A Deep Learning Approach to Predict Film Box Office in the Chinese Domestic Market Based on Feed-Forward Neural Network

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Abstract. With the booming development of the Chinese film market, China has become the world's second-largest film market and the main engine for industry development. In order to improve the efficiency and predictive power of movie box office prediction in the Chinese domestic market, this study proposes a Feed-Forward Neural Networks model with two and three hidden layers by predicting the box office of 478 films in the Chinese market from 2019 to 2022 using movie metadata, post-release rating data, social media related big data and theaters arrangement. Loss curves for the training and validation sets are presented for model comparison with 400 films being used as the training set and 78 films being used as the validation set. The results show that the Feed-Forward Neural Network with three hidden layers has greater fitting and predictive power in model generation, enabling it to effectively predict the movie box office.

Keywords: Box office prediction, Neural Network, Chinese market.

1 Introduction

As one of the most important components of the cultural industry, the motion picture industry has brought enormous economic and social benefits. The cumulative global box office in 2023 exceeded $10 billion in May and the cumulative box office in Mainland China ranked as the world box office champion. The Chinese film market provides positive signals for the recovery of the global film industry and will also inject strong momentum into the development of the film industry. Box office revenue is a crucial indicator for measuring the market value of movie consumption [1]. Beyond its impact on the film itself, the box office also has a strong guiding effect on the pricing of film products and the development of derivative products. Therefore, it is of vital importance to analyze and forecast the box office to assist film investment and scheduling. The box office forecasting system can access and predict the box office and has become a significant reference tool for investment and financing in the international movie industry.

Digital technology has infiltrated the industry chain of motion pictures from production to sales with the rapid development of big data and computer science, including algorithms for online distribution, audience preference analysis, and box office prediction. Recently, there has been a steady increase in the body of literature employing deep learning approaches to predict movie performance. The application of deep learning significantly increases the accuracy of relevant

ICBBEM 2023, May 19-21, Hangzhou, People's Republic of China

DOI 10.4108/eai.19-5-2023.2334363

predictions. Increased accuracy in forecasting box office is beneficial for encouraging production, market investment, and wise use of public funds in the film industry, as well as advancing social welfare and cultural prosperity [2]. However, many studies have been carried out based on Western markets throughout the history of global box office research, for instance, more than half of box office predictions made using machine learning are based on the U.S. market, but only 20 percent on the domestic Chinese market[3]. Compared to the already mature North American film market, box office production in the Chinese market is more challenging. Firstly, the development of the motion picture industry in the Chinese market is relatively late, and box office research is not as mature as in Western countries. Secondly, since the Chinese film industry has grown rapidly over the last few decades, it has become the centerpiece of the country's cultural convergence between media and culture [4], power of social media is unique. Thus, research into the Chinese market is urgently needed.

In this research, we present the development of a model based on a Feed-Forward Neural Network for predicting movie box office in the Chinese market from 2019 to 2022 using movie metadata and big data related to social media on the first day and opening week of release. The Feed-Forward Neural Networks with two hidden layers and three hidden layers were adept at dealing with a wide range of data categories.

2 Related Research

2.1 Research on Movie Box Office Prediction

Despite the fact that predicting the movie box office business is considered exceptionally challenging, several studies have attempted to come up with approaches that can forecast the movie box office. Building computational models such as Neural Networks and Support Vector Machine for exploring correlations between movie-related elements has proven to be particularly effective. While predicting a movie's box office before the launch date, building a model based on a Dynamic Artificial Neural Network (DAN2) with production costs, pre-release marketing expenditures, run time, and seasonality added to the predictive factors, the accuracy could reach 90% [5]. To tackle time series, an end-to-end Deep Neural Network for box office prediction on a daily basis considering both the temporal component and the static attribute component has been proposed by researchers, the structure of this model can effectively deal with prediction problems regarding time series with lower prediction errors [6]. The features that can influence the movie box office have also been explored in past research. The relationship between the movie poster and the box office was explored using the Inception-V3 model and reached an accuracy of 33% [7]. In addition to movie posters, the audiences` reaction was also tested by emotion recognition which can classify up to seven different emotions, researchers successfully predicted movie ratings [8]. With the development of Big Data, using big data to predict a movie's box office has been proven effective[9].

