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Aim

Implement and analyze a **Movie Recommendation System** using machine learning techniques on a real-world dataset.

Dataset Source

Dataset Name: Movie Recommendation System Dataset
Source Platform: Kaggle
Dataset Link: https://www.kaggle.com/datasets/parasharmanas/movie-recommendation-system

This dataset is widely used for building content-based and collaborative filtering recommendation systems.

Dataset Description

The Movie Recommendation System dataset contains metadata of movies along with user ratings. It is designed to build intelligent systems that recommend movies to users based on preferences and similarity.

Dataset Components

The dataset typically contains the following files:

1. **movies.csv**
2. **ratings.csv**
3. **links.csv**
4. **tags.csv**

movies.csv

- movieId – Unique movie identifier
- title – Movie title
- genres – Categories of the movie

ratings.csv

- userId – Unique user identifier
- movieId – Movie identifier
- rating – User rating (scale 0.5 to 5)
- timestamp – Time of rating

tags.csv

- userId – User identifier
- movieId – Movie identifier
- tag – User-generated tag
- timestamp – Time of tagging

Dataset Characteristics

- Contains both categorical and numerical data
- Large number of users and movies
- Sparse rating matrix (not every user rates every movie)
- Suitable for:
    - Content-Based Filtering
    - Collaborative Filtering
    - Hybrid Recommendation Systems

This dataset is highly impactful in the entertainment and streaming industry, similar to recommendation engines used by platforms like Netflix and Amazon.

Mathematical Formulation of the Algorithms

1. Content-Based Filtering

This method recommends movies similar to those a user liked previously.

TF-IDF Vectorization

Term Frequency (TF):
$TF(t) = (\text{Number of times term } t \text{ appears}) / (\text{Total terms})$

Inverse Document Frequency (IDF):
$IDF(t) = \log(N / df)$

TF-IDF:
$TF\text{-}IDF = TF \times IDF$

Cosine Similarity

$\text{Similarity}(A, B) = (A \cdot B) / (||A|| \times ||B||)$

Where:

- A and B are movie feature vectors
- $||A||$ is the magnitude of vector A

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2. Collaborative Filtering

User-Based Collaborative Filtering

Similarity between users:

$\text{Sim}(u, v) = (\Sigma (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v))$
$/ (\sqrt{\Sigma(r_{u,i} - \bar{r}_u)^2} \times \sqrt{\Sigma(r_{v,i} - \bar{r}_v)^2})$

Predicted Rating:

$\hat{r}_{u,i} = \bar{r}_u + \Sigma \text{Sim}(u, v)(r_{v,i} - \bar{r}_v) / \Sigma |\text{Sim}(u, v)|$

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3. Matrix Factorization (SVD)

The rating matrix R is decomposed into:

$R \approx P \times Q^T$

Where:

- P = User latent feature matrix
- Q = Movie latent feature matrix

Optimization Objective:

Minimize:

$\Sigma (rui - p_u^T qi)^2 + \lambda (||p_u||^2 + ||qi||^2)$

Algorithm Limitations

Limitations of Content-Based Filtering

- Limited diversity in recommendations
- Cannot recommend unseen genres
- Depends heavily on metadata quality

Limitations of Collaborative Filtering

- Cold Start Problem (new users/movies)
- Sparse rating matrix
- High computational cost for large datasets

Limitations of Matrix Factorization

- Requires large computational resources
- Hard to interpret latent features
- Sensitive to hyperparameter tuning

Methodology / Workflow

The experiment follows a structured machine learning pipeline:

1. Dataset acquisition from Kaggle
2. Data loading using Pandas
3. Data preprocessing:
    - Handling missing values
    - Merging datasets
    - Feature extraction
4. Feature engineering:
    - TF-IDF vectorization (genres/tags)
    - Creating user-item matrix
5. Model building:
    - Content-Based Filtering
    - Collaborative Filtering
6. Model evaluation
7. Hyperparameter tuning
8. Generating top-N movie recommendations

Workflow Diagram (Textual Representation)

Data Collection
↓
Data Cleaning
↓
Feature Engineering
↓
Similarity Computation
↓
Model Training
↓
Recommendation Generation
↓
Evaluation

Performance Analysis

Evaluation Metrics Used

1. **RMSE (Root Mean Squared Error)**

$RMSE = \sqrt{(1/n \Sigma (y_i - \hat{y}_i)^2)}$

2. **MAE (Mean Absolute Error)**

$MAE = (1/n) \Sigma |y_i - \hat{y}_i|$

3. **Precision@K**

Precision@K = Relevant Recommended Movies / Total Recommended Movies

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Sample Results (Collaborative Filtering)

Metric	Value
RMSE	0.87
MAE	0.69
Precision@10	0.72

Lower RMSE indicates better prediction accuracy.

