



RESTAURANT RECOMMENDATION SYSTEM

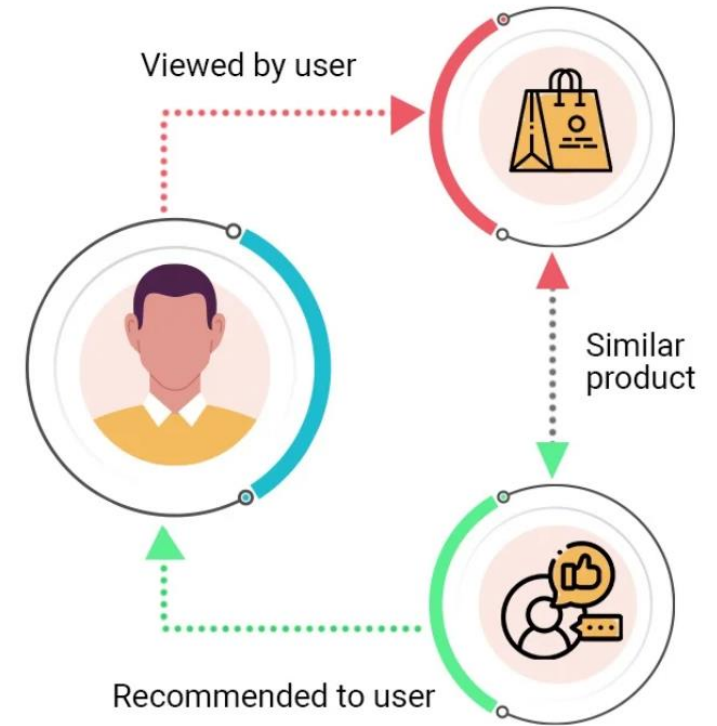
WHAT IS A RECOMMENDATION SYSTEM?



RECOMMENDATION SYSTEM IS AN
INFORMATION FILTERING SYSTEM THAT
SEEKS TO PREDICT THE RATING OR
PREFERENCE A USER WOULD GIVE TO AN
ITEM



IT ASSISTS USERS IN DISCOVERING NEW
ITEMS THAT THEY MAY FIND APPEALING



APPLICATIONS



Streaming Service



E-Commerce
Service



Tourism Service



Healthcare Service



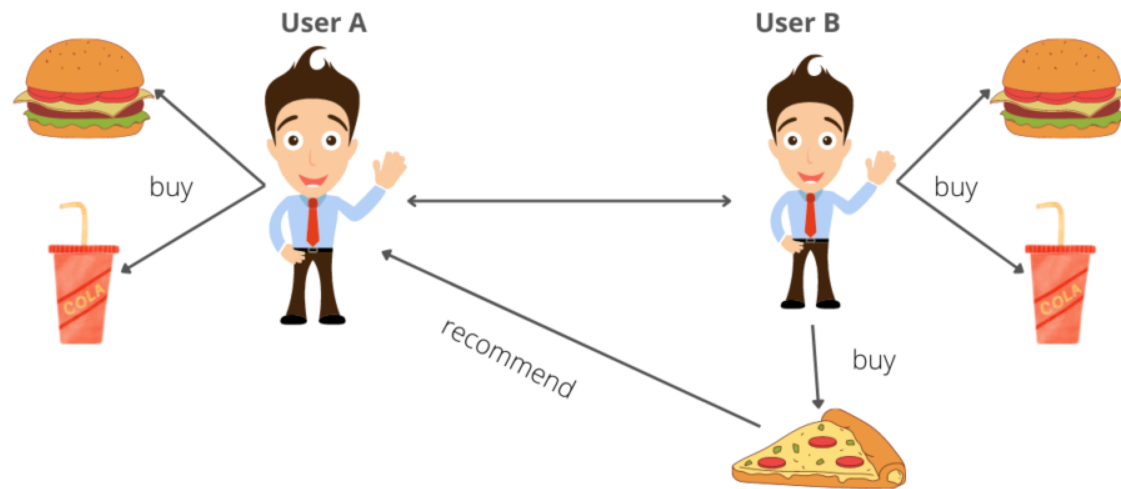
Education Service



Food and Beverages

OUR PROBLEM STATEMENT

Collaborative Recommendation System



The system utilizes the user's historical ratings of multiple restaurants



Based on this data, the system recommends new restaurants that the user has not tried before and predicts that the user will give a high rating

