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Research Article

A Hybrid Movie Recommendation System to Address Data Sparsity Using Genre-Based K-Means and Neural Collaborative Filtering

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Abstract

Recommendation systems play a crucial role in helping users navigate the overwhelming volume of information on digital platforms. However, conventional Collaborative Filtering (CF) methods often suffer from data sparsity, leading to reduced prediction accuracy and limited recommendation diversity. To address this challenge, this study proposes a hybrid recommendation model that integrates K-Means clustering based on genre, release year, and rating statistics into the Neural Collaborative Filtering (NCF) framework. Unlike previous works that rely on a single dimension like genre or demographics for clustering, our model uniquely combines multiple content-based features. Furthermore, we explicitly integrate the cluster labels as additional embedding features within the NCF framework, enabling more nuanced and context-aware representation learning. Using the MovieLens Latest-Small dataset, our hybrid model significantly outperforms the baseline NCF across all metrics, achieving a Mean Absolute Error (MAE) of 0.6097, a Root Mean Square Error (RMSE) of 0.7946, and improvements in Precision@10 (0.6065) and Recall@10 (0.7063). These findings highlight the effectiveness of our novel, content-aware clustering approach in deep learning recommenders, resulting in more accurate, diverse, and contextually relevant movie suggestions.

Keywords: Collaborative Filtering, Data Sparsity, K-Means, Neural Collaborative Filtering, Recommendation System.

Introduction

Recommendation systems play a vital role in filtering information and delivering relevant content to users amidst the explosion of digital data. Collaborative Filtering (CF) is a widely used approach that leverages user–item interaction patterns, however, its performance declines significantly in the presence of data sparsity and the cold-start problem [1], [2]. This is primarily due to the high sparsity of the interaction matrix, which makes it difficult for the system to generate reliable predictions [3], [4].

To address these limitations, various hybrid models have been developed [5]. One such model is Neural Collaborative Filtering (NCF), which employs neural networks to model the non-linear interactions between users and items [1], [6], [7]. Several studies have shown that integrating clustering techniques, such as K-Means, can enhance semantic representations and improve predictive performance [8], [9], [10], [11]. For instance, the CANNBCF model by Althbiti et al. combines clustering and artificial neural networks to effectively tackle data sparsity [10]. Research by Siet et al. also demonstrated that genre-based clustering using K-Means in deep learning models enhances Top-N recommendation accuracy [12], [13]. Similarly, AFOUDI and LAZAAR found that user segmentation based on demographics and K-Means clustering can accelerate the recommendation process.

Building upon these findings, this study proposes a hybrid recommendation model that incorporates K-Means clustering results based on genre, release year, and average rating into the NCF architecture as additional embedding features. This approach not only aims to alleviate sparsity issues but also enriches user and item representations. The primary novelty of our work lies in two key aspects: First, unlike previous works that typically rely on a single dimension such as genre or demographics for clustering, the proposed model combines multiple content-based features simultaneously to create a more comprehensive item representation. Second, instead of treating the clusters as standalone pre-processing tools, we explicitly integrate the cluster labels as additional embedding vectors within the NCF framework, enabling more nuanced and context-aware representation learning. This deep integration allows the

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model to leverage the learned thematic context directly during the training process, a significant advantage over simple feature concatenation. Consequently, the model is expected to yield more accurate and personalized recommendations.

Method

This research was conducted through a structured series of stages aimed at developing and evaluating a hybrid recommendation system model. The process began with data preparation, using the MovieLens Latest-Small dataset as the primary data source. Data cleaning followed, involving file merging, extraction of key attributes such as release year, handling of missing values, and genre formatting. Once the data was cleaned, feature exploration and engineering were performed, including the calculation of average ratings, user interaction counts, and one-hot encoding of genre features. The modeling phase involved two key steps clustering movies using the K-Means algorithm and training a Neural Collaborative Filtering (NCF) model with the cluster labels incorporated as additional features. Model performance was assessed using regression and ranking metrics, namely MAE, RMSE, Precision@10, Recall@10, and NDCG@10. These phases are systematically depicted in the research workflow, as illustrated in **Figure 1**.

