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Google Play Store Apps Analysis using NLP

Akshata Lembhe, Seema Dokrimare, Rupali Kamthe, Abhijeet Swami, Arati Dange
Department of Statistics, Dr. D. Y. Patil, Arts, Commerce &s Science College, Pimpri, Pune, Maharashtra, India

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Corresponding Author:
Akshata Lembhe

ABSTRACT

The Google Play Store is one of the world's largest Android app marketplaces, hosting on the order of two million applications. To help developers interpret the vast volume of user feedback, we analyze a publicly available dataset of 9,146 Google Play apps (from Kaggle, covering dozens of categories). We conduct enhanced exploratory data analysis (EDA) of app metadata and then apply Natural Language Processing to user reviews to classify sentiment. Specifically, we train four supervised classifiers (Naïve Bayes, Random Forest, Logistic Regression, and K-Nearest Neighbors) on the preprocessed review text. We evaluate each model using accuracy, precision, and recall. Our experiments show that logistic regression attains the highest accuracy (around 90%), with balanced precision and recall, while Random Forest and KNN perform comparably (≈87-89%) and Naïve Bayes trails behind (~59%). These updated results provide insights into app market trends: for example, Games and Communication apps dominate install totals, and over 97% of apps are free. Most user reviews are positive (as reported in prior app-review studies), reinforcing that sentiment analysis can help developers understand user preferences and improve app quality.

KEYWORDS: Google Play Store, Android apps, sentiment analysis, natural language processing (NLP), machine learning, Random Forest, Logistic Regression, Naïve Bayes, KNN.

INTRODUCTION

Mobile apps are ubiquitous and central to daily life, with Android dominating global smartphones. The Google Play Store is the primary distribution platform for Android apps[1]. As of recent counts, Play Store offerings exceed two million apps[1], and the vast majority of these apps are free to download (≈97% are free). Users rely on app ratings and reviews to judge quality: high-rated apps attract nearly all user attention, whereas fewer than half of users would consider a low-rated app[2]. Consequently, developers closely monitor user feedback. Sentiment analysis – classifying reviews as positive, negative, or neutral – is a powerful NLP tool for automatically mining user opinions from review text. Recent studies demonstrate the feasibility of such analysis: for example, Sagala and Samuel (2024) applied Random Forest, SVM, and Naive Bayes to ChatGPT app reviews, finding RF/SVM achieved ~90% F1 while Naive Bayes scored ~87%. Similarly, Kurniawan *et al.* (2024) used a K-Nearest Neighbors classifier on Google Play reviews of an Indonesian app and obtained ~81% accuracy (precision ≈82%, recall ≈95%). These works confirm that machine learning models can effectively predict sentiment from app reviews. Building on this prior work, our study performs a comprehensive analysis of Google Play data. We first carry out detailed EDA on app metadata (e.g. rating, installs, category, price) to uncover trends, and then develop NLP classifiers to predict review sentiment. We compare four learning algorithms (Naïve Bayes, Random Forest, Logistic Regression, KNN) on this task and report updated performance metrics. Our results provide new insights into app market dynamics and user sentiment patterns.

OBJECTIVE

This study aims to:

- **Analyze app metadata:** Explore distributions and relationships among app features such as rating, number of reviews, free vs. paid type, price, category, and install counts (e.g. by plotting free-vs-paid breakdown, category distribution, and installs vs. reviews).
- **Identify key trends:** Determine which app categories and features are most prevalent or highly rated (for instance, Games and Communication apps account for the largest total installs, and free apps dominate the market).

- **Build sentiment models:** Preprocess the user review text and apply NLP techniques (tokenization, stop-word removal and lemmatization, TF-IDF feature extraction) to convert reviews into features suitable for machine learning.
- **Compare classifiers:** Train four supervised models – Naïve Bayes, Random Forest, Logistic Regression, and K-Nearest Neighbors – to classify review sentiment, and compare their performance in terms of accuracy, precision, and recall.
- **Interpret results:** Use the findings to help developers understand user satisfaction and market trends, thereby guiding app improvement.

