

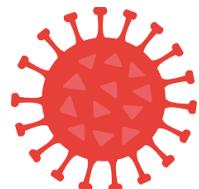
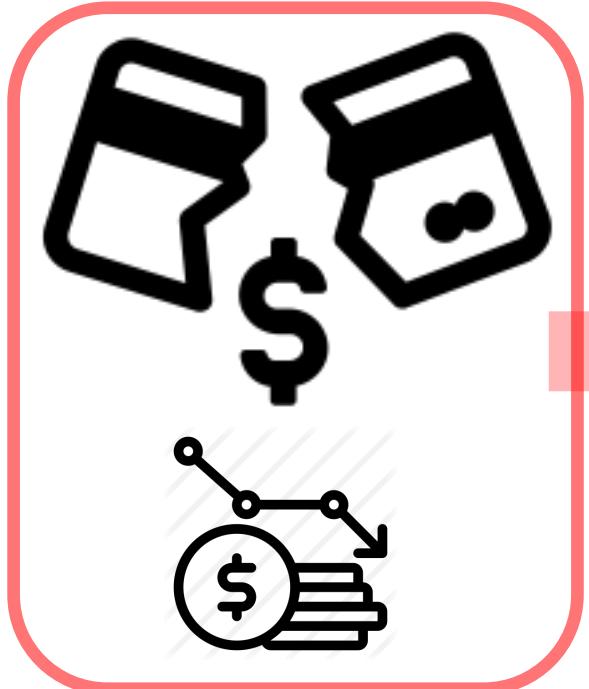


Recommender System on Amazon Game data

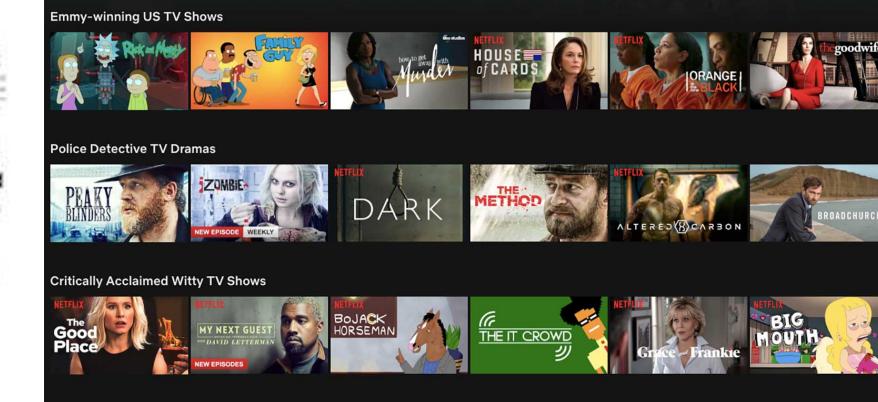
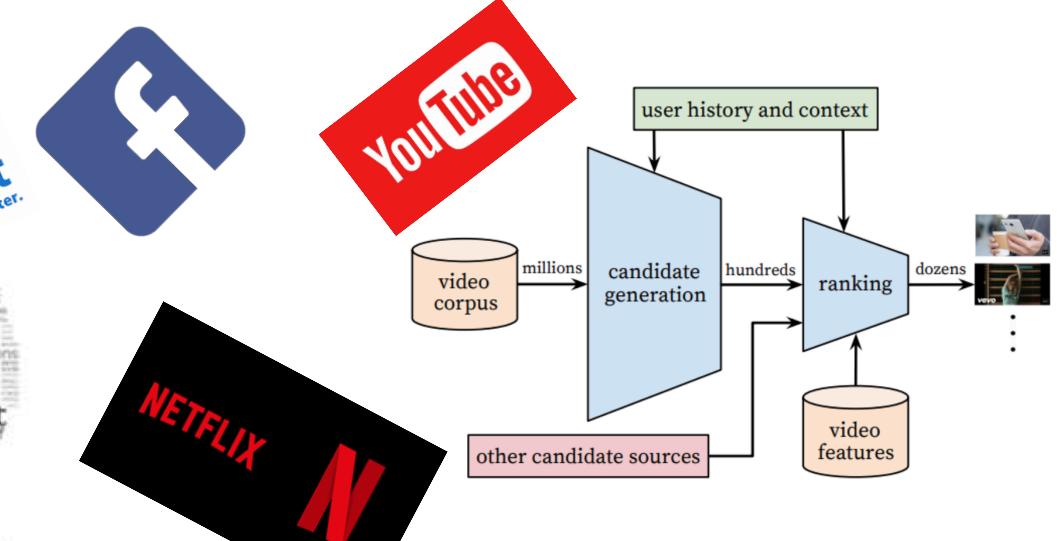
Jae Choi

Contact Info: Jaehyuk0325@gmail.com

PROBLEMS



recommend



amazon.com®

Recommended for You



[Inside Apple: How America's Most Admired--and Secretive--Company Really Works](#)
Our Price: \$9.99
Used & new from \$9.99
[See all buying options](#)

[Help](#) | [Close window](#)