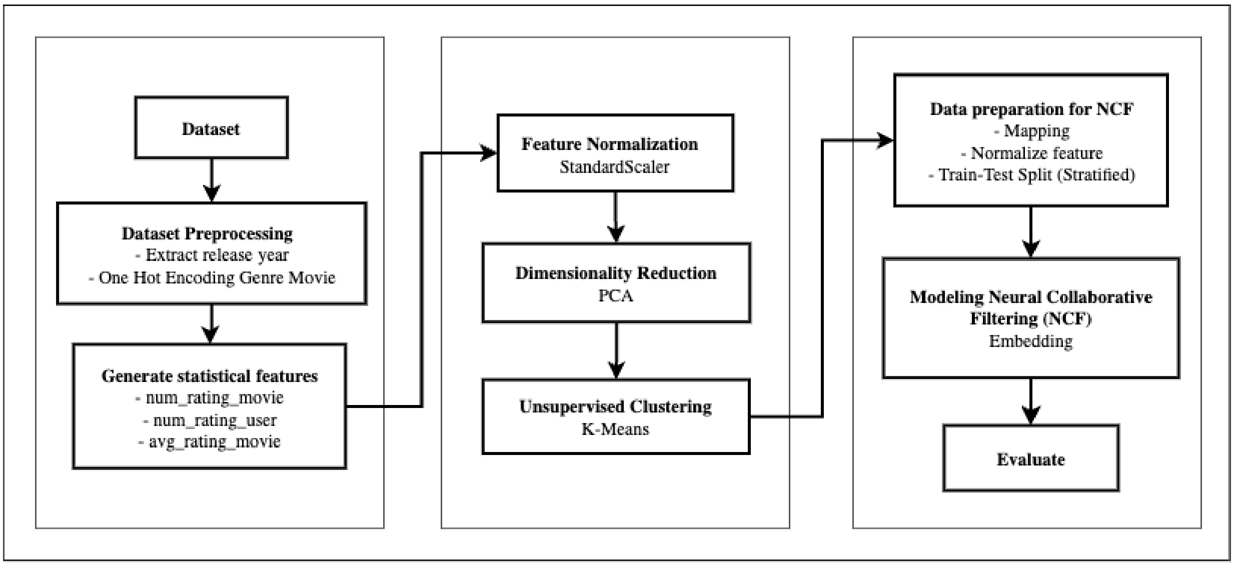

Figure 1. Research Diagram

A. Dataset

The MovieLens Latest-Small dataset is one of the most popular benchmark datasets for developing recommendation systems, as it realistically and structurally represents user–movie interactions [14], [15]. It comprises 100,818 ratings provided by 610 users on 9,711 movies, with a granular rating scale ranging from 0.5 to 5.0. Each record includes attributes such as userId, movieId, rating, and timestamp, along with metadata such as movie titles and genres. The genre information, which is multi-categorical in nature, was transformed into a binary format using one-hot encoding, covering a total of 21 genre types. The dataset's dense, diverse, and complex characteristics present an ideal challenge for evaluating the capability of recommendation models in addressing issues such as data sparsity and content heterogeneity.

Table 1 shows a sample from the movies dataset, containing movie id, title, and a multi-labeled genres field separated by a pipe (|). These genre labels, later one-hot encoded into 21 binary indicators, provide essential content-based features that support clustering and enhance recommendation quality. The examples reflect the dataset's genre diversity, contributing to nuanced user profiling.

Table 1. Movies Dataset

Movie Id	Title	Genres
1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2	Grumpier Old Men (1995)	Comedy|Romance
3	Heat (1995)	Action|Crime|Thriller
4	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller
5	Usual Suspects, The (1995)	Crime|Mystery|Thriller

Table 2 displays user–movie interaction records, comprising User Id, Movie Id, rating, and timestamp. Each entry represents explicit user feedback, forming the basis for collaborative filtering models. The timestamp field enables optional temporal analysis to capture user behavior dynamics over time.

