



# Sinema Pamoja: Personalized Movie Recommendation System

Using Data-Driven Personalization to Enhance Viewer Engagement and Retention

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# Business Problem & Project Goal

The Kenyan movie industry is experiencing growth, with more viewers accessing films through digital platforms

## The Challenge

Viewers face choice overload and may miss movies they'd enjoy → disengagement and reduced loyalty

## Proposed Solution

Build a system to recommend the Top-5 movies each user is most likely to watch and enjoy

## Business Impact:



Boosts viewership and revenue.



Strengthens brand loyalty.



Helps audiences discover hidden gems.



Differentiates Sinema Pamoja from competitors.

# Data Understanding

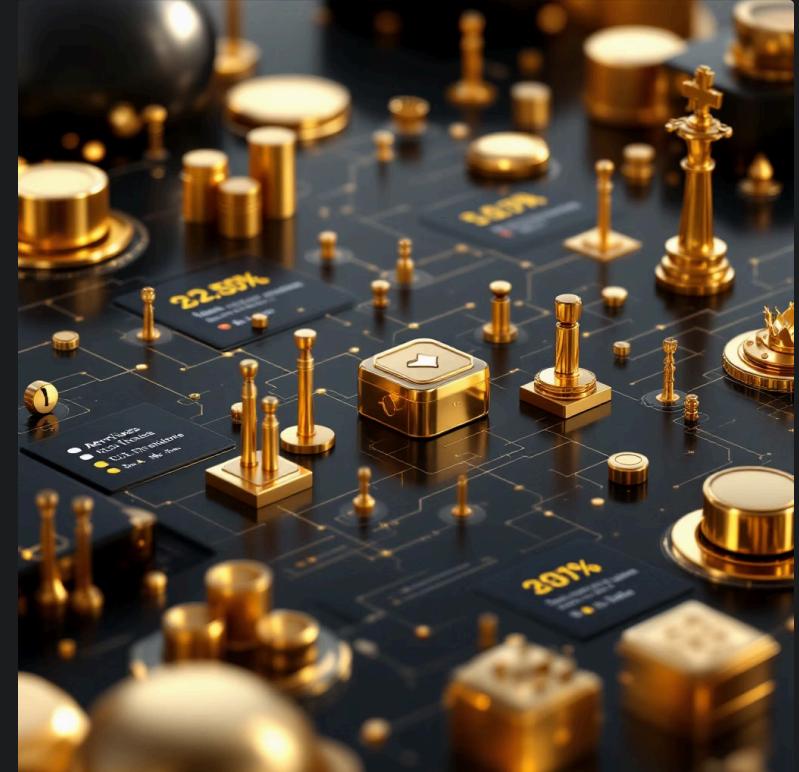
We load the core MovieLens datasets — movies, ratings, links, and tags — into a single comprehensive dataframe

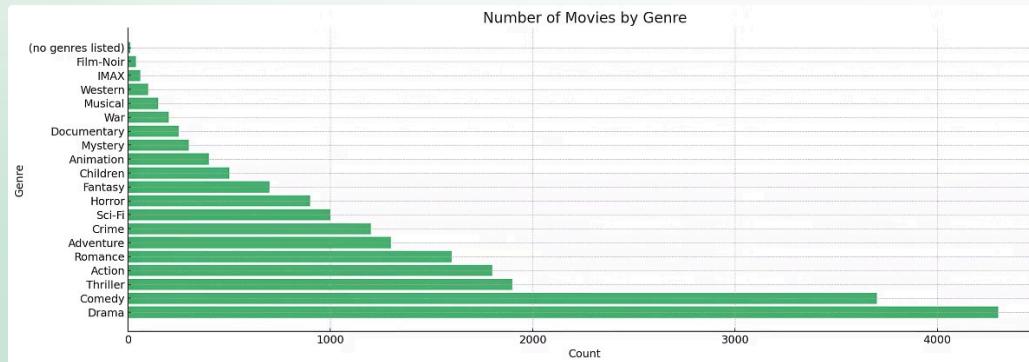
The merging process ensures that all ratings are retained, even if some movies lack tags.

