

# ***Board Games Recommender***

Phua Jia Qing,  
GA DSI 30

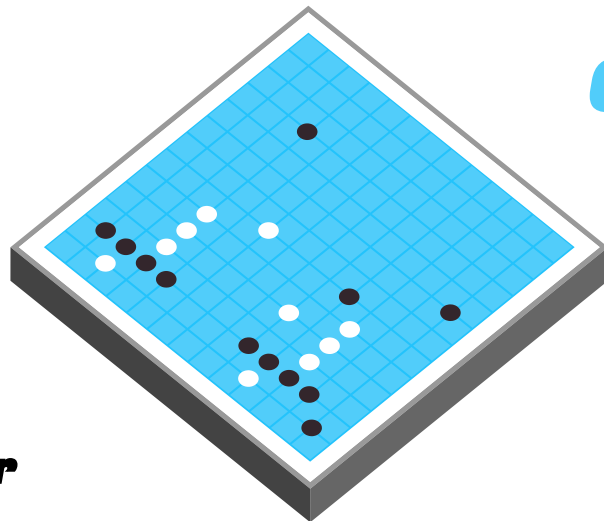


# ***TABLE OF CONTENTS***

**01** ***Problem  
Statement***

**02** ***Dataset & EDA***

**03** ***Recommender  
System***



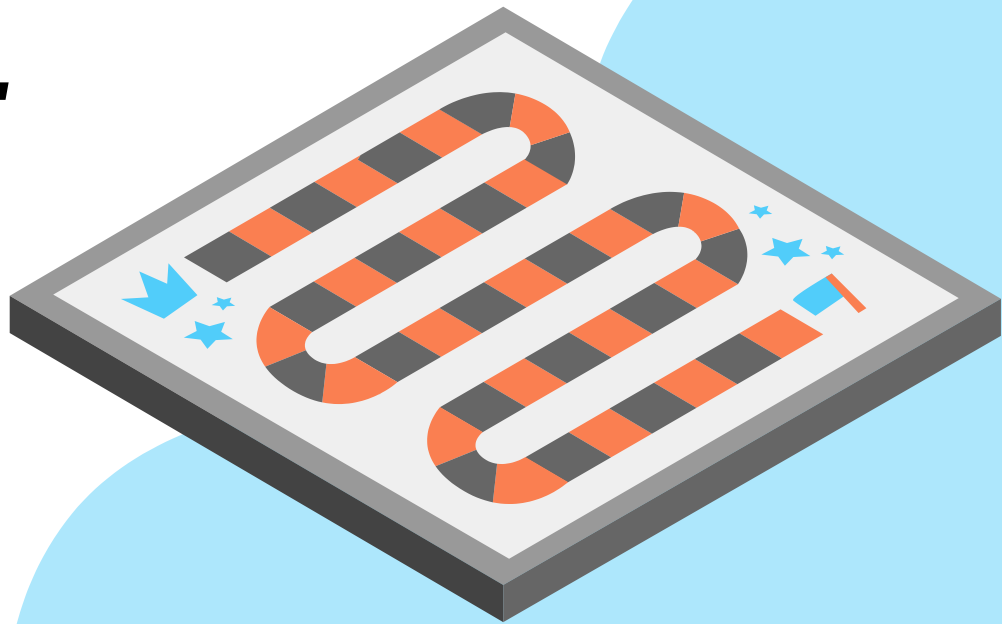
**04** ***Model Evaluation***

**05** ***Conclusion &  
Future Works***

