Can We Trust Consumer Ratings?

EXPLORING THE TRUTH BEHIND GAMESTOP REVIEWS

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INTRODUCTION

The rise of online retail has amplified the importance of consumer reviews in influencing purchasing decisions. In the gaming industry, where new products are constantly introduced and consumer expectations are high, understanding these reviews can provide crucial insights for retailers and developers. This project utilizes a dataset of product reviews from GameStop, a leading figure in the retail gaming sector. The dataset comprises various attributes of reviews, including user ratings, recommendations, and textual feedback from consumers.

The motivation for this project stems from the need to explore beyond mere numerical ratings, delving into the subtleties of what truly influences a consumer to recommend a product. This involves not only analyzing the text of the reviews to gauge sentiment but also correlating these sentiments with the given ratings to identify patterns that may not be immediately apparent from ratings alone.

KEY AUDIENCES

Product Developers and Designers in the Gaming Industry

Insights into what features or aspects of games are highlighted in positive or negative reviews can guide future product development.

Retail Managers and Executives

Individuals in managerial or executive roles within retail companies, especially those in the gaming sector, would find the insights in this project valuable for making informed decisions about product placements, promotions, and customer engagement strategies.

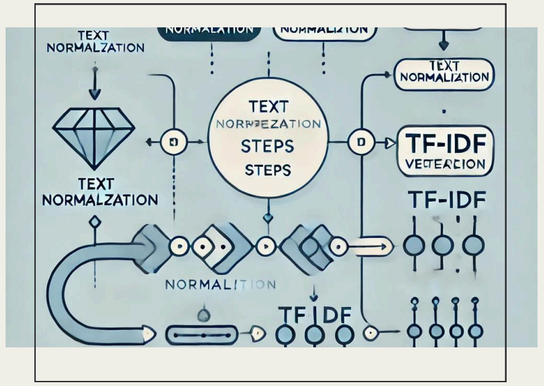
Marketing Professionals

Marketers can use the insights to craft targeted campaigns and understand better how consumer sentiment impacts brand loyalty and product popularity.

EXECUTIVE SUMMARY

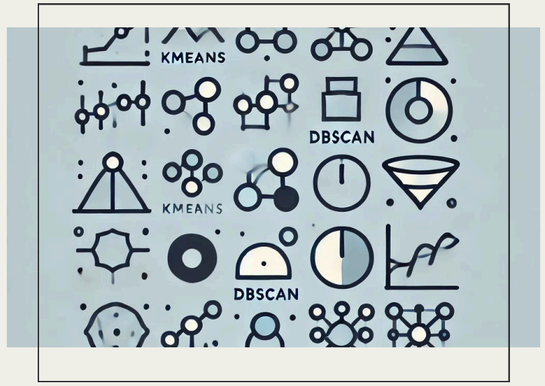
Objective

Identify patterns in consumer behavior and assess the reliability of review ratings as indicators of product recommendations.



Methodology

Employed data preprocessing, TF-IDF vectorization, and machine learning techniques (KMeans, DBSCAN, ensemble models)



Findings

High ratings do not always correlate with positive recommendations, challenging traditional views on consumer feedback.

Impact

Offers actionable insights for retailers to improve marketing strategies and product positioning.

METHODOLOGIES

The analysis began with the initial data import from a comprehensive CSV file containing thousands of reviews. After data cleaning, involving the removal of duplicates and handling missing values to ensure the integrity of the analyses, the text data from reviews underwent extensive preprocessing to convert unstructured text into a structured form.

PREPROCESSING

TOKENIZATION	REMOVAL OF STOPWORDS	LEMMATIZATION
Splitting text into meaningful units such as words.	Eliminating common words that add no significant value to text analysis.	Reducing words to their base or root form.

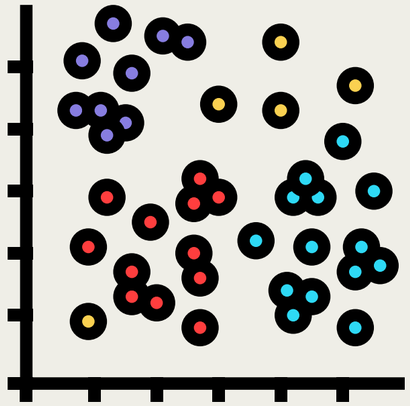
NEXT

Following preprocessing, the text data was vectorized using the Term Frequency-Inverse Document Frequency (TF-IDF) technique, which helps in emphasizing words that are more relevant to the context of the reviews.

