Building a videogame recommendation system from scratch based on user and game data

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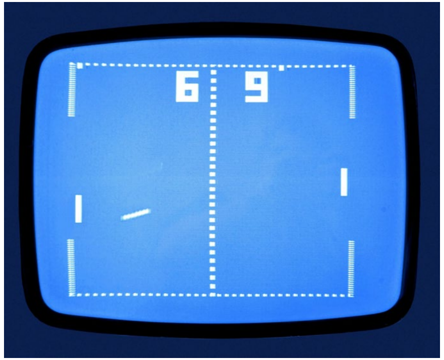
Introduction

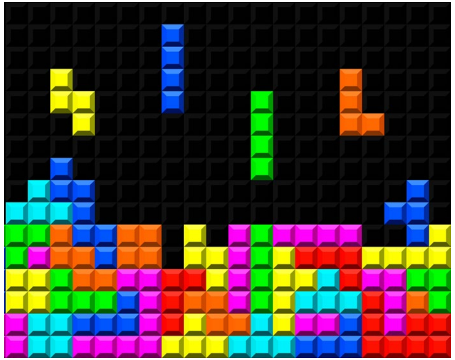
- What is a videogame / video game?
- What is a recommender system?
- The need for recommender systems in game distribution platforms.

Total slides: 52

What is a video game?

Examples of video games





What is a video game?

…but also examples of video games…

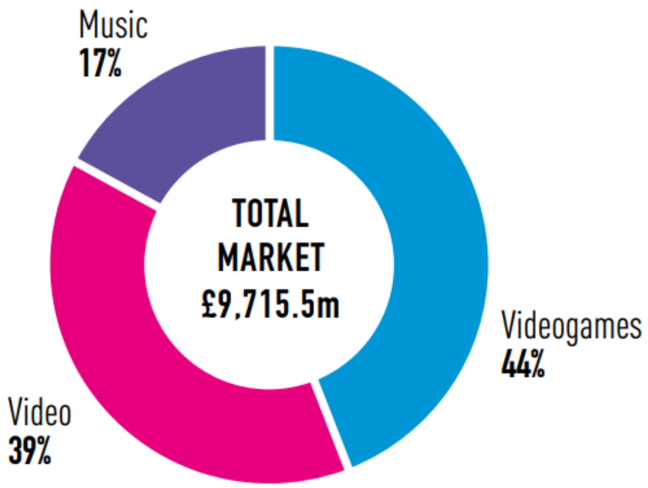
What is a video game?

…and more examples of videogames

The video game industry

Digital Entertainment and Retail association revenue data

ERA ENTERTAINMENT MONITOR: 2021 - (£M)



ERA ENTERTAINMENT MONITOR 2021 - VALUE SALES (£m)	2019	2020	2021	change 20/21
Videogames	3,756.1	4,434.9	4,285.9	-3.4%
Video	2,610.6	3,311.7	3,752.3	13.3%
Music	1,453.7	1,543.6	1,677.3	8.7%
Total value	**7,820.3**	**9,290.2**	**9,715.5**	**4.6%**

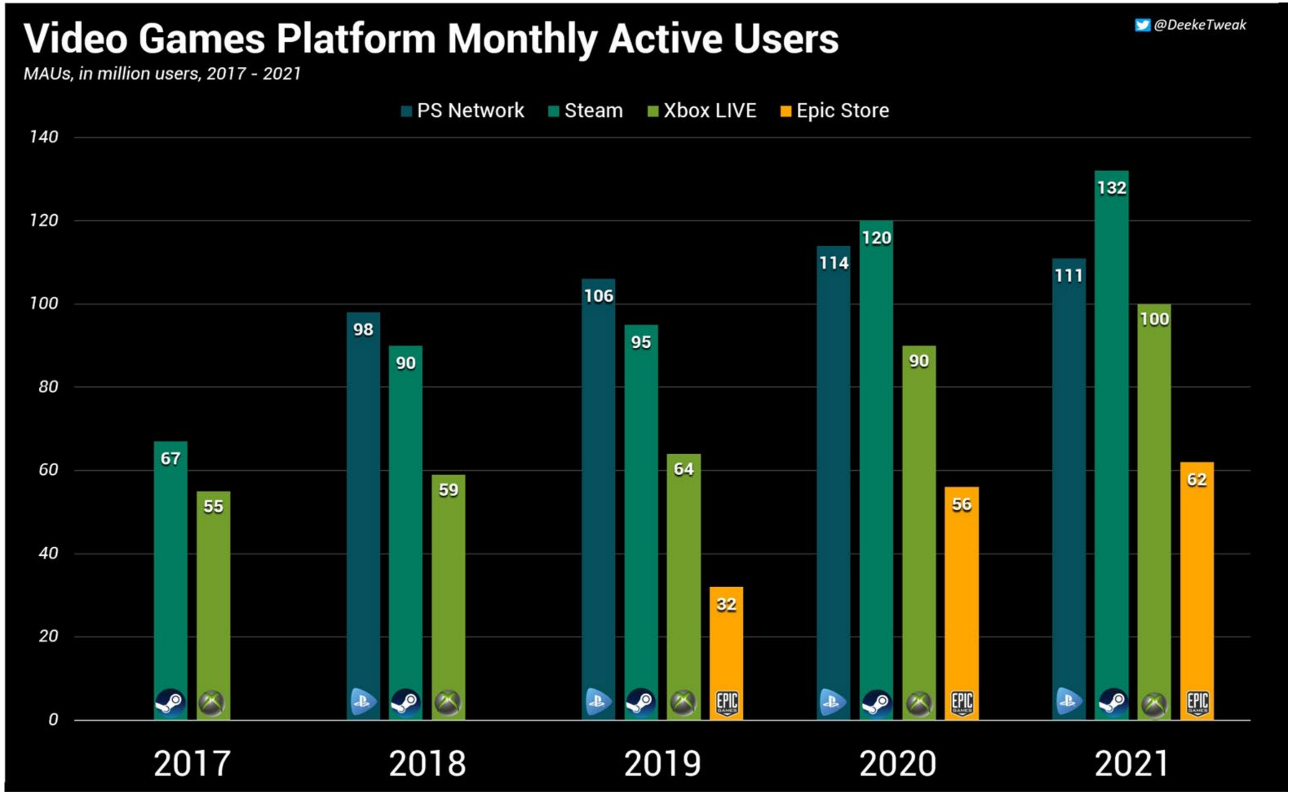
What is Steam, and why?

What is Steam, and why?

- ✓ Public API (Steamworks Web API)
- ☐ Currently the biggest user base
- ☐ Registers user playtime

The video game industry

Steam, PlayStation, Xbox and Epic Games



Steam kept growing after 2022

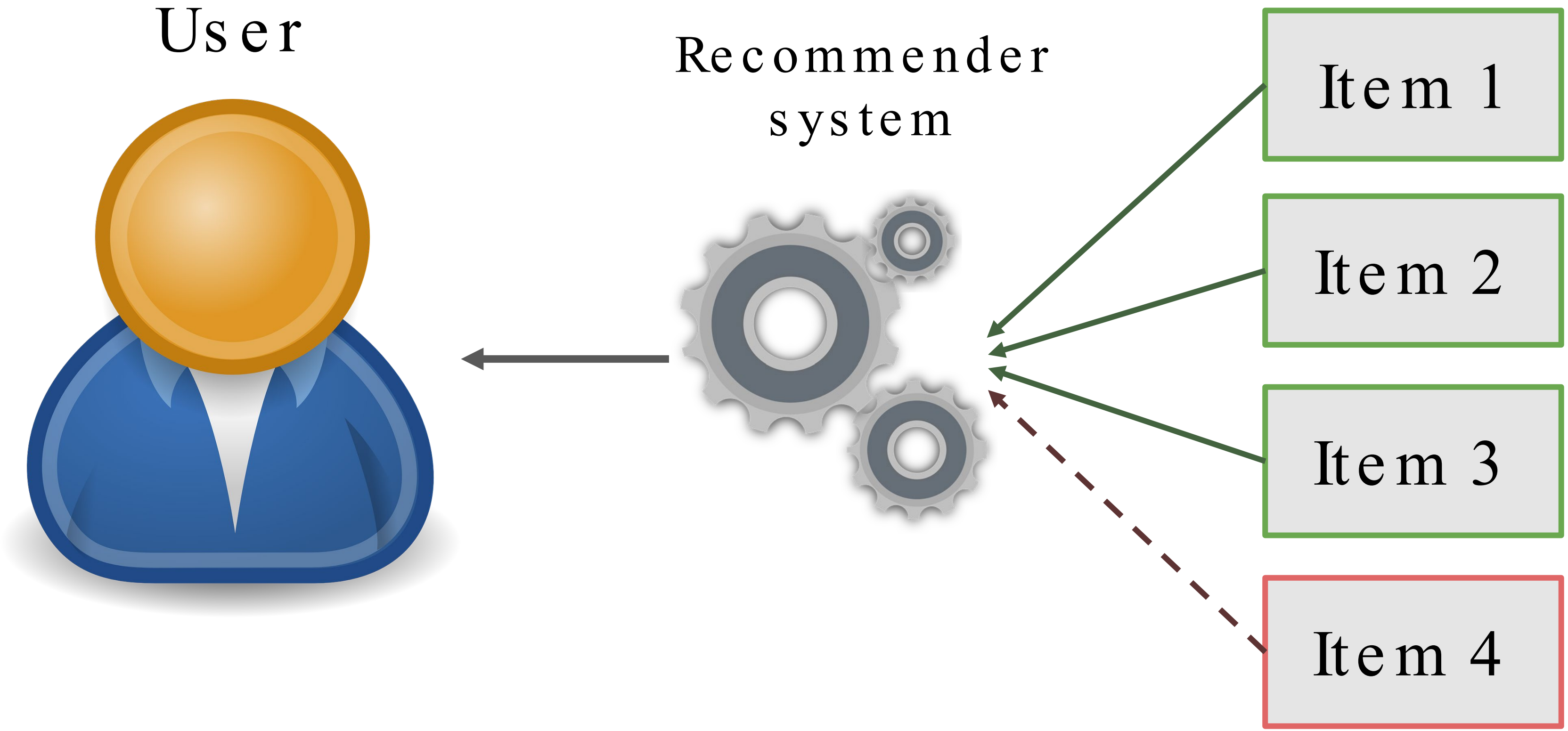
Nobody has enough time to check all of these games out!