**01**

# ***PROBLEM STATEMENT***

Background on Board  
Games



# HISTORY OF BOARD GAMES



**3000 BC**

Senet was a very popular game in ancient Egypt



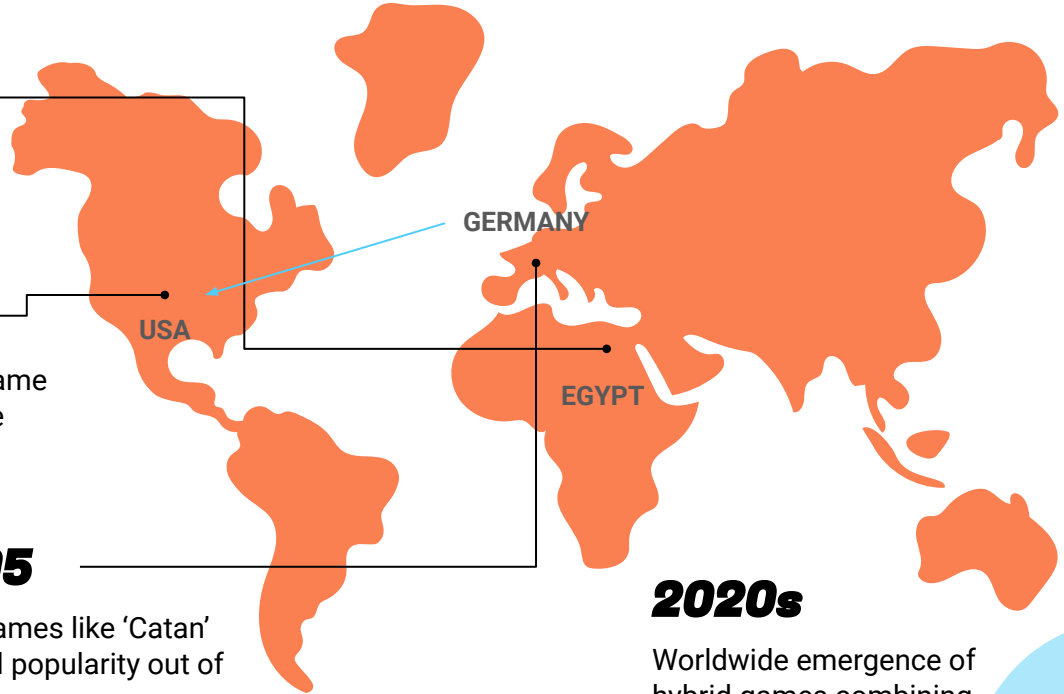
**1900**

First version of the game 'The Landlord's Game'



**1995**

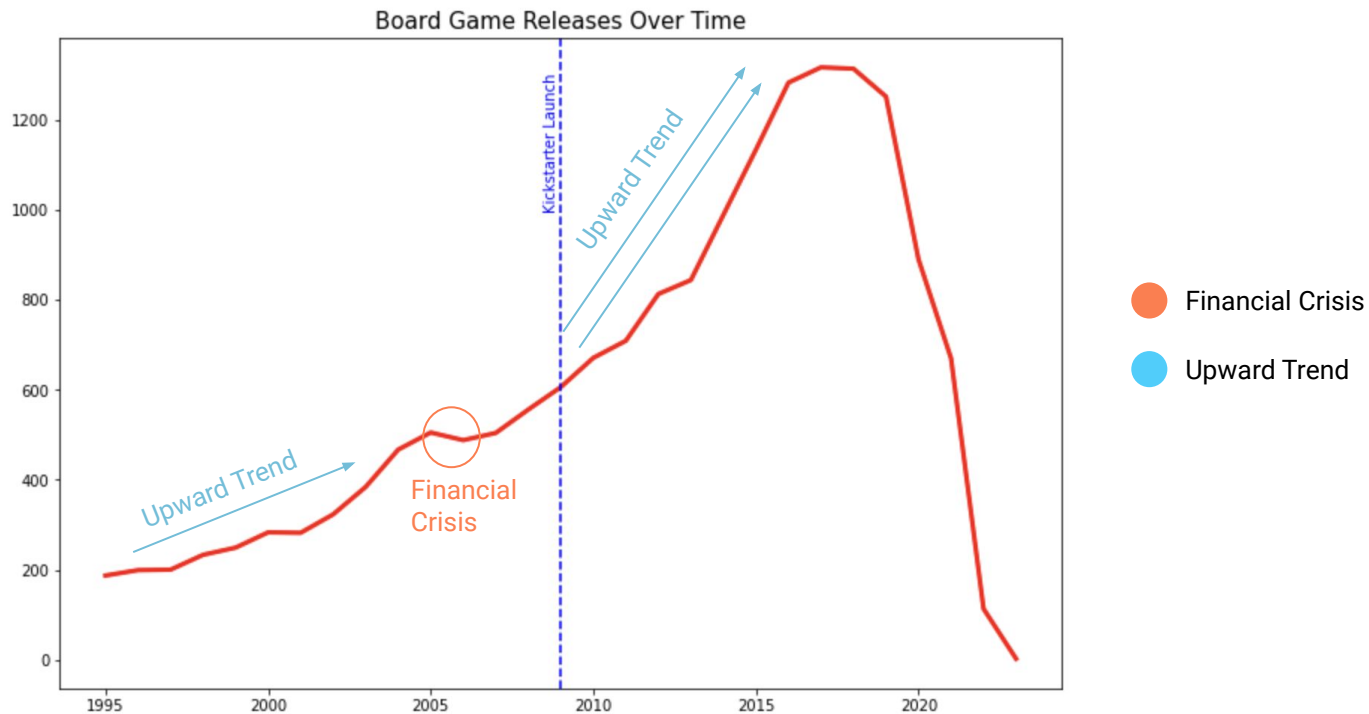
Eurogames like 'Catan' gained popularity out of Europe.