STATISTICAL TECHNIQUES AND MACHINE LEARNING MODELS

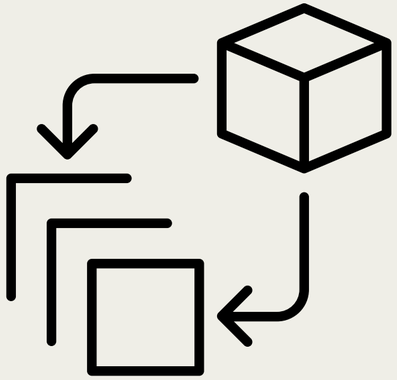
Clustering Analysis

KMeans and DBSCAN were used to identify inherent groupings within the data that signify different patterns in consumer reviews.



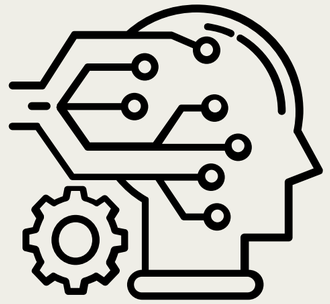
Dimensionality Reduction

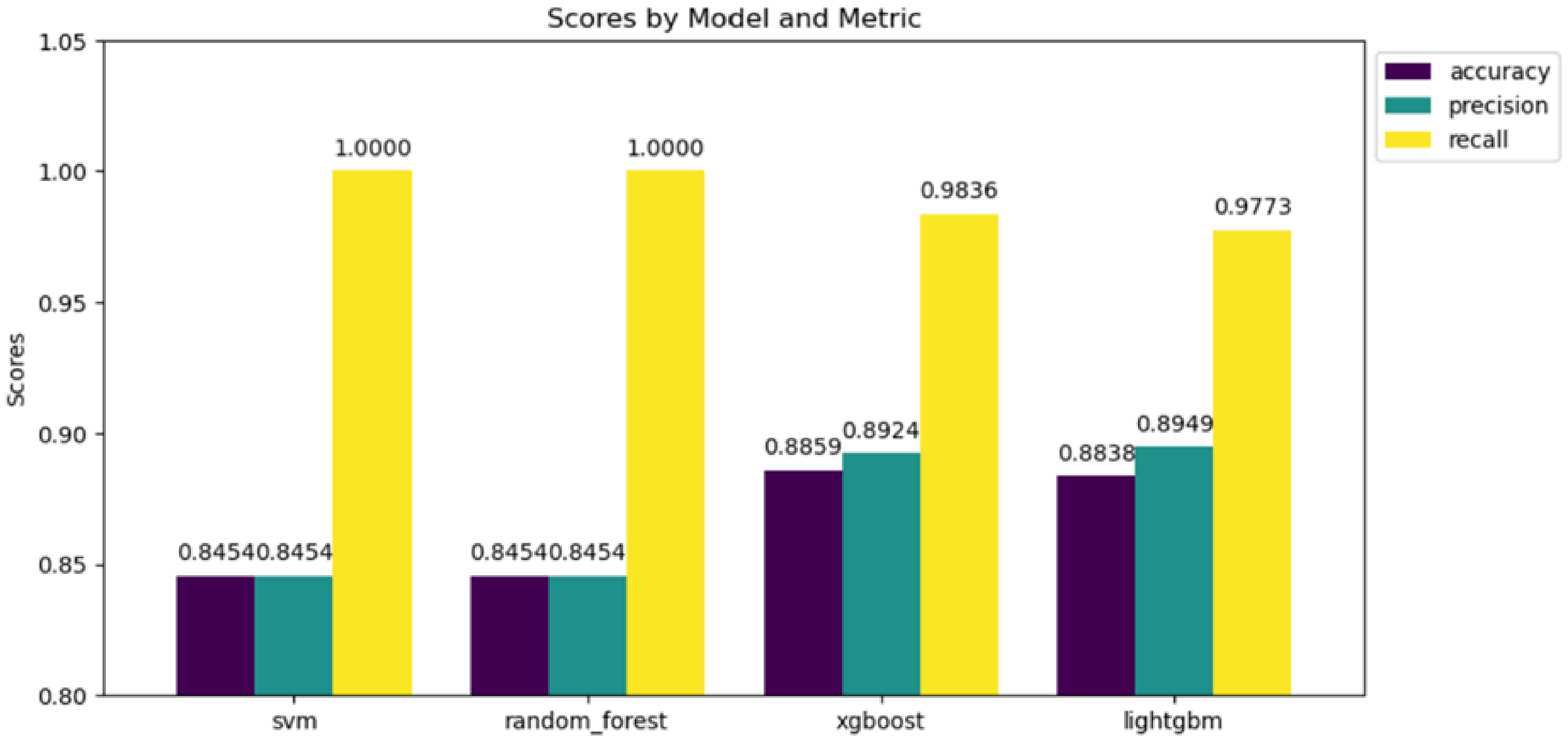
Principal Component Analysis (PCA) was conducted to reduce the number of variables and focus on the most informative aspects that influence review outcomes.

