Movie Recommendation System: Classification and Regression

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***Abstract*—This project introduces an advanced movie recommendation system integrating collaborative filtering, content-based filtering, and regression analysis techniques to enhance personalized film suggestions. The system employs multiple machine learning approaches, including k-nearest neighbors (k-NN), KMeans clustering, and an extended suite of regression models such as linear regression, ridge regression, lasso regression, decision trees, gradient boosting, and ElasticNet. Utilizing the MovieLens dataset as the primary source, the project further refines its analysis by incorporating IMDb metadata, allowing for deeper insights into user preferences and film attributes. The regression models were evaluated across both the standalone MovieLens dataset and the combined MovieLens-IMDb dataset. Among the tested regression models, Gradient Boosting Regressor achieved the best results on the MovieLens dataset. For classification tasks, k-NN achieved the highest performance with a precision of 0.33, recall of 1.00, and F1 score of 0.50. Future work will focus on refining these methods to improve accuracy, scalability, and overall system responsiveness.**

***Index Terms*—machine learning, movie recommendation system, artificial intelligence, content based filtering, collaborative filtering**

I. Introduction

Recommendation systems have become indispensable tools for enhancing user engagement, particularly in streaming platforms and digital content services. This project aims to design a comprehensive movie recommendation system that integrates collaborative filtering, content-based filtering, clustering, and advanced regression models to provide personalized film suggestions. The intended audience includes streaming services and other platforms seeking to increase user retention through tailored recommendations.

Modern recommendation systems leverage algorithms that focus on improving accuracy, scalability, and user satisfaction. Hybrid approaches, which combine collaborative and content-based filtering, have proven particularly effective. Recent research highlights the role of clustering techniques and advanced regression methods in capturing complex user preferences and behavioral patterns. These hybrid systems not only enhance recommendation precision but also address the diverse needs of users.

This project employs the MovieLens dataset as its foundational resource, offering user ratings and detailed movie metadata for analysis. Building on this, the system incorporates k-nearest neighbors (k-NN) for similarity-based recommendations, KMeans clustering to identify groups of similar users and movies, and an expanded suite of regression models—such as gradient boosting and lasso regression—for modeling intricate rating patterns. By combining these methods, the system aims to refine recommendation accuracy and adaptability. Additionally, the project explores the integration of IMDb metadata with the MovieLens dataset, enabling a richer feature set for improved model performance. This holistic approach aligns with contemporary advancements in recommendation system research and highlights the potential of hybrid methodologies to enhance user satisfaction and engagement.

II. Related Work

Recommendation systems have been extensively studied, with various approaches developed to enhance personalization and prediction accuracy. Collaborative filtering (CF) has been a popular method, as shown in studies like [1], which utilized k-nearest neighbors (k-NN) and Singular Value Decomposition (SVD) to enhance CF by comparing similarity metrics such as cosine and Jaccard. Similarly, [2] extended this approach by integrating content-based filtering (CBF) with collaborative methods, using adjusted cosine similarity and KMeans clustering to address the cold-start problem. Both works influenced our choice of cosine similarity as the primary metric for k-NN and clustering techniques, while [3] demonstrated the value of combining CF with regression models, such as ridge and linear regression, particularly for larger datasets. Inspired by these findings, our project integrated CF with regression and clustering to create a hybrid system.

In addition to collaborative and content-based methods, clustering has been widely used to group users or movies based on shared features. For instance, [4] explored the application of KMeans, Birch, and other clustering techniques on the MovieLens dataset, while [5] used hierarchical clustering to address sparsity in CF. These works emphasized the impor-

tance of optimal cluster selection, which guided our decision to use KMeans with a carefully tuned number of clusters to group users and movies effectively. Meanwhile, studies such as [6] and [7] highlighted the role of content-rich metadata, such as textual data and movie attributes, in enhancing CBF. Drawing from these insights, we incorporated TF-IDF and PCA to process IMDb plot keywords, enriching the feature set for hybrid filtering.