MONTH	GAMES THIS MONTH
All 2022	10832
All 2021	10182
All 2020	9515
All 2018	8100
All 2019	7740
All 2017	6240

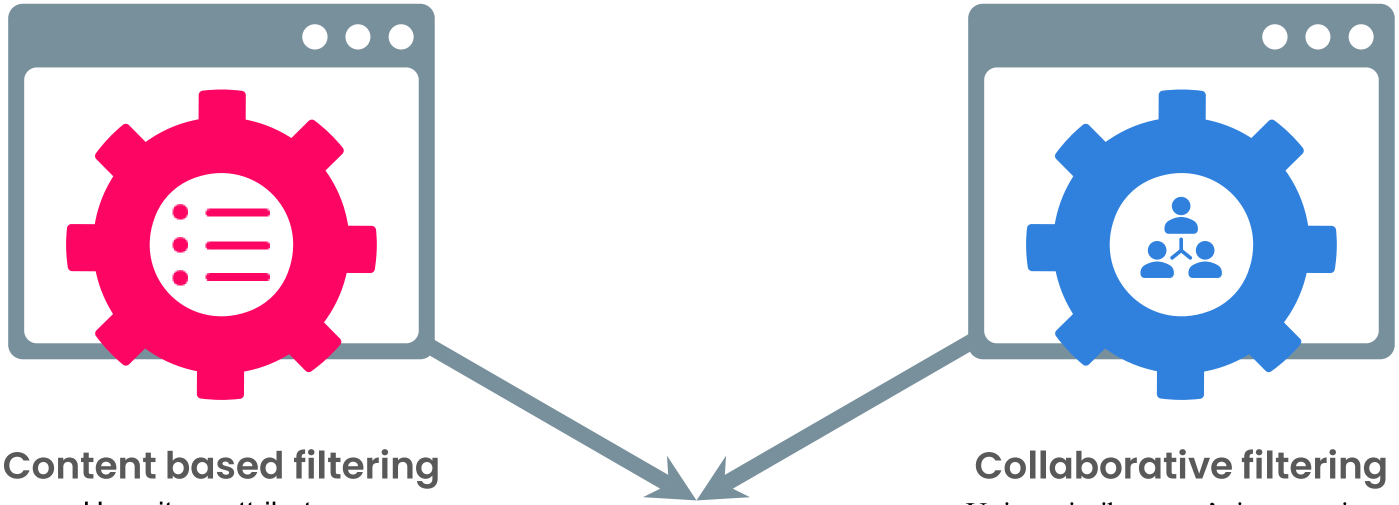
MONTH	GAMES THIS MONTH
All 2023	4862
All 2016	4344
All 2015	2526
All 2014	1373

Source: SteamSpy (29/5/2023)

What is a recommender system?



