Movie rating prediction using heterogeneous graph neural networks

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ABSTRACT

Graph neural networks (GNNs) have recently become prominent in various fields for their ability to model complex relationships in graph structured data. A heterogeneous graph neural networks (HGNNs) extends this capability by handling graphs with multiple types of nodes and edges, known as heterogeneous or multi-relational graphs. In this paper, we propose a novel approach for predicting pre-release movie ratings by constructing a heterogeneous graph that incorporates movie attributes with their connections to actors, directors, and production countries. We explore multiple HGNN architectures, including GCN, SAGE, GAT, FiLM, and GraphTransformer, to forecast movie ratings using IMDb data specifically focused on Netflix movies. Our experimental results demonstrate that GNN-based models outperform traditional benchmarks, with the GAT architecture showing the highest predictive accuracy. These findings highlight the potential of our approach to forecast movie success prior to release, offering valuable insights that could save investors millions of dollars in production and marketing expenditures.

1 INTRODUCTION

The movie industry is a multi-billion-dollar industry, generating approximately $10 billion of revenue annually. It is estimated that 80% of the industry's profits over the last decade is generated from just 6% of the films released; 78% of movies have lost money of the same time period [1]. Therefore, predicting movie ratings before their release is essential to help reduce financial risk by guiding marketing strategies and investment decisions. Additionally, by focusing on films with higher predicted ratings, studios can improve the quality of their releases and increase the percentage of profitable movies. This not only optimizes cost but also increases the overall quality of movie industry.

Several studies have explored movie success prediction using various machine learning techniques and pre-release features, such as genre, budget, and director, to estimate profitability and ratings, including the work by D. Im and M. T. Nguyen (2011) on box office profitability prediction [2]. Similarly, Y. J. Lim and Y. W. Teh (2007) employed movie attributes such as crew, release date to predict movie popularity using classifiers like logistic regression, achieving high accuracy [3].

Previous research on movie rating prediction often relied on traditional methods, such as collaborative filtering or machine learning models, which lacked the ability to capture the intricate relationships between movies, actors, genres, and other important features. These methods were limited by their inability to model the underlying graph structure of data, resulting in a loss of crucial relational information [4]. In contrast, GNNs are explicitly designed to handle such graph-structured data [5].

GNNs has been proven to work great for recommendation systems [6, 7, 8] and has been applied on movies dataset [9, 10] but not for pre-release movie rating forecasting. Those papers mostly rely on post release user feedback. In this paper we propose a solution by representing IMDb movies dataset as heterogeneous graph structure and training a HGNN model on that structure. HGNNs allow us to capture complex relationships and interactions among different entities in the dataset, leading to improved performance in movie rating prediction tasks [11].

2 DATA

In this research we use IMDb dataset for Netflix movies. IMDb, established in 1990 and acquired by Amazon in 1998, is a leading platform for movie, TV series, actor, and director information. It allows users to rate content on a scale from 0 to 10 and leave comments, providing valuable insights for others.

