

# Movie Recommender System

What are you looking for today

spider-man 3

Recommend

spider-man 2



spider-man



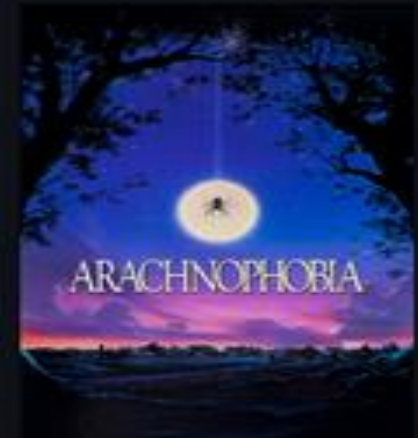
the amazing spi



the amazing spi



arachnophobia



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# Business Understanding



- ▶ With many genres, including action, drama, comedy, science fiction, horror among others, the movie industry is characterized by diverse films and content.
- ▶ Each genre appeals to different tastes and moods, making it hard to pick just one.
- ▶ For a user, this abundance can be both a blessing and a challenge.
- ▶ The sheer volume of movies available can be overwhelming, making it difficult to decide which movie to watch and, more importantly, how to ensure that the chosen movie will be truly enjoyable.
- ▶ In this regard, there is a need for businesses to understand and meet user preferences.

# Problem Statement



- ▶ There is increased competition among movie streaming platforms
- ▶ The performance of a streaming platform, especially in terms of user retention and satisfaction, is closely tied to the effectiveness of its recommendation system.
- ▶ It is challenging for users to select movies which align with their tastes
- ▶ There is need for curated collections and suggestions to help users discover and ultimately watch movies which align with their preferences.
- ▶ This project addresses this challenge by developing a recommendation system which analyzes a user's past viewing habits, ratings, and the behavior of similar users to suggest movies tailored to individual tastes.

# Objective

- ▶ To develop a model that offers top 5 recommendations to a user based on their ratings of other movies

# Data Understanding

- ▶ The data was sourced from MovieLens.
- ▶ The variables were:
  - I. movieId - Unique identifier for each movie.
  - II. title - The movie titles.
  - III. genre - The various genres a movie
  - IV. userId - Unique identifier for each user
  - V. rating - A value between 0 to 5 that a user rates a movie on. A higher rating indicates a higher preference



# Modelling: Baseline Model

- ▶ The Popularity-Based Recommender which suggests movies to users based on their overall popularity was used as baseline model
- ▶ The model's predictions deviate from the actual ratings by approximately 1.0425 units on the rating scale. Given that the ratings are between 0.5 and 5 an, this deviation is large. As such there is need for a better model with higher accuracy

# Advanced Modelling

- ▶ After tuning and optimization the Singular Value Decomposition (SVD) was chosen as the model with the highest accuracy in recommending movies based on a user's past ratings
- ▶ The SVD model had an accuracy of 86%

# Recommender based on user's ratings

- ▶ The function uses past user ratings, deploys the best SVD model to make recommendations. The recommender prompts the user to enter their `user ID` then based on the unique ID it gives recommendations.



# Conclusion

- ▶ The recommendation system has achieved an impressive 86% accuracy in aligning user preferences with movie recommendations. This addresses the challenge of content navigation challenges by delivering tailored movie suggestions ultimately improving watching experience.

# Recommendation

- ▶ The streaming platform should aim to feature movies rated at least `3.5` and above as they cut across most users.
- ▶ Implementation of content-based recommendations which analyze movie attributes such as genre, actors, directors, and user preferences to make more diverse and personalized recommendations.
- ▶ Develop a hybrid recommender system which combine SVD model and content-based recommendation approach to capitalize on the strengths of both methods