2.2 Research on Feed-Forward Neural Network

Over the past few years, there has been an increased interest in examining the idea of deep learning approaches and how well they perform on advanced forecasting tasks in a wide range of industries, such as stock trends [9] and disease diagnoses [11] in the financial and medical fields, respectively. Among these topics, scenario forecasting, or the study of the influence of the input parameters of the model on its output parameters, has a specific place. Scenario prediction allows people to predict how the simulated object will perform in the future and how it might be modified to get closer to the intended result [12]. For scenario prediction, or what we normally call prediction, Neural Networks have been wildly adapted for decades due to their effectiveness in validation and implementation [13]. Neural Networks were first used in box office forecasting in 2006 [14]. Subsequently, it has been used more intensively in this field of prediction and much research has since innovated this approach, such as Artificial Neural Networks. Artificial Neural Networks (ANN) are networks of simple processing units (referred to as 'neurons') that operate on raw data and interact with other elements. The nodes in the graph are artificial neurons, and the directed edges are connections between the input and output layers of neurons. Multi-Layer Feed-Forward (MLF) Neural Networks are the most popular among Neural Networks [15], and the accuracy is higher than other common methods. The support vector machine was commonly employed to forecast box office success, accounting for 21.74% of total frequency contribution, followed by linear regression accounting for 17.39% of the total frequency contribution [16]. However, the prediction accuracy using Neural Network is higher than Support Vector Machine based on both pre-release and post-release features [17].

2.3 Summary of Past Work

Movie box office prediction is an intricate and critical task for studios, film distributors, and marketing staff in their decision-making process. Existing research has attempted to find different mechanisms and ways to reliably predict box office[18]. While past attempts have yielded important findings and improved accuracy, some limitations are hard to ignore. First, variable diversity is limited because many models consider only six or seven features and lack the application of Big Data. Second, most research is based on the already mature Western market. Attention to a fast-growing market like China is not enough. Third, some studies only consider pre-release variables, lacking predictive studies that combine pre- and post-release data with a limited time gap. Last but not least, the models of some studies are far more complex, resulting in limited practicality. Therefore, a practical prediction model based on the Chinese market with various variables, including Big Data, is urgently needed.

3 Methodology

3.1 Sample Collection

The purpose of this study was to find a suitable model for forecasting the movie box office in the Chinese market. A Multi-Layer Feed-Forward (MLF) Neural Network for movie box office production was created to accomplish this. Since movie metadata and social media-related data are abundant as big data development progresses, sample and feature collection should be carefully considered. This paper selects Chinese cinema box office data for the four-year period from 2019 to 2022, which has strong timeliness and applicability compared to other existing movie box office forecasting models. Data sources for this study are well-known film websites including Maoyan, Taopiaopiao, and Dengta professional databases. As for social media data, we mainly collected data from Sina Weibo, Wechat, Tiktok, and Bilibili. These platforms' data were manually checked for unit and text errors as well as data cleaning during the transmission process to remove duplicate, incorrect, and missing data. A total of 478 films were indexed.

3.2 Feature Description

In this session, feature selection and description are discussed. Previous research has comprehensively explored the impact of multiple factors on movie box office, providing guidance for identifying movie-related statistics. The current study builds on previous studies by using traditional pre-release movie characteristics such as genre, sequel, star rating, and budget along with post-release movie theater scheduling data and social media-related characteristics including the number of Likes and Shares on Weibo.

Genre. The film genre conveys crucial information about a film, and genres are often used as explanatory variables in box office forecasting [19]. Based on the introduction page of each film on Dengta Professional APP, our study included 9 genres: Animation, Drama, Comedy, Romance, Horror, Science Fiction, Action, Documentary, and War.

Sequel. When developing box office forecasts, it is critical to take sequels into account because sequels have a unique place in the motion picture business since they are connected with the original film. Studies have shown that reviews and ratings of the original film have a direct impact on the performance of the sequel [20], and many sequels have a marketing advantage with a reputation built up by the film's predecessor.

Special Effect. In our model, we considered the special effects of a film. The same movie presented in 2D, 3D, and IMAX formats will bring a distinct experience to consumers. As a typical experience product, the film's projection conditions, and technology are very important.

Country of Production. Because the development of the film industry varies by country, film-producing countries have a strong association with the box office [21]. Since we are targeting films released in the Chinese market, we keep track of each film's country of production in our model.