Main types of recommender systems

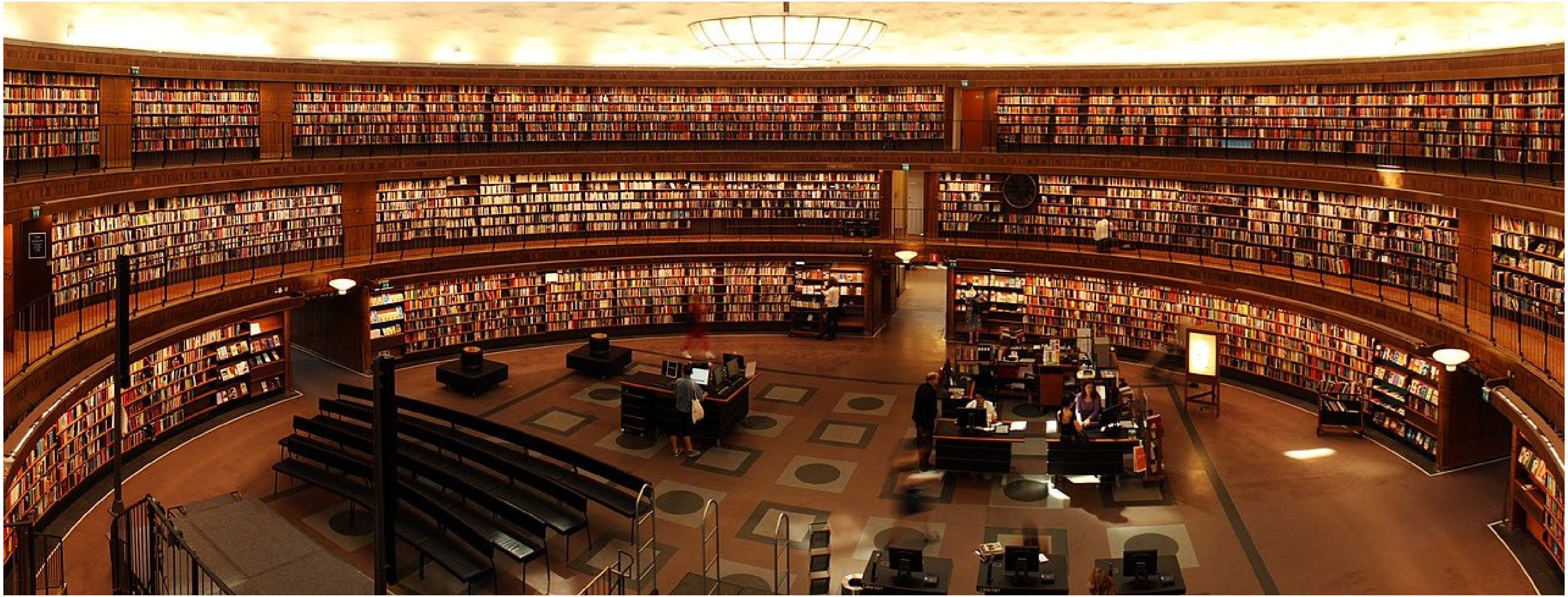


Content based filtering
Uses item attributes

Collaborative filtering
Using similar user's interactions

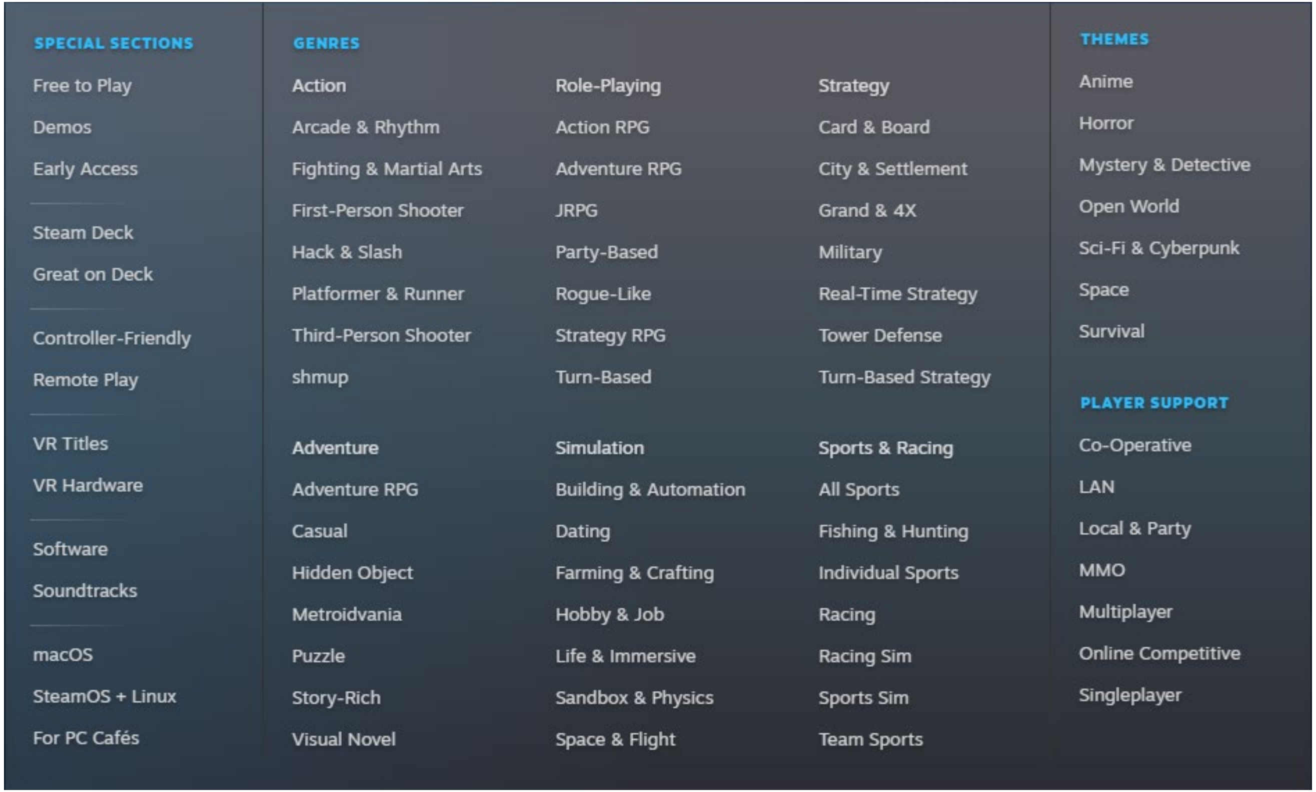
Hybrid
A mix of both approaches

Imagine entering a library…



…but none of these were ordered. But even if they are?

Tags only help you find a specific genre or theme



Like an ordered library

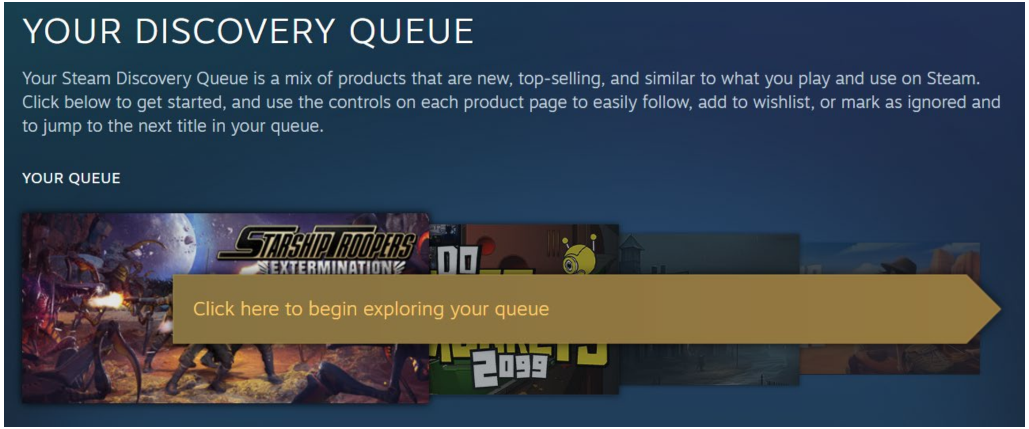
Good enough! **But we can do better.** Users need to:

- Manually check the genre/theme
- Unable to search for multiple tags from here
- Some are very vague (“Racing”, “Military”)

The need for recommender systems

- >68,000 games on Steam as of last month
- >800 new games per month
- Not enough time to check if you are interested in every game
- Steam has the Discovery Queue, but mostly shows popular games

Steam solved this issue, but…

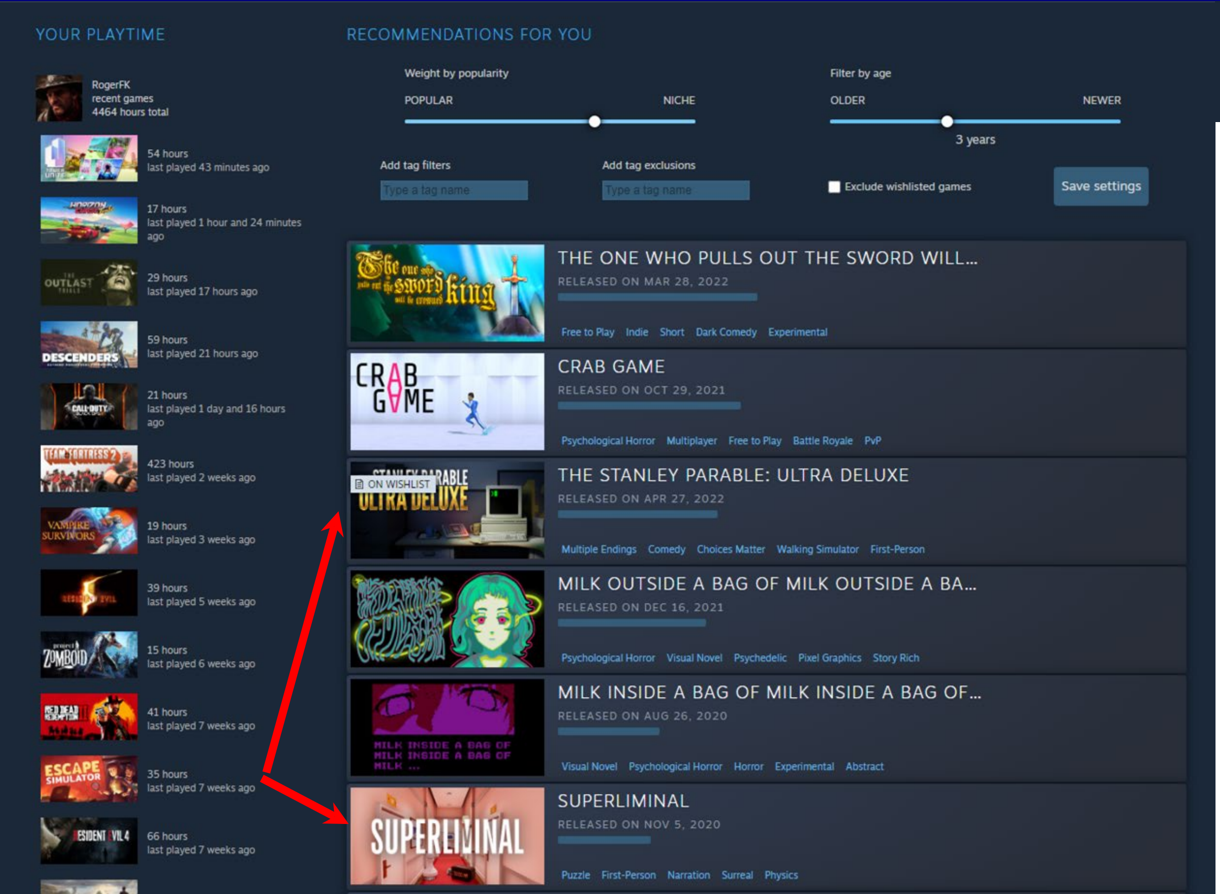


Your Discovery Queue

Your Steam Discovery Queue is a powerful, new way of exploring the most popular new releases that you haven't yet seen. You can quickly browse through games that are suggested for you, and you can choose to follow the game, add it to your Wishlist, purchase it, or indicate that you are not interested. Your Discovery Queue is automatically refreshed each day with new, top-selling releases.

Steam interactive recommender

PLAYERS LIKE YOU LOVE...



Our solution

A Videogame Recommender System

Concepts

User = player

Who we are trying to predict for.

Item = game

What we are trying to predict.

Playtime

The *'interest'* of a player in a game

Structure of the project

01

Sourcing our data

Steamworks API, crawl user libraries starting from reviews

02

Filtering and preprocessing

Get a subset of users, and define 'interest'

03

Recommender systems

Built from scratch, both collaborative filtering and content based

04

Experiments and results

Test against our subset of users (from 02)

steamreviews

SQL

pandas

datasketch

Sourcing our data

No way to get a list of Steam users directly.