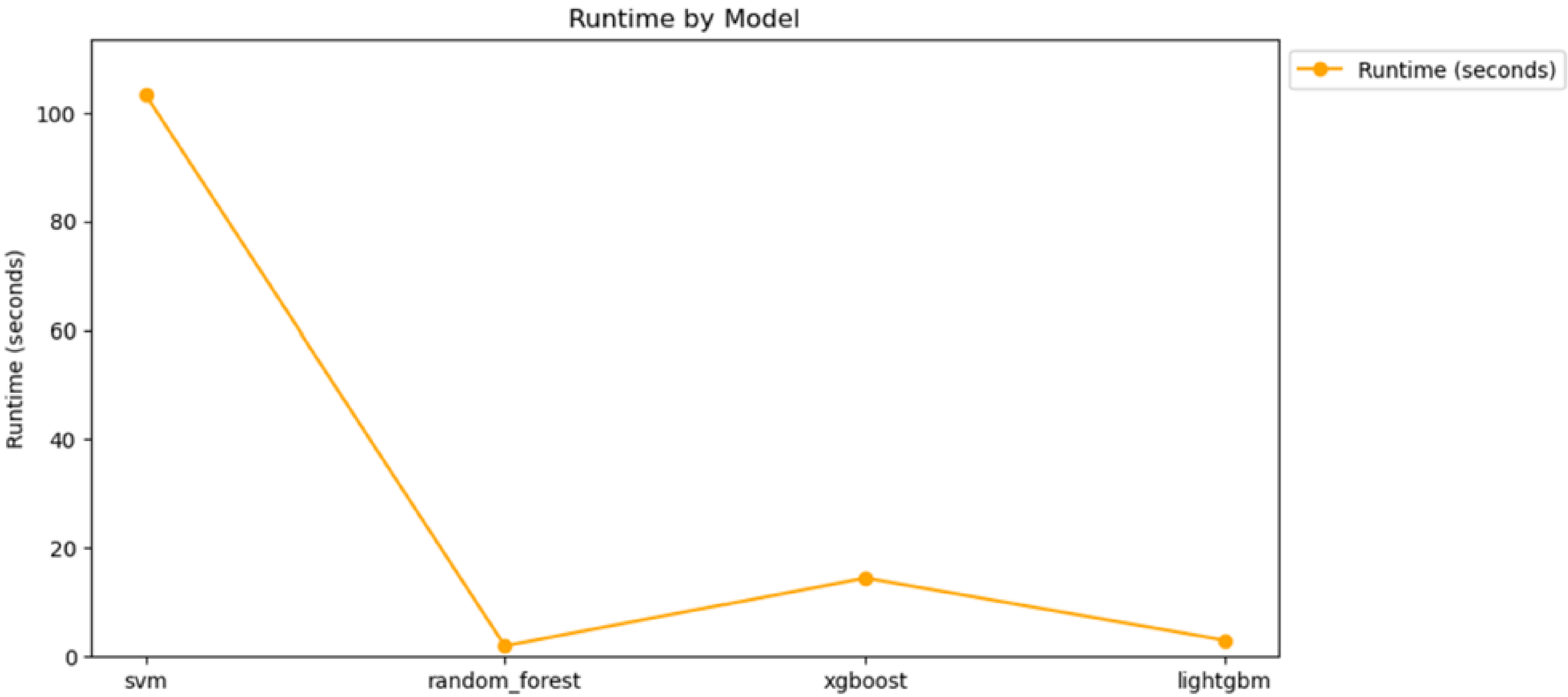


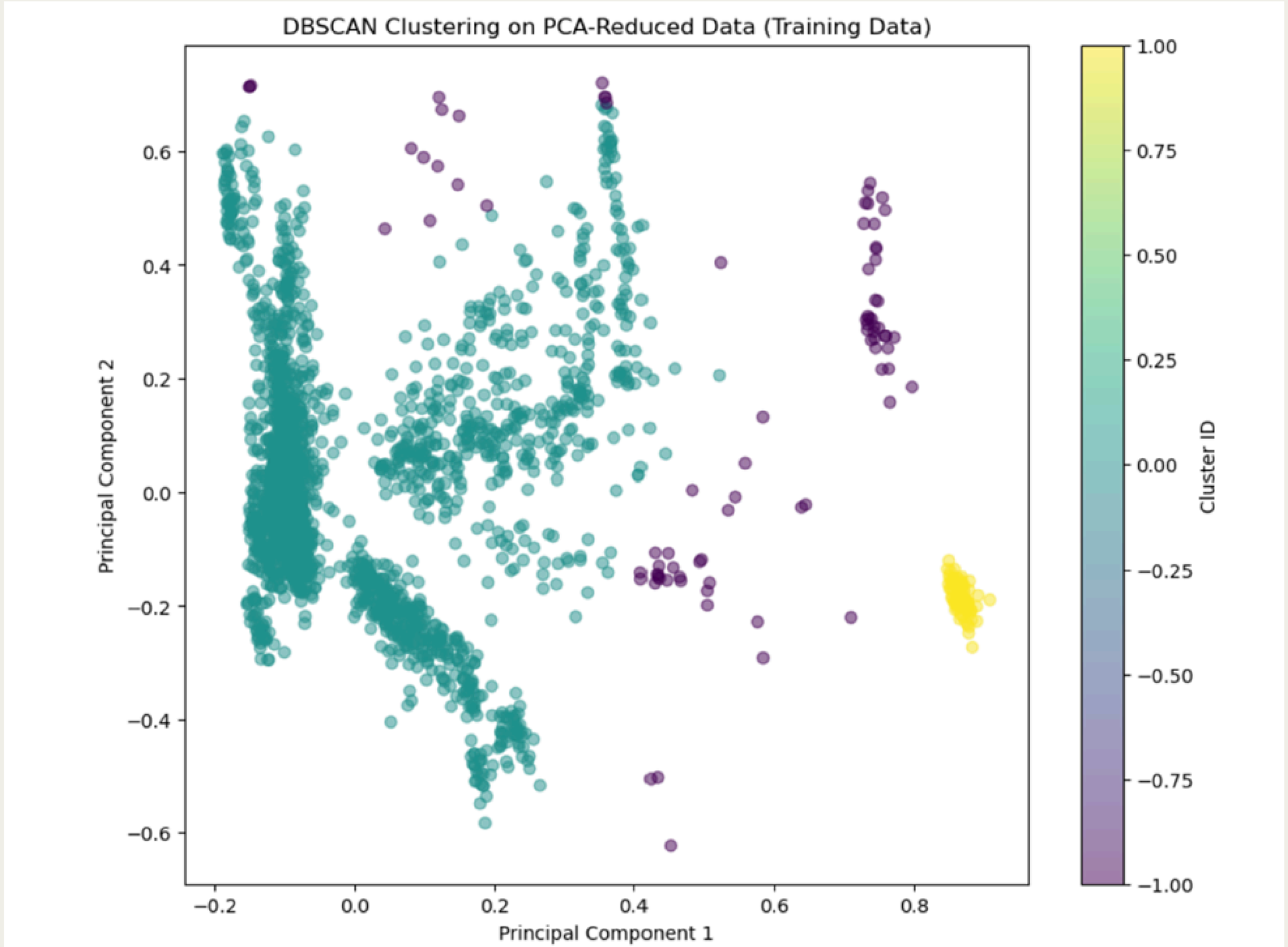
Predictive Modeling

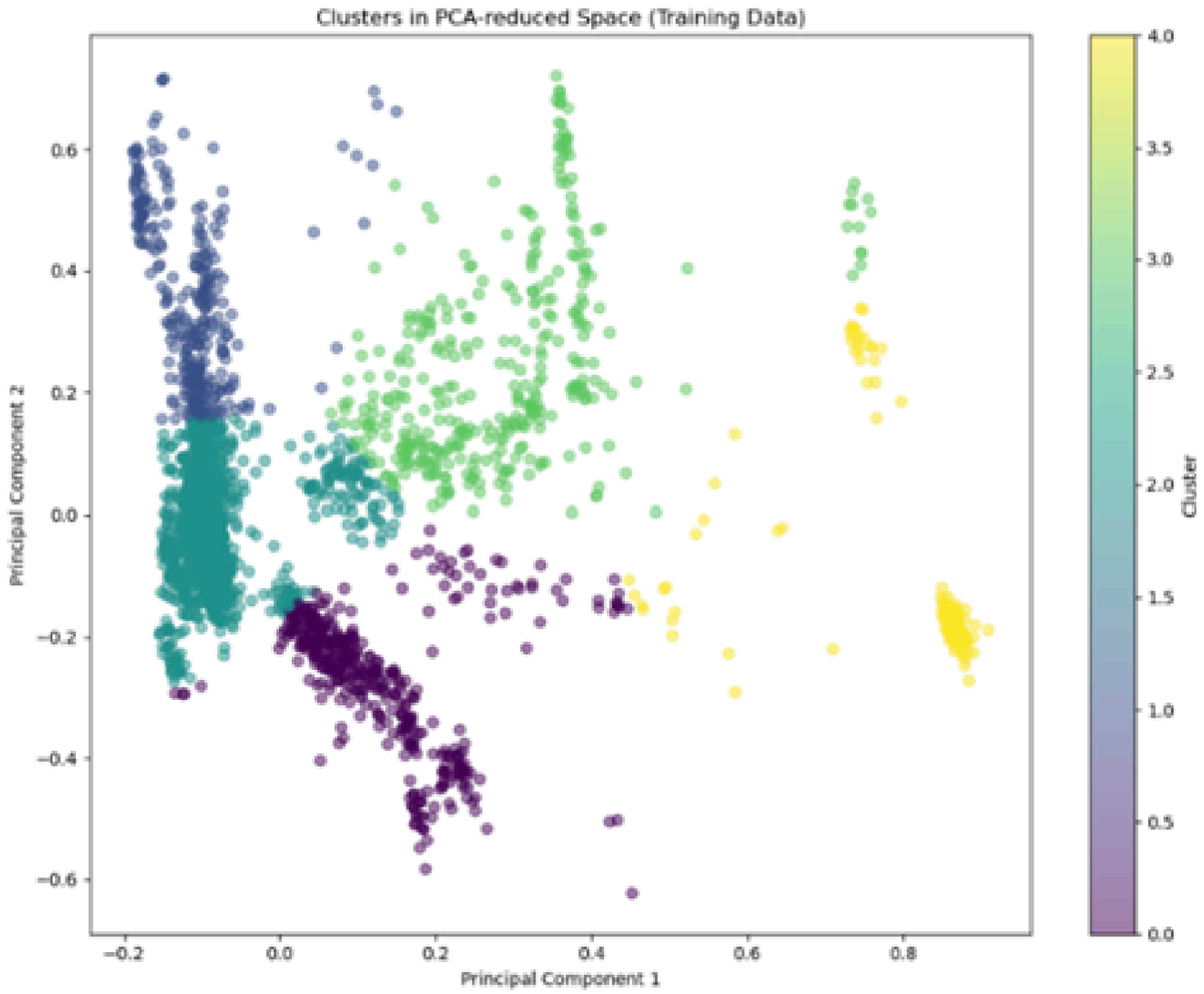
Several machine learning models, including Support Vector Machines (SVM), Random Forest, and Gradient Boosting Machines (XGBoost), were applied to predict the likelihood of product recommendations based on review texts and ratings. Each model was carefully tuned using GridSearchCV to find the optimal parameters for best performance.

