

Social Network Analysis of the Professional Community Interaction - Movie Industry Case

Iliia Karpov¹[0000-0002-8106-9426] and Roman Marakulin¹[0000-0003-0738-1267]

Higher School of Economics, Moscow, Russia {karpovilia,marakromrom}@gmail.com

Abstract. With the rise of the competition in the movie production market, because of new players such as Netflix, Hulu, HBO Max, and Amazon Prime, whose primary goal is producing a large amount of exclusive content in order to gain a competitive advantage, it is extremely important to minimize the number of unsuccessful titles. This paper focuses on new approaches to predict film success, based on the movie industry community structure, and highlights the role of the casting director in movie success. Based on publicly available data we create an “actor”-“casting director”-“talent agent” - “director” communication graph and show that usage of additional knowledge leads to better movie rating prediction.

Keywords: Social Network Analysis · Movie Rating · Machine Learning · Prediction · IMDb · Node2Vec

1 Introduction

The movie industry is undergoing significant changes. Online streaming platforms such as Netflix, HBO Max, Hulu, Disney Plus, Amazon Prime and others, have become extremely popular. The main goal of these platforms is to get as many recurrent users as possible by creating exclusive titles that are only available on one of the platforms, and the amount of content will increase rapidly over the next few years and competition between movie producers will become more fierce.

In order to produce greater amounts of movie titles, producers must invest more in production, considering that it is an extremely risky and expensive type of investment. Media companies or streaming platforms are eager to minimize the number of unsuccessful titles because they will lose their competitive advantage, and lose their market share. This leads to new models and approaches to the estimation of future success of a movie based on the data that is available before a company invests in a project

Traditional solutions classify a future title’s success based on statistical information like budget, genre, duration, and so on. The movie industry seems to be quite a close community where a lot of people interact with each other by taking part in similar projects or having the same talent agents – the people who find jobs for an actor and process the incoming offers. To the best of our knowledge, there are no specific approaches to predict movie success when taking into

account the information about title principals and their position in the movie industry community. Those features seem to be important because it may be useful to have a casting director who has authority in the movie community and will more likely be able to gather the best cast that will lead a movie to success. However, success may be considered in different ways: academy award, earnings, and rating. In this study, success will be measured by movie ratings taken from IMDb, because awards are often given to movies that meet the current public agenda. Earning strongly depends on marketing spending and brand popularity, for example “The Avengers: End Game” had a \$200 million marketing budget with an extremely popular brand and 220 million production budget that led to \$1.6 billion in box office revenue.

The main contributions of the paper are the following:

- We propose a joint dataset that incorporates statistical and social network data from three different sources. To the best of our knowledge, this is the first dataset that takes into account social contacts of casting directors and talent agents.
- We study the network structure of the movie community and use the obtained information to predict the future success of a movie title. Our experiment shows that social network information can improve classification accuracy from 4 to 6 % depending on the classification method
- We find out that a casting director is more important than actors in terms of feature importance for the film rating. This leads to the opportunity of predicting the movie’s success at an early stage when actors are not even approved for the role.

The rest of this paper proceeds as follows. Section 2 contains an overview of the previous studies regarding movie community analysis and a titles’ rating prediction. Section 3 describes the obtained dataset. The 4-th Section contains the details of the movie community graph generation and description. Section 5 is devoted to a movie success classification model, and the conclusion is expressed in 6 Section.

2 Related work

In this chapter, previous studies related to graph-based movies analysis and its success prediction are observed.

Michael T. Lash and Kang Zhao [1] were focused on feature engineering that allowed them to predict the success of a movie more accurately. They built a model that classified movies into 2 groups depending on ROI. As a result, they have achieved a ROC-AUC 0.8-0.9. The data sample contained 14,097 films with 4,420 actors. The independent variables were mainly monetary, for example, the average profit of films for the period, how much the actors earn on average from a film, etc. The social network analysis was used to extract indications of the interactions between actors and directors and use it as features in a classification model.

