Sales prediction by integrating heat and sentiments of product dimensions

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Abstract: The accuracy of sales prediction models based on the big data of online word-of-mouth (eWOM) is still not satisfied. We argue that eWOM contains heat and sentiments of different product dimensions, which can improve the accuracy of these models. In this paper, we propose a dynamic topic analysis (DTA) framework in order to extract heat and sentiments of product dimensions from the big data of eWOM. Finally, we propose an autoregressive-heat-sentiment (ARHS) model, which integrates heat and sentiments of dimensions into the baseline predictive model. The empirical study in movie industry confirms that heat and sentiments of dimensions can improve the accuracy of sales prediction model. ARHS model is better for movie box-office revenue prediction than other models.

Keywords: big data; sales prediction; online word-of-mouth; dynamic topic model; dimension heat; dimension sentiment

1. Introduction

Sales prediction is an important step of product and service management, because it is a foundation for business operations likes promotional marketing. Sales prediction with high accuracy and timeliness can allow firms to reduce the profit losses and improve market performance [1]. With the superiority of big data in online review systems, the frequency of sale prediction become higher than before to acquire more accurate of prevision to support real time decision making. However, the accuracy of these models is still not satisfied. We need extract more predictive information from the high-frequency online big data to improve sales prediction accuracy.

High-frequency big data, such as online word-of-mouth (eWOM) [2] and online search data (OSI) [3], contains timely information and can improve the accuracy of sales prediction [4]. However, the accuracy of sales prediction is still not satisfied for irregular or non-seasonal sales trends [5,6]. EWOM implies detailed information, such as the heat and sentiments of product dimensions, which previous predictive models do not consider. These factors have effects on product sales [7,8]. To improve accuracy of sales prediction, this paper proposes a framework to extract heat and sentiments of product dimensions from eWOM simultaneously and then integrates them into sales prediction model.

We choose movie industry as our research context. We crawl reviews from IMDb.com, online search data from google.com and film-related data from BoxOfficeMojo.com. Finally, we get a big data set including film-related data, Google Trends and 349269 reviews of 122 movies.

In order to extract heat and sentiments of product dimensions, we propose a dynamic topic analysis (DTA) framework in this study, which integrates machine-learning technique and lexicon-

47 based method. It has two major functions. First, DTA captures product dimensions from eWOM
48 without manual annotation. Second, DTA can extracts heat and sentiments of the extracted
49 dimensions simultaneously. After that, we integrate dimension heat and sentiments to construct a
50 new sales prediction model called autoregressive-heat-sentiment (ARHS) model. We get three movie
51 dimensions from online reviews: *star*, *genre* and *plot*. We find that the proposed ARHS model has a
52 better accuracy for predicting movie box-office revenue. Furthermore, ARHS model can predict sales
53 of all kinds of products, which have enough eWOM.
54   We organize the remainder of this paper as follows. Section 2 describes the related literatures.
55 Section 3 describes our methodology. Section 4 shows the results of our empirical study. The final
56 section summarizes the main conclusions and discusses the implications of our study.

57 **2. Literature Reviews**

58 *2.1 EWOM's effect on sales*

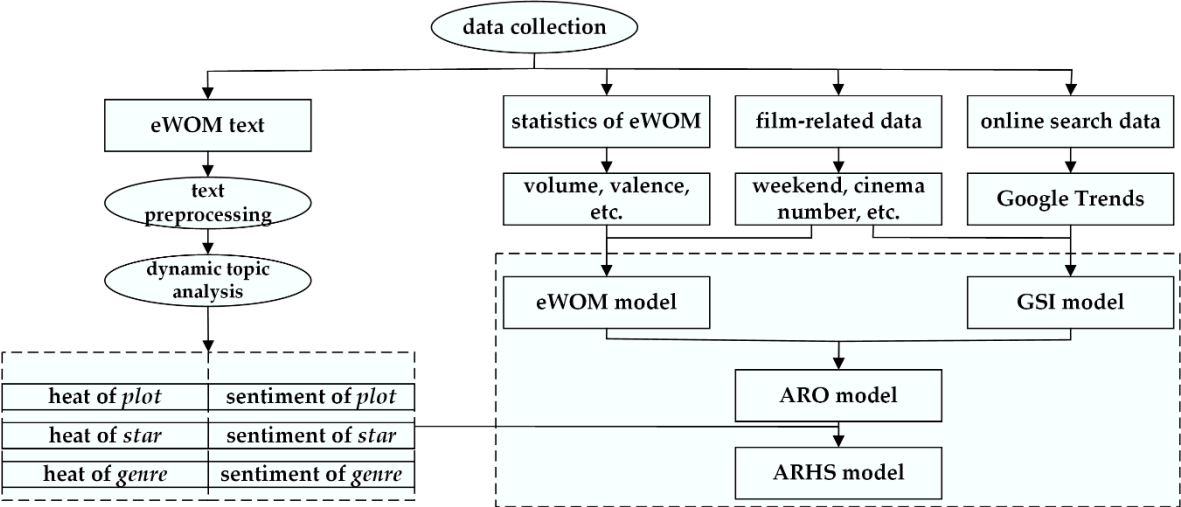
59   As argued by [9], eWOM can reduce consumers' uncertainty about products by reduce the
60 information asymmetry between reviewers and potential consumers.
61   Volume of eWOM represents the amount of information supplied by reviewers, such as the
62 number of online reviews. Previous studies show that volume of eWOM is positively associated with
63 movie box-office revenues [10,11]. Talking heat of product dimensions reflects the amount of
64 information about product dimensions. Therefore, heat of some dimensions can influence product
65 sales differently based the weightage of these dimensions [7]. We demonstrate that dimension heat
66 has predictive power in predicting movie box-office revenues in this paper.
67   Valence of eWOM can be the average rating on the rating scale (e.g. 1-5) or the binary of positive
68 and negative, which also can be regard as overall sentiment of eWOM. The overall sentiment of
69 eWOM transmits reviewers' emotion to consumers. However, the aggregation process of the overall
70 sentiment may offset the dimension-specific sentiments. This can be one of the reasons for why prior
71 studies found overall sentiment of eWOM has no effect on movie box-office revenues [10,12]. Chen
72 and Xie [13] demonstrate that eWOM provides product-dimension preference information that help
73 consumer find products that match their needs. Potential consumers will have a different attitude to
74 the product after perceiving the sentiments of different dimensions of the product from online
75 reviews [8]. We argue that analyzing eWOM sentiments of different product dimensions can provide
76 new insights for sales prediction and overcome the shortcoming of overall sentiment.

