Predicting Video Game Playtime Before Purchase

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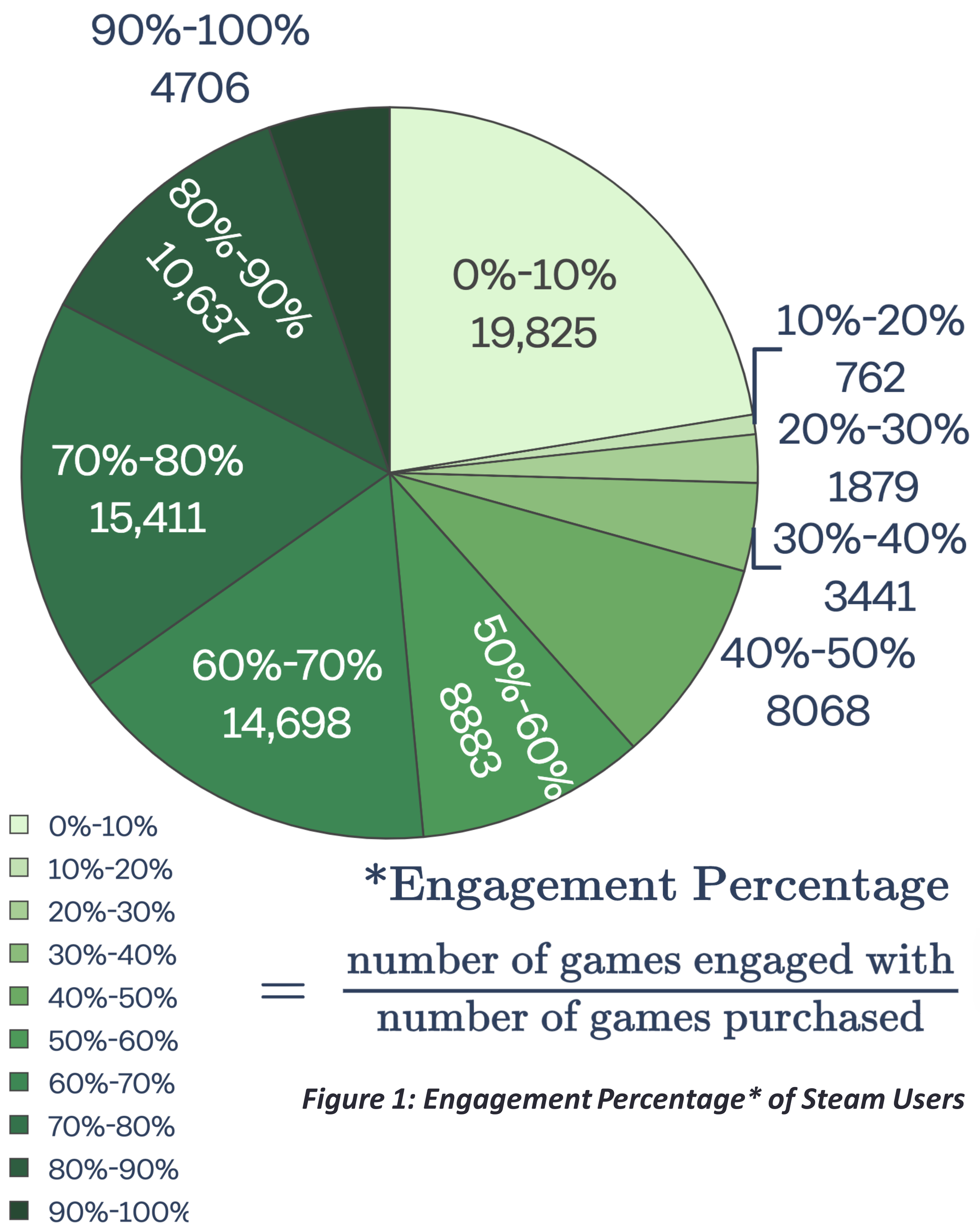
BACKGROUND/MOTIVATION

- E-commerce companies recommend items that users are more likely to **buy**.
- These companies are motivated by profits; they may prioritize **selling products** over ensuring **positive user engagement** with products.



$$\text{*Engagement Percentage} = \frac{\text{number of games engaged with}}{\text{number of games purchased}}$$

Figure 1: Engagement Percentage of Steam Users*

OBJECTIVE

Our goal is to explore **what factors determine user engagement** and why users might purchase products they do not intend to use. To accomplish this, we aim to build a reasonably accurate predictor that will **predict if a user will play a game before purchasing**.

