Steam Game Recommender

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01 Business Problem

Steam wants to improve their recommendation system, to attract more users to use their platform

Our tasks:

1. Analyze current gaming trends through ratings
2. Create models that will predict what users will rate a game they don't already own

02 Data Analysis

Dataset consists of over 40 million rows of data

- Games.csv
  - Title, Positive Ratio, Price, …
- Recommendations.csv
  - Helpful, funny, is_recommended, …
- Games_metadata.json
  - Description and Tags
- Users.csv
  - Products, Reviews

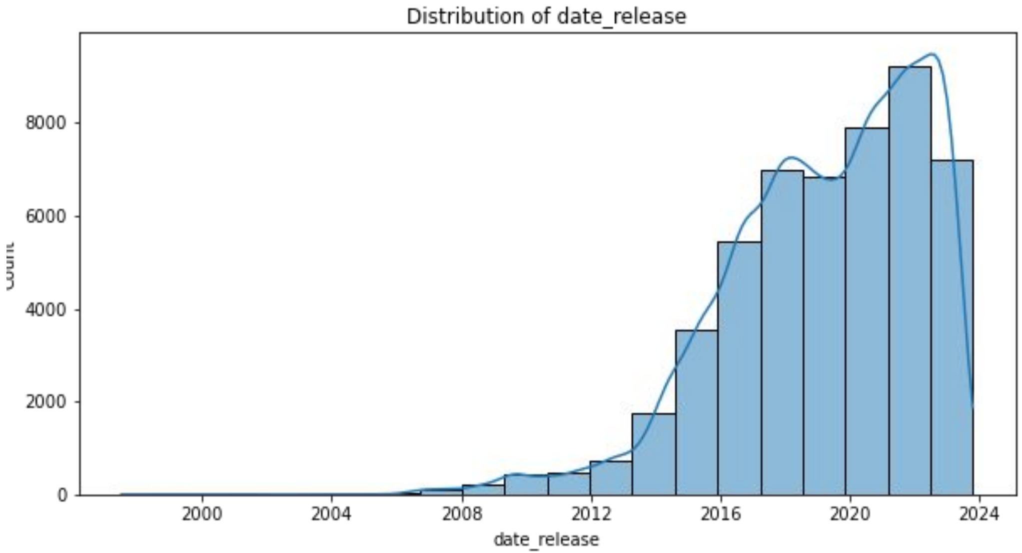
Stratified sample of ~100,000 rows

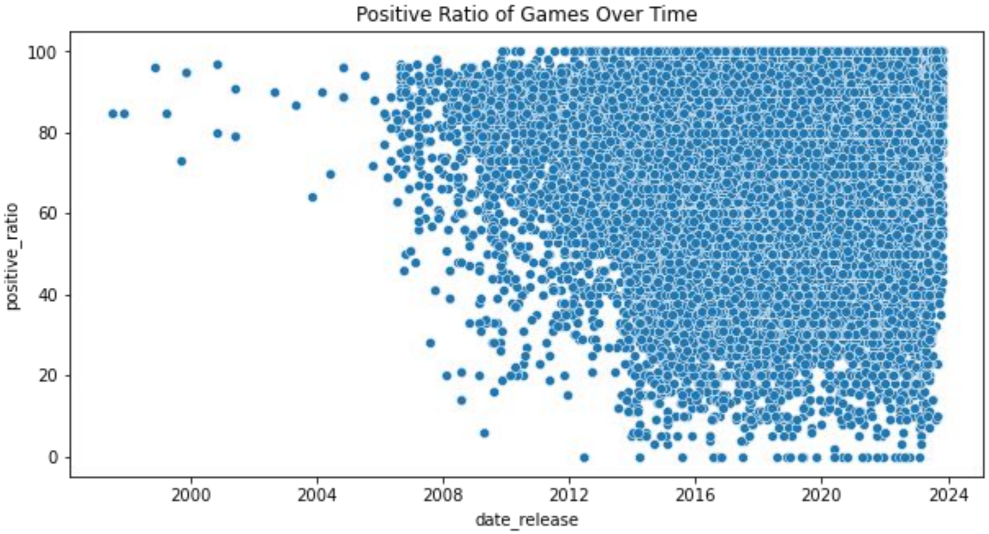
Source: Steam Game Recommendation

Data Filtering

Notes:
- More games released lately
- Highly rated games are more recent

1. Filtered dataset from 2010 - Present



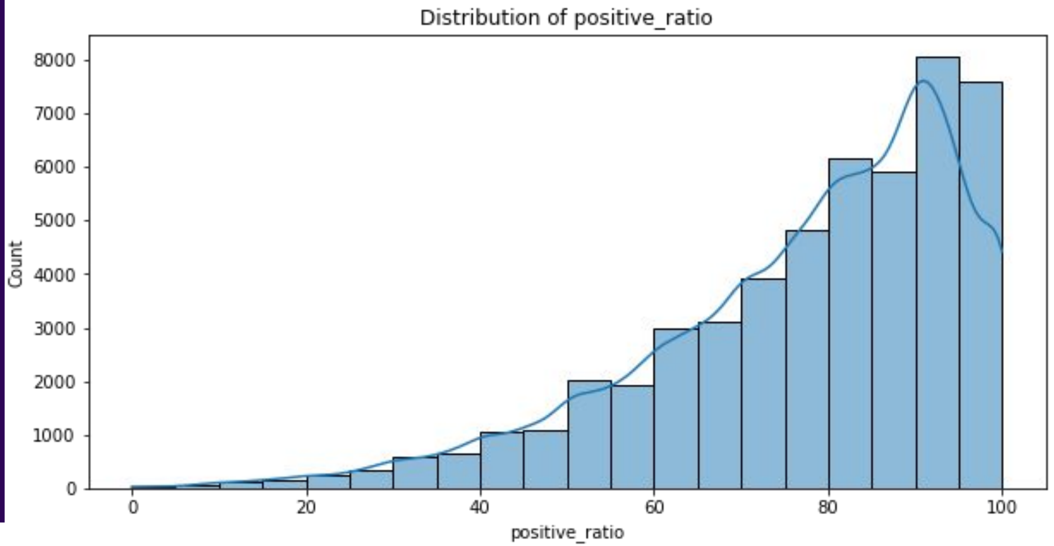


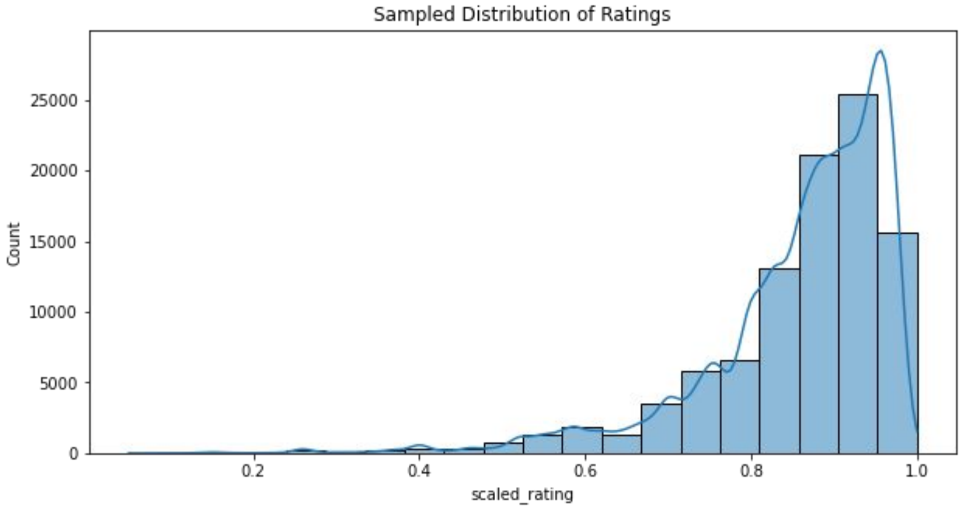
Data Filtering

Sampled dataset:

- ~ 100,000 rows
- Decent representation of data
- Majority of ratings are higher