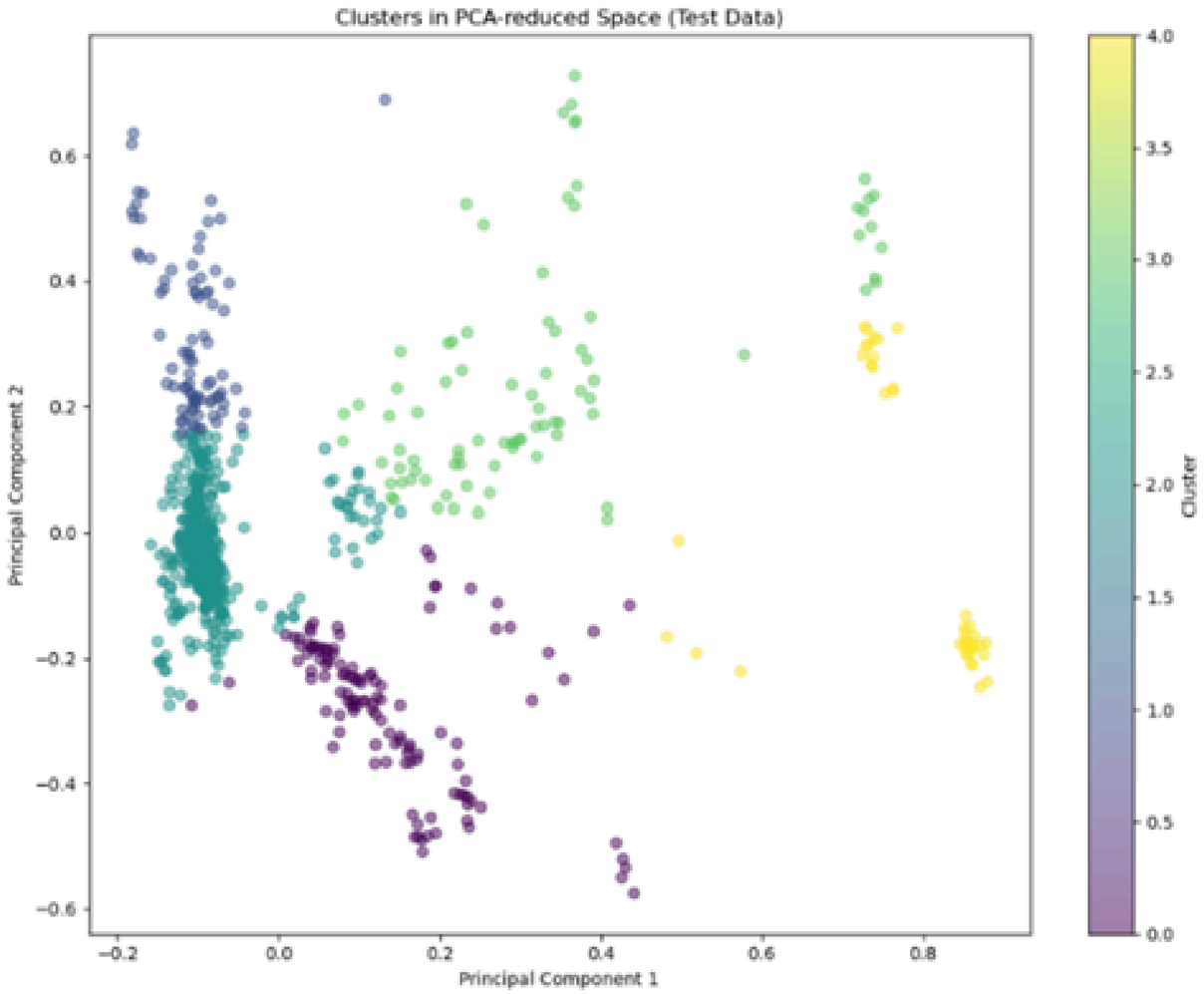


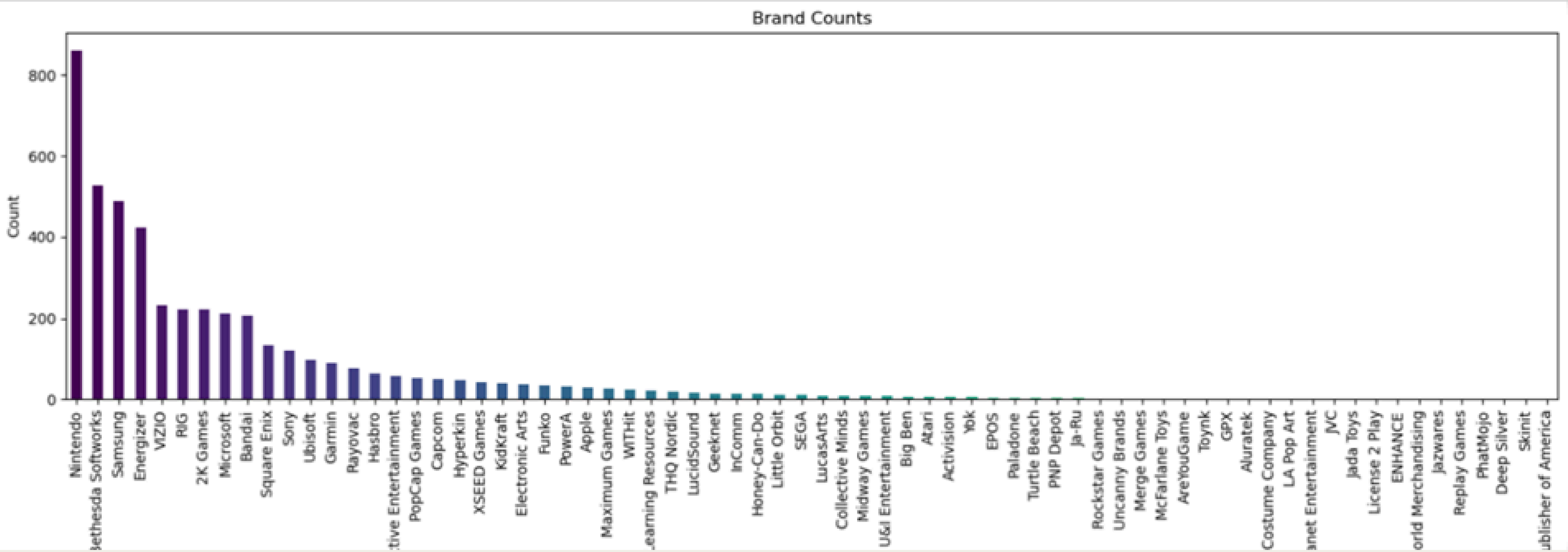

Scores by Model and Metric
Scores
1.05
1.00
0.95
0.90
0.85
0.80
accuracy
precision
recall
1.0000
1.0000
0.9836
0.9773
0.8454
0.8454
0.8454