The authors of the paper “We Don’t Need Another Hero - Implications from Network Structure and Resource Commitment for Movie Performance”, have made a similar work [2]. They used common movie attributes such as year, budget, and etc. Also, they used SNA methods to extract features about the interactions between actors in movies, for example, the normalized number of contacts of a given film’s crew with teams from other movies.

Krushikanth R. Apala and others [3] collected data from social networks, such as comments on trailers on YouTube, the popularity of actors on their Twitter pages and so on, and predicted the success of the film in terms of money. As the main result, they showed that the popularity of the actors is a very important factor in the success of a film.

Bristi, Warda Ruheen, Zakia Zaman, and Nishat Sultana [4] have been trying to improve IMDb rating prediction models using five different machine learning approaches: bagging and random forest classifiers, decision tree classifier, KNearest Neighbours and Naïve Bayes classifiers. Also, the researchers divided movie titles into classes based on their IMDb rating (Figure 5), making it a dependent variable for classifiers. In order to handle class imbalance, authors used the Synthetic Minority Oversampling Technique (SMOTE) algorithm which balances classes by taking random observations from datasets that are close in feature space, and generating new samples by linear interpolation between selected data records. Also, the researchers used resampling. As a result, they achieved a 99.23 accuracy metric using random forest. However, there were only 274 movie titles in the dataset and the results were provided for a training dataset only.

Another attempt to predict IMDb scores was taken by Rudy Aditya Abarja and Antoni Wibowo in their article “Movie Rating Prediction using Convolutional Neural Network based on Historical Values” [5]. The main idea of the article is to implement Convolutional Neural Network (CNN) to predict a movie’s IMDb rating. Authors utilized the IMDb movie data from Kaggle which contained historical features, such as average movies rating by director, an actor’s average movie rating, average genre rating and so on. Also, some metadata features, such as budget, duration and release date, were used. As a result, the researchers achieved 0.83 MAE, which is 0.11 better than the best baseline model with 0.94 MAE. Also, Ning, X., Yac, L., Wang, X., Benatallah, B., Dong, M., & Zhang, S showed [6] that deep learning models outperform classical machine learning baselines on the IMDb datasets.

3 Dataset Exploration

In this paper we use joint features from several publicly available databases. The first part of the dataset was obtained from the official IMDb web page which provides the following information: title name, language, production year, duration in minutes, genre, director name, writer name, film crew, including persons primary profession, name, and date of birth, IMDb rating, and number of votes. The second part of the dataset is from the Rotten Tomatoes database that adds information about a movie statistic, such as tomatometer rating, number of

votes, number of positive votes, and number of negative votes. This information is used as the retrospective data about a film crew’s previous projects. The third part of the dataset is IMDb Pro – an extension to IMDb that contains more complete information about people in the movie industry, for example, talent agent contacts, filmography with current status for every movie, his earning from a movie title, extended biography, and some ratings such a STARMeter and number of news articles, which shows how popular an actor is. The data about his talent agent’s contact allows to make a connection between an actor and a talent agent. The combined dataset contains information about 85,855 movie titles.

Based on this data the following features were extracted:

- Country in which a movie has been produced;
- Genre of a movie title, for example, horror or drama;
- Title, that is the name of the title and its IMDb ID;
- Type of production, for example, movie or series;
- Year a movie title has been produced;
- Duration, that is a movie title runtime in minutes;
- Primary language of the movie/series;
- Movie crew, that is actors’ names and their IMDb IDs, director name and IMDb ID
- IMDb user rating;
- Number of votes;
- Metascore user rating;
- Number of reviews from critics and users on IMDb;
- Budget of a movie that has been spent on production;
- Income, that is gross income worldwide;
- User rating on RottenTomatoes;
- Age rating (PG, PG-13 and etc.)

Most of the budget, USA gross income, metascore, and worldwide gross income values are missing.