77 *2.2 EWOM-based and GSI-based sales prediction*

78   Online search data is the index (from 1 to 100) of the frequency of the object searched in online
79 search engine, such as Google.com. It has been used for predicting movie box-office revenues [14].
80 Bughin [15] finds that valence of eWOM influences sales larger than Google Trends. Geva et al. [3]
81 find that adding Google search data to models based on the more commonly used eWOM data
82 significantly improves accuracy of prediction model. They also find that Google search index (GSI)
83 models based on inexpensive Google Trends provide accuracy that is comparable, at least, to that of
84 eWOM-based prediction models. These studies have proved online search data and eWOM both
85 have powerful predictive ability. However, the predictive abilities of heat and sentiments of product
86 dimensions have not researched yet. This research try to improve the prediction accuracy of movie
87 box office revenues by proposing a comprehensive model, which first time integrates heat and
88 sentiments of product dimensions simultaneously.

89 **3. Materials and Methods**

90   Figure 1 shows the framework of our study, which helps researchers to conduct a sales prediction
91 model for products with abundant eWOM. First, we conduct eWOM model and GSI model, which
92 integrate eWOM and Google Trends into autoregressive model, respectively. Then we integrate online
93 search data into eWOM model following the method of [3], and name this baseline model
94 autoregressive-online (ARO) model. Finally, we use DTA to extract the heat and sentiments of different

95 dimensions of movies from eWOM and integrate them into ARO model to see if the new model, ARHS
96 model, has a better prediction accuracy.

97
98   Figure 1. Framework for constructing ARHS model

99 *3.1 Data and Variables*

100 3.1.1 Data collection

101   EWOM takes many forms, including online reviews [2], blogs [16], microblogs [17], etc. With
102 movies as our research object, we focus on online reviews because statistics suggest that online reviews
103 are more prevalent than other types of eWOM in movie industry [18]. We choose IMDb.com as the
104 resource of online reviews because it is the biggest movie review website in the world. We select movies
105 by the rule in the website. After data filtering, we identify 349269 reviews for 122 movies each released
106 for more than 49 days with at least 100 reviews. We use the threshold, 100 reviews, to guarantee that
107 reviews is enough to train DTM. Our final data set is an online big data set, which contain most of the
108 movie genres shown in Table 1. We chose 49 days as study period in order to achieve a panel data set
109 with enough observations to reach credible experimental results. We divide the data set into two parts
110 based on time to avoid overfitting. The first part is training set for training prediction model. The second
111 part is test set for testing the out-sample performance of the trained model.
112

Table 1. Category of Movies

Genre	Freq.	MAPP rating	Freq.
comedy	37	R	57
drama	38	PG-13	50
action	13	PG	14
thriller	14	NC-17	1
sci-Fi	10	Total	122
horror	9		
animation	8		
romance	2		
crime	6		
fantasy	5		
adventure	3		
sports	2		
music	2		
documentary	1		
war	1		

113   Table 2 lists the statistics of eWOM and film-related variables. First, we measure eWOM valence
114 and volume represented by $v_{t,2}$ and $v_{t,1}$. Valence is the mean of daily reviews' ratings, which reflects
115 the overall sentiment of reviewers on a special movie [19]. Volume is the daily number of reviews [18].

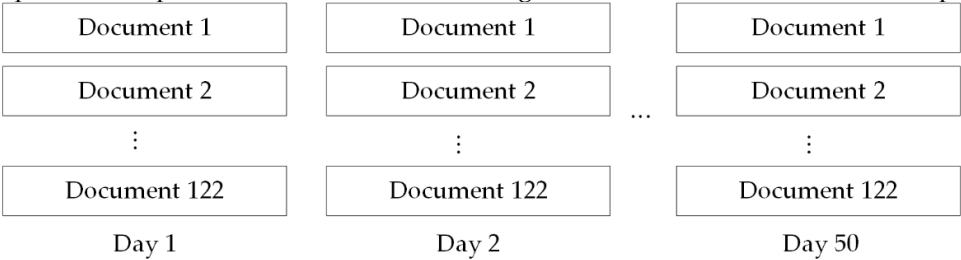
116 Second, we use variable $v_{t,3}$ to denote the number of days since the movie release to consider the time
117 effect. Third, we set the dummy variable $v_{t,4}$ to one if the day is weekend and zero otherwise to
118 consider the seasonal effect. Fourth, the variable $v_{t,5}$ represents the number of cinemas, which play the
119 films [20]. Finally, we use the Google Trends of movie names as online search data, which ranges from
120 one to 100.