Solutions:

1. Test random valid SteamIDs and see if they exist (not time efficient)
2. Scrape online users from their website (might get banned from Steam / too slow)
3. Crawl reviews from selected games from their API (the most compliant, efficient way)

Sourcing our data

01
Manually select games

Pick popular games to get a good amount of different gamers.

02
Crawl all available reviews of the games

Get the users who reviewed these games

03
Store user and game data

User data includes their SteamID and the number of games owned

04
Gather user libraries

We can filter out private users and those with private game lists, including playtimes

But why not crawl the reviews of these users instead of using playtimes?

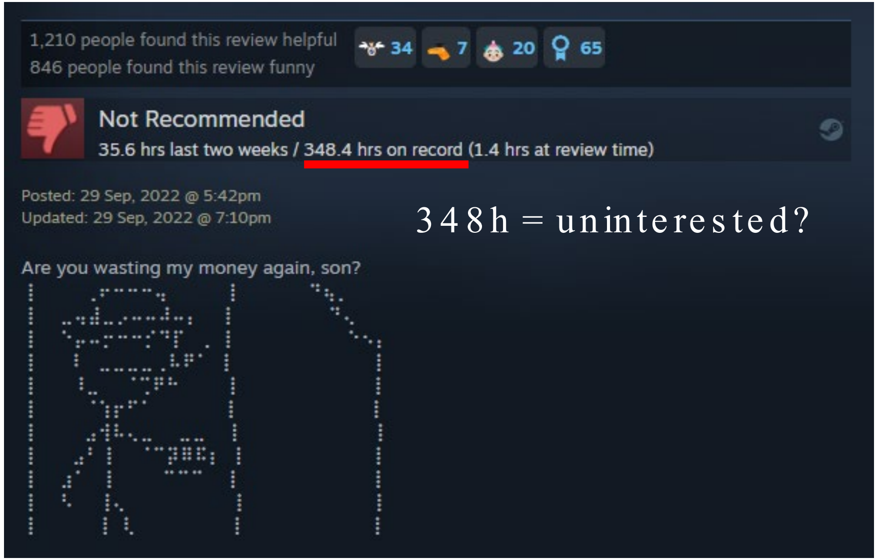
Why not crawl reviews of a user?

Unable to crawl all reviews of a particular user

but…

- Users do not leave reviews for all of their games
- “Troll” reviews

Examples of reviews in FIFA 23



348h = uninterested?

Why use playtimes

PROS

1. People have limited time: if they spend it in game A rather than game B, it hints they prefer it
2. We can get all playtimes, unlike all reviews
3. Not all games are reviewed, neither positively or negatively

CONS

1. You might get burned out after 500h in a game
2. Some people need 20 hours to find out if they dislike a game
3. Some games (e.g. Strategy/Simulation games) take a lot of time to play, but might not be as interesting to the user as smaller, shorter games (e.g. Adventure games)

Gathering item attributes

Content-Based recommender systems

- Hypothesis: if a game is very similar to another, a user might be interested in it
- Steam provides information about games

Details
Name, price, controller support, Mac OS support, release date...

Tags
User-defined, ordered by priority

Genres and categories
Limited, unweighted

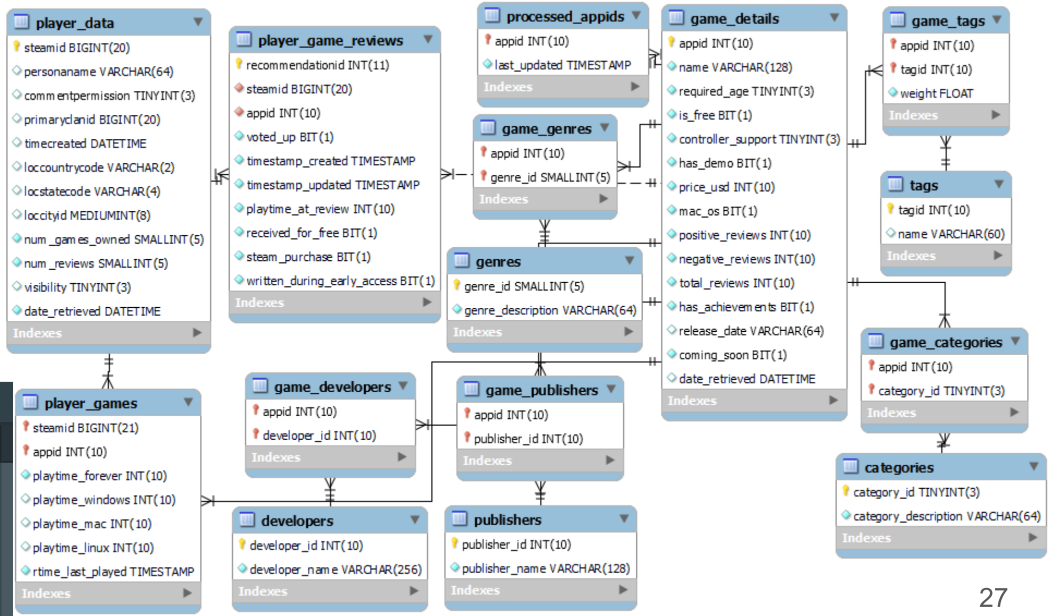
Developers and publishers

Our data

steam_tfg_jgg	7.0 GiB
candidate_appids	4.6 MiB
categories	16.0 KiB
developers	4.5 MiB
game_categories	13.5 MiB
game_details	5.5 MiB
game_developers	5.5 MiB
game_genres	10.5 MiB
game_publishers	5.5 MiB
game_tags	10.5 MiB
genres	16.0 KiB
player_data	164.5 ...
player_games	6.5 GiB
player_game_reviews	274.6 ...
processed_appids	16.0 KiB
publishers	2.5 MiB
tags	32.0 KiB

steam_tfg_jgg.player_games: 50,045,823 rows total (approximately), limited to 1,000

steamid	appid	playtime_fore...	rtime_last_played
76,561,198,115,515,666	660,880	2,957,082	2023-03-29 22:20...
76,561,197,970,402,743	385,800	2,940,686	2023-04-11 20:00...
76,561,198,098,325,355	333,600	2,894,283	2023-04-05 18:02...
76,561,198,098,325,355	385,800	2,893,240	2023-04-05 18:02...
76,561,198,098,325,355	420,110	2,893,202	2023-04-05 18:02...



Tags and IDF: an hypothesis

Tags

User-defined, ordered by priority

IDF (Inverse Document Frequency)

IDF = In documents, IDF penalizes terms that are too frequent when ranking documents in search engines, like Google

Hypothesis:

"If a tag is too common, it might not be too useful for us"

Defining and normalizing “interest”

Formal explanation

Let ***u*** be a user (or player) and ***i*** be an item (or game). Let us define the function ***I(u, i)*** as the interest a user ***u*** has over the item ***i***,which yields a value between 0 and 1, where 0 means no interest and 1 means maximum interest.

Then we can define “implicit interest” as the play time spent by a player ***u*** playing game ***i***, normalized from 0 to 1, where ***I(u, i)* = 1** (“the game the player is most interested in”) is the game with the highest playtime.

For example, if user ***u*** has three games i_1, i_2 and i_3 with playtimes of $I(u,i_1)$, $I(u,i_2)$ and $I(u,i_3)$ of 100h, 50h and 20h respectively, then $I(u,i_1) = 1$ and $I(u,i_2)$, $I(u,i_3)$ will be based on the user’s maximum playtime / interest, $I(u,i_1)$ in our case.