Regression models have also been extensively used in recommendation systems. For example, [8] compared regression-based methods with CF, finding that ridge regression often outperformed traditional CF in terms of accuracy for larger datasets. Similarly, [9] demonstrated the effectiveness of regularized models like ElasticNet in capturing non-linear relationships in user-item interactions. Inspired by these results, we included ElasticNet and ridge regression in our system to handle the complex relationships in combined MovieLens and IMDb datasets. Furthermore, [10] explored tree-based models, such as Gradient Boosting and Random Forest, for recommendation tasks. While these models showed promise in non-linear data environments, their high computational cost limited their scalability. Our project addressed these challenges by employing Gradient Boosting with carefully tuned parameters, which ultimately outperformed other regression models in our experiments.

Finally, hybrid systems combining multiple methods have proven to be highly effective in overcoming the limitations of standalone approaches. For instance, [11] and [12] integrated CF and CBF with deep learning techniques, such as neural collaborative filtering and autoencoders, demonstrating significant improvements in recommendation accuracy. While our project did not incorporate deep learning due to computational constraints, the success of these hybrid models validated our decision to combine CF, CBF, and regression techniques. The diverse range of methods explored in these studies provided a robust foundation for designing our recommendation system, which leveraged the strengths of each approach to deliver accurate and personalized recommendations.

III. Recommendation Systems

In today's vast and ever-growing online environments, finding the right products or content can be challenging for users. This is where recommendation systems come into play, helping both to enhance user satisfaction and increase company profits. For instance, a user searching for a movie to watch might spend considerable time browsing, filtering results by various parameters like director or actor, and could potentially overlook a film they would greatly enjoy. Recommendation systems can offer suggestions tailored to the user's preferences, even if they have never heard of the film or its cast.

A. Approaches in Recommendation Systems

There are several approaches to designing a recommendation system, often using similarities between users, similarities between items, or a hybrid of both. These methods are commonly categorized as collaborative filtering (CF), content-based filtering, and hybrid filtering, with most systems employing one of these approaches.

1) Collaborative Filtering (CF): Collaborative filtering (CF) recommends items based on similarities between users. By finding relationships between the preferences of User A and User B, for instance, a system can suggest items that one has enjoyed to the other. CF can be further divided into memory-based, model-based, and hybrid approaches. In the memory-based approach, recommendations are made by calculating similarities between users, while model-based CF uses statistical methods or machine learning to predict ratings for unrated items.

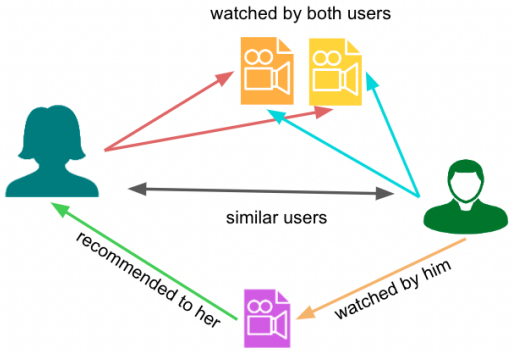

Fig. 1. Visualization of Collaborative Filtering (CF)

2) Content-Based Filtering: Content-based filtering analyzes the characteristics of items that the user has previously enjoyed, then suggests new items with similar attributes. This approach requires detailed information about the items, such as director, actors, and genre.

3) Hybrid Filtering: Hybrid filtering combines collaborative and content-based methods to mitigate the limitations of each approach. For example, CF can struggle with new items that have not yet been rated, while content-based filtering may fail to suggest diverse items outside of a user's known preferences. By integrating both approaches, hybrid filtering can improve recommendation diversity and accuracy.

B. Challenges in Recommendation Systems

Developing a recommendation system that reliably aligns with user preferences is complex and requires more than just knowing user preferences. It involves understanding the context around items, making sophisticated computations, and addressing various challenges.