0.8454
0.8859
0.8924
0.8838
0.8949
svm
random_forest
xgboost
lightgbm

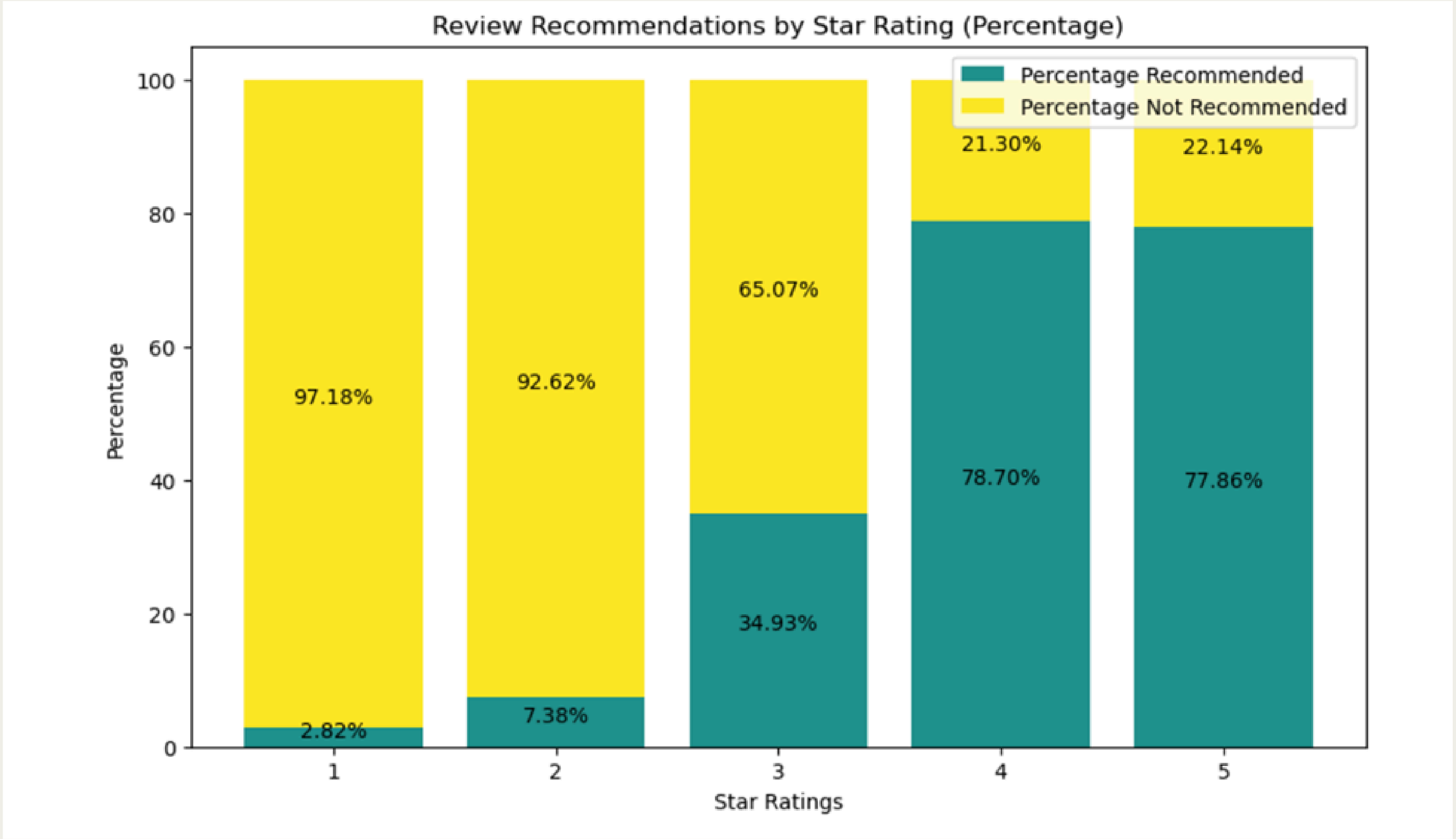

Runtime by Model
Runtime (seconds)
100
80
60
40
20
0
svm
random_forest
xgboost
lightgbm
Runtime (seconds)


