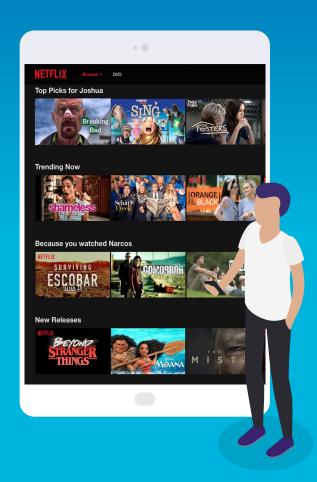
# MovieLens Recommendation Systems



How do companies know what you like?



# Recommendation Systems:



#### **MovieLens Data**

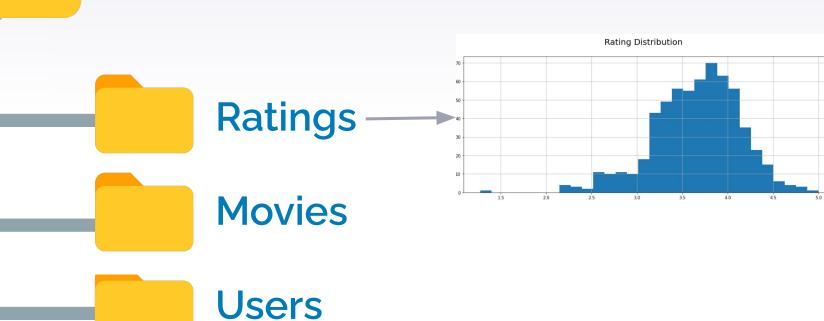
This dataset describes 5-star rating and free-text tagging activity from a movie recommendation service called MovieLens.

