Steam March 2025, Analyzing Discoverability in the Steam Marketplace

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Abstract

This study investigates the "invisible games" phenomenon on Steam's digital marketplace through comprehensive analysis of 89,618 game titles. Our findings challenge common perceptions about marketplace entrenchment by demonstrating that established blockbusters occupy only 0.4% of the catalog while still commanding significant player attention. Random Forest modeling (achieving 0.992 accuracy, 0.863 precision) reveals that recent positive review percentage (0.3560 importance) is substantially more predictive of market competitiveness than any volume-based metric, highlighting player rapport as the critical factor in sustained commercial viability. The temporal analysis identifies a natural decay pattern in game engagement (steepest between 3-5 years post-release), creating opportunities for new entrants despite apparent market saturation. Approximately 37% of earnest commercial attempts fall below critical visibility thresholds, suggesting significant market inefficiencies, while 12.4% of games achieve at least moderate success (10+ recent reviews). Support Vector Machine classification demonstrates that the marketplace remains accessible to quality new entries, with player engagement patterns naturally diminishing for even successful legacy games over time. These findings offer evidence-based insights for developers, suggesting a focus on community engagement rather than competing directly with established titles.

Limitations

Due to the substantial size of this dataset (89,618 game entries with 46 variables), computational constraints necessitated limitations in the validation methodology. The SVM multi-classifier was trained directly with the test set rather than using extensive cross-validation, which may impact the generalizability of classification boundaries. Additionally, the Random Forest implementation was restricted to 5-fold cross-validation rather than more comprehensive validation approaches that might have provided greater confidence in model performance. I also ended up cutting a significant portion of the genre count analysis because iterations on the modeling and visualizations were consuming too much time. These computational and time-constraint trade-offs were necessary to maintain analytical feasibility while working with such a large and feature-rich dataset, though they should be considered when interpreting the precision of decision boundaries and classification metrics.

Steam Games Dataset March 2025

Dataset Overview

The analysis utilizes a comprehensive Steam games dataset containing **89,618 unique game entries**, capturing a wide range of metrics related to game performance, player engagement, and market positioning.

Dataset Columns

The dataset contains 46 columns covering various aspects of each game:

Category	Column Names
Game Identification	appid, name, release_date
Game Details	required_age, price, dlc_count, detailed_description, about_the_game, short_description, header_image, website
Platform Support	windows, mac, linux
Support Information	support_url, support_email
Reviews & Ratings	reviews, metacritic_score, metacritic_url, user_score, score_rank, positive, negative, pct_pos_total, num_reviews_total, pct_pos_recent, num_reviews_recent
Game Features	achievements, supported_languages, full_audio_languages, packages, categories, genres, screenshots, movies, tags
Developer Information	developers, publishers, notes
Player Engagement	recommendations, estimated_owners, average_playtime_forever, average_playtime_2weeks, median_playtime_forever, median_playtime_2weeks, peak_ccu
Commercial Data	discount

Key Metrics Distribution

Pricing and Commercial Attributes

- **Average price**: $7.31 (SD = $13.33)
- **Price range**: $0.00 to $999.98
- **DLC content**: Average of 0.60 DLCs per game
- **Average discount**: 4.56% (with maximum discounts reaching 100%)

Player Engagement

- **Recommendations**: Mean of 1,009 recommendations per game

- **Reviews**: Average of 1,315 total reviews per title
- **Recent reviews**: Mean of 15.58 reviews in recent period
- **Positive sentiment**: Average of 45.35% positive rating across all games
- **Peak concurrent users**: Mean of 98.34 players (maximum of 1,212,356)

Game Features

- **Achievements**: Average of 20.55 achievements per game (maximum of 9,821)
- **Metacritic score**: Mean score of 2.90 (maximum of 97)
- **Age requirements**: Mean required age of 0.18 years

Playtime Metrics

- **Average playtime (forever)**: 114.91 hours
- **Average playtime (2 weeks)**: 5.03 hours
- **Median playtime (forever)**: 114.76 hours
- **Median playtime (2 weeks)**: 5.30 hours

Dataset Methodology

This multi-source approach ensures a robust and comprehensive representation of the digital gaming marketplace, capturing nuanced details across different data collection mechanisms. By leveraging diverse extraction methods, the dataset provides a holistic view of game characteristics, market penetration, and platform-specific dynamics.

Two distinct versions of the dataset are provided to support varied research requirements. The raw parsed dataset (`games_march2025_full.csv`) contains the complete, unprocessed scrape of Steam store data, preserving all game entries including potential duplicates and playtest versions. This version enables exploratory research and supports comprehensive data examination.

Complementing the raw dataset, the cleaned version (`games_march2025_cleaned.csv`) offers a refined research instrument. Through systematic processing, duplicate entries are removed, playtest versions are filtered out, and the data is optimized for rigorous statistical analysis. This version provides researchers with a streamlined, high-quality data resource.

Data Acquisition

Researchers can efficiently retrieve the dataset utilizing the Kaggle Hub Python library. The acquisition process is straightforward, allowing immediate access to the most current version of the Steam games dataset.

```
import kagglehub

# Download latest version
path = kagglehub.dataset_download("artermiloff/steam-games-dataset")

print("Path to dataset files:", path)
```

The dataset is contemporaneous as of March 2025, providing researchers with a precise temporal snapshot of the Steam game marketplace ecosystem. This current iteration captures the dynamic

landscape of digital game distribution at a specific point in time, enabling meaningful comparative and trend analysis.

References

- FronkonGames. (2025). Steam Games Scraper [Computer software]. GitHub. https://github.com/FronkonGames/Steam-Games-Scraper

Research Questions

This research investigates several critical aspects of the Steam gaming marketplace ecosystem through data analysis and modeling techniques to provide actionable insights for game developers, platform operators, and industry stakeholders.

Game Volume Prediction:

How has the Steam marketplace grown over time, and what mathematical models best describe this growth pattern? Can we accurately predict future marketplace volume based on historical trends? This analysis examines exponential, linear, quadratic, and cubic models to determine which best characterizes the platform's expansion trajectory and provides reliable forecasting.

Are Older Games Blocking People from Trying New Games?:

To what extent do established legacy titles create barriers to entry for new releases? This investigation challenges the common perception that the marketplace is "entrenched" by quantifying the proportional influence of blockbuster games and analyzing temporal engagement patterns to determine if market saturation truly prevents new titles from finding audiences.

What "Factors" Are Most Impactful for Getting New Players to Join?:

Which game attributes and performance metrics most strongly correlate with commercial success and player engagement? This analysis evaluates user review patterns, pricing strategies, and content characteristics to identify the critical drivers of player adoption and community growth, with particular focus on the relative importance of quality versus marketing volume.