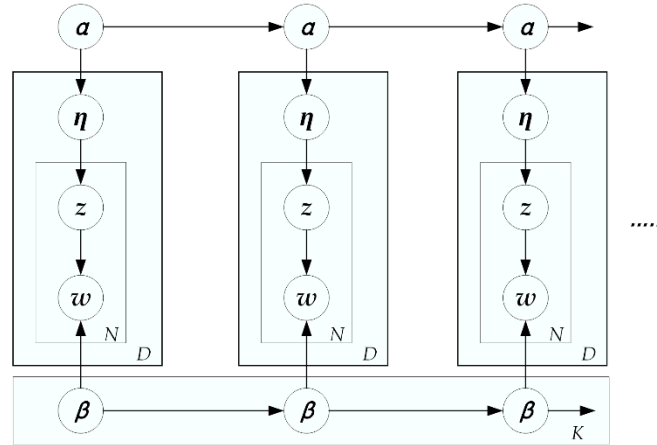
121

Table 2. Key Variables for each movie: Numerical

Variable	Description (for each movie)	Measure and Data Sources
Sales	Daily box-office revenue	Dollars (log-transformation); BoxOfficeMojo.com
$v_{t,1}$	Daily number of reviews	Number (log-transformation); IMDb.com
$v_{t,2}$	Daily valence of reviews	Average of daily ratings (1-10); IMDb.com
$v_{t,3}$	Days from initial release	Number (1-49)
$v_{t,4}$	Whether the day is weekend	1= the day is weekend (Fri, Sat and Sun),0 = others
$v_{t,5}$	Daily number of cinemas	Number (log-transformation); BoxOfficeMojo.com
$v_{t,6}$	Daily Google Trends of movie name	Number (0-100); Google.com

122 3.1.2 Dynamic topic analysis

123 For 122 movies, we construct the framework DTA by integrating dynamic topic model (DTM) [21],
124 lexicon-based method [22] and Stanford NLP technique [23] to derive the dimension heat and
125 sentiments from online reviews. We obtain 122 daily documents by integrating hundreds of daily
126 reviews of each movie into one document. Finally, the daily documents over 50 days comprise our
127 review corpus. The corpus contains 349269 reviews. Figure 2 shows the structure of the corpus.

128
129 Figure 2. The structure of our review set
130 We pre-process each document by using the steps used in the study of Guo, Barnes, and Jia (2017).
131 First, we eliminate non-English words and spell errors, such as web sites, punctuations and numbers.
132 Then, we use Stanford NLP package for word text tokenization, part-of-speech tagging, and word
133 stemming. Finally, each document becomes a word-of-bag.
134 To extract product dimensions from large corpus of text data effectively, previous studies have
135 used latent Dirichlet allocation (LDA) model to extract product dimensions from large number of online
136 reviews [24,25]. DTM is more suitable for extracting product dimensions from our structured review
137 set [21], and is an extend method of LDA [26]. DTM can quickly discover a mixture of connected topics
138 from huge number of documents over different time windows that LDA alone cannot achieve.
139 As a machine learning method, DTM is highly efficient to handle online big data. We use DTM to
140 extract product dimensions, heat of these dimensions, words that represent each dimension and
141 changes of these factors over different time windows. DTM assumes that a review comprises a sequence
142 of N words, $d = (w_1, w_2, \ldots, w_N)$, D reviews form a review set, $C_t = [d_1, d_2, \ldots, d_D]$, whilst T review
143 sets form a corpus over T time windows, $C = \{C_1, C_2, \ldots, C_T\}$. It also assumes that reviewers share K
144 dimensions across the corpus over the T time windows. In each time window, DTM assumes
145 reviewers express their experience about product or service over K dimensions. For instance, a
146 reviewer may comment the movie in the review based on three dimensions with different heat and
147 sentiments: 30% and 4.9 for movie stars, 40% and 3.4 for story plot, and 30% and 2.1 for background
148 music. 30% is the dimension heat of movie stars, which means that a third of the review is about movie

149 stars. 4.9 is the sentiment strength of movie stars, which means that the reviewer has a strong sentiment
150 with movie stars.
151   The DTM model consists of three hierarchies, and has correlation between different time-windows.
152 Figure 3 shows the probabilistic graphical model of DTM. The circle w is the observable words. Circle
153 Z and η are latent variables. The rectangular boxes represent replications. The outer boxes represent
154 documents, and the inner boxes mean repeatedly generating dimensions and words within a
155 document. α and β are hyper-parameters at the document set level. DTM samples α and β based
156 on the distributions of preceding α and β respectively so that we can extract the same dimensions in
157 document sets of all time windows.

158
159 <center>Figure 3. DTM model with plate notation</center>
160   In DTM modelling, the followed steps formulated the generative process of a review set in time
161 window (day) t:
162   1. Draw parameter $\beta_t | \beta_{t-1} \sim N(\beta_{t-1}, \sigma^2 I)$
163   2. Draw parameter $\alpha_t | \alpha_{t-1} \sim N(\alpha_{t-1}, a^2 I)$
164   3. For each document:
165   (a) Draw dimension distribution $\eta \sim N(\alpha_t, \delta^2 I)$
166   (b) For each word:
167   (1) Draw dimension $Z = k \sim Mult(\pi(\eta))$
168   (2) Draw word $W_{t,d,n} = w \sim Mult(\pi(\beta_{t,k}))$,
169 where $\pi(\beta_{k,t})_w = \frac{e^{(\beta_{k,t,w})}}{\sum_w e^{(\beta_{k,t,w})}}$ maps the multinomial natural parameters to the mean parameters,. For a
170 K-dimension model with N words, $\beta_{t,k}$ denotes the N-vector of words distribution for dimension k
171 on day t. The value of DTM parameters that we must set are the first value of parameter α, the first
172 value of parameter β and the number of dimensions K. The first values of parameter α and β are
173 set according to experience: $\alpha = 0.01$ and $\beta = 50/K$. Through comparing the perplexity of DTM and
174 semantics of dimensions when using different value of K, we determine the optimal number of
175 dimensions. Finally, we find three movie dimensions that can represent the review corpus perfectly.
176 The formula of perplexity of DTM for the document set on day t is as follows:

$$perplexity(C_t) = exp\left(-\frac{\sum_{d=1}^{D} \sum_{n=1}^{N_d} \log \sum_{k=1}^{K} p(W_{d,n} = w | Z_{d,n} = k) p(Z_{d,n} = k | d)}{\sum_{d=1}^{D} N_d} \right). \quad (1)$$