DATASET - YELP



Popular platform for
restaurant and business
ratings and reviews



5 json files – information
about users, businesses,
reviews, checkins, tips



~8GB data with many US
states and cities



Huge dataset with high
sparsity



DATA PROCESSING

User id	Item id	Rating
1	a	1
1	b	2
2	a	3
2	c	2
3	c	5

Data

	item a	item b	item c
user 1	1	2	nan
user 2	3	nan	2
user 3	nan	nan	5

Utility Matrix

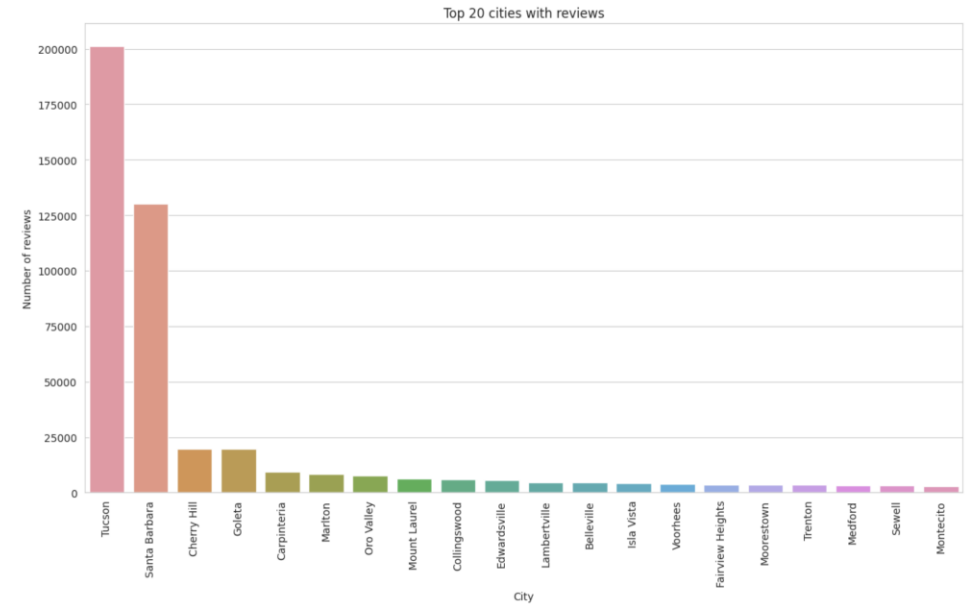
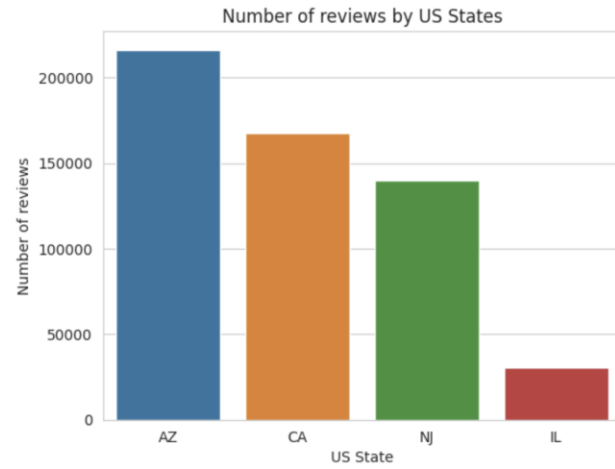
Parsing JSON and
merging to CSV