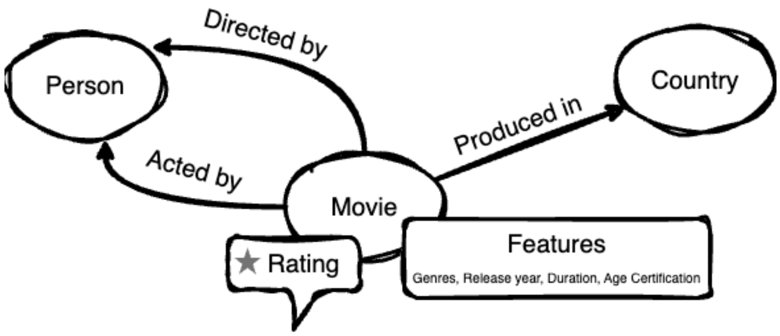
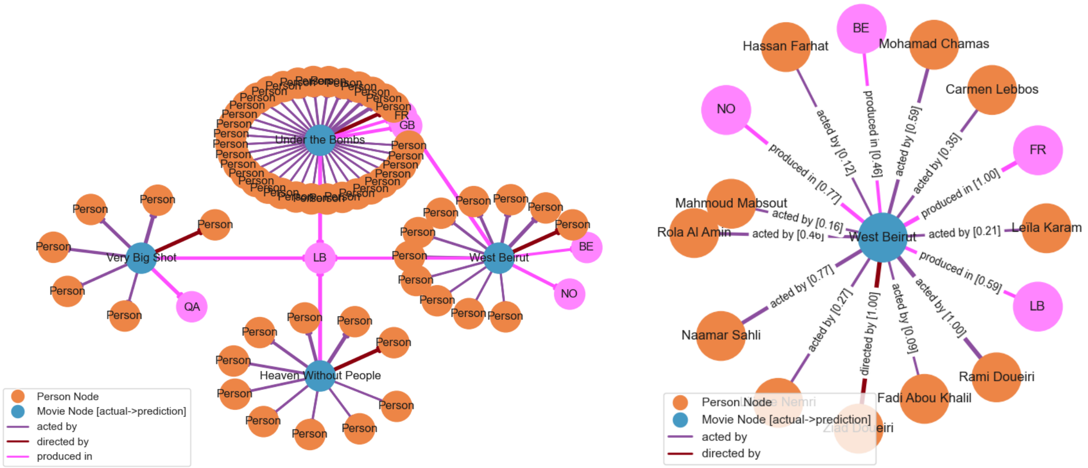


*Figure 1. A graph representation of Netflix's movie database. The graph has relationships between movies and people via **Produced in** and **Acted by** edges, as well as **Directed by** edges between movies and countries. Movies include attributes such as **genre**, **release year**, and **duration**, with their **rating** used as labels.*



(a) All the movies produced by Lebanon (LB).

(b) The movie 'West Beirut'.

Figure 2. A section of graph representation of the movie's dataset. There are two movies produced in Lebanon and two others that list Lebanon as a production country. Each of these four movies is connected to various person nodes through "acted_by" or "directed_by" relationships.

Many users rely on these ratings and reviews to discover new films and shows, making IMDb an essential tool for making informed viewing choices. On the other hand, Netflix is a global streaming platform with a vast library of TV shows and movies available to subscribers, offering instant access with a single click. This large, worldwide audience generates a higher volume of ratings and reviews, creating a richer dataset for more accurate predictions.

The "Netflix TV shows and Movies" dataset available on Kaggle consists of movies with its attributes like the title, genres, release date, runtime and of course the IMDb rating. By exploring the latter as kernel density estimation (KDE) (see Figure 3), we can see that there are movies with fewer than 1000 votes. To ensure a more accurate reflection of movie ratings, we filtered out movies that weren't popular enough to receive sufficient votes. Specifically, we excluded all movies with votes below the 20th percentile, corresponding to a threshold of 1152 votes.

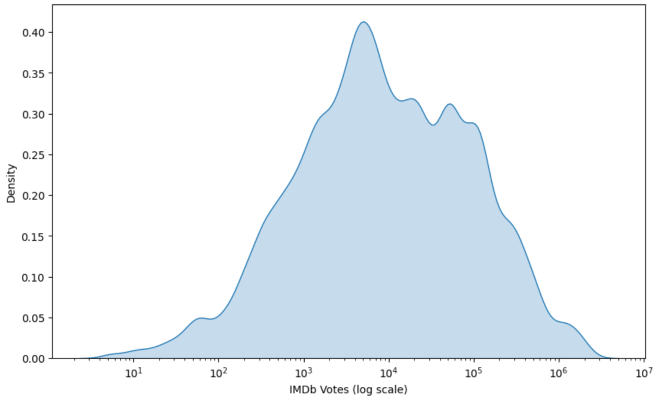


Figure 3. *KDE of IMDb Votes with log scale.*

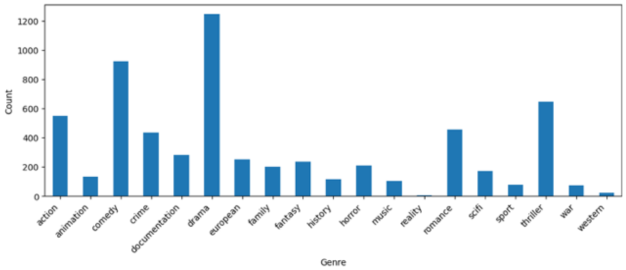


Figure 4. Count of Movies by Genre.

