Re-tweeting from a Linguistic Perspective

Aobo Wang, Tao Chen and Min-Yen Kan
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Introduction

Q: What makes a tweet worth sharing?

• from a linguistic perspective
Introduction

• Something we know

  – Social network effects exert marked influence on retweeting
    (Wu et al., 2011; Recuero et al., 2011)
Motivation

• Something we want to know

Q: Are there specific linguistic signals that mark a tweet as valuable and worthy of sharing?
Tasks

1. **Linguistically Motivated Tweet Classification**
   - The specific function of the individual tweet

1. **Analysis of Linguistic Feature**
   - Linguistic features of tweets

1. **Retweetability**
Literature Review

- **Manual Classification**
  - Naaman et al., 2010
  - 9 genres classification
  - 3379 tweets sampled from 350 users

- **Objective**
  - Q: How does the message type relate to other variables?
  - Q: How does users’ content related to user characteristics?

- **Limited scale analysis**
- **No automatic classifier**
Literature Review

- **Automatic Classification**
  - Sriram et al. 2010
    - 5 genres classification scheme
    - Supervised method using Naïve Bayes Classifier
    - 5407 manually labeled tweets
    - Domain-specific features from
      - author’s profile (e.g., # of followers, # of favorites)
      - lexicon of tweets (e.g., #hashtags, URLs)
      - metadata (time phrases).
Literature Review

- **Automatic Classification**
  - Ramage et al. 2010
  
  - Semi-supervised method, indirect tweet level classification

  1. Unsupervised labelling tweets with topic label
     - Get topic labels with LDA as *Topic Set A*
     - Treat *Hashtag*, *Emoticons*, and *Social Signal (@user)* as *Topic Set B*

  2. Manually classify the *Set A+B* into 4 genres.

  3. Train Labeled LDA classification model with the *Set A+B* topic labels

- We know little about the linguistic features of tweets.
- Classify tweets based on the functions of tweets using linguistic features.
Hypothesis

• Tweets with particular function will be used when users have corresponding motivations of tweeting.

• People’s motivations in posting tweets determine their writing styles.

• Such styles can be characterized by the content and linguistic features of tweets.

  – “I am presenting in Salon now.”
Data Set Collection

- More than 9 million tweets crawled by Twitter Stream API
- Pre-processing
  - Exclude tweets with URLs from our current study
  - Break the hashtags into separate words
    (e.g., #growingup → growing up)
  - Tokenizing on emoticons, usernames (@user) and “RT if”-like (“retweet if”) syntax patterns.
Data Annotation

- **Classification scheme and Example tweets**

<table>
<thead>
<tr>
<th>Level-1</th>
<th>Level-2</th>
<th>Motivation</th>
<th>Example</th>
<th>Corpus count (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opinion</td>
<td>Abstract</td>
<td>Present opinions towards abstract objects</td>
<td>God will lead us all to the right person for our lives. Have patience and trust him.</td>
<td>291 (33.8%)</td>
</tr>
<tr>
<td></td>
<td>Concrete</td>
<td>Present opinions towards concrete objects</td>
<td>i feel so bad for nolan. Cause that poor kid gets blamed for everything, and he’s never even there.</td>
<td>99 (11.5%)</td>
</tr>
<tr>
<td></td>
<td>Joke</td>
<td>Tell jokes for fun</td>
<td>Hi. I’m a teenager &amp; I speak 3 languages: English, Sarcasm, &amp; Swearing (; #TeenThings)</td>
<td>86 (10.0%)</td>
</tr>
<tr>
<td>Update</td>
<td>Myself</td>
<td>Update my current status</td>
<td>first taping day for #growingup tomorrow! So excited. :)</td>
<td>168 (19.6%)</td>
</tr>
<tr>
<td></td>
<td>Someone</td>
<td>Update others’ current status</td>
<td>My little sister still sleep ...</td>
<td>66 (7.7%)</td>
</tr>
<tr>
<td>Interaction</td>
<td></td>
<td>Seek interactions with others.</td>
<td>#Retweet If you’re #TeamFollowBack</td>
<td>81 (9.4%)</td>
</tr>
<tr>
<td>Fact</td>
<td></td>
<td>Transfer information</td>
<td>Learnt yesterday: Roman Empire spent 75% of GDP on infrastructure. Roads, aqueducts, etc.</td>
<td>23 (2.7%)</td>
</tr>
<tr>
<td>Deals</td>
<td></td>
<td>Make deal</td>
<td>Everybody hurry! Get to Subway before they stop serving LIMITED TIME ONLY item 'avocados'.</td>
<td>29 (3.4%)</td>
</tr>
<tr>
<td>Others</td>
<td></td>
<td>Other motivations.</td>
<td>Ctfu Lmfao At Kevin Hart ;</td>
<td></td>
</tr>
</tbody>
</table>

