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Enhancing Film Box Office Predictions: Integrating Online Reviews and Web Search Trends

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Abstract:

As authentic indicators of consumer behavior during the decision-making process, online reviews and web search data are extensively utilized in sales forecasting. This study examines the film industry to investigate the interplay between online reviews and web search effects. By utilizing the Baidu index for films and online reviews comprising 3360 panel data points, the study aims to forecast box office revenues. The empirical findings reveal two key insights: first, the predictive accuracy of models using inexpensive search trend data is comparable to that of models based solely on online reviews. Second, incorporating search trend data into models based on online reviews significantly enhances predictive accuracy, indicating that a combined model more effectively predicts box office trends.

Keywords:

Box office; word-of-month; search trends; purchase decision.

1. Introduction

After the reform of the cinema system in 2002, China's film industry continued to develop rapidly. In 2015, domestic box office revenue reached 44.1 billion yuan, becoming the world's second largest film market [1]. While the film industry brings high box office revenue, there are risks such as high investment cost, multiple factors influencing the box office and difficulty in estimating the return on investment. Taking China's film market as an example, the actual film investment return rate is less than 30%, and only a few films make profits [2]. For the market, the scientific box office prediction has important practical significance for the risk control and business decision of the film industry.

The study of film box office began at the end of 1980s. Litman(1983) first added the methodology of communication and economics into the box office prediction, which laid the basic model and method for the study of film box office[3]. Since then, the academic circle began to study the prediction of film box office and gradually made great achievements[4-6]. Compared with the more mature research system of box office prediction in foreign countries, the domestic box office prediction started late, and the analysis and prediction methods were single. The acquisition of data through questionnaires or experiments was time-consuming, costly and inefficient. Modern Internet search engines are widely used, make the consumers can anywhere at any time before the movie, there is no limit on the basic information, low cost access to movies, especially many network platform in real time on the quality of the film reviews and ratings information, make consumers can direct viewing experience and word of mouth information, help the formation of the judgment or decision. Therefore, the use of Internet search index and review data to predict box office has become a new research direction. However, existing studies only discuss the relationship between online reviews or web search index and box office, and rarely combine the two organically to study the impact on box office [7-9] .At the same time, there are obvious deviations and limitations in social media data, such as underrepresentation of consumer groups and potential intentional manipulation. It is difficult to eliminate the deviations only by improving the model, and additional data sources should be introduced to enrich the prediction model based on online comments[10,11]. Based on this, this paper intends to combine online review and web search index with traditional prediction model to explore the substitution effect of Internet search index on online review and the linkage effect of the two on film box office.

The research idea of this paper is as follows: firstly, relevant literature is reviewed. Based on the decision-making process of consumers, the panel data are collected by crawling Baidu index and Douban film review on the Internet. After that, the combination model of web search index and online review was established to predict the box office of the film in the release cycle, which provided the basis for the cinema line companies to make reasonable propaganda strategies and arrange the film screenings.

2. Literature review

2.1 Predictions based on online reviews

Online review refers to the fact that consumers release feedback and evaluation information based on the use of products on the Internet. The popularity of social media platforms enables users to widely disseminate product information, and the use of online reviews to predict sales performance has become a hot topic in the research and sales industry. In the book sales industry, Chevalier et al.(2006) found a significant positive relationship between amazon's online book reviews and book sales by collecting information about them[12]. Studies generally show that the number of reviews positively affects box office revenue[13,14], but there is no consistent conclusion on the relationship between reviews sentiment polarity and box office. Liu Yong(2006) used artificial methods to quantify the sentiment tendency of reviews, and believed that there was no significant relationship between the valence and box office[15]. However, Chintagunta et al.(2010) believe that the sentiment expressed by online reviews has a positive impact on box office revenue[16]. On the one hand, Rui et al.(2013) pointed out that after using different classification criteria to classify the sentiment polarity of reviews, the conclusion that the sentiment polarity of reviews affects the box office is inconsistent with the former[17]. On the other hand, Duan et al.(2009) pointed out that the possible reason for the inconsistent results was that these studies used cross-section data to build prediction models[18]. On the one hand, cross-section data is not convenient to control the differences between different films, and fails to reflect how online reviews affect box office income dynamically over time.