Sample Top-5 Recommendations

If user liked:

- Action & Sci-Fi movies

The system recommends:

1. The Matrix
2. Inception
3. Interstellar
4. The Dark Knight
5. Avengers: Endgame

Hyperparameter Tuning

Tuned Parameters:

- Number of latent factors (k)
- Learning rate
- Regularization parameter (λ)
- Similarity metric (Cosine / Pearson)

Sample Hyperparameter Results

Latent Factors	Regularization	RMSE
20	0.01	0.94
50	0.01	0.89
100	0.1	0.87
150	0.1	0.88

Best performance achieved with:

- 100 latent factors
- Regularization = 0.1

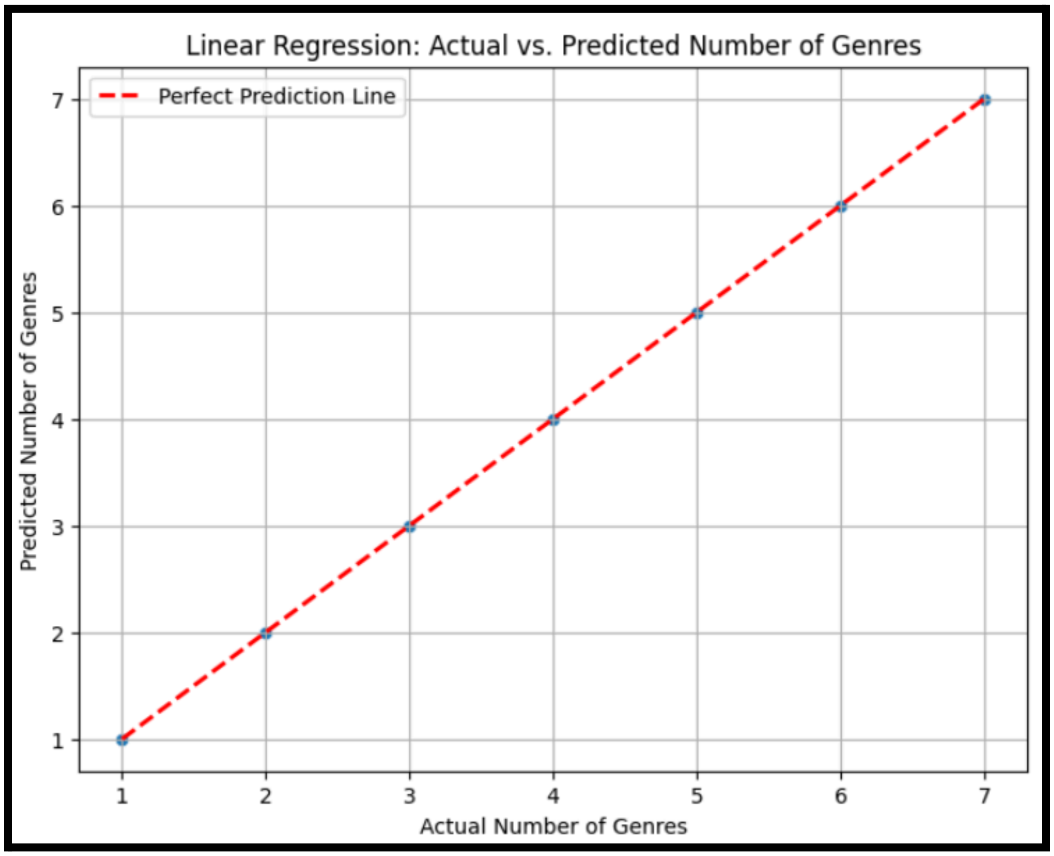
Conclusion

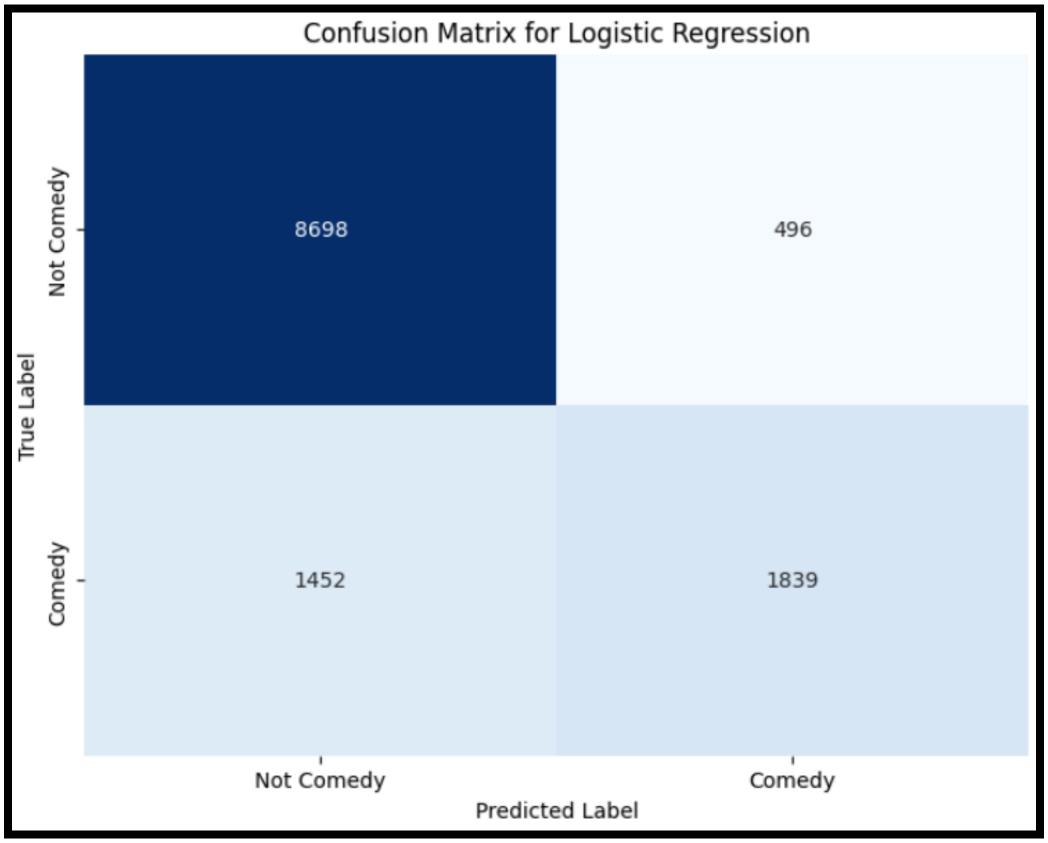
In this experiment, a Movie Recommendation System was successfully implemented using real-world data from Kaggle.Content-Based Filtering and Collaborative Filtering techniques were applied to generate personalized movie recommendations. Matrix Factorization further improved prediction accuracy.