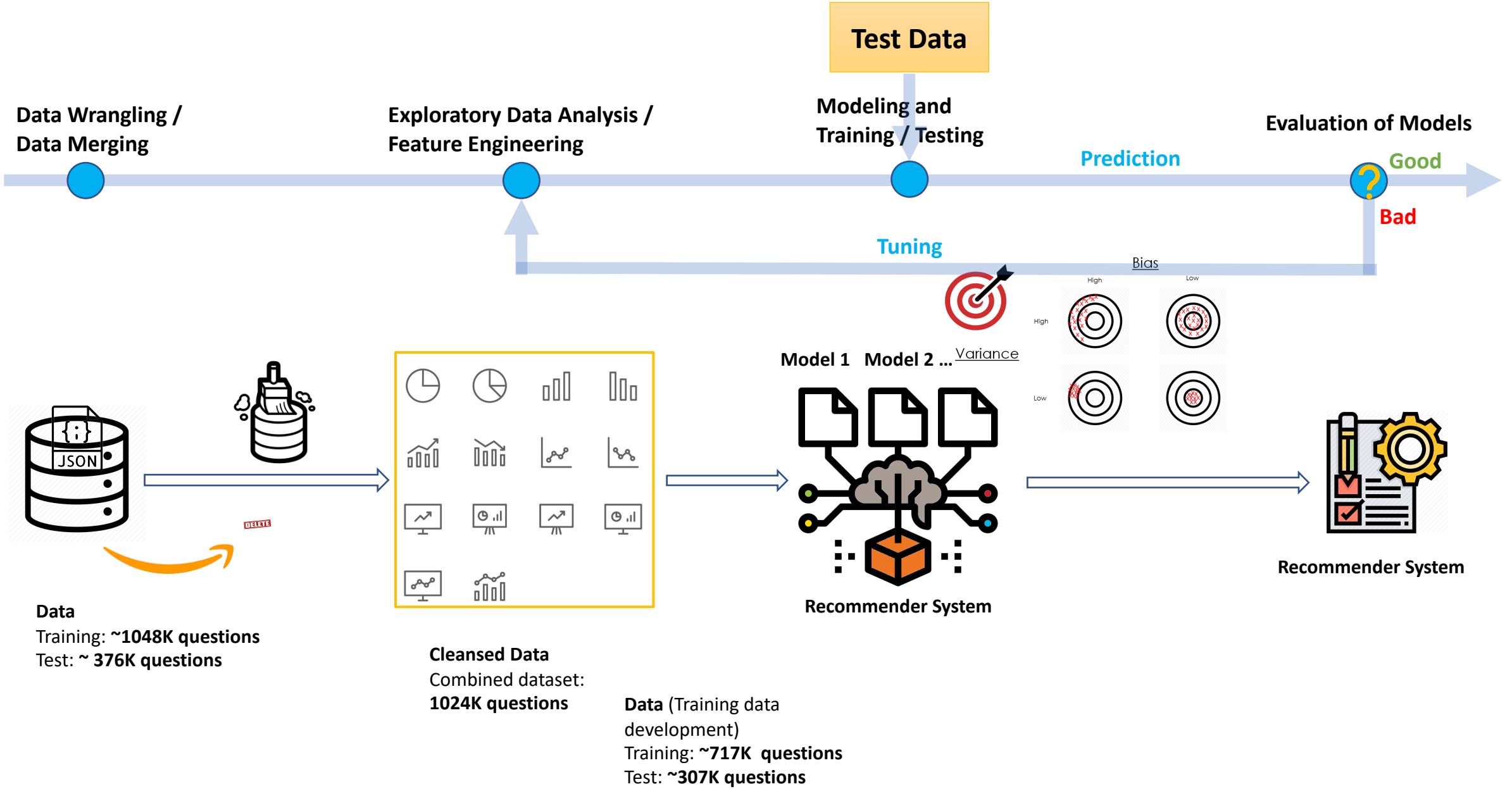
Rate this item
 5 4 3 2 1

I own it
 Not interested

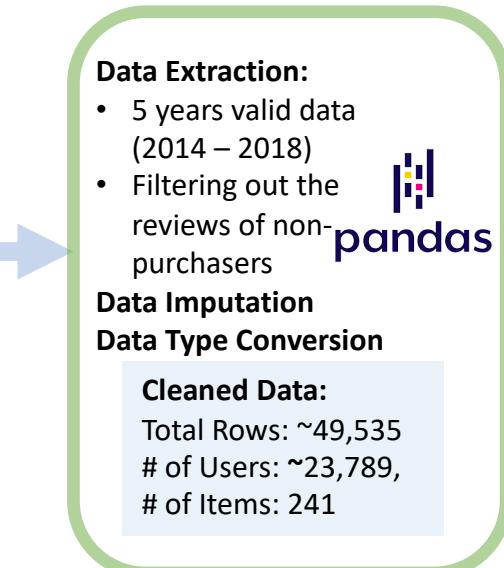
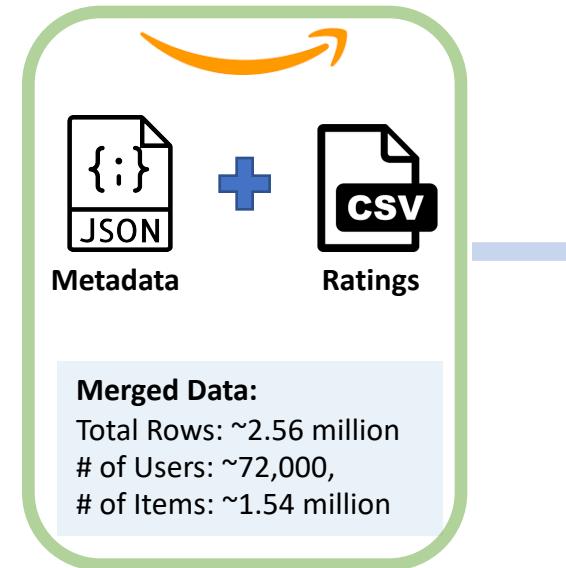
This was a gift
 Don't use for recommendations

[The Toyota Way : 14 Management Principles from the World's Greatest Manufacturer \(Kindle Edition\)](#)

