# Recommender System Video Games

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#### **The Business Problem**

Companies have large catalogues of products.

Impossible for customers to try every single product.

Helps users discover products that they may not have otherwise found.

Leads to more conversions and increased revenue.

## **Data Overview**

Amazon Customer Reviews Dataset

0	Ratings: 1,/00,000+	
0	Unique users: 1,000,000+	User 1
0	Unique games: 56,000+	
0	Sparsity: <b>0.003</b> %	
		•
		•

User u

Game 1		*****			Game <i>i</i>
×		X		X	
	X	X			
			Х		X
				X	
×	Х		X		X
		X	X		
×	Х	X		X	X
	Х		X		
		X			

## **Subsetting the Data**

- The casual gamer
  - Has reviewed more than 5 games
  - Has not reviewed more than 300 games (Youtubers / professional reviewers)
- Games liked by the casual gamer
  - Has received more than 400 reviews
- Time frame
  - Ratings from 2010 2015
  - o Train: 2010 2013
  - o Test: 2014 2015

### **Data Subset**

#### • Subset:

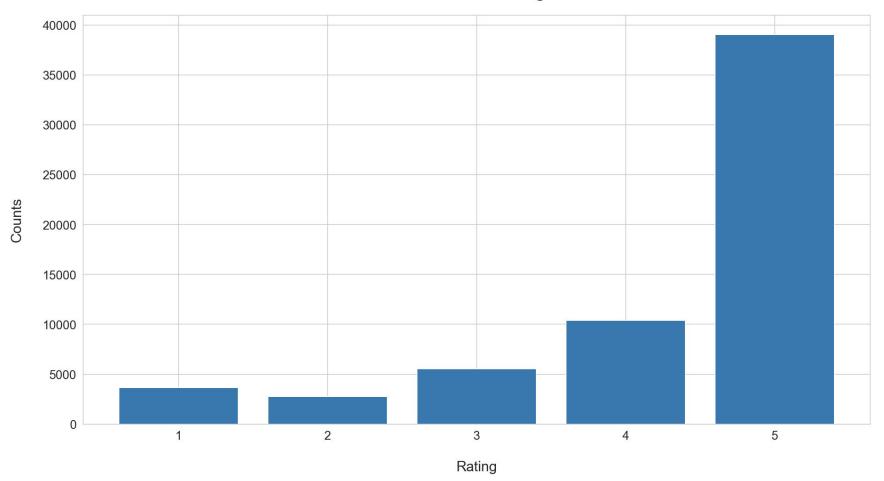
o Ratings: 33,000+

O Unique users: 13,000+

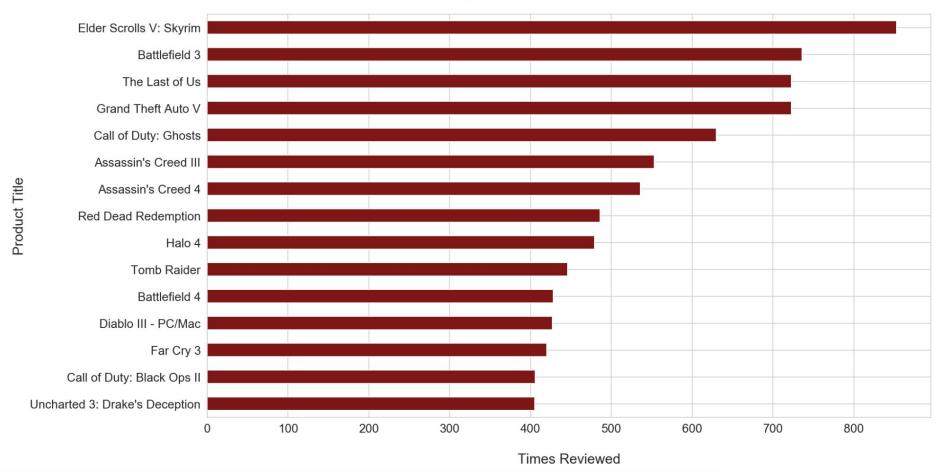
Unique games: 200+

Sparsity: 1.126%

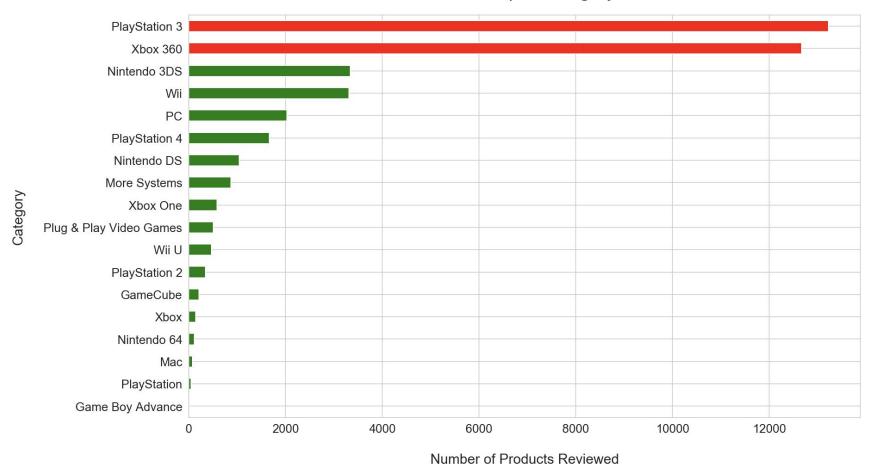
#### Number of Ratings



Top 20 Most Reviewed Games



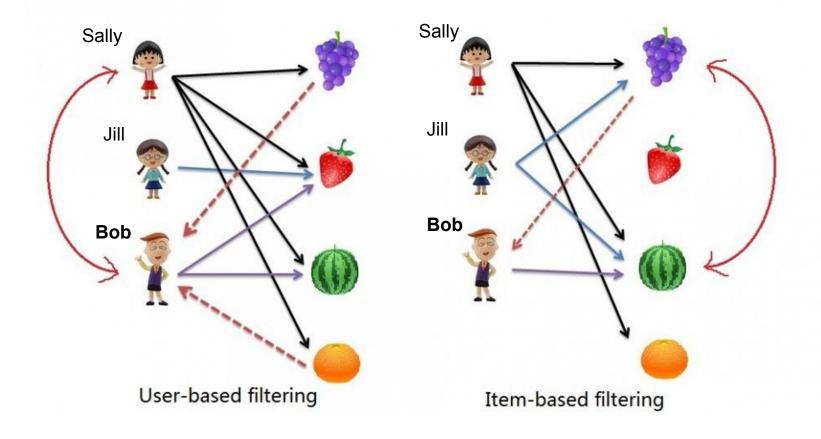
#### Reviews per Category



## **Approach**

- Modelling
  - User-based collaborative filtering
  - Item-based collaborative filtering
  - Latent factor models (Matrix Factorization)
- Evaluation
  - Choose 3 best models based on:
    - Root Mean Squared Error
    - Mean Precision
    - Mean Average Precision