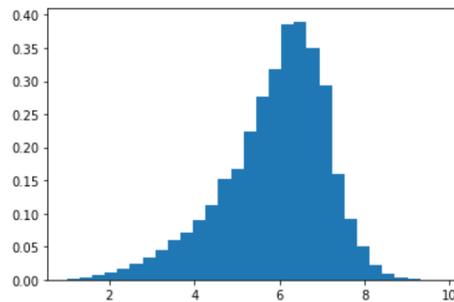


Fig. 1. IMDb rating distribution

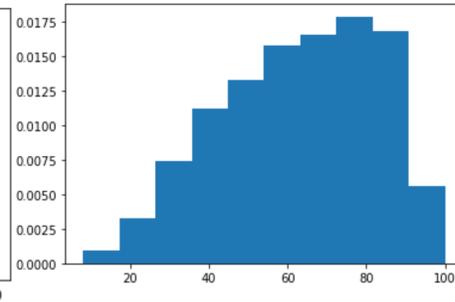


Fig. 2. RottenTomatoes user rating distribution

IMDb score distribution is left skewed but quite close to normal 1 There is no need to try to make the distribution normal, because in this research the classification problem is considered, so the IMDb scores will be divided into the following four intervals: 0-3, 4-5, 6-7, 8-10. Rotten Tomatoes users more often rate films with a lower number of points (Figure 2), making the distribution quite close to the IMDb rating distribution.

As can be seen in Figure 3, the IMDb score does not heavily depend on genre. Only adult, horror, and sci-fi movies have significantly lower average IMDb scores, however, these genres make a small portion, around 1%, of all records. Also, it can be noted that documentary movies have a better average IMDb rating, which is probably because these movies are usually filmed specifically for smaller groups of people, for example, the National Geographic fans, and they are not often presented in cinemas or featured on Netflix and other streaming platforms. Because of this, they hold a small portion of observations in the dataset.

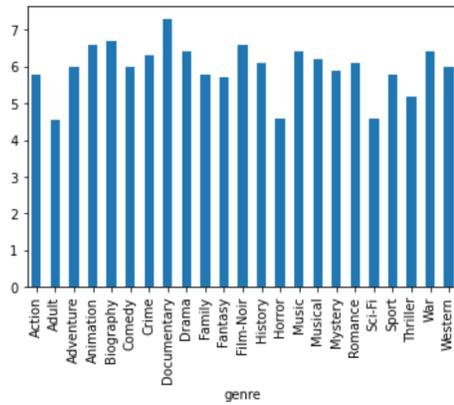


Fig. 3. IMDb rating among genres

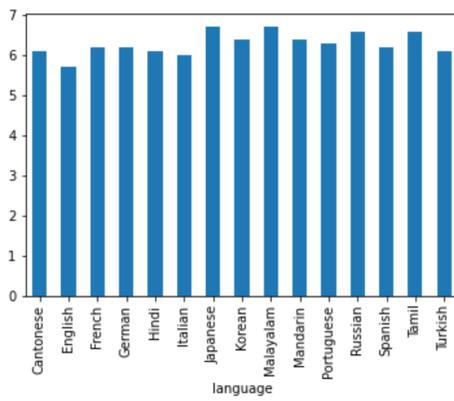


Fig. 4. IMDb rating among languages

Language also does not have a significant influence on the IMDb score (Figure 4), which is quite obvious and leads to the intuition that it does not matter where a movie was produced, and if it is good, it gets high rating, if it is bad, it gets low rating. Most of the movie titles have English, French, Spanish and Japanese as primary languages.