1. Train test split using “stratify”
2. Train test split (1) for models





Target Variable: Positive Ratio

03 Modeling

Goal: Predict ratings of games users don't already have

Metrics:

- **Main Metric:** Root Mean Squared Error (RMSE)
  - How far predictions are from the actual values
- Mean Absolute Error (MAE)
  - Difference between the predicted and actual ratings
- Precision at *k* (P@k)
  - Proportion of recommended games in the top k that are relevant
- Recall at *k* (R@k)
  - Shows how well the recommender system is at capturing all relevant items within a limited list of recommendations

Collaborative-based Filtering Pipeline

1. Combine Data: Recommendations.csv & Games.csv
   - Columns: user_id, app_id, positive_ratio (scaled → 0 - 1)
   - ~ 40 million rows of data

2. Train Test Split the data to get ~100,000 rows of the data

3. Used Surprise library to Train Test Split
   a. Baseline and SVD: directly train/tune model
   b. KNN: Train Test Split again because of insufficient memory ~30,000 rows

4. Grid search to find best parameters

5. Evaluate the models
   - RSME, MAE, P@k, R@k
   - Sorted the ratings from best to worst

Collaborative-based Filtering Models

Baseline Model (not tuned)

- Acts as a baseline model to compare other models to
- Uses ALS as base model

Singular Value Decomposition (“n_factors”: 10, “n_epochs”: 40, “lr_all”: 0.02, “reg_all”: 0.1)

- Matrix Factorization technique
- Reduces the number of features of a dataset by reducing the space dimension

K-Nearest Neighbors (“k”: 10, “min_k”: 1, “sim_options”: {“name”: cosine, “user_based”: True})

- Finds the K nearest neighbors to a given data point based on distance metrics
    - Cosine, Pearson, Mean Squared Difference
- To run KNN I had to take a sample of the sampled dataset, which was ~ 30,000 rows

Collaborative-based Filtering Metrics

Baseline Model (not tuned)

Train RMSE: 0.052	Test RMSE: 0.060	Ave. Train P@10: 1.0	Ave. Test P@10: 1.0
Train MAE: 0.024	Test MAE: 0.028	Ave. Train R@10: 0.89	Ave. Test R@10: 0.88

Singular Value Decomposition (“n_factors”: 10, “n_epochs”: 40, “lr_all”: 0.02, “reg_all”: 0.1)

Train RMSE: 0.013	Test RMSE: 0.048	Ave. Train P@10: 0.99	Ave. Test P@10: 0.99
Train MAE: 0.008	Test MAE: 0.023	Ave. Train R@10: 0.96	Ave. Test R@10: 0.93

K-Nearest Neighbors (“k”: 80, “min_k”: 8, “sim_options”: {“name”: cosine, “user_based”: True})

Train RMSE: 0.076	Test RMSE: 0.114	Ave. Train P@10: 0.99	Ave. Test P@10: 0.99
Train MAE: 0.031	Test MAE: 0.083	Ave. Train R@10: 0.99	Ave. Test R@10: 0.93

Content-based Filtering Pipeline

1. Create Dataset: Games.csv & Games_metadata.csv
    - Columns: app_id, title, description, tags
    - ~ 50,000 rows of data