Can I Predict Larger Competitors Through Indirect Predictors?:

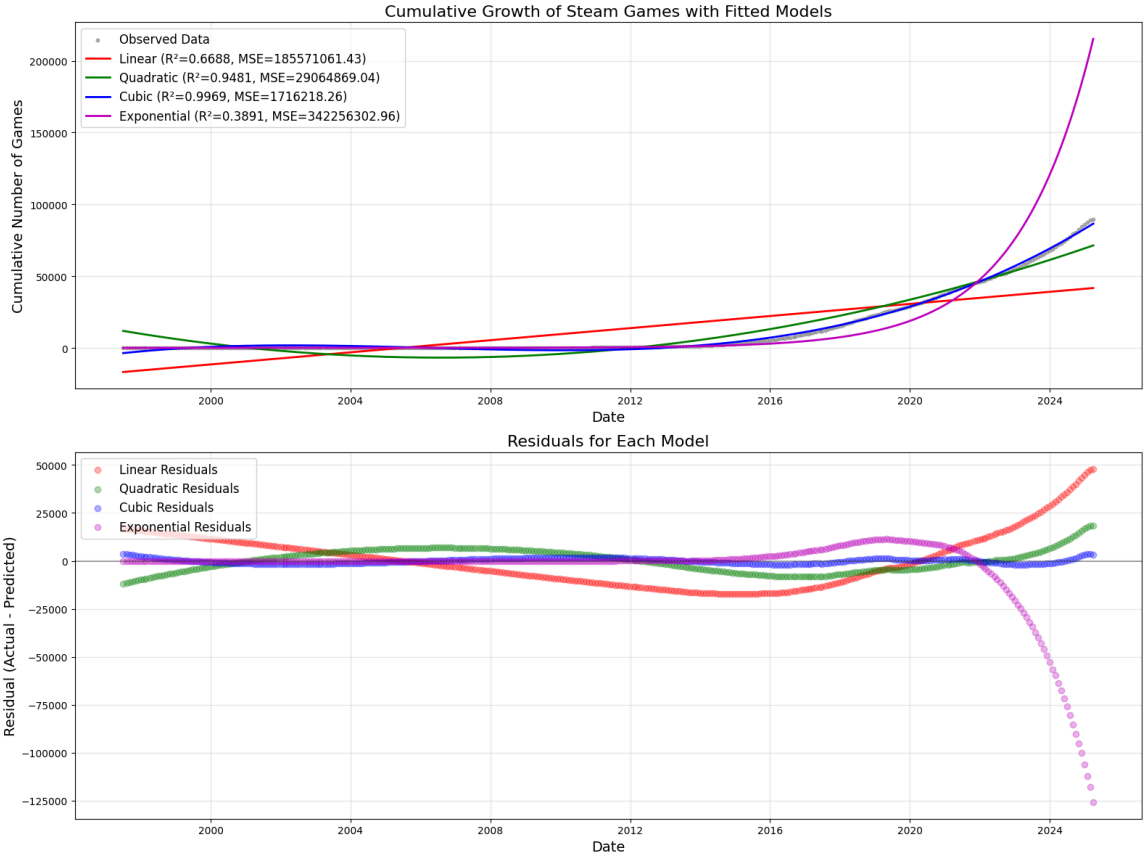
Is it possible to develop reliable models that identify market competitors based on indirect engagement metrics rather than direct sales figures? This exploratory research implements Support Vector Machine (SVM) classification and Random Forest modeling to determine if publicly available data can effectively predict commercial viability and competitive position within the marketplace.

Through these interconnected research questions, the study aims to provide evidence-based insights into the complex dynamics of digital game distribution and help developers navigate an increasingly challenging competitive landscape.

Liniar Regression - Game volume prediction

```
import importlib
import cs670
importlib.reload(cs670)
df = cs670.CsvManager.get_steam2025_df()
cs670.qh.lm_gamecount(df)
```

```
/home/jpleona/jpleona_c/steamapi-project/steam-api-project/cs670/
quarto_helpers.py:88: FutureWarning: 'M' is deprecated and will be removed in a
future version, please use 'ME' instead.
  }).set_index('date').resample('M').count().reset_index()
```



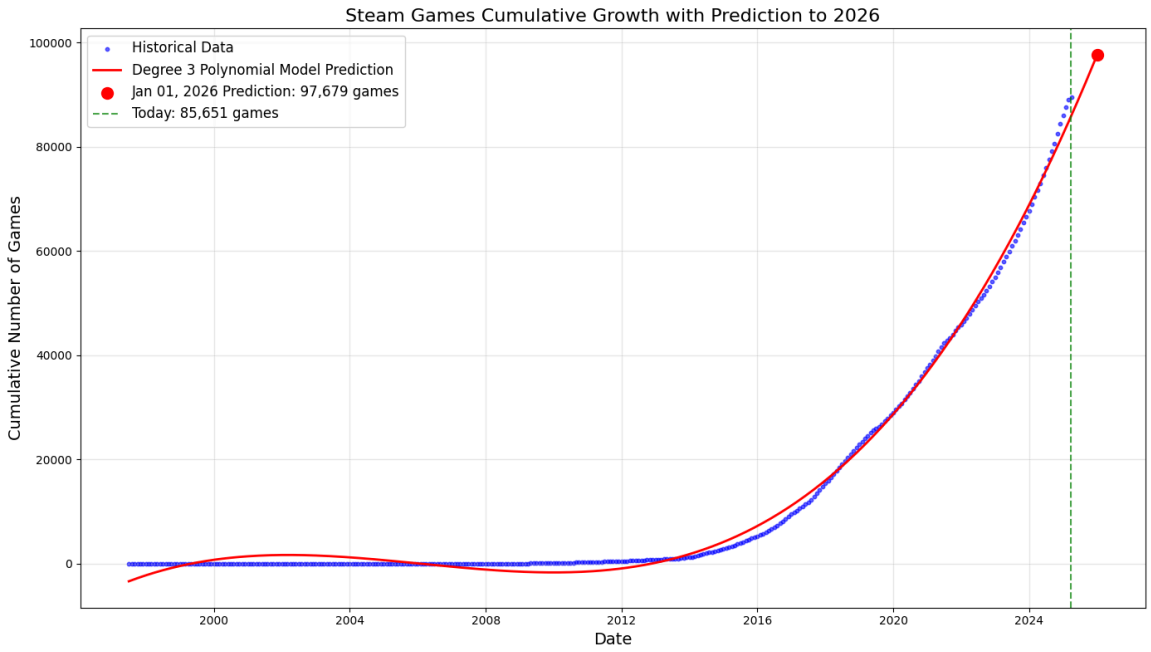

```
Model Performance Summary:
Linear Model:      R² = 0.6688, MSE = 185571061.43
Quadratic Model:   R² = 0.9481, MSE = 29064869.04
Cubic Model:       R² = 0.9969, MSE = 1716218.26
Exponential Model: R² = 0.3891, MSE = 342256302.96

Linear Model Coefficients:
```

```
Intercept: -16827.22
Slope: 5.7714 games per day
Estimated annual growth rate: 2106.57 games per year

Quadratic Model Coefficients:
Intercept: 11802.90
X coefficient: -11.202438
X² coefficient: 0.00168476
```