4 Network Model

4.1 Graph Generation

In order to analyze the movie industry community, it should be presented in the form of a directed graph by the following rules:

- Actors, directors, casting directors and talent agents are nodes;
- Actor – actor link appears when two actors mutually take part in a movie title, the link is bidirectional;
- Actor – director link appears when an actor and director mutually take part in a movie title as actor and director respectively,. The direction of the link comes from director to actor, because a director approves an actor for the role in a movie;
- Actor – talent agent link appears when an actor is the client of a talent agent,. The direction is from actor to talent agent, because agents work for actors, assigning them to roles and castings;
- Actor – casting director link appears when an actor and casting director mutually take part in a title, as actor and casting director respectively. The direction is from casting director to actor because casting directors find actors who would fit a role;
- Director – casting director link appears when director and casting director mutually take part in a movie title as director and as casting director respectively. The direction is from director to casting director because director approval is required.

Following this approach, the entire graph has 50 million links for the existing dataset, so, due to computational limitations, the number of nodes was decreased using the Forest-fire based [7] algorithm. In the first step, the one hundred most popular actors have been taken. Following this, titles where an actor has starred should be taken, then the rest of the cast, directors and casting directors should be taken, This should be repeated until one huge connected component is created. Finally, talent agents should be added to the graph. The generated graph has 59,443 nodes and 704,175 edges. The average clustering coefficient is 0.57, and the average shortest path is 8.

4.2 Graph Description

The graph (Figure 5) has a core-periphery power law structure. The top three nodes by degree are casting directors: Mary Vernieu (casting director for “Deadpool” and another 421 titles), Kerry Barden (casting director for “The Spotlight”), Avy Kaufman (casting director for “The Sixth Sense”). The actor with the highest degree is Nicolas Cage.

Figure 6 shows that the graph follows the power law distribution of the node degrees - most of the nodes have small degree, which stand for new or unknown actors mostly. Most of the nodes have small eigenvalue centralities which can as nodes with high level of influence are not connected directly. Betweenness centrality distribution (Figure 7) is concentrated in the area of small values as well, that is there is no nodes that strongly controls the network and the shortest paths often goes through different nodes. Hubs and authorities algorithm shows that the top hubs are casting directors and the top authorities are highly popular actors, such as Nicole Kidman, Robert De Niro, Bruce Willice, Julianne Moore and Morgan Freeman. The results seem to be reasonable, because casting