Subset US states –
AZ, NJ, IL, CA

Filter users with at
least 10 reviews

Create Utility
Matrix

EXPLORATORY DATA ANALYSIS



EVALUATION CRITERIA - RMSE

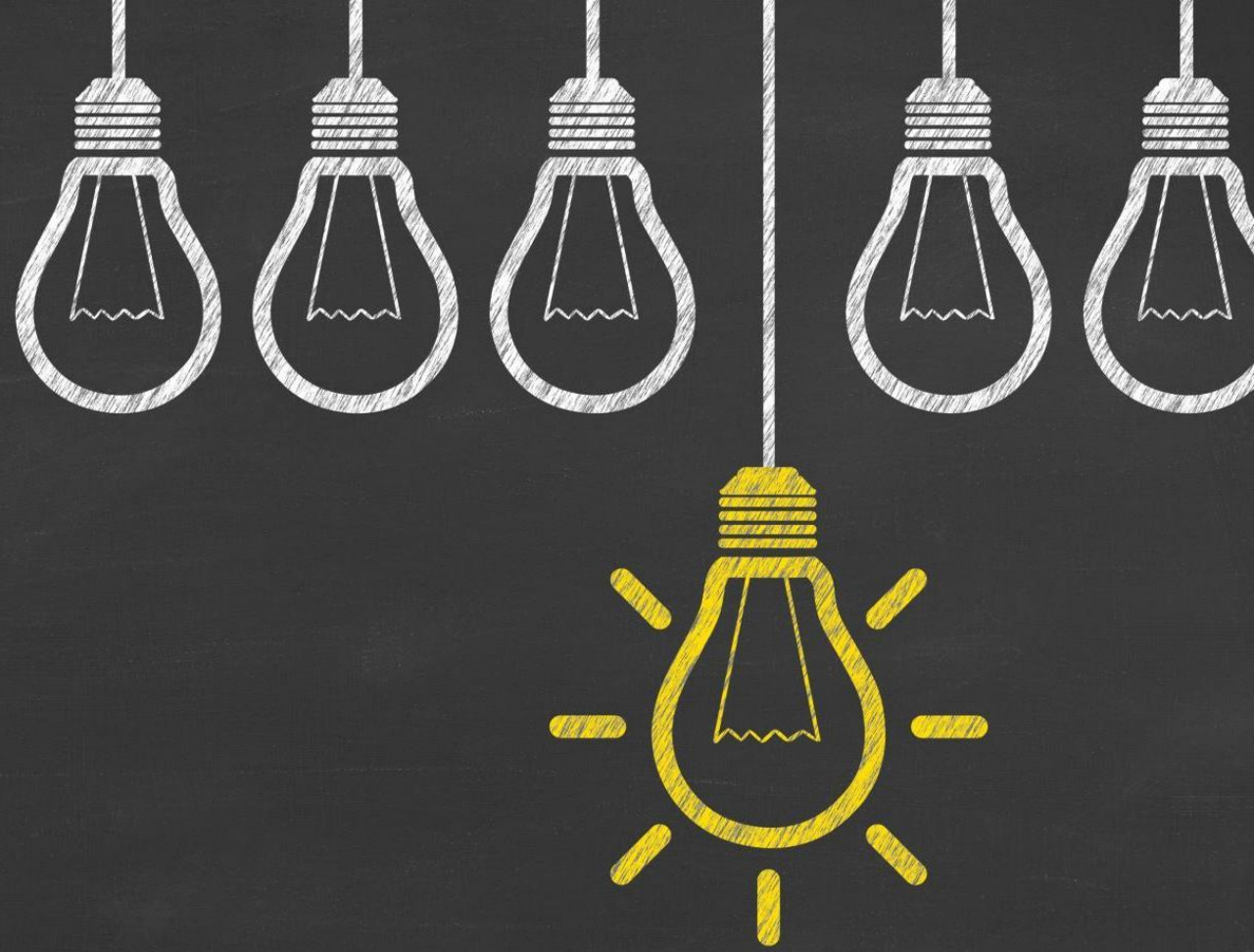
$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}}$$



Train test split: For each user, randomly add 30% ratings to test set



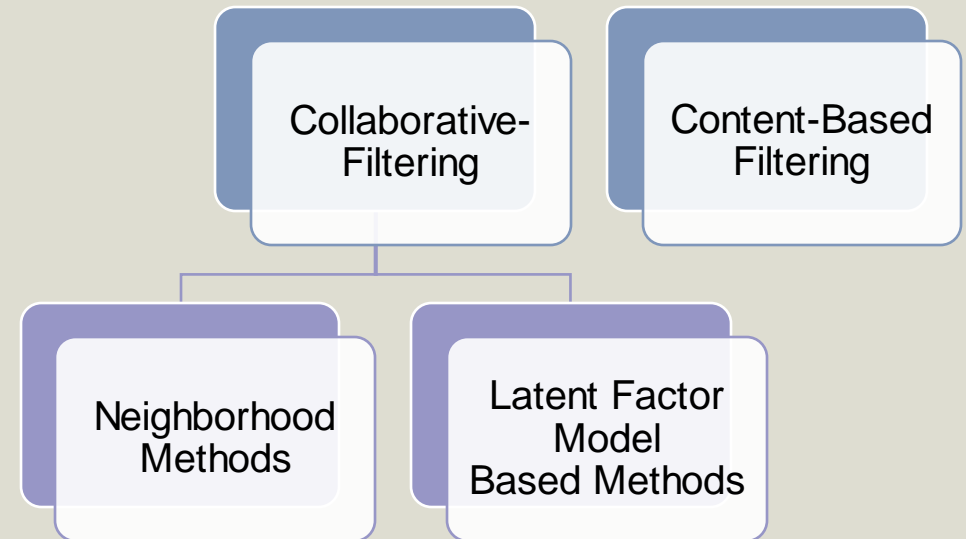
Root mean square error (RMSE) between predicted ratings and actual ratings