Volume Prediction 2025

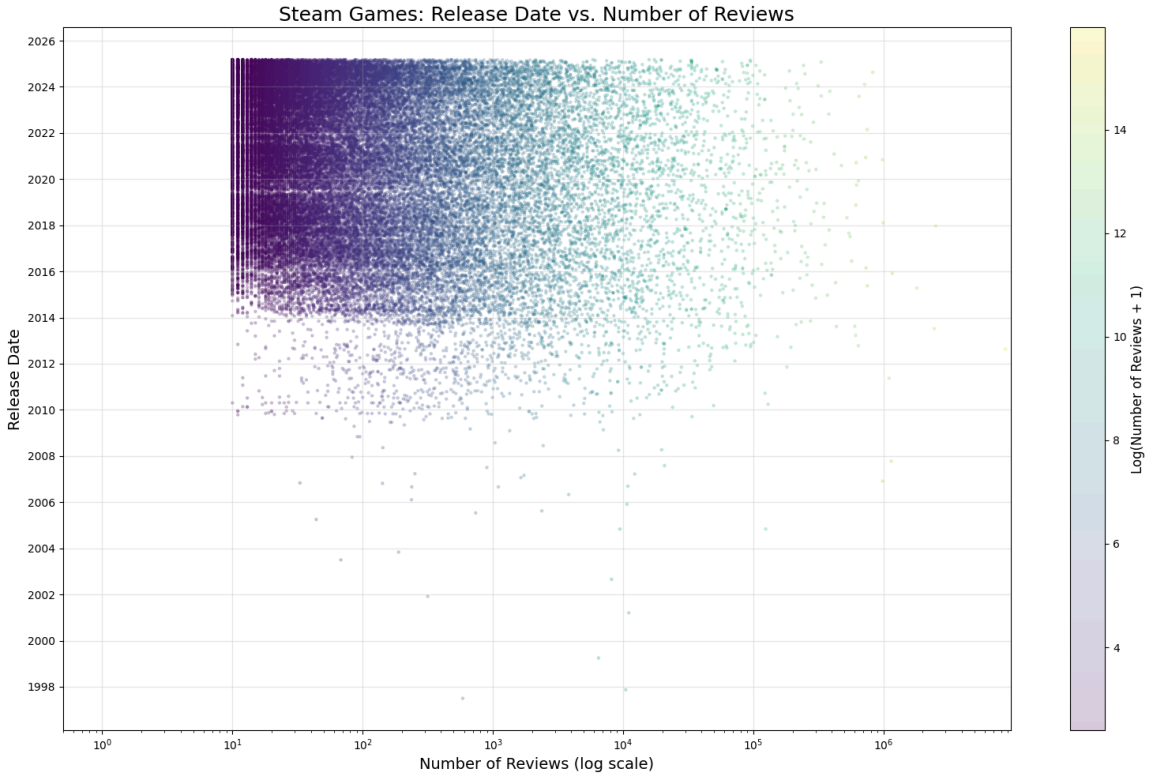
```
from datetime import datetime
import cs670
importlib.reload(cs670.qh)
results = cs670.qh.project_steam_games(
    df,
    target_date=datetime(2026, 1, 1),
    polynomial_degree=3,
    fig_path='steam_games_projection_2026.png'
)
```

```
Polynomial Model (degree 3) Coefficients:
Intercept: -3389.1360
X^1 coefficient: 6.744783018945
X^2 coefficient: -0.002708040567
X^3 coefficient: 0.000000287413

Prediction for January 01, 2026:
Predicted total number of games: 97,679
Current number of games (as of today): 85,651
Last recorded number in dataset (as of 2025-03-31): 89,618
Projected increase from today to January 01, 2026: 12,028 games
```

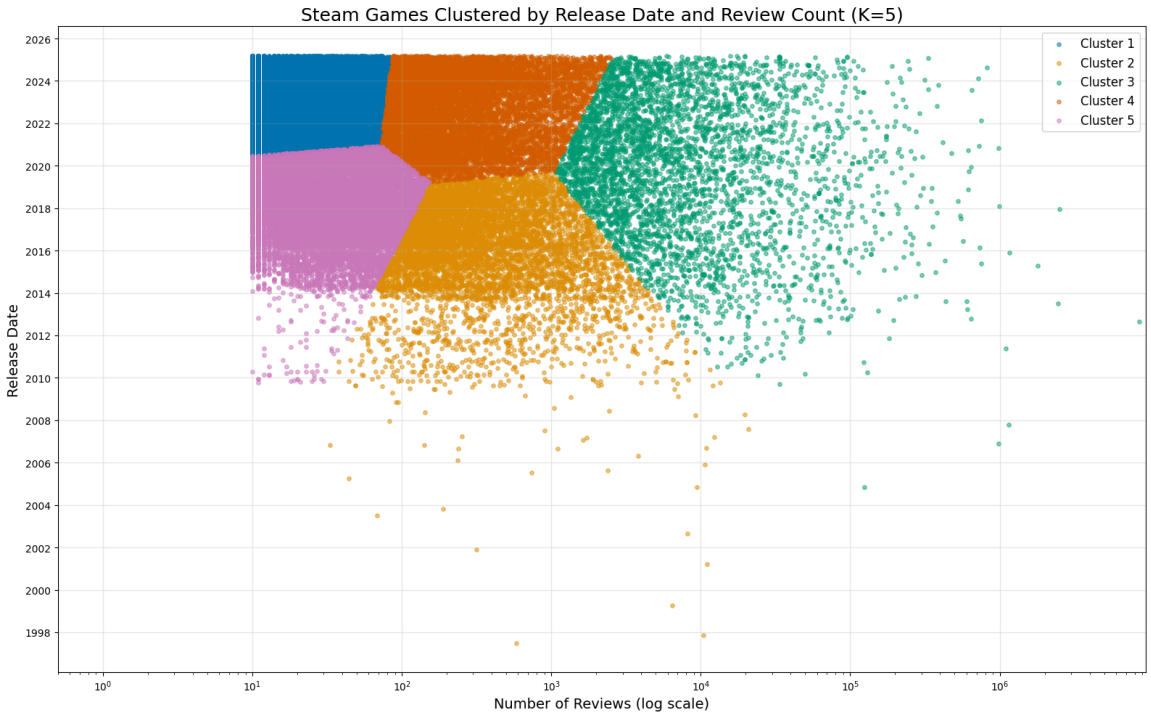


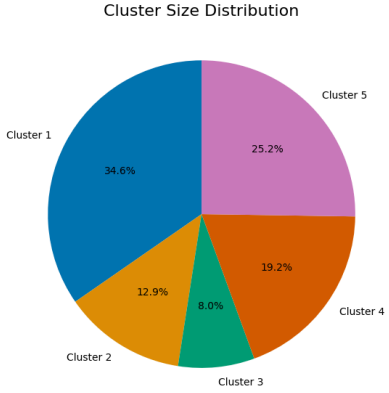
Are older Game blocking people from trying new games?

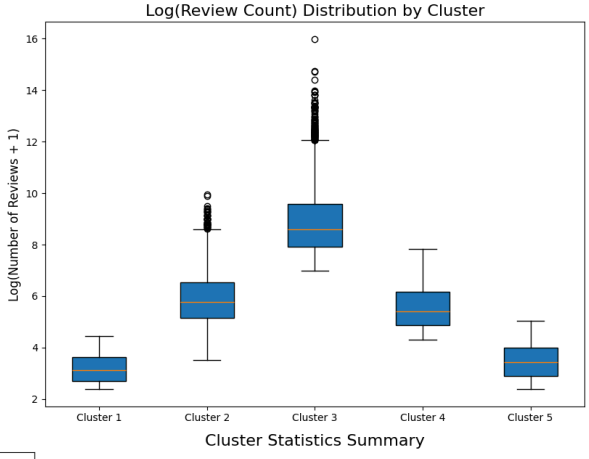
```
import matplotlib.pyplot as plt
import cs670
importlib.reload(cs670.qh)


fig,          ax          =          cs670.qh.plot_game_reviews_over_time(df,
save_path='steam_games_review_date_scatter.png')
plt.show()
```