After filtering out all the outliers and converting the relational structure into graph representations using the schema depicted in Figure 1, we end up with approximately 39K nodes, including over 2100 popular movies. Those movies are connected to their associated actors, directors, and production countries (see Figure 2). In total, there are around 50K edges between these nodes. Figure 2a illustrates a portion of this graph, showing all movies produced in Lebanon along with their actors, directors, and additional production countries. Figure 2b zooms into one of those movies to see the relations more detailed.

Examining the count of popular movies per genre (see Figure 4), it's clear that our dataset is not uniformly distributed. Most movies fall into genres like Drama and Comedy, with Drama having the highest count, exceeding 1200. Genres like Action and Thriller also have significant representation. In contrast, genres such as Reality and Western have much lower counts. This variation does not impact our research, so we will keep the dataset as is.

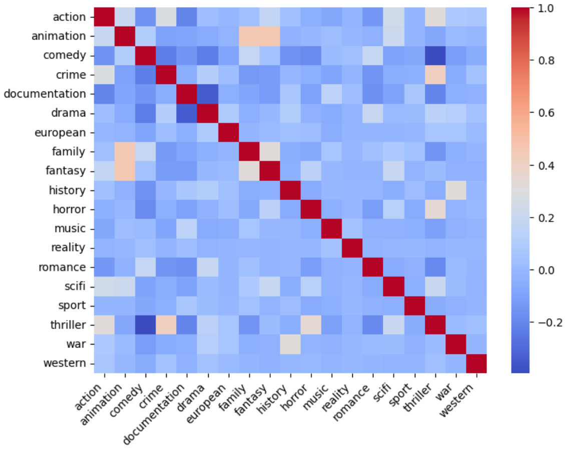


Figure 5. Correlation matrix of movie genres.

When we look at the correlation matrix of movie genres, we can observe that most genres don't exhibit strong correlations with each other, except for Animation, which shows a moderate correlation with Family and Fantasy genres. Additionally, there is a slight correlation between Crime and Thriller, while a negative correlation exists between Thriller and Comedy. This indicates that we can't reduce the dimensionality by eliminating correlated features, so we will need to work with all 22 dimensions.

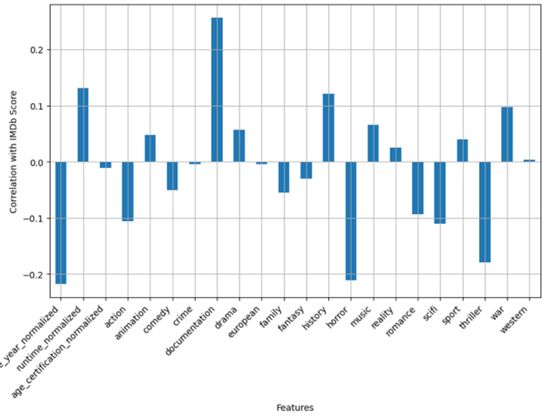


Figure 6. Correlation between IMDb score (rating) and every other feature.

From Figure 6, we can see that there isn't a strong correlation between most movie features and IMDb scores. However, documentary movies tend to receive higher ratings compared to other genres, while Horror and Thriller films are generally rated lower. Additionally, older movies tend to have higher ratings compared to more recent releases.

3 RELATED WORKS

Marovic et al. (2011) used movie and user data from IMDb to compare various methods for movie rating prediction [12]. They examined content based, collaborative, and hybrid approaches, implementing models such as regression trees, neural networks, k-Nearest Neighbor (k-NN), personality diagnosis, SVD-kNN. Their study aimed to identify the optimal approach for predicting user ratings on a given movie. Other studies [13, 14] have similarly utilized user data to predict movie ratings, focusing on delivering a personalized user experience by employing collaborative filtering techniques to achieve this. In another study, R. Parimi and D. Caragea (2013) [15] applied machine learning algorithms to predict the box office success of movies before their release. They introduced a graph-based network to structure the dependency relationships between movies, considering factors like shared actors, directors, and genres. By utilizing these connections to extract features for their classification model, they were able to enhance prediction accuracy. This approach outperforms traditional methods that treat each movie as an independent entity.