- **Cold Start Problem**: New users or items lack sufficient rating data, making it difficult for CF systems to make recommendations.
- **Sparsity Problem**: If users have rated only a small portion of items, it can create gaps that reduce recommendation accuracy.
- **Scalability Problem**: As systems need to serve large numbers of users and items simultaneously, ensuring efficient performance can be challenging.

- **Gray Sheep Problem**: Some users may have unique preferences that do not align with any user group, making personalized recommendations harder to generate.
- **Neighbor Transitivity Problem**: In sparse data environments, two users with similar tastes might not have rated any common items, making it difficult for the system to identify them as similar.

IV. Data

A. Data Source

The dataset for this project was primarily sourced from **MovieLens**, a widely utilized dataset in recommendation system research. For this project, the **small MovieLens dataset** was used, which includes ratings for 1,000 movies and approximately 100,000 user reviews. Two primary tables, `ratings` and `movies`, were employed. The `ratings` table contains fields such as `userId`, `movieId`, `rating`, and `timestamp`, capturing user interactions with each movie. The `movies` table provides metadata through fields like `movieId`, `title`, and `genres`, which are essential for content-based filtering and regression tasks.

In addition to MovieLens, the **IMDb 5000 Movie Dataset** was incorporated to enhance the feature set. The IMDb dataset includes metadata for approximately 5,000 movies, with features such as `director_name`, `gross`, `budget`, `duration`, and `plot_keywords`. This additional dataset allowed for the exploration of richer features, such as director popularity and plot-based text analysis, to improve model performance. Key fields from the IMDb dataset were integrated with the MovieLens dataset using `movieId` as the linking key.

To ensure fair and efficient evaluation, the MovieLens dataset's small version was used for both regression and classification tasks. The integration with IMDb provided a more comprehensive feature set for regression analysis, allowing the models to capture more nuanced relationships between user preferences and movie attributes. This dual-dataset approach was critical for testing the robustness of the recommendation system and understanding the impact of enriched metadata on prediction accuracy.

B. Data Splitting and Usage

To ensure robust evaluation of the recommendation models, the ratings data was divided into training and testing sets using the `train_test_split` function. This split allowed us to test model performance on unseen data. The **movies** table was used for content-based filtering, leveraging genres and titles to generate relevant recommendations.

C. Data Cleaning and Preprocessing

The data underwent several preprocessing steps to enhance the system's accuracy and reliability:

1) Data for Classification Algorithms:

a) MovieLens Dataset: The MovieLens dataset was used to generate the classification model features. User and movie attributes were processed, including one-hot encoded genres and TF-IDF vectors for titles. The data consisted of 1,000 movies and 100,000 ratings, allowing for effective collaborative and content-based classification.

- **Duplicate Removal**: While no missing or duplicate entries were found in the initial dataset, a check was conducted to ensure data consistency.
- **Ignore Timestamp**: The Timestamp column was ignored, as our models do not rely on time-based recommendations. This simplification allowed the models to focus on user preferences and movie features without the influence of temporal factors.
- **User-Movie Matrix Creation**: Two user-movie matrices were created from the **ratings** data to facilitate collaborative filtering, with missing ratings filled as zero values.
- **Genre Processing**: Genres in the **movies** table were split and one-hot encoded to create a binary genre matrix. This matrix was essential for content-based recommendations.
- **Title Feature Extraction**: Titles were vectorized using TF-IDF, creating a sparse matrix to capture title similarity between movies.
- **Combined Feature Matrix**: The genre and title matrices were combined using `scipy.sparse.hstack`, creating a comprehensive content matrix that improved recommendation quality based on both genre and title similarities.

2) Data for Regression Algorithms:

a) MovieLens Dataset: The MovieLens dataset was processed to create features suitable for regression tasks. User ratings and movie attributes were combined to generate predictive features. The dataset consisted of 1,000 movies and 100,000 ratings, focusing on collaborative and content-based regression.

