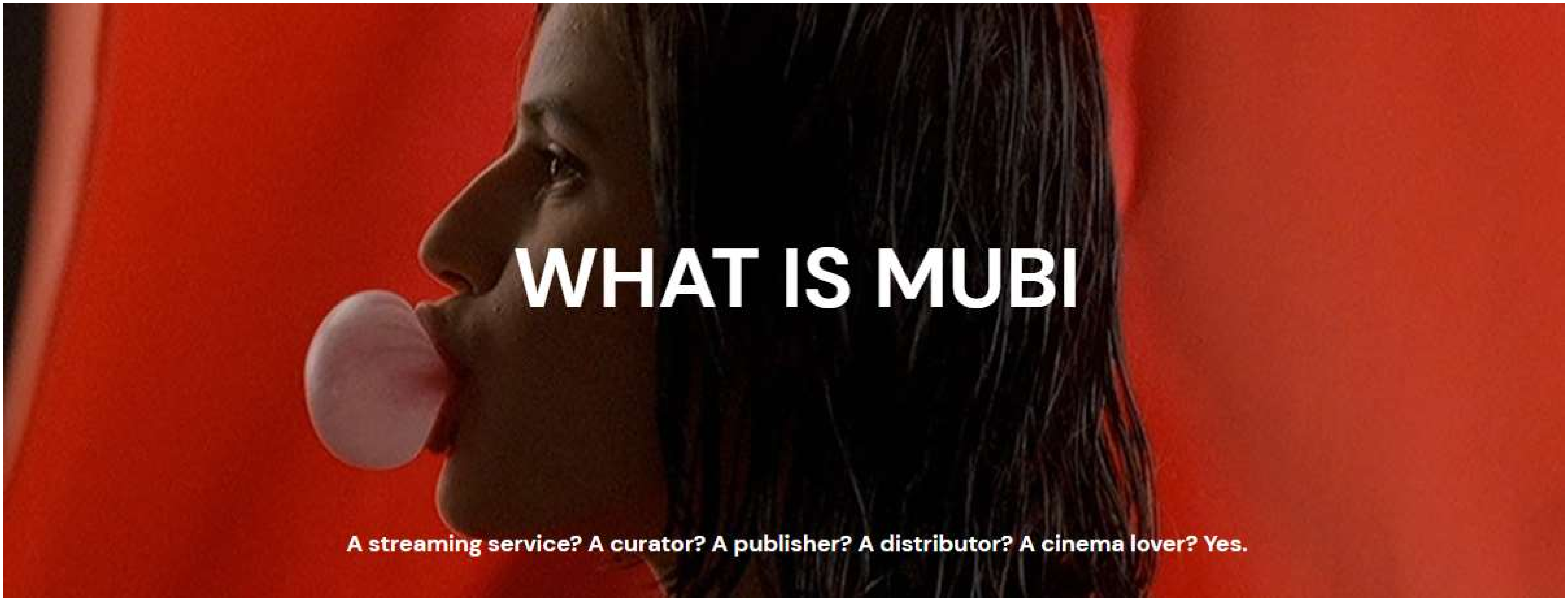
WHAT SHOULD YOU WATCH NEXT?