Companies: $P(Buy \mid Interests)$

vs.

Our Goal: $P(Play \mid Purchased)$

If they buy it, what would be the probability that they **engage with the game**?

SOLUTION

Our approach is to build a **binary classifier** to predict whether the user will engage with a game the user has not purchased yet. For our project, we used two machine learning models.

Logistic Regression Model

Feature Selection of User-Game Interactions

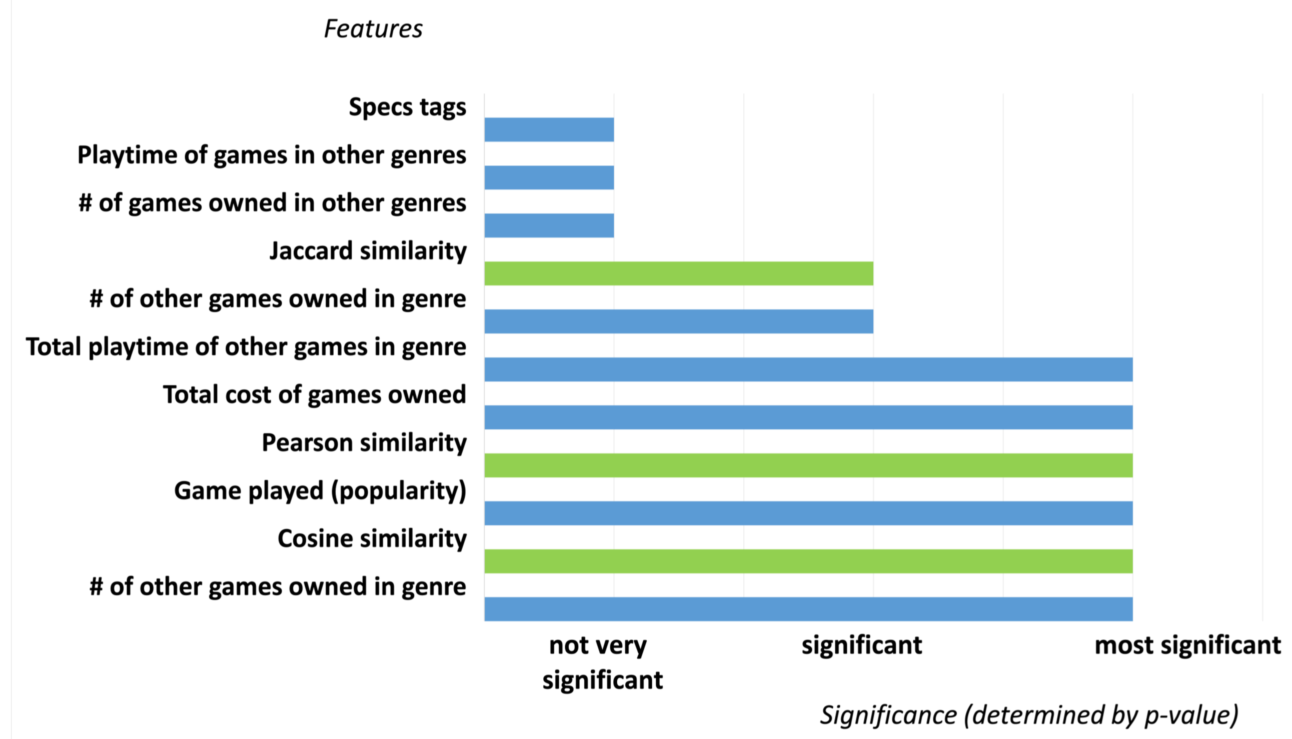


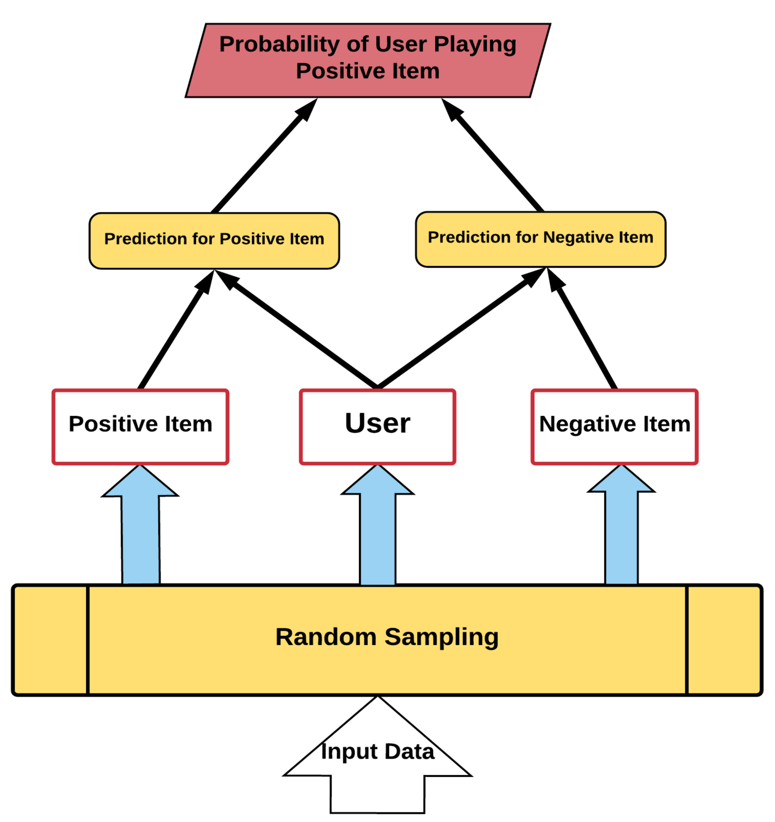
Figure 2: Significance of Features – Significance (α) ≤ 0.00001 for most significant features; α ≤ 0.001 for significant features; α ≤ 0.05 for not very significant features

Feature Engineering of Similarity Measures

Features	Accuracy
Jaccard Similarity	87.1%