STEPS

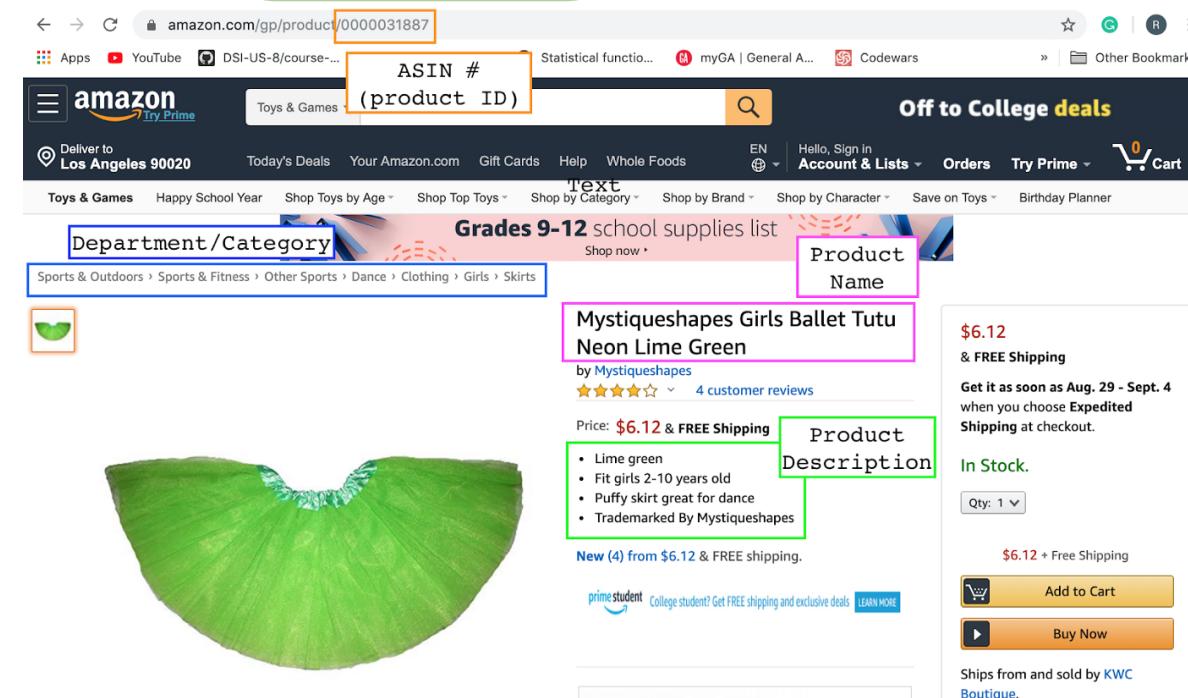


DATA WRANGLING

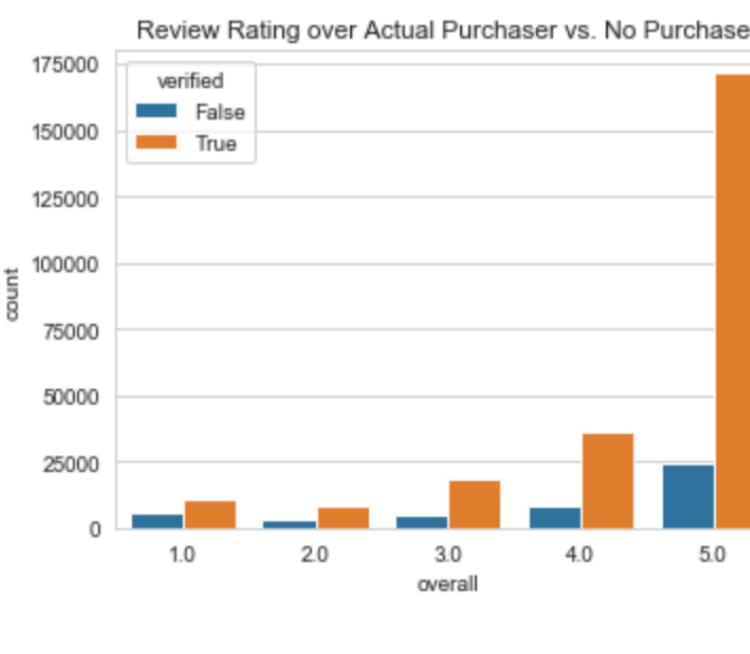
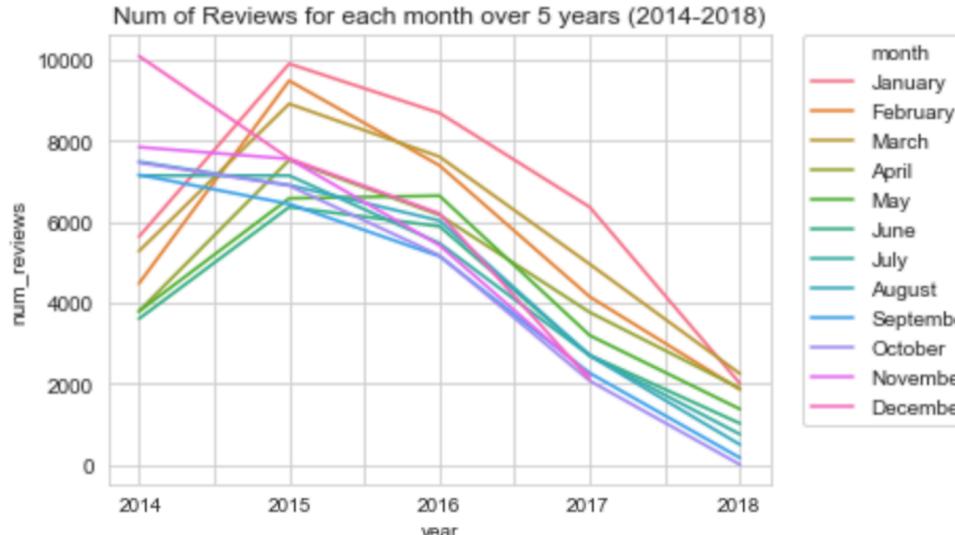


User-Item Matrix

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1



EDA



Yearly Reviews (2014 – 2018)

- Rising trend 2014 – 2015
- Falling trend 2015 – 2018
- # of reviews over WINTER season tends >> that over SUMMER season.

Monthly Reviews (2014 – 2018)

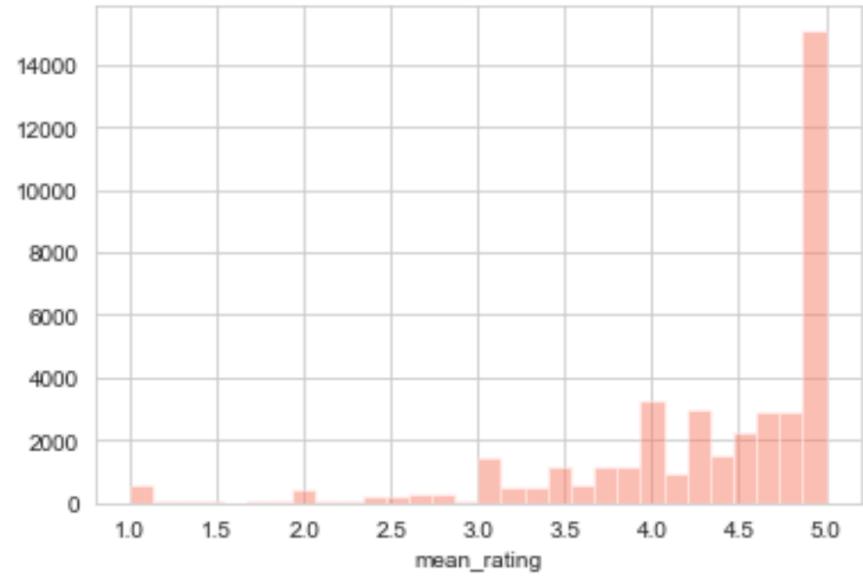
- Increment over SUMMER break.
- Falling trend Jan – June

Real Buyer vs. No Buyer

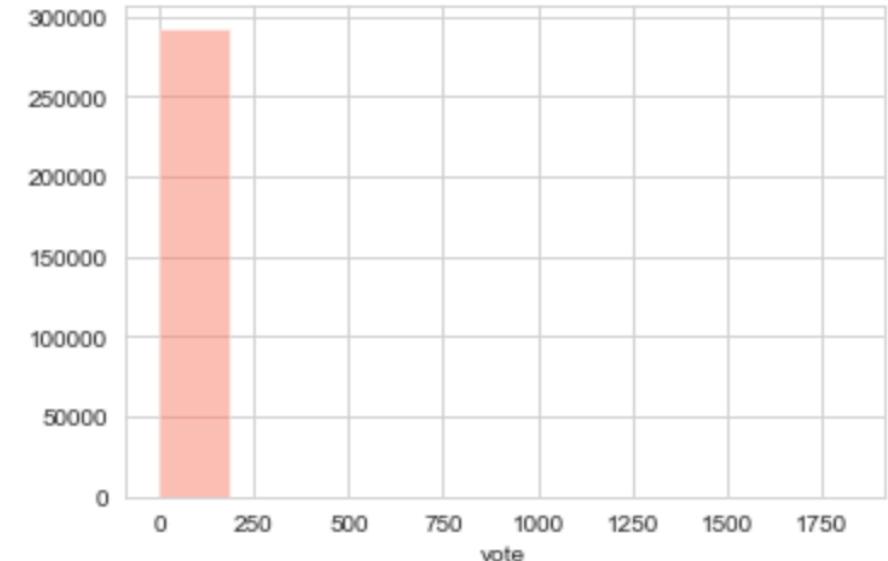
- Both are LEFT skewed
- Data of real buyers is skewed more dramatically.