A DEEP FEED-FORWARD NEURAL NETWORK MOVIE RECOMMENDER

Sahar Manavi



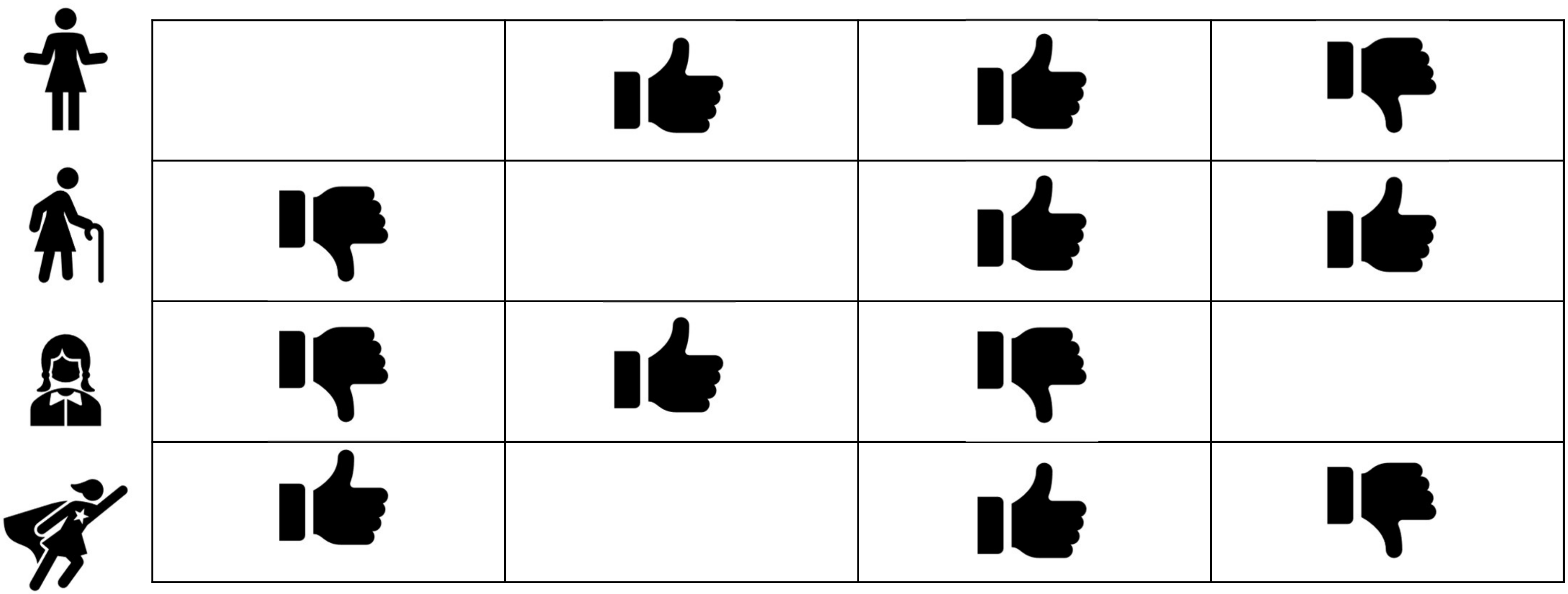
- Streaming platform for auteur cinema.
- Specializes in hand-selecting movies for its users to enjoy.
- Currently has over 225,000 movies and over 450,000 registered users.

MUBI

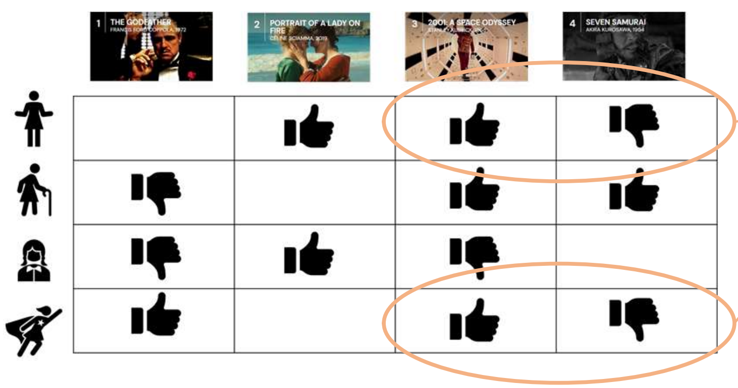
WHY DOES MUBI NEED A RECOMMENDER SYSTEM?

- A growing user base and film catalogue are fantastic things.
- However, a brand based on hand curation will find it harder and harder to keep up as the numbers go up.
- Can we partially automate in order to reduce the burden on human curators while still keeping the human aspect?

