

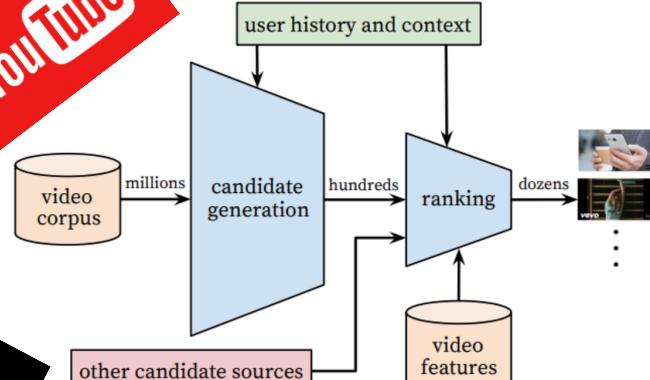
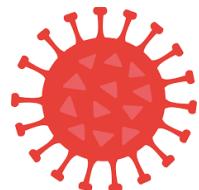
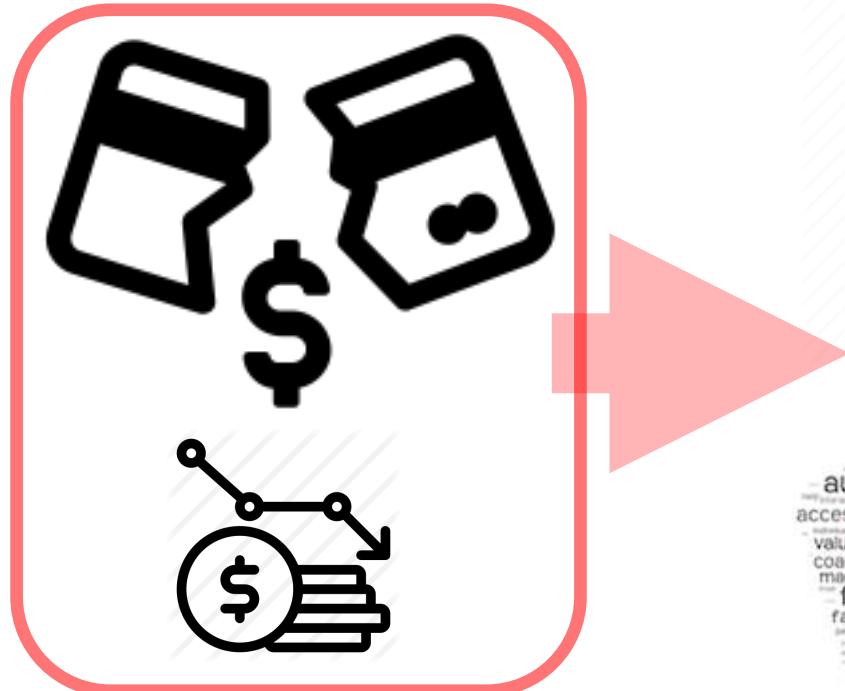


# Recommender System on Amazon Game data

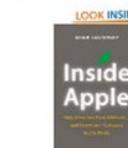
Jae Choi

Contact Info: [Jaehyuk0325@gmail.com](mailto:Jaehyuk0325@gmail.com)

# PROBLEMS



Recommended for Yo

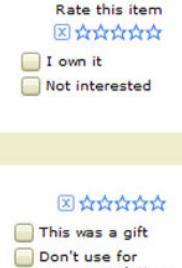


**Inside Apple: How America's Most  
Admired--and Secretive--Company  
Really Works**  
**Our Price: \$9.99**  
**Used & new from \$9.99**