## Dataset includes:

- **User ratings** - how much users liked a movie (1–5 stars)
- **Movie details** - title and genre
- **User-generated tags** - words users add to describe movies (e.g. *funny*, *action-packed*, *romantic*)
- **Links** - connects movies to external sites like IMDb or TMDb for extra details

After merging, the dataset provides a rich foundation for building personalized recommendations





# Exploratory Data Analysis (EDA)

- Drama and Comedy dominate the catalog with the largest number of movies
- Action and Thriller also have strong representation among popular genres
- Niche genres like Film-Noir, IMAX, and Western are rare, reflecting the long-tail of movie availability

## Content Balance

The dataset is heavily skewed toward mainstream genres, highlighting the need for personalization to help users explore beyond the most common categories

## Genre Popularity

Romance, Adventure, Crime and Sci-fi genres also have strong representation beyond Drama and Comedy

## Movie Popularity

Musicals, War, and Documentaries remain limited

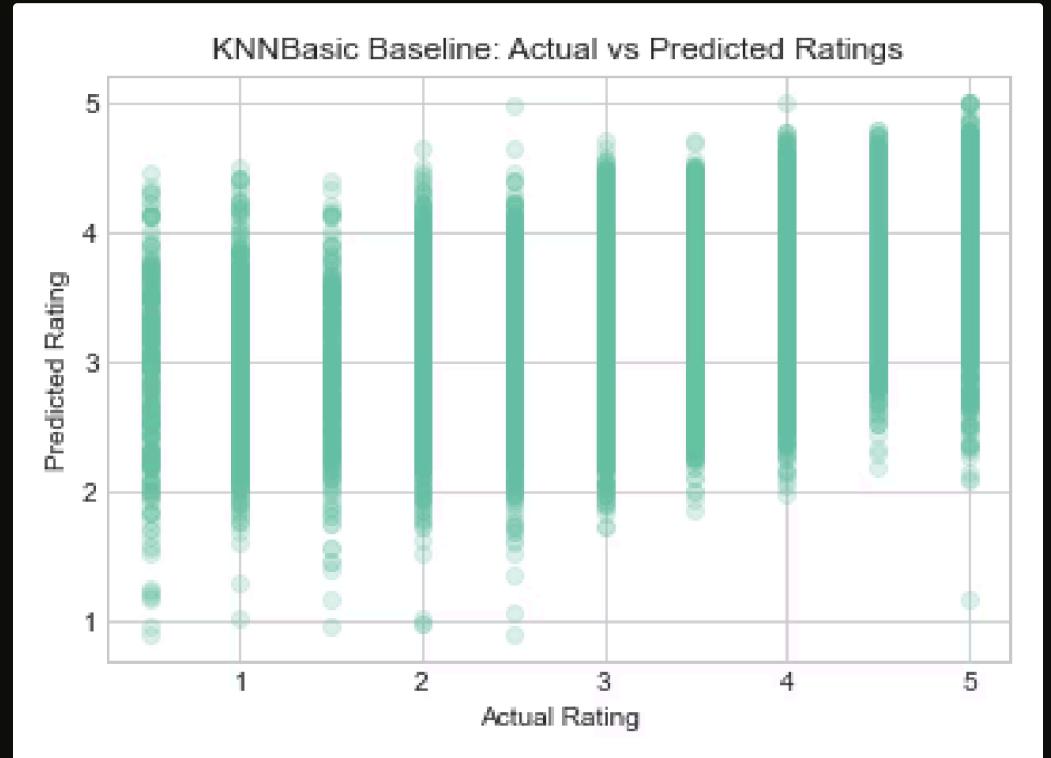
# Baseline Modeling – KNN

KNN is intuitive — the model predicts ratings by looking at the  $k$  nearest users or items and averaging their ratings