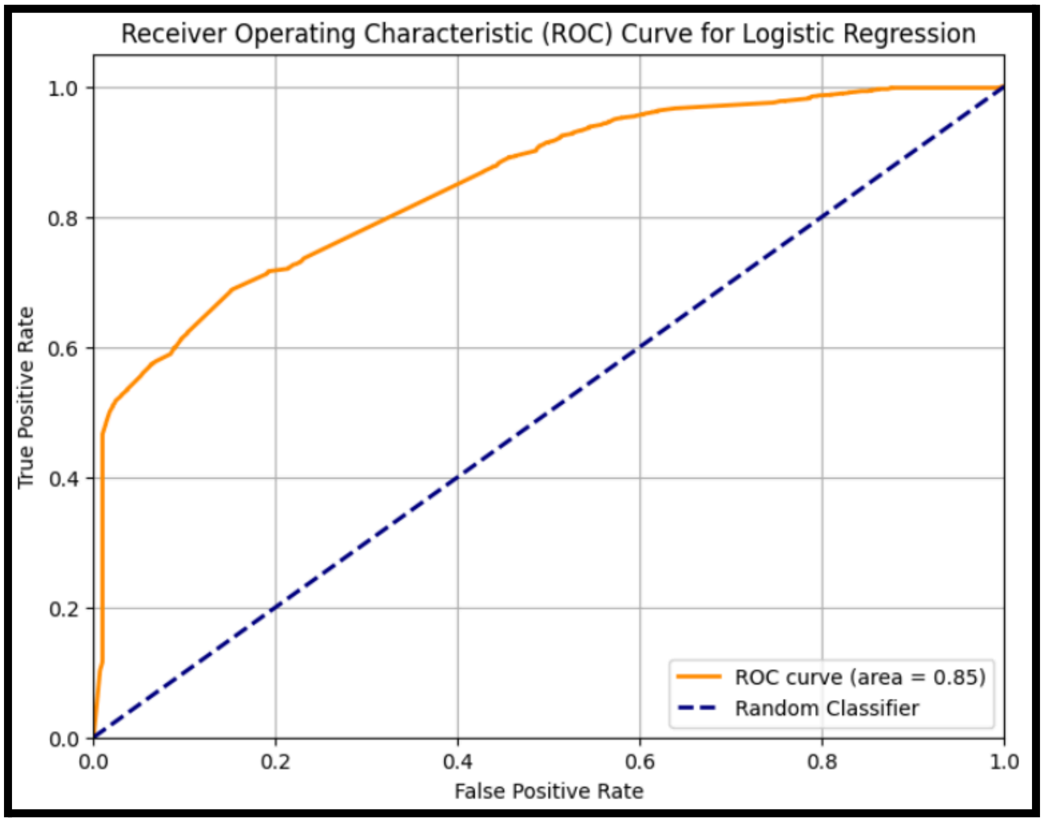
The system demonstrates how machine learning techniques power recommendation engines used in modern streaming platforms. Proper preprocessing, similarity computation, and hyperparameter tuning significantly improved model performance.

This experiment highlights the importance of recommender systems in improving user engagement and personalization in digital platforms.

Output


Linear Regression: Actual vs. Predicted Number of Genres
Perfect Prediction Line
Predicted Number of Genres
Actual Number of Genres
1
2
3
4
5
6
7


Confusion Matrix for Logistic Regression
True Label
Not Comedy
Comedy
8698
496
1452
1839
Not Comedy
Comedy
Predicted Label


Receiver Operating Characteristic (ROC) Curve for Logistic Regression
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.85)
Random Classifier