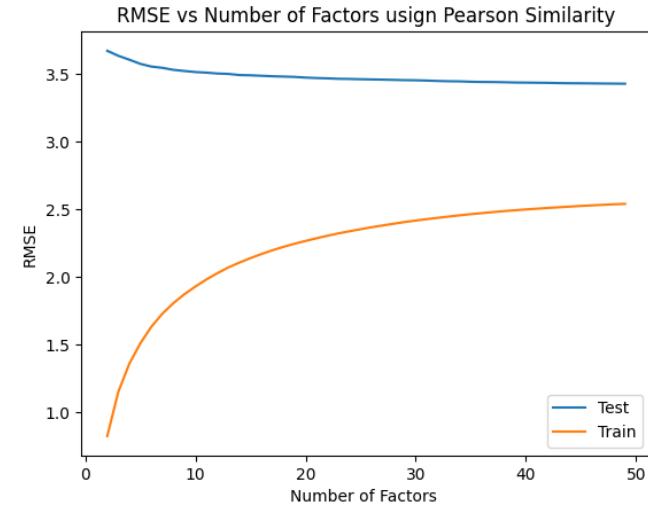
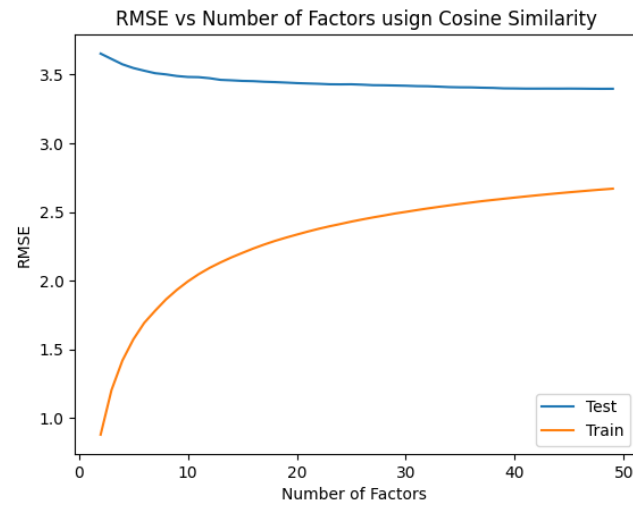


		Item					
		W	X	Y	Z		
User	A		4.5	2.0		A	1.2 0.8
	B	4.0		3.5		B	1.4 0.9
	C		5.0		2.0	C	1.5 1.0
	D		3.5	4.0	1.0	D	1.2 0.8
		Item					
		W	X	Y	Z		
		1.5	1.2	1.0	0.8		
		1.7	0.6	1.1	0.4		