The above studies used online reviews as a supplement to traditional data for box office prediction, but the existing online review data has the following shortcomings :(1) relatively small sample size. In fact, only about 10% of social media website users will post comments on the website, and most of the comments are generated by only 1% of users. Most users are still quiet "observers" and "lurkers". (2) the representativeness is biased. Dellarocas(2007) shows that individuals with extreme consumption experience (positive and negative) are more likely to post comments on the Internet[19]. Meanwhile, Mayzlin(2014) points out that individuals or companies intentionally manipulate online comments[20]. It can be seen from the above that the prediction effect will be reduced if the box office is predicted solely through online reviews.

2.2 Predictions based on web search

Compared with online reviews, the web search index does not convey emotional evaluations, and is more objective and true to the public's “degree of attention”. Moreover, it costs relatively low to use the search index as a measure of consumer purchase intent. Wu et al.(2009) clarified the reasons for using the search data to predict future sales. He believes that the web search log is “the real signal of the decision maker's intention”: one is that the search index data is easy to collect and clean; the second is that it does not need too much Content encoding or analysis[21]. In addition, the number of online search users is large, and it is not easy to be manipulated by others, and the representativeness is relatively good. In recent years, web search data has also been applied to the prediction of movie box office. Hand et al.(2012) found that on the basis of the time series model, adding the Google search index can improve the short-term prediction accuracy of the box office[9]; Wang Lian and Jia Jianmin(2014) used the Baidu search index for the first time in China to predict the box office of the movie and improve the domestic box office forecast accuracy[6], but it is based only on the static data of the film's release week, and the film market is a process of rapid change and constant adaptation of demand and supply.

By comparing online reviews based predictions and web search index based predictions, it can be found that both have their own advantages and limitations in predicting performance. However, the existing research only use a single data source based on online reviews or search index to predict box office, there is little research of the two alternative role, and combining the two as a predictor to explore the impact on the box office. Based on this, this article based on the daily box office data of 120 movies, dynamically predicts the daily box office during the movie release period. This paper intends to compare the box-office prediction models based on online reviews and search indexes to explore whether the prediction accuracy of low-cost web search data can be compared with the prediction accuracy of online reviews. At the same time, combined with online reviews and web search indexes, the interactive influence mechanism of the two on box office is explored, aiming to establish a low-cost and efficient prediction model for managers.

3. Theoretical framework

The traditional purchase decisions of consumers can be divided into five periods: demand cognition, information collection, comparison, forming purchase decisions and post-purchase evaluation[22], namely the "attention-interest-appetite-memory-action" model (AIDMA model) proposed by American scholar Lewis[23]. In response to the rapid development of the Internet, Japan dentsu group has improved AIDMA model and put forward AISAS model, namely "attention - interest - search - action - sharing" model in the context of web2.0, in which information search behavior is most related to the final consumption behavior of consumers and has the greatest influence [24]. When it is impossible to accurately judge the quality of a film, potential moviegoers often search for information through many channels to reduce the risk of movie watching. The emergence of search engines enables consumers to search for basic information such as the release date, leading actor, film introduction and trailer of the movie before watching the movie. With the help of the comments and star rating of the third-party platform, the quality of the film is preliminaries analyzed to improve the decision-making quality of watching the movie. Thus it can be seen that the information left by potential moviegoers in search engines, social media and other network application systems is the real record of consumers' decision-making process.

Therefore, starting from the purchase decision-making process of consumers, this paper integrates the relationship between Internet search, online review and film box office into the existing box office prediction model, discusses the linkage effect of the two on box office, and thus establishes the research framework of this paper, as shown in figure 1. Since there is not only a correlation between consumer information search behavior and box office revenue, but also a time lag relationship, and the leading and easy access of Internet search information, it is possible to predict the box office.

