



Presenting Vi(sion) Studio's “Digital Cinema Night”  
March 2022

# Objective & Business Value

- **Objective** — Vi(sion) studios would like to offer a service called “Digital Cinema Night” where users can build a “Cinema Night” around specific movies
- **Business Value** — “Digital Cinema Night” will bring unique value to their users, and build long-term loyalty, by offering an experience for their users around a movie of choice vs. what users currently do
  - add items to their queue or have services automatically play movies without knowledge of recommendations

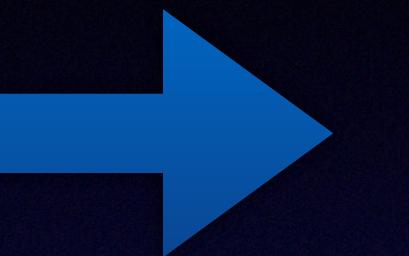
# Data Source - MovieLens



- “**Users were selected at random for inclusion. All selected users had rated at least 20 movies. No demographic information is included. Each user is represented by an id, and no other information is provided.**”
- **Data:** 9724 unique entries and 610 unique users
- **Attributes:** Title, Year, Genre, Rating

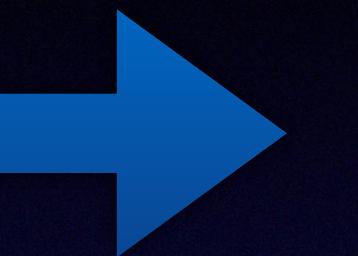
# Methodology

DATA



- 9724 entries,  
610 unique  
users
- Metrics used:  
1. Movie Titles  
2. User Ratings