**Why baseline?** It's simple, interpretable, and sets the benchmark floor

## Results:

- **RMSE**  $\approx 0.9$  → On average, predictions differ from actual ratings by just under one star
- **MAE**  $\approx 0.7$  → Most predictions are within about three-quarters of a star of the true rating
- There is visible spread, meaning the model sometimes over- or under-predicts by 1–2 stars
- Overall, KNN captures general trends but lacks precision compared to more advanced models like SVD



# Advanced Models – SVD & NMF

Matrix factorization (SVD, NMF) reduces high-dimensional rating data into latent features that capture hidden taste factors



## SVD

Captures patterns like *Action vs Romance* preferences

## NMF

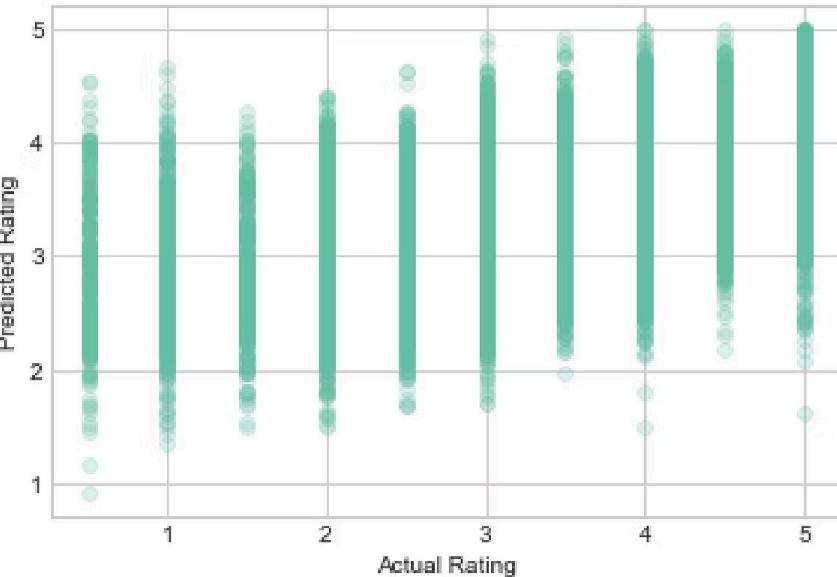
Ensures interpretability while improving prediction accuracy

## Results

Both outperform KNN in accuracy and Top-5 ranking quality

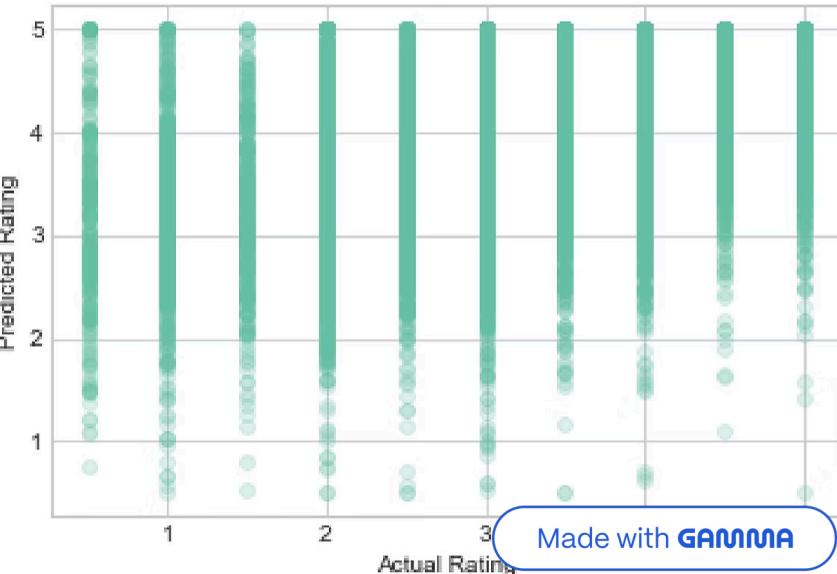
SVD: Actual vs Predicted Ratings

SVD: Actual vs Predicted Ratings



NMF: Actual vs Predicted Ratings

NMF: Actual vs Predicted Ratings





# Model Comparison

- **KNN (Baseline):** RMSE  $\approx 0.9$ , MAE  $\approx 0.7$  — predictions usually off by less than 1 star
- **NMF (Advanced):** Higher RMSE and MAE than KNN and SVD — less effective in capturing user preferences
- **SVD (Advanced):** Lowest RMSE ( $\approx 0.87$ ) and MAE ( $\approx 0.67$ ) — most accurate and consistent predictions