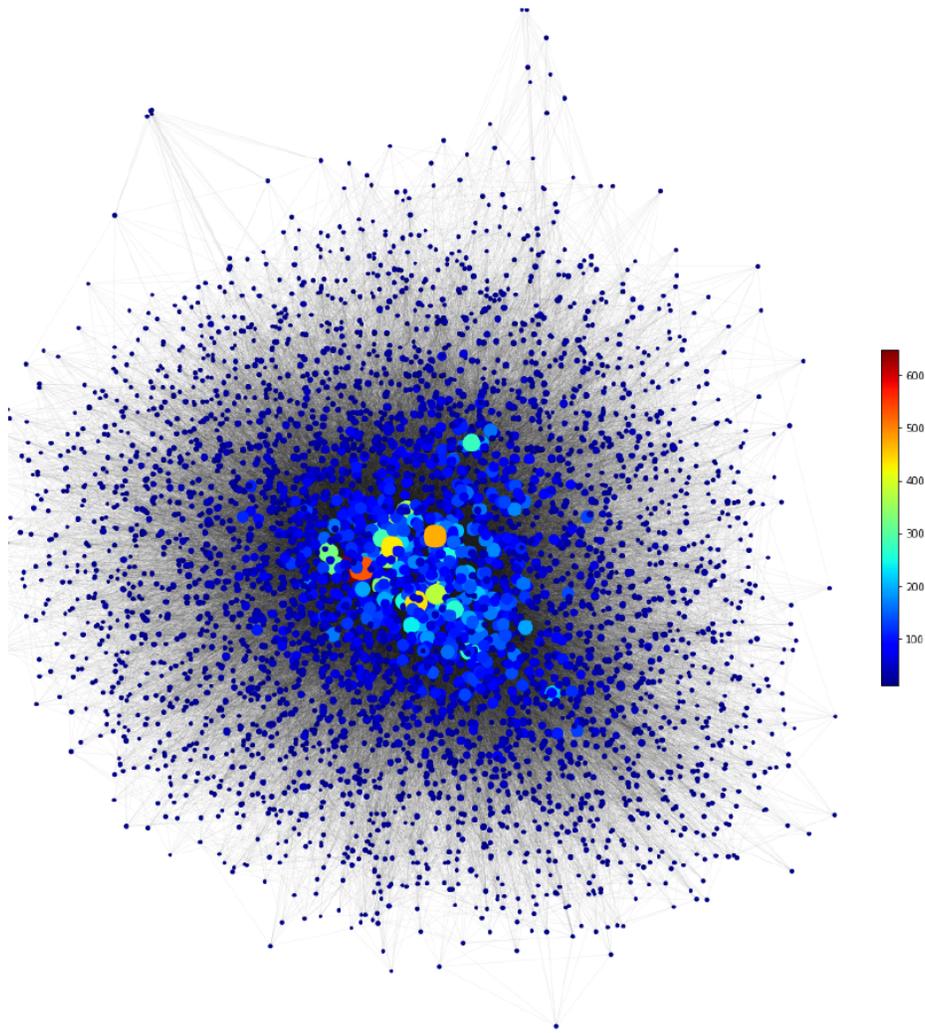


Fig. 5. Movie industry community graph

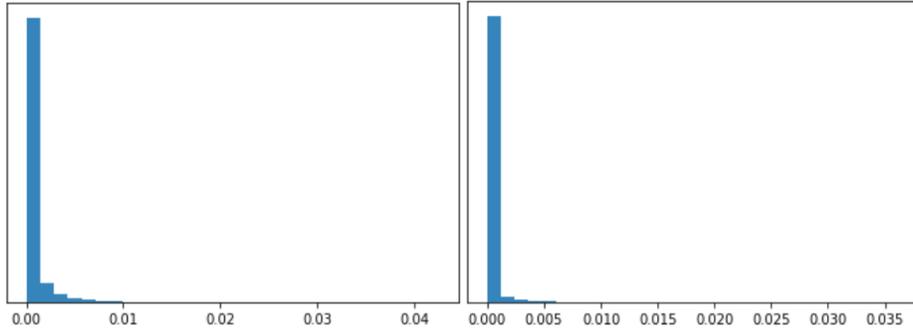


Fig. 6. Degree centrality distribution **Fig. 7.** Betweenness centrality distribution

directors indeed work with a lot of people in movie industry and have a lot of contacts.

4.3 Random Walk Network Model

Node2Vec is an algorithm that generates nodes representations in vector format. The algorithm creates low-dimensional nodes representations of a graph using random walks through a graph. The main idea of the method is that random walks through a graph may be considered as a sentence in a corpus in the following way [8]:

- Every node is treated like a single word;
- Every walk through nodes of a graph is a sentence;
- Then, a skip-gram may be applied to every sentence, that was created by a random walk;

The main parameters of Node2Vec algorithm that may be controlled and adjusted are number of walks, length of each walk, p – the probability to return to the neighbour of the previous node, q – controls the probability to go away from the previous node during a random walk. In the current study we consider number of walks and its length as constants equal to 200 and 80 respectively, because it seems to be relevant for the graph of this size and computational power limits. Parameters p and q are considered from 1 to 4 each, so there are 16 models for each pair of parameters, since there is no intuitive understanding what probabilities will work in the best way for the current graph. Further in the research, each model will be used separately in prediction models. As a result, the model returns a 24-dimensional vector, that describes a node, which is a member of the movie industry community.

5 Experiment

First of all, the past average ratings of a movie title’s crew should be considered, because these variables were important in the previous studies reviewed in the

chapter two. We will calculate average IMDb and RottenTomatoes rating of the movies for a director, casting director, writer and actors, so they will be considered in the models and we will be able to see whether the additional SNA information about their position in the network will affect the results or not. Secondly, graph embeddings for movie team members should be obtained. In this study, we will consider vectors for directors, casting directors and four main actors of a movie. In case of boosting model the mean vector for actors will be taken and in case of neural network model embedding vectors will be taken as is.

