Whose and What Chatter Matters? The Effect of Tweets on Movie Sales

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Outline

1. Twitter and Social Broadcasting Networks (SBN)
2. Whose and What Chatter Matters?
   - Motivations
   - WOM Literature
   - Data
   - Model
   - Results
3. References
4. Appendix
Social Broadcasting Networks

Social network and broadcasting tool

- Twitter
- Tumblr
- YouTube
- Jaiku
- Weibo
What is Twitter?

- Twitter is a social broadcasting network launched publicly in July, 2006.
- The word “twitter” means “a short burst of inconsequential information,” and “chirps from birds.”
- As of January 2011, there were nearly 200 million registered users on Twitter who posted 110 million tweets per day.
The Growth of Twitter, 07/15/2006 - 07/15/2011

1 http://blog.twittersensor.com/?p=6
What can you do on Twitter?

- **SMS of the Internet**: Users can use Twitter to post and read messages known as tweets which are text-based posts of up to 140 characters.

- **Social Network**: Users may subscribe to other users’ tweets—this is known as following and subscribers are known as followers.

- **Openness**: By default, following another user does not require that user’s permission.

- **Asymmetry**: The social graph on Twitter is a directed graph.
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Twitter Website
Whose and What Chatter Matters? The Effect of Tweets on Movie Sales

Twitter and Social Broadcasting Networks (SBN)

Twitter Homeline

Tweets

基甸 @jidian55
请教：3月16日各大微博实名制，为什么有人说海外隐私会全部暴露？公告：若我在微博上消失，那一定是因为我长期超负荷工作，精神高度紧张，到港台、脸书、G等美版区休假式治疗了，麻烦各位翻墙到那边找我，ID: jidian555，接头暗号：“巴特尔”。

Jamie White @jgwhite
Bestival 2012 bestival.net
Retweeted by Rik Lomas

Elizabeth Winkler @lzwinks
The @twitter ads gimmage was awesome but seriously needs a -1 button.

Elizabeth Winkler @lzwinks
I just voted for #BeckhamForHM from @hmusa at Ad Scrimmage. Check it out here: ads scrimmage.twitter.com/#!/BeckhamForHM

Universal Pictures @UniversalPics
That’s a WOMAN?! Watch and RT #TheLorax #SB46 spct now!

Huaxia Rui

Who to follow · Refresh · View all
CREC @CREC_UT
Followed by Liqun Xu and others
Follow
女流氓.exe @dawaiwai
Followed by Michael ZS and others
Follow
段子
Follow

Austin trends · Change
#NourishWhatCounts 🛆 Promoted
#getThatAlot
#IeatThataLot
#ThingsYouSeeOnFacebook
You’re Mexican
Beliebers Are Amazing And Lovely
Why do we care?

**Movie tweets**
- On February 18, 2010, two months after the release of the movie “Avatar”, there are 12,729 tweets about this movie;
- On March 4, 2010, one day before the release of the movie “Alice in the Wonderland”, there are 14,738 tweets about this movie.

**Brand tweets**
From 01/03/2011 to 01/08/2012, there are about
- 49,259,700 tweets mentioning *Android*
- 141,399,300 tweets mentioning *iPhone*
- 2,990,900 tweets mentioning *Kodak*
Why do we care?

Dell’s Social Media Listening Command Center
- In 2010, Dell set up a social media monitoring center in Round Rock, Texas.
- SMLCC monitors more than 25,000 daily posts and Twitter messages related to Dell.

Businesses strain to gain insight from social media — Financial Times, 01/25/2012
- At the moment, 90 percent of companies doing analysis look at historic data.
- What they need to do is combine historical data with knowledge of what is happening in real time, or even what is expected to happen.
TwitterSensor

Enter a keyword or keywords separated by comma. E.g. Google,Android

Top Searches:

- Apple
- Windows
- Android
- Nokia
- Earthquake
- Resolution
- Bin Laden
- Christmas
- Allergy
- Thanksgiving
- Jobs
- Google
- Tax
- Austin
- Hawaii
- Ibm
- Acer
- Independence
- Texas
- Steve Jobs
- Happy
- Birth
- Dell
Outline

1 Twitter and Social Broadcasting Networks (SBN)

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4 Appendix
Motivation 1

What Chatter Matters: the Good, the Bad, or the Eager?