- **Collect Labels through Amazon’s Mechanical Turk**
  - 860 tweets in total
  - Fleiss’ kappa: Level-1 = 0.79; Level-2 = 0.43
Method

• **Labeled LDA Classification**
  – Tweet level classification on **Level 1**
  – 5-fold validation
  – Feature selection
    - **Content**
    - **Discourse relations**
    - **Hashtags**
    - **Interaction Lexical patterns**
    - **Named Entities**
    - **Tense**

• **Incremental training**
Classification Result

• Weighted average F-1 Score

<table>
<thead>
<tr>
<th></th>
<th>Level-1</th>
<th>Level-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>C (baseline)</td>
<td>.625</td>
<td>.413</td>
</tr>
<tr>
<td>CD</td>
<td>.637</td>
<td>.432</td>
</tr>
<tr>
<td>CH</td>
<td>.629</td>
<td>.415</td>
</tr>
<tr>
<td>CI</td>
<td>.642</td>
<td>.422</td>
</tr>
<tr>
<td>CN</td>
<td>.611</td>
<td>.409</td>
</tr>
<tr>
<td>CT</td>
<td>.635</td>
<td>.427</td>
</tr>
<tr>
<td>CDHIT</td>
<td>.670</td>
<td>.451</td>
</tr>
</tbody>
</table>

• Distribution

- Opinion: 45%
- Interaction: 28%
- Update: 21%
- Others: 7%
Tasks

1. Linguistically Motivated Tweet Classification
   – The specific function of the individual tweet
   – More than 9 million tweets

1. Analysis of Linguistic Features
   – Linguistic features of tweets
   – More than 1.5 million retweets

1. Retweetability
Emoticons and Sentiment

- :) → positive :-( → negative

Q: Do emoticons actually indicate sentiment of message?
- Randomly select 200 posts with smilies and 200 posts with frownies
- Label their sentiment manually
- Evaluate Go et al. (2009)’s API on our annotated corpus

- Use emoticons carefully to detect sentiment

<table>
<thead>
<tr>
<th></th>
<th>Positive</th>
<th>Neutral</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retweets with :)</td>
<td>55 (27.5%)</td>
<td>140 (70%)</td>
<td>5 (2.5%)</td>
</tr>
<tr>
<td>Retweets with :(</td>
<td>9 (4.5%)</td>
<td>118 (59%)</td>
<td>73 (36.5%)</td>
</tr>
<tr>
<td>Predicted Positive</td>
<td>43</td>
<td>30</td>
<td>0</td>
</tr>
<tr>
<td>Predicted Neutral</td>
<td>11</td>
<td>206</td>
<td>12</td>
</tr>
<tr>
<td>Predicted Negative</td>
<td>7</td>
<td>29</td>
<td>62</td>
</tr>
</tbody>
</table>

Majority is neutral tweets
Mistake neutral posts for emotional ones

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Named Entities

Q: What types of NEs do people mention in their tweets?
- Extract NEs by UW Twitter NLP Tools (Ritter et al., 2011)
- Select the top 100 correctly recognized NEs
- Manually categorize NEs against their 10 classes scheme (defined by Ritter et al. 2011)