On the other hand, in the field of representation learning for heterogeneous networks, Dong et al. (2017) introduced the metapath2vec model [16], which significantly advances scalable representation learning. The model utilizes meta-path-based random walks to capture the structural and semantic relationships in heterogeneous networks. By applying a skip-gram model to these walks, metapath2vec effectively learns low-dimensional embeddings for nodes. The experimental results demonstrate that metapath2vec outperforms existing methods in various tasks, such as node classification and clustering, highlighting its efficacy in capturing rich information from heterogeneous graphs.
the Heterogeneous Graph Attention Network (HAN) introduced by Wang et al. (2019) [11] presents a significant advancement. HAN leverages hierarchical attention mechanisms to effectively manage the complexity of heterogeneous graphs, which consist of diverse node and link types. The model employs node-level attention to assess the importance of a node's neighbors based on meta-paths, and semantic-level attention to evaluate the significance of different meta-paths. This dual attention mechanism enables the generation of node embeddings that encapsulate rich semantic information.

4 APPLYING HGNNs

Due to the relatively small size of our graph, we followed the splitting approach outlined in the paper "FastGCN: Fast Learning with Graph Convolutional Networks via Importance Sampling" by J. Chen et al. (2018) [17]. The dataset was split into training, validation, and testing sets, with 70%, 10%, and 20% of the data allocated to each, respectively.

To test different graph architectures, we developed a three-layer model framework that is implemented by all models. The first layer is dynamically initialized, followed by a hidden layer with four dimensions and an output layer of one dimension. We apply a Leaky ReLU activation function between these layers. Utilizing this framework, we created five models using: GCN, SAGE, GAT, FiLM, and GraphTransformer [18, 19, 20, 21, 22].

These architectures were specifically chosen for their ability to capture different types of relationships and patterns in graph data. The GCN, a fundamental Graph Convolutional Network, effectively captures local node features and incorporates edge weights, making it well-suited for general relational data [18]. We chose SAGE because it efficiently gathers information from neighboring nodes, and its ability to generalize to unseen nodes is especially useful in our scenario, where new movies might be frequently introduced. We selected the mean as aggregation method because it suits the characteristics of movie features [19]. On the other hand, GAT employs attention mechanisms to assess the significance of neighboring nodes, enabling the model to concentrate on the most impactful connections for rating prediction. This allows GAT to emphasize crucial relationships, by assigning higher importance to lead actors, acclaimed directors, or major production countries, while giving less weight to less influential contributors [20]. FiLM (Feature-wise Linear Modulation), like GAT, emphasizes key relationships but also allows the model to adaptively modulate features, providing flexibility in how different attributes impact the prediction [21].
GraphTransformer uses self-attention to capture global dependencies, crucial for understanding distant interactions. This helps identify and emphasize how past actor-director collaborations, even if not directly linked, can influence a movie's rating prediction [22]. Each of these architectures provides a comprehensive exploration of local and/or global patterns, potentially enhancing the accuracy of movie rating predictions.
For benchmarking, we created a dummy model that simply returns the mean rating as its prediction, which in our case is rating of 6.4.

Model	MSE	MAE	R^2 score
Benchmark	0.01987	0.11352	0
GraphGCN	0.01608	0.09444	0.19038
GraphSAGE	0.01628	0.09556	0.17994
GraphGAT	**0.01560**	0.09262	**0.21430**
GraphFiLM	0.01732	0.09518	0.12757
GraphTrsfmr	0.01607	**0.09178**	0.19089

Table 1. Comparison of the Mean Square Error, Mean Absolute Error and R^2 score *between our models and the benchmark.*

While all our models outperformed the benchmark (see Table 1), the improvements were smaller than we had anticipated, indicating that there is still work to be done. Examining their training loss over epochs (see Figure 7), we observe that, despite differences in learning rates and early stability, all models eventually converge to a low and stable loss, indicating they effectively learned from the data.