Cosine Similarity	87.9%
Pearson Correlation	88.1%

- The similarity measures are calculated between the game of interest and the user's most played game in two weeks and most played of all time.
- Many of the significant features fit our expectations – users tend to play games in genres they like and games that are popular.
- It is surprising that total cost of games is more significant than the total number of games owned.

Latent Factor Model



- **Bayesian Personalized Ranking** with a sigmoid activation function
- **Maximize the difference** between the prediction value of a user's positive item and that of a user's negative item

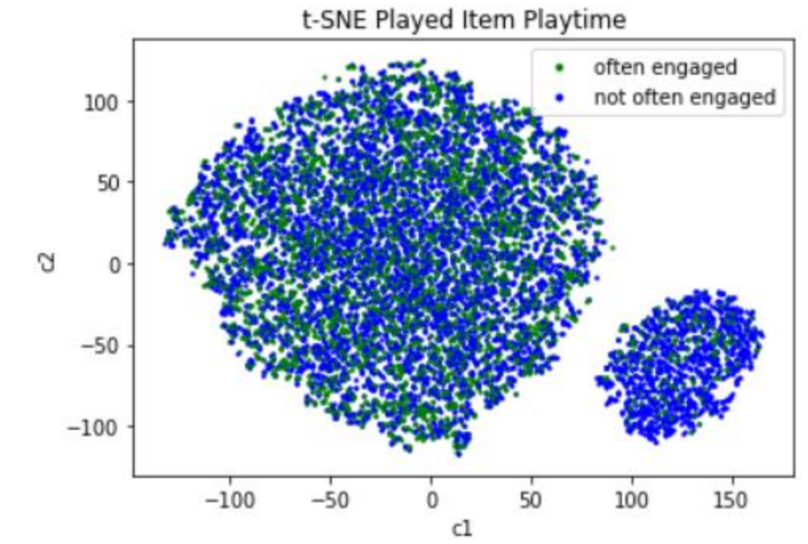


Figure 3: t-SNE for played items engagement Engaged if Mean Playtime < Median Playtime