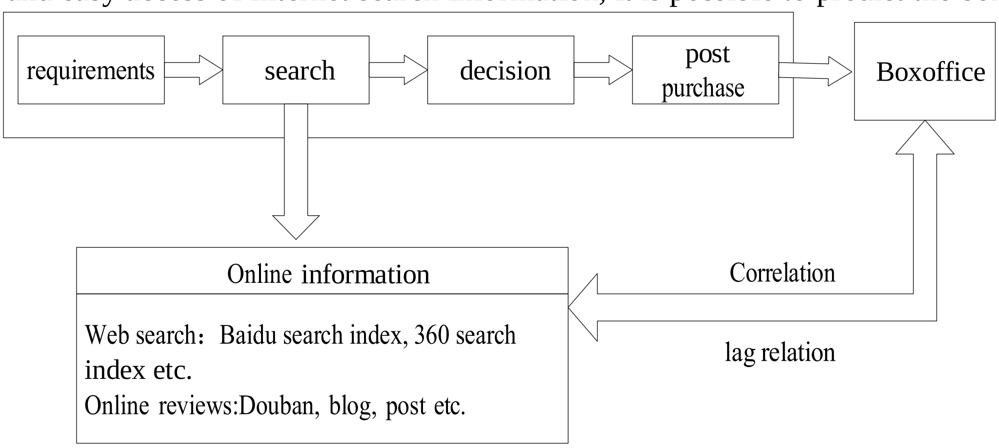

Figure 1 consumer information search and box office revenue model

4. Empirical analysis

4.1 Data and variables

In this paper, films released in mainland China in 2016 were selected as the research object, and the box office data were obtained from Entgroup, which was updated once a day. This paper excluded films with incomplete box office data and ambiguous names, and finally adopted 120 films as the empirical object of this paper to collect the daily box office and total box office data of 120 films within the period of release (4 weeks).

The author used a program developed by himself to capture the review data of films on Douban website in days, including review time and digital rating, and found that the number of user reviews of most films soared in the early stage of the release of films, and then dropped significantly. This model is very similar to the box office life cycle of films.

Referring to the commonly used indicator factors in existing research on film box office, the control variables in this paper include: screenings (indicated by Screen), types of films (indicated by Genre), whether they are sequels or adaptations (indicated by Sequel), whether they are holidays (indicated by Holiday), release days (indicated by Age), origin (indicated by Country), etc. Since some variables may have non-normal distribution, logarithmic transformation of some independent variables and dependent variables is required. Detailed definitions of each variable are shown in table 1.

Table 1 Description and definition of major variables

variable	explainnation
i,t	i： Number of sample films; T: day t after the movie was released
LN$Boxoffice_{i,t}$	The daily box office of the film i on day t (natural logarithmic form)
LN$Search_{i,t\text{-}1}$	Daily search index of film i on day t (natural logarithm form)
LN$Volume$ $_{i,t\text{-}1}$	Number of reviews of film i on day t (natural logarithmic form)
$Valence$ $_{i,t\text{-}1}$	Reviews score of film i on day t
LN$Screen$	Daily screenings of film i on day t
LNAge_t	Number of days in which movie i is released (natural logarithm form)
$Holiday_{i,t}$	Dummy variable, whether the day is a holiday or not
Genre	Dummy variables , reflect the movie type
Country	Dummy variables, domestic and other films
Sequel	Dummy variable , reflects whether the film is a sequel or an adaptation

According to the research, the box office of a film in the first month after its release accounts for more than 85% of the total box office revenue. Therefore, this paper focuses on the box office income in the first 4 weeks (28 days) after the release of the film, and obtains panel data with a capacity of 3360 (120 sections 28 days). The descriptive statistics of panel data are shown in table 2.