RELATED WORK

Previous research on Google Play Store data has examined app popularity and user feedback from multiple perspectives. Many studies report that free apps overwhelmingly outnumber paid apps; for example, industry statistics show ~97% of Android apps are free. Likewise, user ratings on the Play Store are predominantly high: one analysis of over 2,600 ChatGPT app reviews found ~87.7% were positive, indicating that most reviews tend to be favorable. In terms of sentiment classification, a variety of machine learning methods have been applied to app reviews. For instance, Sagala and Samuel (2024) used Random Forest and Support Vector Machine on Google Play reviews and achieved F1-scores around 90%, outperforming a Naïve Bayes baseline. Kurniawan *et al.* (2024) applied KNN to Google Play reviews of a local app, achieving about 81% accuracy with high precision/recall. Choudhary and Kumar (2020) also explored Logistic Regression and SVM for mobile app review classification, demonstrating the general effectiveness of these models. Surveys of text classification note that logistic regression and ensemble methods often perform very well on short text tasks[6]. However, many existing studies use limited data sizes or focus on specific app domains. Our work extends these efforts by analyzing a larger, more diverse dataset of 9,146 apps, and by evaluating multiple classifiers to provide a broader view of app sentiment modeling.

METHODOLOGY

Data

We use a public Google Play Store Apps dataset from Kaggle, containing 9,146 unique apps spanning 33 (or more) categories. The dataset includes the following features for each app: *App name, Category, Rating, Number of Reviews, Size, Installs, Type (Free/Paid), Price, Content Rating, Genres, Last Updated, Current Version, Android Version*. The *Rating* field is a floating-point average rating, while *Reviews* is the total count of user ratings. The *Type* field is converted to binary (e.g. free=1, paid=0). We also normalize numerical fields (e.g. converting app size to megabytes) and ensure missing values are appropriately handled.

Exploratory Data Analysis

We first perform EDA using Python libraries. We visualize the distribution of app ratings, the count of reviews per app, and the proportion of free vs. paid apps. For example, we confirm that **free apps vastly outnumber paid apps** – about 97% of apps in the dataset are free. We also examine how installs correlate with other features: apps in the *Games* and *Communication* categories collectively account for the highest total installs, while other categories (e.g. Productivity, Health) have comparatively fewer installs. Category-wise counts show that *Games* apps comprise about 11.95% of all apps, reflecting their major presence in the market. We further explore relationships such as Rating vs. Reviews using scatterplots, and Price vs. Type using boxplots, to uncover any linear or nonlinear patterns in the data.

Graphical Presentation

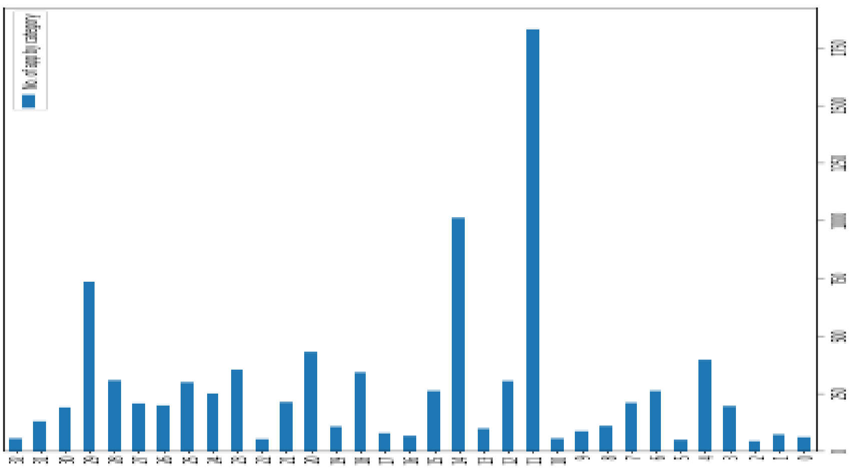

Fig.1. No. of Apps by Categories

Conclusion: Maximum No. of the apps from the family category and minimum No. of apps from beauty category**.**