ANALYZE /  
PREPARE

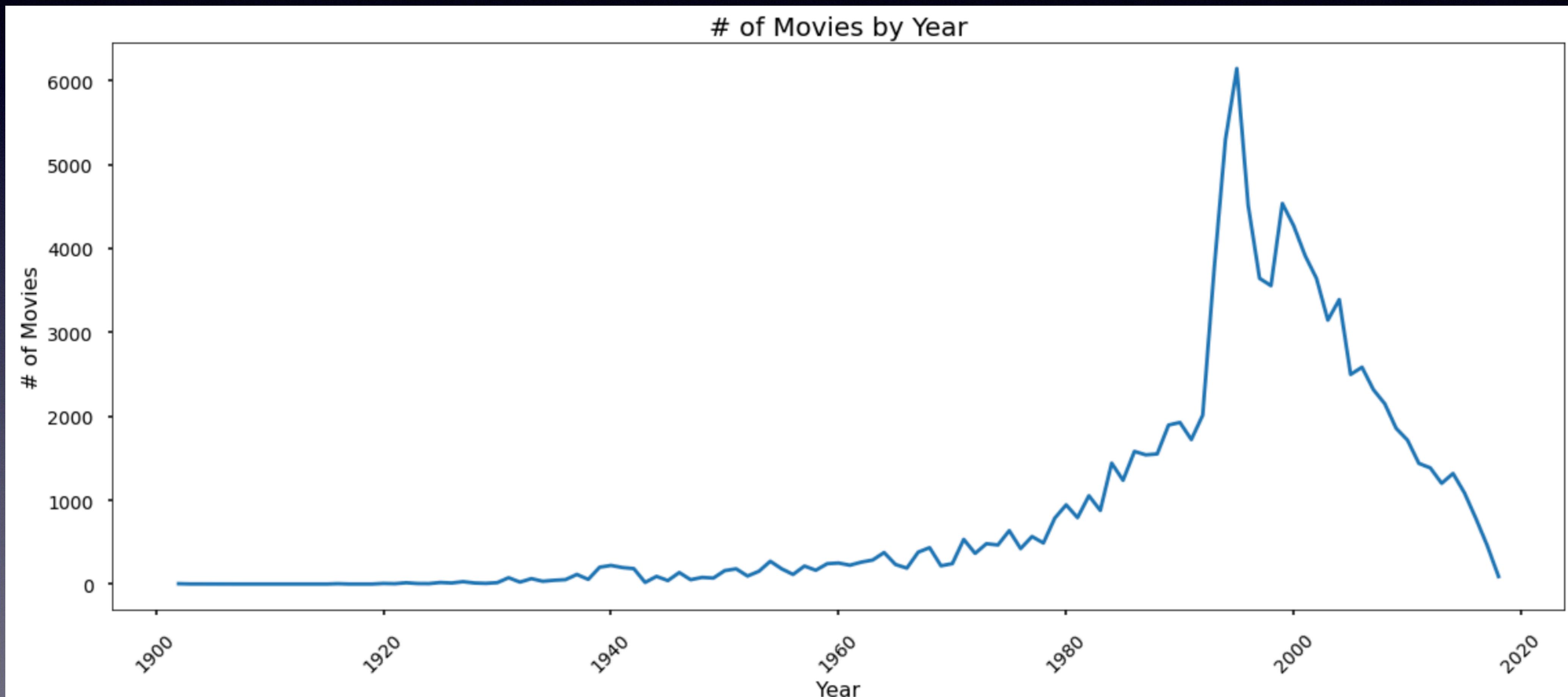


- Refined  
dataset
- Added Year,  
and Ratings  
Counts

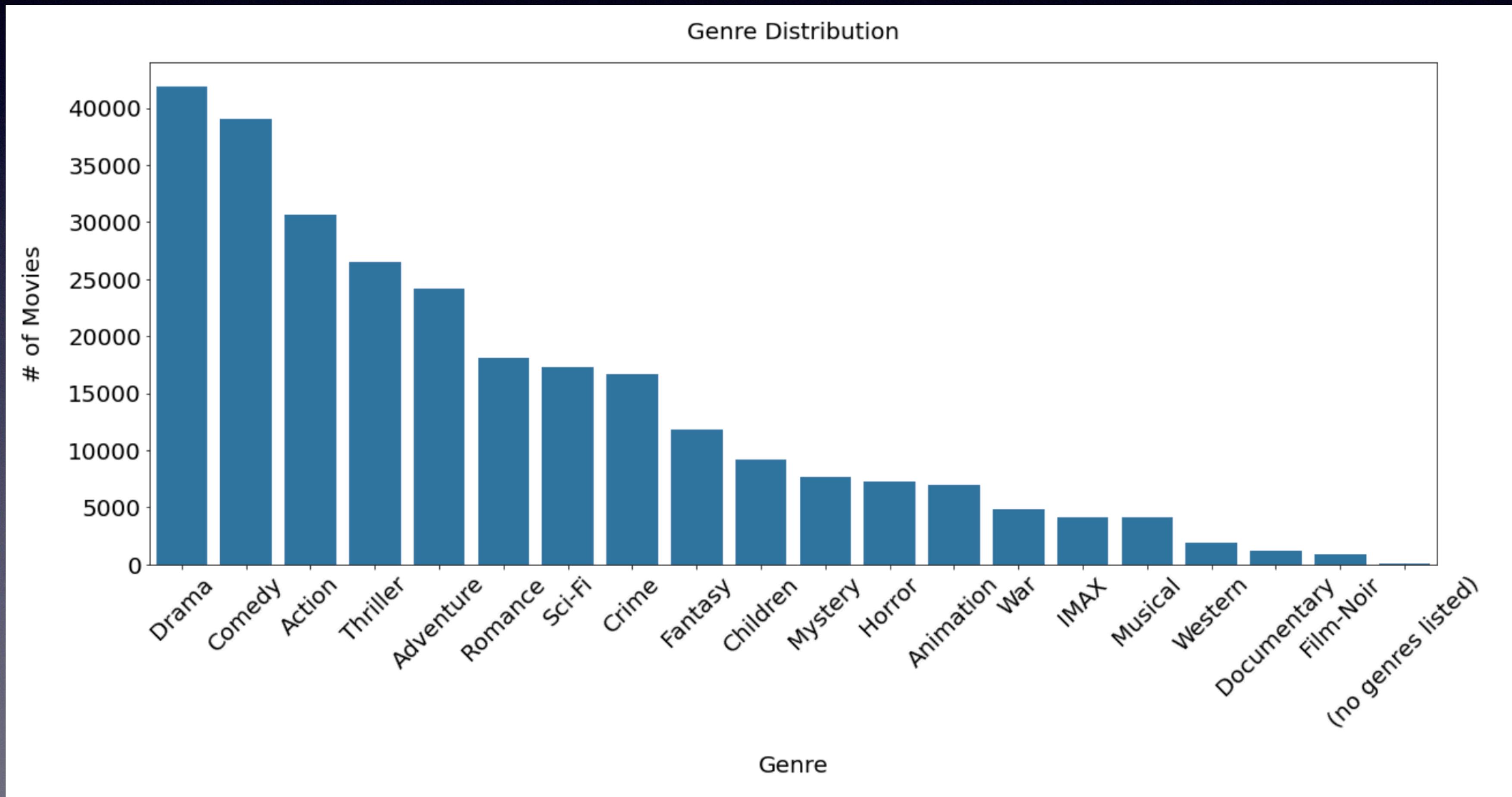
MODEL

1. Singular Value  
Decomposition  