Different normalization techniques

$$x = playtime$$

$$\frac{x}{\max(I(u, i_n))}$$

$$\frac{\log(x)}{\log(\max(I(u, i_n)))}$$

$$\frac{\sqrt{x}}{\sqrt{\max(I(u, i_n))}}$$

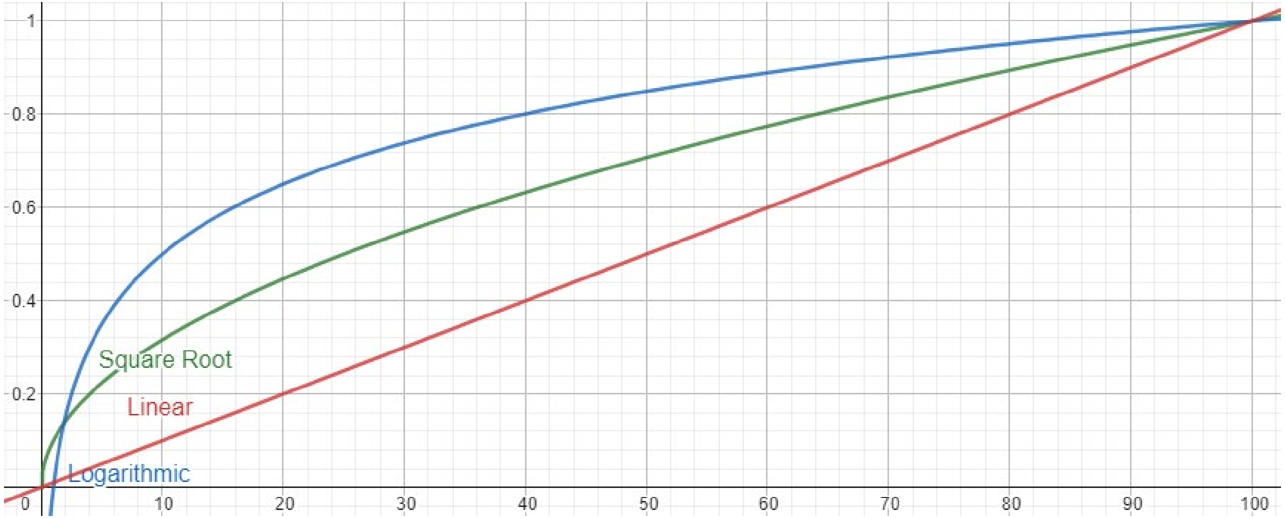
Defining and normalizing "interest"

In other words…

We define the interest over a game, for each user, as the time they have spent playing that game relative to their most played game

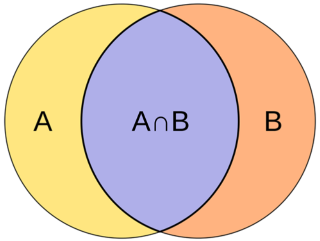
Different normalizations techniques

Linear	Logarithmic	Square Root
$\frac{x}{\max(I(u, i_n))}$	$\frac{\log(x)}{\log(\max(I(u, i_n)))}$	$\frac{\sqrt{x}}{\sqrt{\max(I(u, i_n))}}$



MinHash, LSH Ensemble and similarity

Jaccard similarity $$\frac{|A \cap B|}{|A \cup B|}$$



"The number of items in common divided by the number of items of both sets"

Quick way of finding similar items: **MinHash LSH**, which approximates Jaccard and indexes those matches above a threshold t (saves all matches of Jaccard › t)

But Jaccard penalizes big sets, which might contain more information…

LSH Ensemble

by Erkang Zhu

$$\frac{|A \cap B|}{|A|}$$

Collaborative filtering (CF): relevant games

When MinHashing and using the LSH Ensemble, we can take top games

User X library	
ELDEN RING	100h
Counter-Strike	80h
Baldur's Gate	40h
RimWorld	10h
Subnautica	5h

>60% of max playtime →

User X MinHash
ELDEN RING
Counter-Strike

Collaborative filtering (CF): similarity

We want similar users to our target: LSH Ensemble to filter out unwanted users

Then apply one of these functions, taking into account every owned game where $R_{u,i}$ is the rating of a user over an item:

Raw: $$\sum_{i \in I_u \cap I_v} R_{u,i} \cdot R_{v,i}$$ "Just multiply ratings"

Cosine: $$\frac{\sum_{i \in I_u \cap I_v} R_{u,i} \cdot R_{v,i}}{\sqrt{\sum_{i \in I_u \cap I_v} R_{u,i}^2} \cdot \sqrt{\sum_{i \in I_u \cap I_v} R_{v,i}^2}}$$ "Take into account the total time spent in all games"

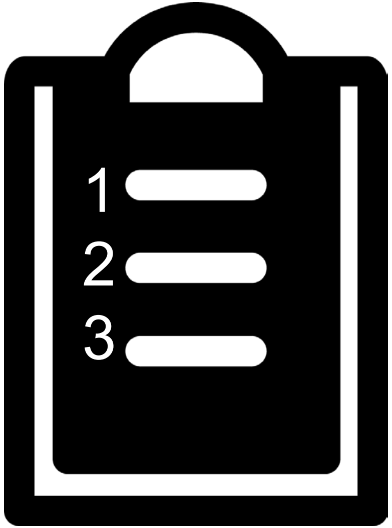
Pearson: $$\frac{\sum_{i \in I_u \cap I_v} (R_{u,i} - \overline{R_u}) \cdot (R_{v,i} - \overline{R_v})}{\sqrt{\sum_{i \in I_u \cap I_v} (R_{u,i} - \overline{R_u})^2} \cdot \sqrt{\sum_{i \in I_u \cap I_v} (R_{v,i} - \overline{R_v})^2}}$$ "Same as before, but use average ratings into account"

Remember: ratings = interest = playtime

Collaborative filtering (CF): scoring

N = number of games to recommend
K = number of similar users to use

1. Pick the top **K** similar users according to the selected method (which internally uses the LSH Ensemble)
2. Keep track of a dictionary **game -> score**
3. For **user** in all **K** similar users:
    a. Get all games of **user**
        i. **game += interest(user) × similarity(user, target)**^{2}
4. Order the list of games and return top **N**



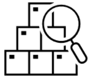
Content-Based Filtering (CBF): finding games

Find the “preferred” game of the user

User Y library	
Action, RPG	100h
Horror, Action	80h
Racing, Sports	40h
Adventure, Indie	10h
Sports, Indie	5h

User Y attribute weight map	
Action	180h
RPG	100h
Horror	80h
Sports	45h
Racing	40h
Indie	15h
Adventure	10h

Content-Based filtering (CBF): similarity



Same as before, but we take item attributes (tags, genres, etc.) and tweak the LSH Ensemble threshold

Only with tags: To score tags we can adapt our CF, but instead of $R_{u,i}$ being the rating of a user over an item, it's item's weight of a tag:

Raw: $$\sum_{i \in I_u \cap I_v} R_{u,i} \cdot R_{v,i}$$ "Just multiply weights"

Cosine: $$\frac{\sum_{i \in I_u \cap I_v} R_{u,i} \cdot R_{v,i}}{\sqrt{\sum_{i \in I_u \cap I_v} R_{u,i}^2} \cdot \sqrt{\sum_{i \in I_u \cap I_v} R_{v,i}^2}}$$ "Penalize those with many tags"

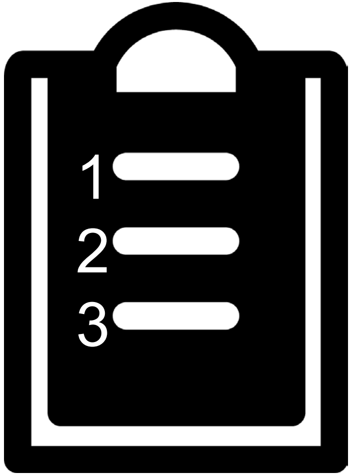
Pearson: $$\frac{\sum_{i \in I_u \cap I_v} (R_{u,i} - \overline{R_u}) \cdot (R_{v,i} - \overline{R_v})}{\sqrt{\sum_{i \in I_u \cap I_v} (R_{u,i} - \overline{R_u})^2} \cdot \sqrt{\sum_{i \in I_u \cap I_v} (R_{v,i} - \overline{R_v})^2}}$$ "Penalize tags with low priority (**bad!**)"