<table>
<thead>
<tr>
<th>Class</th>
<th>Opinion</th>
<th>Update</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>PERSON</td>
<td>41.2%</td>
<td>44.7%</td>
<td>38.8%</td>
</tr>
<tr>
<td>GEO-LOC</td>
<td>7.8%</td>
<td>28.9%</td>
<td>25.4%</td>
</tr>
<tr>
<td>COMPANY</td>
<td>15.7%</td>
<td>6.6%</td>
<td>10.4%</td>
</tr>
<tr>
<td>PRODUCT</td>
<td>5.9%</td>
<td>5.3%</td>
<td>6.0%</td>
</tr>
<tr>
<td>SPORTS-TEAM</td>
<td>2.0%</td>
<td>5.3%</td>
<td>1.5%</td>
</tr>
<tr>
<td>MOVIE</td>
<td>7.8%</td>
<td>5.3%</td>
<td>7.5%</td>
</tr>
<tr>
<td>TV-SHOW</td>
<td>3.9%</td>
<td>0.0%</td>
<td>3.0%</td>
</tr>
<tr>
<td>OTHER</td>
<td>15.7%</td>
<td>3.9%</td>
<td>7.5%</td>
</tr>
</tbody>
</table>

- Person Names are dominating.
- Geographical locations are less often mentioned in Opinion
Hashtags

Q: Any positional preference for embedding hashtags?

<table>
<thead>
<tr>
<th>Position</th>
<th>Example Tweets</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>End</td>
<td>Success is nothing without someone you love to share it with. #TLT</td>
<td>69.1</td>
</tr>
<tr>
<td></td>
<td>Goodmorning Tweethearts....wishing u all blessed and productive day! #ToyaTuesday</td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>I just saw the #Dodgers listed on Craig’s List.</td>
<td>20.7</td>
</tr>
<tr>
<td>Beginning</td>
<td>#ihateit when random people poke you on facebook</td>
<td>8.9</td>
</tr>
</tbody>
</table>

- **Enders**: peak at around 3 or 11 → Twitter slang, time and location
- **Middlers**: peak at around 7 → Single keyword
- **Beginners**: peak at around 11 → subject+verb+object

Q: Any patterns to how people form hashtags?

![Graph showing Twitter hashtag usage patterns]
Discourse Relation and Sentence Similarity

- **Discourse Relation**
  - End-to-end discourse parser by Lin et al. (2010)
  - PDTB-styled discourse relations (Prasad et al. 2008)

- **Sentence Similarity**
  - Example:
    
    "On Twitter people follow those they wish they knew. On Facebook people follow those they used to know."

- **Five most frequent relations**
  - Computed by Syntactic Tree Matching model (Wang et al. 2009)

- **Higher Sentence Similarity**
  - Common in Opinions
  - More sentimental
  - Be retweeted more often
Tasks

• **Linguistically Motivated Tweet Classification**
  – The specific function of the individual tweet
  – More than 9 million tweets

• **Analysis of Linguistic Feature**
  – Linguistic features of tweets
  – More than 1.5 million retweets

• **Retweetability**
Literature Review

• Previous work
  – Retweet rate prediction using GLM; Suh et al., (2010)
  – Retweet probability prediction using CRF; Peng et. Al (2011)
  – Retweet volume prediction using Logistic Regression; Hong et al.(2011)

• Previously Examined Feature Sets
  – Author’s profile
    ➢(e.g., # of followers/followees/friends; activity of self/friend),
  – Tweet metadata
    ➢(e.g., time interval,# of previously retweeted, # of favorited tweets)
  – Twitter-specific features
    ➢(URL , Hashtags, @user)
What does the tweet itself contribute to its retweetability?

