong>0.296</strong></td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.670</td>
<td>0.767</td>
<td>0.24</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.735</td>
<td>0.742</td>
<td>0.243</td>
</tr>
<tr>
<td>SMO</td>
<td>0.676</td>
<td>0.738</td>
<td>0.256</td>
</tr>
<tr>
<td>AdaBoostM1</td>
<td>0.669</td>
<td>0.87</td>
<td>0.031</td>
</tr>
</tbody>
</table>

Prediction accuracy (Bird Flu)

We use Random Forest for all following experiments.
Comparison with Two Baselines

**Baselines**

*Random people contact*
- Randomly select and ask a sub-set of qualified candidates

*Popular people contact*
- Sort candidates in our test set by their follower count in the descending order

<table>
<thead>
<tr>
<th>Approach</th>
<th>Retweeting Rate in Testing Set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Public Safety</td>
</tr>
<tr>
<td>Random People Contact</td>
<td>2.6%</td>
</tr>
<tr>
<td>Popular People Contact</td>
<td>3.1%</td>
</tr>
<tr>
<td>Our Prediction Approach</td>
<td><strong>13.3%</strong></td>
</tr>
</tbody>
</table>

Comparison of retweeting rates
Live Experiment

• To validate the effectiveness of our approach in a live setting, we used our recommender system to test our approach against the two baselines
• Randomly selected 426 candidates who had recently tweeted about “bird flu” in July 2013
• Each approach selected top 100 candidates based on its criteria

<table>
<thead>
<tr>
<th>Approach</th>
<th>Retweeting Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random People Contact</td>
<td>4%</td>
</tr>
<tr>
<td>Popular People Contact</td>
<td>9%</td>
</tr>
<tr>
<td>Our Prediction Approach</td>
<td><strong>19%</strong></td>
</tr>
</tbody>
</table>

Comparison of retweeting rates in live experiment
To wrap up...

• We have presented a feature-based prediction model that can automatically identify the right individuals at the right time on Twitter
• We have also described a time estimation model
• In the experiments, our approaches doubled the retweeting rates over the two baselines
• With our time estimation model, our approach outperformed other approaches significantly
• Overall, our approach effectively identifies qualified candidates for retweeting a message within a given time window
Thanks!

For more information, contact:
Jeffrey Nichols
jwnichols@us.ibm.com
@jwnichls
Why Retweet a Stranger’s Request?

We randomly selected 50 people who retweeted and asked them why they chose to retweet (33 replied)

Main reasons to retweet our requested message

• Trustworthiness of the content
  “Because it contained a link to a significant report from a reputable media news source”

• Content relevance
  “Because it happened in my neighborhood”

• Content value
  “my followers should know this or they may think this info is valuable”
Real-Time Retweeter Recommendation

The interface of our retweeter recommendation system: (a) left panel: system-recommended candidates, and (b) right panel: a user can edit and compose a retweeting request.