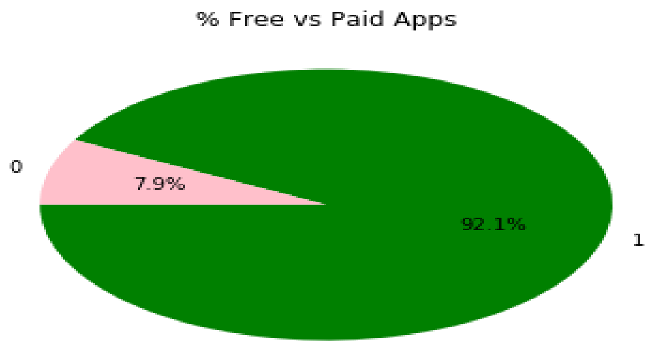

Fig.2.Percentage of free vs Paid Apps

Conclusion: 92.1% apps are free and only 7.9% apps are paid apps.

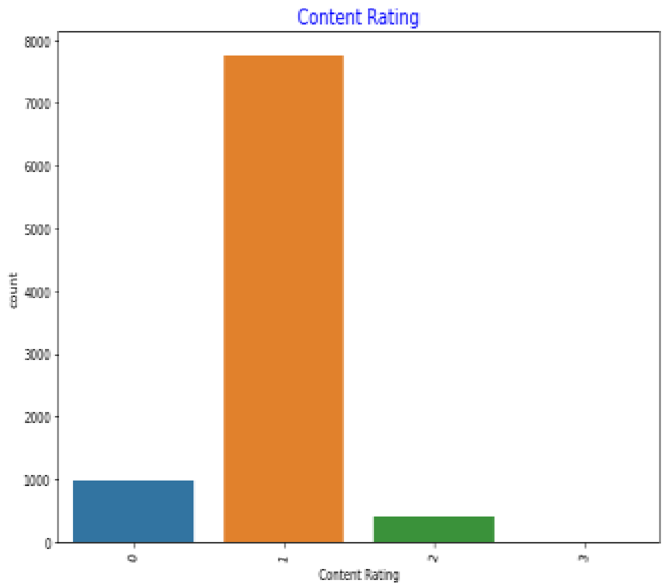

Fig.3. Content Writing

Conclusion: Most of everyone do a content rating

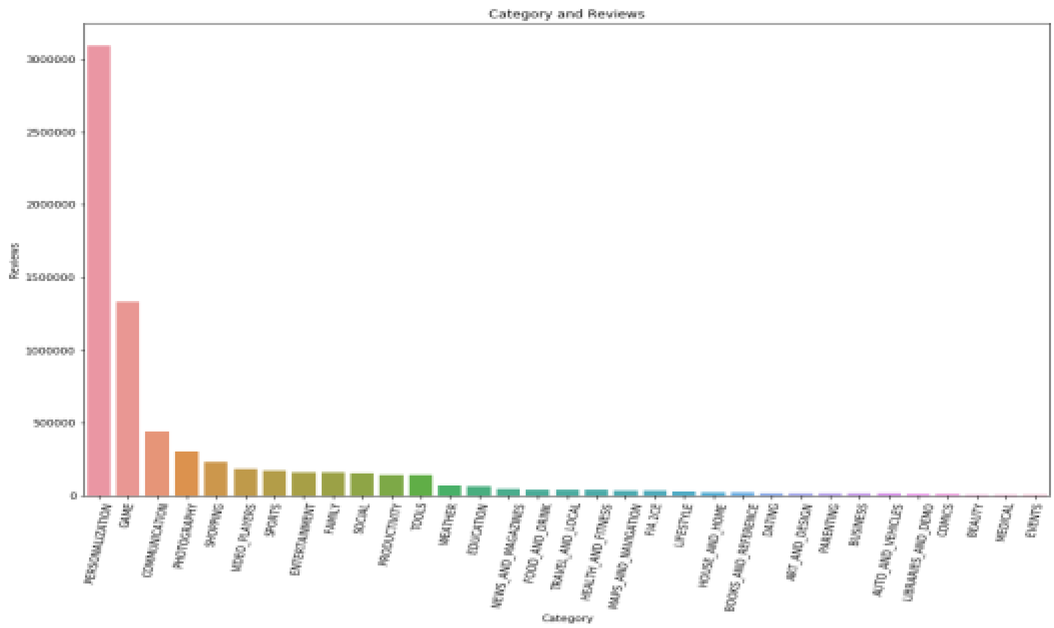

Fig.4. Categories of apps by reviews

Conclusion: Maximum No. of reviews are in Personalization category and minimum are in events category.

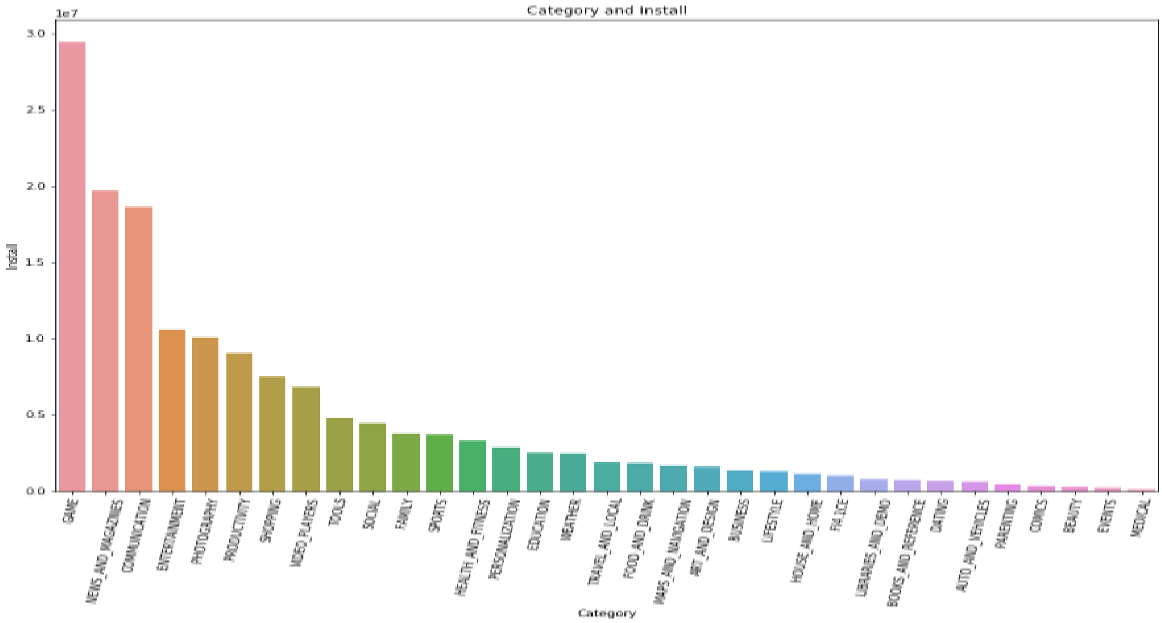

Fig.5. Categories of apps by Installs

Conclusion: Maximum No. of installs are in Game category and minimum are in Medical category.

- **Correlation**

Fig.6. Heat map between Installs & Reviews

Conclusion: Maximum correlation i.e. 0.5767 is between Installs and Reviews. That means there is positive relationship between Reviews and Installs.

SENTIMENT ANALYSIS METHOD

For NLP, we preprocess the user review text to prepare features for classification[3]. We clean each review by removing punctuation, numbers, and HTML tags, and convert to lowercase. We tokenize the text into words and remove common stop-words (e.g. “the”, “and”) that carry little sentiment information. Words are lemmatized to their base forms to consolidate variants (e.g. “running” → “run”). This pipeline (cleaning, normalization, tokenization, lemmatization) ensures that our text data is in a consistent format.