Table 2. Ratings Dataset

User Id	Movie id	Rating	Timestamp
1	1	4.0	964982703
1	3	4.0	964981247
1	6	4.0	964982224
1	47	5.0	964983815
1	50	5.0	964982931

B. *Feature Engineering*

Feature engineering began by merging user interaction data and movie metadata from the ratings.csv and movies.csv files using the Movie Id as the key. The release year was extracted from the movie title column using a numeric pattern enclosed in parentheses, converted into a numeric format, and missing values were imputed using the median [14]. Movie genres, originally presented in a multi-categorical string format, were transformed into binary vectors using one-hot encoding, covering 21 distinct genres [16]. This representation enables the model to capture movie content more granularly and enhances the analysis of user preferences across various genre categories [2], [17]

Table 3. Genres Before One-Hot Encoding.

Movie Id	Title	Genres
1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2	Grumpier Old Men (1995)	Comedy|Romance
3	Heat (1995)	Action|Crime|Thriller
4	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller
5	Usual Suspects, The (1995)	Crime|Mystery|Thriller

Table 3 displays the original multi-genre format, where each movie is associated with several genres in a single text field. This unstructured format was unsuitable for modeling and therefore converted.

Table 4. Genres After One-Hot Encoding

movieId	Adventure	Animation	…	Thriller	Mystery
1	1	1	…	0	0
2	0	0	…	0	0
3	0	0	…	1	0
4	0	0	…	1	1
5	0	0	…	1	1

Table 4 shows the result of one-hot encoding, where each genre is represented as an individual binary column, allowing for structured learning of content-based features.

Several numerical features were added to enhance contextual information: movie rating count indicates a movie's popularity, average rating reflects its perceived quality, and user rating count captures user activity level. These features were integrated into the clustering process to produce more meaningful movie representations [3], [17], [18], [19]

Table 5. Augmented Movie–User Interaction Features

User Id	Movie Id	Release Year	Movie Rating Count	User Rating Count	Average Rating
1	804	1996	8	232	3.653123
1	1210	1983	196	232	3.813701
1	2018	1942	38	232	3.656226
1	2628	1999	140	232	3.548818

User Id	Movie Id	Release Year	Movie Rating Count	User Rating Count	Average Rating
1	2826	1999	26	232	3.633111

Table 5 summarizes the final feature set, combining temporal, popularity, and engagement indicators—laying the groundwork for more context-aware recommendation modeling.

C. K-Means

To improve the way the model understands and organizes movies, clustering was applied to group together films with similar characteristics. The K-Means algorithm was chosen for its simplicity, computational efficiency, and proven ability to handle large and complex datasets [2], [12], [20]. While other methods like DBSCAN could identify arbitrary shapes, K-Means is particularly well-suited for our objective of creating well-defined, spherical movie groups based on a combination of content and popularity features. This approach ensures that the resulting clusters are easily interpretable and directly align with our goal of enriching the NCF model with thematic context [5], [18]. The grouping process used key information such as genre categories, release year, number of times a movie had been rated, and its average rating. These combined elements helped the model identify patterns based on both content and popularity, making the movie groups more meaningful and context-aware [8], [17], [21], [22].

Prior to clustering, Principal Component Analysis (PCA) was applied to reduce the 22-dimensional feature space into two principal components, aiming to simplify computation while retaining the essential structure of the data [8], [21]. The optimal number of clusters was determined by evaluating K values from 2 to 5 using three internal validation metrics: Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index [20], [22], [23].