Rating Matrix = User Matrix X Item Matrix

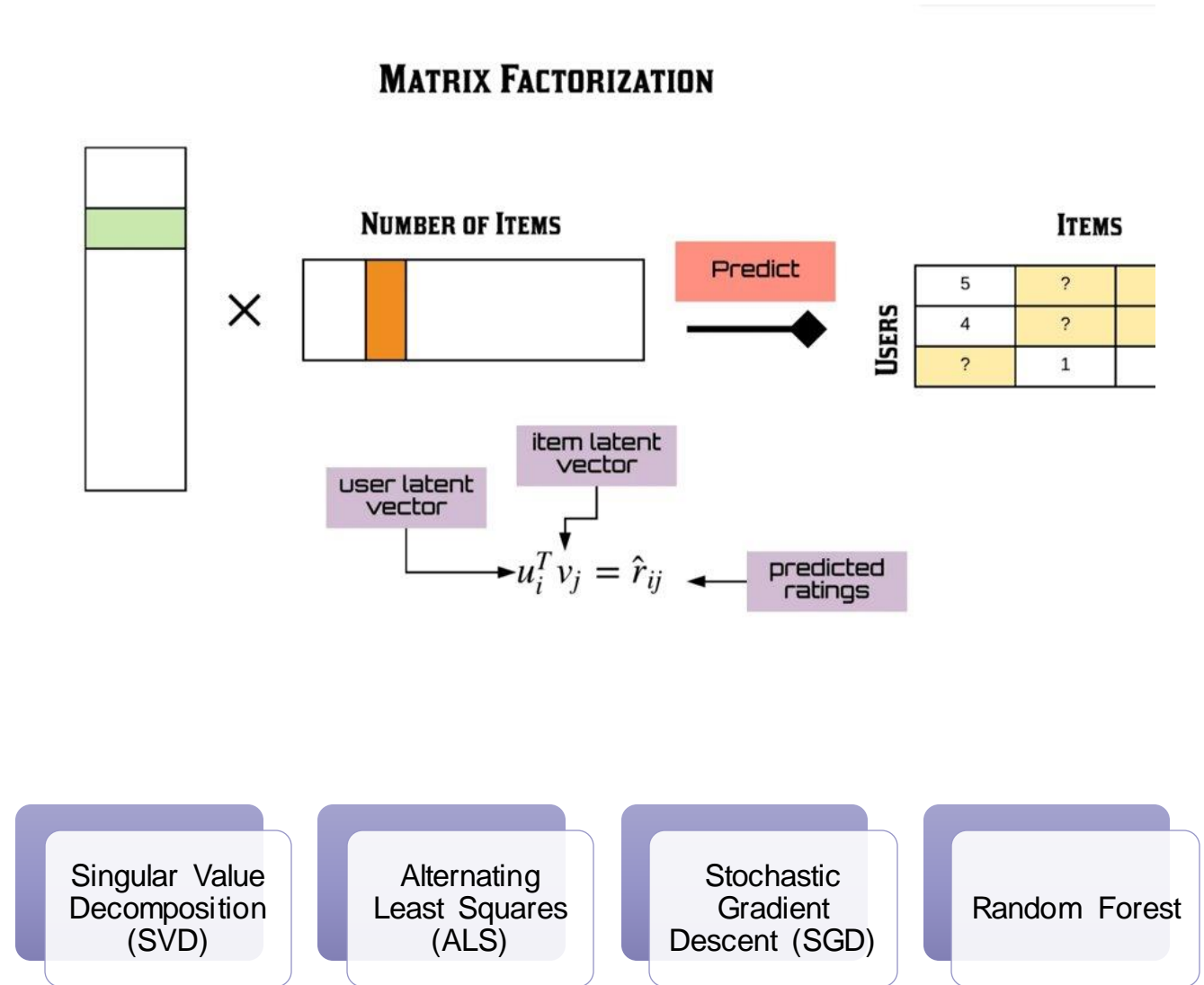
TECHNIQUES



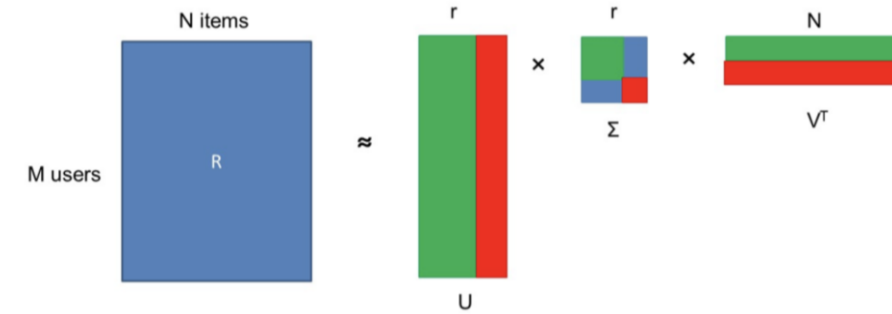
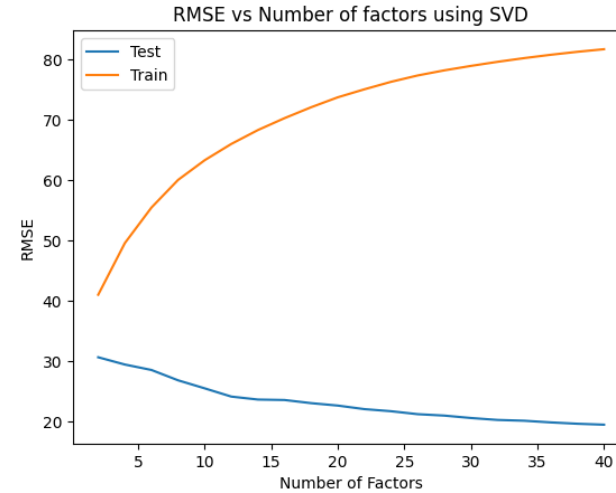