EDA

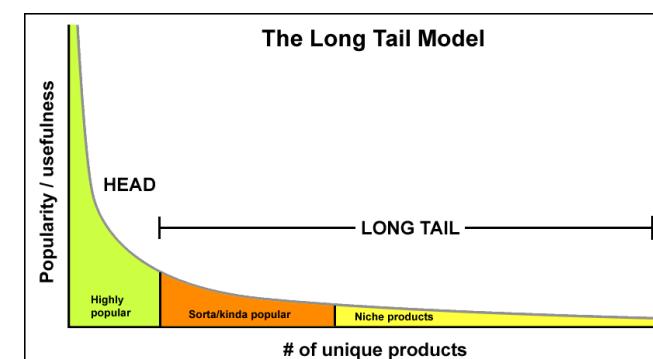
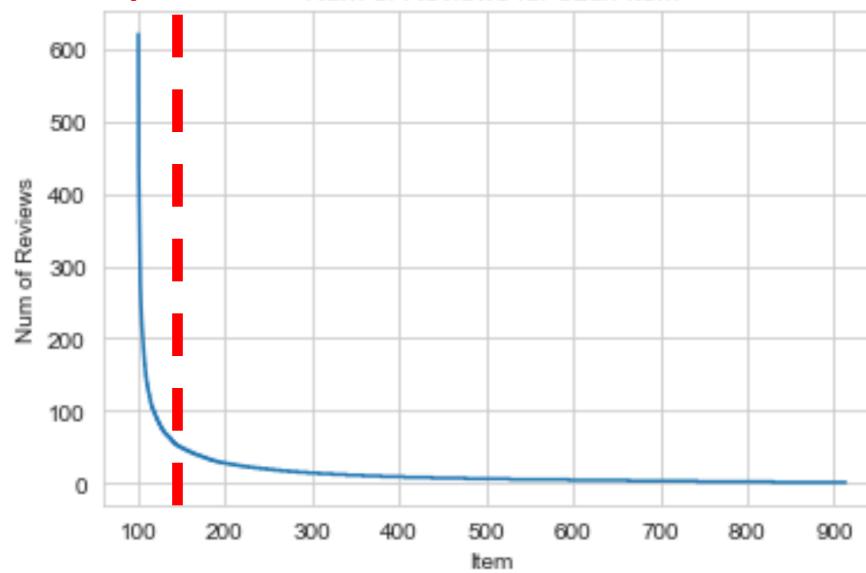
Mean of Ratings for each User



Num of Votes for the Review



Top 20% cut Num of Reviews for each Item



Mean of Reviews (2014 – 2018)

- Trend over only real buyers.