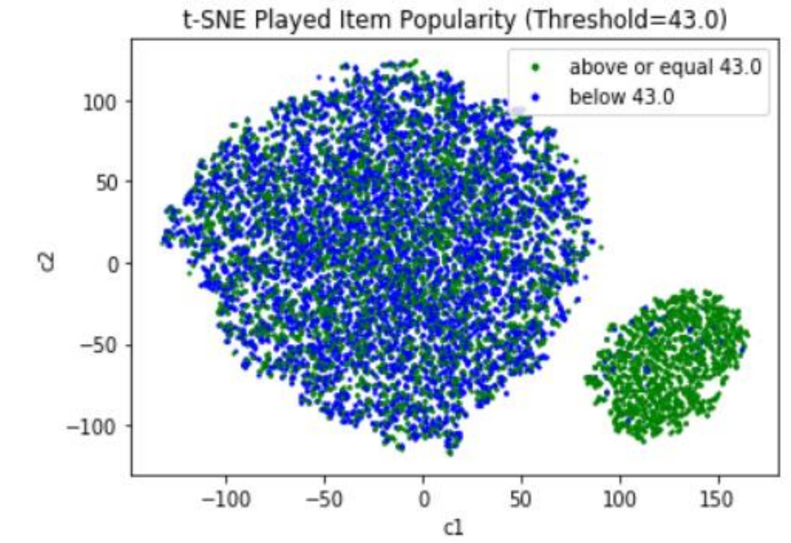


Figure 4: t-SNE for played items popularity Popularity Threshold = Median Popularity (43)

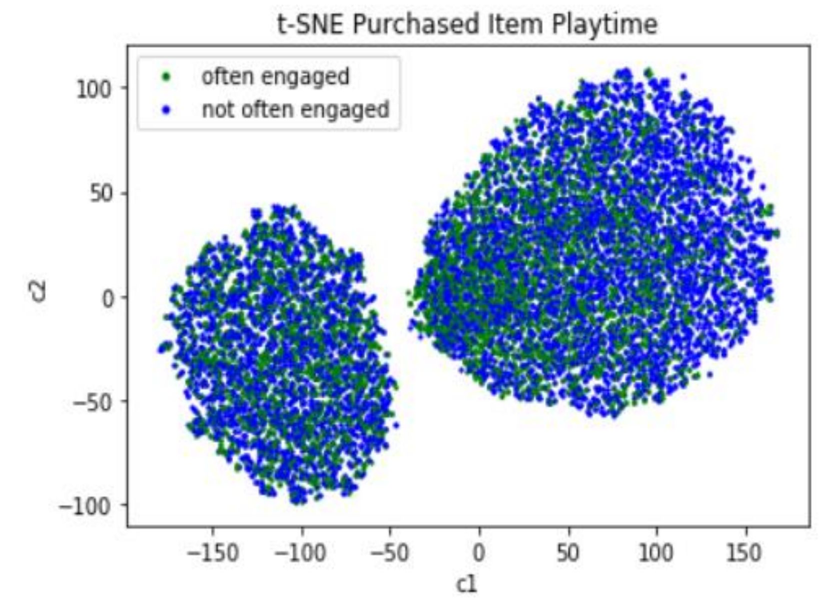


Figure 5: t-SNE for purchased items engagement Engaged if Mean Playtime < Median Playtime