Table2 Descriptive statistics of the sample

variable	meaning	Sample size	mean	stddev	minimum	maximum
Boxoffice	Daily boxoffice	3360	752.0748	2273.391	0.01	31607.5
Search	Web search index	3360	44064.64	150586.5	261	2196167

Volume	Number of reviews	3360	350.0149	975.3075	1	13452
Valence	Online scoring	3360	2.852901	.9968838	1	5
Screen	screening	3360	11621.31	19285.06	8	135831

4.2 Unit root test

Like time series data, panel data need to carry out unit root test and construct VAR model for co-integration test before establishing econometric model, so as to avoid false regression. Table 3 shows that the variable sequence in this paper is stable.

Table3 Unit root test results

test method	lnBoxoffice	lnSearch	lnVolume	Valence	lnScreen
LLC-T	-13.2611***	-11.6***	-5.49418***	-14.4030***	-3.42056***
IPS-W	-10.9320***	-9.21087***	-6.93801***	-22.6142***	-6.84662***
ADF-FCS	538.278***	531.150***	444.075***	989.526***	390.074***
PP-FCS	581.605***	312.381***	668.951***	1645.99***	412.666***
result	stable	stable	stable	stable	stable

"*", "**" and "***" mean significant at 10%, 5% and 1% respectively.

4.3 Model setting and result analysis

Based on the theoretical model in this paper, in order to comprehensively analyze the effect of online reviews and Internet search and the prediction ability of the prediction model, the following three multiple linear regression models are estimated and analyzed in this paper:

$$\ln Boxoffice_{it} = \beta_1 \ln Search_{i,t-1} + \beta_2 Screen_{it} + \beta_3 Holiday_{it} + \beta_4 \ln Age_t + \beta_5 Genre_i + \beta_6 Country_i + \beta_7 Sequel_i + u_i + \varepsilon_{it} \quad (1)$$

$$\ln Boxoffice_{it} = \beta_1 \ln Volume_{i,t-1} + \beta_2 Valence_{i,t-1} + \beta_3 Screen_{it} + \beta_4 Holiday_{it} + \beta_5 \ln Age_t + \beta_6 Genre_i + \beta_7 Country_i + \beta_8 Sequel_i + u_i + \varepsilon_{it} \quad (2)$$

$$\ln Boxoffice_{it} = \beta_1 \ln Search_{i,t-1} + \beta_2 \ln Volume_{i,t-1} + \beta_3 Valence_{i,t-1} + \beta_4 Screen_{it} + \beta_5 Holiday_{it} + \beta_6 \ln Age_t + \beta_7 Genre_i + \beta_8 Country_i + \beta_9 Sequel_i + u_i + \varepsilon_{it} \quad (3)$$

Model (1) and model (2) respectively explore the impact of online reviews and web search index on box office. Model (3) integrates online reviews and web search index on the basis of model (1) and model (2) to analyze the linkage mechanism between the two and box office. The u_i captures all the time-invariant, unobservable heterogeneity of each film in the sample, such as budget, distribution, marketing costs, and the intrinsic quality of the film. In order to reduce the heteroscedasticity of panel data and obtain unbiased and consistent estimation, this paper USES the generalized least square method (GLS) to estimate parameters, and the estimated results of the model are shown in table 4.

Table4 Regression results of the models

variables	Online reviews model		Web search index model		Combined model	
	coefficient	stddev deviation	coefficient	stddev	coefficient	stddev
LNSearch	-	-	0.147***	0.0232	0.127***	0.0248

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LNVolume	0.0911***	0.0161	-	-	0.0540***	0.0175
Valence	0.0482**	0.0224	-	-	0.0408*	0.0223
LNScreen	1.018***	0.0124	1.011***	0.0121	1.002***	0.0127
Holiday	0.736***	0.0229	0.716***	0.0229	0.718***	0.0230
LNAge	-0.222***	0.0303	-0.227***	0.0306	-0.188***	0.0309
D.Action	.	.	.	.	.	.
.Animation	-0.508***	0.138	-0.504***	0.156	-0.478***	0.1389
.Romance	-0.394***	0.143	-0.464***	0.163	-0.459***	0.144
.Thriller	-0.586***	0.192	-0.595***	0.217	-0.489**	0.193
Country	-0.0850	0.113	-0.216*	0.125	-0.118	0.113
Sequel	0.138	0.126	0.172	0.142	0.153	0.126
Constant	-4.012***	0.242	-4.733***	0.320	-4.974***	0.306
R2	0.928		0.926		0.932	
Wald chi2	42437.89***		42747.56***		42802.19***	

①for the sake of brevity, it is not included in the table, except for the dummy variable, d.ager, which is not significant on the 10% scale.

