

Unveiling Film Tastes: A Personalized Movie Journey through Smart Recommendations

A hand holding a black remote control is in the foreground, pointing towards a television screen. The screen displays the word 'NETFLIX' in large, orange, blocky letters. The background is a blurred indoor setting with a wooden surface and two potted plants.

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Optimizing Viewer Engagement through Personalized Movie Recommendations

Business Landscape Today

Content Saturation

Failed Business

Poor User Experience

Project Business Objectives

- Strategic personalization for viewer loyalty.
- Turning user choices into enhanced experiences.
- Data-Driven solutions for business Success

Dataset Overview

Data Source: Movielens

Ratings Dataset: userId, movieId, rating, timestamp

Movie Dataset: title, genres.

Tags Dataset: userId, movieId, tag

Business Relevance of the Data

- Explore user view through ratings.
- Genre Insights for personalized recommendations.
- User-Generated Tags to get user perceptions



Data Analysis Process Overview

Data Collection, cleaning & Preprocessing

Acquiring
datasets from
Movielens.

Handling of
missing data for
accurate insights.

Exploratory Data Analysis

Uncovering
patterns and user
preferences
through
visualizations

Identifying trends
to inform
strategic
decisions

Feature Engineering

Creating new
features to refine
dataset relevance

Aligning data with
recommendation
system
requirements

Machine Learning & Evaluation

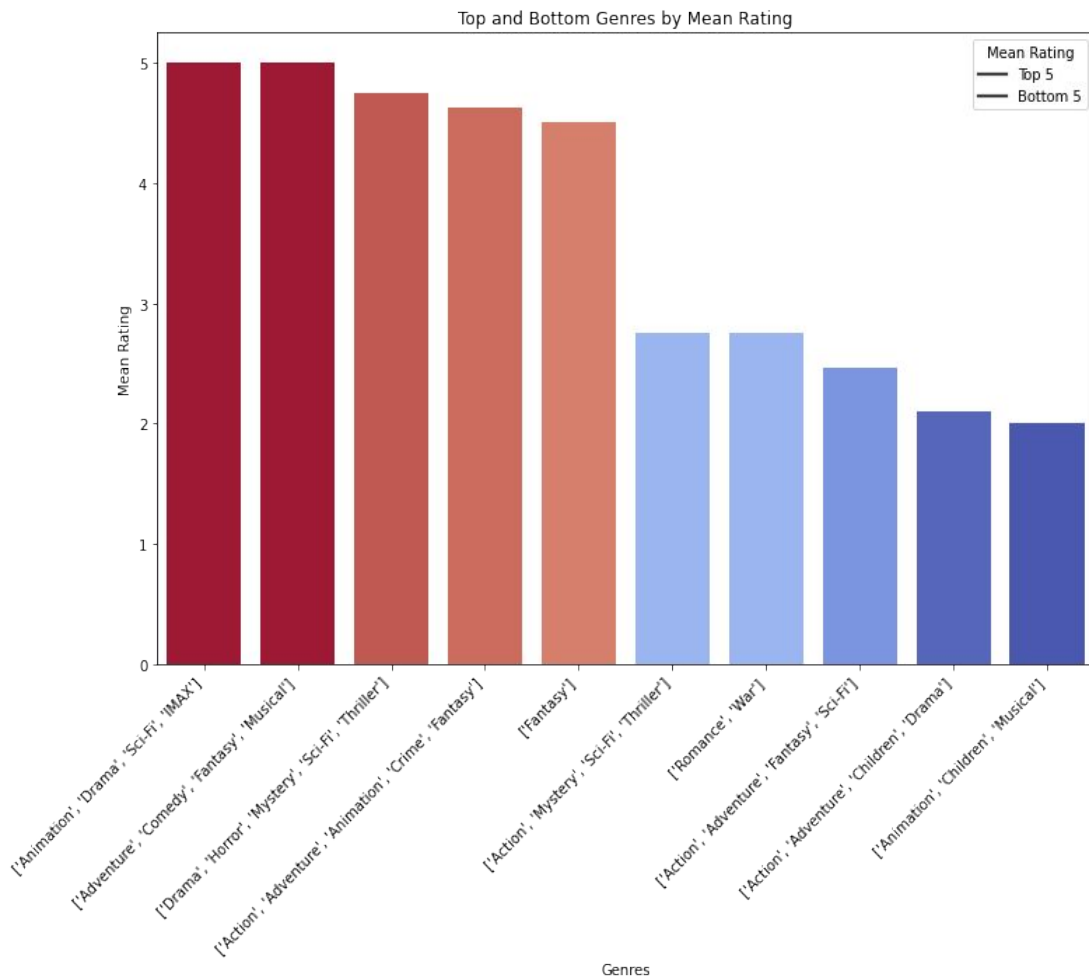
Implementing
advanced machine
learning models for
recommendation
system development.