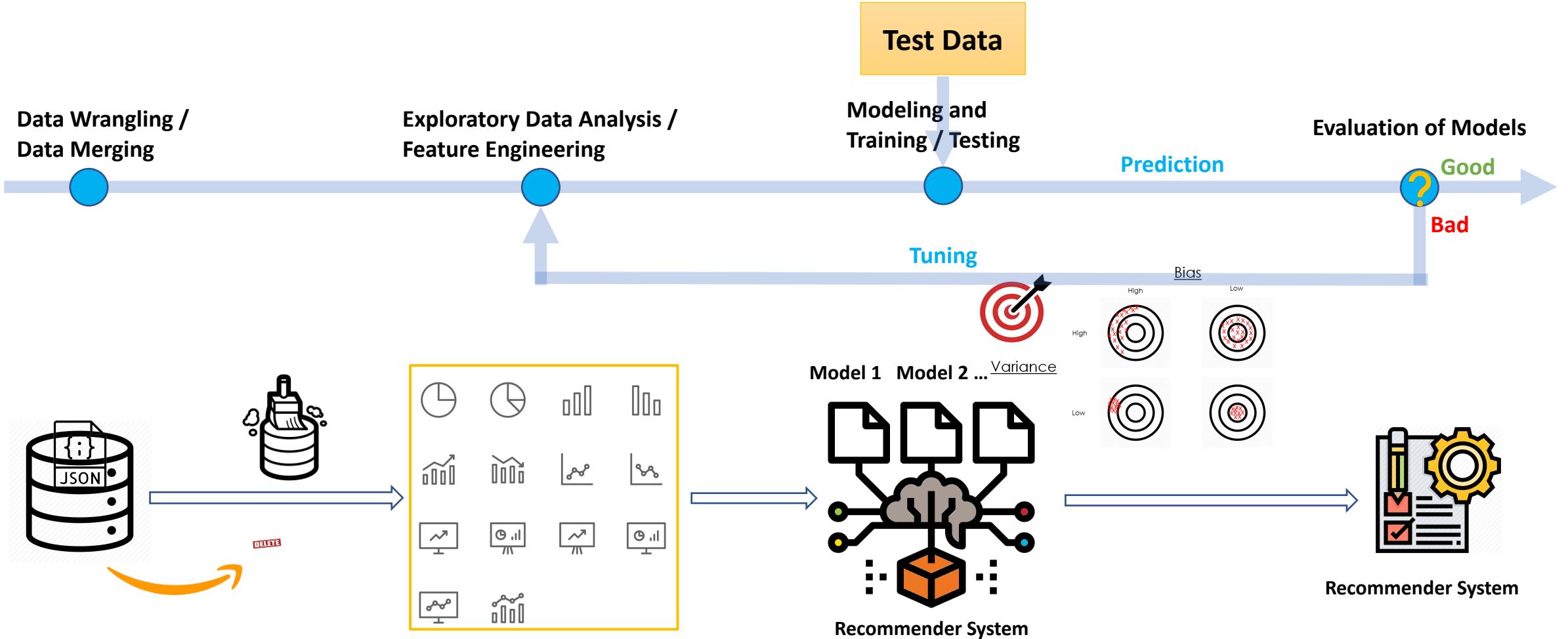
**Because you purchased.**



## The Toyota Way : 14 Management Principles from the World's Greatest Manufacturer



# STEPS



## Data

Total Rows: ~2.56 million  
# of Users: ~72K,  
# of Items: ~1.54 million

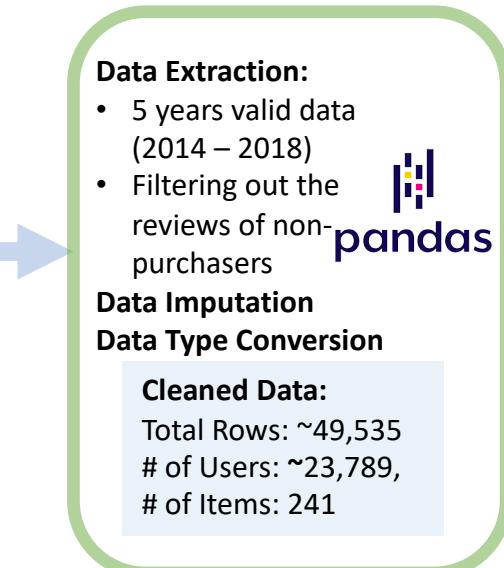
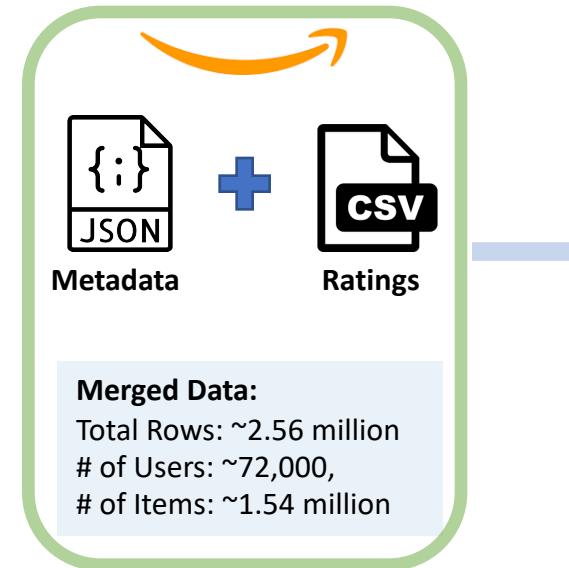
## Cleaned Data:

Total Rows: ~50k  
# of Users: ~23k,  
# of Items: 241

## Data Split

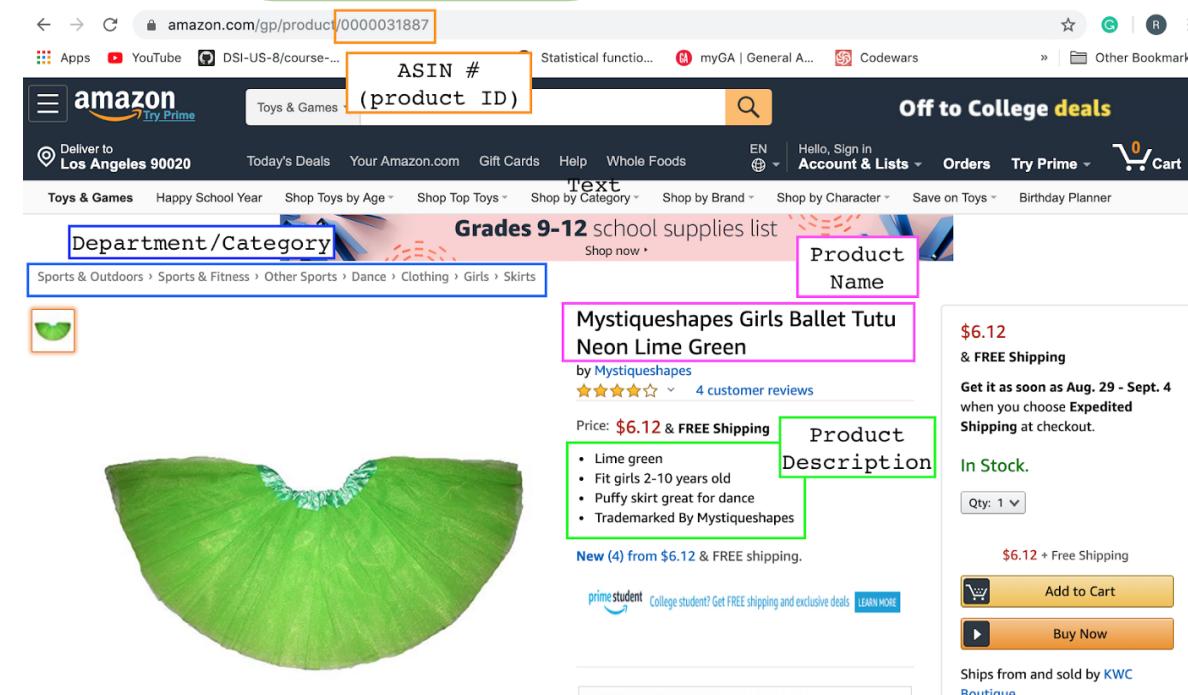
Trainset: **~34.7k**  
Testset: **~14.8K**