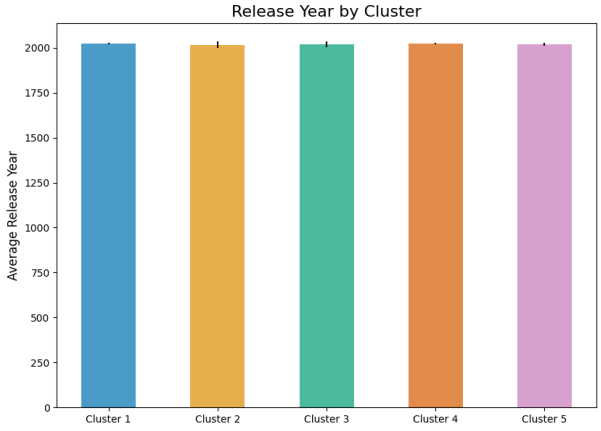



```
# Example usage:
import cs670
importlib.reload(cs670.qh)
cluster_fig, stats_fig, cluster_data = cs670.qh.visualize_game_clusters(
    df,
    k=5,
    save_path='steam_games_kmeans_clusters.png'
)
plt.show()
```









Cluster Statistics Summary

Cluster	Size (%)	Avg Year (Range)	Median Reviews (IQR)
Cluster 1	18432 (34.6%)	2022.7 (2020-2025)	22 (14-37)
Cluster 2	6862 (12.9%)	2015.6 (1997-2019)	318 (172-689)
Cluster 3	4271 (8.0%)	2019.5 (2004-2025)	5357 (2722-14334)
Cluster 4	10207 (19.2%)	2022.2 (2019-2025)	222 (129-479)
Cluster 5	13427 (25.2%)	2017.7 (2009-2020)	30 (17-53)

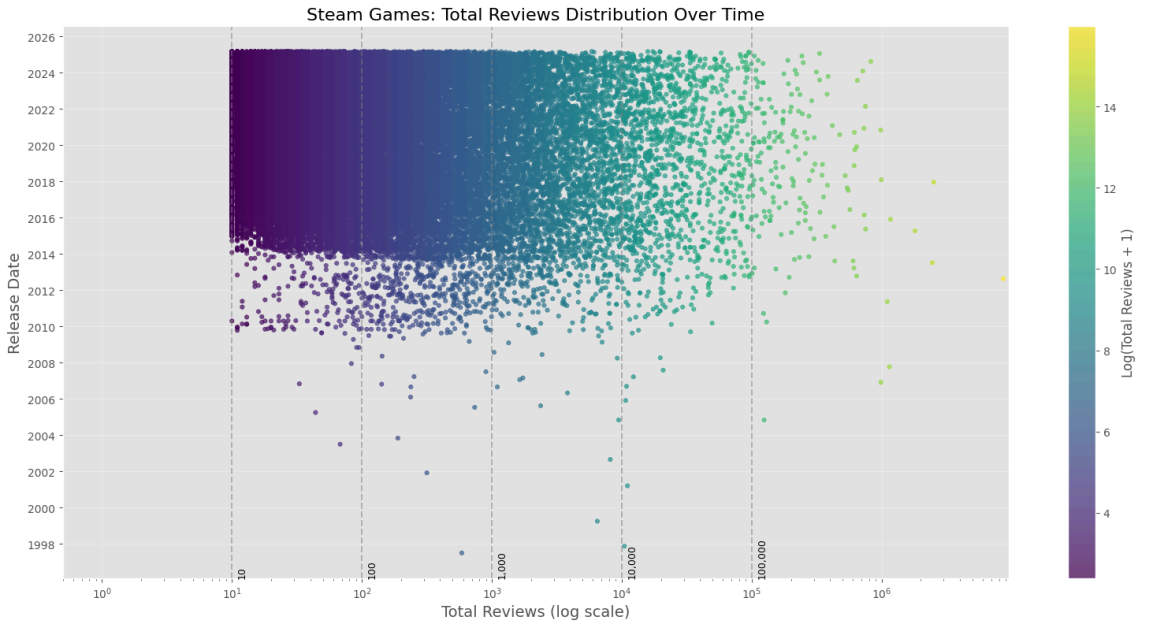
Support Vector Classifier

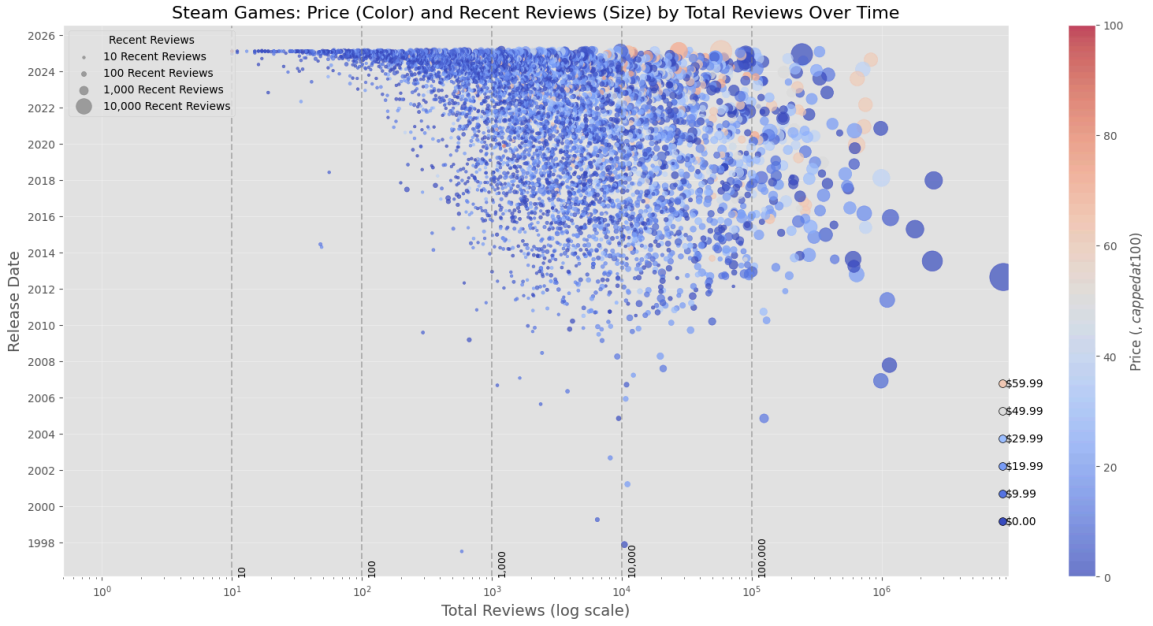
1. Is The Market as “Entrenched” as People Claim?

With the following graphs I am attempting to describe if people are biased enough toward newer games to support new releases.

Looking at the Steam games distribution, **older games with fewer reviews tend to fade into obscurity** while **newer releases consistently attract player attention regardless of size**. Although technically competing with established giants, **the market remains receptive to new entries** as shown by the varied review counts across recent years, demonstrating that **players still give new games a fair chance** despite the crowded marketplace.