USER SIMILARITY COLLABORATIVE FILTERING

ALGORITHMS FOR
LATENT FACTOR MODEL
BASED COLLABORATIVE
FILTERING



SINGULAR VALUE DECOMPOSITION (SVD)



Popular matrix factorization technique

SVD learns low-dimensional representations of users and items that capture their preferences and characteristics

Latent Concept/Factors: Cuisine, price range, atmosphere etc

U: User-concept association

S: Singular value matrix, explains importance of each concept

V: Item-concept association, how much does item have a particular concept

Struggles with sparsity

STOCHASTIC GRADIENT DESCENT (SGD)

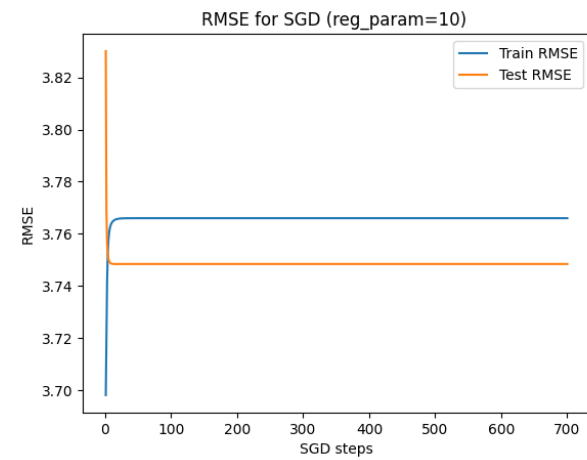
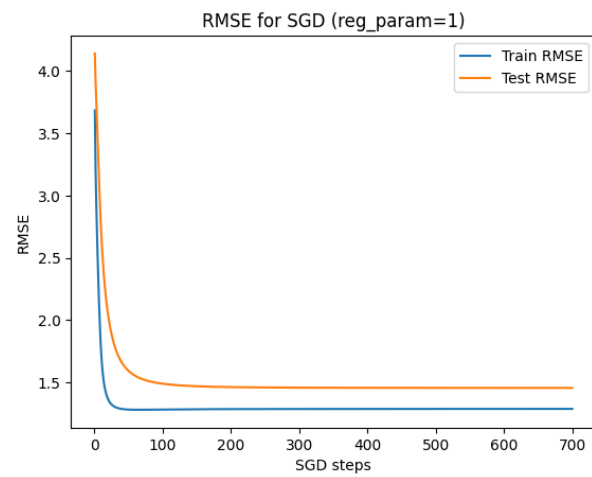
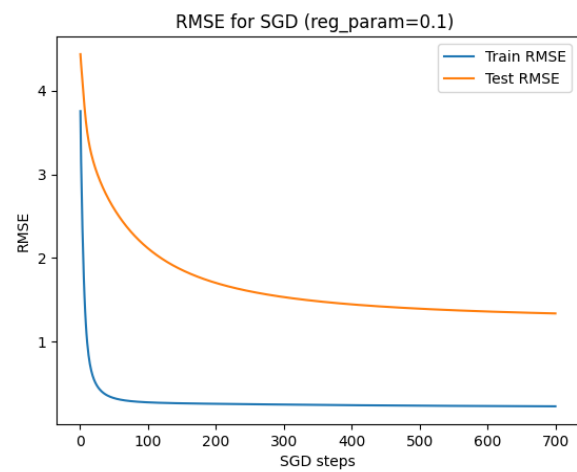
Optimization algorithm for learning latent factors in system

Objective Function: Difference between Predicted **ratings** and **actual ratings**

Goal: Minimize **objective function**

Iterative updates to parameters based on gradients

Result: Learned user and item latent factors



SGD

ALTERNATING LEAST SQUARE (ALS)