Budget. The production budget of a film is seen as a significant indicator of box office revenues frequently used in film-related studies [22]. If a film has a greater expenditure on production, it has a better chance of gaining popularity through publicity. As a result, films with a larger budget have a better chance of earning more money.

Star Power. Numerous previous studies have been conducted to assess whether a film's star power has a beneficial impact on box office profits. The study found that Star Power is beneficial to a movie's box office, and stars are estimated to be worth about $3 million in movie ticket sales on average [23]. However, evidence from China tells a different story. Studies in the Chinese market show that the celebrity power of actors has a direct negative impact on the financial success of films, while estimates of log-linear parameters reveal that directors have a significant positive effect on the commercial success of Chinese films. Final estimates confirm that the overall effect of celebrity power on Chinese box office sales is positive and substantial [24]. Therefore, based on previous research [25], we considered both the effects of actors and directors by collecting the number of awards, followers, and each other's Internet search data (Baidu index) into our model.

Social Media Buzz. The impact of social media buzz on the movie box office has long been discussed, especially for the high efficiency and social impact as a marketing medium [26]. Interestingly, the impacts of Earned Social Media (ESM) and Own Social Media (OSE) proved to be different and box office revenues reacted faster to ESM than to OSM, and the response to

OSM persisted longer[27]. In this paper, we considered both ESM and OSE. For ESM, we collected Weibo topic discussion volume and Weibo topic reading volume, TOP 3 Bilibili video reading volume and Tiktok Topic Screaming volume. For OSE, we collected the number of followers, likes, forwards and reviews on Sino Weibo at the end of the first week, TOP 3 reading volumes of Wechat posts, Reading Volume of official materials. In addition, films released on the Chinese market have detailed information about social media buzz in Dengta Professional APP. In this study, we considered the big data relating to social media on launch day and the first week. We keep a record of the Internet search data (Baidu index) of the released day together with the bid data from social media, including the number of people registered excited about the movie, the news buzz of the movie, the buzz on Weibo, Weixin, Tiktok, the number of searches on major search engines, the buzz created by the movie trailer and Popcorn Index.

First-week box office and ratings. According to studies [28], the first two weeks of revenue account for 25% of a film's overall earnings. Thus, the total ticket sales of a particular film can be predicted with a high degree of accuracy once the first week's box office is available. In addition, film ratings and critics' reviews have a great impact on the box office and are critical performance predictions [29]. In our study, we collected ratings and the number of raters from Maoyan, Taopiaopiao, and Douban for the first week.

Movie theaters’ arrangement. Movie theaters’ arrangement is an important factor for the box office[30]. We collected data on the number of screens in the first week. In addition, we also collected audience numbers, prime screens, screening ratio, and prime screening ratio.

Soundtrack. The movie soundtrack has not received enough attention as an indicator of the movie box office; however, researchers have found that the soundtrack can affect movie ratings by genre and feature [31]. In addition, the search volume and originality of the soundtrack could also affect movie revenues [32]. In our study, we want to explore more possibilities of how movie soundtrack influences the box office, so we use music promotion data in our model.

3.3 Data Preparation

Data is collected, cleaned, and processed before being converted into a tensor format for model training. Before building our neural network, we first preprocess our data by initializing and regularizing our selected features, containing both the training and validation sets. Two datasets are required for prediction using MLF Neural Network, one for training and one for prediction. In our study, data from 400 movies are used for model training, and data from 78 movies are used for final prediction. In our final prediction mode, movie information flows forward through the network, from inputs, original data, to outputs, estimated box office, by continuously optimizing the weighting coefficient of each data. The network works on one movie at a time, estimating the box office based on our input values, and data from our selected features.

3.4 Model Build Up

Our model was built using PyTorch. Following a previous study based on the Chinese market [33], our model construction proceeded in the following steps.

Determine input and output. Since there are 96 labels in the data, the size of the model input layer is 96, the size of the hidden layer is 97, and the size of the output layer is 1, which is the tensor of the calculated box office.

Determine the activation function and the learning function. The activation function between layers uses ReLU function, and the learning function is linear(). To ensure the suitability of the model for all film genres, this study did not select top box office films as the test set as in previous studies, but randomly selected the first 400 films as the training set and the last 78 films as the test set. And the parameters of the model are tuned by a feed-forward algorithm to minimize the loss function.