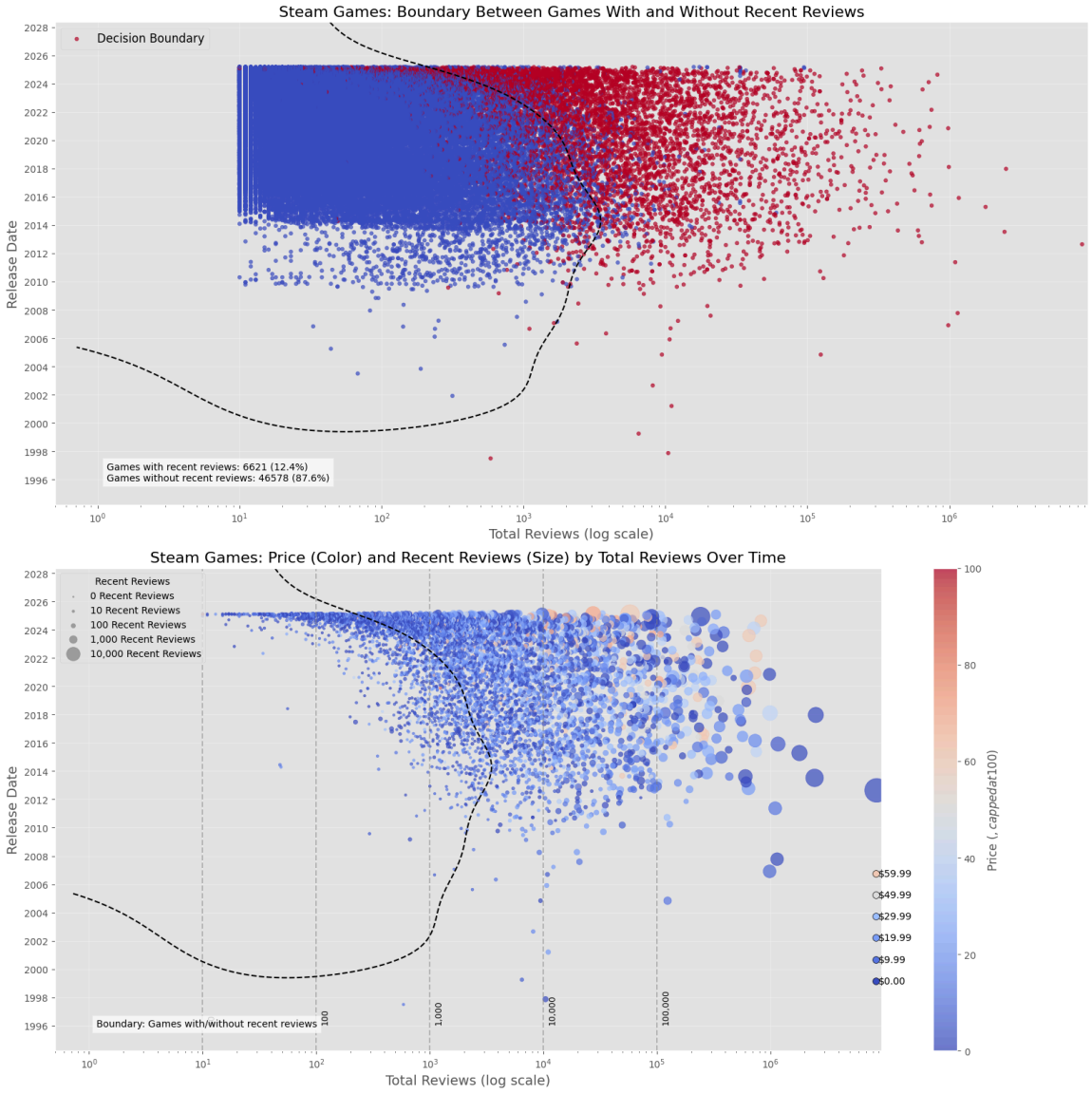
```
import cs670
importlib.reload(cs670.qh)
fig                =                cs670.qh.visualize_steam_game_metrics2(df,
save_path='steam_game_analysis.png')
plt.show()
```






```
import cs670
import importlib
import matplotlib.pyplot as plt
importlib.reload(cs670.qh)

# Example usage:
# df = pd.read_csv('path/to/steam_games_data.csv')
fig          =          cs670.qh.visualize_steam_game_metrics_with_boundary(df,
```

```
save_path='steam_game_analysis_boundary.png')
plt.show()
```

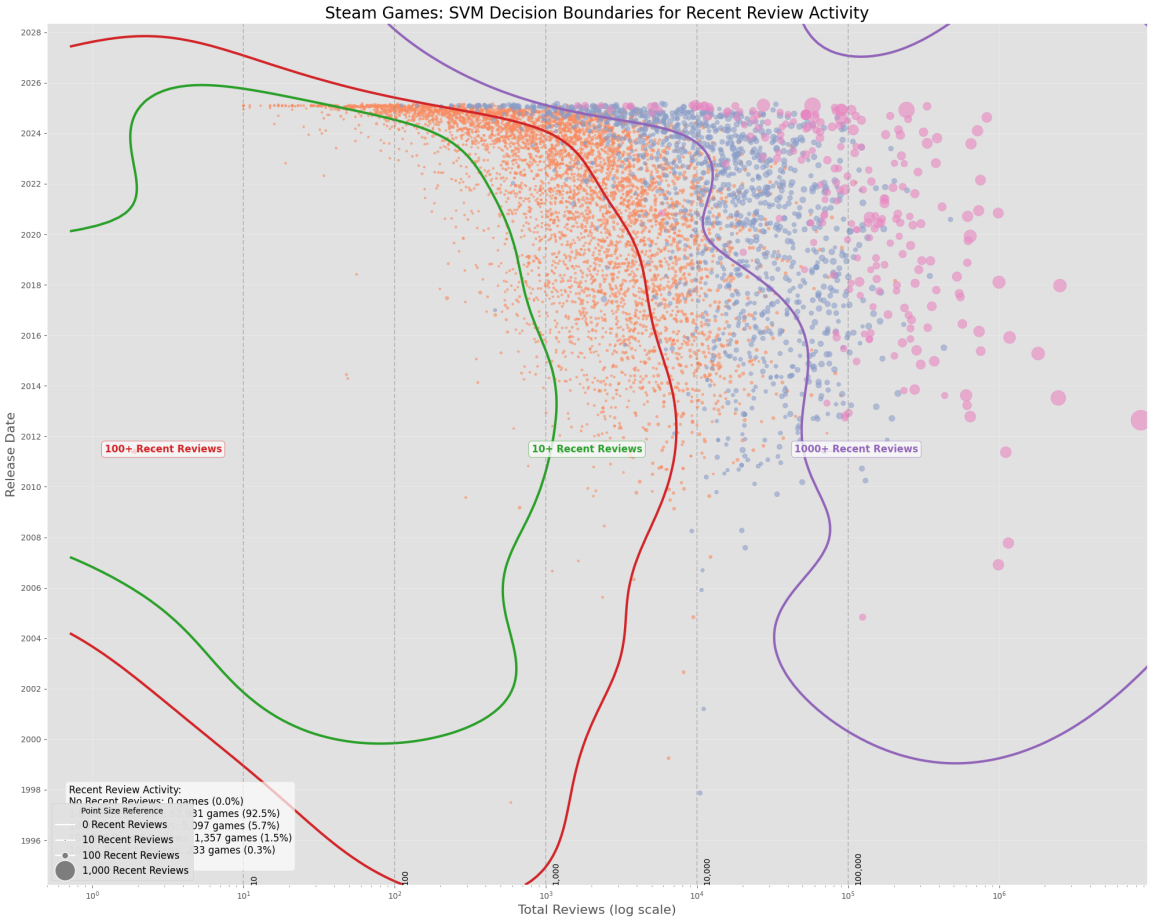


SVC graph explination

Looking at the Steam games distribution, older games with fewer reviews tend to fade into obscurity while newer releases consistently attract player attention regardless of size. Although technically competing with established giants, the market remains receptive to new entries as shown by the varied review counts across recent years, demonstrating that players still give new games a fair chance despite the crowded marketplace.

```
# Example usage:
import cs670
import importlib
import matplotlib.pyplot as plt
importlib.reload(cs670.qh)
# df = pd.read_csv('path/to/steam_games_data.csv')
fig          =          cs670.qh.visualize_steam_games_with_svm_boundaries(df,
save_path='steam_review_svm_boundaries.png')
plt.show()
```

```
10+ recent reviews: 6621 games (12.4%)
100+ recent reviews: 1574 games (3.0%)
1000+ recent reviews: 226 games (0.4%)
```