# DATA WRANGLING

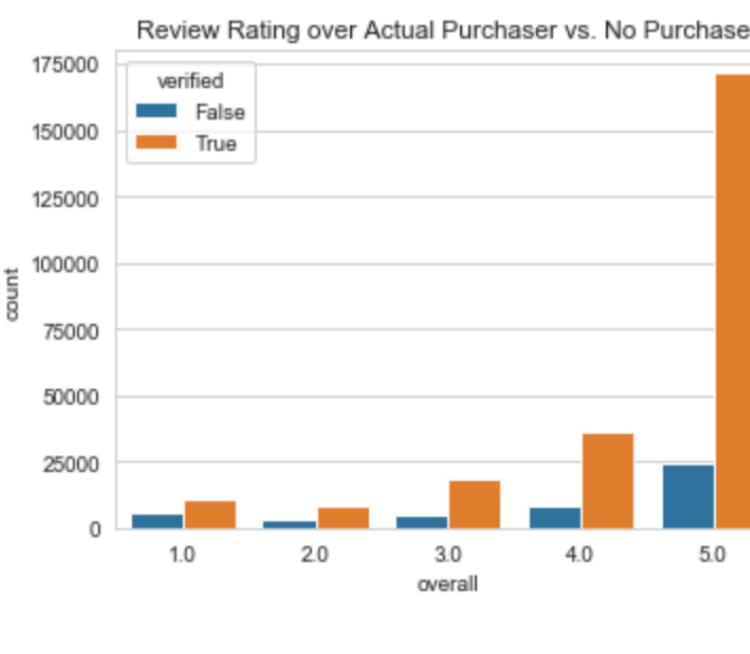
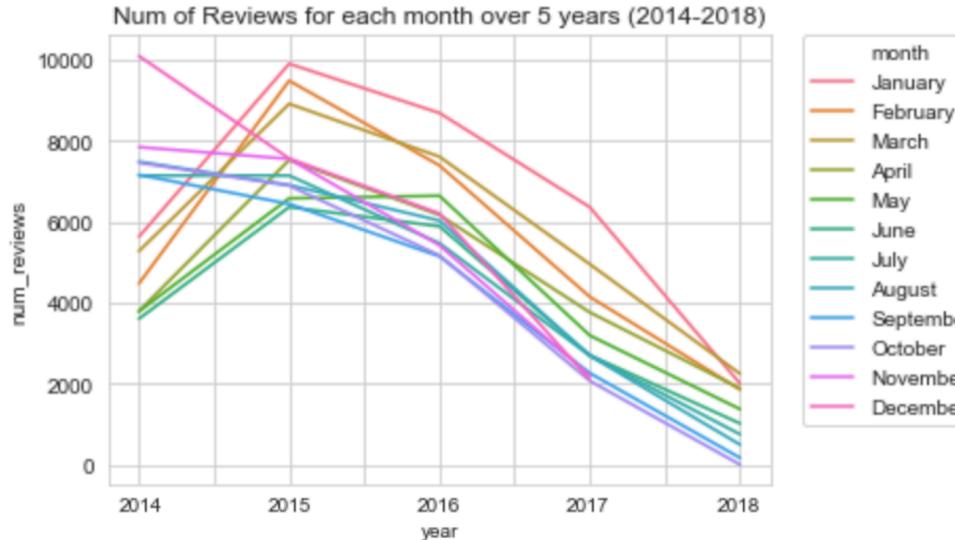
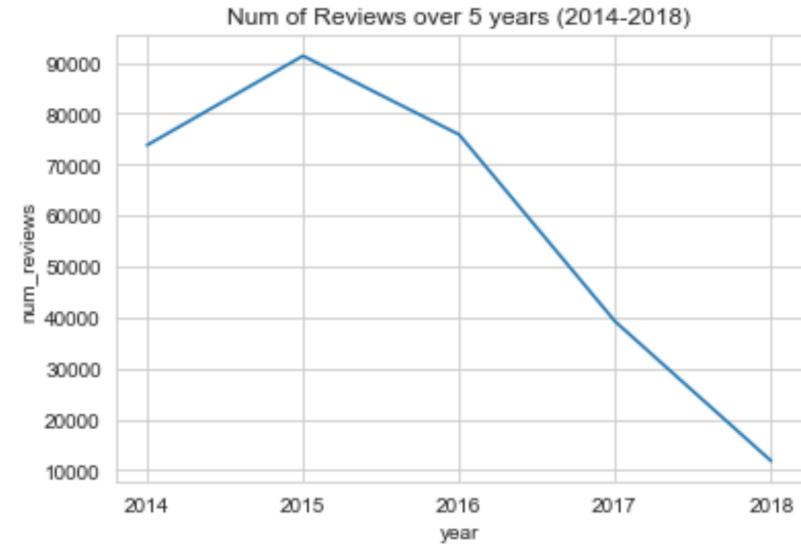


User-Item Matrix

	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)

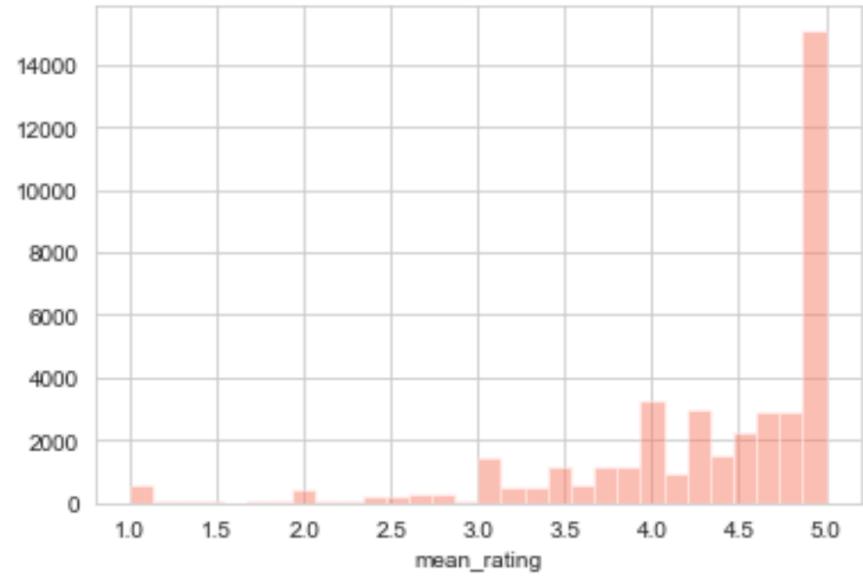
- Increment over SUMMER break.
- Falling trend Jan – June