Decide the number of hidden layers and nodes. Discretized movie box office profits are used to train this network. And training can be done separately for each input data modality. The number of parameters increases with the size of the hidden layer nodes, too few hidden layer nodes will lead to a network that cannot fully learn and remember the feature information of the dataset, too many will lead to too many parameters leading to higher training costs of the network, and may also lead to overfitting, so a suitable number of hidden layer nodes should be selected. Plotting the model's loss curve is of vital importance since it visually demonstrates the accuracy of the model. When the loss curves of the training and validation sets tend to be flat and close, we assume that the model has sufficiently learned the feature information of the entire dataset after several training Epochs. In our study, we tried to build a Multi-Layer Feed-Forward (MLF) Neural Network with two hidden layers using Scale to normalize all features and Unsqueeze to increase the dimensionality of the Label column to two dimensions, the same dimensionality to be trained in the model. As can be seen from **Figure 1. [1]**, when building a Multi-Layer Feed-Forward (MLF) Neural Network with two hidden layers, we need 170 epochs.

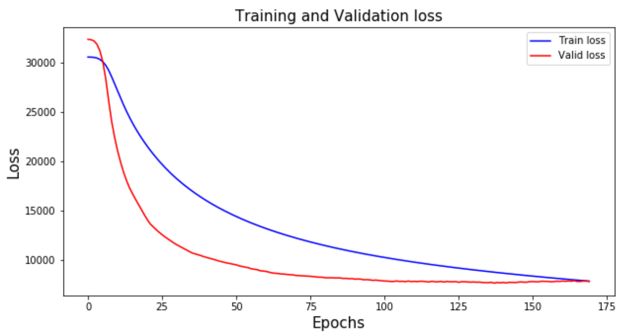

Fig. 1. Loss curve for Feed-Forward Neural Networks with 2 hidden layers.

Set the learning rate, expected error and training times. The learning rate is set at 0.01, the expected error is 0.001, and the maximum number of training times is 5000. A parameter reset function is defined to ensure that training starts from zero each time the loop re-executes. After all the steps, model simulation can be performed.

3.5 Model Testing

In our study, the trained model is tested, and the model can be validated with a test dataset to avoid overfitting. The final MSE is calculated on the validation set. The resulting error is used to estimate the predicted quality of the trained network. Finally, the Scattergram of predicted and actual values is constructed. Since each time before training the model, the training and validation sets are selected in a disordered order and then trained, the results of the curves and Scattergrams drawn after each code execution will be different, and the closer the positions of both Prediction and Ground Truth are, the more the model can correctly predict the box office of the validation set data.

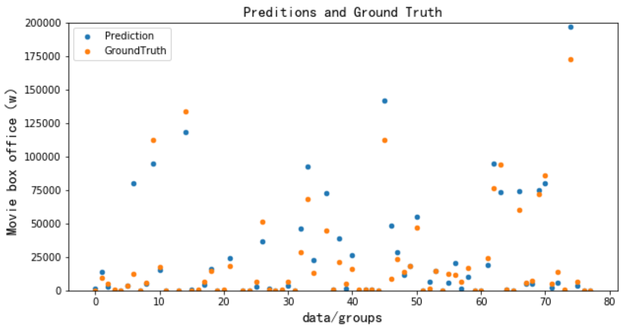

Fig. 2. Scattergram of predicted and actual box office with 2 hidden layers.

From **Figure 2. [2]** above, the model produces excellent prediction outcome in both training and testing sets. To better explore simulation fitting degree, we also built a Feed-Forward Neural Network with three hidden layers, hoping to find the best model to predict movie box office. We repeated the steps above and changed the epochs to 65 to fit our new model based on **Figure 3. [3]**. And the final Scattergram as in **Figure 4. [4]** represents better prediction accuracy.