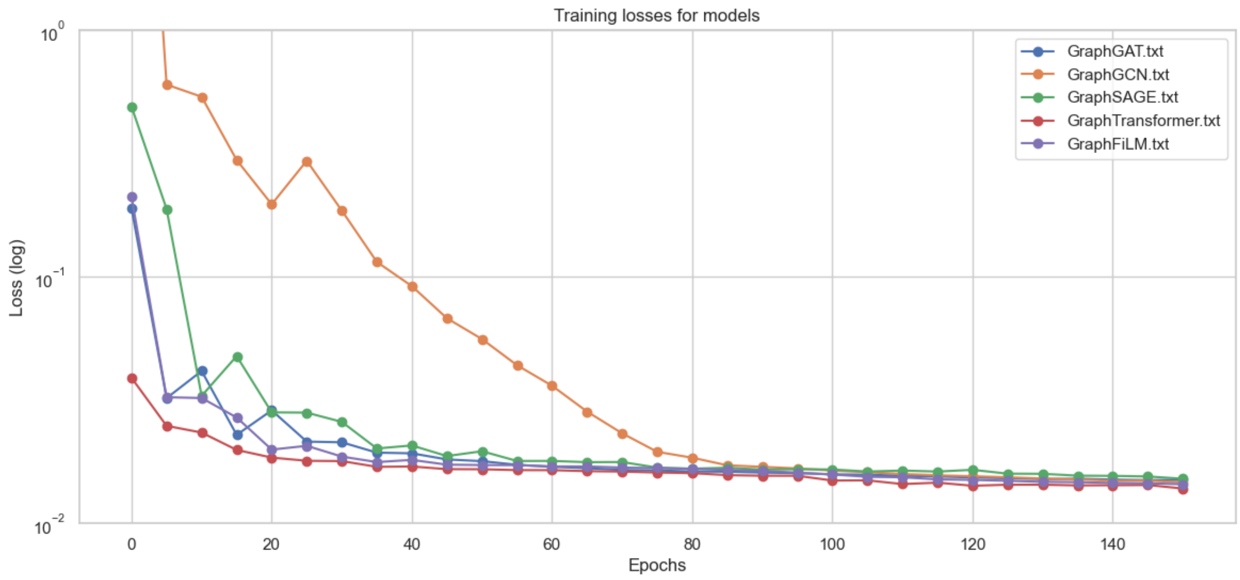


Figure 7. Training loss over epochs (log scale).

Notably, GraphGCN exhibits fluctuations during the initial epochs but eventually smooths out, achieving similar stability to the other models. Based on this this information (see Table 1and Figure 7) we conclude that the best performing model is based on the GAT architecture; therefore, we will proceed to evaluate that model.

5 EVALUATION

As seen in Figure 8, the distribution of actual ratings (green) shows a wider spread and greater variance, while our predictions (blue) by GAT model are more concentrated around the center. This indicates that while the model predicts the central tendency reasonably well, it has difficulty capturing the full range of the ratings, especially for movies with very low scores.

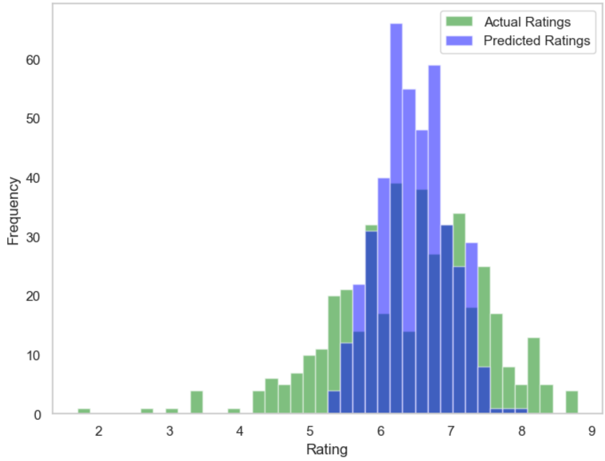


Figure 8: The distributions of actual (green) and predicted (blue) movie ratings.