- **Timestamp Removal**: The `timestamp` column was removed.
- **Merging Datasets**: The **ratings** and **movies** tables were merged on the `movieId` field, linking user interactions with movie metadata.
- **Genre One-Hot Encoding**: The `genres` field in the **movies** table was split and one-hot encoded, resulting in a binary matrix that indicates the presence of each genre for a movie. This matrix was essential for generating features for regression models.
- **User and Movie Statistics**: Additional features were derived:
  - **Average User Rating**: The average rating given by each user was calculated and added as a feature (`avg_user_rating`).
  - **Average Movie Rating**: The average rating received by each movie was calculated and added as a feature (`avg_movie_rating`).
  - **User-Genre Averages**: For each user, average ratings for movies of specific genres were computed

and included as features. This added granularity by capturing user preferences for different genres.

- **Feature and Target Separation**: The resulting features included `avg_user_rating`, `avg_movie_rating`, and the user-genre averages. The `rating` column served as the target variable for regression tasks.

b) MovieLens + IMDb Dataset: The integration of MovieLens and IMDb datasets provided a richer feature set for regression tasks, combining user ratings, movie metadata, and additional features such as budget, duration, and plot keywords. The dataset consisted of 1,000 movies and 100,000 ratings from MovieLens, enhanced with approximately 5,000 movies from IMDb.

- **Timestamp Removal**: The `timestamp` column was removed.
- **Merging Datasets**: The **ratings** data from MovieLens and the extended metadata from IMDb were merged using the `movieId` field. This allowed the inclusion of features like `director_name`, `budget`, `gross`, and `plot_keywords`.
- **Genre One-Hot Encoding**: The `genres` field was split and one-hot encoded, resulting in a binary matrix indicating the presence of each genre for a movie.
- **Plot Keywords Processing**: The `plot_keywords` field from IMDb was processed using TF-IDF to create a sparse matrix, capturing textual similarities between movies. To reduce dimensionality, PCA was applied, generating 20 principal components that represented the most significant textual features.
- **Label Encoding for Categorical Fields**: Categorical fields such as `language`, `country`, and `director_name` were label-encoded to ensure compatibility with regression models.
- **User and Movie Statistics**: Additional features were derived:
  - **Average User Rating**: The average rating given by each user was calculated and added as a feature (`avg_user_rating`).
  - **Average Movie Rating**: The average rating received by each movie was calculated and added as a feature (`avg_movie_rating`).
  - **User-Genre Averages**: For each user, average ratings for movies of specific genres were computed and included as features.
- **Feature and Target Separation**: The combined feature set included metadata from IMDb (`duration`, `budget`, `imdb_score`), user-genre averages, and principal components from plot keyword analysis. The `rating` column served as the target variable for regression tasks.
- **Feature Scaling**: All features were scaled using `StandardScaler` to normalize values and improve regression model performance.

V. System Design & Proposed Solutions

This project implements 18 different recommendation models, categorized into content-based filtering, collaborative filtering, and hybrid approaches. Below is a detailed description of each model, its purpose, input parameters, and outputs.

A. Content-Based Filtering

- **Purpose**: Content-based filtering recommends movies similar to a specified movie by analyzing its intrinsic features, such as genres and titles.
- **Models Used and Parameters**:
  - **k-Nearest Neighbors (k-NN)**:
    - **Parameters**: `metric='cosine'`, `algorithm='brute'`.
  - **K-Means Clustering**:
    - **Parameters**: `num_clusters=70`.
- **Input**: Movie ID (`movieId`) and number of recommendations (`num_recommendations`).
- **Output**: A list of movies similar to the input movie.
- **Workflow**:
  - Preprocess the `genres` field by splitting and one-hot encoding it to create a binary genre matrix.
  - Process movie titles using TF-IDF to capture textual similarities.
  - Combine genre and title matrices to form the content feature matrix.
  - Apply:
    - **k-NN**: Compute cosine similarity between the input movie and others.
    - **K-Means**: Cluster movies and recommend others from the same cluster.