**2020s**

Worldwide emergence of hybrid games combining multiple genres.

# BOARD GAME RELEASES





# ***EGYPT***

Board game originated from

## ***5,000 YEARS***

Existed for

## ***30 BILLIONS***

Forecast market value in 2028



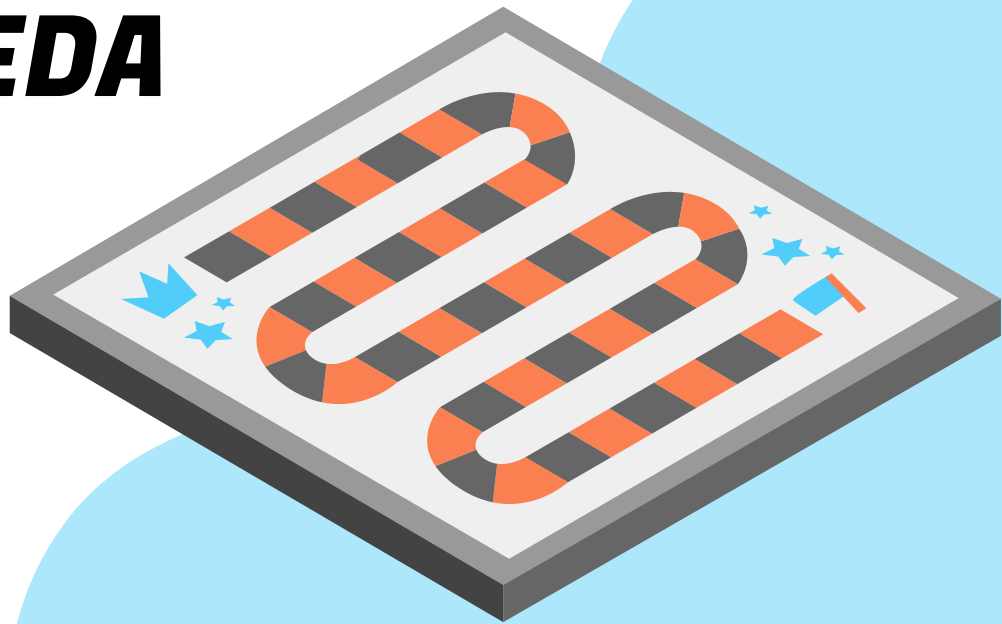
## ***Problem Statement:***

Build a good recommender  
system for board games

**02**

# ***DATASET & EDA***

Cleaning the data





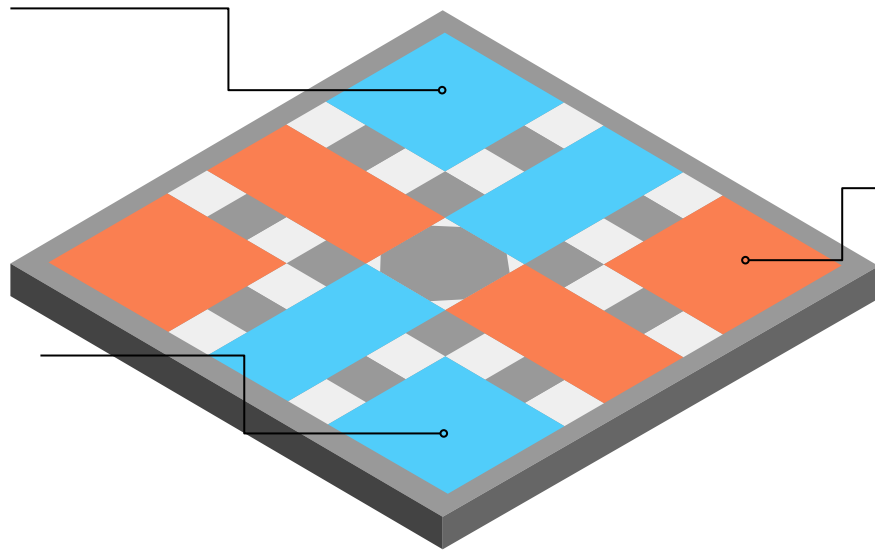
# ***BOARDGAMEGEEK***

## ***BOARD GAME COMMUNITY***

Online community with  