of Reviews for Each Item

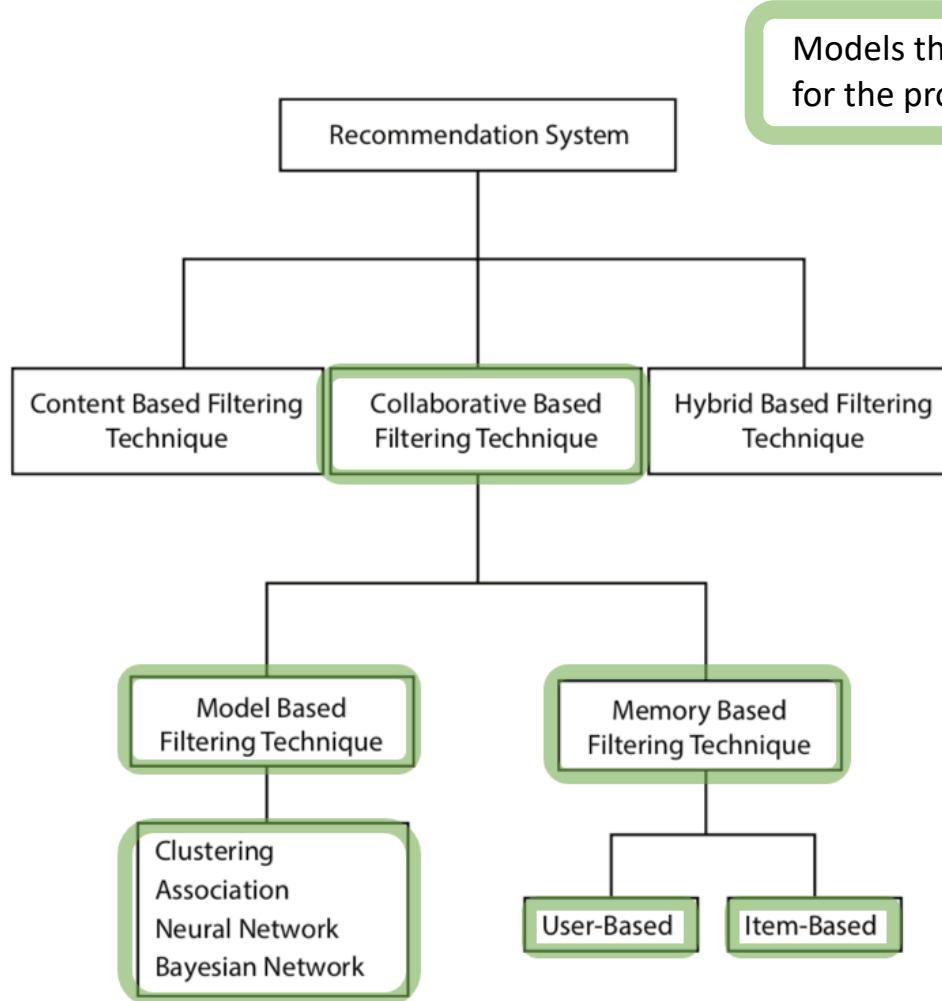
- Popularity cut top 20 %

of Votes for Reviews

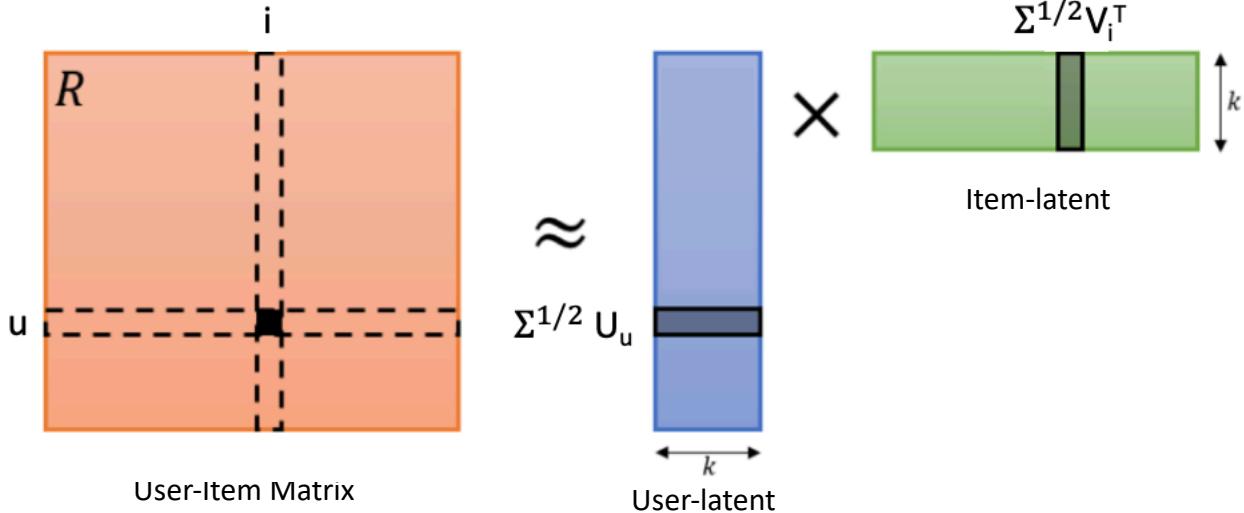
- Range of # of votes (Mostly < 250).
- Some OUTLIERS over 1500 votes

MODELING

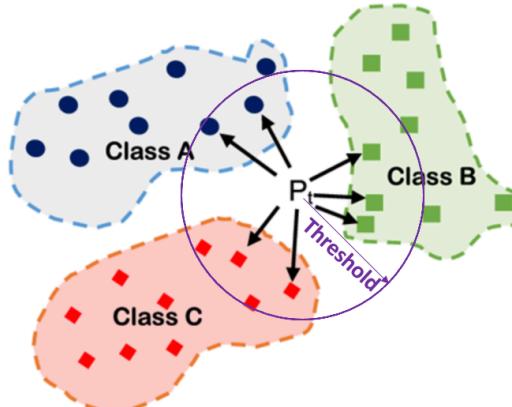
Recommender System Types



Model-based:
**Matrix
Factorization**



Memory-based:
KNN



A table showing user ratings for five items (Item1 to Item5) across five users (Alice, User1, User2, User3, User4). The last row for Alice is highlighted in yellow, and the last column for Item5 is also highlighted in yellow. A circular arrow labeled 'Similarity' is shown to the right of the table.

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

A second table showing user ratings for five items (Item1 to Item5) across five users (Alice, User1, User2, User3, User4). The first column for Alice is highlighted in yellow, and the last row for Item5 is also highlighted in yellow. A circular arrow labeled 'Similarity' is shown to the right of the table.

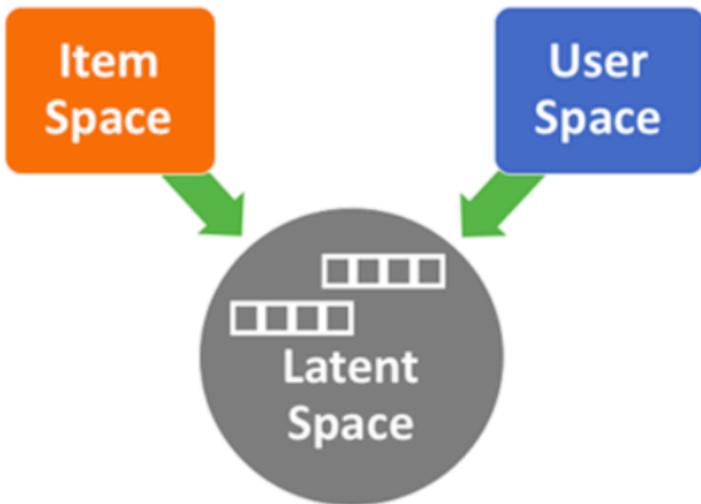
	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