Model (SVD)
2. KNN Baseline Model  
(KNNB)
3. Non-Negative Matrix  
Factorization Model  
(NMF)

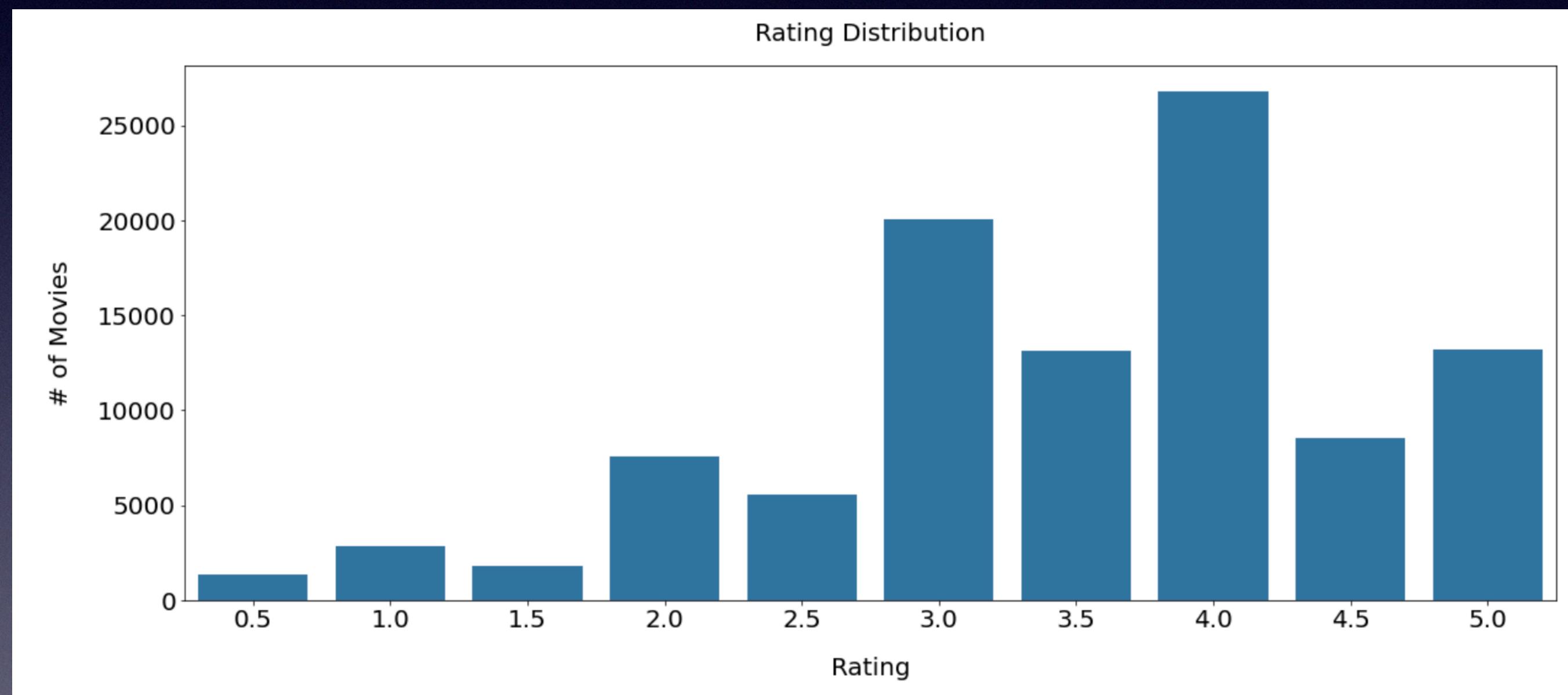
About the data: the majority of movies were from 1990s to the early 2000s