more than 2 million users

## ***BOARD GAME INFORMATION***

Updated on a real-time  
basis



## ***BOARD GAME RATING***

Users leave rating and  
reviews

# ***CLEANING DATASETS***

***01: 'Games'***



***02: 'Games\_info'***

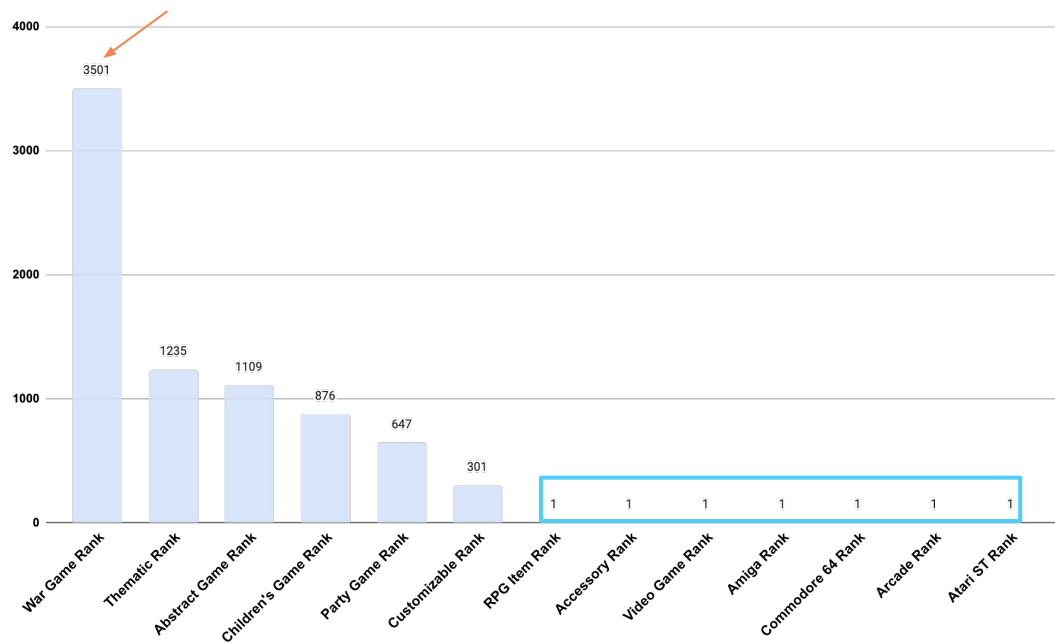


***03: 'Reviews'***



- Drop duplicates and some empty values.
- Feature engineering and scale down dataset
- Merge 'Games' & 'Games\_info'

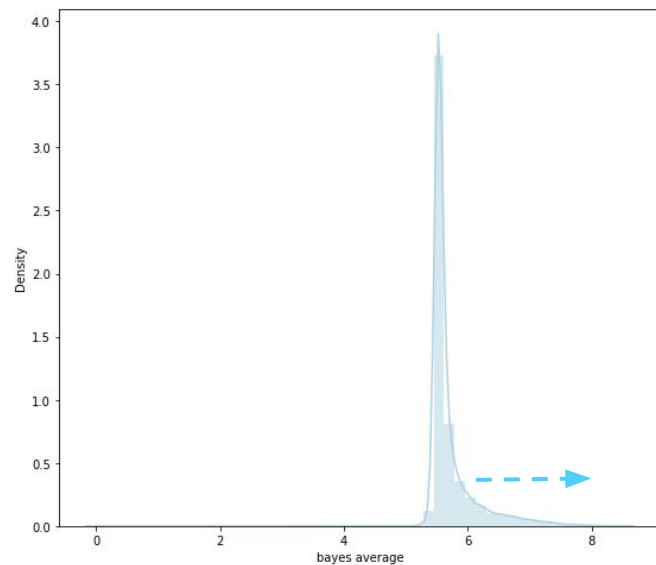
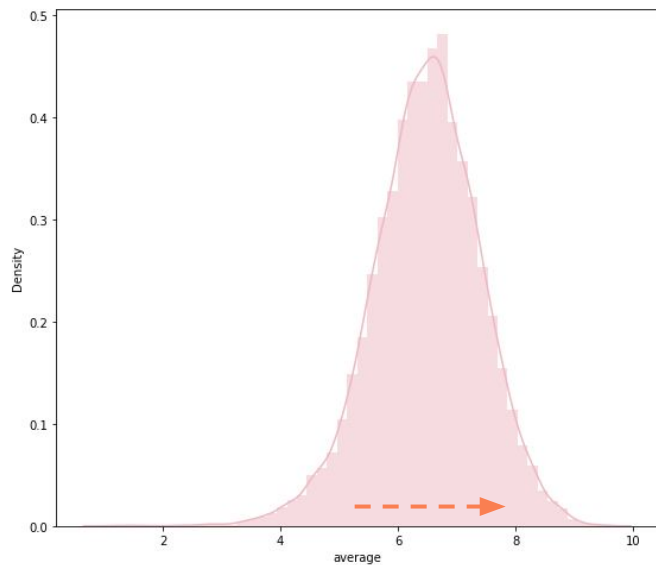
# TOP CATEGORY