Applying metrics to
assess model
performance.

Insights

Deriving
actionable
insights from the
analysis to inform
strategic
decisions.

Exploratory Data Analysis [EDA]



Genres based on mean ratings.

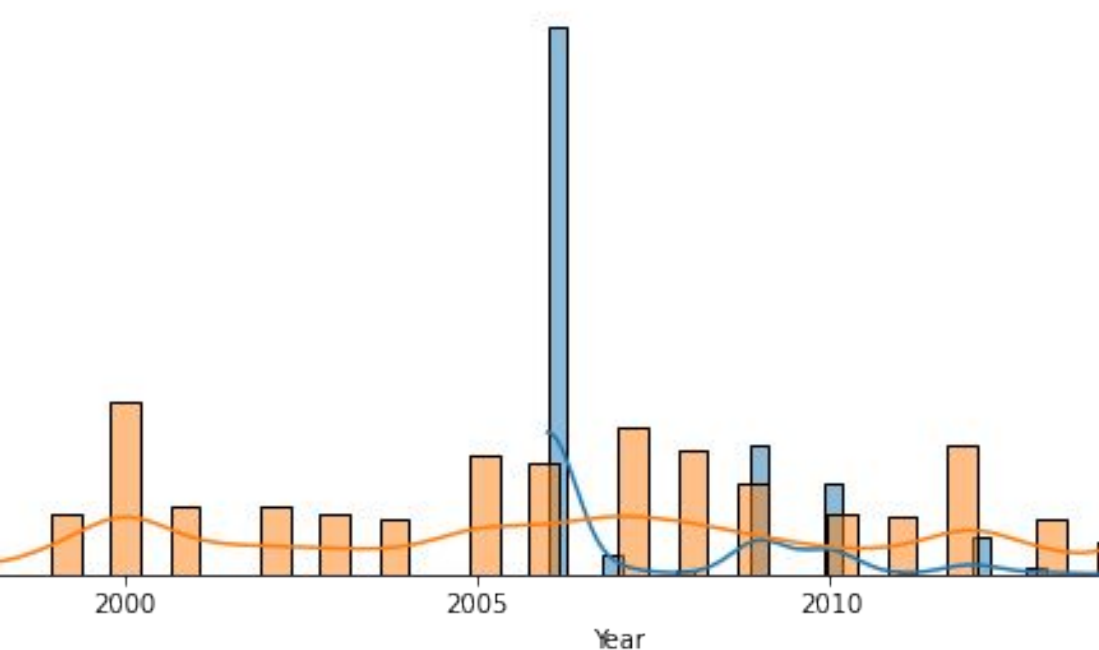
Top Genres: Animation, Drama, Sci-Fi, IMAX, Adventure, Comedy, Fantasy, Musical have ratings of 5.0.

Bottom Genres

Action, Mystery, Thriller, Romance, War have lower ratings around 2.7.

Exploratory Data Analysis [EDA]