Content-Based Filtering: scoring

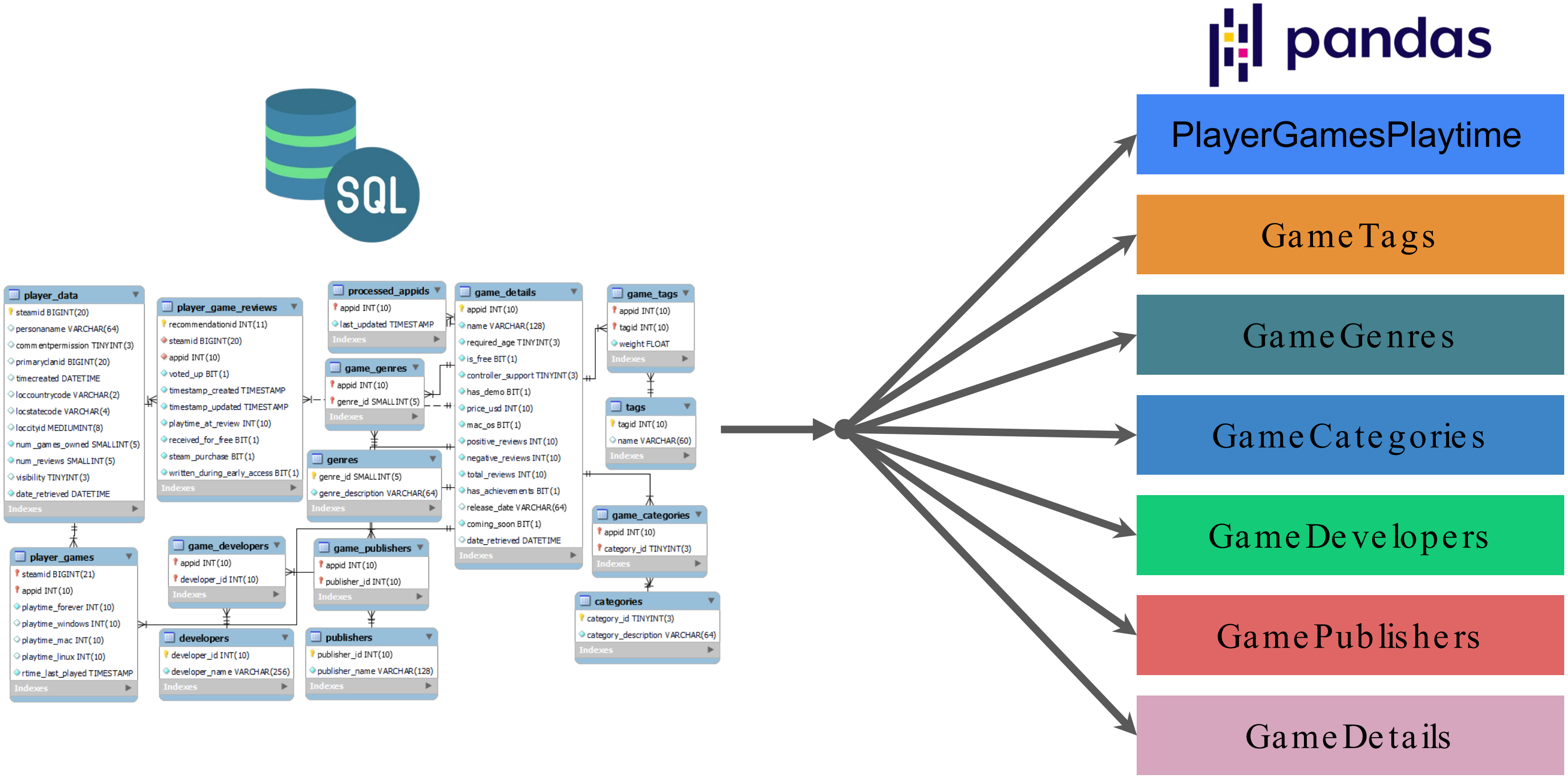
Preferred game	
Action	180h
RPG	100h
Horror	80h
Sports	45h
Racing	40h
Indie	15h
Advent.	10h

N = number of games to recommend
"Preferred game" = our item weight map
LSH threshold: ***t*** = "games above this approx. Jaccard similarity"

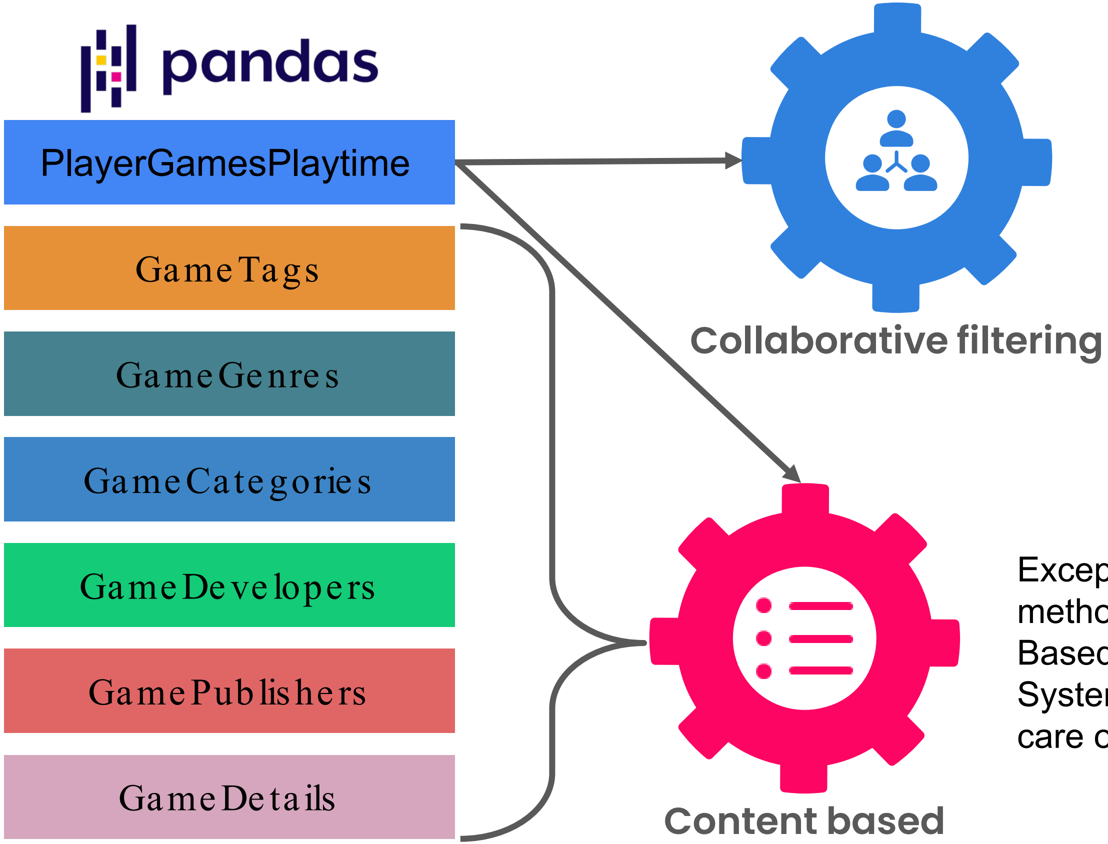
1. Pick the similar games above the LSH threshold ***t*** to our "preferred game"
2. For **game** in all **K** similar games:
    a. **game** score = the real similarity to our "preferred game"
3. Order the list of games by their score and return top **N**



Structuring our data



Recommender systems



Except for specific methods, our Content Based Recommender System class takes care of all of the logic

Experiments and results: Measuring accuracy

Split 80% / 20%

Our two ways to measure accuracy:

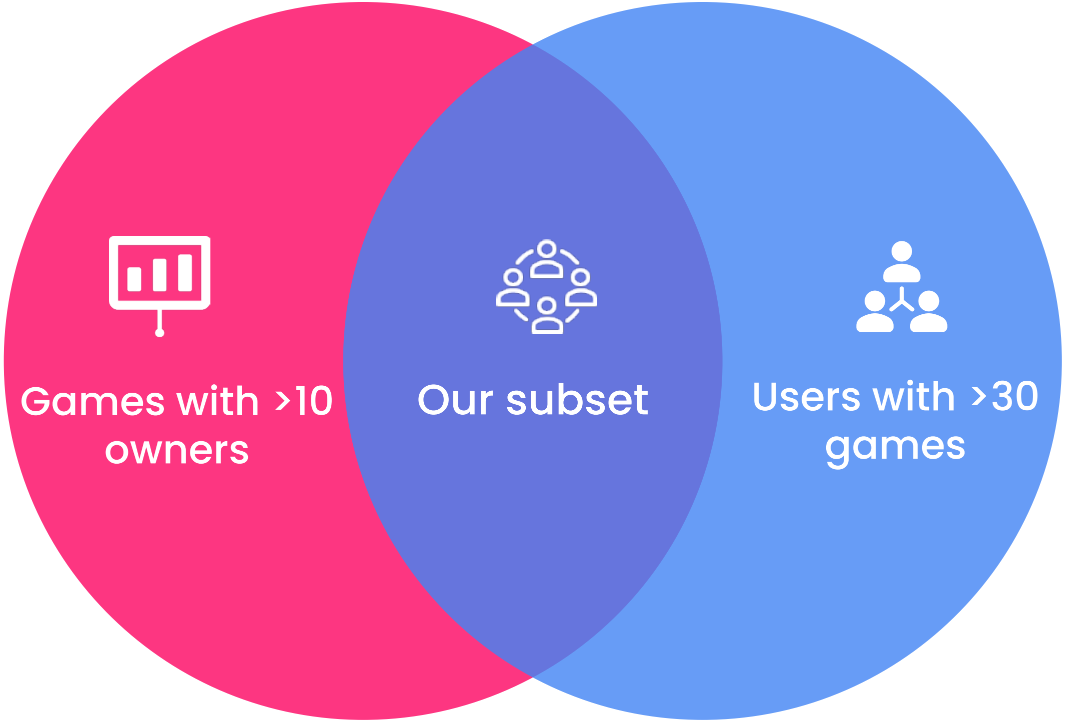
(Always at 5, 10 or 20 top results)