- Best Category
- Least Category

# AVERAGE & BAYES AVERAGE

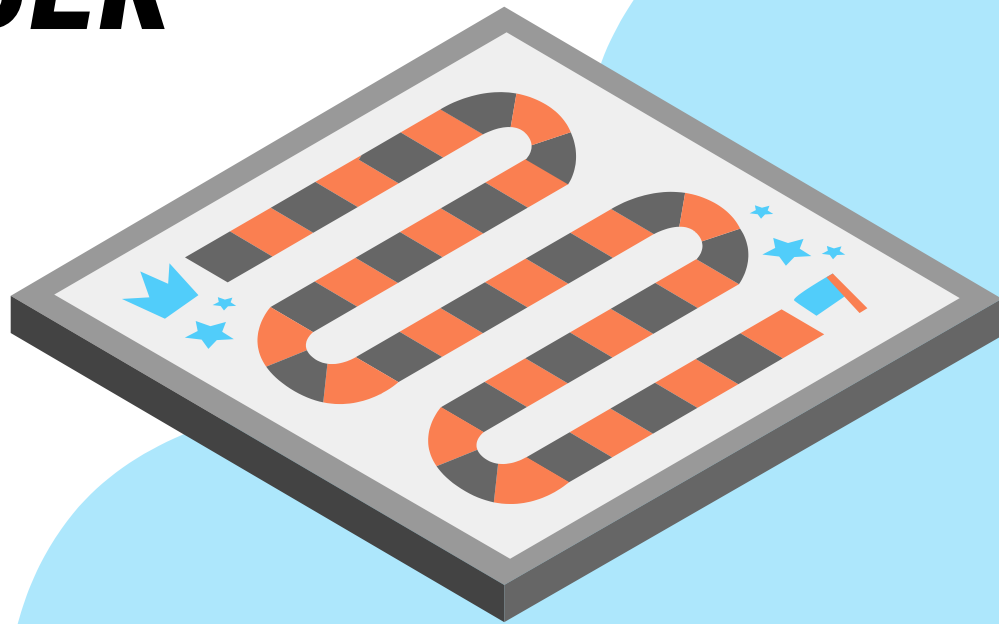
Distributions of Ratings



**03**

# ***RECOMMENDER SYSTEM***

Collaborative Filtering  
Recommender System



# ***BENEFITS OF RECOMMENDER SYSTEM***



## ***Personalisation***

User's preference



## ***Customer Satisfaction***

Efficient time spent



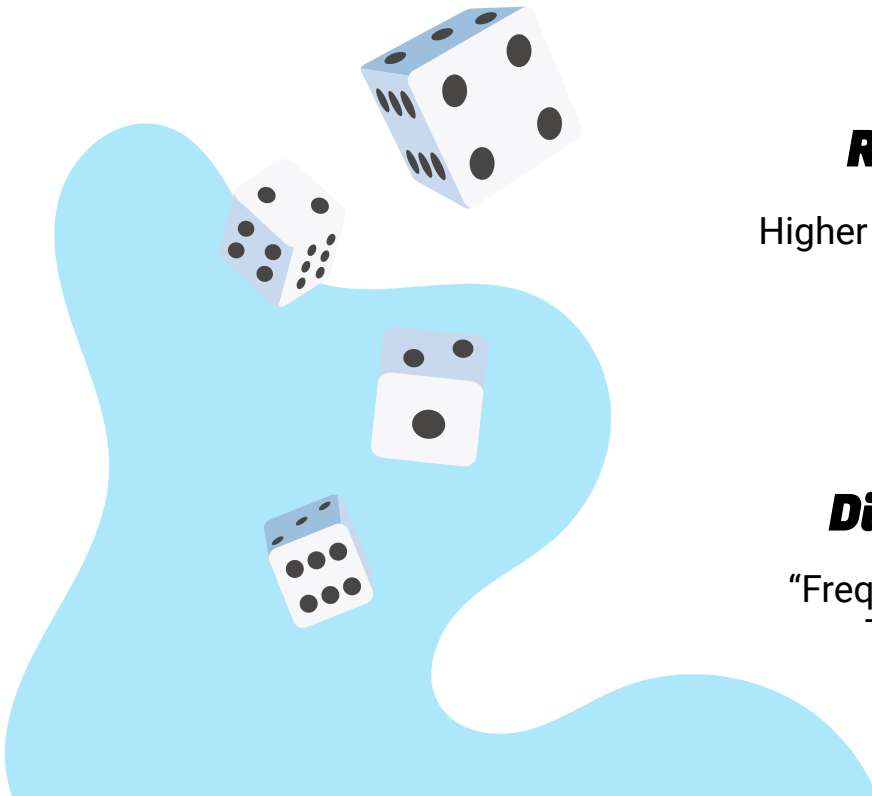
## ***Revenue***

Higher conversion rate



## ***Discovery***

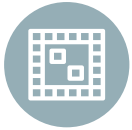
"Frequently Bought Together"