## Real Buyer vs. No Buyer

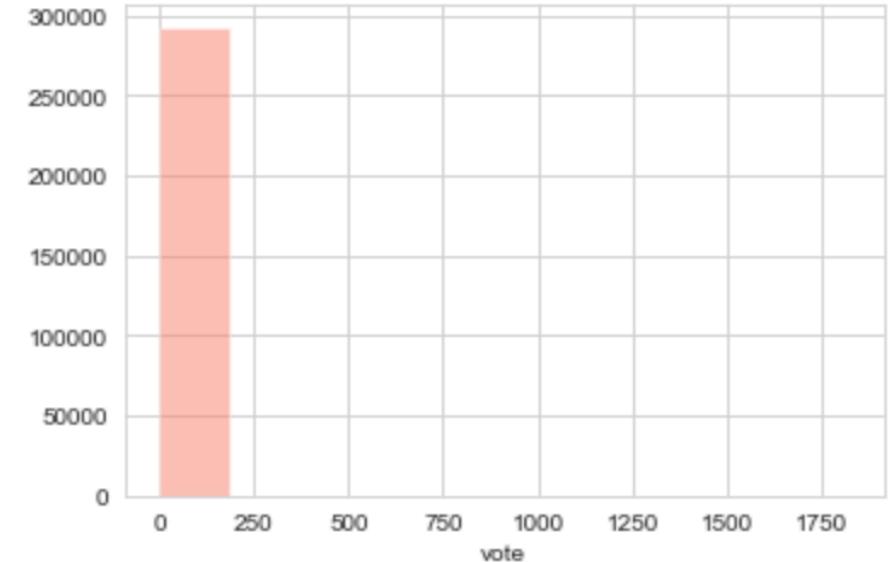
- Both are LEFT skewed
- Data of real buyers is skewed more dramatically.

# EDA

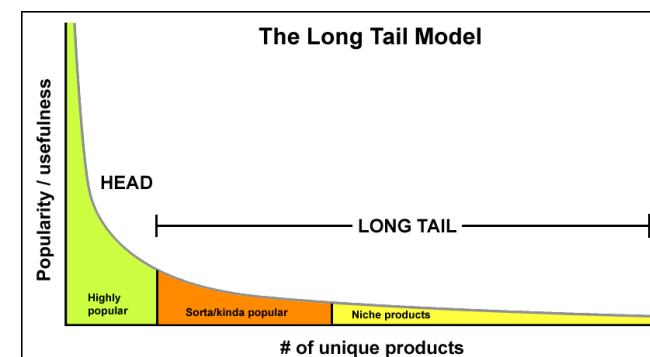
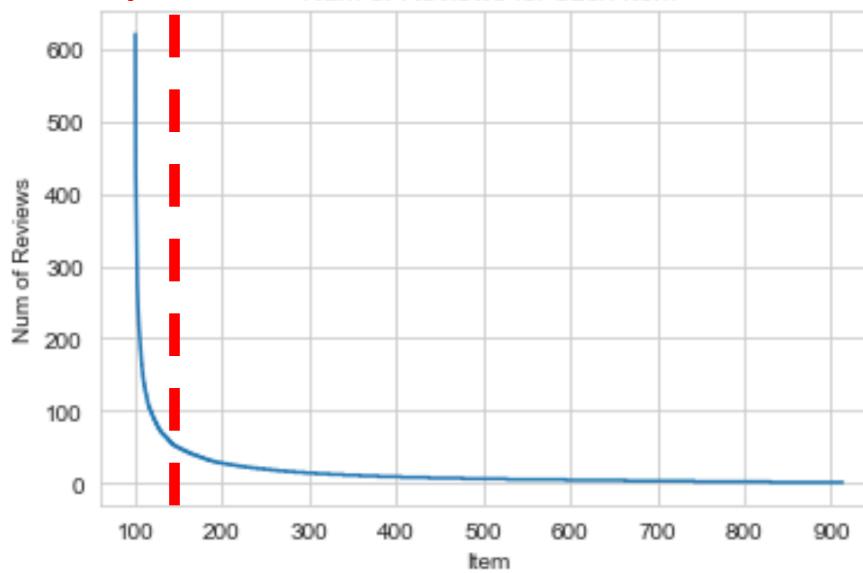
Mean of Ratings for each User