B. Collaborative Filtering

- **Purpose**: Collaborative filtering recommends movies by analyzing user interactions and identifying patterns in user preferences.
- **Models Used and Parameters**:
  - **k-Nearest Neighbors (k-NN)**:
    - **Parameters**: `metric='cosine'`, `algorithm='brute'`.
  - **K-Means Clustering**:
    - **Parameters**: `num_user_clusters=100`.
- **Input**: User ID (`userId`) and number of recommendations (`num_recommendations`).
- **Output**: A list of recommended movies based on user similarity or cluster membership.
- **Workflow**:
  - Construct a user-movie matrix from the `ratings` table, where rows represent users and columns represent movies. Missing values are filled with zeros.
  - Apply:
    - **k-NN**: Compute cosine similarity between users to find the most similar users. Recommend movies that these similar users have rated highly but the target user has not seen.
    - **K-Means Clustering**: Cluster users based on their movie preferences. Recommend movies highly

rated by other users in the same cluster as the target user.

C. Hybrid Filtering

- **Purpose**: Hybrid filtering combines collaborative and content-based approaches with regression techniques to recommend movies based on user preferences and movie attributes.
- **Datasets and Features**:
  - **MovieLens Dataset**:
    - **Target**: `rating`.
    - **Features**: `avg_user_rating`, `avg_movie_rating`, and user-genre averages.
    - **Description**: User and movie data processed from MovieLens, focusing on collaborative filtering and basic content features.
  - **MovieLens + IMDb Dataset**:
    - **Target**: `rating`.
    - **Features**:
      - **User and movie statistics**: `avg_user_rating`, `avg_movie_rating`.
      - **IMDb metadata**: `num_voted_users`, `imdb_score`, `duration`, `budget`, `country_encoded`, `language_encoded`, `director_encoded`.
      - **Content-based features**: Plot words with TF-IDF PCA components.
    - **Description**: The MovieLens dataset enriched with IMDb metadata for deeper analysis of movie attributes.
- **Models Used and Parameters**:
  - **Linear Regression**:
    - No regularization.
  - **Ridge Regression**:
    - `alpha=1.0`.
  - **Lasso Regression**:
    - `alpha=0.1`.
  - **ElasticNet Regression**:
    - `alpha=0.1`, `l1_ratio=0.5`.
  - **Decision Tree Regression**:
    - `random_state=42`.
  - **Gradient Boosting Regression**:
    - `random_state=42`.
  - **k-Nearest Neighbors (k-NN) Regression**:
    - `n_neighbors=3`.
- **Input**: User ID (`userId`) or Movie ID (`movieId`), depending on the regression task.
- **Output**: Predicted ratings for unwatched movies.
- **Workflow**:
  - Preprocess data:
    - For MovieLens: Extract `avg_user_rating`, `avg_movie_rating`, and user-genre averages as features.
    - For MovieLens + IMDb: Include additional features such as `imdb_score`, `budget`, and `plot_keywords` (via TF-IDF + PCA).
  - Split the dataset into training and testing sets (`test_size=0.2`, `random_state=42`).
  - Train models:
    - Apply each regression model to predict the `rating`.
    - Evaluate performance using metrics such as MAE, RMSE, and R^2.
  - Recommend movies with the highest predicted ratings for the user.

D. Evaluation and Initial Results

The performance of each model is evaluated using appropriate metrics based on the recommendation type. Metrics include **Precision@k**, **Recall@k**, **F1 Score@k**, **Mean Absolute Error (MAE)**, and **Root Mean Squared Error (RMSE)**. Results for different filtering approaches are detailed below.