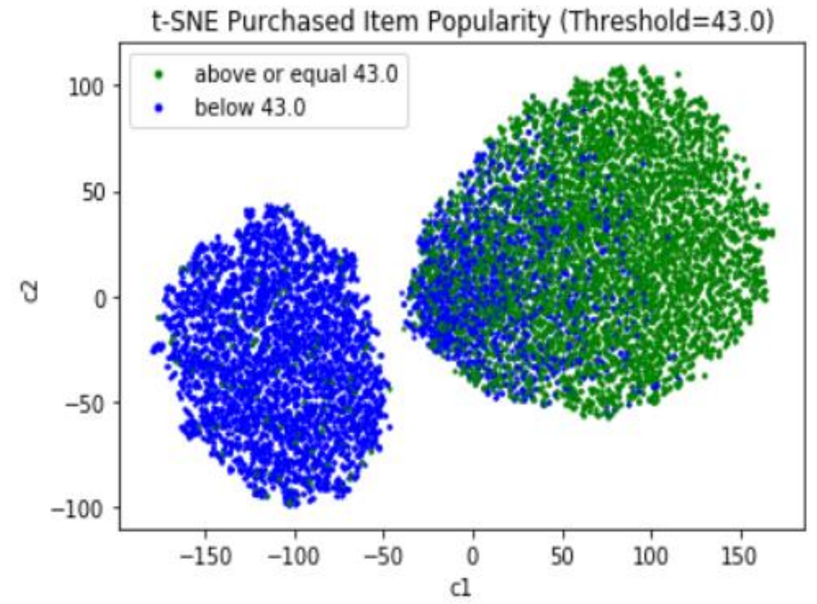


Figure 6: t-SNE for purchased items popularity Popularity Threshold = Median Popularity (43)

RESULTS

Model	Objective	Accuracy
Logistic Regression	Predict Playtime with Implicit Feedback	91.1%
BPR	Determine Whether a User will Purchase a Game	93.5%
BPR	Determine Whether a User will Play a Game	71.6%

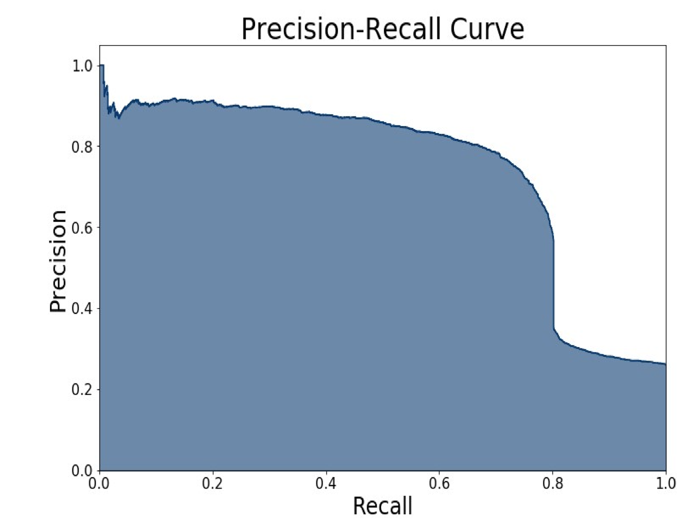


Figure 7: Precision-Recall curve for logistic regression model with all features.

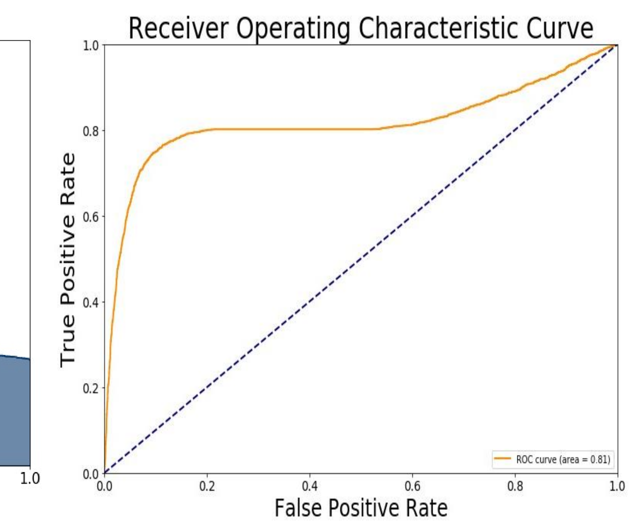


Figure 8: ROC curve for logistic regression model with all features.

The curves show that the logistic regression model is successful in predicting imbalanced classes (25% of games that are engaged with over all games owned).

DISCUSSION

- The logistic regression model in our approach shows that game genres have a large impact on predicting the user's engagement.
- The BPR performs **better** on predicting **user interest** (influence by *game popularity*) than predicting **user engagement** (influenced by *game playtime*).
- Our future work will focus on constructing a recommender system that combines both **BPR** and **feature engineering** and recommends users a list of games on the market which they are most likely to engage with in the future.

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