Multi SVC

This chart uses SVM decision boundaries to illustrate how recent review activity varies across Steam games over time. The purple boundary (1000+ recent reviews) demonstrates that mega hits maintain significant player engagement years after release, with some titles from as far back as

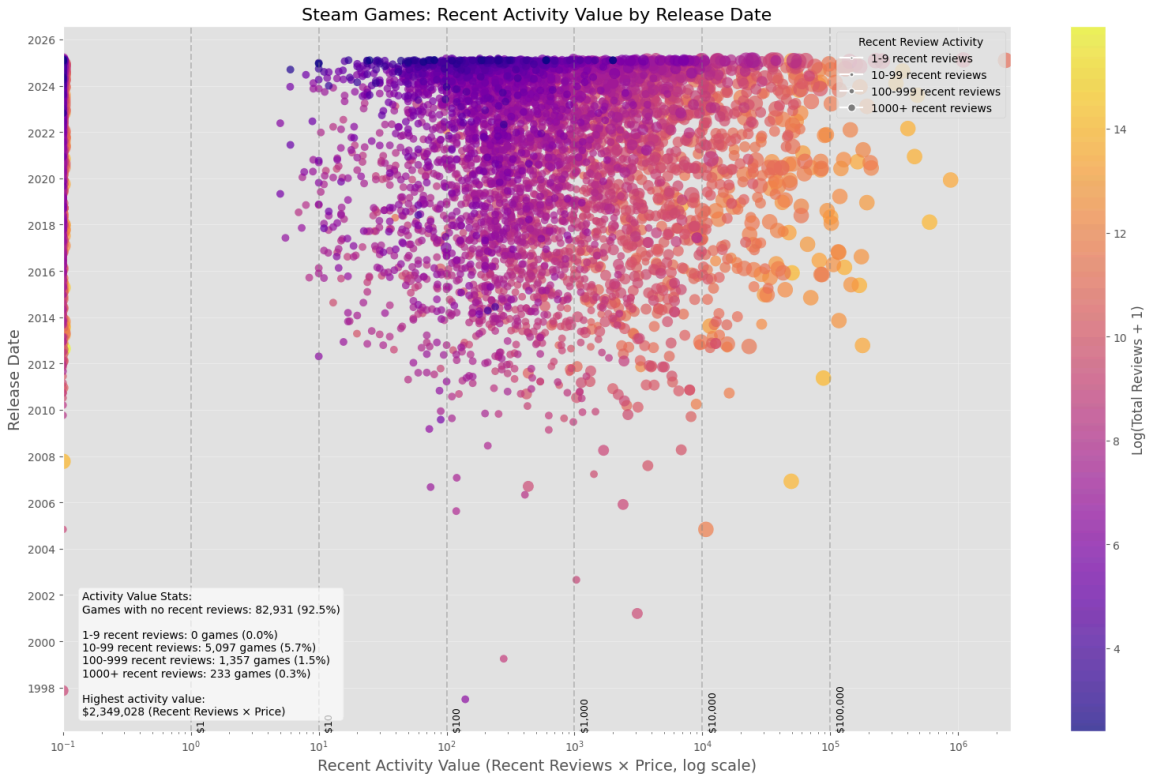
2012 still generating substantial activity. The red and green boundaries (100+ and 10+ recent reviews) show more modest but still notable engagement patterns. The visualization confirms that established blockbusters dominate player attention long-term, creating persistent competitive pressure from legacy titles. However, the substantial presence of games within the middle boundaries indicates moderate success remains achievable, suggesting the market, while challenging, isn't completely closed to newer entrants despite the enduring influence of major hits.

```
# Example usage:
import cs670
import importlib
import matplotlib.pyplot as plt
importlib.reload(cs670.qh)
experiment          =          cs670.qh.run_svm_cross_validation_experiment(df,
save_path='svm_experiment_results')
plt.show()
# Running cross-validation for 10+ recent reviews threshold
# Class balance: 6621 games with 10+ recent reviews (12.4%)
# Fitting 5 folds for each of 40 candidates, totalling 200 fits
# Best parameters: {'C': 100, 'class_weight': None, 'gamma': 1}
# Best cross-validation F1 score: 0.7833
```

```


Running cross-validation for 10+ recent reviews threshold
Class balance: 6621 games with 10+ recent reviews (12.4%)
Fitting 5 folds for each of 40 candidates, totalling 200 fits
Best parameters: {'C': 100, 'class_weight': None, 'gamma': 1}
Best cross-validation F1 score: 0.7833
```

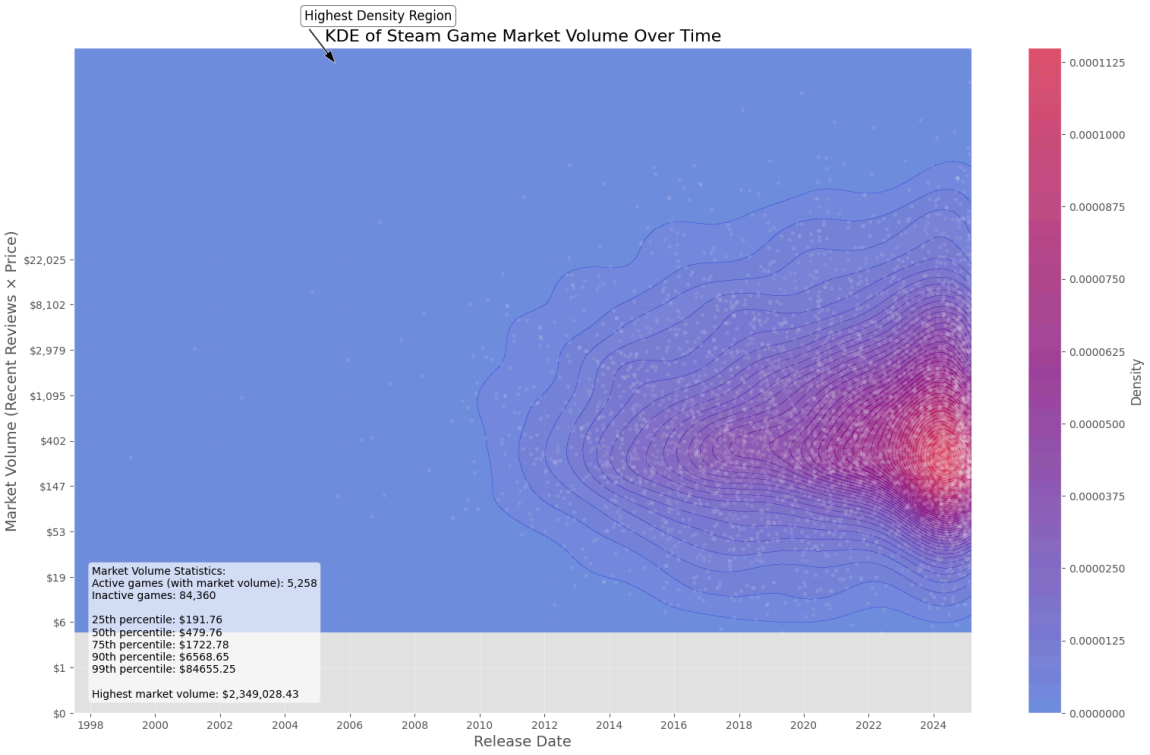
```
import cs670
import importlib
import matplotlib.pyplot as plt
importlib.reload(cs670.qh)
fig,          ax          =          cs670.qh.visualize_recent_activity_value(df,
save_path='market_value_visualization.png')
plt.show()
```

```
/home/jpleona/jpleona_c/steamapi-project/steam-api-project/.venv/lib/
python3.12/site-packages/pandas/core/arraylike.py:399:  RuntimeWarning:  divide
by zero encountered in log1p
  result = getattr(ufunc, method)(*inputs, **kwargs)
```