MODELING

Content-based Filtering

Hybrid Filtering

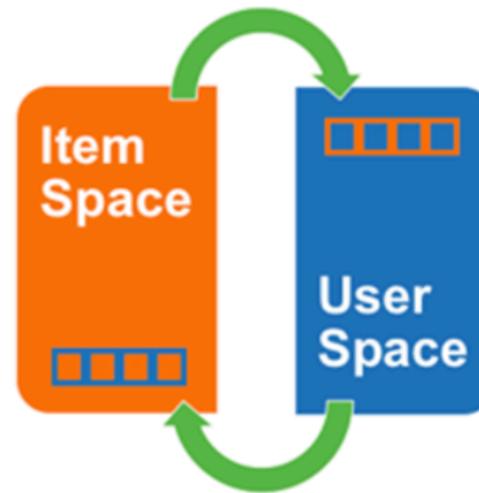
Model-based CF



Latent Model

- SVD
- SVD++
- NMF

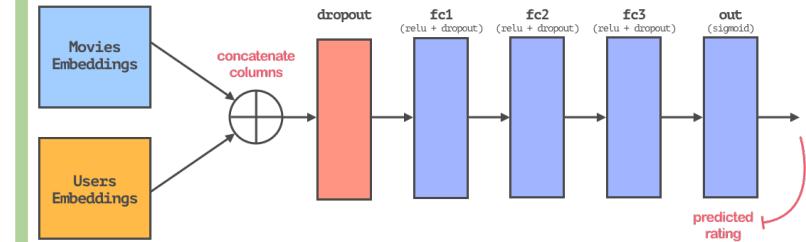
Memory-based CF



Neighborhood Model

- KNN
- KNN with Means
- KNN with Z-score

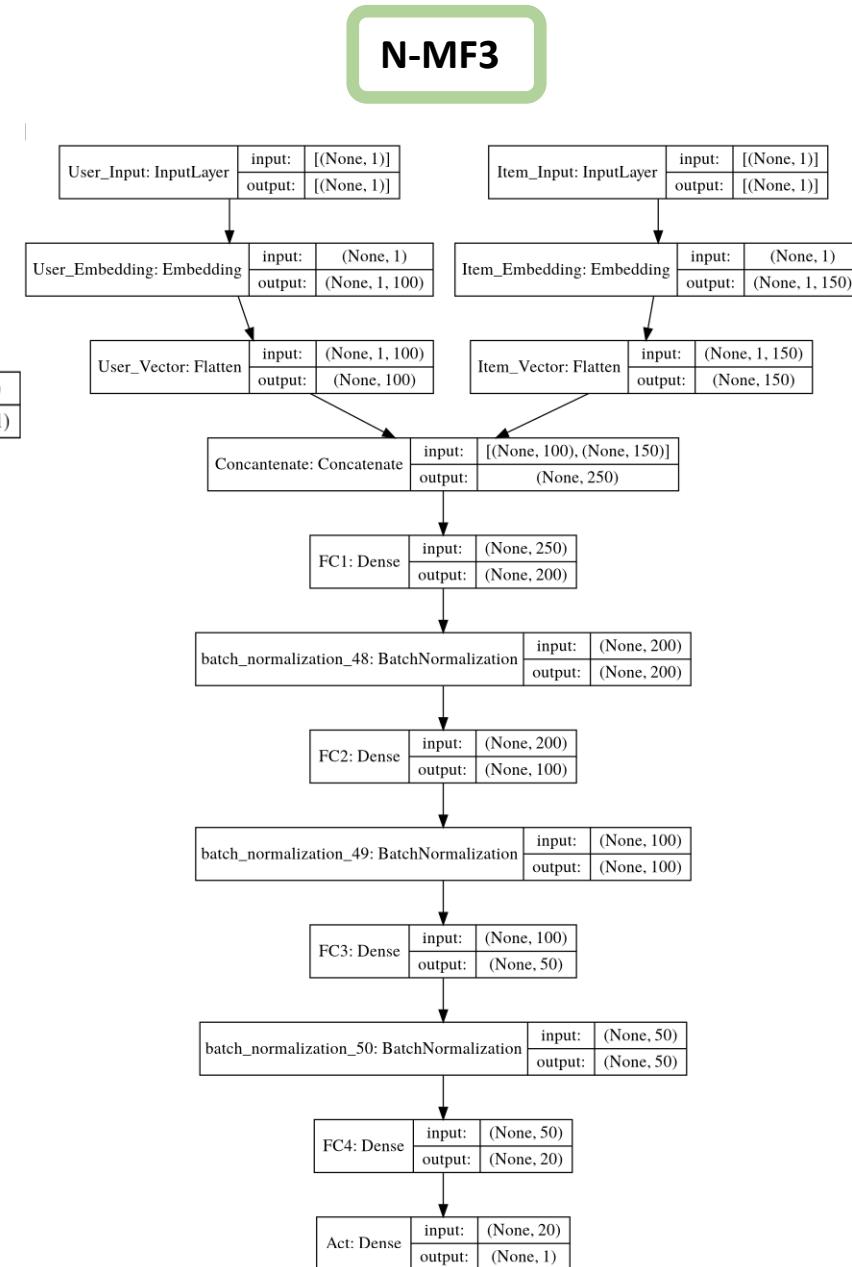
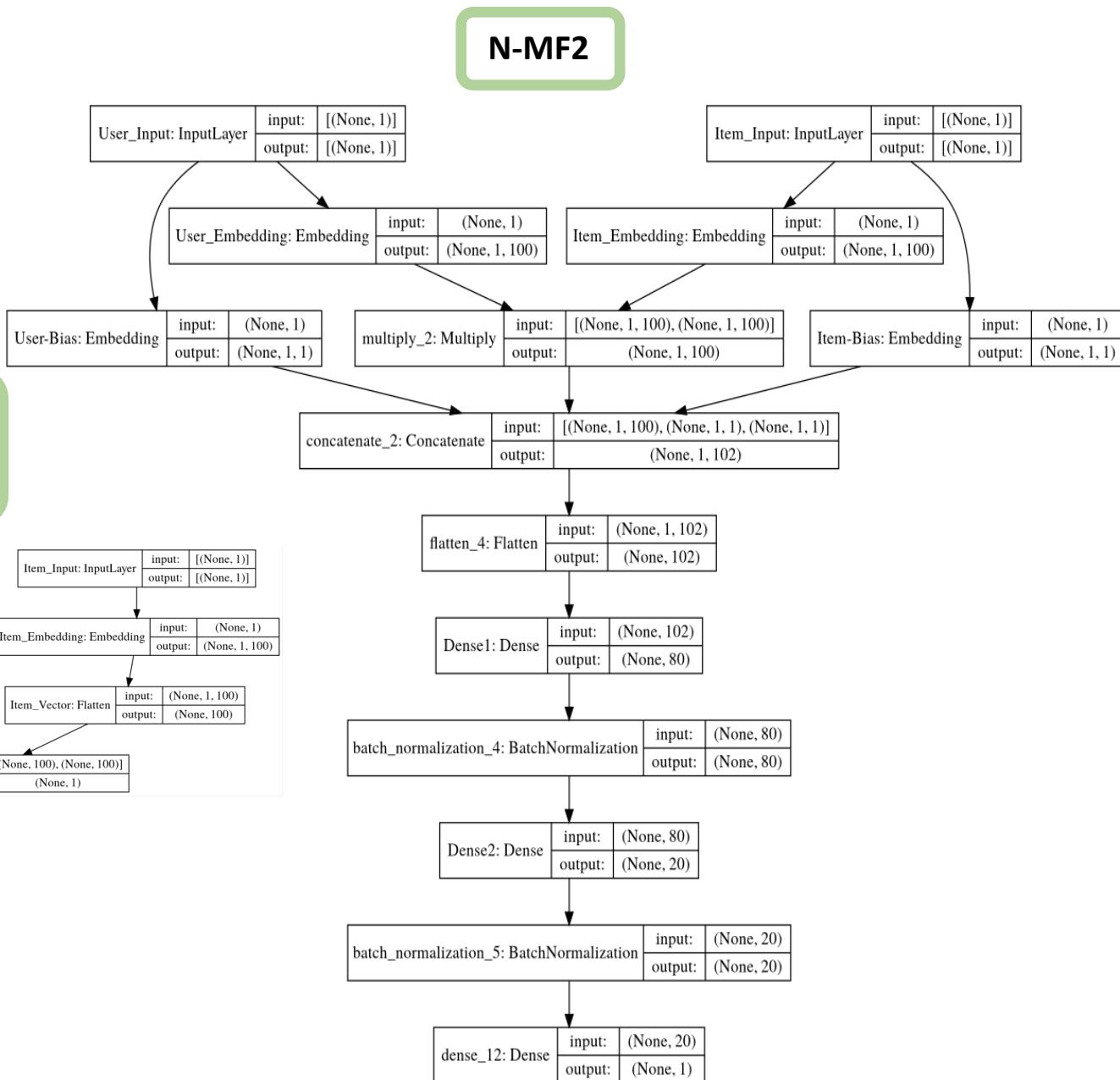
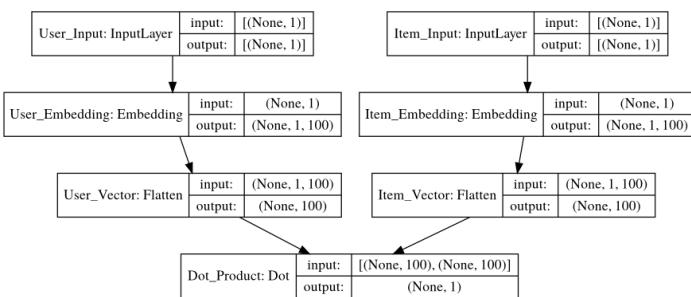
Deep Learning based Recommender System