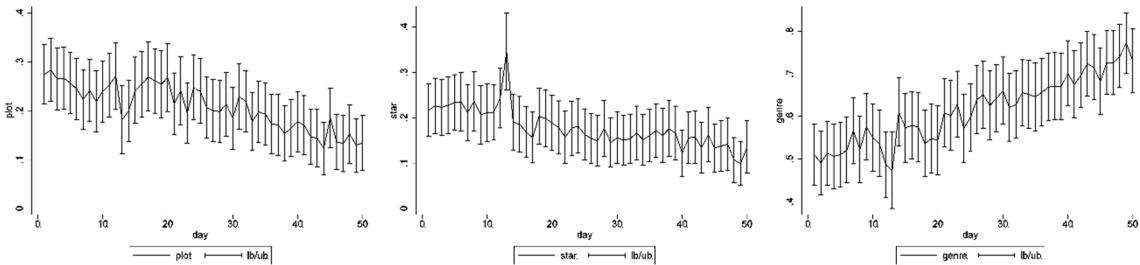
177 C_t is the document set on day t. D is the number of documents on day t. N_d is the number of words
178 in document d. K is the number of dimensions. $p(W_{d,n} = w | Z_{d,n} = k)$ is the heat of word w in
179 dimension k. $p(Z_{d,n} = k | d)$ is the heat of dimension k in document d. DTM learning with Gibbs
180 Sampling can generate the heat of words and dimensions simultaneously. Let $\vartheta_{i,t}$ be the heat of the
181 kth dimension of the ith movie on day t. $\vartheta_{i,t}$ can be calculated as follows:

$$\vartheta_{i,t,k} = \frac{\sum_{d=1}^{D_{i,t}} p(Z = k | t, d, i)}{D_{i,t}}, \quad (2)$$

182 where $p(Z = k | t, d, i)$ is the heat of dimension k in document d of movie i. $D_{i,t}$ is the number of
183 documents for movie i on day t. In our research context, $D_{i,t}$ equals one.

184   We name the three dimensions *plot*, *star* and *genre* following the method in Guo et al. (2017). Table
185   3 shows the changes of dimension *plot* in different time windows.
186   Table 3. The change of words and their weightages of dimension *plot*

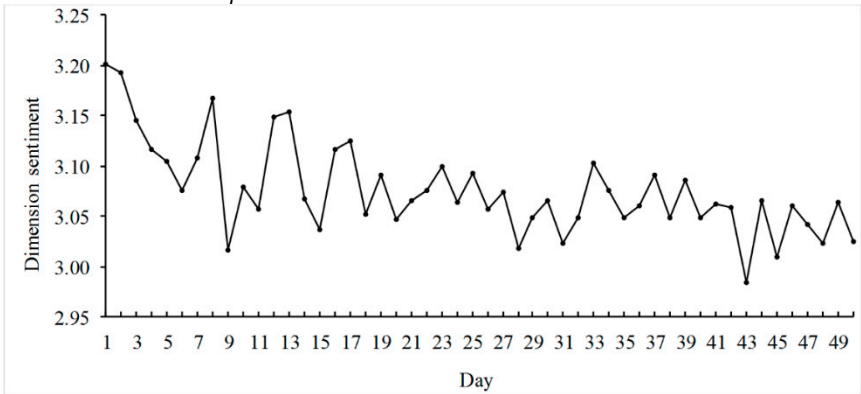
plot	*weight*	*plot*	*weight*	*plot*	*weight*
story	0.9%	*plot*	0.5%	*plot*	0.5%
plot	0.4%	*story*	0.4%	*story*	0.4%
book	0.4%	*book*	0.3%	*book*	0.4%
horror	0.3%	*horror*	0.3%	*horror*	0.3%
dark	0.2%	*dark*	0.3%	*dark*	0.2%
original	0.3%	*original*	0.2%	*original*	0.2%
scary	0.2%	*scary*	0.2%	*scary*	0.2%
real	0.2%	*maze*	0.2%	*maze*	0.2%
pretty	0.2%	*pretty*	0.2%	*pretty*	0.2%
action	0.2%	*love*	0.2%	*house*	0.2%

187   Dimensions heat is the proportion that reviewers talk about the product dimension in eWOM. For
188   example, heat of dimension *plot* denotes the proportion that consumers talk about the *plot*-related
189   information in reviews. Figure 4 shows the heat of three movie dimensions changes over the 50 days

190
191   Figure 4. Average heat of the three dimensions over 122 movies
192   Then, we use the sentiment lexicon and syntax relation to calculate dimension sentiments. Lexicon-
193   based method by using a public-recognized sentiment lexicon is more objective and suitable for big
194   data sentiment analysis than machine-learning-based method that needs expert annotations. Because
195   expert annotation has a high time cost, and it exists deviations between humans. Most studies about
196   dimension sentiment analysis divide the dimensions into positive or negative class [27]. Sentiment
197   analysis methods are different according to different application requires. Our study calculate the
198   sentiment strength of each dimension that can forecast movie box-office revenues. We extract the
199   syntactic relations between dimension words and sentiment words in the daily review sentences by
200   using the Stanford NLP package. We obtain the sentiments of dimension words based on the extracted
201   relations. Table 4 shows the main sentiment mining rules used in our framework.
202   Table 4. The main rules for sentiment mining of dimension words

Syntax relations	Examples	word sentiments
Nominal subject	The *plot* is *boring*.	*Plot*: 3.0
Adjectival modifier	She is a *good actor*.	*Actor*: 3.8612
Direct object	I *enjoy 3D*.	*3D*: 3.9782
Open clausal complement	I think the actor *enjoys acting*.	*Acting*: 3.9782
Adverb modifier	Tom *performed earnestly*.	*Perform*: 3.5
Relative clause modifier	I saw the *actor* who people *dislike*.	*Actor*: 3.5417

203   Finally, we calculate average daily sentiment strength of dimensions for each movie. Let $s_{i,n,d}$ be
204   the sentiment value reflect to the nth dimension word appear at the ith time in document d for one
205   movie. Then, the sentiment of the kth dimension for one movie on t^{th} day can be formulated as follows:

$$\theta_{t,k} = \frac{1}{N} \sum_{n=1}^{N} \frac{1}{D} \sum_{d=1}^{D} \frac{1}{I} \sum_{i=1}^{I} s_{i,n,d}. \qquad (3)$$

206 Intuitively, $\theta_{t,k}$ represents the average strength of sentiment of kth dimension. Figure 5 shows the
207 average sentiments of dimension *plot* of 122 movies.