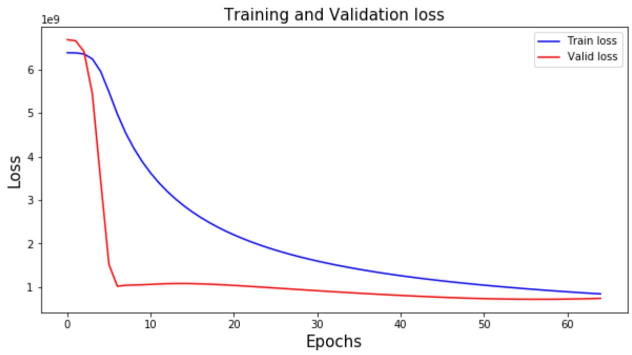

Fig. 3. Loss curve for Feed-Forward Neural Networks with 3 hidden layers.

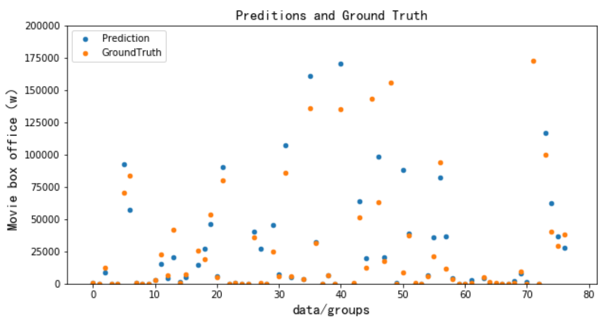

Fig. 4. Scattergram of predicted and actual box office with 3 hidden layers.

4 Results

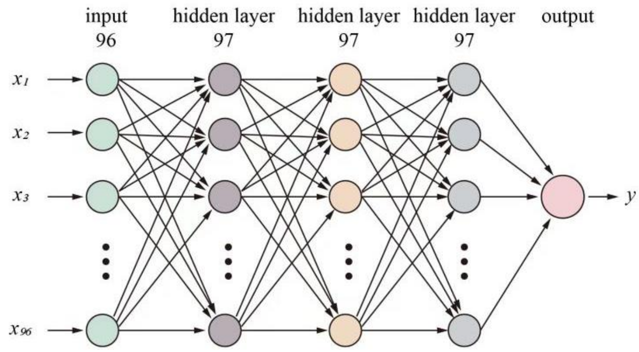

Fig. 5. Feed-Forward Neural Networks with 3 hidden layers

There are two main approaches in the current research on how to confirm the merits of the model. The first is turning the prediction problem into a classification problem. Instead of predicting an estimated number of box office revenues, a film is classified according to its box office revenue into one of several categories, ranging from a "flop" to a "blockbuster." Predictive accuracy could be easily calculated by how many predictions fall into the right category. Another way is to explore how well the predicted results fit the actual box office and quantify modeling accuracy using mean squared error (MSE) in relation to a random input distribution. In our study, we choose the latter to determine accuracy. By comparing the loss curves, it was discovered that the model with three hidden layers, as shown in **Figure 5. [5]** was better in terms of prediction, because the validation loss had leveled off by less than the 10th epochs which is significantly less than that of two hidden layers. The scattergrams also support our findings.

5 Discussion and Conclusion

The main goal of the current study was to find new models for movie box office prediction with a Deep Learning approach. In our research, we have tested movie box office prediction model using Feed-Forward Neural Networks with 2 and 3 hidden layers, respectively. By drawing the Training and Validation loss curve and scattergrams on prediction and movies' actual box office, we can conclude that when predicting movie box office massive social media big data, using Feed-Forward Neural Networks with 3 hidden layers represents the best curve fitting.

The finding of this study expands our understanding of features that could influence a film`s box office in Big Data Era. Besides, given that our model is stable, accurate, and efficient, it can be applied to investigating prediction problems in economic performance in the entertainment industry, cognitive science, and other domains. Our research unveils novel possibilities for box office forecasts for those in the movie industry. Since the forecast can be done one week after the release, the filmmakers and movie studios can quickly adjust marketing strategies based on the forecast results and achieve better market performance in the fast-developing Chinese market.

However, our research also faces some limitations. The major limitation of the present study is the limited sample size, since we only have 478 movies in total, future research could be built upon a larger sample size with a greater time leap. In addition, the data used in our research are selected based on previous studies, and each variable used could lack a more in-depth measurement of the proportion since we choose more than one data for one specific feature. Thus, considerably more work will need to be done to weigh the proportion of variables for the selected feature.