- Neural Matrix Factorization 1
- Neural Matrix Factorization 2
- Neural Matrix Factorization 3

MODELING

N-MF1
(Neural-Matrix Factorization)



EVALUATION OF MODELS

Model Evaluation Metrics

- **RMSE:** Root Mean Squared Error. Lower value is better.
- **MAE:** Mean Absolute Error. Lower value is better.
- **Precision@k:** number of recommended items that are actually rated within top-k over number of top-k. Higher value is better.
- **Recall@k:** number of recommended items that are relevant over number of recommended items. Higher value is better.
- **HR:** Hit Rate; how often we are able to recommend a left-out rating. Higher is better.
- **cHR:** Cumulative Hit Rate; hit rate, confined to ratings above a certain threshold. Higher is better.
- **Coverage:** Ratio of users for whom recommendations above a certain threshold exist. Higher is better.
- **Diversity:** $1 - S$, where S is the average similarity score between every possible pair of recommendations for a given user. Higher means more diverse.
- **Novelty:** Average popularity rank of recommended items. Higher means more novel.

$$Prec@k = \frac{\# \text{ of Relevant Items Recommended in top-k}}{k \text{ (# of Items that Recommended)}}$$

$$Recall@k = \frac{\# \text{ of Relevant Items Recommended in top-k}}{\# \text{ of Relevant Items}}$$

$$HR = \frac{\# \text{ of Hit}}{\# \text{ of Users}}$$

$$cHR = \frac{\# \text{ of Hits of ratings above threshold}}{\# \text{ of Users}}$$

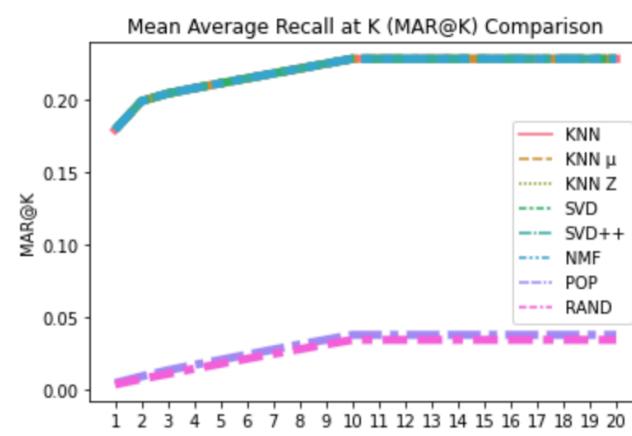
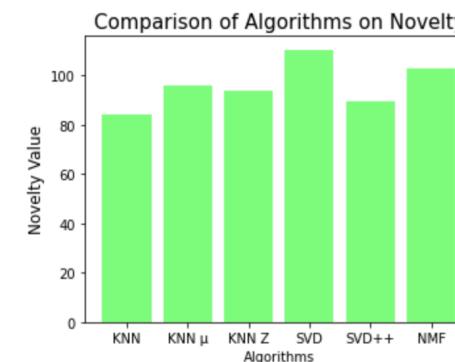
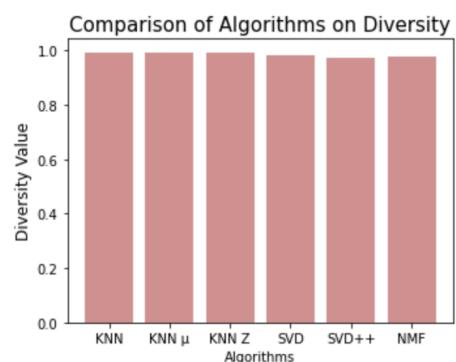
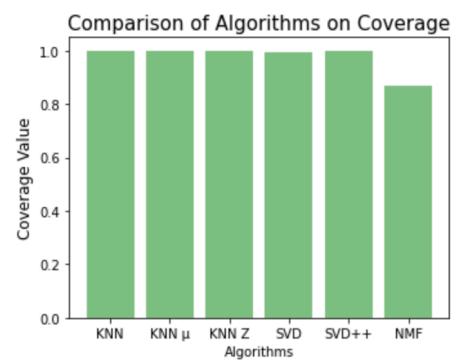
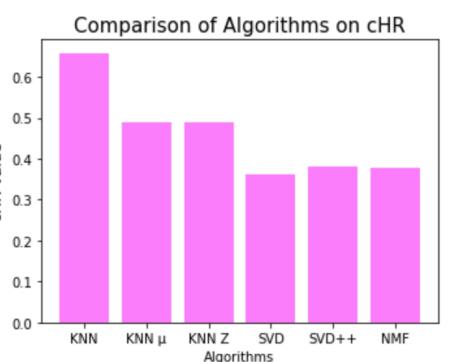
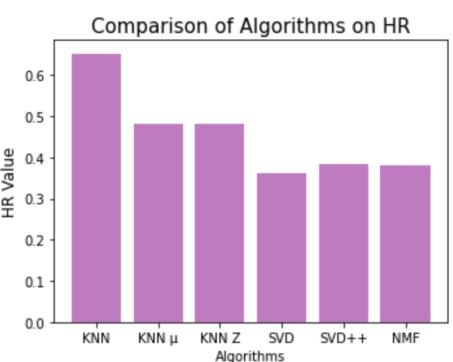
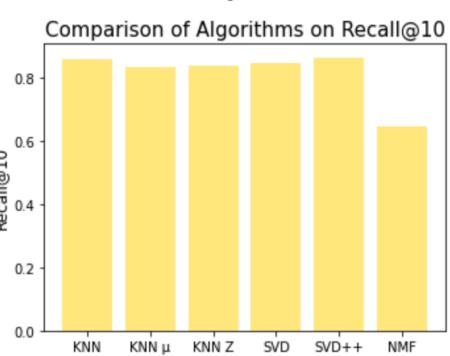
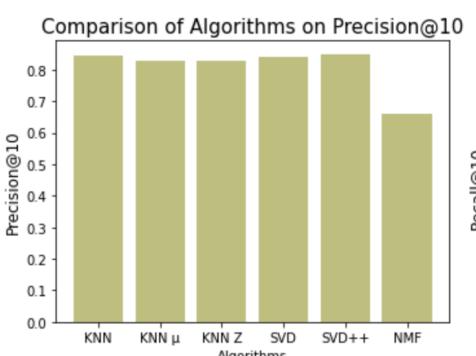
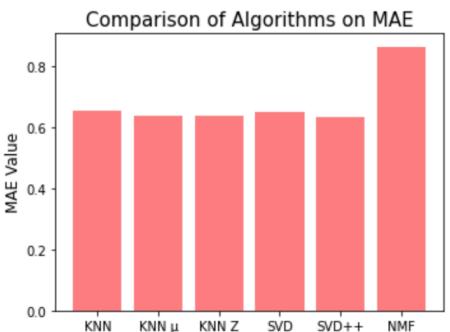
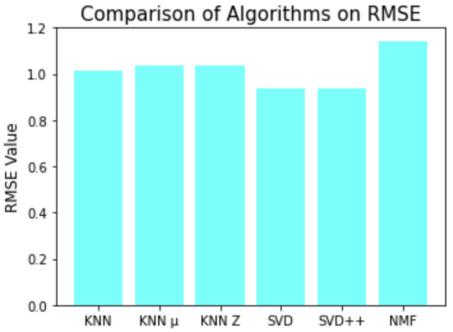
$$Cvg = \frac{\# \text{ of Users above threshold}}{\# \text{ of Users}}$$