208
209 Figure 5.   Average sentiments of dimension *plot* over 122 movies
210 In Table 5, we describe the key variables of dimensions.
211 Table 5. Key Variables for each movie: Dimensions

Variable	Description	Measures
$\vartheta_{t,1}$	The heat of dimension *plot* on day t	Probabilistic
$\vartheta_{t,2}$	The heat of dimension *star* on day t	Probabilistic
$\vartheta_{t,3}$	The heat of dimension *genre* on day t	Probabilistic
$\theta_{t,1}$	The sentiment of dimension *plot* on day t	Numerical value
$\theta_{t,2}$	The sentiment of dimension *star* on day t	Numerical value
$\theta_{t,3}$	The sentiment of dimension *genre* on day t	Numerical value

212 3.1.3 Descriptive analysis

213 Table 6 shows the summary statistics of variables. We can see the sales, volume ($v_{t,1}$), theatres
214 ($v_{t,5}$) are right-skewed distribution and the skewness of volume and sales is very large. That means
215 very few movies have high box-office revenues or high customer attentions, and most movies have low
216 box-office revenues or low customer attention. The distributions of valence ($v_{t,2}$) are relatively evenly
217 distributed. Dimension heat ($\vartheta_{t,i}$) is between zero and one. The median of dimension sentiment ($\theta_{t,i}$)
218 is three.
219 Table 6. Summary statistics of key variables

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Sales	1039207	263875	35167017	10	2204483.7	5.351	46.855
$v_{t,1}$	22.11526	11	506	0	38.754737	3.956	26.541
$v_{t,2}$	3.801627	4	10	0	3.6083277	0.162	1.410
$v_{t,5}$	1483.412	1195	4324	1	1264.8718	0.343	1.634
$v_{t,6}$	33.49281	28	100	2	21.922873	1.101	3.815
$\vartheta_{t,1}$	0.269317	0.009709	0.99999565	1.93E-06	0.4063216	1.082	2.284
$\vartheta_{t,2}$	0.135738	0.009709	0.99999565	2.16E-06	0.3078812	2.184	5.992
$\vartheta_{t,3}$	0.594945	0.95943	0.99999488	1.43E-06	0.4544953	-0.426	1.250
$\theta_{t,1}$	3.073407	3	4.83333	0.130435	0.3685301	-3.347	28.987
$\theta_{t,2}$	3.094447	3	4.90476	0.130435	0.3519009	-2.837	28.437
$\theta_{t,3}$	3.086102	3	4.60417	0.130435	0.299457	-3.282	35.261

220 Figure 6 (a) shows the relationship between Google Trends and box-office revenues of movie
221 *Gravit*. Figure 6 (b) shows the relationship between eWOM volume and box-office revenues of movie
222 *Gravity*. We can see that they eWOM and GSI both have high correlations with movie box-office
223 revenues.

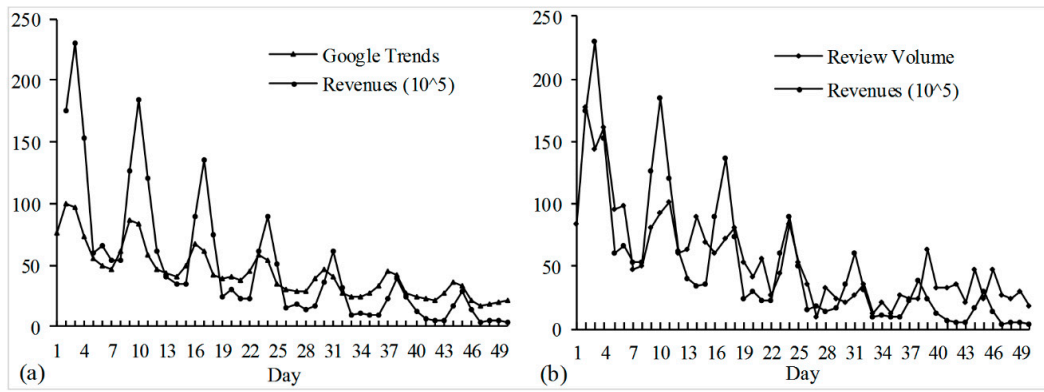



Figure 6. The relationship between online information and box-office revenues of movie *Gravity*. (a) The relationship between Google Trends and box-office revenues. (b) The relationship between review volume and box-office revenues.

3.2 Predictive Model

To forecast movie box-office revenues, we construct the proposed approach based on autoregressive model, because regressive model is the most efficient predictive model [5]. We also need to address some methodological concerns. First, we take a log-transform to some skewed variables to make them similar with normal distribution. Second, we use the variance inflation factor (VIF) to assess multivariate multicollinearity. The VIF values are lower than the threshold five, so multicollinearity was not a serious issue [28]. We use the first 40-days data to train predictive model and the last 9-days data to test the trained model.