COLLABORATIVE FILTERING



COLLABORATIVE FILTERING



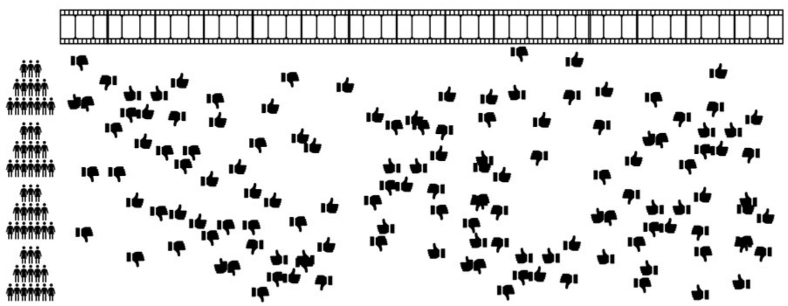
These two users rated two films similarly. They've also each watched and rated one film the other has not.

We can consider that their tastes are similar, and therefore they may rate the other two movies similarly.

In this (very simple) case we'd make the following recommendations:

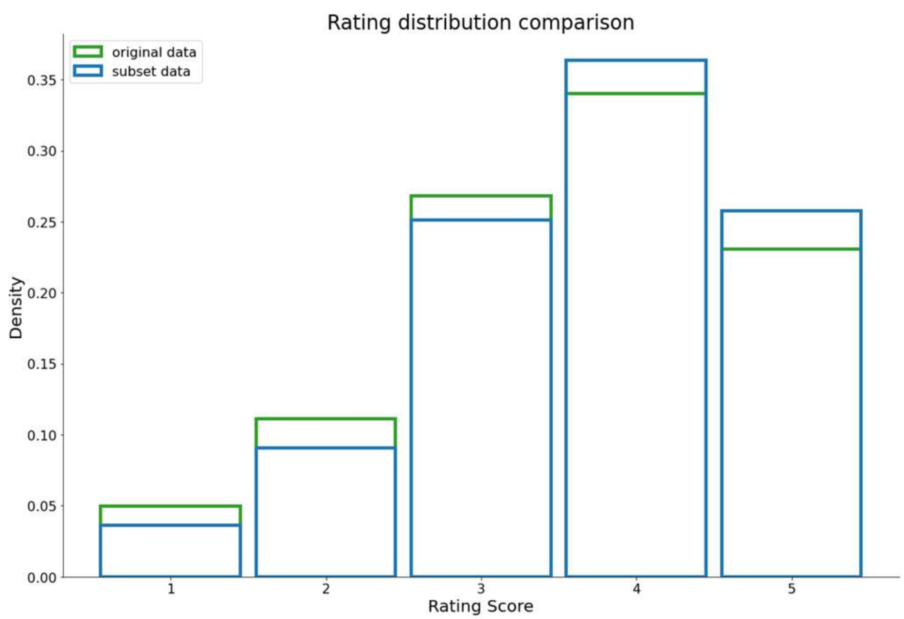
COLLABORATIVE FILTERING

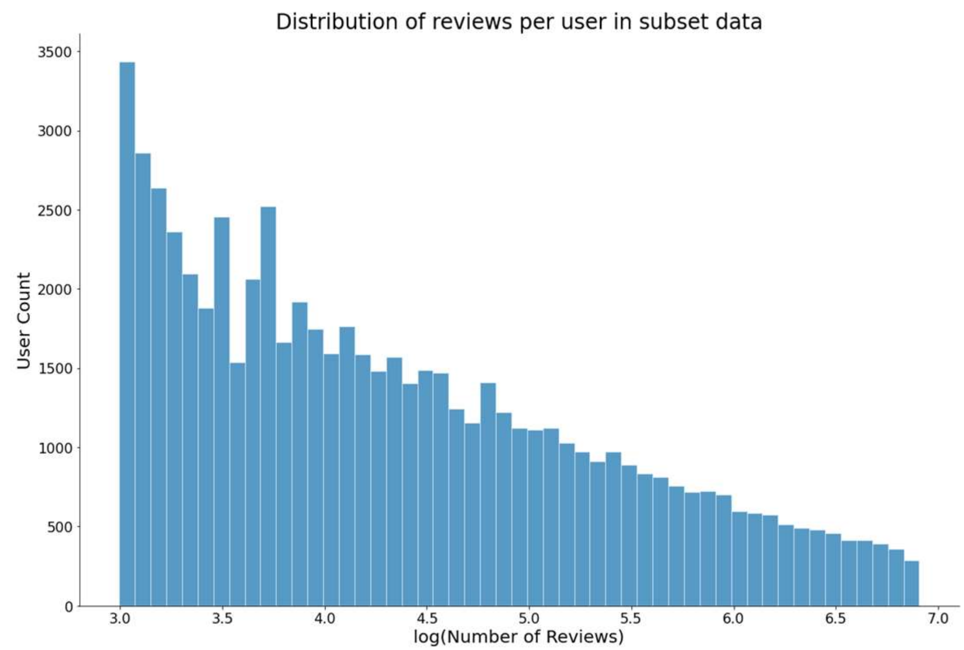
While the previous example is simplistic, the concept holds true. We can expand our pool from 4 movies and 4 users to 100s of thousands of movies and users.