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

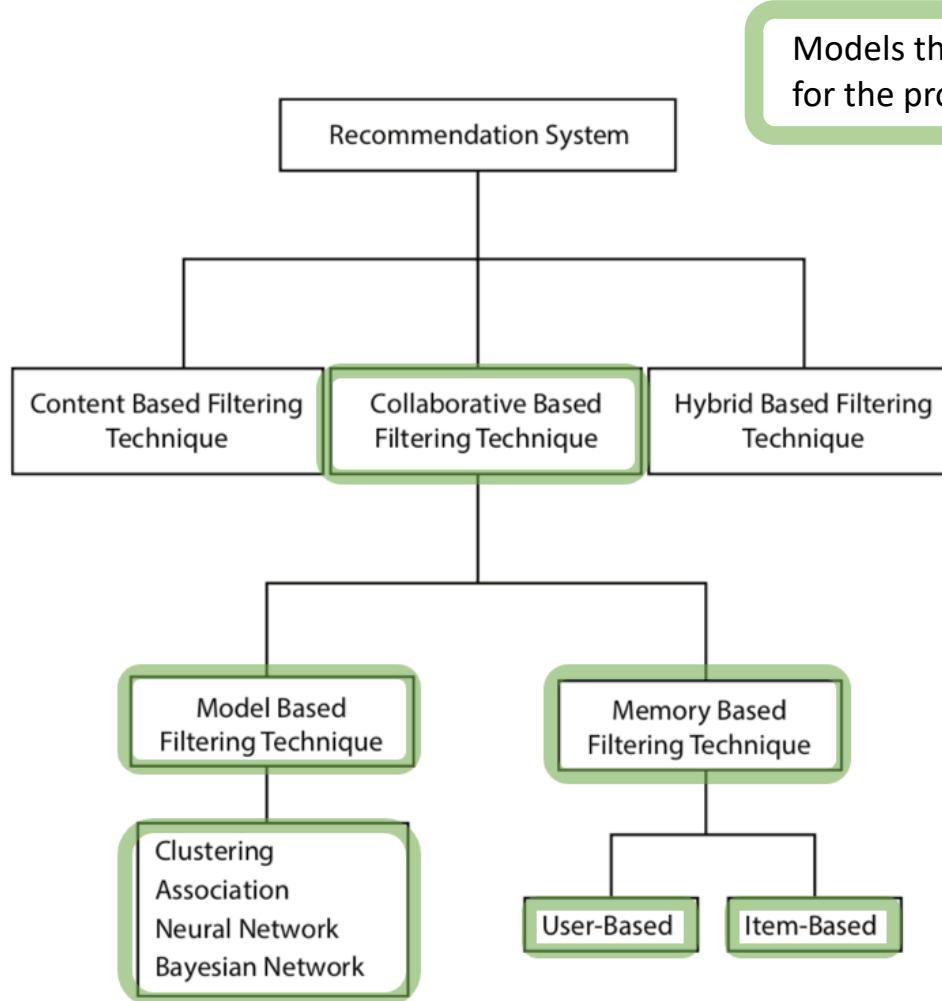
- Popularity cut top 20 %

# of Votes for Reviews

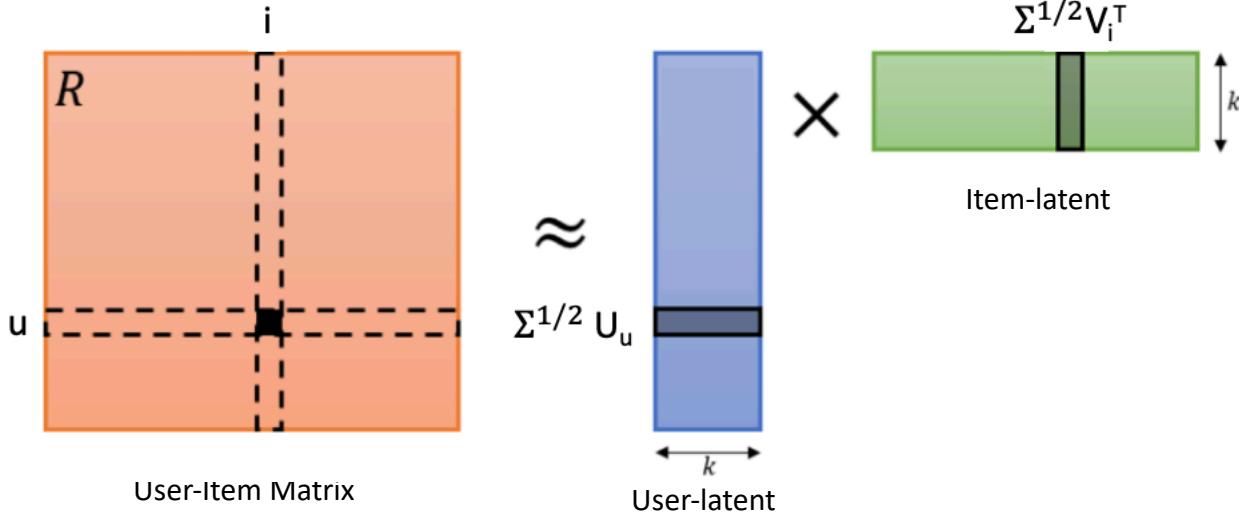
- Range of # of votes (Mostly < 250).
- Some OUTLIERS over 1500 votes

# MODELING

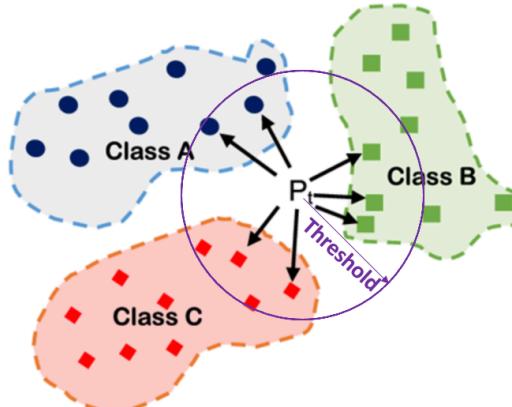
## Recommender System Types



Model-based:  
**Matrix  
Factorization**



Memory-based:  
**KNN**



A table showing user ratings for five items (Item1 to Item5). The last row for User4 is highlighted with yellow boxes around the values for Item1, Item4, and Item5. 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. The last row for User4 is highlighted with yellow boxes around the values for Item1, Item2, Item3, and Item5. A circular arrow labeled 'Similarity' is shown to the right of the table.

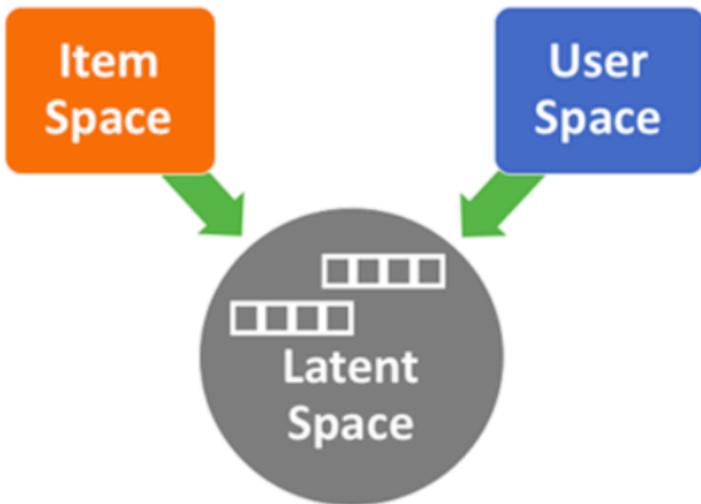
	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

