

# **Netflix Prize Dataset Recommender System**

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# Introduction

## Netflix Prize Competition

- Open Competition for team or individual participants
- \$1 million grand prize
- > 10% Improvement over 2006 Netflix Cinematch algorithm
  - Based on Root Mean Squared Error (RMSE)
- Competition started October 2, 2006
- Grand Prize awarded September 29, 2009
  - Team “Belkor’s Pragmatic Chaos” with 10.6% better RMSE

# EDA & Preprocessing

- **Original Data Dimensionality**

- 100,480,507 Ratings
- 480,189 Users
- 17,770 Movies

- **Sample**

- 510,852 Ratings
- 1,934 Users
- 11,866 Movies

movie_id	user_id	rating	date
1	1488844	3	2005-09-06

# Modeling each user

- For each user, found a dataset of similar users B such as  $d(A, B) \leq \text{threshold}$

$$d(A, B) = \frac{1}{n \cdot 5^2} \sum_i (r_{A_i} - r_{B_i})^2$$



movie	cluster_avg_rating	user_A_rating
movie_1	Known	Maybe Known
movie_2	Known	Maybe Known
...	....	...

- Run linear regression and other regression models.
- Tried different distance thresholds. Smaller threshold → Better accuracy but less movies with predictions and smaller training & testing set.
- Also, small threshold → some users with no other similar users → cannot predict nor recommend any movie.

# Modeling each user

- We found threshold = 0.02 to be a good middle ground. Mean  $R^2 = 0.65$ , and enough data to train and evaluate for most users (73 movies on average).
- This threshold means a 0.07 unit distance on average. For example, if A rated a movie with a 5, B will be similar to A if he rated the same movie with at least a 4.3.
- We got perfect  $R^2$  for some users and even negative for others.
- This model could be used for those users for which it performs well.
- It can also be used to identify abnormal users (negative or very small  $R^2$ ), and take them out when training other more sophisticated models.
- The threshold could also be selected automatically for each user.
- The dataset could be augmented with IMDb features, which could drastically improve the results.

# Item-Item Collaborative Filtering

- Method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating).
- Assumption of the collaborative filtering approach is such that if person A has the same opinion of person B about something, then A is more likely to have B's opinion on a different issue than that of a randomly chosen person.
- Considered Pearson R, Kendall-Tau Rank, and Spearman Ranking Correlation.
- Pearson R and Spearman Ranking were selected for analysis.

# Analysis of Recommendations

- **“Miss Congeniality” results included “Another Stakeout” for both correlations**
- **“The Godfather” results included “Latter Days” for both correlation**
- **Comparison between Collaborative Filtering (correlation) and Linear Regression:**
  - **No overlap between Linear Regression and Collaborative Filtering for “Flubber” and “Ice Age”**
  - **Overlap between Pearson R and Spearman Ranking Correlation**
- **Different approaches definitely yield different results**
- **Netflix “perturbed” the dataset**
  - **Statistical modification**
  - **Protection of users identity**

# Conclusion

- **Learned about Recommender Systems**
- **Recommender Systems are very complex!**
- **Experienced “The Curse of Dimensionality”!**
- **Improvements for the Future:**
  - Utilize IMDB, MovieLens, Gross Revenue, and other metadata
  - Parallel computing, GPUs, and Neural Networks
  - Experimentation with Self Organizing Maps or Self Organizing Feature Maps (SOM/SOFM) & Sparse Matrices



# References

<https://www.kaggle.com/netflix-inc/netflix-prize-data>

<https://www.netflixprize.com/faq.html>

[https://en.wikipedia.org/wiki/Netflix\\_Prize](https://en.wikipedia.org/wiki/Netflix_Prize)

<https://www.statisticssolutions.com/correlation-pearson-kendall-spearman/>

<https://github.com/amir-jafari/Data-Mining>

**Stanford Lecture Series 41-45: Overview on Recommender Systems:**

<https://www.youtube.com/watch?v=6BTLobS7AU8>

<https://www.youtube.com/watch?v=2uxXPzm-7FY>

<https://www.youtube.com/watch?v=1JRrCEgiyHM>

<https://www.youtube.com/watch?v=h9gpufJFF-0>

<https://www.youtube.com/watch?v=VZKMyTaLI00>