SVD clearly outperforms the baseline KNN model and NMF, reducing errors and making more reliable predictions. This demonstrates the business value of moving from a simple baseline to an advanced model

# Business Value & Conclusion



Personalized recommendations:  
keep users engaged longer



Higher satisfaction → stronger loyalty  
& repeat usage



Helps **Sinema Pamoja** stand out with  
data-driven personalization

## Next Steps:

### Deploy

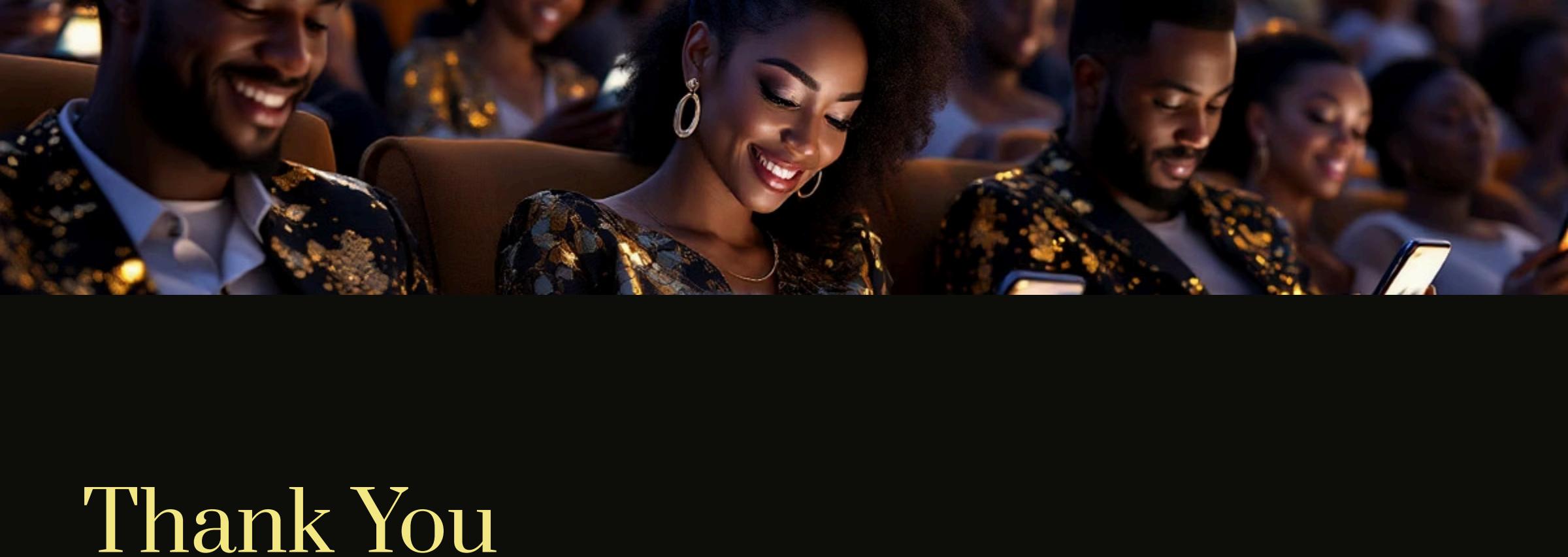
Deploy recommender prototype

### Enhance

Add hybrid (content + collaborative)  
for new users

### Integrate

Integrate into **Sinema Pamoja**  
platform



# Thank You

*We appreciate your time and attention*

Open for questions and feedback