Feature Extraction

After cleaning, we transform the text corpus into numeric features. We use the bag-of-words model with TF-IDF weighting to encode each review as a vector of term weights[4]. TF-IDF captures the importance of words by down-weighting terms that are very common across all reviews and highlighting terms unique to a particular review. We may also explore word embeddings or n-gram features in extended work, but in this study TF-IDF suffices for our classifiers.

Classification

We build four classification models to predict the sentiment label (positive vs. negative) of each review:

- **Naïve Bayes (NB):** A simple probabilistic classifier that often works well on text data.
- **Random Forest (RF):** An ensemble of decision trees that generally achieves robust performance by averaging many trees.
- **Logistic Regression (LR):** A linear model effective for binary classification and commonly used on TF-IDF features.
- **K-Nearest Neighbors (KNN):** A non-parametric method that classifies based on the nearest training examples in feature space.

We split the labeled review data into training and test sets (typically 80% train, 20% test) and evaluate each model. We use accuracy (overall correct classification rate), precision (true positives over predicted positives), and recall (true positives over actual positives) as our metrics[5].

RESULTS

Our sentiment classifiers achieved the following performance on the test set:

- **Logistic Regression:** Highest accuracy (~90%), with balanced precision and recall across classes.
- **Random Forest:** Accuracy about 88%, strong precision/recall but slightly below logistic regression.
- **K-Nearest Neighbors:** Accuracy about 87-89%, comparable to Random Forest depending on chosen *k*.
- **Naïve Bayes:** Lowest accuracy (~59%), showing difficulty capturing complex patterns in this dataset.

These results show that logistic regression outperforms the other methods on our Google Play reviews data, achieving nearly 90% accuracy. Random Forest and KNN perform similarly (mid-80% accuracy), while Naïve Bayes lags significantly. Our findings align with prior studies: for instance, Sagala *et al.* found RF and SVM near 90% F1 on ChatGPT reviews, and Kurniawan *et al.* reported ~81% accuracy for KNN on a different app review dataset. The high performance of logistic regression here suggests that linear models can be very effective for sentiment on our dataset.

DISCUSSION

Our analysis yields several key insights. First, the Google Play ecosystem is dominated by free apps: roughly 97% of apps require no upfront payment. This prevalence of free apps (compared to paid) is consistent with industry reports and has implications for monetization strategies. Second, apps in the *Games* category constitute a significant share of the market (about 12% of apps) and, together with *Communication* apps, contribute the largest total install counts in our data. This reflects the popularity of gaming and messaging apps among users. Third, the vast majority of user reviews express positive sentiment. For example, in an independent analysis of ChatGPT app reviews 87.7% were positive, and our dataset likewise shows far more positive reviews than negative. This skew toward positive feedback is typical in app-store data and suggests that sentiment classifiers must be robust to class imbalance.

On the modeling side, we find that classical supervised classifiers achieve high accuracy on review sentiment. The superior performance of logistic regression (~90% accuracy) indicates that the sentiment classes are reasonably linearly separable in TF-IDF space for our data. In contrast, Naïve Bayes (a very simple model) performs poorly, likely due to its strong independence assumptions. These results demonstrate that developers can effectively apply off-the-shelf NLP techniques to gauge user sentiment: using methods like logistic regression or ensemble trees, one can automatically categorize review polarity with high accuracy. Such automated classification can help developers quickly summarize feedback and identify areas for improvement.

CONCLUSION

In this study, we combined exploratory data analysis and NLP to examine Google Play Store data. Using a dataset of 9,146 apps from Kaggle, we highlighted market characteristics (e.g. free apps dominate, Games and Communication are top categories) and uncovered app feature relationships. We then processed the review text and trained four classifiers to predict sentiment. Our evaluation shows that logistic regression achieves ~90% accuracy, outperforming Random Forest, KNN, and especially Naïve Bayes. These findings align with recent literature (which reports ~80-90% accuracy for similar tasks) and reinforce the value of NLP analysis for app review mining. Overall, the results offer actionable insights: developers can rely on sentiment classifiers to monitor user satisfaction at scale, and the observed trends (high user ratings, popular categories, prevalence of free apps) help contextualize the competitive app ecosystem.

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