# ***Types of Recommender System***



***Popularity-Based***



***Collaborative Filtering***



***Content-Based Filtering***



# POPULARITY RECOMMENDER

The list of recommendations for the user: 10

	user	name	score	new_rank
13	10	Citadels	313	1.0
0	10	7 Wonders	311	2.0
34	10	Pandemic	310	3.0
31	10	Love Letter	309	4.0
47	10	The Castles of Burgundy	307	5.0

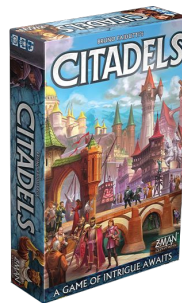
The list of recommendations for the user: 100

	user	name	score	new_rank
13	100	Citadels	313	1.0
0	100	7 Wonders	311	2.0
34	100	Pandemic	310	3.0
31	100	Love Letter	309	4.0
47	100	The Castles of Burgundy	307	5.0

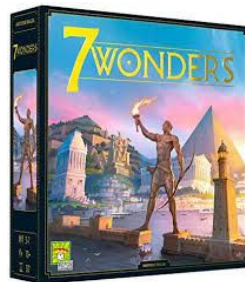
The list of recommendations for the user: 150

	user	name	score	new_rank
13	150	Citadels	313	1.0
0	150	7 Wonders	311	2.0
34	150	Pandemic	310	3.0
31	150	Love Letter	309	4.0
47	150	The Castles of Burgundy	307	5.0

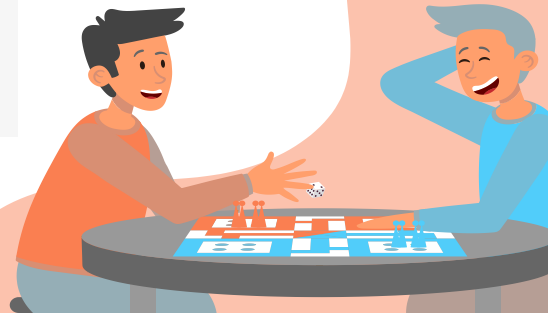
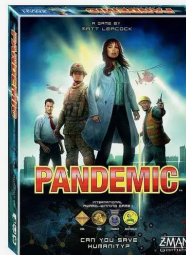
## 01: Citadels