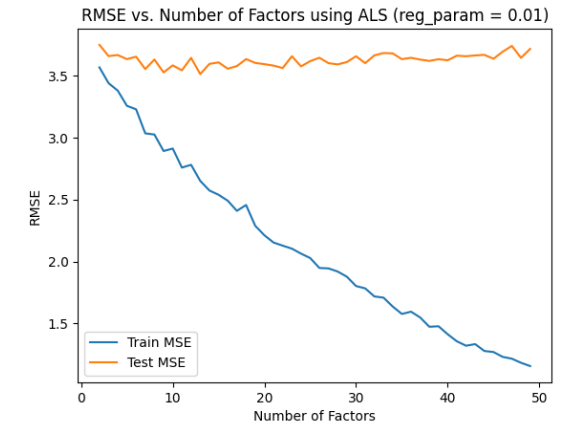
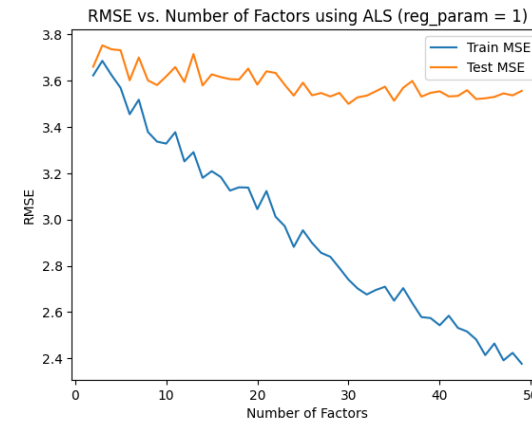
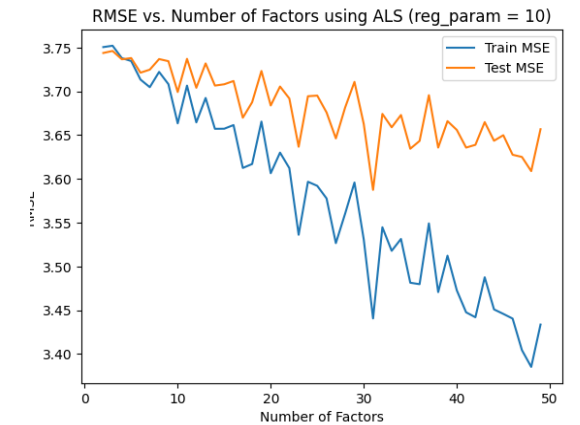
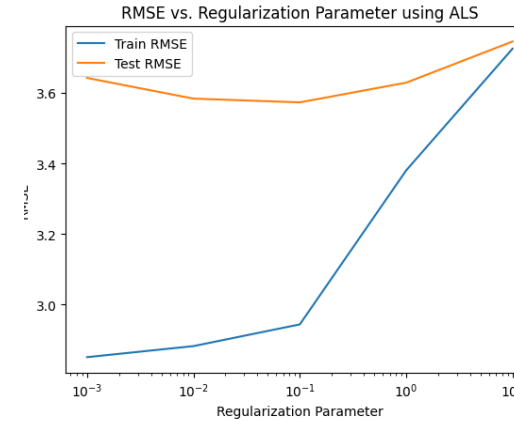
Method for performing matrix factorization by iteratively solving for the user and item factors



Learns k -dimensional feature vectors for each user and item, where k is the number of latent features



The function that predicts the value of a data instance given the feature vectors is a simple function of the dot product between the corresponding feature vectors



