# Recommendation System

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#### Overview

**Source:** MovieLens

- **Authors:** GroupLens

Main Feature: Ratings

**Goal:** Recommendation system that suggested five movies based off prior users' ratings



#### **Business Problem**

- Over 8 million movies
- Limited time
- Prone to suggestion
  - Users watches recommended videos 70% of the time on Youtube

<u>Improve</u> streaming services by offering <u>better recommendations</u>



# Targeted Streaming Services



max



# **Data Understanding**

Number of users: 610

Number of Movies: 9,742

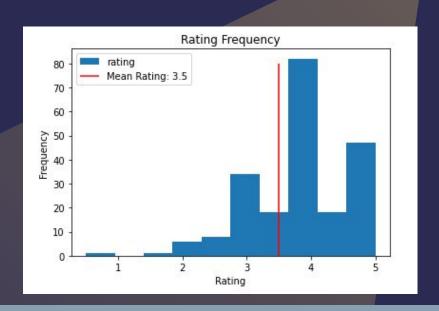
Number of reviews: 100,836

Dataset features: Rating, Genre and

Tags\*

Rating Range: o (Bad) →5 (Good)

- o.5 steps



# **Data Preparation**

- 1. Remove <u>timestamp</u> from dataset (Not Needed)
- 2. Create **training** and **testing** set (Test Accuracy)
- 3. Standardize Genres (Content Filtering)

#### Methods

Main Library: Surprise

**Memory Based Modeling:** KnnBasic, **KnnBaseline**, KnnWithMean

Clusters grouping similar items

Model Based Modeling: SVD Singular Value Decomposition

- Matrix decomposition

Best Performing: KnnBaseline

#### Measurement

RSME: (Root Square Mean Error)

Average error for the predicted rating

NDCG: (Normalized Discounted Cumulative Gain)

Method to **compare ranked list** and relevance

Used RSME for **interpretability** 

### **Additional Conditions**

- 1. Model won't recommend seen movies
- 2. Consider new users and movies (Cold Start)

# **User 1 Recommendations**

Model: KnnBaseline

Added filtering: Top Favorite Genres

**Includes Favorite Genres** 

Ghost in the Shell (Kôkaku kidôtai) (1995)

Singin' in the Rain (1952)

Notorious (1946)

Sicario (2015)

Big Short, The (2015)

#### **Cold Start**

A cold start is a problem when a **new user or item** is added without **prior history** in the current system.

User Case: A new user is added needs a recommendation.



Item Case: A new movie is added and need to be recommended.

# Ex. New User Recommendations

Most Rated Movies	Most Popular Movies
Paper Birds (Pájaros de papel) (2010)	Pulp Fiction (1994)
Act of Killing, The (2012)	Shawshank Redemption, The (1994)
Jump In! (2007)	Forrest Gump (1994)
Human (2015)	Silence of the Lambs, The (1991)
L.A. Slasher (2015)	Matrix, The (1999)

**Most Rated:** All rated 5 stars

**Most Popular:** Movies with the most users rated.

#### **New Movies**

- 1. Average Action Movie Rating: ~3
- Never be recommended...
- 2. User Favorite Genre weight?

<u>User 1 Top Watched Genres</u> → Recommend Action Movies

action adventure sci-fi	11
comedy	11
action adventure thriller	8
action drama war	8
comedy drama	6
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#### Conclusion

Best Performing Model: <u>KnnBaseline</u> (.8708)

Cold Starts: Content Filtering and other method are needed for new users and items.

Two filtering are needed for a recommendation system

- Collaborative for current users and movies
- Content for new users and movies

### Limitations

#### 21 users $\rightarrow$ 26,663 of the total reviews (25%)

- Bias toward certain genres, series, age, etc.
- 5 10% write reviews unprompted
  - More likely to leave negative reviews if any.

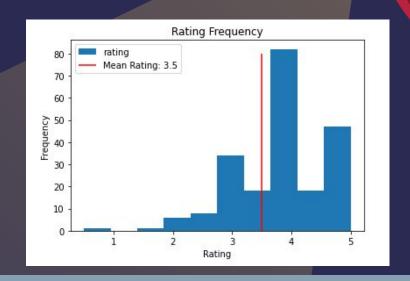
#### **Review Bombing**

 A group of people leaving a large amount of negative reviews to negatively impact the movies

# **Next Steps**

#### **Factor Genres**

- Certain <u>combination</u> might be favorable More Data
- More data = <u>Better</u> modeling Diverse Users
- More <u>variety</u> in ratings



#### Questions?

Original Source:

https://grouplens.org/datasets/movielens/latest/

Email: phungtommy109@gmail.com

Github: <a href="https://github.com/Tommyphung1">https://github.com/Tommyphung1</a>

Notebook: <a href="https://github.com/Tommyphung1/Project\_4">https://github.com/Tommyphung1/Project\_4</a>