$$Dvr = 1 - S$$

$$Nvl = \sum_{i=0}^k \frac{\text{Rating}(i) \text{ that current User gave}}{\text{Rank}(i)}$$

EVALUATION OF MODELS

Model Performance Comparison

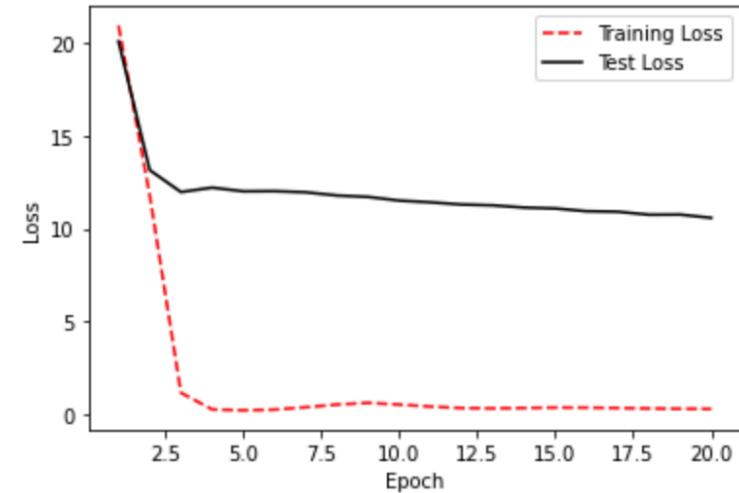


Model	RMSE	MAE	Pr@10	Re@10	HR	cHR	Cvg	Dvs	Nvl
KNN	1.012	0.656	0.843	0.857	0.652	0.659	1.0	0.991	84.2
KNN μ	1.037	0.638	0.827	0.835	0.481	0.488	1.0	0.993	96.0
KNN Z	1.037	0.641	0.829	0.836	0.480	0.488	1.0	0.993	94.1
SVD	0.935	0.651	0.838	0.848	0.360	0.361	0.99	0.980	110.5
SVD++	0.938	0.634	0.850	0.864	0.384	0.381	1.0	0.970	89.6
NMF	1.143	0.866	0.659	0.646	0.382	0.379	0.87	0.977	103.0

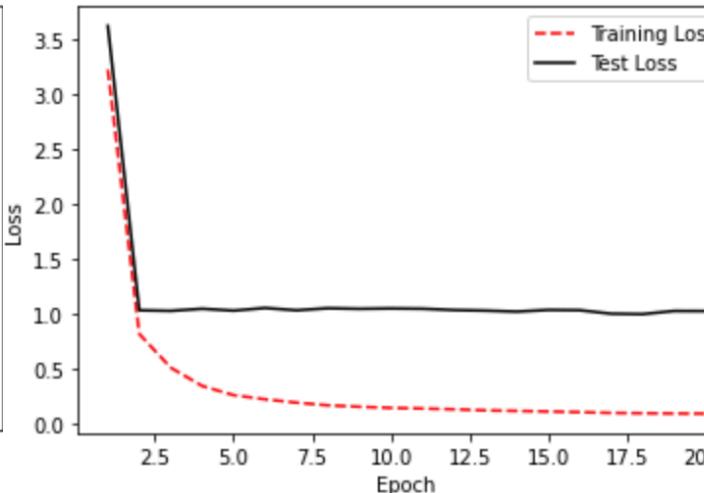
EVALUATION OF MODELS

Model Performance Comparison

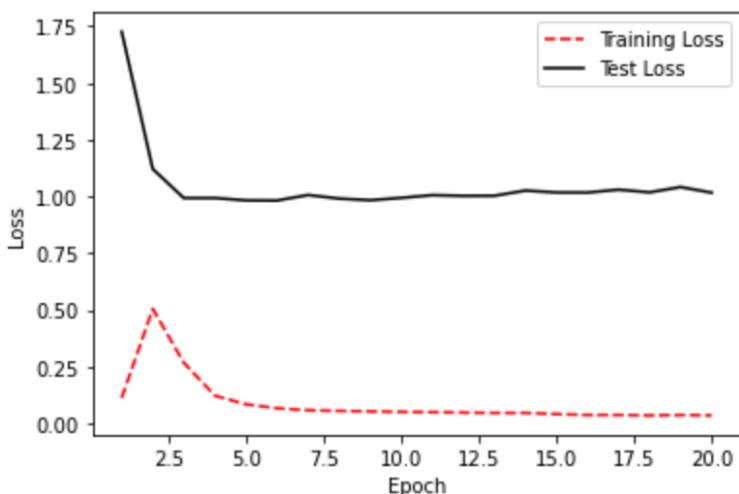
Training Loss vs. Test Loss for N-MF1



Training Loss vs. Test Loss for N-MF3



Training Loss vs. Test Loss for N-MF2



Model	RMSE
KNN	1.012
KNN μ	1.037
KNN Z	1.037
SVD	0.935
SVD++	0.938
NMF	1.143
N-MF1	3.254
N-MF2	1.008
N-MF3	1.011

N-MF1

- Underfitting

He Normal Initialization
Lower Regularization Rate
Add Bias
Add 2 Fully Connected Layers
ReLU
Batch Normalization

N-MF2

- Overfitting

He Normal Initialization
Same Regularization Rate
Concat two latents
add 4 Fully Connected Layers
ReLU
Batch Normalization

N-MF1

- Generalized (compared first two)

FUTURE WORK

- **Various Metrics:** N-MF models can be evaluated with other metrics including Rank-less and Rank-aware metrics.

NOTE: it is suggested to use Rank-less like Precision@k, Recall@k, and Hit@k, and Rank-aware like MAP(Mean Average Precision) and nDCG (normalized Discounted Cumulative Gain) with penalizing rank; red mark is the unused metrics for this projects.

- **Time Comparison:** Comparison of training time can bring more values on this project.
- **More Model Comparison:** The project can be expanded with Content-based and Hybrid Filtering.