Table 6. Features Used for Movie Clustering

Feature Name	Type	Description
Adventure	Binary (0/1)	Indicates Adventure genre
Animation	Binary (0/1)	Indicates Animation genre
Children	Binary (0/1)	Indicates Children genre
Comedy	Binary (0/1)	Indicates Comedy genre
...	...	...
year	Numeric	Release year extracted from movie title
avg_rating_movie	Numeric	Average rating of the movie
num_ratings_movie	Numeric	Total number of ratings received by the movie

Table 6 summarizes the features employed during the clustering process, comprising binary indicators for genre and numeric descriptors for year of release, average rating, and rating count.

D. Neural Collaborative Filtering

The Neural Collaborative Filtering (NCF) model is a deep learning–based recommendation approach that captures non-linear user–item interaction patterns. It utilizes embedding layers to transform user and item identifiers into fixed-size latent vectors, which encode implicit preference signals [24], [1], [16], [25], [26]. These embeddings are augmented with additional numerical features—such as the movie's average rating, total number of user interactions, release year, and cluster labels derived from K-Means—to enrich the input representation with both content-based and behavioral information [3], [17], [19], [27].

Table 7. Structured Inputs to the Neural Collaborative Filtering Model

Input Component	Data Type	Description
user_idx	Integer (ID)	Unique user index (after mapping)
movie_idx	Integer (ID)	Unique movie index (after mapping)
cluster_idx	Integer (ID)	Cluster label assigned to movie (from K-Means)
avg_rating	Float	Average rating of the movie
num_ratings_movie	Float	Total number of ratings received by the movie
num_ratings_user	Float	Total number of ratings given by the user
year	Float	Release year extracted from the movie title

Table 7 summarizes the structured inputs to the NCF model, where embedding indices and numerical features jointly capture user behavior and item characteristics to improve recommendation accuracy.

The complete input is then passed through a sequence of fully connected layers, equipped with batch normalization, Leaky ReLU activations, and dropout regularization [24]. This architecture enables the model to learn complex preference functions and deliver robust predictions, outperforming traditional matrix factorization methods [28], [29]. In this study, the inclusion of cluster labels introduces thematic context, allowing the model to generalize better across semantically grouped items.

E. Evaluation Metrics

The model evaluation employs two primary approaches: regression metrics to assess the accuracy of rating predictions, and Top-K metrics to evaluate the relevance of top-ranked recommendations [23]. This dual approach offers a comprehensive perspective on system performance, covering both numerical precision and the quality of suggested items.

Mean Absolute Error (MAE) quantifies the average magnitude of errors between predicted ratings ($\hat{y}_i$) and actual values (y_i), treating all deviations equally regardless of their direction [23]. A lower MAE signifies that the model's predictions closely approximate true user ratings. In contrast, Root Mean Square Error (RMSE) incorporates the square of prediction errors, thereby assigning greater penalty to larger deviations; consequently, a lower RMSE indicates higher prediction accuracy [23]. Beyond these pointwise metrics, ranking-based evaluations offer further insights into recommendation quality. Precision@K assesses the proportion of relevant items within the top-K recommendations, reflecting the model’s ability to select pertinent items [30]. Recall@K complements this by measuring the extent to which relevant items are retrieved within the top-K results, capturing the model’s comprehensiveness in identifying user preferences. Meanwhile, Normalized Discounted Cumulative Gain at K (NDCG@K) evaluates both the relevance and ranking order of recommended items, assigning higher scores to relevant items that appear earlier in the list. By normalizing the DCG with respect to an ideal ranking, NDCG ensures comparability across users and provides a balanced measure of both precision and ranking quality [9], [30].