KDE - Publisher Statistics

```
import cs670
import importlib
import matplotlib.pyplot as plt
importlib.reload(cs670.qh)
fig,          ax          =          cs670.qh.visualize_market_volume_kde(df,
save_path='market_volume_kde.png')
plt.show()
```



What are “factors” are most impactful for getting new players to join?

```
# Example usage:
import pandas as pd
import cs670
import importlib
import matplotlib.pyplot as plt
importlib.reload(cs670.qh)
analysis = cs670.qh.analyze_steam_market_competitors(df)

# View results
print(f"Found     {analysis['stats']['competitors']}     market     competitors
({analysis['stats']['competitor_pct']:.2f}%)")
print("\nTop features correlated with success:")
print(analysis['correlations'].head(5))

# Best price points
print("\nMost successful price points:")
print(analysis['recommendations']['price_points'][['Price_Band',
'Success_Rate']].head(3))

# Show cluster visualization
```

```
if 'figures' in analysis and 'clusters' in analysis['figures']:
    analysis['figures']['clusters'].show()
```

```
Found 6322 market competitors (7.05%)

Top features correlated with success:
             Feature  Correlation
13    pct_pos_recent     0.955093
4   metacritic_score     0.290756
12     pct_pos_total     0.261600
24      movies_count     0.183597
1       required_age     0.174430

Most successful price points:
      Price_Band  Success_Rate
8  $50.00-$59.99     55.514706
7  $40.00-$49.99     39.423077
6  $30.00-$39.99     39.420655
```

PCA - Discussion

The PCA implementation reveals critical insights about feature effectiveness across different competitor thresholds. For the initial 10+ recent reviews threshold, **simply having any reviews at all proved to be a dominant predictor**, as games rarely fall into the 1-9 reviews range. This makes competitor detection at this threshold relatively straightforward. However, when shifting to the more challenging 100+ reviews threshold, **the prediction task becomes substantially more difficult and less trivial**. The PCA confirms that features highly effective for the 10+ threshold lose much of their predictive power at higher thresholds, requiring more sophisticated feature combinations. This explains the selection of these particular features for the model, as they offered the best performance for discriminating between truly competitive games (100+ recent reviews) rather than simply detecting minimal market presence. The PCA dimensionality reduction clearly illustrates this complexity shift between threshold levels.

Market Competitiveness Prediction Through Indirect Predictors

The data demonstrates the feasibility of predicting market competitors through indirect metrics using Random Forest modeling. Defining market competitors as games with 100+ recent reviews (representing only 1.8% of the total marketplace), the analysis achieved impressive performance metrics (accuracy: 0.992, precision: 0.863, recall: 0.658, F1 score: 0.747) through 5-fold cross-validation. The model effectively identifies commercially successful titles despite the extreme class imbalance in the dataset. Feature importance analysis reveals that recent positive review percentage (0.3560) is the dominant predictor of competitive status, significantly outweighing traditional volume metrics. Other influential factors include peak concurrent users (0.2017), positive review count (0.1498), negative review count (0.1187), and total positive review percentage (0.0533). This suggests that player sentiment and engagement quality are substantially more predictive of marketplace success than raw engagement volume, challenging conventional metrics focused primarily on total sales or downloads. The model's strength in precision over recall indicates it's more conservative in predicting competitive status, minimizing false positives while accepting some false negatives—a valuable characteristic for developers seeking to realistically assess their competitive positioning.