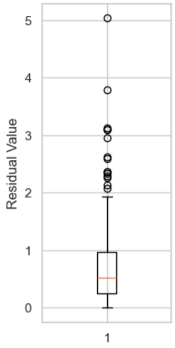


Figure 9. Error box for residuals.

In Figure 9, we observe that most residuals are closely clustered around 0.5, suggesting that the model's predictions are generally accurate for most movies. However, the presence of several outliers reaching up to 5 indicates instances where the model significantly underperforms. This reinforces the idea that while the model performs well for the central distribution of ratings, it struggles with extreme cases.

6 CASE STUDIES

Now let's look at the most inaccurate predictions made by GAT model (see Table 3).

Movie Title	IMDB Rating	Predicted rating	residual
Himmatwala	1.7	6.707263	5.007263
Indoo Ki Jawani	3.0	6.765801	3.765801
365 Days	3.3	6.407984	3.107984
Main Aurr Mrs Khanna	3.4	6.475968	3.075968
Cuties	3.4	6.469944	3.069944

Table 3. Inaccurate predicted movies.

As anticipated, from Table 3 we observe that top 5 inaccurately predicted movies have ratings below 5, confirming that our model struggles to perform well on lower-rated movies. The movie with the worst predicted rating was "Himmatwala".

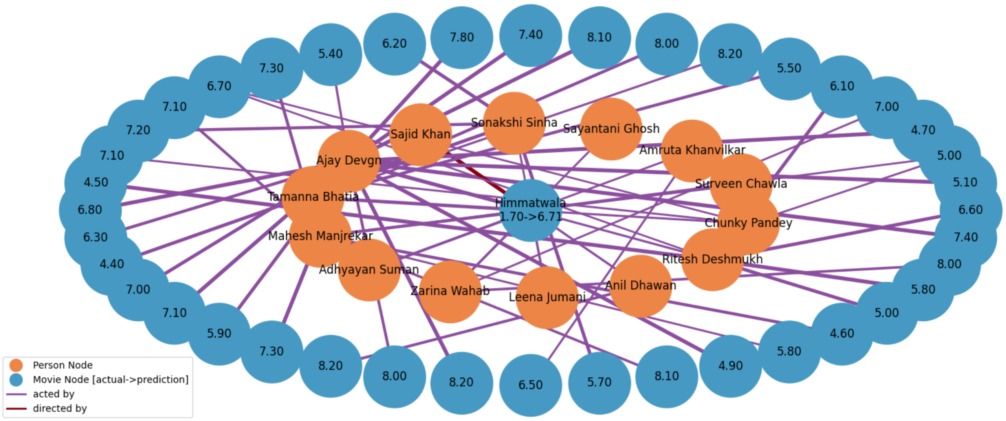


Figure 10 The inaccurate prediction: The relations of movie "Himmatwala" without country nodes.

When we look at above-mentioned movie closely (see Figure 10, note: country nodes are removed to avoid cluttering the graph), we can see that almost all actors involved in that film had previously acted in movies rated higher than 4.5. Therefore, the model was correct in predicting that this movie would be a successful movie as well, since most of casted actors are somewhat successful. This indicates that we are missing additional information about movies that influences their success, such as the planned budget, screenplay quality, or other external factors. Now let's look at the most accurate predicitons of our model.

Movie Title	IMDB rating	Predicted rating	Residual
David Cross: Making America Great Again	6.5	6.500573	0.000573
Burning Sands	6.0	5.997471	0.002529
Phir Hera Pheri	7.1	7.105605	0.005605
The Replacements	6.6	6.591538	0.008462
All Together Now	6.5	6.489522	0.010478

Table 2. Most Accurate predicted movies.

Again we can see the same pattern here, all correctly predicted movies are around 6.4 mean rating. Next let's see what relations the most accuratly predicted movie "David Cross: Making America Great Again" has.

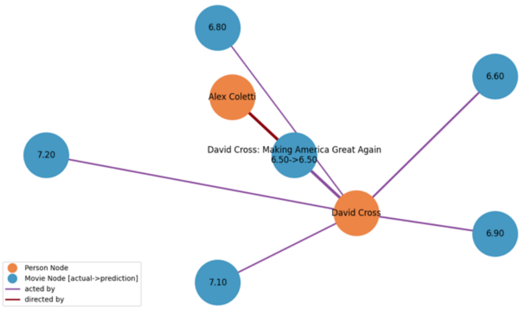


Figure 11. Most accurate prediction: The movie "David Cross: Making America Great Again" without country nodes.