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$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_1 - \hat{y}_i)^2} \tag{2}$$

$$Precision@K = \frac{|R_K \cap T|}{K} \tag{3}$$

$$Recall@K = \frac{|\, R_K \cap T|}{T} \tag{4}$$

$$DCG@K = \sum_{i=1}^{K} \frac{2^{rel_i} - 1}{log_2(i+1)} \tag{5}$$

$$NDCG@K = \frac{DCG@K}{IDCG@K} \tag{6}$$

Results

A. Clustering Result

To assess clustering quality and identify the optimal number of clusters (K), internal validation metrics were computed for K values ranging from 2 to 5. The evaluation employed three widely accepted metrics: Silhouette Score, Davies–Bouldin Index, and Calinski–Harabasz Index. As detailed in Table 8, the configuration with K = 4 demonstrated the most favorable trade-off—exhibiting a relatively high Silhouette Score, the lowest Davies–Bouldin Index, and the highest Calinski–Harabasz Index. These results collectively suggest that this configuration achieves a desirable balance between intra-cluster compactness and inter-cluster distinctiveness, indicating the presence of well-separated and cohesive groupings.

Table 8. Cluster Validation

Number of Cluster (K)	Silhouette Score	Davies-Bouldin Index	Calinski-Harabasz Index
2	0.3776	1.1163	55919.6373
3	0.4680	0.7764	93569.007
4	0.4503	0.7730	105118.5134
5	0.4360	0.7944	99004.3475

Table 8 reports the internal clustering validation scores for each K value. The configuration with K = 4 emerged as optimal, balancing compactness and separation most effectively.

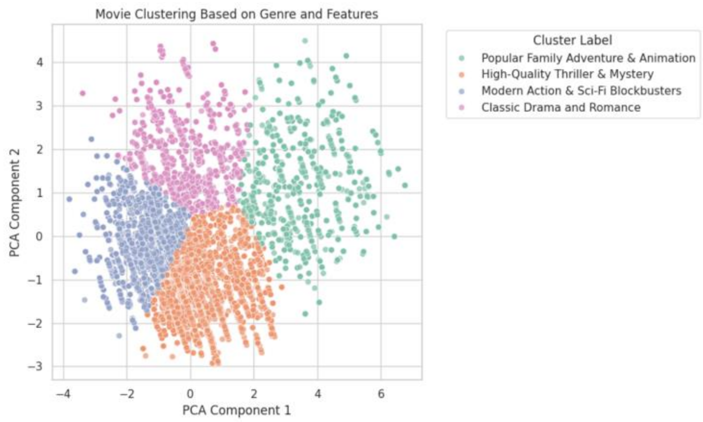

Figure 2. Visualization of Movie Clustering Based on Genre and Additional Features

Figure 2 illustrates the two-dimensional projection of movie clusters obtained via PCA. The visualization displays four distinct groups, each representing movies with similar genre and statistical characteristics [19].

B. Hybrid Model

The performance of the proposed hybrid Neural Collaborative Filtering (NCF) model was assessed using the MovieLens Latest-Small dataset, with evaluation conducted across five standard metrics: MAE, RMSE, Precision@10, Recall@10, and NDCG@10. Compared to the baseline NCF model, the hybrid approach consistently demonstrated superior predictive accuracy and recommendation quality. Specifically, the hybrid model achieved a lower MAE (0.6507 vs. 0.8161) and RMSE (0.8547 vs. 1.0017), indicating improved estimation of user ratings. Furthermore, Precision@10 and Recall@10 increased to 0.5855 and 0.6902, respectively, suggesting enhanced relevance and coverage in top-K recommendations.

Table 9. Model Evaluation Results

Metric	NCF	Hybrid (K-Means + NCF)
MAE ↓	0.8161	0.6097
RMSE ↓	1.0017	0.7946
Precision@10 ↑	0.5598	0.6065
Recall@10 ↑	0.6706	0.7063
NDCG@10 ↑	0.9983	0.9983

Table 9 presents a quantitative comparison between the baseline and hybrid NCF models. The hybrid configuration demonstrates consistent gains across all evaluation metrics, reflecting improved learning of user-item interactions and recommendation relevance.