With this much data, we can leverage the power of Artificial Neural Networks to find the underlying patterns in the data.

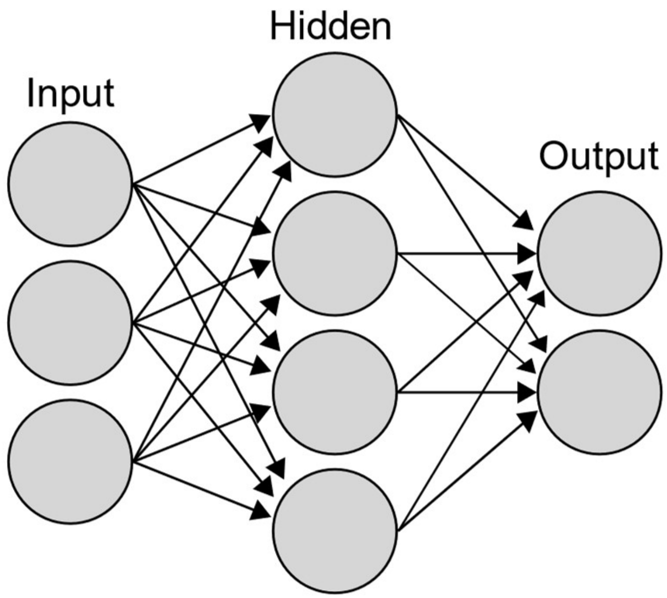
THE DATASET


Rating distribution comparison
original data
subset data
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
1
2
3
4
5
Rating Score


Distribution of reviews per user in subset data
User Count
0
500
1000
1500
2000
2500
3000
3500
3.0
3.5
4.0
4.5
5.0
5.5
6.0
6.5
7.0
log(Number of Reviews)