DBSCAN Clustering on PCA-Reduced Data (Training Data)
Principal Component 2
Principal Component 1
Cluster ID
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.2
0.0
0.2
0.4
0.6
0.8
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Clusters in PCA-reduced Space (Training Data)
Principal Component 2
Principal Component 1
Cluster
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.2
0.0
0.2
0.4
0.6
0.8
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0


Clusters in PCA-reduced Space (Test Data)
Principal Component 2
Principal Component 1
Cluster
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.2
0.0
0.2
0.4
0.6
0.8
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0


Brand Counts
Count
0
200
400
600
800
Nintendo
Bethesda Softworks
Samsung
Energizer
VIZIO
RIG
2K Games
Microsoft
Bandai
Square Enix
Sony
Ubisoft
Garmin
Rayovac
Hasbro
tive Entertainment
PopCap Games
Capcom
Hyperkin
XSEED Games
KidKraft
Electronic Arts
Funko
PowerA
Apple
Maximum Games
WITHit
earning Resources
THQ Nordic
LucidSound
Geeknet
InComm
Honey-Can-Do
Little Orbit
SEGA
LucasArts
Collective Minds
Midway Games
U&I Entertainment
Big Ben
Atari
Activision
Yok
EPOS
Paladone
Turtle Beach
PNP Depot
Ja-Ru
Rockstar Games
Uncanny Brands
Merge Games
McFarlane Toys
AreYouGame
Toynk
GPX
Aluratek
Costume Company
LA Pop Art
anet Entertainment
JVC
Jada Toys
License 2 Play
ENHANCE
orld Merchandising
Jazwares
Replay Games
PhatMojo
Deep Silver
Skinit
ublisher of America


Review Recommendations by Star Rating (Percentage)
Percentage Recommended
Percentage Not Recommended
Percentage
Star Ratings
0
20
40
60
80
100
1
2
3
4
5
97.18%
92.62%
65.07%
21.30%
22.14%
2.82%
7.38%
34.93%
78.70%
77.86%

RESULT

The findings challenge the traditional reliance on numerical ratings as sole indicators of product quality and consumer satisfaction. Instead, they advocate for a more holistic approach to analyzing consumer reviews, incorporating both numerical data and textual analysis to gain a fuller understanding of consumer behavior.

The results from the predictive models provided robust tools for predicting consumer recommendations based on review texts. The use of SHAP values in interpreting these models shed light on the influence of specific words and phrases in reviews, enhancing our understanding of what drives consumer recommendations.

RESULT AND DISCUSSION

The analysis revealed several intriguing insights into consumer behavior and review patterns:

- Review Rating Discrepancies: It was observed that high star ratings do not necessarily correlate with recommendations. This discrepancy highlights the complexity of consumer satisfaction and suggests that numerical ratings alone may not fully capture consumer sentiment.
- Brand Popularity and Consumer Loyalty: Certain brands consistently received higher ratings and recommendations, indicating strong brand loyalty among consumers. This finding underscores the importance of brand reputation in the gaming industry.
- Clustering Patterns: The clustering analysis helped identify distinct groups of reviewers based on their review patterns and preferences, offering a nuanced understanding of the target customer base.

FUTURE WORK

Temporal Analysis of Reviews

Analyzing how reviews change over time with respect to product life cycles could offer valuable insights into trends in consumer satisfaction and product durability.

Expansion of Data Sources

Incorporating review data from additional platforms could help validate the findings across different segments of the market and enhance the generalizability of the models.

Integration with Sales Data

Combining review data with actual sales data to correlate the impact of consumer reviews on sales performance. This would provide actionable insights for optimizing inventory and marketing strategies based on consumer feedback.

Advanced Machine Learning Techniques

Employing more complex machine learning algorithms, such as Neural Networks, Named Entity Recognition (NER), or Topic Modeling could provide more nuanced insights into the content of the reviews, allowing for better categorization and understanding of key themes and topics.

Thank you!

Special Thanks to David Lara-Arango for his support in this project.