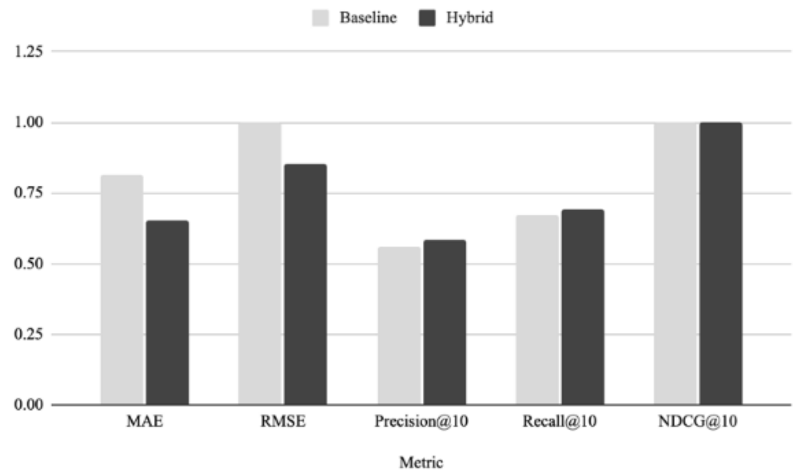

Figure 3. Comparison of Model Evaluation Results

Figure 3 highlights the substantial performance improvements of the hybrid model in both prediction accuracy and recommendation relevance. The inclusion of cluster-based features helps the model better understand user interests across thematic movie groups by providing a high-level, content-aware signal that alleviates data sparsity. The lower MAE and RMSE values of the hybrid model indicate that it can more accurately estimate unseen ratings, especially for cold-start items, because the cluster labels provide a strong initial context. Furthermore, the improvements in Precision@10 and Recall@10 suggest that the model not only predicts ratings more accurately but also recommends a higher proportion of relevant items, indicating better performance in a ranking-based context. The consistent gains across all metrics demonstrate that the hybrid approach successfully integrates the strengths of content-based clustering and collaborative filtering, leading to a more robust and effective recommendation system. While the model shows significant improvement, it is important to note that computational complexity increases due to the additional clustering and embedding layers, which could be a factor in larger-scale applications. Future work could also explore the impact of different cluster configurations on model scalability [27].

Table 10. Recommend movies for user

Movie Id	Movie Title	Cluster Category	Average Rating
365	Forrest Gump (1994)	High-Quality Thriller & Mystery	3.935667
50	Usual Suspects, The (1995)	Modern Action & Sci-Fi Blockbusters	3.862828
1198	Raiders of the Lost Ark (1981)	Classic Drama and Romance	3.839264
527	Schindler's List (1993)	Modern Action & Sci-Fi Blockbusters	3.847178
858	Godfather, The (1972)	Modern Action & Sci-Fi Blockbusters	3.846719

Table 10 presents a quantitative comparison between the baseline and hybrid NCF models. The hybrid configuration demonstrates consistent gains across all evaluation metrics, reflecting improved learning of user-item interactions and recommendation relevance.

Conclusion

This study successfully developed and evaluated a hybrid movie recommendation model that combines K-Means clustering with Neural Collaborative Filtering (NCF) to address the issue of data sparsity. The model enriches the NCF input by incorporating clustering features derived from K-Means, which utilizes movie content information such as genres and ratings. Our findings confirm that this novel integration of content-based clustering addresses the limitations of traditional CF and pure NCF models by providing a robust and context-aware representation. Evaluation results on the MovieLens Latest-Small dataset show significant and statistically validated improvements in prediction accuracy (MAE reduced to 0.6097, RMSE to 0.7946) and recommendation quality (improvements in Precision@10 and Recall@10) compared to the pure NCF model. The main limitations of this study include the use of a relatively small, static dataset and the reliance on a single clustering algorithm. In the future, this approach could be further enhanced by exploring more flexible clustering algorithms like DBSCAN to capture non-linear cluster shapes, integrating more dynamic contextual features from user session data, and testing the model on a larger, more dynamic dataset to validate its scalability and generalizability.

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