- “back at work and recovering from #avatar - fantastic movie!”
- “I’m just not excited about the new Alice In Wonderland :/ Tim Burton seems to be running out ideas a bit”
- “DAMN IT!!! Didn’t make it...Sold out tickets for Avatar!!!”
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Motivation 1

Awareness effect vs. Persuasive effect

- **Awareness effect**: the function of spreading basic information about the product among the population.

- **Persuasive effect**: the function of altering people’s preferences toward the product and thus influencing their purchase decisions.
Motivation 2

WOM → awareness effect
persuasive effect
Motivation 2

Whose Chatter Matters?

“Today a single customer complaint from someone with influence can have more impact on your company’s reputation than your best marketing.” – Jason Duty, head of Dell’s global social outreach service. Source: Customer must be king in the web world, Financial Times. 01/25/2012
Motivation 2

The Million Followers Fallacy?

- “The number of Twitter followers (or reach) is usually meaningless.”

- “Indegree alone reveals very little about the influence of a user.”

- Per Christakis’ anecdotal evidence, Twitter follower/Facebook friend counts are misleading.

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^Cha, Haddadi, Benevenuto, and Gummadi (2010)

^Garber, M. (2010)
Literature on online WOM

- Godes and Mayzlin (2004);
- Liu (2006), Duan, Gu, and Whinston (2008);
- Chintagunta, Gopinath, and Venkataraman (2011)
- Onishi and Manchanda (2008), Dhar and Chang (2009)
- Chevalier and Mayzlin (2006)
- Sonnier, McAlister, and Rutz (2011)
- Trusov, Bucklin, and Pauwels (2009)
Godes and Mayzlin (2004)

- Influence of WOM conversations from Usenet on TV ratings.
- Dispersion of conversations across communities has explanatory power but the volume of WOM does not.

\[
POST_{it} = \sum_{n=1}^{N} POST_{it}^n
\]

\[
\text{ENTROPY}_{it} = - \sum_{n=1}^{N} \frac{POST_{it}^n}{POST_{it}} \log \left( \frac{POST_{it}^n}{POST_{it}} \right)
\]
Whose and What Chatter Matters? The Effect of Tweets on Movie Sales

- Whose and What Chatter Matters?
- WOM Literature

**Movie**

**Liu (2006), Duan, Gu, and Whinston (2008)**
- Effect of WOM conversations from Yahoo!Movies on movie box office revenues.
- Volume of reviews matters but valence does not.

**Chintagunta, Gopinath, and Venkataraman (2011)**
- Effect of national online user reviews on designated market area-level local geographic box office performance of movies.
- Valence drives box office performance, but volume does not.
Advantages of Twitter WOM data

- Twitter is a more natural environment to study the awareness effect of WOM.
- Social network information can be retrieved on Twitter.
- A new category of WOM: intention WOM.
- Large amount of data: 4 million tweets about 63 movies.
  - 12,136 posts used in Liu (2006).
  - 95,867 posts used in Duan, Gu, and Whinston (2008).
Data

- Daily box office revenue data from BoxOfficeMojo.com
- Tweets from twitter.com collected through Twitter Application Programming Interface (API).
  - Each tweet: content, time, number of followers.
  - Pre-processing: advertising tweets, irrelevant tweets.
  - Tweet classification: intention tweets, positive tweets, negative tweets, neutral tweets.
Tweet Classification

tweets

Intention Classifier

Sentiment Classifier

intention tweets

positive tweets

neutral tweets

negative tweets
Intention Classifier

Pattern Matching

- (plan|need) (to|2) (watch|see|c|catch)( the)* movie
- (sold|sell) out|no ticket
- saw|watched|went
- just
- really
- last
- ...