# MODELING

## Content-based Filtering

## Hybrid Filtering

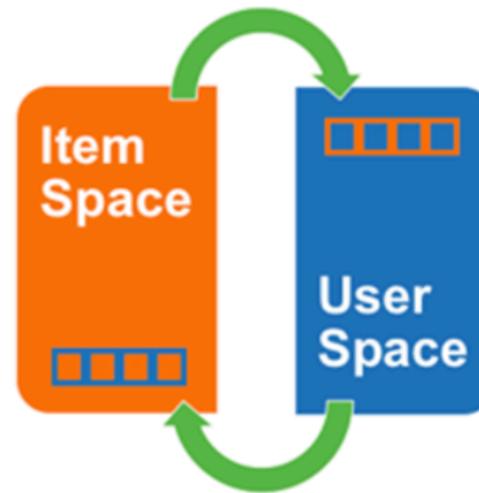
### Model-based CF



Latent Model

- SVD
- SVD++
- NMF

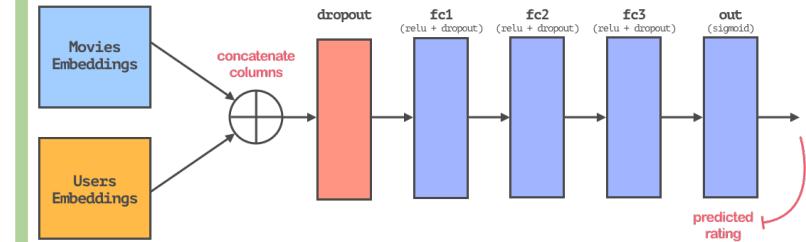
### Memory-based CF



Neighborhood Model

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

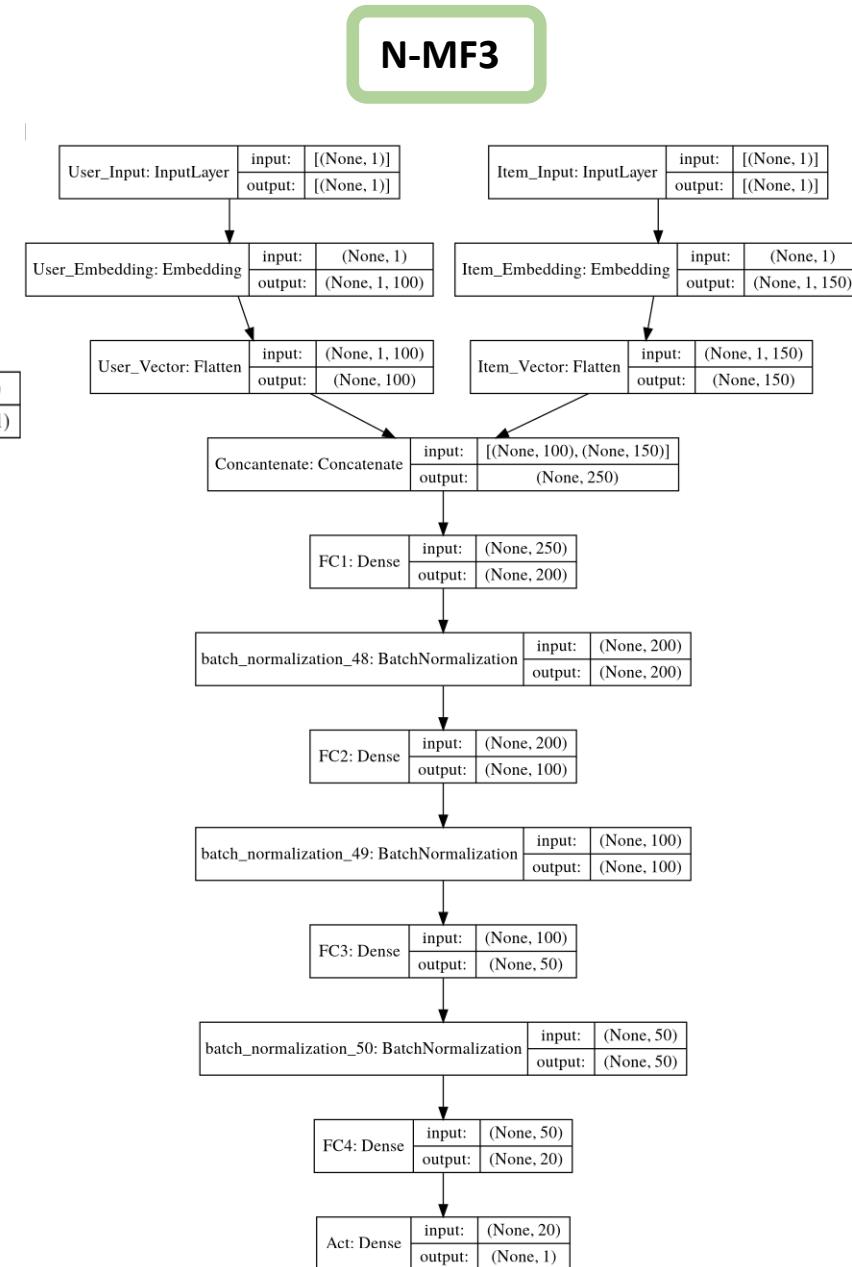
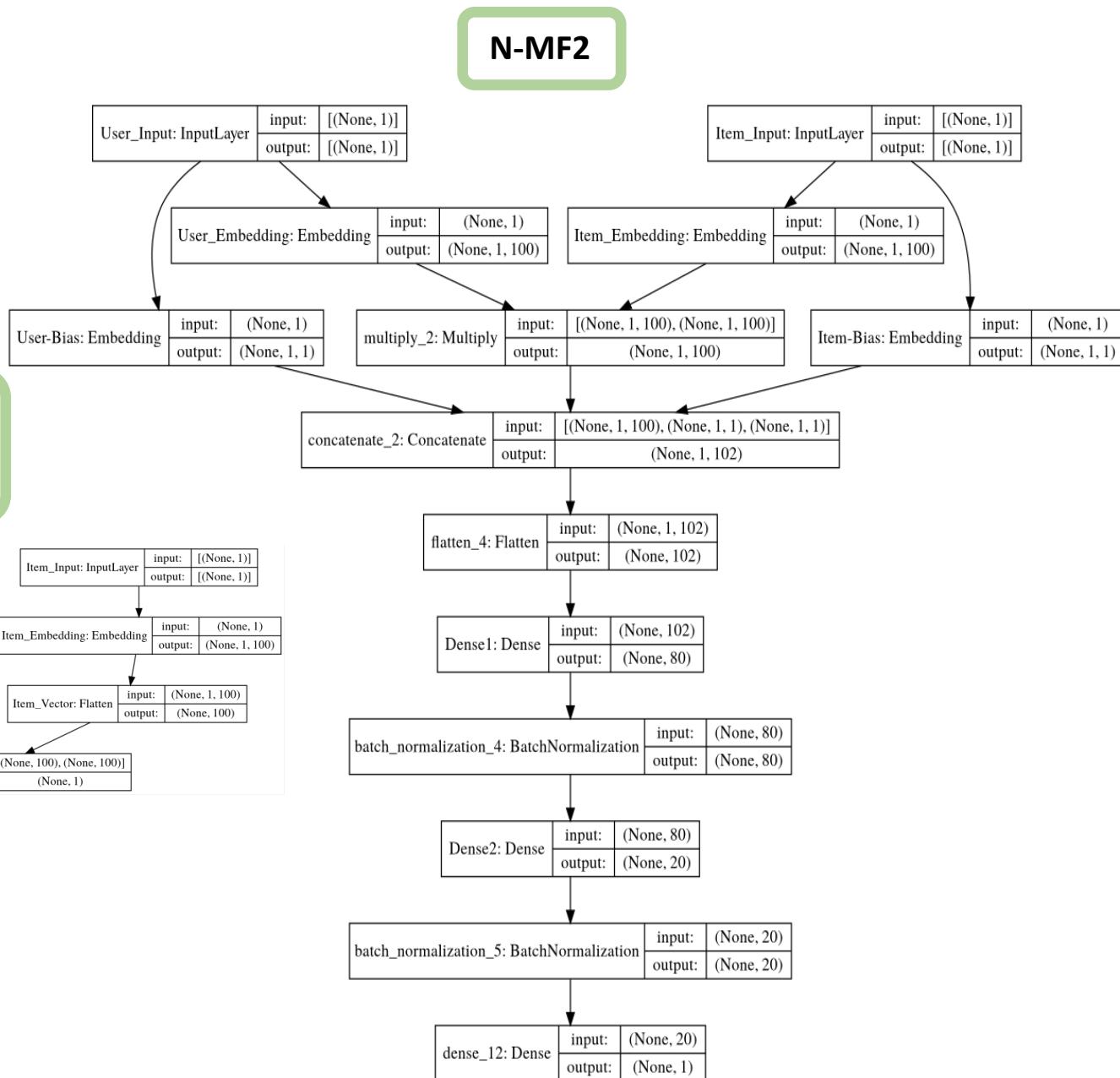
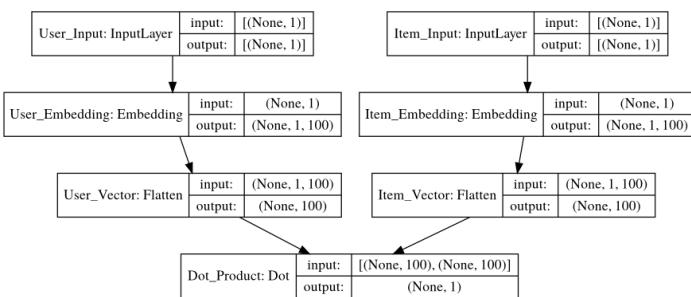
### Deep Learning based Recommender System