②"*", "**" and "***" mean significant at 10%, 5% and 1% respectively.

This paper combines online reviews and web search data to improve the accuracy of box office prediction. However, the risk of adding a second data source is that if the newly introduced data source does not contain additional valuable information, it may lead to overfitting and ultimately reduce the accuracy of the out-of-sample prediction. Therefore, the advantage of the model combining the two data sources is that the two data sources contain non-overlapping and useful information. In order to avoid multicollinearity among variables as far as possible, this paper conducts multicollinearity test. The variance inflation factor (VIF) value of each variable is less than 10, and there is no multicollinearity.

The results show that the combination model can explain the variance of 92.55% and 92.64% of the box office revenue respectively, and the combined model can explain the variance of 93.01% of the revenue, which indicates that the combination of Internet search and online comment can improve the interpretation variance of the model. Secondly, the results of the combination model show that the combination of Internet search and online review does not change the influence direction and magnitude of the two, that is, Internet search, number of reviews and star rating of reviews have a positive impact on box office revenue.

In terms of control variables, the results show that Screen (number of screenings) and Holiday (whether it is a Holiday or not) have significant effects on the promotion of box office revenue. There is a significant negative relationship between Age (film release days) and box office revenue. At the initial stage of film release, consumers' enthusiasm for films is relatively high. However, as the release time increases, consumers' enthusiasm decreases and box office also declines. Whether the film is adapted or sequel has no significant relationship with the box office revenue.

4.4 Predictive power test

The standard fitting prediction method was adopted, and the samples were divided into training samples (about two-thirds) and prediction samples (about one-third) to test the predictive power of the three models in this paper. Using the judgment method proposed by Hyndman and Koehler(2006), mean absolute percentage error (MAPE) and square root error (RMSE) were selected to measure the prediction accuracy of the model[25]. The calculation formula is as follows: $MAPE = \frac{1}{n}\sum_{i=1}^{n} |\frac{y_i - \hat{y}_i}{y_i}|$;

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$; Where, y_i is the actual box office value, $\hat{y}_i$ is the predicted box office value, n is the number of samples, and the prediction results of the three models are shown in table 5 below.

Table5 out of sample prediction

evaluation criterion	Online reviews model	Web search index model	Combined model
MAPE	0.264	0.259	0.247
RMSE	0.523	0.522	0.493

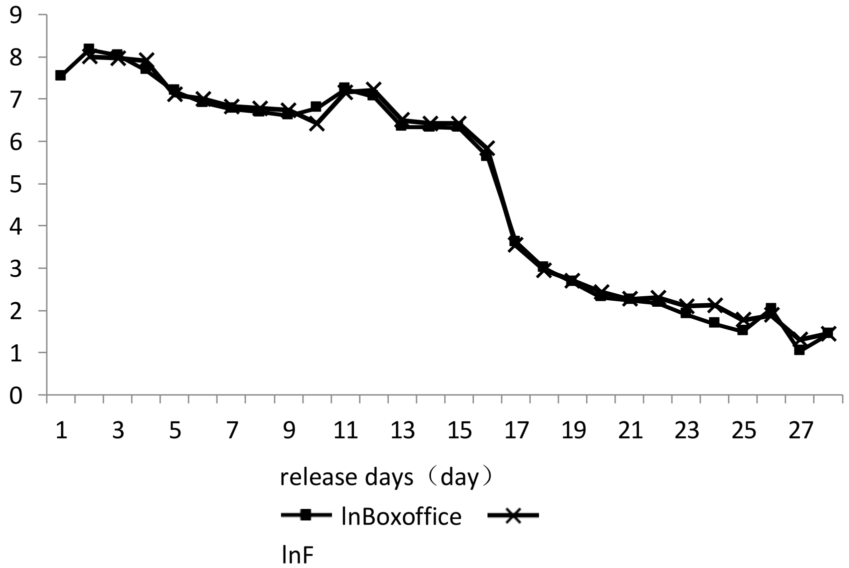

Figure2 the actual box office and the predicted box office of the film anti-corruption storm 2