Also, because of reduction of the amount of data considered in chapter three the distribution of among buckets should be the same as in original dataset. In our case the original dataset has 53% of the observations into “6-7” bucket, 37% into “4-5” bucket, 8% into “0-3” bucket and 2% into “8-10” bucket. The reduced dataset has 56% of the observations into “6-7” bucket, 35% into “4-5” bucket, 7% into “0-3” bucket and 2% into “8-10” bucket, so the new distribution among classes is quite similar to the original.

Finally, since current dataset is imbalanced, we perform SMOTE algorithm [9] in order to get equal number of samples in each class.

As for the comparison metric of the classification results the accuracy will be used [10], because it is simple and suitable for the current multiclass classification problem.

5.1 Random Forest Models

The first model to test whether social network analysis features from movie industry community does improve the model is gradient boosting over random forest using CatBoost [11] Python library.

The best results for the gradient boosting over random forest classification without SNA parameters were obtained with the following parameters:

- Depth = 5;
- l2_leaf_reg = 1;
- Learning rate = 0.05

The best Accuracy = 0.68.

The best results for the gradient boosting over random forest classification with SNA parameters were obtained with the following parameters:

- Depth = 4;
- l2_leaf_reg = 1;
- Learning rate = 0.03

The best Accuracy result is 0.74, it is 6% gain due to social network features of the movie industry community.

Comparing the results between models with different features produced by Node2Vec with different parameters, shows no much difference between the results, which is around 0.05 between the most extreme cases, however, the best was obtained with $P = 2$ and $Q = 2$ (Table 1).

P,Q	1	2	3	4
1	0.7404	0.7368	0.7363	0.7371
2	0.7375	0.7410	0.7386	0.7373
3	0.7407	0.7355	0.7371	0.7360
4	0.7353	0.7386	0.7368	0.7393

Table 1. Accuracy results for different P and Q

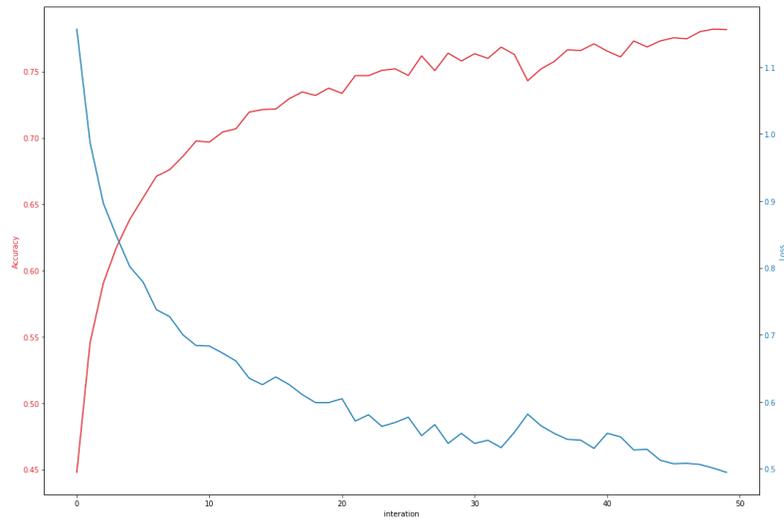


Fig. 8. Neural network model coverage with graph features

According to the feature importance, the most important network features were the ones describing directors' nodes, the second were the ones describing casting directors' and third were the ones describing actors' nodes. Basically, that result shows the importance of casting director who is always in the background, because the importance of each feature indicates how much on average the prediction changes if the feature value changes.

5.2 Random Forest Model

The second test to check whether the SNA features affects the prediction results or not is to use random forest (RF) classification model. To find the optimal parameters grid search approach was used.