## 02: 7 Wonders



## 03: Pandemic





# ***COLLABORATIVE FILTERING***

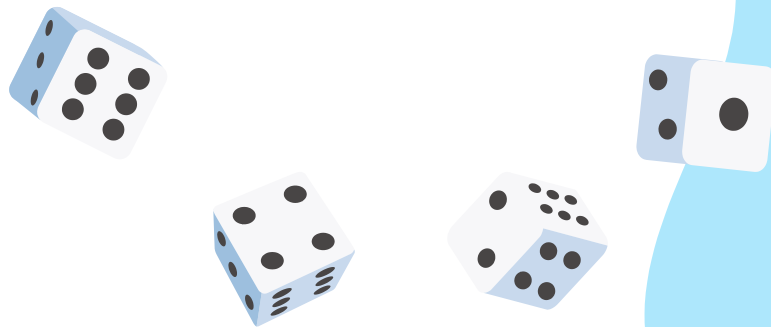
## ***USER-BASED***

***Similar Users***

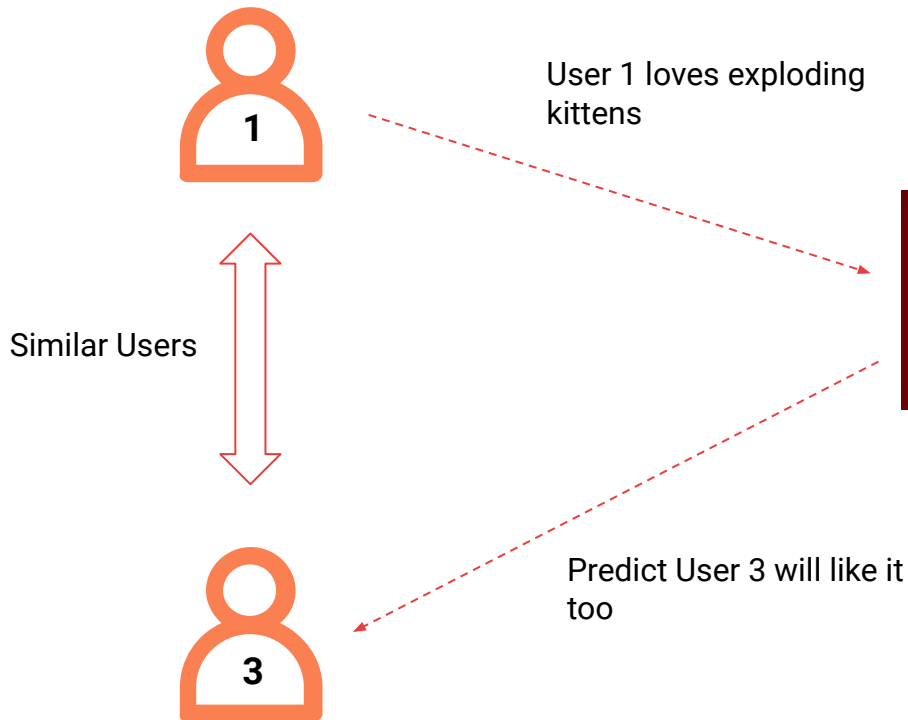


## ***ITEM-BASED***

***Similar Board Games***



# USER-BASED CF



**Target User: User 3**

# ***CONS OF USER-BASED CF***

## ***NEW USER***



Difficult to find  
similar user

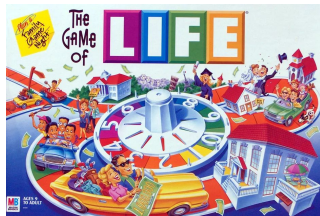
## ***LIMITED CHOICES***

Small pool of games  
left unplayed

# ITEM-BASED CF



Similar Games



10



10



8-10



Predict similar games to monopoly

Target Item:  
Monopoly



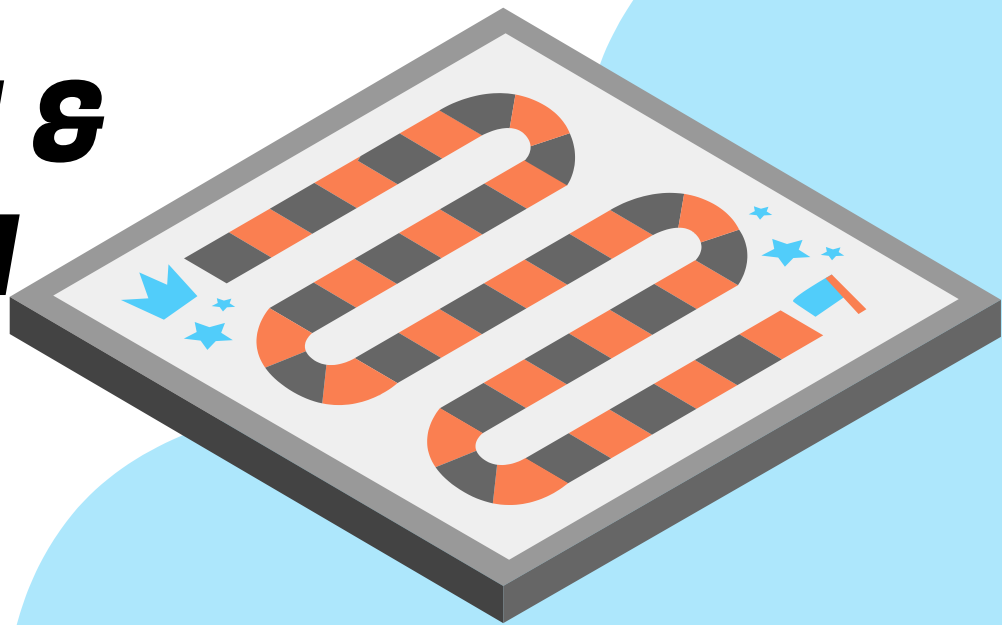
## ***SUMMARY***

A recommender system would be helpful in attending to every user's personal needs and attracting new users