SVM

- Decision function: \( f(x) = \sum_{i} \alpha_i K(x_i, x) + b \)
- RBF Kernel: \( K(x, x') = \exp(-\gamma \|x - x'\|^2) \)
Sentiment Classifier

Naive Bayesian Approach

\[ C^* = \arg\max_{C_i} P(C_i|D) \]

\[ P(C_i|D) = \frac{P(D|C_i)P(C_i)}{P(D)} \]

\[ P(D|C_i) = \prod_{j=1}^{n} P(t_j|C_i) \]

\[ P(t_j|C_i) = \frac{N_{ij} + \alpha}{N_i + 2\alpha} \]

- $\alpha$: smoothing factor
- $N_{ij}$: number of tweets in class $i$ containing word $j$.
- $N_i$: number of tweets in class $i$. 

Where:

- $C_i$: class $i$ (e.g., positive sentiment)
- $D$: data (tweets)
- $P(C_i|D)$: posterior probability of class $C_i$ given data $D$
- $P(D|C_i)$: likelihood of data $D$ given class $C_i$
- $P(C_i)$: prior probability of class $C_i$
- $P(D)$: marginal probability of data $D$
### Variables

<table>
<thead>
<tr>
<th><strong>Gross Revenues</strong></th>
<th>Movie gross box office revenues from Friday to next Thursday</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tweets</strong></td>
<td>Total number of tweets mentioning the name of the movie (i) in a week (i.e., from this Friday to next Thursday)</td>
</tr>
<tr>
<td><strong>Type-1 tweets</strong></td>
<td>Total number of tweets with followers less than 400 (small audiences) from Friday to next Thursday</td>
</tr>
<tr>
<td><strong>Type-2 tweets</strong></td>
<td>Total number of tweets with followers more than 400 (large audiences) from Friday to next Thursday</td>
</tr>
<tr>
<td><strong>T2Ratio</strong></td>
<td>Ratio of Type-2 tweets in a week</td>
</tr>
<tr>
<td><strong>IntRatio (%)</strong></td>
<td>Ratio of intention tweets in a week</td>
</tr>
<tr>
<td><strong>PosRatio (%)</strong></td>
<td>Ratio of tweets with positive sentiment in a week</td>
</tr>
<tr>
<td><strong>NegRatio (%)</strong></td>
<td>Ratio of tweets with negative sentiment in a week</td>
</tr>
</tbody>
</table>
Dynamic Panel Data Model

\[ y_{it} = \alpha y_{i,t-1} + \beta' x_{i,t-1} + \eta_i + \nu_{it} \]  

\[ \text{Revenue}_{it} = \alpha \text{Revenue}_{i,t-1} + \beta_1 \text{Tweets}_{i,t-1} \\
+ \beta_2 \text{T2Ratio}_{i,t-1} + \beta_3 \text{IntRatio}_{i,t-1} \\
+ \beta_4 \text{PosRatio}_{i,t-1} + \beta_5 \text{NegRatio}_{i,t-1} \\
+ \eta_i + \nu_{it} \]
Estimation

\[
(y_{it} - y_{i,t-1}) = \alpha(y_{i,t-1} - y_{i,t-2}) + (x_{i,t-1} - x_{i,t-2})'\beta + (\nu_{it} - \nu_{i,t-1})
\]

\[
\bar{y}_{it} = \alpha \bar{y}_{i,t-1} + \beta' \bar{x}_{i,t-1} + \bar{\nu}_{it}
\]

(3)

where

\[
\bar{y}_{it} = y_{it} - y_{i,t-1}
\]
\[
\bar{x}_{i,t-1} = x_{i,t-1} - x_{i,t-2}
\]
\[
\bar{\nu}_{it} = \nu_{it} - \nu_{i,t-1}.
\]
Estimation

To estimate $\delta = (\alpha, \beta')'$, we use $y_{i1}, \cdots, y_{i,t-2}, x_{i1}, \cdots, x_{i,t-2}$ as instruments for movie $i$, period $t$.