It contains 100836 ratings across 58098 movies based on 610 users



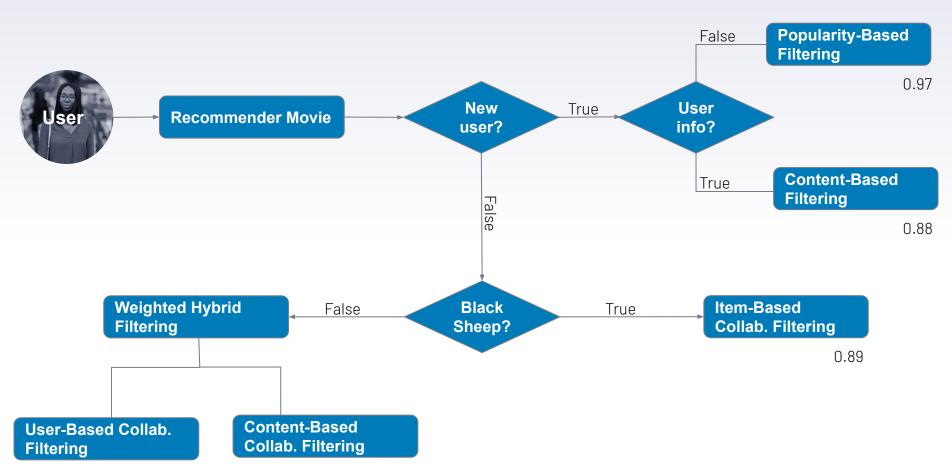


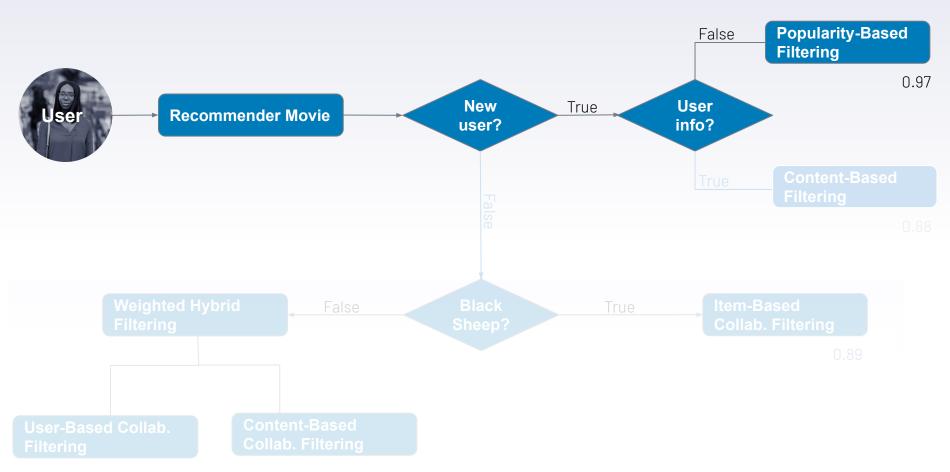




### Our Model



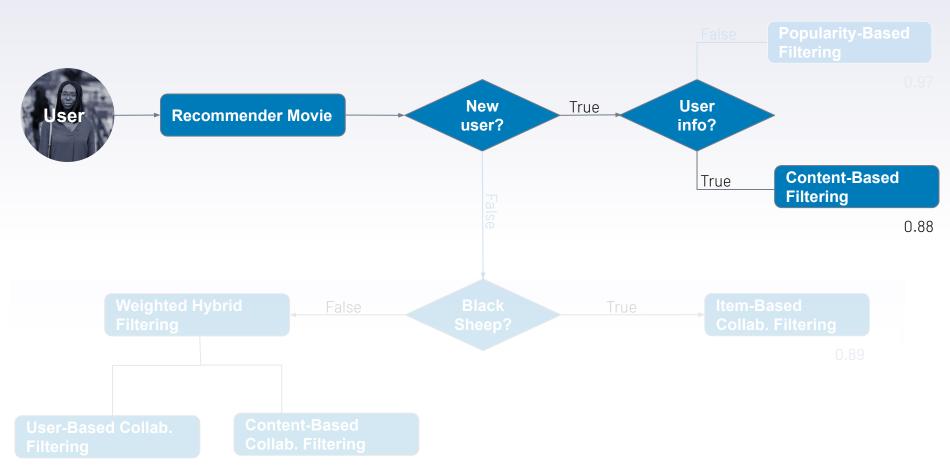




## Popularity Based Recommendation

- Non-personalized recommendations for when we have no data!
- We set Item Popularity as a baseline as it avoids creating niches. Users might want to be suggested movies that are popular even though they do not match their taste 100%

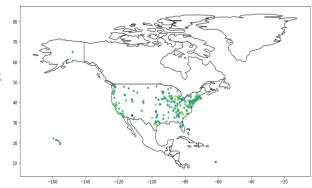
The winners of the Netflix Prize Competition used item popularity as a ranking function. As it enables to find a personalized ranking function rather than just item popularity, to satisfy taste of members with varying tastes.



# **Content-Based Preprocessing**

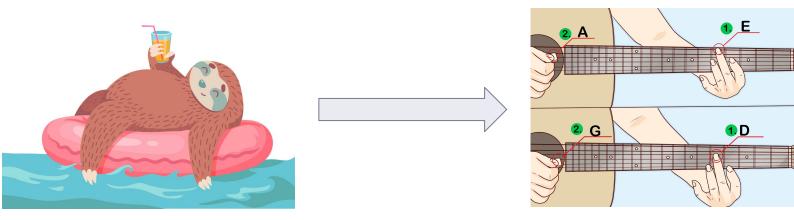
- Ratings Flagged data issues to try out various models
  - Sampling
  - Guy in a bad mood
  - Transform Ratings
- Movies Parse title, years, dummified genres,
- **User** Demographics, mapped zip code to coordinates
- User/Movies Low usage: 7.38% (Ohsoso troll 13%)

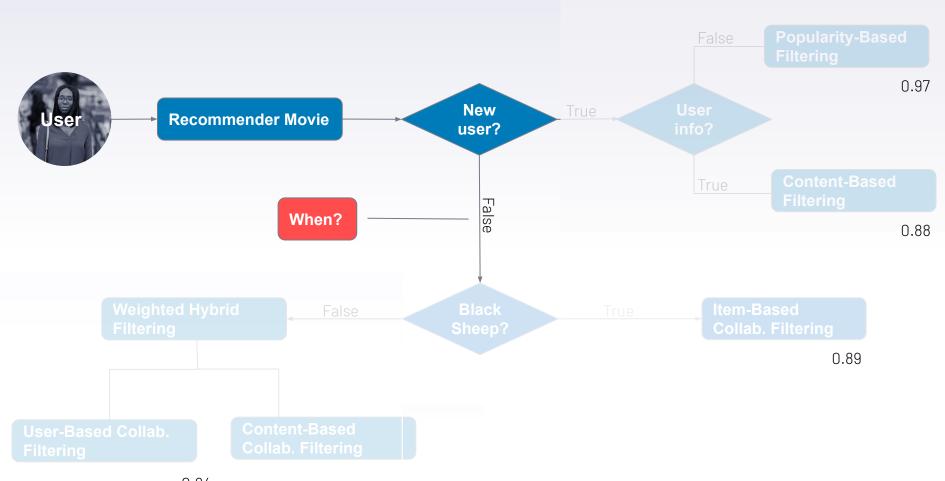
Next Steps: Web crawling to get more movie information

