Extracting Diverse Sentiment Expressions With Target-dependent Polarity from Twitter
Lu Chen, Wenbo Wang, Meenakshi Nagarajan, Shaojun Wang, and Amit P. Sheth

Extracting a diverse and richer set of sentiment-bearing expressions, including formal and slang words/phrases

Assessing the target-dependent polarity of each sentiment expression

A novel formulation of assigning polarity to a sentiment expression as a constrained optimization problem over the tweet corpus
OMG I have to Tweet that!
A Study of Factors that Influence Tweet Rates

Emre Kıcıman, emrek@microsoft.com
Event Diffusion Patterns in Social Media

Analyze how real-world events spread and interact with other events across diverse social media (news, blog and SNS) and understand the underlying structure of user network using ICWSM’11 Spinn3r dataset.

- Cricket Game Cancellation
- Queensland Floods 2011
- Australian Open 2011

Information is propagated across sites through hyperlinks in the text of a post.

- 90% of SNS posts and 50% of blog posts make citations to news articles.

Unbalanced interactions between users on events: 55% of users cite less than 5% other users.

Minkyoung Kim, Lexing Xie, Peter Christen

ICWSM 2012
Virality and Susceptibility in Information Diffusions

Tuan-Anh HOANG, Ee-Peng LIM
Living Analytic Research Centre
School of Information System, Singapore Management University

**Viral (information) items:** pieces of information that are easily to be diffused through word-of-mouth

**Viral users:** people that are good at diffusing information

**Susceptible users:** people that are easily to be convinced
Would you follow a (automated) complete stranger?

Online social experiment

Bot interacting with real users

Gain popularity with simple automated activity

Polarization of reactions

People are strange when you’re a stranger: Impact and influence of bots on social networks

L.M. Aiello, M. Deplano, R. Schifanella, G. Ruffo
ARC²S Group - http://arcs.di.unito.it
Jaram Park video presentation
You Too!? Mixed-Initiative LDA Story Matching To Help Teens in Distress

Karthik Dinakar* Birago Jones* Henry Lieberman+ Rosalind Picard* Carolyn Rose* Matthew Thoman++ Roi Reichart*

* MIT Media Lab+ MIT CSAIL + Carnegie Mellon University++ Northeastern University

Teenage Distress
- Negative effects of bullying are well known
- Bullying in the context of teenage drama
- Psychiatry: need to foster cognitive empathy

Mitigation: hypothesis
- Detection of distributions of teenage drama
- Using detection to power reflective thinking
- Indexing appropriate help material

Extracting high-level themes
Let $T =$ # of themes in teenage stories
$D =$ # of stories
$N =$ # words in the corpus.

Let $P(z) =$ distribution over themes $z$ in a
particular story, & $P(w|z) =$ probability
mass over word $w$ given theme $z$.

$$P(w_a) = \sum_{b=1}^{T} P(w_a|z_a = b)P(z_a = b)$$

$$\theta^{(d)} = P(z) \quad \varphi^{(b)} = P(w|z = b)$$

$$\alpha = \frac{50}{T} \quad \beta = 0.01$$

Story thematic distributions

Thematic story matching
- Apply model to a new story to get a
thematic distribution
- Similarity metric: Kullback-Liebler
divergence to fetch similar old stories

Evaluation+ Error Analysis
- Q1: Validity of themes extracted
- Q2: Similarity & usefulness of showing
matched stories
- Strong results for LDA+ versus control
- New stories with outlier themes didn’t
match well
- Promising results: current actual
deployment on MTV www.athineline.org

Results

n = 12 participants control = tf-idf cosine similarity

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<thead>
<tr>
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<th>% Strongly Agree</th>
<th>% Agree</th>
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<tr>
<td>LDA+ Control</td>
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Corpora
- MTV’s www.athineline.org – fighting bullying
- 5500 personal stories of distress
- Severity poll ratings for each story
- Third party advice as comments for each story

Distressing personal experience Severity poll ratings

<table>
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<th>Female, 15</th>
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<tr>
<td>Thems this guy who is way older than me and attends a different school and he asked me out and I said no ever since I told him me he was harrasement making facebook status’s about me saying I sold myself and calling me a &quot;****&quot;</td>
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<td>UNDER</td>
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| SHARE |

Collection of stories

Latest Disjoint Allocation

T clusters of word distributions

Sockologistic assignment of themes

Assign themes to word clusters

Stories with theme distributions

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