NEURAL NETWORKS: THE BASICS

Data goes in the input layer

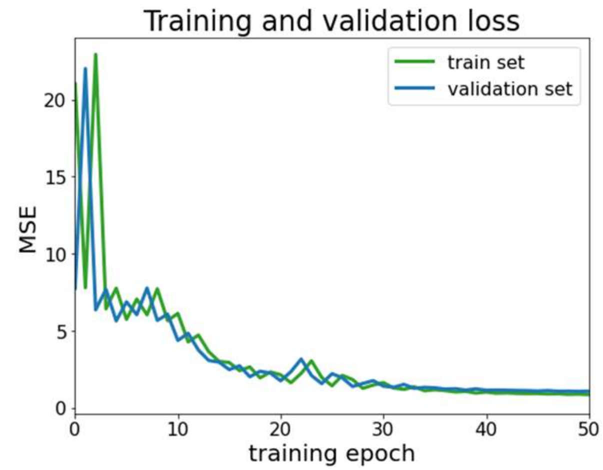


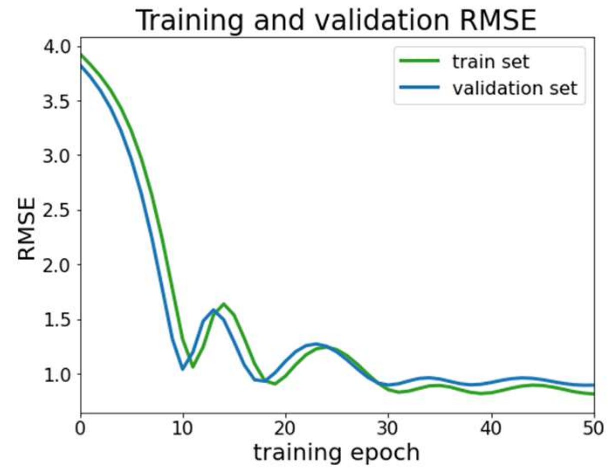
Results come out of the output layer

Learning happens in the hidden layers. The model tries to optimize its loss function and evaluation metric.

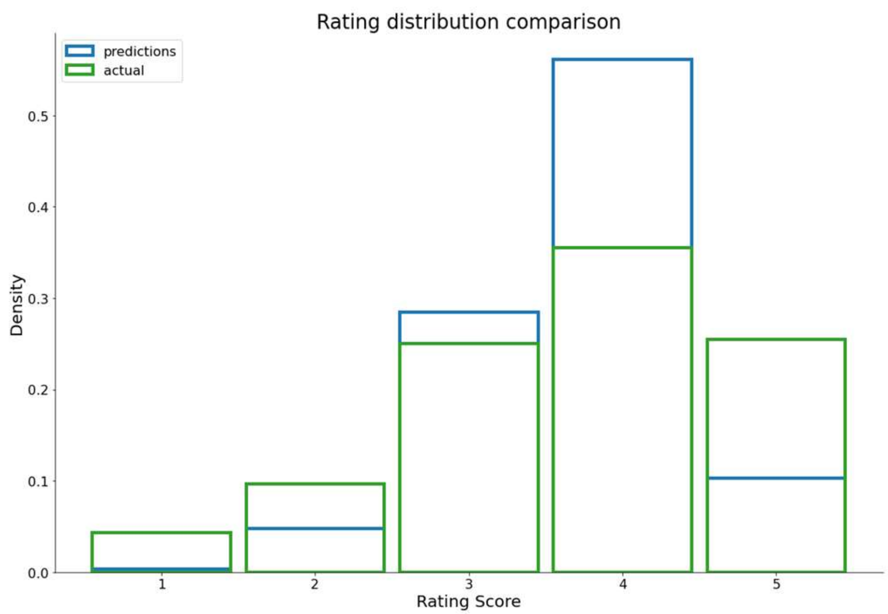
NEURAL NETWORKS: THE BASICS

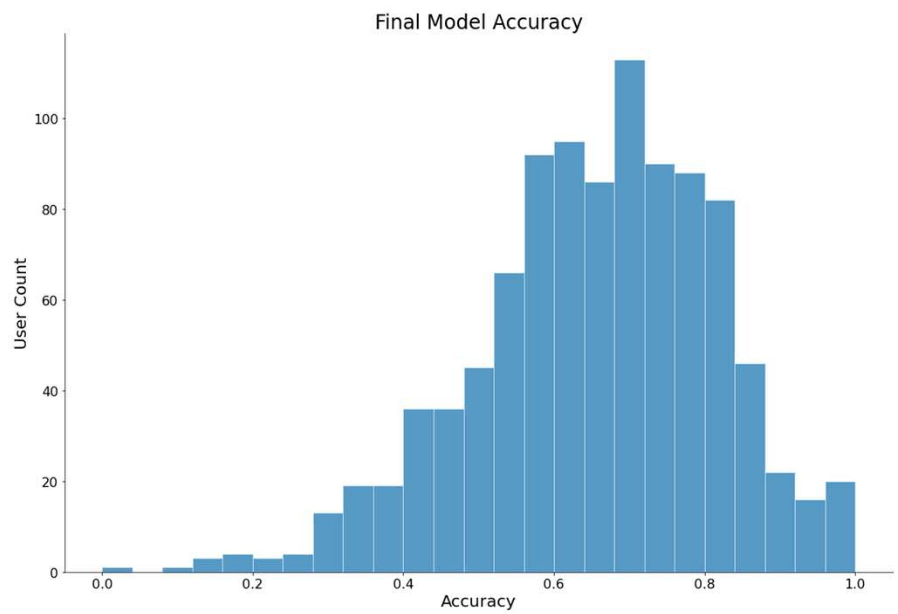
- When training a model, you run multiple iterations called epochs.
- Each epoch, the model learns the dataset a little better (or so you hope).
- The model's goal is to optimize its loss function. In this case, we used mean standard error, so we wanted to lower it as far as possible.