3.2.1 Autoregressive Model

We start with an autoregressive (AR) model as our base model to forecast movie box-office revenues. We use AR model with parameter p to model the relationship between preceding box-office revenues and current box-office revenue as follows:

$$\log(Sales_t) = \alpha + \sum_{i=1}^{p} \varphi_i \log(Sales_{t-i}) + \epsilon_t, \tag{4}$$

where $\varphi_1, \varphi_2, \ldots, \varphi_p$, are the parameters to be estimated, α is the effect of combination of time-invariant variables, such as production budgets and genres of movies, and ϵ_t is an error term.

3.2.2 Autoregressive-online Model

Besides preceding box-office revenues, online information, such as Google Trends and eWOM volume, might greatly influence box-office revenues. According to the discussion in above sections, we propose a predictive model by integrating online information into AR model. This model include all variables of previous GSI models and eWOM models. Our ARO model is similar to the model proposed in [3], and can be formulated as follows:

$$\log(Sales_t) = \alpha + \sum_{i=1}^{p} \varphi_i \log(Sales_{t-i}) + \sum_{i=0}^{q} \sum_{j=1}^{J} \rho_{i,j} v_{t-i,j} + \epsilon_t, \tag{5}$$

where $v_{t,j}$ represents the jth online information variable on day t. We determine p and q by comparing the model accuracy when using different p and q. φ_i and $\rho_{i,j}$ are parameters that need estimations. Parameter q specifies the lags of preceding days of online information variables. J indicates the number of these variables.

3.2.3 Autoregressive-heat-sentiment Model

According to previous studies, heat and sentiments of product dimensions are very important to sales [7,8]; thus, it is desirable to integrate the heat and sentiments of movie dimensions into predictive

255 model to achieve better accuracy. In this section, we extend ARO model to ARHS model. We formulate
256 ARHS model as follows:

$$\log(Sales_t) = \alpha + \sum_{i=1}^{p} \varphi_i \log(Sales_{t-i}) + \sum_{i=0}^{q}\sum_{j=1}^{J} \rho_{i,j} v_{t-i,j} + \sum_{i=0}^{\gamma}\sum_{k=0}^{K} \omega_{i,k} \vartheta_{t-i,k}$$

$$+ \sum_{i=0}^{\delta}\sum_{k=0}^{K} \mu_{i,k} \theta_{t-i,k} + \epsilon_t, \tag{6}$$

257 where p, q, γ and δ are user-defined parameter, ϵ_t is an error term, and $\varphi_i, \rho_{i,j}, \omega_{i,k}$ and $\mu_{i,k}$ are
258 parameters that need estimations. $\vartheta_{t,k}$ and $\theta_{t,k}$ are the heat and sentiments of the kth dimension at
259 time t, which are obtained by using DTA. p, q, γ and δ specify how far the model "looks back" into
260 the history, whereas J and K specify how many related variables that we would like to consider. J
261 and K are fitted as we discussed in section 3.1. We use least square method to train all the models.

4. Results

263 In this section, we compare ARHS model with AR model, eWOM-based model, GSI-based
264 model and ARO model to validate its effectiveness.
265 We use the *mean absolute percentage error (MAPE)* to measure the performance of predictive
266 models in this paper.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|Pred_i - True_i|}{True_i} \times 100\%, \tag{7}$$

267 where n is the number of predictions that made on the testing data, $Pred_i$ is the predicted box-
268 office revenue, and $True_i$ represents the true value of the box office revenue. In statistic, $MAPE$ is a
269 suitable measure of accuracy for the time-series-value predictions. We can compare the error of fitted
270 time series because it is a percentage error. All the $MAPE$ results reported herein are mean value of
271 independent runs of 122 movies on different days. This metric is robust to compare the performance
272 of sales prediction models [3,29].

4.1 Parameter determination for ARHS model

274 In ARHS model, Parameters p, q, γ and δ provide the flexibility to fine tune the model to
275 optimal performance. We now study how the choices of these parameter values affect the prediction
276 accuracy.

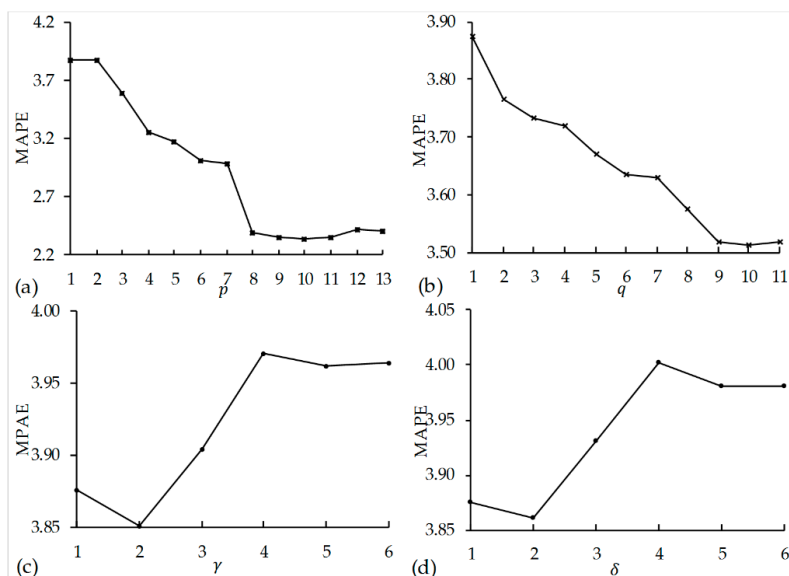
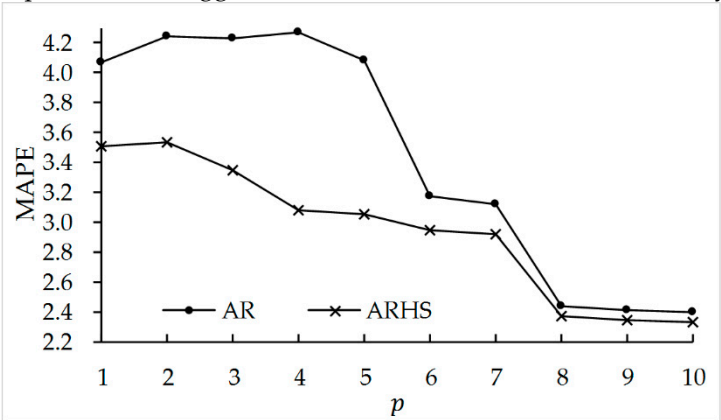