Distribution of Timestamps Over the Years



Temporal Analysis of ratings and tags

Fluctuations in the trend of ratings over the years

Consistent rating over the years

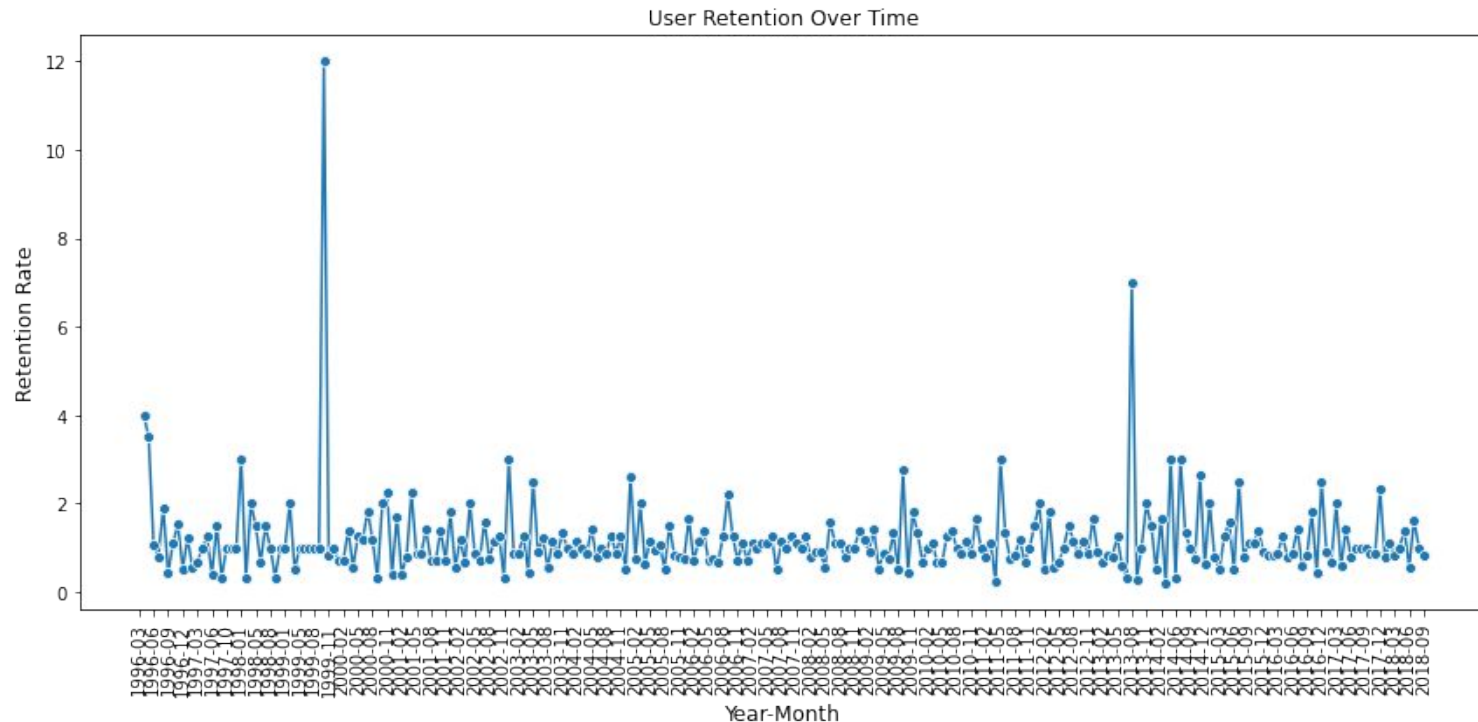
Tags originated around 2006, with an initial surge of 50,000.

Decline in tag activity

Resurgence starting from 2015.

The counts continue to increase, reaching around 70,000 in 2017

Feature Engineering



User Retention over time

Fluctuations in the platform's ability to retain users

Peak around August to November 1999 and August to November 2013

indicate critical periods of user engagement

Machine Learning Modeling and Evaluation Metrics

Item-item collaborative filtering

Recommend movies to a user based on the preferences of other users who liked the same movies.

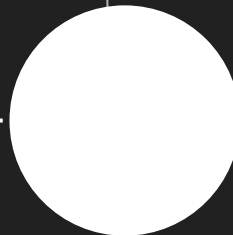
The RMSE 0.7924



User-Item Collaborative Filtering

Recommend movies based on the preferences of similar users

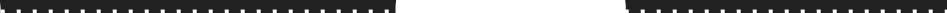
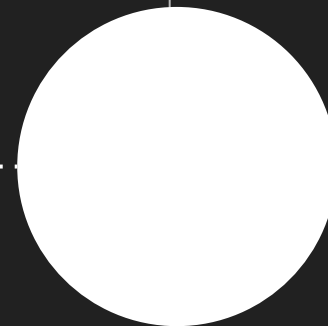
The RMSE 0.7389



Neural Collaborative Filtering (NCF)

Showcases deep learning prowess, and meticulous tuning

Test loss of 0.54



Conclusions and Insights

- The recommendation system has achieved a 74% accuracy in aligning user preferences with movie recommendations.
- An accurate recommendation system contributes significantly to user experience and the platform's success
- Getting deeper analysis of user engagement metrics in response to personalized recommendations.

Thank You

Any Questions,
comments and Insights
Are highly valued.