Precision $\frac{|\{Rel\} \cap \{Ret\}|}{|\{Ret\}|}$

Recall $\frac{|\{Rel\} \cap \{Ret\}|}{|\{Rel\}|}$

We will also measure time efficiency

Extracting a subset



Baseline

P@K = Precision at K. **R@K** = Recall at K

Combination	P@5	P@10	P@20	R@5	R@10	R@20	Time (s)
Random	0.0046	0.0041	0.0042	0.0014	0.0025	0.0048	4.71
Top rated	0.0016	0.0010	0.0073	0.0005	0.0006	0.0087	705.54

Anything close or below 0.0046 in precision at 5 or below 0.0014 on recall at 5 means it performs worse than our random recommender

Our findings: Content Based Filtering

Top results for Content Based Filtering

Separated by each recommender system:

t means the LSH ensemble threshold

w_{idf} means the weight for our "IDF hypothesis"

Underscored highlights the best combination for each recommender system

Bold highlights the best overall for Content Based Filtering

Categories	P@5	P@10	P@20	R@5	R@10	R@20	Time (s)
t=0.42	0.0370	0.0304	0.0251	0.0114	0.0185	0.0302	1869.48
t=0.55	0.0242	0.0150	0.0082	0.0076	0.0094	0.0103	**63.37**
Genres							
t=0.30	0.0030	0.0035	0.0044	0.0007	0.0018	0.0049	4119.41
t=0.80	0.0016	0.0022	0.0022	0.0003	0.0013	0.0027	235.48
Others							
Details	0.0440	0.0334	0.0257	0.0134	0.0199	0.0310	21246.19
Developers	**0.0606**	**0.0554**	**0.0467**	**0.0187**	**0.0343**	**0.0571**	1397.43
Publishers	0.0570	0.0502	0.0402	0.0168	0.0301	0.0477	3021.03

Raw Game Tags	P@5	P@10	P@20	R@5	R@10	R@20	Time (s)
t=0.30, w_{idf}=0.60	0.0472	0.0382	0.0318	0.0137	0.0217	0.0364	9379.58
t=0.42, w_{idf}=0.60	0.0476	0.0382	0.0317	0.0138	0.0217	0.0361	9571.94
Cosine Game Tags							
t=0.42, w_{idf}=0.60	0.0376	0.0316	0.0284	0.0105	0.0178	0.0320	1626.74
Pearson Game Tags							
t=0.55, w_{idf}=0.60	0.0274	0.0240	0.0210	0.0076	0.0134	0.0235	561.59

Our IDF hypothesis: is it useful?

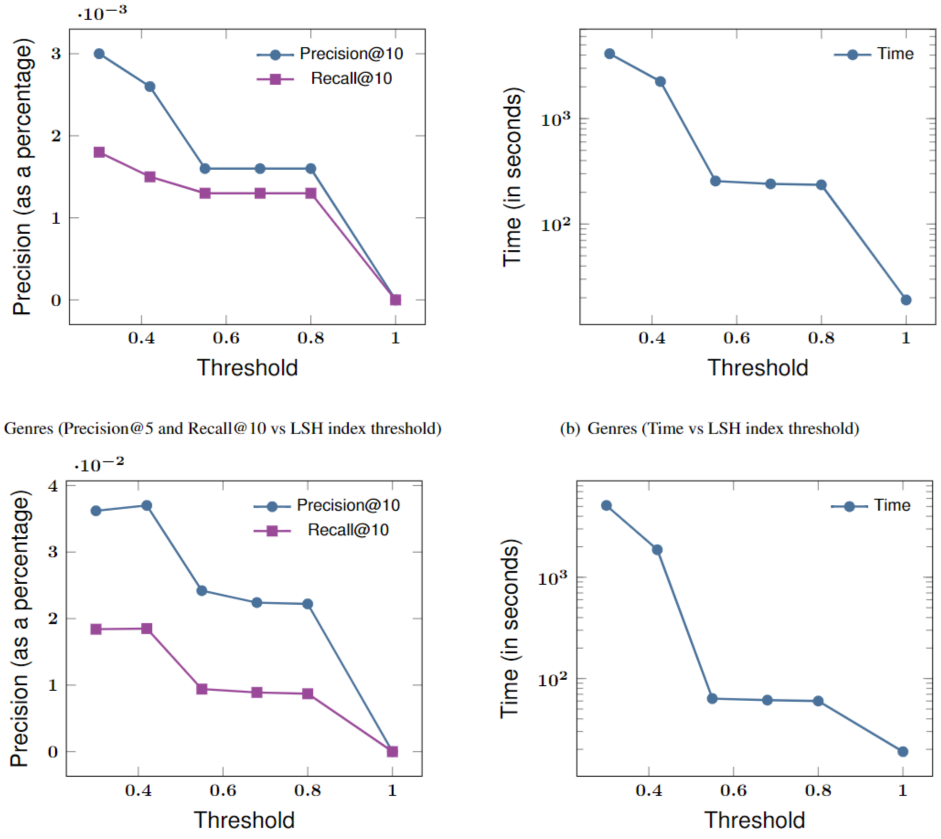
Combination	P@5	P@10	P@20	R@5	R@10	R@20	Time (s)
t=0.30, w_{idf}=0.00	0.0376	0.0306	0.0262	0.0109	0.0175	0.0302	13594.60
t=0.30, w_{idf}=0.15	0.0376	0.0320	0.0269	0.0108	0.0183	0.0304	14949.60
t=0.30, w_{idf}=0.30	0.0414	0.0340	0.0290	0.0117	0.0191	0.0328	11879.06
t=0.30, w_{idf}=0.60	0.0472	0.0382	0.0318	0.0137	0.0217	0.0364	9379.58
t=0.42, w_{idf}=0.00	0.0372	0.0307	0.0264	0.0108	0.0175	0.0303	10241.59
t=0.42, w_{idf}=0.15	0.0372	0.0319	0.0271	0.0107	0.0183	0.0307	9034.59
t=0.42, w_{idf}=0.30	0.0414	0.0340	0.0289	0.0117	0.0192	0.0328	8600.51
t=0.42, w_{idf}=0.60	0.0476	0.0382	0.0317	0.0138	0.0217	0.0361	9571.94
t=0.55, w_{idf}=0.00	0.0378	0.0307	0.0262	0.0110	0.0175	0.0302	3052.29
t=0.55, w_{idf}=0.15	0.0376	0.0322	0.0265	0.0108	0.0184	0.0302	2954.21
t=0.55, w_{idf}=0.30	0.0416	0.0344	0.0278	0.0117	0.0194	0.0313	2873.44
t=0.55, w_{idf}=0.60	0.0452	0.0372	0.0306	0.0129	0.0209	0.0348	2313.82
t=0.68, w_{idf}=0.00	0.0336	0.0298	0.0245	0.0095	0.0173	0.0281	963.79
t=0.68, w_{idf}=0.15	0.0340	0.0297	0.0255	0.0094	0.0169	0.0288	918.73
t=0.68, w_{idf}=0.30	0.0366	0.0306	0.0260	0.0100	0.0175	0.0295	865.00
t=0.68, w_{idf}=0.60	0.0394	0.0323	0.0248	0.0112	0.0183	0.0286	824.77

t=0.80, w_{idf}=0.00	0.0328	0.0288	0.0244	0.0091	0.0165	0.0276	850.73
t=0.80, w_{idf}=0.15	0.0334	0.0291	0.0248	0.0093	0.0164	0.0280	806.09
t=0.80, w_{idf}=0.30	0.0354	0.0298	0.0247	0.0096	0.0169	0.0278	752.47
t=0.80, w_{idf}=0.60	0.0392	0.0309	0.0235	0.0111	0.0175	0.0271	720.42
t=1.00, w_{idf}=0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	69.07
t=1.00, w_{idf}=0.30	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	86.11
t=1.00, w_{idf}=0.60	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	68.21
wt=0.75, w_{idf}=0.00	0.0376	0.0306	0.0262	0.0109	0.0175	0.0302	23142.23
wt=0.75, w_{idf}=0.30	0.0432	0.0364	0.0304	0.0122	0.0205	0.0344	19974.60
wt=0.75, w_{idf}=0.60	0.0472	0.0381	0.0317	0.0137	0.0216	0.0363	20120.96
wt=1.00, w_{idf}=0.00	0.0360	0.0296	0.0243	0.0104	0.0170	0.0280	8675.47
wt=1.00, w_{idf}=0.30	0.0410	0.0334	0.0280	0.0117	0.0191	0.0322	8134.27
wt=1.00, w_{idf}=0.60	0.0460	0.0360	0.0286	0.0135	0.0207	0.0329	6528.09

It has proven to be useful across different combinations

Boosting the scores of uncommon tags =better results.

