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

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1. Whose and What Chatter Matters?
   - Motivations
   - Data
   - Model
   - Results
   - TwitterSensor
Word-of-Mouth (WOM) Research

Word-of-mouth is often considered to be the most credible information source to consumers for the purchase of a new product or new service.

- Offline period (before 2003)
- Online period (since 2004)
- Big Data period (present)
The Effect of WOM on Product Sales

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 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!!!”
Motivation 2

“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.  

1 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.”\(^a\)
- “Indegree alone reveals very little about the influence of a user.”\(^b\)
- Per Christakis’ anecdotal evidence, Twitter follower/Facebook friend counts are misleading.\(^c\)
- Recently, Evan Williams hinted that a simple measure of followers “doesn’t capture your distribution” and follower counts may soon become the second most important number to users.

\(^a\)Avnit, A. (2009), Berinato, S. (2010)
\(^b\)Cha, Haddadi, Benevenuto, and Gummadi (2010)
\(^c\)Garber, M. (2010)
Why Twitter WOM data?

- Twitter is a more natural environment to study the awareness effect of WOM (push vs. pull).
- More social network information is available from Twitter.
- A new category of WOM: intention WOM.
- Volume: 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
    - intention tweets
    - positive tweets
    - neutral tweets
    - negative tweets
  - Sentiment Classifier
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

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

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

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

- \( \alpha \): smoothing factor
- \( N_{ij} \): number of tweets in class \( i \) containing word \( j \).
- \( N_i \): number of tweets in class \( i \).
### 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>Ad</strong></td>
<td>Advertising expenditure in a week</td>
</tr>
<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

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

\( Revenue_{it} = \alpha Revenue_{i,t-1} + \beta_0 Ad_{i,t-1} + \beta_1 Tweets_{i,t-1} \)  
\[ + \beta_2 T2Ratio_{i,t-1} + \beta_3 IntRatio_{i,t-1} \]  
\[ + \beta_4 PosRatio_{i,t-1} + \beta_5 NegRatio_{i,t-1} \]  
\[ + \eta_i + \nu_{it} \]
Estimation

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

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

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

$$Z_i = \begin{bmatrix} y_{i1} & x_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & y_{i1} & y_{i2} & x_{i1} & x_{1,2} & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & y_{i1} & y_{i,T-2} & x_{i1} & \cdots & x_{i,T-2} \end{bmatrix}.$$
The GMM estimator minimizes the criterion

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

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

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tweets</td>
<td>5.35***</td>
<td>0.36</td>
</tr>
<tr>
<td>T2Ratio</td>
<td>75,653.54***</td>
<td>18,229.72</td>
</tr>
<tr>
<td>IntRatio</td>
<td>154,698.00***</td>
<td>38,300.25</td>
</tr>
<tr>
<td>PosRatio</td>
<td>116,681*</td>
<td>61,798.56</td>
</tr>
<tr>
<td>NegRatio</td>
<td>−136,926.9*</td>
<td>70,445.52</td>
</tr>
<tr>
<td>Lag Revenue</td>
<td>0.30***</td>
<td>0.01</td>
</tr>
<tr>
<td>Ad</td>
<td>155.1425</td>
<td>203.7851</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
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<tr>
<td>Tweets</td>
<td>Total number of tweets mentioning movie (i) in a week</td>
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<td>Ratio of type 2 tweets in a week</td>
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<td>IntRatio (%)</td>
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No. Weekly Observations: 433
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.
TwitterSensor

- Individually, each tweet might be inconsequential and “boring”;
- Collectively, the Twitterverse might reveal interesting patterns.
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TwitterSensor

![Graph showing TwitterSensor search results for debt over time]

Top Searches:
- Apple
- Windows
- Android
- Nokia
- Earthquake
- Resolution
- Bin Laden
- Christmas
- Thanksgiving
- Allergy
- Jobs
- Google
- Hawaii
- Austin
- Tax
- Ibm
- Acer
- Independence
- Texas
- Steve Jobs
- Happy
- Birth
- Mac
TwitterSensor

Figure 2: http://www.twittersensor.com
TwitterSensor
References


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References