- 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.

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

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

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

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

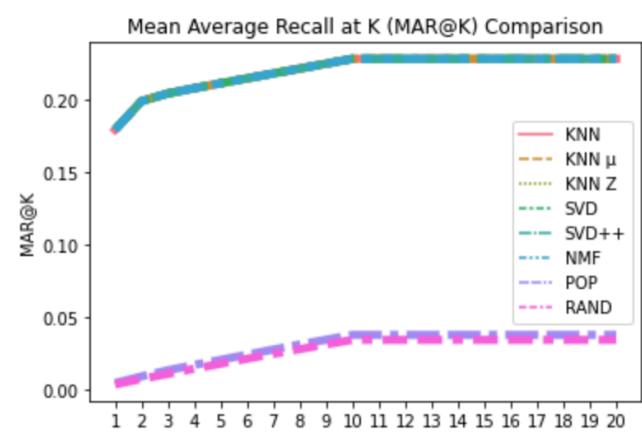
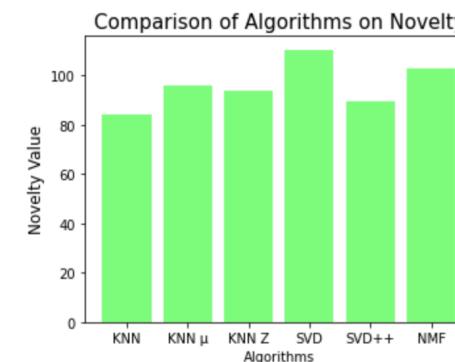
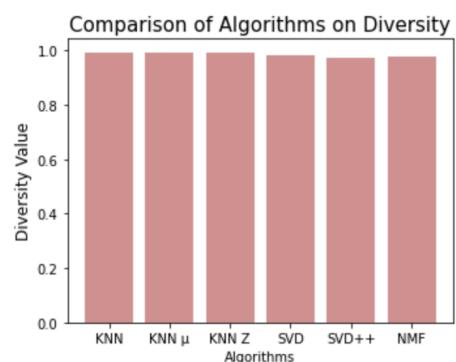
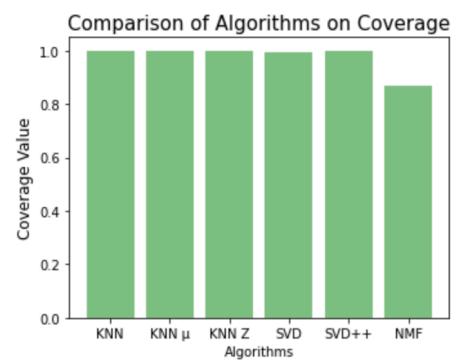
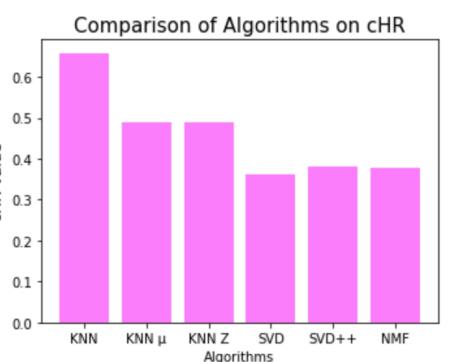
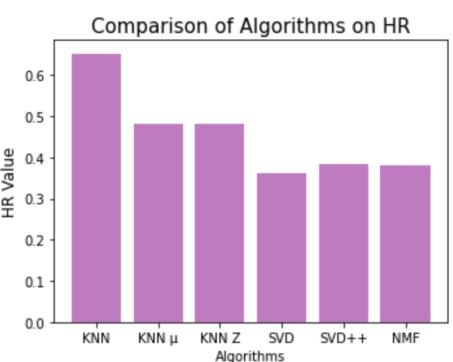
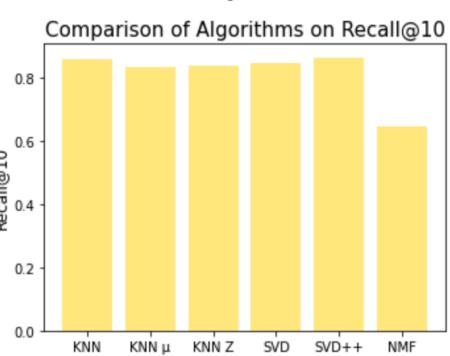
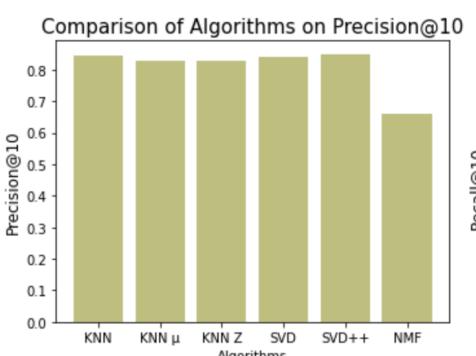
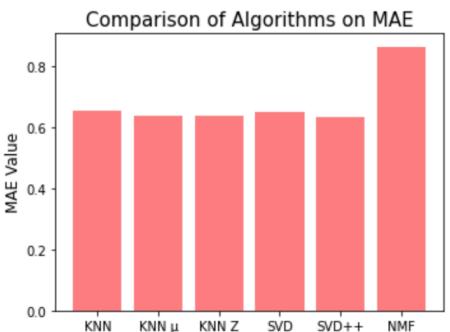
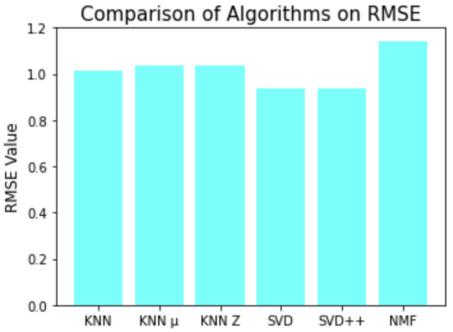
$$Cvg = \frac{\# \text{ of Users above threshold}}{\# \text{ of Users}}$$