References

[1] He, Q., & Hu, B. (2021). Research on the influencing factors of film consumption and box office forecast in the digital era: based on the perspective of machine learning and model integration. Wireless Communications and Mobile Computing, 2021, 1-10. https://doi.org/10.1155/2021/6094924.

[2] Wang, D., Wu, Y., Gu, C., Wang, Y., Zhu, X., Zhou, W., & Lin, X. M. (2022). A movie box office revenues prediction algorithm based on human-machine collaboration feature processing. Journal of Engineering Research. https://doi.org/10.36909/jer.ICCSCT.19489.

[3] Ahmad, I. S., Bakar, A. A., Yaakub, M. R., & Muhammad, S. H. (2020). A survey on machine learning techniques in movie revenue prediction. SN Computer Science, 1, 1-14. https://doi.org/10.1007/s42979-020-00249-1.

[4] Leung, W. F., & Lee, S. (2019). The Chinese film industry: Emerging debates. Journal of Chinese Cinemas, 13(3), 199-201. https://doi.org/10.1080/17508061.2019.1678235.

[5] Ghiassi, M., Lio, D., & Moon, B. (2015). Pre-production forecasting of movie revenues with a dynamic artificial neural network. Expert Systems with Applications, 42(6), 3176-3193. https://doi.org/10.1016/j.eswa.2014.11.022.

[6] Ru, Y., Li, B., Liu, J., & Chai, J. (2018). An effective daily box office prediction model based on deep neural networks. Cognitive Systems Research, 52, 182-191. https://doi.org/10.1016/j.cogsys.2018.06.018.

[7] Özkan, O. N. Atak and Ş. Işik. (2018). Using movie posters for prediction of box-office revenue with deep learning approach. In: 2018 26th Signal Processing and Communications Applications Conference (SIU). Izmir. pp. 1-4. https://doi.org/10.1109/SIU.2018.8404649.

[8] Shetty, C., Khan, A., Singh, T., & Kharatmol, K. (2021). Movie review prediction system by real time analysis of facial expression. In: 2021 6th International Conference on Communication and Electronics Systems (ICCES). Coimbatre. pp. 1109-1113. https://doi.org/10.1109/ICCES51350.2021.9489171.

[9] Wang, Z., Zhang, J., Ji, S., Meng, C., Li, T., & Zheng, Y. (2020). Predicting and ranking box office revenue of movies based on big data. Information Fusion, 60, 25-40. https://doi.org/10.1016/j.inffus.2020.02.002.

[10] Singh, R., & Srivastava, S. (2017). Stock prediction using deep learning. Multimedia Tools and Applications, 76, 18569-18584. https://doi.org/10.1007/s11042-016-4159-7.

[11] Xu, J., Xue, K., & Zhang, K. (2019). Current status and future trends of clinical diagnoses via image-based deep learning. Theranostics, 9(25), 7556.

[12] Yasnitsky, L. N., Mitrofanov, I. A., & Immis, M. V. (2020). Intelligent system for prediction box office of the film. In: Integrated Science in Digital Age: ICIS 2019. Munich. pp. 18-25. https://doi.org/10.1007/978-3-030-22493-6_3.

[13] Adya, M., & Collopy, F. (1998). How effective are neural networks at forecasting and prediction? A review and evaluation. Journal of forecasting, 17(5-6), 481-495. https://doi.org/10.1002/(SICI)1099-131X(1998090)17:5/6<481::AID-FOR709>3.0.CO;2-Q.

[14] Sharda, R., & Delen, D. (2006). Predicting box-office success of motion pictures with neural networks. Expert Systems with Applications, 30(2), 243-254. https://doi.org/10.1016/j.eswa.2005.07.018.

[15] Svozil, D., Kvasnicka, V., & Pospichal, J. (1997). Introduction to multi-layer feed-forward neural networks. Chemometrics and intelligent laboratory systems, 39(1), 43-62. https://doi.org/10.1016/S0169-7439(97)00061-0.

[16] Mbunge, E., Fashoto, S. G., & Bimha, H. (2022). Prediction of box-office success: A review of trends and machine learning computational models. International Journal of Business Intelligence and Data Mining, 20(2), 192-207. https://doi.org/10.1504/IJBIDM.2022.120825.