# The most popular genres: Drama, Comedy, and Action



Users tend to rate in whole numbers  
and 4 (out of 5) is the most popular rating



# All models created showed strong results/predictions

- We used the metric RMSE (root mean square error) to evaluate our models
- This metric tells us how far a model's predictions are from actual results

## Singular Vector Decomposition Model (SVD)

- \* Pre-Tuned RMSE: 0.95
- \* **Tuned RMSE: 0.86**

## k-Nearest Neighbor Baseline Model (KNNB)

- \* Pre-Tuned RMSE: 0.96
- \* **Tuned RMSE: 0.39**

## Non-Negative Matrix Factorization Model (NMF)

- \* Pre-Tuned RMSE: 1.12
- \* **Tuned RMSE: 0.30**

\* For example, SVD Model's final RMSE is 0.86, which means that our model's predicted ratings on average are 0.86 points away from their actual ratings using this model

# Results & Recommendations

## Summary of recommendations

- **Use SVD Model to launch**
  - While all models showed improvement after tuning and KNN Baseline and NMF Models have low RMSEs (predictions are close to actual ratings), in order to reduce the risk of over-fitting, the SVD Model - with a strong RMSE of 0.86 - is recommended
- **Test for 6 months and re-evaluate**
  - Revisit KNN Baseline and/or NMF Models if necessary
- **Launch concept with Millennial (or Millennial-enthusiast) audience**
  - Movies leaned toward 1990s to early 2000s
  - Opportunity to build early loyalty with an influential demographic

# Bringing your vi(sion) to life - the experience: DIGITAL CINEMA NIGHT

## 1. Users Input Movie

```
cinema_night_for('Toy Story')
```

## 2. Digital Cinema Night is created!

title	correlation	RatingsCount
Toy Story	1.000000	215
Incredibles, The	0.643301	125
Finding Nemo	0.618701	141
Aladdin	0.611892	183
Monsters, Inc.	0.490231	132
Mrs. Doubtfire	0.446261	144

# Bringing your vi(sion) to life: DIGITAL CINEMA NIGHT

## MORE EXAMPLES

```
cinema_night_for('Toy Story')
```

Incredibles, The	0.643301	125
Finding Nemo	0.618701	141
Aladdin	0.611892	183
Monsters, Inc.	0.490231	132
Mrs. Doubtfire	0.446261	144

```
cinema_night_for('Shawshank Redemption, The')
```

Four Weddings and a Funeral
Schindler's List
Usual Suspects, The
Ocean's Eleven
Green Mile, The

```
cinema_night_for('Godfather, The')
```

Godfather: Part II, The
Schindler's List
Fight Club
Saving Private Ryan
Goodfellas

\* backend results

\* what users will see

# Future Work

- Build functionality around genre and year choices
- Extend audience beyond initial millennial focus
- Expand dataset with more movie choices & continually refine “Digital Cinema Night” system to make stronger recommendations to users
- Build exquisite user interface

	genre	avg_rating
0	Adventure	3.50886
1	Animation	3.62998
2	Children	3.41311
3	Comedy	3.38471
4	Fantasy	3.491
5	Romance	3.50651
6	Drama	3.65619
7	Action	3.44798
8	Crime	3.65849
9	Thriller	3.49376
10	Horror	3.25834
11	Mystery	3.63246
12	Sci-Fi	3.45601
13	War	3.80815
14	Musical	3.56368
15	Documentary	3.79779
16	IMAX	3.61834
17	Western	3.58394
18	Film-Noir	3.92011



# THANK YOU!!