The best results for the RF model without SNA parameters were achieved with the following set of the parameters:

- Depth = 6;
- max_features = auto;
- n_estimators = 250;

The best results for the RF model with SNA parameters were achieved with the following set of the parameters:

- Depth = 5;
- max_features = auto;
- n_estimators = 350;

The best accuracy result for the model without SNA features is 0.638 and the best accuracy results for the model with SNA features 0.671. So, as we can see the social network features improved the result but it is worse than the best accuracy score of the previous model.

5.3 Decision Tree Model

The third model is simple decision tree. Once again optimal parameters were chosen by grid search approach.

The best results for the model without SNA parameters were achieved with the following set of the parameters:

- max_depth = 300;
- max_features = auto;
- criterion = gini;

The best results for the model with SNA parameters were achieved with the following set of the parameters:

- Depth = 400;
- max_features = auto;
- criterion = gini;

The best accuracy result without SNA is 0.611 and the best result with SNA is 0.601. So, in this case the results are quite similar, that is probably because of the high input dimension.

5.4 Neural Network Models

The final test is to build neural network and compare the results considering different input vector for the actors, taking it as is. The classification model without movie industry community network features [12] architecture contains three layers with dropout:

Layer type	Shape	Param
Dense	64	18688
Dropout	64	0
Dense	16	1040
Dropout	16	0
Dense	4	68

Table 2. Neural network architecture

The result for the first model is 0.74, which is better comparing to the relative result obtained with the gradient boosting over random forest model

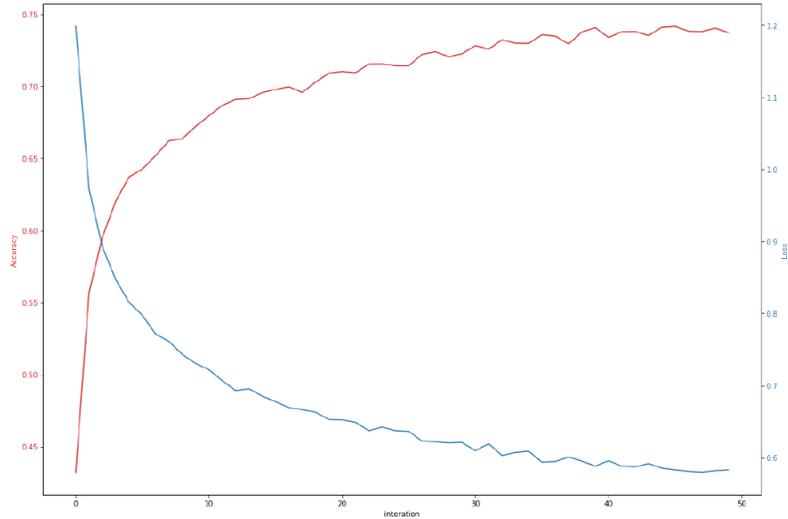


Fig. 9. Neural network model coverage with graph features

The same model with additional movie industry community network features has achieved result with Accuracy = 0.78 (Figure 9), which is better than model without these features and better than boosting model created earlier. However, the difference between neural network models with and without graph features has become slightly smaller.

6 Conclusions

Features extracted from movie industry community graph do improve predictions results as shown at Table 3. Director of a movie has more influence on movie success than casting director and actors. Also, we can notice that there is no much difference between Node2Vec model that have different random walk parameters.

	Without SNA features	With SNA features
RF + GB	0.684	0.743
RF	0.638	0.671
Decision Tree	0.611	0.601
NN	0.741	0.781

Table 3. Accuracy results for different models

Also, as it can be seen in the 3 most of the models showed that social network features obtained using Node2Vec to get the embeddings improved the prediction results even though data without SNA has information about movie crew - average rating for the previous titles, so it can be concluded that SNA features are significant and a position in the movie industry community does affect future movie success.