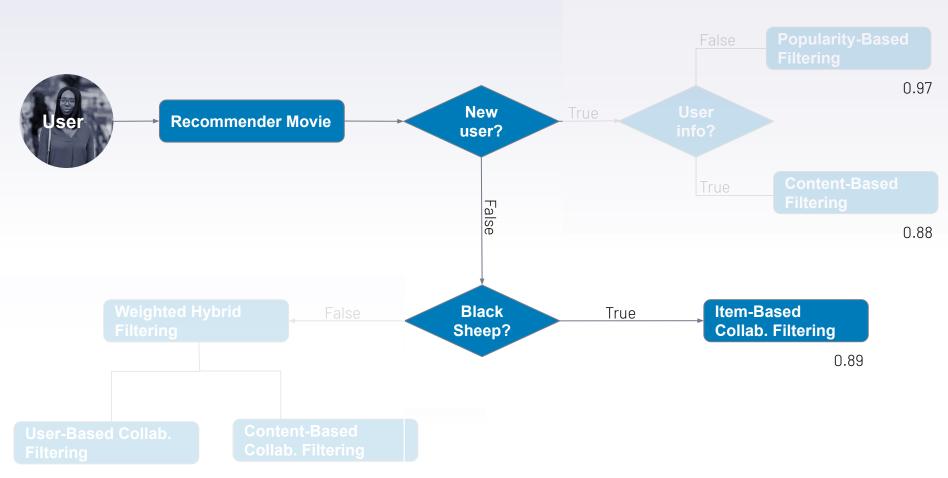


# **Content-Based Filtering**

- Lazy Predict: Getting intuition of what works best
- **Preprocessing:** Scaling & Dummifying variables
- **Pipeline & Tuning:** Optimizing hyperparameters with 5-fold CV







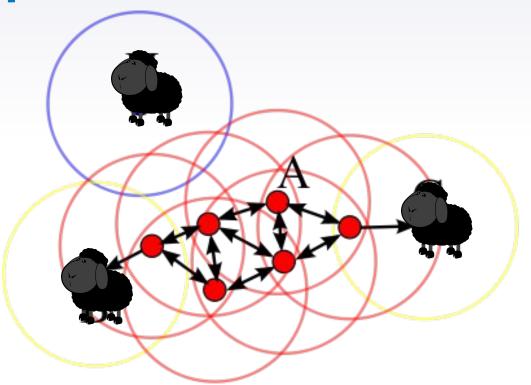
## **Black Sheeps**

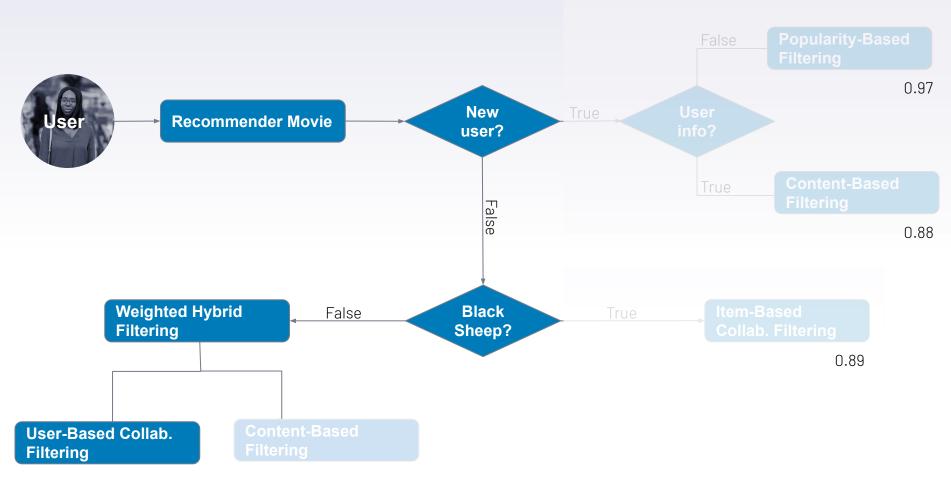
#### - DBSCAN with:

- User Demographics
- Preferred Genre

#### Item-Based KNN:

Recommending 'weird' people similar things to what they like



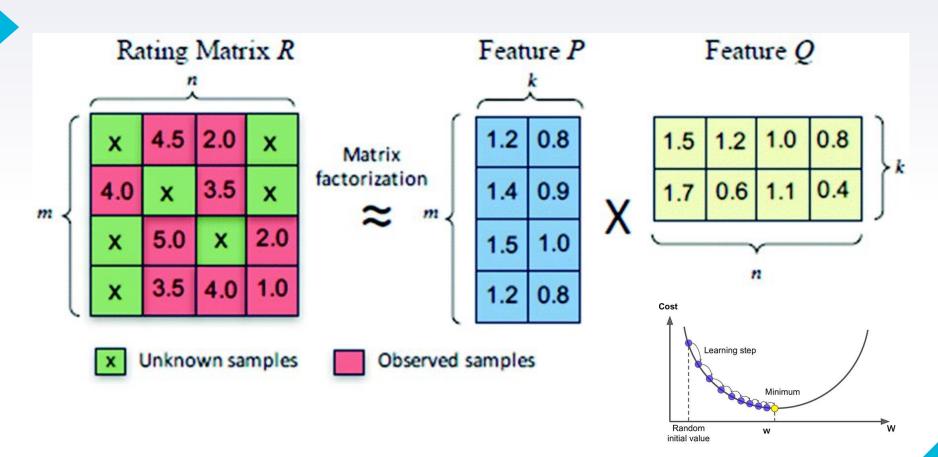


# Collaborative Filtering

We implemented **Singular Value Decomposition (SVD)** model since it was giving us the lowest RMSE after hyperparameter tuning compared to other collaborative filtering models like KNN inspired ones.

#### **RMSE**

NormalPredictor	1.42
BaselineOnly	0.87
SlopeOne	0.89
CoClustering	0.94
KNNBasic	0.93
KNNWithMeans	0.87
KNNWithZScore	0.87
KNNBaseline	0.86
SVD	0.85

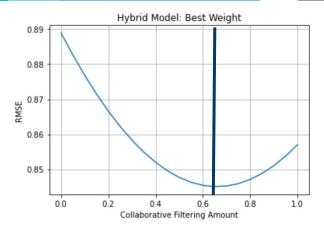


## **Hybrid Recommendation**

Filtering (SVD)

Content-Based (Random Forest) 35%

**Weighted Hybrid Recommendation**RMSE: 0.84



#### RMSE

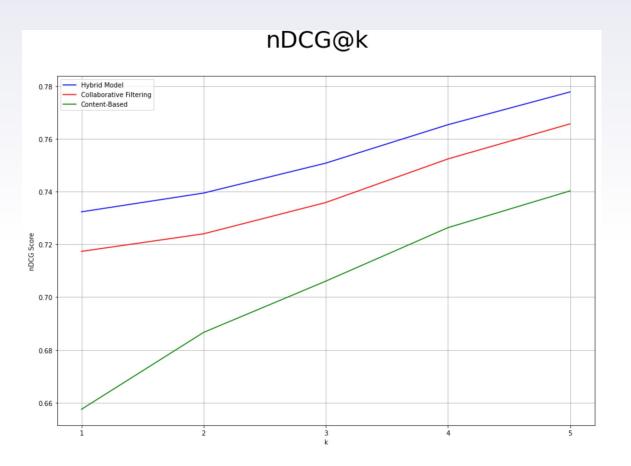
Collaborative Filtering 0.856962

Content-Based 0.888943

Hybrid Approach 0.845025

#### nDCG @ k

- Range: 0-1



#### nDCG@k 4.7 5 4.6 3 Rank Switch with true ratings Prediction 4.2 4 MODEL for User 3.5 4 3.1 5 Normalize by Replicate for each Calculate for k Calculate DCG Score Dividing by user and take numbers of Ideal Ranking recommendations average $DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{log_2(i+1)}$

# Let's try it together!

## **Future Improvements**

- Cold Start: resolve "new items" issue
- Find optimal minimal number of watched movies so that a user stops being new
- Let our model decide which users are black sheep!
- Combining Popularity Based and Content Based for diversity
- Linearly blend SVD and RBM to reduce error
- Display percentage of how much the user might enjoy a recommended movie





# THANKS!

**Any questions?** 