1) Collaborative Filtering:

- Models evaluated:
  - k-Nearest Neighbors (k-NN) User-Based Collaborative Filtering
  - Collaborative-Based KMeans Clustering
- Performance Metrics:

TABLE I
COLLABORATIVE FILTERING MODEL PERFORMANCE METRICS

Model	Precision@k	Recall@k	F1 Score@k
k-NN User-Based Collaborative (k=6)	0.33	1.00	0.50
Collaborative-Based KMeans	0.20	1.00	0.33

2) Hybrid Filtering:

- Models evaluated:
  - Decision Tree Regression
  - Linear Regression
  - Ridge Regression
  - Lasso Regression
  - ElasticNet Regression
  - KNN Regression
  - Gradient Boosting Regression
- Performance Metrics:

TABLE II
REGRESSION MODEL PERFORMANCE METRICS(MOVIELENS DATASET)

Model Name	MAE	RMSE
Decision Tree Regression	0.7791	1.084
Linear Regression	0.6081	0.8012
Ridge Regression	0.6080	0.8012
Lasso Regression	0.6509	0.8443
ElasticNet	0.6360	0.8295
KNN Regression	0.6732	0.8985
Gradient Boosting	0.6037	0.7957

TABLE III
REGRESSION MODEL PERFORMANCE METRICS (IMDB + MOVIELENS DATASET)

Model Name	MAE	RMSE
Decision Tree Regression	0.8122	1.1300
Linear Regression	0.6253	0.8190
Ridge Regression	0.6253	0.8190
Lasso Regression	0.8122	0.8338
ElasticNet	0.6352	0.8291
KNN Regression	0.6969	0.9266
Gradient Boosting	0.6202	0.8126

VI. DISCUSSION

The project aimed to develop a robust movie recommendation system using various filtering and regression-based approaches. While previous experiments with regression models, such as linear and ridge regression, provided moderate performance (as shown in Figure **??**), the current system demonstrated significant improvements in prediction accuracy through enhanced feature engineering and dataset integration.

A. Feature Importance

One of the critical factors contributing to the improved performance was the introduction of user- and movie-specific features, specifically `avg_user_rating` and `avg_movie_rating`. These features effectively captured user preferences and movie popularity, which significantly impacted the performance of hybrid regression models. For example, incorporating these features into the regression models led to notable reductions in both Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

Additionally, handling genre information played a vital role in improving the recommendations. Initial experiments employed one-hot encoding for genres, where genres were converted into binary (0-1) features. While this approach provided some insight into genre contributions, it failed to fully leverage the relationship between users and genres. By calculating user-specific average ratings for each genre, the system captured user preferences at a more granular level, leading to significant improvements in prediction accuracy.

B. Impact of IMDb Integration

The integration of the IMDb dataset introduced several new features, such as `imdb_score`, `budget`, `duration`, and textual data from `plot_keywords`. These features provided a richer context for understanding movie characteristics. However, extensive testing revealed that not all features contributed equally to model performance. For instance:

- **Textual Features**: Features derived from `plot_keywords` were processed using TF-IDF and dimensionality reduction (PCA). This approach ensured that only the most relevant components were used, thereby avoiding overfitting and reducing computational complexity.
- **Numerical Features**: Features such as `budget` and `gross` were less impactful due to missing or skewed values in the IMDb dataset, highlighting the challenges of working with heterogeneous data sources.

Ultimately, the combination of MovieLens and IMDb data allowed the system to explore richer feature interactions, but the most substantial improvements came from carefully curated features, such as user-genre averages and movie popularity metrics.