The results show that the MAPE of the online reviews model and the web search index model is 25.9% and 27.5%, respectively. The MAPE value of the combined model was 24.7%. Compared with both MAPE and RMSE indexes, the prediction effect of the combined model was significantly better. In comparison with similar studies, Liu(2006) took the number of moviegoers as the proxy variable of the star rating of reviews, and the prediction error MAPE of the box office revenue in the first week of the film release was 38%[15]. Wang lian et al.(2014) weekly prediction model based on the web search data has an error of 39.9%[6]. From the above comparison, it can be found that online reviews and web search data can indeed supplement traditional data to improve the accuracy of box office prediction.

Figure2 shows the comparison between the predicted box office and the actual box office of "anti-corruption storm 2", in which lnBoxoffice is the logarithm of the actual box office, and lnF is the predicted value of the combined model. As can be seen from the comparison curve in figure2, there is a good fit between the predicted box office of online review and web search index and the actual box office, which once again proves that the web search index and online review have a better prediction effect.

In order to compare whether there are significant differences in the prediction accuracy of the above three models, this paper uses the method proposed by Diebold and Mariano(2002) to carry out DM test on the out-of-sample prediction results[26]. The results are shown in table6.

Table 6 DM test results

ModelA	ModelB	MAPE(ModelB)-MAPE(ModelA)
Online reviews model	Web search index model	-0.0055
Combined model	Web search index model	-0.0118**
Combined model	Online reviews model	-0.0173***

"*", "**" and "***" mean significant at 10%, 5% and 1% respectively.

It can be seen from table6 that the combined model based on online review and web search index has the best prediction effect, which is significantly better than the online review model and web search index model at the significant level of 5%. On the basis of the prediction model based on the online review data, the accuracy of the prediction can be improved by 1.7% by adding the web search data, indicating that the web search data contains other important information not included in the online review. At the same time, it can be seen from table6 that compared with the online review prediction model, the prediction model based on web search index data has achieved an improvement of 0.05%. However, this difference is not statistically significant, that is, the prediction performance of the model based on web search data can be comparable to that of the model based on online review data.

5. Conclusion

This study enhances existing research on box office prediction by examining the decision-making process of consumers regarding movie-watching, and investigating the interaction between online reviews and search trend data from social media platforms. The empirical findings indicate that both online reviews and web search indices can accurately predict box office revenues. The research reveals several key points:

1. The predictive accuracy achieved using web search data can match that of models using online reviews. When timely information from online reviews is difficult to obtain, search trend data can serve as a cost-effective alternative, offering a more accessible method for box office forecasting and decision support.

2. Expanding box office prediction models to include web search indices alongside online reviews significantly improves prediction accuracy. It is recommended that companies already investing in reviews-based prediction data also collect low-cost web search data to enhance prediction accuracy.

3. Cinema managers should actively monitor online review information, promoting various forms of word-of-mouth communication among users to leverage word-of-mouth awareness. Post-premiere, managers should focus on monitoring and responding to the sentiments expressed in word-of-mouth communications to encourage positive reviews.

The study acknowledges certain limitations. Specifically, it uses consumer digital ratings as the measure of online reviews and does not conduct sentiment analysis on the textual content of film reviews. Future research could include sentiment analysis to explore the impact of word-of-mouth further. Additionally, while this study utilizes Douban film reviews and web search indices, future research could incorporate review data from platforms such as Weibo, blogs, and other forums to broaden the scope of analysis.

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