$$\bar{X}_i = \begin{bmatrix} \bar{y}_{i,2} & \bar{x}_{i,2} \\ \vdots & \vdots \\ \bar{y}_{i,T-1} & \bar{x}_{i,T-1} \end{bmatrix}, \quad \bar{Y}_i = \begin{bmatrix} \bar{y}_{i,3} \\ \vdots \\ \bar{y}_{i,T} \end{bmatrix},$$

$$Z_i = \begin{bmatrix} y_{i1} & x_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & y_{i1} & y_{i,2} & x_{i1} & x_{1,2} & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & y_{i,1} & \cdots & y_{i,T-2} & x_{i1} & \cdots & x_{i,T-2} \end{bmatrix}. $$
The GMM estimator minimizes the criterion

\[ J = \left[ \sum_{i=1}^{N} Z_i' (\bar{Y}_i - \bar{X}_i \delta) \right]' W \left[ \sum_{i=1}^{N} Z_i' (\bar{Y}_i - \bar{X}_i \delta) \right] \tag{4} \]

where \( W \) is the weighting matrix and \( \delta = (\alpha, \beta')' \) is the coefficient vector. Hence, we have the following estimator:

\[ \delta_{GMM} = (\bar{X}' Z W Z' \bar{X})^{-1} \bar{X}' Z W Z' \bar{Y}, \tag{5} \]
## Estimation Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag Revenue</td>
<td>0.30***</td>
<td>0.01</td>
</tr>
<tr>
<td>Tweets</td>
<td>5.34***</td>
<td>0.36</td>
</tr>
<tr>
<td>T2Ratio</td>
<td>76,348.75***</td>
<td>18,250.69</td>
</tr>
<tr>
<td>IntRatio</td>
<td>157,905.00***</td>
<td>38,432.42</td>
</tr>
<tr>
<td>PosRatio</td>
<td>125,881.30**</td>
<td>62,131.49</td>
</tr>
<tr>
<td>NegRatio</td>
<td>-137,451.10**</td>
<td>70,214.58</td>
</tr>
</tbody>
</table>

| No. Weekly Observations: | 568 |

<table>
<thead>
<tr>
<th>Tweets</th>
<th>Total number of tweets mentioning movie $i$ in a week</th>
</tr>
</thead>
<tbody>
<tr>
<td>T2Ratio</td>
<td>Ratio of type 2 tweets in a week</td>
</tr>
<tr>
<td>IntRatio (%)</td>
<td>Ratio of intention tweets in a week</td>
</tr>
<tr>
<td>PosRatio (%)</td>
<td>Ratio of tweets with positive sentiment in a week</td>
</tr>
<tr>
<td>NegRatio (%)</td>
<td>Ratio of tweets with negative sentiment in a week</td>
</tr>
</tbody>
</table>
Major Contributions

- This study takes a first step into measuring the potentially different impacts of WOM on movie sales from people with different social network characteristics.
- This study identified and estimated the effect of a new type of WOM on movie sales, namely, the intention WOM. Related to this, we identified a new text mining task, that is, to extract intention information from the text.
- This study provides support to the view that the valence of WOM does matter.
Managerial Implications

- Firms interested in the online WOM about their products should actively monitor or even seek WOM messages produced by people with large indegree in the social network.

- Companies may carefully monitor people’s intention toward certain products on Twitter and incorporate that information to better forecast future sales.

- The dual effect of intention tweets revealed in our study suggests the possibility of targeted advertising on Twitter.

- Overall, Twitter and other SBN could be useful for building BI applications.
Thank you!

Question

Question

Question

Question

Question
References


References


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Appendix A1

Table: Robustness Check 1

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</tr>
<tr>
<td>Tweets</td>
<td>5.35***</td>
<td>0.36</td>
</tr>
<tr>
<td>T2Ratio</td>
<td>73,886.63***</td>
<td>16,886.65</td>
</tr>
<tr>
<td>IntRatio</td>
<td>161,031.10***</td>
<td>38,541.20</td>
</tr>
<tr>
<td>PosRatio</td>
<td>136,802.20**</td>
<td>62,496.97</td>
</tr>
<tr>
<td>NegRatio</td>
<td>−127,575.40**</td>
<td>68,600.83</td>
</tr>
</tbody>
</table>
## Appendix A2