In Figure 11, we can see that the movie has only one actor and one director connected to it. The director did not participate in any other films, whereas the actor involved in five different movies with ratings close to 6.4.

Next, let's explore the movies featuring some well-known actors; for instance, we'll examine all the movies that Tom Cruise and Tom Hanks participated in.

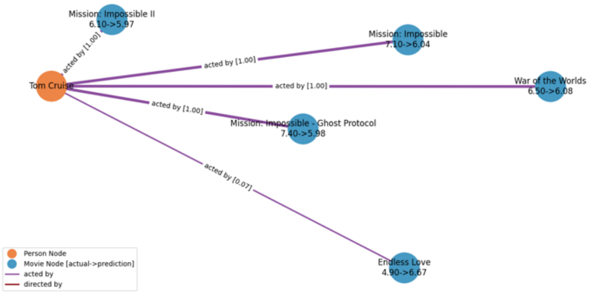


Figure 12. Tom Cruise Movies

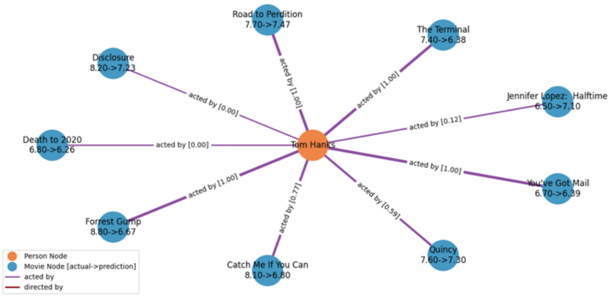


Figure 13. Tom Hanks Movies

From Figures 12 and 13, it's clear that the model accurately predicted most of Tom Hanks' movies but was less accurate with Tom Cruise's films. Notably, "Mission Impossible: Ghost Protocol" received a much lower predicted rating of 5.98 compared to its actual rating of 7.4. We will leave further investigation of this discrepancy for future work.

7 FUTURE WORK

Through our movie-watching experiences, we've all noticed that some actors excel in certain genres but may perform poorly in others. For example, an actor who shines in action roles might not deliver the same level of performance in dramatic or comedic settings. These genre-specific strengths and weaknesses are often reflected in audience ratings and critical reviews. Therefore, we suggest incorporating movie genres as edge attributes to enhance the model's ability to capture actors' performance across different genres.

Another potential improvement is to expand the graph by adding edges between movies for their sequels and prequels. This will allow the model to capture relationships between related films, which may influence a movie's rating based on the success or failure of its predecessors or successors.

We can further improve the graph by incorporating connections between movies, actors, and their awards or nominations. Adding this data would provide the model with valuable insights into how critical acclaim and industry recognition affect a movie's success.

Finally, we could enrich the movie features by adding embeddings of the screenplay and financial information. Incorporating screenplay embeddings would allow the model to capture the narrative structure, genre conventions, and thematic elements, potentially revealing patterns related to a movie's success or critical reception. Adding financial data, such as production budgets, marketing expenses, and box office earnings, could help the model understand the economic factors influencing a film's performance, providing a more comprehensive picture of the variables impacting movie ratings.

8 CONCLUSION

This study explored the use of HGNNs for predicting movie ratings by constructing a heterogeneous graph of movie attributes, actors, directors, and production countries. Among the evaluated HGNN architectures (GCN, SAGE, GAT, FiLM, and GraphTransformer) the GAT model demonstrated the best performance, emphasizing the value of attention mechanisms in capturing complex relationships. Our experiments with IMDb data for Netflix movies showed that HGNNs outperform traditional benchmarks, offering a promising approach for pre-release movie predictions. These findings suggest that accurate forecasting could guide investment decisions, potentially saving millions in production and marketing costs. Future work could involve integrating additional features and merging other datasets to enhance predictive accuracy further.

9 ACKNOWLEDGMENT

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