CBF: precision and recall vs time



(a) Genres (Precision@5 and Recall@10 vs LSH index threshold)

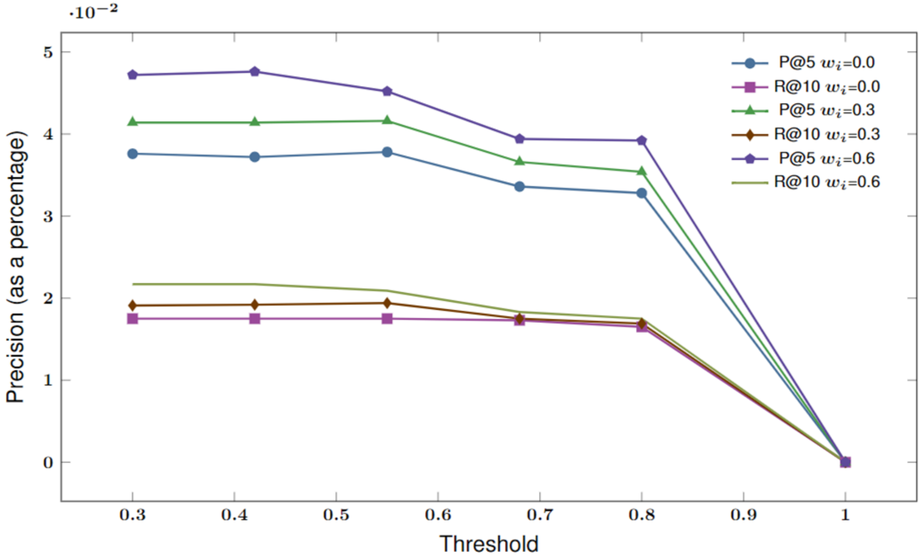
(b) Genres (Time vs LSH index threshold)

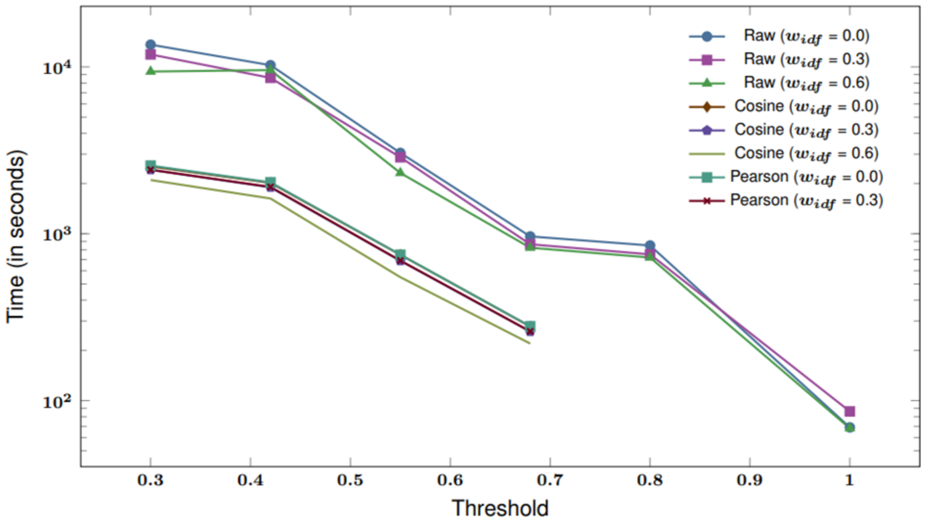
(c) Categories (Precision@5 and Recall@10 vs LSH index threshold)

(d) Categories (Time vs LSH index threshold)

Precision and recall resemble execution time logarithmically for genres and categories
the more increase the threshold (less items to check)

CBF: precision and recall vs time





Same happens for our Game Tags based recommender system

(Cosine and Pearson graphs omitted for brevity)

Our findings: Collaborative Filtering

Results for Collaborative Filtering

Separated by each recommender system

t, the LSH ensemble threshold

t_{rel} means the minimum playtime relative to the top played game for a user to include it in the MinHash

Underscored highlights the best combination for each recommender system

Bold highlights the best overall for Collaborative Filtering

Combination	P@5	P@10	P@20	R@5	R@10	R@20	Time (s)
Raw (Linear)	0.0530	0.0401	0.0314	0.0146	0.0220	0.0348	65261.46
Raw (Log)	0.0692	0.0528	0.0401	0.0191	0.0289	0.0438	65443.07
Raw (Square Root)	0.0594	0.0479	0.0364	0.0164	0.0261	0.0399	65674.90
Cosine (Linear)	0.0540	[illegible]	0.0312	0.0149	[illegible]	0.0346	61063.86

We picked t_{rel} = 0.6 and t = 0.8 because our results at 10 and 20 were better, and the time to execute was the lowest for Pearson.

Combination	P@5	P@10	P@20	R@5	R@10	R@20	Time (s)
t_{rel}=0.60, t_{lsh}0.60	0.3100	0.272	0.208	0.0710	0.1225	0.1879	6,420
t_{rel}=0.60, t_{lsh}0.80	0.3260	0.286	0.2125	0.0755	0.1289	0.1953	5,160
t_{rel}=0.80, t_{lsh}0.60	0.342	0.274	0.2110	0.0798	0.124	0.1896	7,020
t_{rel}=0.80, t_{lsh}0.80	0.348	0.277	0.2065	0.0813	0.1256	0.1861	5,760

Table 4.3: Precision and recall results for CF. Parameters used: t_{rel} = 0.6, t = 0.8. User similarity followed by the normalization approach in parentheses.

Content-Based vs Collaborative

Details	0.0440	0.0334	0.0257	0.0134	0.0199	0.0310	21246.19
Developers	**0.0606**	**0.0554**	**0.0467**	**0.0187**	**0.0343**	**0.0571**	1397.43
Publishers	0.0570	0.0502	0.0402	0.0168	0.0301	0.0477	3021.03

Pearson (Linear)	0.1954	0.1672	0.1281	0.0581	0.0983	0.1512	94042.03
Pearson (Log)	**0.2136**	0.1753	0.1356	**0.0632**	0.1030	0.1587	95043.25
Pearson (Square Root)	0.2056	**0.1787**	**0.1389**	0.0605	**0.1048**	**0.1625**	95983.37

Concluding remarks

Implemented from scratch:

- Data crawler (using SQL)
- Tag scrapper (using Scrapy)
- Playtime normalizer
- Recommender Systems
- Own experiments

We found out CF outperforms CBF, but further optimizations could make everything viable.

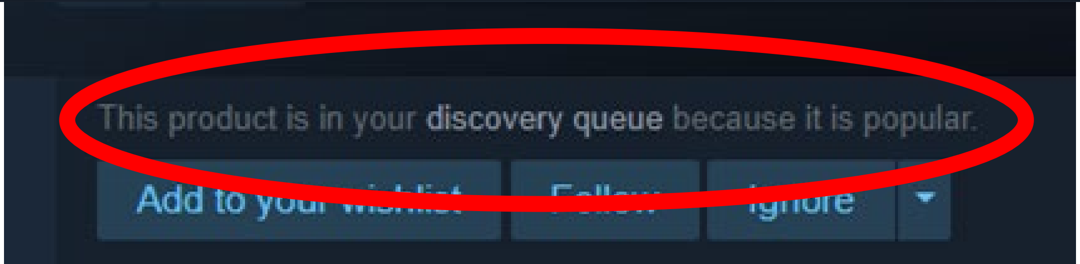
Future work

- We would have loved testing more LSH Ensemble thresholds to see if time efficiency is worth lower precision
- More data and comparers, as well as more sophisticated methods (like Artificial Intelligence, specially in our Game Details recommender system)
- We would like to see the performance and precision impact of LSH Ensemble in different domains (music, movies, etc.)
- Real-world deployment and viability
- Further optimization + Using our recommender systems as baselines for performance

The end
Thanks for your attention!

Presentation by Jorge González Gómez. Special thanks to Alejandro Bellogin

Personal example of discovery queue



More examples of “troll” reviews

Zombie game: troll reviews, or they really like it?
And “how much” do they like it?

Longer reviews are not trolls, but do they like the game more than the player with 453 hrs?

Caveat: unable to determine if people with 0.6hrs are more interested than one with 11.2hrs who actually disliked the game

Different hybrid approaches

Method	Description
Weighted	Each recommender system is assigned a weight, and the final score is the weighted sum of the scores from each recommender system.
Switching	Each recommender system is assigned a threshold, and the final score is the score from the recommender system that passes the threshold.
Mixed	The final score is a combination of the scores from each recommender system.
Feature Combination	The features from each recommender system are combined to create a new recommender system.
Cascade	The first recommender system is used to create a list of recommendations, and then a second recommender system is used to re-rank the list of recommendations.
Feature Augmentation	The output of a recommender system is used as an input for another recommender system.
Meta-level	The model learned by a recommender system is used as an input for another recommender system.