In the present research the movie industry community have been studied by actor-casting director-talent agent-direct graph analysis and the following goals have been completed:

- The unique data about casting directors and talent agents has been collected by scrapping web pages;
- The network structure of the movie community has been presented in terms of graph and analyzed providing information that describes how this community works;
- The embeddings that describe nodes have been obtained;
- The models predicting IMDb score has been created and the information of the different combinations of the features sets has been collected and analyzed.

Based on the obtained results by achieving these goals it may be concluded that movie community industry does follow the common social network properties, such as power law distribution, that is there are small number of members who has a significant number of connections with other people from the community. Also, it has been shown that casting directors are important member of the movie community as they are network hubs. Moreover, during the current research it has been shown that features that describes network structure of the movie industry community does influence the IMDb rating. The most important is the group of features regarding director of a movie titles, the second most important is the group of features that contains information about casting directing directors, so, these people do affect the movie success. Also, as it was described

in the previous studies, the network model shows better results predicting IMDb score.

However, this study has some limitations, such as reduced dataset due to computational resources, so the future researches may include:

- Analysis of the whole graph with all principals of a movie, because it may give more insights;
- Usage of the social network model for best strategies in order to get the cast, because it may be more efficient to spend resources on a popular casting director or actor or talent agent that will bring other people because they are valuable members of the community

7 Acknowledgements

The article was prepared within the framework of the HSE University Basic Research Program.

References

1. Michael T. Lash and Kang Zhao. Early predictions of movie success: The who, what, and when of profitability. *Journal of Management Information Systems*, 33:874 – 903, 2016.
2. B. Meiseberg, Thomas Ehrmann, and Julian Dormann. We don’t need another hero — implications from network structure and resource commitment for movie performance. *Schmalenbach Business Review*, 60:74–98, 2007.
3. Krushikanth R. Apala, Merin Jose, Supreme Motnam, Chien-Chung Chan, K. Liszka, and F. D. Gregorio. Prediction of movies box office performance using social media. *2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2013)*, pages 1209–1214, 2013.
4. Warda Ruheen Bristi, Zakia Zaman, and N. Sultana. Predicting imdb rating of movies by machine learning techniques. *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, pages 1–5, 2019.
5. Rudy Aditya Abarja and Antoni Wibowo. Movie rating prediction using convolutional neural network based on historical values. *International Journal of Emerging Trends in Engineering Research*, 8(5):2156–2164, 2020.
6. Xiaodong Ning, Lina Yac, Xianzhi Wang, Boualem Benatallah, Manqing Dong, and Shuai Zhang. Rating prediction via generative convolutional neural networks based regression. *Pattern Recognition Letters*, 132:12–20, 2020. Multiple-Task Learning for Big Data (MTL4BD).
7. Jure Leskovec, Jon Kleinberg, and Christos Faloutsos. Graph evolution: Densification and shrinking diameters. *ACM Trans. Knowl. Discov. Data*, 1(1):2–es, March 2007.
8. Aditya Grover and J. Leskovec. node2vec: Scalable feature learning for networks. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016.
9. N. Chawla, K. Bowyer, L. Hall, and W. P. Kegelmeyer. Smote: Synthetic minority over-sampling technique. *J. Artif. Intell. Res.*, 16:321–357, 2002.

10. P. Baldi, S. Brunak, Y. Chauvin, C. A. Andersen, and H. Nielsen. Assessing the accuracy of prediction algorithms for classification: an overview. *Bioinformatics*, 16 5:412–24, 2000.
11. Anna Veronika Dorogush, V. Ershov, and A. Gulin. Catboost: gradient boosting with categorical features support. *ArXiv*, abs/1810.11363, 2018.
12. Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, Manjunath Kudlur, Josh Levenberg, Rajat Monga, Sherry Moore, Derek G. Murray, Benoit Steiner, Paul Tucker, Vijay Vasudevan, Pete Warden, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. Tensorflow: A system for large-scale machine learning. In *Proceedings of the 12th USENIX Conference on Operating Systems Design and Implementation*, OSDI'16, page 265–283, USA, 2016. USENIX Association.