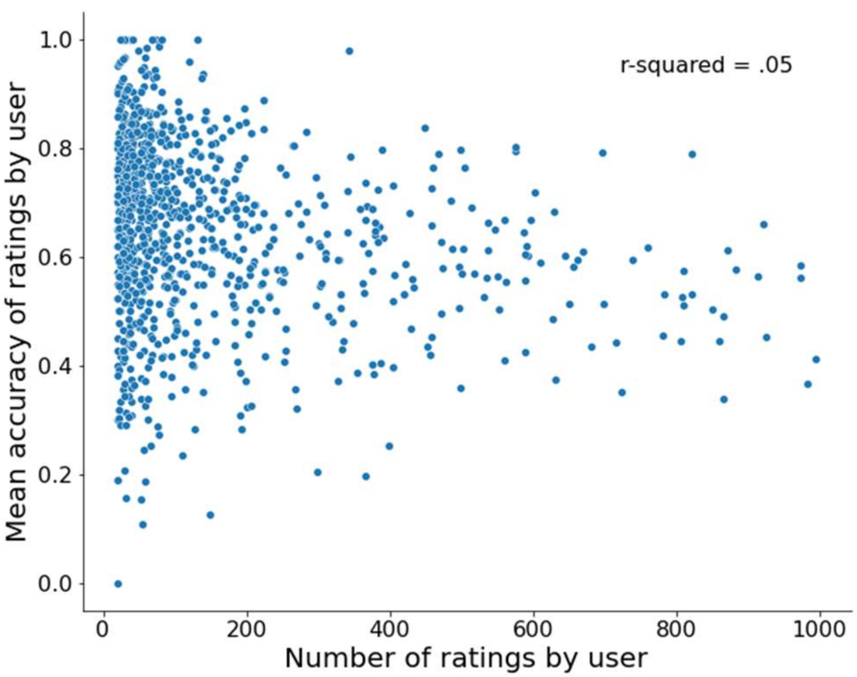


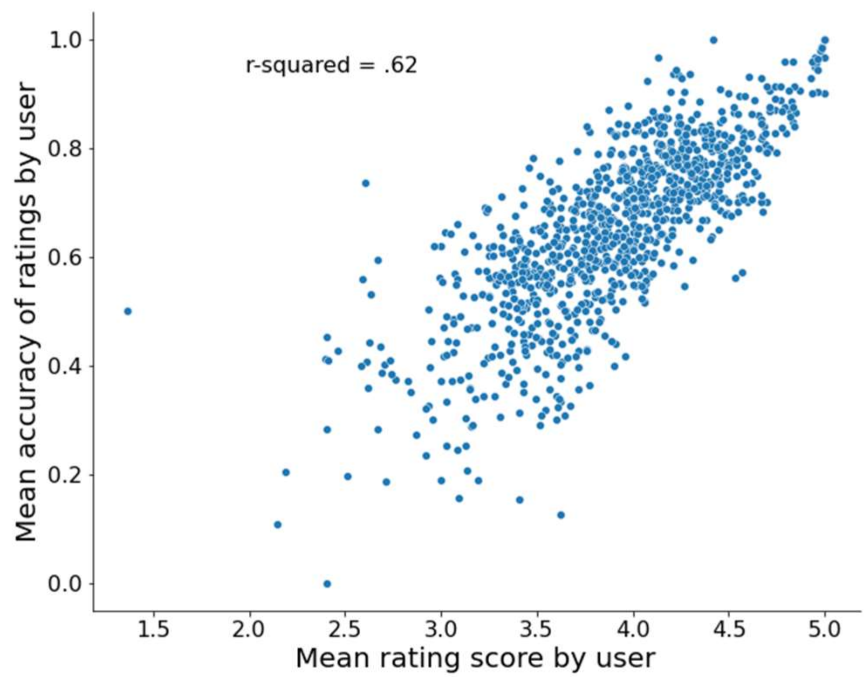
MODEL ASSESSMENT





MODEL ASSESSMENT





NEXT STEPS

- We obviously want to improve the model. This can be done by adding more features to the model.
- These features can be about the movies, the users, or the ratings. Or any combination of them!