[17] Quader, M. O. Gani, D. Chaki and M. H. Ali (2017). A machine learning approach to predict movie box-office success. In: 2017 20th International Conference of Computer and Information Technology (ICCIT), Dhaka. pp. 1-7. https://doi.org/10.1109/ICCITECHN.2017.8281839.

[18] Rhee, T. G., & Zulkernine, F. (2016). Predicting movie box office profitability: a neural network approach. In: 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA). Anaheim. pp. 665-670. https://doi: 10.1109/ICMLA.2016.0117.

[19] Ma, H., Kim, J. M., & Lee, E. (2020). A 2020 perspective on “Analyzing dynamic review manipulation and its impact on movie box office revenue”. Electronic Commerce Research and Applications, 41, 100950. https://doi.org/10.1016/j.elerap.2020.100950.

[20] Belvaux, B., & Mencarelli, R. (2021). Prevision model and empirical test of box office results for sequels. Journal of Business Research, 130, 38-48. https://doi.org/10.1016/j.jbusres.2021.03.008.

[21] Z. Zhang, B. Li, Z. Deng, J. Chai, Y. Wang and M. An. (2015). Research on Movie Box Office Forecasting Based on Internet Data. In: 2015 8th International Symposium on Computational Intelligence and Design (ISCID). Hangzhou. pp. 83-86. https://doi.org/10.1109/ISCID.2015.228.

[22] Wasserman, M., Mukherjee, S., Scott, K., Zeng, X. H. T., Radicchi, F., & Amaral, L. A. (2015). Correlations between user voting data, budget, and box office for films in the internet movie database. Journal of the Association for Information Science and Technology, 66(4), 858-868. https://doi.org/10.1002/asi.23213.

[23] Elberse, A. (2007). The power of stars: Do star actors drive the success of movies?. Journal of marketing, 71(4), 102-120. https://doi.org/10.1509/jmkg.71.4.102.

[24] Peng, F., Kang, L., Anwar, S., & Li, X. (2019). Star power and box office revenues: evidence from China. Journal of Cultural Economics, 43(2), 247-278. https://doi.org/10.1007/s10824-018-9338-0.

[25] Karniouchina E V. Impact of star and movie buzz on motion picture distribution and box office revenue[J]. International Journal of Research in Marketing, 2011, 28(1): 62-74. https://doi.org/10.1016/j.ijresmar.2010.10.001.

[26] Ding, C., Cheng, H. K., Duan, Y., & Jin, Y. (2017). The power of the “like” button: The impact of social media on box office. Decision Support Systems, 94, 77-84. https://doi.org/10.1016/j.dss.2016.11.002.

[27] Feng, N., Shi, Y., Li, Y., Li, D., Zhang, J., & Li, M. (2023). An Exploration of the Dynamics Between Social Media and Box Office Performance. Information Systems Frontiers, 1-18. https://doi.org/10.1007/s10796-023-10389-3.

[28] Litman, B. R., & Kohl, L. S. (1989). Predicting financial success of motion pictures: The'80s experience. Journal of Media Economics, 2(2), 35-50. https://doi.org/10.1080/08997768909358184.

[29] Hu, Y. H., Shiau, W. M., Shih, S. P., & Chen, C. J. (2018). Considering online consumer reviews to predict movie box-office performance between the years 2009 and 2014 in the US. The Electronic Library. https://doi.org/10.1108/EL-02-2018-0040.

[30] Sochay, S., & Litman, B. (1992). Export markets and the US motion picture industry. Journal of Media Economics, 5(3), 31-55. https://doi.org/10.1080/08997769209358226.

[31] Gillick, J., & Bamman, D. (2018). Telling stories with soundtracks: an empirical analysis of music in film. In: Proceedings of the First Workshop on Storytelling. New Orleans. pp. 33-42. https://doi.org/10.18653/v1/W18-1504.

[32] Xu, H., & Goonawardene, N. (2014). Does movie soundtrack matter? the role of soundtrack in predicting movie revenue. In: PACIS 2014 Proceedings. Taiyuan. Pp. 350.https://aisel.aisnet.org/pacis2014/350.

[33] Dai, D., & Chen, J. (2021). Research on mathematical model of box office forecast through BP neural network and big data technology. In: Journal of Physics: Conference Series. IOP Publishing. Kunming. pp. 042118. https://doi.org/10.1088/1742-6596/1952/4/042118.