2. Combine all text data into one column

3. Preprocess the combined features using NLTK

4. Sklearn Train Test Split

5. Vectorize combined_features (TF-IDF)

6. Calculate Cosine Similarity through batches, because of memory issue

7. Evaluate the model
    - RSME, MAE, P@k, R@k
    - Sorted the similarity scores from best to worst

Content-based Filtering Model

NLTK & TF-IDF & Cosine Similarity

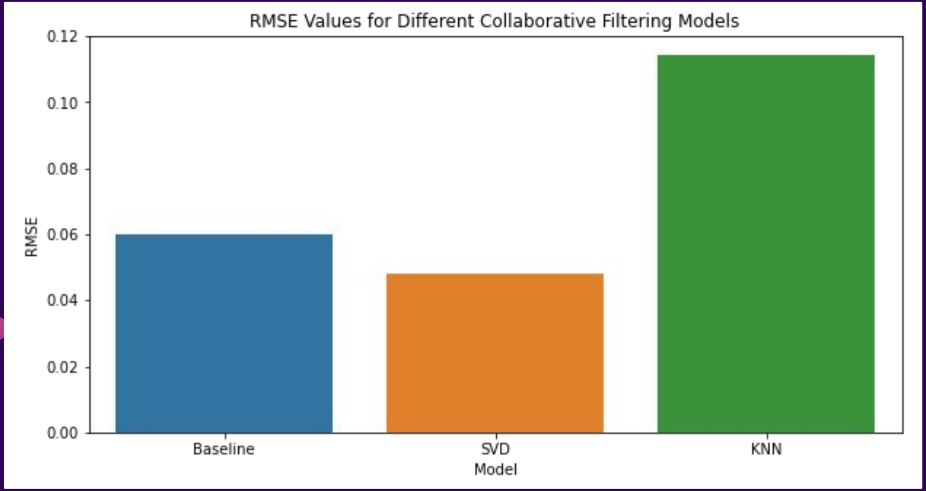
- NLTK (Natural Language Toolkit)
  - Tokenization, Lemmatization, Stopwords
- TF-IDF (Term Frequency-Inverse Document Frequency)
  - measures how important a word is to a document in a collection or corpus of documents
- Cosine Similarity determines the distance between the neighbors

Content-based Filtering Model

NLTK & TF-IDF & Cosine Similarity

Train RMSE: 0.084	Test RMSE: 0.090	Ave. Train P@10: 0.72	Ave. Test P@10: 0.73
Train MAE: 0.068	Test MAE: 0.067	Ave. Train R@10: 0.91	Ave. Test R@10: 0.89

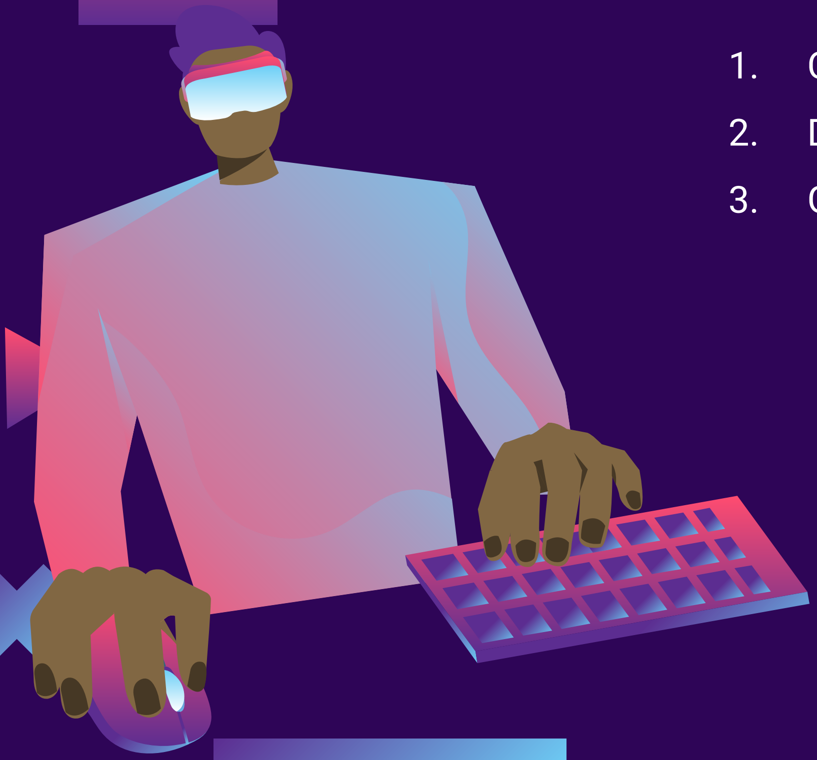
04 Conclusion



Suggestion: **SVD Collaborative Model**

- Lowest RMSE (main metric)
- All other metrics scored well
- Was able to run the most number of rows (more variability)

05 Next Steps



1. Create a Hybrid Models / Explore other models
2. Deploy and test on the web for real users
3. Get more RAM!!

Thanks!

Do you have any questions?

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