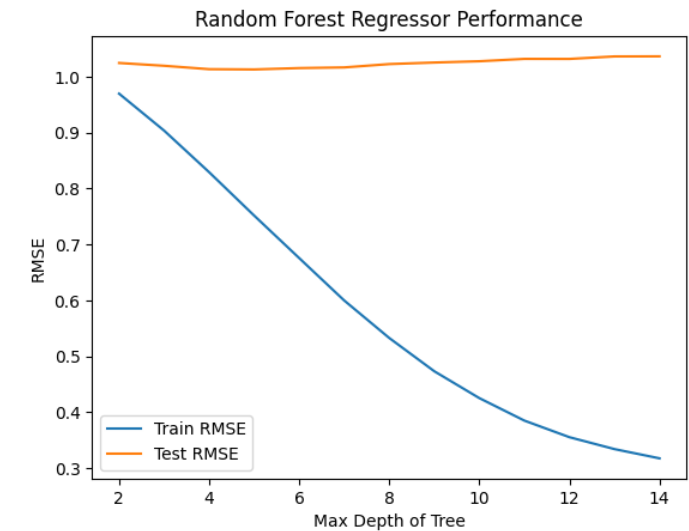
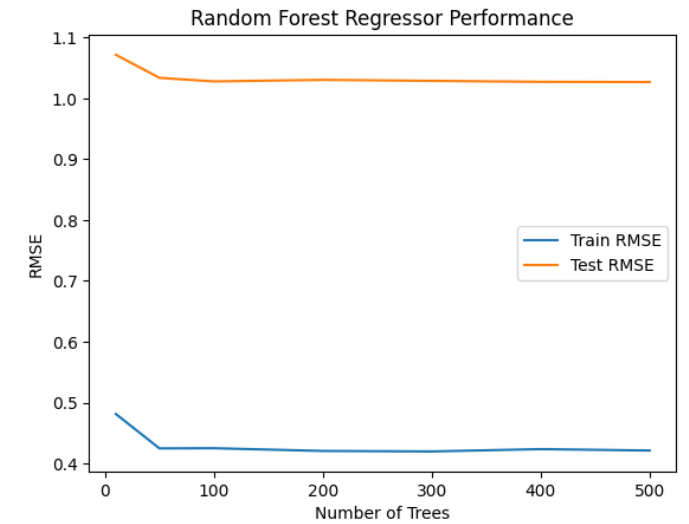
RANDOM FOREST

Latent feature vectors for users and items are learned using SGD for predicting item ratings

The learned feature vectors are concatenated for a specific user-item pair and used as an input variable

The target variable is the rating given by the user to the item, and the problem is transformed to a regression problem

The model predicts the rating a user would give to an item based on their past behavior and the behavior of other similar users



RESULTS

Type	Model	Train RMSE	Test RMSE
Latent Factor Model Based Methods	SVD (Singular Value Decomposition)	81.6	19.4
Latent Factor Model Based Methods	ALS (Alternating Least Square)	2.3	3.6
Latent Factor Model Based Methods	SGD (Stochastic Gradient Descent)	1.2	1.5
Latent Factor Model Based Methods	Random Forest Regressor	0.32	1.1
Neighborhood Method	Cosine Similarity	2.5	3.41
Neighborhood Method	Pearson Similarity	2.5	3.45

	user_id	name	stars	review_stars
6407	-BZn63YaADy9GpzHdncDtA	Reytas Filipino Cuisine	4.5	4
27232	-BZn63YaADy9GpzHdncDtA	Trappixx Jamaican Restaurant	3.0	4
50169	-BZn63YaADy9GpzHdncDtA	Jjang Ga Nae	4.0	5
82538	-BZn63YaADy9GpzHdncDtA	Thaimax	2.5	4
262353	-BZn63YaADy9GpzHdncDtA	Dolsot House	4.0	5
329974	-BZn63YaADy9GpzHdncDtA	Outback Steakhouse	2.5	3
350506	-BZn63YaADy9GpzHdncDtA	Phil's Deli And Market	4.0	3
380630	-BZn63YaADy9GpzHdncDtA	Pho Viet	4.5	2
411276	-BZn63YaADy9GpzHdncDtA	Hên Vietnamese Eatery	4.5	4
449253	-BZn63YaADy9GpzHdncDtA	Naked Lunch	4.5	4
497494	-BZn63YaADy9GpzHdncDtA	Kyuramen	4.5	4

User's Rated Places

```
array(["People's Pizza", 'Pho Eden', 'Eden Korean Restaurant',  
      'Hanoi Cuisine', 'Zushi Dozo'], dtype=object)
```

Recommended Places

RESULTS - RECOMMENDATIONS



CONCLUSION AND FUTURE SCOPE

Ensemble Techniques

Content-based Recommendation

Addressing Cold Start problem

More Scalable System



REFERENCES

- Yelp, I. (2022, March 17). *Yelp dataset*. Kaggle. Retrieved April 6, 2023, from <https://www.kaggle.com/datasets/yelp-dataset/yelp-dataset>
- Recommendation systems: Principles, methods and evaluation. Egyptian Informatics Journal. Retrieved April 6, 2023, from <https://www.sciencedirect.com/science/article/pii/S1110866515000341>
- (PDF) *collaborative filtering recommender systems - researchgate*. (n.d.). Retrieved April 25, 2023, from https://www.researchgate.net/publication/200121027_Collaborative_Filtering_Recommender_Systems