## **Collaborative Filtering**



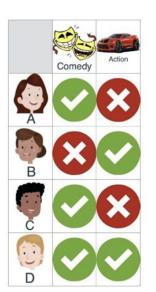
### **Matrix Factorization**

Characterizes items

 and users by vectors

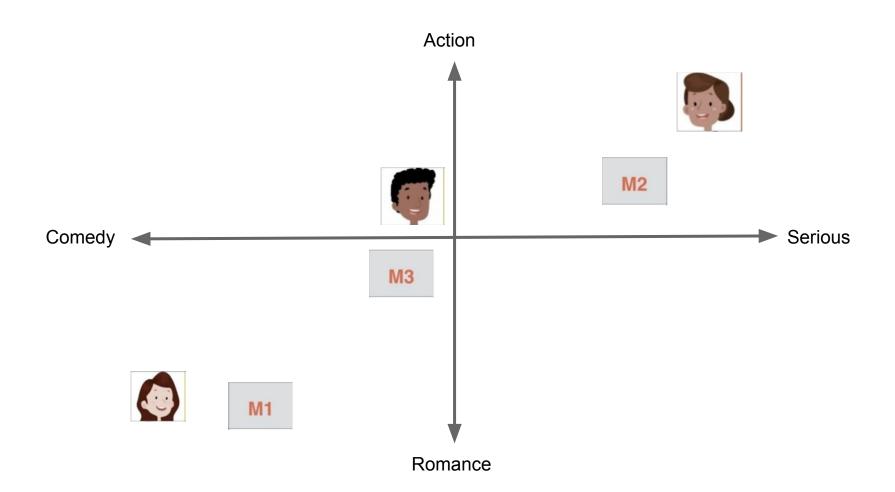
 of latent factors

 Latent factors inferred from item rating patterns



	M1	M2	МЗ	M4	M5
Comedy	3	1	1	3	1
Action	1	2	4	1	3

	M1	M2	МЗ	M4	M5
4	3	1	1	3	1
	1	2	4	1	3
	3	1	1	3	1
(1)	4	3	5	4	4



## **Success Criteria / Metrics**

- Root Mean Squared Error (RMSE)
  - Measure of how close predicted ratings are to actual ratings.
  - o Problem:
    - Predicts 5 stars for many games
    - Poor at choosing which of those to recommend

## **Success Criteria / Metrics**

Mean Precision

$$Precision = \frac{\text{# of our recommendations that are relevant}}{\text{# of items we recommended}}$$

- 'Relevant' = Rated 4 or above
- Mean Average Precision (MAP)
  - Average Precision (AP) Average of Precision scores up to a given cutoff.

AP@N = 
$$\frac{1}{m} \sum_{k=1}^{N} (P(k) \text{ if } k^{th} \text{ item was relevant}) = \frac{1}{m} \sum_{k=1}^{N} P(k) \cdot rel(k)$$

MAP@N = 
$$\frac{1}{|U|} \sum_{u=1}^{U} (AP@N)_u = \frac{1}{|U|} \sum_{u=1}^{U} \frac{1}{m} \sum_{k=1}^{N} P_u(k) \cdot rel_u(k)$$

## **Mean Average Precision Intuition**

Rank	Recommendation	Result	Precision
1	Call of Duty	True Positive	1
2	Grand Theft Auto	False Positive	1/2
3	Assassin's Creed	False Positive	1/3

$$AP = \frac{1 + 1/2 + 1/3}{3} = 0.61$$

Rank	Recommendation	Result	Precision
1	Assassin's Creed	False Positive	0
2	Grand Theft Auto	False Positive	0
3	Call of Duty	True Positive	1/3

$$AP = \frac{0 + 0 + 1/3}{3} = 0.11$$

## **Quantitative Findings**

	Root Mean Squared Error	Mean Precision	Mean Average Precision
Matrix Factorization Model	1.09	0.85%	8.22%
User Based Model	1.33	1.50%	16.03%
Item Based Model	1.21	1.47%	16.31%



#### Shooters Adventure Open World



















#### **Bought before 2014**







ASSASSIN'S

BATTLEFTELD 3

Shooter

#### **Matrix Factorization**



Adventure



**User-based** 



Adventure



Shooter

#### Item-based



**Open World** 



Shooter

#### **Bought after 2014**



Milds course day.

**Adventure** 



Shooter



ASSASSIN'S

**Open World** 

## **Limitations**

- Ratings are explicit feedback
- Implicit feedback would be helpful to gauge interest
  - Browsing history
  - Search patterns
  - Mouse movements

#### **Conclusions**

#### Lessons

- The business case defines the success metric
- For marketplace recommenders, precision / ranking based metrics are preferred

#### Next

- Fix Mario problem
- Deployment
- Content based filtering
- Deep learning

## Thank You