C. Challenges Encountered

While the project achieved promising results, several challenges were encountered during the development process:

- **Feature Engineering Complexity**: Designing effective features, such as user-genre averages, required multiple iterations and computational resources. Initial attempts, such as using raw genre encodings, provided limited performance improvements and emphasized the need for more refined feature extraction techniques.
- **Model Limitations**: Some models, such as Support Vector Regression (SVR), were tested but could not be fully evaluated due to long computation times and scalability issues. This highlighted the trade-offs between model complexity and practical feasibility when dealing with large datasets.
- **Dataset Integration**: While the integration of the IMDb dataset enriched the feature set, it introduced challenges related to missing data and feature scaling. For instance, categorical features like `language` and `country` required careful preprocessing (label encoding), and numerical features like `budget` needed normalization to align with the MovieLens data.

D. Comparison with Literature

The findings of this project align with recent studies emphasizing the effectiveness of hybrid approaches that integrate collaborative and content-based methods with regression techniques. For example, previous works [1], [2] demonstrated the utility of cosine similarity in user-based models and clustering for grouping similar users or movies. Our use of k-Nearest Neighbors (k-NN) and KMeans clustering builds on these insights and further validates the role of clustering in improving recommendation accuracy, particularly when paired with feature engineering.

Regression-based models also proved instrumental in this project, aligning with findings in [3], [8], where regression techniques outperformed traditional methods on larger datasets. By incorporating features such as user and movie averages, as well as enriched metadata, we observed significant performance gains, with Gradient Boosting achieving the best results on the combined MovieLens and IMDb dataset (MAE: 0.6202, RMSE: 0.8126). Similarly, studies such as [10] highlighted the capability of tree-based models to handle non-linear relationships effectively, which we confirmed in our experiments.

Text-based features also played a key role, inspired by studies [6], [7] that demonstrated the value of processing textual data like plot keywords using TF-IDF and dimensionality

reduction. By adopting these techniques, we improved the system's ability to capture nuanced movie characteristics and enhance recommendation quality. This aligns with the hybrid approaches discussed in [11], [12], which combine multiple data sources and techniques for superior results.

In summary, this project underscores the importance of combining diverse approaches and leveraging enriched datasets for recommendation systems. The improvements achieved reflect recent advancements in the field and demonstrate the potential of hybrid models for addressing complex recommendation tasks.

VII. Conclusion

This project successfully developed a robust movie recommendation system by integrating collaborative filtering, content-based filtering, and advanced regression models. The system utilized k-nearest neighbors (k-NN), KMeans clustering, and an expanded suite of regression models, including linear regression, ridge regression, lasso regression, ElasticNet, and Gradient Boosting, to provide personalized recommendations based on user preferences and enriched film metadata.

The results demonstrated significant improvements in prediction accuracy compared to earlier iterations. Regression-based approaches, particularly Gradient Boosting, excelled in predicting movie ratings, achieving the best performance across both the standalone MovieLens dataset and the combined MovieLens-IMDb dataset (MAE: 0.6202, RMSE: 0.8126). Features like `avg_user_rating` and `avg_movie_rating` played a crucial role in enhancing the accuracy of regression models by capturing user and movie-level interactions effectively.

For classification tasks, k-NN user-based collaborative filtering achieved the highest performance, with a Precision@k of 0.33, Recall@k of 1.00, and F1 Score@k of 0.50. The combination of user-genre averages and one-hot encoded genres contributed significantly to the system's ability to recommend relevant movies, highlighting the importance of feature engineering.

The integration of IMDb metadata further enriched the feature space, introducing attributes such as `imdb_score`, `duration`, `budget`, and textual features derived from `plot_keywords`. While not all features contributed equally, the use of TF-IDF and PCA for dimensionality reduction ensured computational efficiency and avoided overfitting.

Overall, this project highlights the potential of hybrid recommendation systems that combine collaborative filtering, content-based filtering, and regression techniques. By leveraging enriched datasets and advanced feature engineering, the system effectively captured complex user behaviors and provided accurate, personalized movie recommendations. Future work can focus on refining non-linear models, incorporating deep learning techniques, and addressing challenges such as sparsity and cold-start problems to further enhance system performance.

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