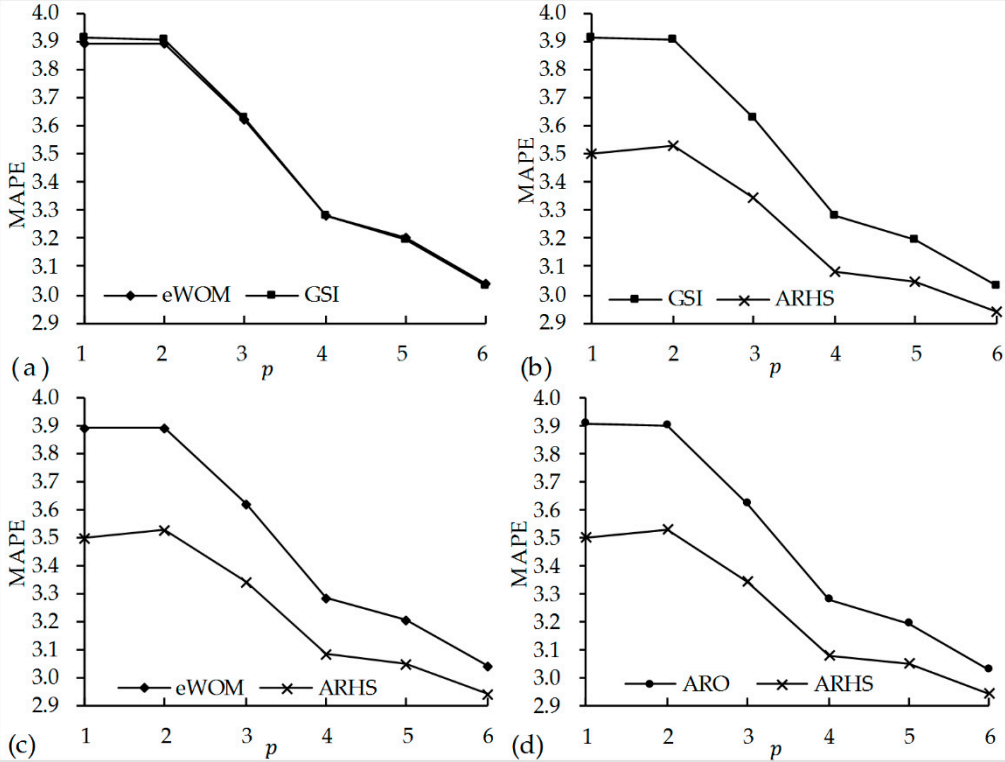
Figure 7. The effects of parameters on the prediction accuracy. (a) Effects of p. (b) Effects of q.
(c) Effects of γ. (d) Effects of δ.

280 First, we vary p with fixed values of parameters q, γ and δ ($q = \gamma = \delta = 1$) to study how
281 preceding box-office revenues affect the prediction accuracy of ARHS model. As shown in Figure 7a,

282   the model achieves its best prediction accuracy when $p = 10$. The change of accuracy is minor after
283     $p = 8$. The accuracy even goes down after $p = 11$. These findings suggest that p should be large
284   enough to factor in all significant influences of preceding box-office revenues, but should not be too
285   large to let irrelevant preceding box-office revenues reduce prediction accuracy.
286   Then, with fixed value of p, γ and δ values ($p = \gamma = \delta = 1$), we then vary the value of q from
287   one to 11 to study its effect on prediction accuracy. Figure 7b shows that the model also achieves its
288   best performance when $q = 10$. However, the accuracy is basically the same after $q = 9$, which
289   means that numerical online information will affect box-office revenues in the next nine days. From
290   the above results, we can suggest that the predictive power of numerical online information for box-
291   office revenues last a little longer than preceding box-office revenues.
292   By using fixed values of p, q and δ ($p = q = \delta = 1$), we vary γ from one to six to study the
293   prediction accuracy of ARHS model. As shown in Figure 7c, the ARHS model achieves the best
294   prediction accuracy at $\gamma = 2$, which implies that the effect of dimension heat captured from the text
295   of eWOM lasts two days.
296   We also vary δ from one to six, with fixed p, q and γ ($p = q = \gamma = 1$). As shown in Figure 7d,
297   ARHS model achieves the highest accuracy at $\delta = 2$, which implies that the effects of dimension
298   sentiments on box-office revenues also last two days.
299   From the results above, we can conclude that product dimension information captured from
300   online comments has a shorter effect on box-office revenues than numerical online information. We
301   think the reason is that consumers only look through the text of eWOM posted in recent days, but
302   glance over the numerical information of eWOM posted in a longer period before they decide to see
303   a movie.

304   *4.2 Comparison with other prediction models*

305   To verify the superiority of ARHS model, we compare its performance with other models'
306   performance.
307   First, we compare ARHS model ($q = 10, \; \delta = \gamma = 2$) against AR model. As shown in Figure 8,
308   ARHS model constantly outperforms AR model as p ranges from one to ten. We can see that ARHS
309   model has a much better accuracy when p is small, which implies that eWOM of movie can supply
310   more predictive power when we know little about preceding box-office revenues. When p equals
311   four our proposed sales prediction model improve the MAPE of AR model at 27.65%. When the lags
312   of sales equals eight, the improvement of MAPE is the smallest. However, it has a 2.69%
313   improvement. These improvements suggest that ARHS model has a better accuracy.