- However, human intervention is part of MUBI’s business model, and we will never need to get rid of it entirely.
- Semi-automating the process lowers our accuracy threshold for what we can consider a successful model.

NEXT STEPS: A/B TESTING

GROUP A		GROUP B
One set of users will continue to get fully hand-curated film recommendations.	Test variables	Another set of users will get recommendations that come from a hybrid system of model suggestions that are then hand-curated.
We will use employee time spent curating these recommendations as the baseline time.	Metric 1: Employee time investment	Will this method take less employee time, or will it be the same?
We have historic watch-rates and ratings for our hand-curated suggestions.	Metric 2: Suggestion watch rate and ratings	We will track how these metrics change when using model-inspired recommendations.

HOW IT WORKS

1. Entry point notebook loads a user's profile

```
recs.establish_user_stats(43744268)
recs.user_id
```

```
43744268
```

2. Human recommender can explore user's highest and lowest rated movies

```
recs.get_user_top_movies(n=3)
```

```
Here are 3 of this user's top rated movies:
Amadeus  (5/5)
Brokeback Mountain  (5/5)
The Exorcist  (5/5)
```

```
recs.get_user_bottom_movies(n=3)
```

```
Here are 3 of this user's lowest rated movies:
Eternal Sunshine of the Spotless Mind  (2/5)
RoboCop  (3/5)
Punch-Drunk Love  (3/5)
```

3. Print a list of top-rated movies for the user

```
recs.get_recs(n_recs=5)
```

```
Suggestion: The Chinese Lives of Uli Sigg. Estimated rating: 4.8.
Suggestion: Only in Your Dreams. Estimated rating: 4.7.
Suggestion: Verses of Love. Estimated rating: 4.6.
Suggestion: Queens. Estimated rating: 4.6.
Suggestion: Rififi in the City. Estimated rating: 4.5.
```

HOW IT WORKS

You can print out more recommendations, but the objective is to make less work for the humans.

```
recs.get_recs(n_recs=20)
```

```
Suggestion: Alfred Hitchcock Presents: Premonition. Estimated rating: 4.7.
Suggestion: The Little Prince. Estimated rating: 4.6.
Suggestion: Berlin '36. Estimated rating: 4.6.
Suggestion: 1933. Estimated rating: 4.6.
Suggestion: Iran: A Cinematographic Revolution. Estimated rating: 4.6.
Suggestion: Pioneer. Estimated rating: 4.4.
Suggestion: Asedillo. Estimated rating: 4.4.
Suggestion: 2nd War Hats. Estimated rating: 4.3.
Suggestion: The Devil's Tomb. Estimated rating: 4.3.
Suggestion: The Singing Ringing Tree. Estimated rating: 4.3.
Suggestion: Eclipse of the Sun Virgin. Estimated rating: 4.3.
Suggestion: Beata ignoranza. Estimated rating: 4.3.
Suggestion: A Woman in Berlin. Estimated rating: 4.3.
Suggestion: The Man Who Knew Too Much. Estimated rating: 4.2.
Suggestion: Terror and Black Lace. Estimated rating: 4.2.
Suggestion: The Doll. Estimated rating: 4.2.
Suggestion: Haysha Royko. Estimated rating: 4.1.
Suggestion: In the Land That Is Like You. Estimated rating: 4.1.
Suggestion: Going Berserk. Estimated rating: 4.1.
Suggestion: The Case Is Closed. Estimated rating: 4.1.
```

From this list, the human recommender picks out several recommendations to send to the user.