– Surface level features
  - Presence of hashtags, @user, quotation, 3 hashtag positions
  - Tweet length, hashtag counts

– Linguistic features
  - Presence of 16 types of discourse relations; 10 NE types; Verb tenses;
    3 sentiment polarity strengths
  - Sentence similarity value

• Whether a tweet is shared with others is best understood by modeling each function independently?
  - Level-1 functions: Opinion, Interaction, Updates, Others

  Tweet content is not factored
Experiment

- **Task Definition**
  - \( \text{RTpF} = \frac{\# \text{ of Retweets}}{\text{Followers count}} \)
  - Given the content of a tweet, perform a multi-class classification that predicts its range of \( \text{RTpF} \) ratio.
    - Non-retweets (“N”, \( \text{RTpF} = 0 \)),
    - Low (“L”, \( \text{RTpF} < 0.1 \)),
    - High (“H”, \( \text{RTpF} > 0.1 \))
Experiment

- **Data Set**
  - Selected from 9 million dataset
  - Balanced data size of three RTpF classes.

- **Method**
  - Logistic Regression model in Weka3
  - 10-fold cross validation
Result

- Individual regression models
- Aggregate models for all three classes

<table>
<thead>
<tr>
<th>Class</th>
<th>$F_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opinion</td>
<td>0.57</td>
</tr>
<tr>
<td>Update</td>
<td>0.54</td>
</tr>
<tr>
<td>Interaction</td>
<td>0.53</td>
</tr>
<tr>
<td>All w/o L-1 class</td>
<td>0.42</td>
</tr>
<tr>
<td>All w/ L-1 class</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Independent models perform better than combined model

The usage of Level-1 feature improves performance
Observation and Remarks

• **Opinion**

<table>
<thead>
<tr>
<th>Salient Features</th>
<th>Weight</th>
<th>Example Tweets</th>
<th>RTpF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentence Similarity</td>
<td>10.34</td>
<td>“twitter is where people vent to vent, facebook is where people vent to get attention”</td>
<td>0.84</td>
</tr>
<tr>
<td>Conjunction</td>
<td>-21.09</td>
<td>“#Cancer #Scorpio and #Pisces will become quiet and withdrawn when things get tough and they need to think.”</td>
<td>0.10</td>
</tr>
<tr>
<td>Quotation</td>
<td>-19.2</td>
<td>“If you obey all the rules, you miss all the fun - Katharine Hepburn”</td>
<td>0.22</td>
</tr>
</tbody>
</table>

– Beautiful sentence structure
– Avoid complex conjoined components
– Make your words originally
Observation and Remarks

- **Update**

<table>
<thead>
<tr>
<th>Salient Features</th>
<th>Weight</th>
<th>Example Tweets</th>
<th>RTpF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past</td>
<td>-5.2</td>
<td>“I fell for your personality, and your looks were just a bonus”</td>
<td>0.08</td>
</tr>
<tr>
<td>Present</td>
<td>1.3</td>
<td>“Lying in bed, wondering if its worth it to get up”</td>
<td>0.17</td>
</tr>
</tbody>
</table>

- Shows the least bias towards any particular feature
- Prefers present tenses to past tense
Observation and Remarks

• **Interaction**
  
  – “--->RETWEET<--- If you want more followers #TeamFollowBack | #TFB | #InstantFollowBack | #500ADay | #MustFollow @iTweetHeavyTGOD”

<table>
<thead>
<tr>
<th>Salient Features</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentence Similarity</td>
<td>-55.33</td>
</tr>
<tr>
<td>Hashtag Count</td>
<td>5.34</td>
</tr>
</tbody>
</table>

– Keep direct and simple while interacting with specific friends
– In the form of question answering or voting
Observation and Remarks

- Globally

<table>
<thead>
<tr>
<th>Class</th>
<th>Salient Feature</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>All w/o -1 class</td>
<td>Hashtag Count</td>
<td>22.03</td>
</tr>
<tr>
<td>All w/ L-1 class</td>
<td>Sentence Similarity</td>
<td>9.8</td>
</tr>
</tbody>
</table>

- Hashtags are positive triggers
- L-1 Class features are important
Conclusion

• Understanding and classify the function of the tweet is interesting in its own right.

• It is also useful in predicting the retweetability.

• Release
  – A corpus of 860 annotated tweets
  – Functional classifier
  – Online demo

• Tweets containing URLs and the features from social network perspective will be taken into consideration in future work.
Thank you very much!

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