314
315   Figure 8. Comparison with autoregressive prediction model
316   Then, we conduct experiments to compare ARHS ($\delta = q = \gamma = 1$) model against eWOM model,
317   GSI model [14] and ARO model [3]. Our study and previous studies prove that these models are
318   better than AR model. As shown in Figure 9a, eWOM model and GSI model nearly have the same
319   performance in accuracy. As shown in Figure 9b, 9c, and 9d, we can see that ARHS model always
320   outperforms eWOM model, GSI model and ARO model during p ranges from one to six. Thus,
321   ARHS model is the best among these models. The effects of eWOM text on box-office revenues

322   decrease over time, and our test is at the end of movies' release time. Therefore, comparing with
323   eWOM model, GSI model and ARO model, ARHS model improves the MAPE not very high. We
324   argue that the accuracy improvement of ARHS model will be higher at earlier periods of movie
325   release. Because of the high gross of movies, even very little improvement in forecasting accuracy
326   might result in a difference in millions of dollars. ARHS model is meaningful to movie marketers and
327   theatre managers.

328
329   Figure 9. Comparisons of model accuracy. (a) Comparison of eWOM model and GSI model. (b)
330   Comparison of GSI model and ARHS model. (c) Comparison of eWOM model and ARHS model.
331   (d) Comparison of ARO model and ARHS model.

332   *4.3 Time robustness*

333   In order to verify the time robustness of ARHS model, we compare its accuracy in different
334   predictive period. We use the first 20-days, 30-days and 40-days data as training data and the
335   following 9-days data as testing data respectively. Figure 10 shows the results. The prediction
336   accuracy increases during $0 < p < 8$ increases and nearly does not change after $p \geq 8$. The
337   prediction accuracy of 21-29th days is always better than the accuracy of 31-39th days, and the
338   prediction accuracy of 31-39th days is better than that of 41-49th days. That means ARHS model's
339   prediction performance is better in the initial stage of movie released, and the earlier the better.
340   Therefore, we can conclude that heat and sentiments of dimensions have greater predictive power in
341   the early days of movie release.

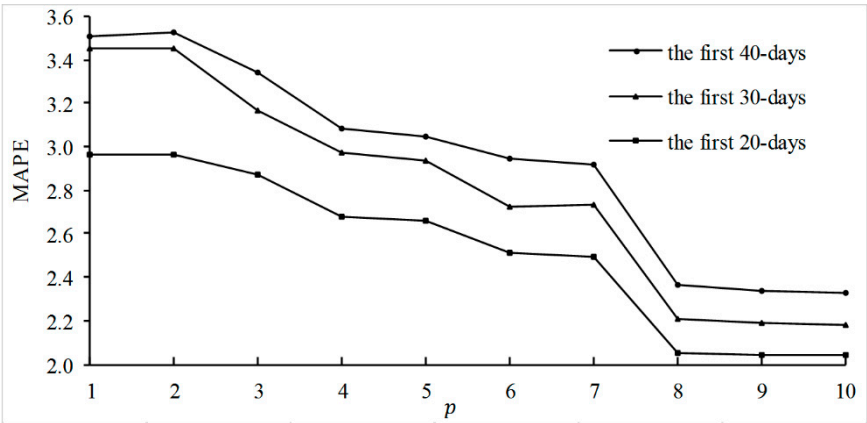



Figure 10. Comparison of different prediction intervals.

5. Conclusion and Discussion

The predictive model for movie box-office revenue is still not satisfied. Previous research demonstrate that eWOM text implies heat and sentiments product dimensions that influence product sales [7,8]. Thus, we propose a method called dynamic topic analysis (DTA) to extract the heat and sentiments of product dimension from eWOM. From the results of DTA, we obtain heat and sentiments of three movie dimensions: *plot*, *genre* and *star*. Then, to improve accuracy, we propose ARHS model by integrating dimension heat and sentiments into the predictive model of movie box-office revenues. By comparing performance with other predictive models, ARHS model is better. We also find that ARHS model performs much better in the early stage of product release.

Our paper has some contributions to managerial implications. First, marketers can use DTA to extract the heat and sentiments of product dimensions from eWOM. This information has great predictive power. Therefore, they can make different marketing strategies at different time according to the different predictive power of these dimension information. Second, the optimal parameters of ARHS model suggest that the predictive power of numerical aspects of eWOM lasts longer than that of eWOM text: heat and sentiments of product dimensions. Therefore, managers should pay attention to numerical aspects of eWOM over a long period and only pay attention to the text of new eWOM. Third, theaters can adjust the projection room number for different movies according to predicted daily box-office revenues.

Our research has some theoretical implications. First, DTA provides a framework for researchers to extract the heat and sentiment of multidimensional constructs in many social studies. Second, dimension heat and sentiments indeed improve the accuracy of prediction model. Researchers can use them to predict sales of other products, outcome of election and price of stock. Third, we propose the superior ARHS model for movie box-office revenue prediction.

This paper also has some limitations. We only predict daily box-office revenues to demonstrate the predictive power of dimension heat and sentiments. To improve our theory, we shall predict weekly or monthly sales for different products in future research. Additionally, we only use one type of eWOM in this paper. We should use multi-type of eWOM in future research to have a more robust result.

Author Contributions: Conceptualization, X.L. and C. J.; methodology, X.L.; software, X. L.; validation, X.L., Y.D. and Z. W.; formal analysis, X.L. and Y.L.; investigation, X.L.; resources, X.L.; data curation, X.L.; writing—original draft preparation, X.L.; writing—review and editing, X.L., C.J.; visualization, X.L.; supervision, X.L., Z.W., Y.L.; project administration, C.J., Y.D.; funding acquisition, C.J..

Funding: This research was funded by National Natural Science Foundation of China (NSFC), key grant number: 71731005 and grant number: 71571059.

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