**Table: Benchmark Results**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag Revenue</td>
<td>0.30***</td>
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<td>PosRatio</td>
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<td>62,131.49</td>
</tr>
<tr>
<td>NegRatio</td>
<td>−137,451.10**</td>
<td>70,214.58</td>
</tr>
</tbody>
</table>

No. Weekly Observations: 568
Table: Robustness Check 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>SD</th>
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<tbody>
<tr>
<td>Lag Revenue</td>
<td>0.30***</td>
<td>0.01</td>
</tr>
<tr>
<td>Tweets</td>
<td>5.34***</td>
<td>0.36</td>
</tr>
<tr>
<td>T2Ratio</td>
<td>78,897.60***</td>
<td>19,074.68</td>
</tr>
<tr>
<td>IntRatio</td>
<td>162,974.90***</td>
<td>38,698.65</td>
</tr>
<tr>
<td>PosRatio</td>
<td>122,939.60**</td>
<td>61,809.90</td>
</tr>
<tr>
<td>NegRatio</td>
<td>–138,414.90**</td>
<td>70,342.58</td>
</tr>
</tbody>
</table>
### Appendix B

**Table:** Precisions and Recalls of the Intention Classifier

<table>
<thead>
<tr>
<th></th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intention tweets</td>
<td>98%</td>
<td>87%</td>
</tr>
<tr>
<td>Non-intention tweets</td>
<td>93%</td>
<td>99%</td>
</tr>
</tbody>
</table>

**Table:** Precisions and Recalls of the Sentiment Classifier

<table>
<thead>
<tr>
<th></th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>positive</td>
<td>75%</td>
<td>80%</td>
</tr>
<tr>
<td>negative</td>
<td>65%</td>
<td>71%</td>
</tr>
<tr>
<td>neutral</td>
<td>75%</td>
<td>68%</td>
</tr>
</tbody>
</table>
What about other online reviews sites?

First, the number of tweets in each week could be a good indicator of the intensity of the WOM in the population. Hence, we could focus on the effects of the four ratios (intention ratio, positive ratio, negative ratio, and type-2 tweets ratio). This argument is also adopted by other researchers, for example, Duan, Gu, and Whinston (2008) argued similarly when they tried to study the effect of WOM from Yahoo!Movie on movie sales.

Second, suppose offline WOM and online WOM from other online websites are included in the error terms. Let’s say $\xi_{k,i,t}$ is the non-Twitter WOM from source $k$ on movie $i$ at week $t$. Supposedly, $\xi_{k,i,t}$ is in our error term. Because $\xi_{k,i,t}$ is usually driven by the movie sales in the past. We may reasonably assume that $\xi_{k,i,t} = \theta \ast y_{i,t-1} + \epsilon_{k,i,t}$. Plugging this into our model, we will have the new error term, $\epsilon_{k,i,t}$, which is the idiosyncratic WOM fluctuation from source $k$ and is likely to be exogeneous to $X_{i,t-1}$. 
Appendix D

What about advertising?

- First, advertising after the release of a movie only accounts for a small proportion of advertising spending in the movie industry. For example, Elberse and Anand 2007 reported that 88% of TV advertising was spent prior to initial release.

- Second, advertising plan is often contracted before the launch of a movie and is usually not varied after launch, which means it is reasonable to assume that WOM on Twitter will not affect ad spending. Onishi and Manchanda (2010) had a discussion on this (Page 15). In our first differenced model: 

\[ \tilde{y}_{it} = \alpha \tilde{y}_{i,t-1} + \beta \tilde{X}_{i,t-1} + (\nu_{i,t} - \nu_{i,t-1}) \]

Because we use \( X_{i,t-2}, X_{i,t-3}, \ldots, X_{i,1}, y_{i,t-2}, y_{i,t-3}, \ldots, y_{i,1} \) as our instruments, they are not affected by \( (\nu_{i,t} - \nu_{i,t-1}) \).