04

# ***MODEL EVALUATION & CONCLUSION***

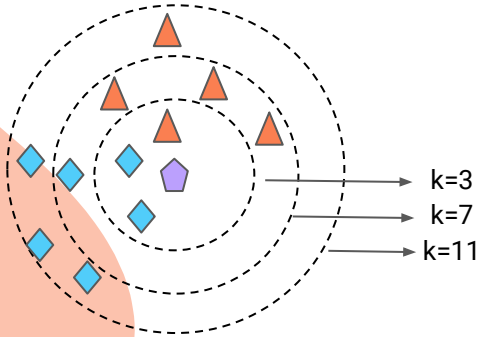
Best performing model



# MODELS

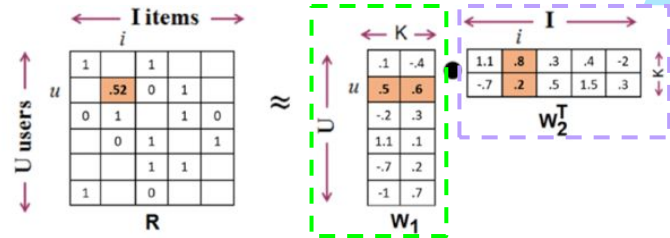
## KNN

Make predictions using the average rating of top-k nearest neighbours



## Matrix Factorization

Decomposing user-item interaction matrix into the product of 2 lower dimensionality rectangular matrices



# ***MODEL FLOW***



## ***Models***

9 base models



## ***GridSearchCV***

ALS vs SGD



## ***Best Model***

With best  
parameters and  
best scores



# BASE MODELS

	<i>train_rmse</i>	<i>test_rmse</i>
<i>base_knn_baseline</i>	0.1200	0.1500
<i>base_knn_zscore</i>	0.1171	0.1505
<i>base_baseline_only</i>	0.1475	0.1517
<i>base_svdpp</i>	0.1425	0.1518
<i>base_slop</i>	0.1484	0.1542
<i>base_knn_basic</i>	0.1262	0.1562
<i>base_nmf</i>	0.1563	0.1620
<i>base_svd</i>	0.137	0.1622
<i>base_cluster</i>	0.6338	0.6425

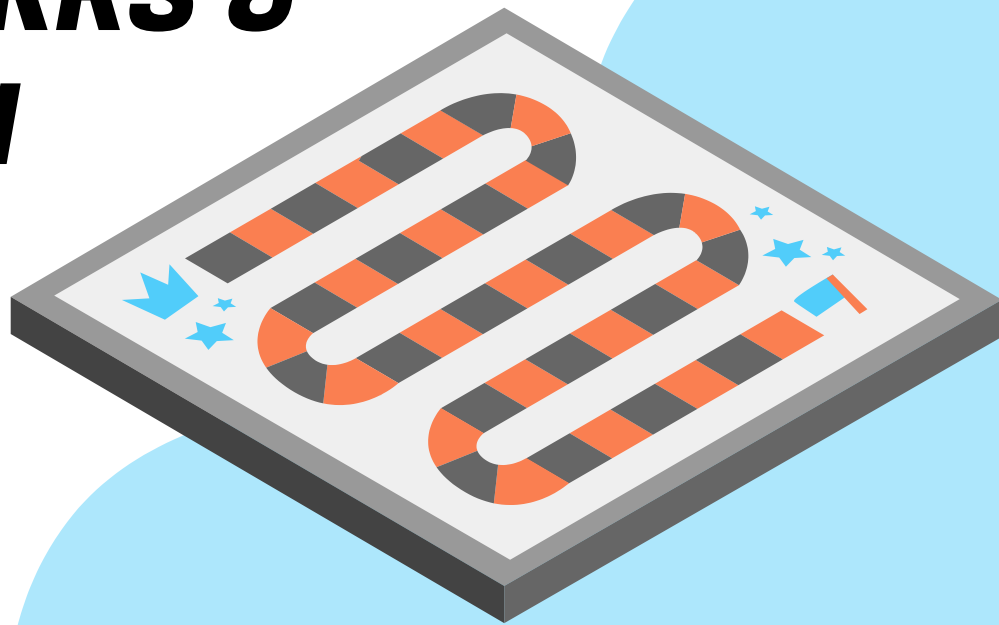
## ***BEST MODEL***

	<i>train_rmse</i>	<i>test_rmse</i>
<i>base_knn_baseline</i>	0.1200	0.1500
<i>knn_als_1</i>	0.1195	0.1497
<i>knn_sgd_1</i>	0.1149	0.1554

**05**

# ***FUTURE WORKS & CONCLUSION***

Hybrid Recommender  
System

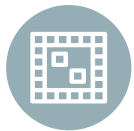


# ***FUTURE WORKS***



## ***Evaluation Metric***

Try using other metric like  $\text{precision@K}$ ,  $\text{recall@K}$



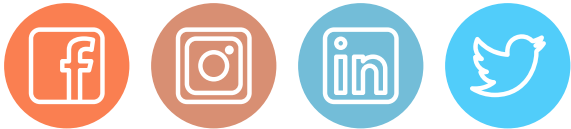
## ***Hybrid***

Combine collaborative filtering and content-based filtering



# ***THANKS!***

Do you have any questions?



This presentation template was created by **Slidesgo**, including icons by **Flaticon**, and infographics & images by **Freepik**.