$$Dvr = 1 - S$$

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

# EVALUATION OF MODELS

## Model Performance Comparison

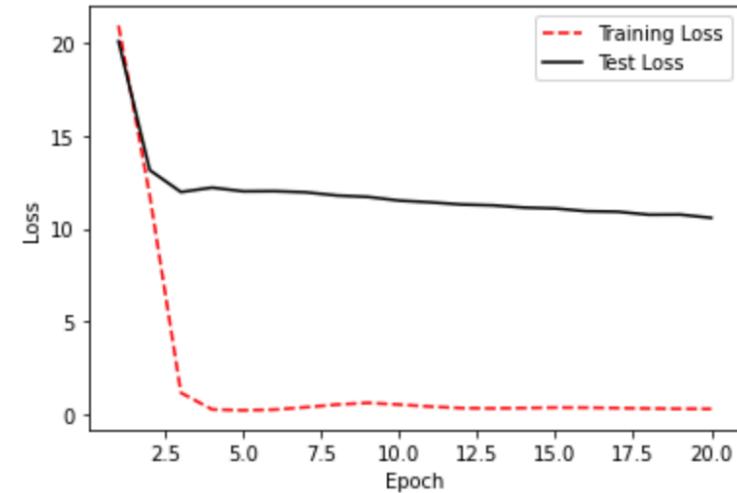


Model	RMSE	MAE	Pr@10	Re@10	HR	cHR	Cvg	Dvs	Nvl
KNN	1.012	0.656	0.843	0.857	0.652	0.659	1.0	0.991	84.2
KNN $\mu$	1.037	0.638	0.827	0.835	0.481	0.488	1.0	0.993	96.0
KNN Z	1.037	0.641	0.829	0.836	0.480	0.488	1.0	0.993	94.1
SVD	0.935	0.651	0.838	0.848	0.360	0.361	0.99	0.980	110.5
SVD++	0.938	0.634	0.850	0.864	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

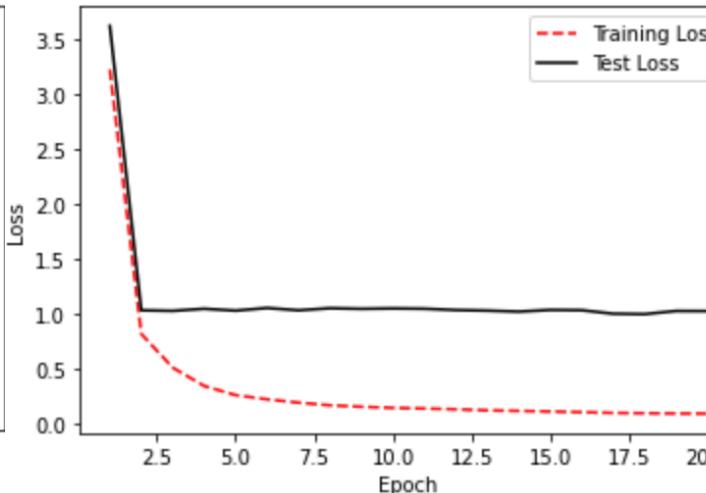
# EVALUATION OF MODELS

## Model Performance Comparison

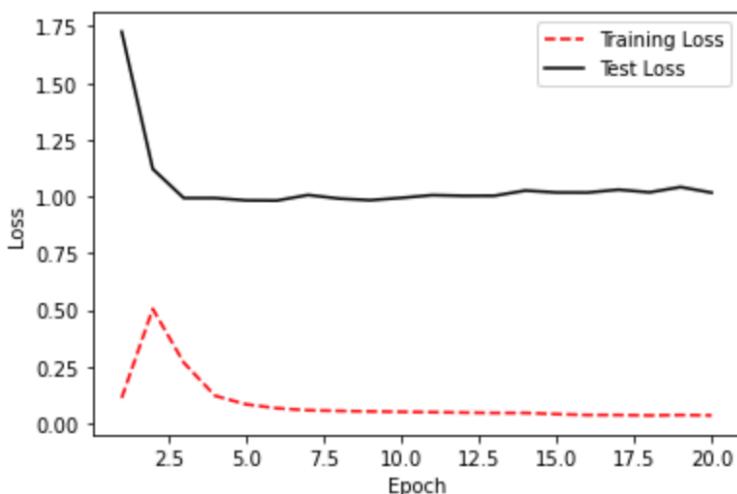
Training Loss vs. Test Loss for N-MF1



Training Loss vs. Test Loss for N-MF3



Training Loss vs. Test Loss for N-MF2



### 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)

Model	RMSE
KNN	1.012
KNN $\mu$	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

# 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.