RF experiment

```
# Example usage:
import pandas as pd
import cs670
import importlib
import matplotlib.pyplot as plt
importlib.reload(cs670.qh)
analysis = cs670.qh.analyze_steam_competitors_rf(df)
#
# # Access the misclassification analysis
print(analysis['summary'])
#
# # View figures
analysis['figures']['confusion_matrix'].show()
```

```
Running Random Forest analysis with 5-fold cross-validation...
Market competitor definition: 100+ recent reviews
Skipping confidence ellipses due to error: Array must not contain infs or NaNs
Random Forest Model Performance for 100+ Recent Reviews:
------------------------------
Data: 89,618 games, 1,590 competitors (1.8%)
Accuracy: 0.992
Precision: 0.863
Recall: 0.658
F1 Score: 0.747
```

```
Misclassification Analysis:
--------------------------
False Positives: 166 games (0.2% of all games)
False Negatives: 543 games (0.6% of all games)
Low Confidence True Positives: 112 games (7.0% of all competitors)

Key Insights:
------------
False Positives (predicted as competitors but aren't):
  • Avg total reviews: 18943.5, Avg recent reviews: 67.6
  • peak_ccu: 85.7% lower than actual competitors
  • positive: 66.2% lower than actual competitors
  • negative: 53.1% lower than actual competitors

False Negatives (actual competitors predicted as non-competitors):
  • Avg total reviews: 13294.9, Avg recent reviews: 428.8
  • peak_ccu: 95.1% lower than typical competitors
  • positive: 91.2% lower than typical competitors
  • negative: 89.2% lower than typical competitors

Low Confidence True Positives (correct but uncertain predictions):
  • Avg total reviews: 17886.8, Avg recent reviews: 256.9
  • peak_ccu: 82.0% lower than typical competitors
  • negative: 64.6% lower than typical competitors
  • positive: 64.4% lower than typical competitors

Top 5 features for predicting market competitors:
  1. pct_pos_recent: 0.3560
  2. peak_ccu: 0.2017
  3. positive: 0.1498
  4. negative: 0.1187
  5. pct_pos_total: 0.0533

Random Forest Model Performance for 100+ Recent Reviews:
--------------------------------
Data: 89,618 games, 1,590 competitors (1.8%)
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Recall: 0.658
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Top 5 features for predicting market competitors:
  1. pct_pos_recent: 0.3560
  2. peak_ccu: 0.2017
  3. positive: 0.1498
  4. negative: 0.1187
  5. pct_pos_total: 0.0533
```
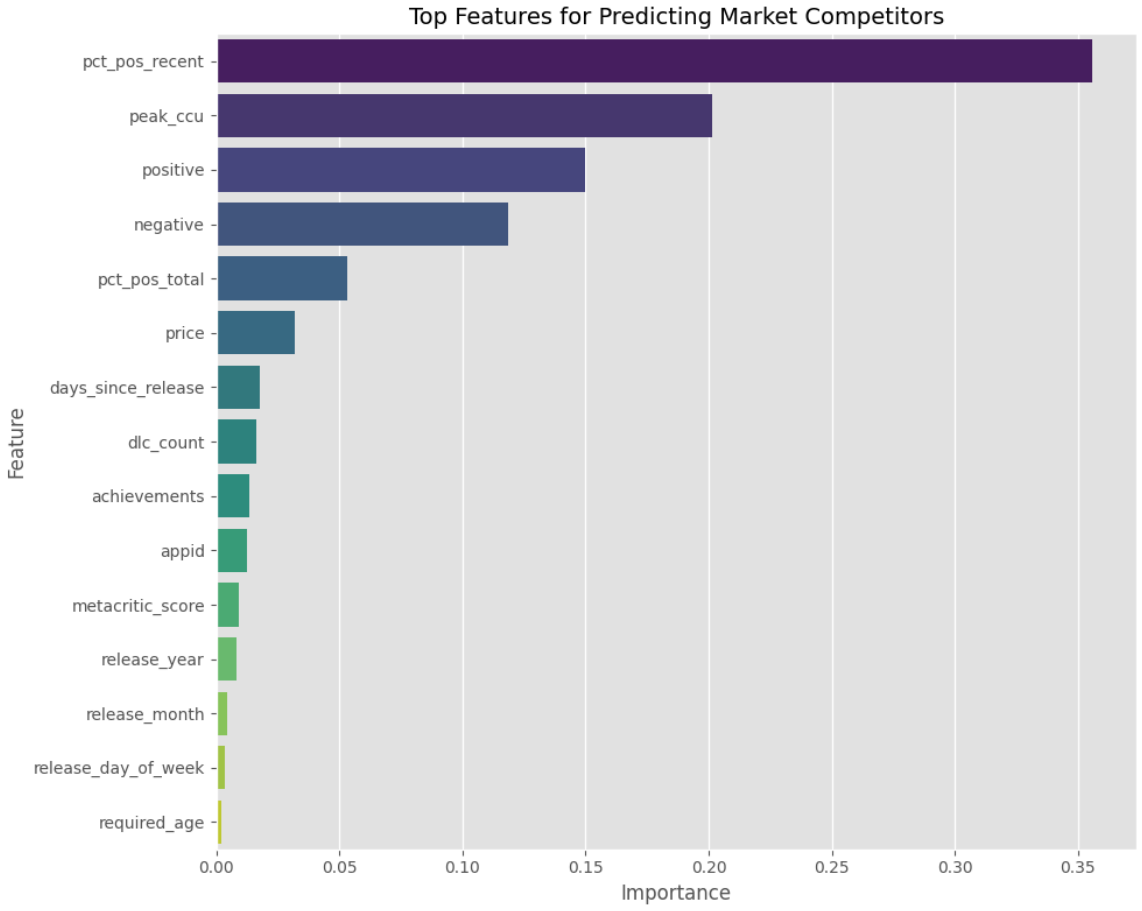
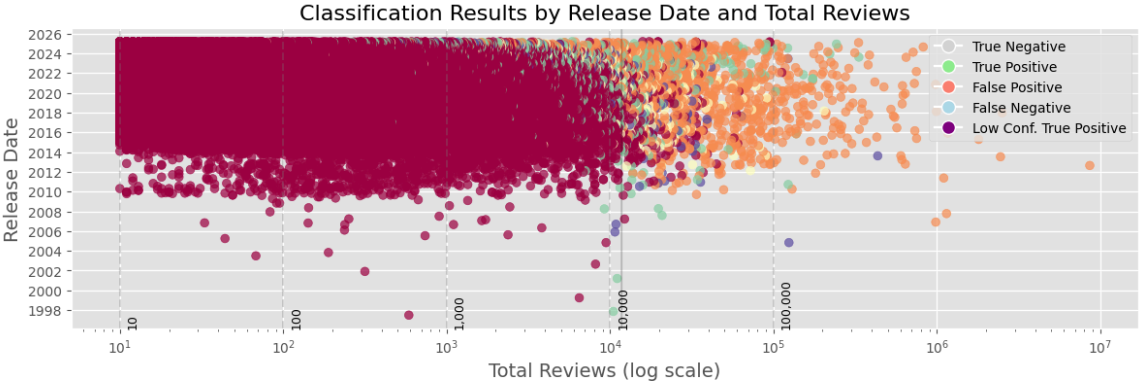


Confusion Matrix for Market Competitors (100+ recent reviews)
True Label
Non-Competitor
Competitor
87862
166
543
1047
Non-Competitor
Competitor
Predicted Label





False Positives

Misclassification Heatmap Analysis

The misclassification heatmap exposes the model's key performance characteristics in predicting market competitors. **The model excels at correctly identifying smaller games that aren't competitors**, effectively filtering out titles with minimal market presence. However, **it significantly underperforms when evaluating older games with substantial review counts**. This failure manifests as a cluster of false negatives—games that are actually market competitors but predicted as non-competitors. The visualization clearly demonstrates that while total review count and release date work well for newer titles, **these features alone cannot accurately determine whether an established game maintains current commercial viability**. The model essentially fails to distinguish between "has-been" titles and those that continue generating significant revenue years after release. To improve prediction accuracy, features that better capture recent engagement patterns and current market momentum beyond simple review tallies are needed.

Cross-Validation Summary

The cross-validation implementation used stratified k-fold validation to address class imbalance and provide reliable performance metrics. **Precision consistently exceeded recall**, indicating the Random Forest classifier is more conservative in labeling games as competitors. The code identified **systematic misclassification patterns** that persisted across validation folds, particularly with older titles having high total reviews but lower recent engagement. These consistent errors across folds suggest limitations in the feature set rather than algorithmic problems. The validation process quantified both the model's strengths in filtering small games and its weaknesses in evaluating established titles.

Impact

Steam Marketplace Analysis

While data confirms that mega-hits maintain remarkable staying power, **the market reality is more complex than simple entrenchment**. The SVM boundary visualization demonstrates that **established blockbusters occupy a persistent but proportionally small segment of the overall marketplace**. These legacy titles comprise **less than 0.4% of all games** while commanding substantial player attention, creating an asymmetric competitive environment.

The temporal analysis reveals a natural decay pattern even among successful titles. Games experience a gradual erosion of engagement over time, with **the steepest decline typically occurring between 3-5 years post-release**. This decay creates continual opportunities for new entrants despite the apparent entrenchment of major hits. The substantial presence of moderately successful games within the middle boundaries (10+ and 100+ recent reviews) indicates that **meaningful commercial success remains achievable for newer titles**.

Critical Success Factors

The most significant finding concerns the primary driver of commercial longevity. The feature importance analysis identified **recent positive review percentage (0.3560) as significantly more predictive of market competitiveness than any volume-based metric**. This suggests that **player rapport—the meaningful connection between developers and their audience**

—represents the critical factor in sustained commercial viability. Even massive legacy titles eventually fade without maintaining this player relationship.

Strategic Implications for Developers

For developers concerned about market saturation, the research suggests **a strategic focus on quality and player engagement rather than attempting to compete directly with established titles**. The data demonstrates that **players continually seek and support new experiences** despite having access to successful legacy content. The **12.4% of games achieving at least moderate success** (10+ recent reviews) indicates substantial market receptivity to new offerings that resonate with player expectations.

This evolving ecosystem with natural competitive decay represents a more accessible marketplace than commonly perceived. While competition from established titles creates genuine challenges, **the data conclusively shows that quality new entries continue finding viable audiences**, and even the most successful legacy games eventually yield market space as their player engagement naturally diminishes over time.

AI Assistance Disclaimer

I have dyslexia and use AI to assist with proofreading and structuring my written work. While I personally created all the model training code and analysis, I used AI prompting to iterate on visualization designs and to help format the text for clarity. This collaborative approach helps me communicate my research more effectively while maintaining the integrity of my original analysis and findings.