Causal Impact Analysis on Android Market

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***Abstract*—Google play store contains a large repository of apps for android users. Play store has two billion active users that have two million apps to download and use. App developers are competing to get a higher success rate and increase user satisfaction but little information is known to developers for succeeding in the android market. This paper presents a comprehensive analytical study on Google play store apps ratings, installs and reviews. This study focuses on the evaluation of the parameters required for the success of an app in different categories. For this purpose data of 10k apps and its reviews are analyzed using exploratory data analysis. This study focuses on finding a correlation between higher ratings, no of installs, reviews with app info like its category, size, and price. We are also going to analyze user reviews to get useful insights. The evaluation shows that personalization, productivity and games categories are performing very well in the android market both in terms of ratings and installs. Most high rated apps are sized below 40MB and priced below 30$, except game apps that are performing well even if they are bulky. Common customer complaints are functional errors and issues like infrequent updates, excessive ads, limited functionality and high purchase price.**

Keywords—Android; Google; statistics; mobile applications; data visualization

I. Introduction

Google Play Store is a digital service run and developed by Google. The android market serves as a digital store, providing a wide range of apps for education, entertainment, business, lifestyle, food and health etc. In 2017, on Twitter, Google announces that Android devices have more than two million active users monthly. Available numbers of apps on the Google Play Store exceeds 2.6 million in 2018 [1]. According to the analytics of Nielson, United States users stay more active on android apps instead of the web on an average of 56 minutes per day [2]. Android users can install both free and paid apps from the Google Play Store.

Due to high competition in the Android market, a lot of research has been triggered in this field. Despite having millions of users of android applications, aggregated information about these applications is still not well known. Specifically about succeeding in the android market, the impact of developer's actions on app familiarity, pricing of apps and achieving membership in top app lists [3]. There are a number of questions that still do not have a clear answer [22]. How different characteristics lead to an app success? What is the success determinant of an app, its rating or no of installs? What app features to choose from before development? Which apps category has more potential for new developers? In which category high-quality apps are needed? What are the common good and bad reviews?

Recent studies on demand, supply and value creation in mobile app markets suggests that demand factors mainly include app rank, popularity, quality updates and fermium strategy while supply is triggered by features such as marginal cost, file size, app portfolio diversity [25].

To answer all these questions, in this study, we are going to analyze Google Play Store apps ratings and reviews to evaluate the parameters required for the success of an app in different categories. Analyze the android market and get useful insights by using data of 10k play store apps. By finding a correlation between Google Play Store apps ratings, no of installs and user reviews with app size, price and category to evaluate the parameters required for the success of an app in different categories.

The paper is organized into the following sections: Section II briefly discusses the background research on this problem. Section III highlights data and methodology chosen for our analysis. Section IV describes the evaluation of each parameter and Section V concludes this paper.

II. Literature Review

Google apps have many characteristics than that of web services. With the increase in the use of the smartphone, there is extreme spread in use of Google apps. Affordability and flexibility of smartphone devices is the central reason for the exceptional growth of the Android market in recent years [4]. No of downloads, ratings and satisfaction tends to be higher for blockbuster apps [5]. In a study conducted on prime ranking elements for mobile apps, shows that probability of an app success influenced by its app size, release date, number of languages it supports and popularity of its category [21].

A major source of feedback to developers is the star rating in the Google app store. Ratings computed using the Amazon rating system aggregates the lifetime rating of an app into one rating that is presented on the app store. It is not vibrant enough to grab the diversity of user satisfaction due to the evolution of apps and does not encourage developers to refine their apps with time [7]. In a recent study, an automated system is recommended that can facilitate developers to understand user text reviews and to improve their app features for better user experience [6].

The apps release strategy is an important aspect of app success. Skilled developers believe that user response is influenced by the app release strategy [8]. Price, release date, release content details are salient factors for app rating according to a causal analysis study conducted on the release of popular apps from Google Play and Windows Phone Store for 52 weeks [9].

After the successful release of an app, another step is the need for updates to emerge apps over time. Research has shown that updating apps more often, lead to a high rank of apps [10]. In comparison to Google Play, updates have a higher impact on downloads in iTunes, mainly for the reason that Google Play Store lack quality control due to which developers release both high and low-quality updates without worrying about the quality of update [11]. According to another study, for an update to have more effect on rating developers should focus on the declaration of features instead of bug fixing [12].

Apps are generally divided into two categories, free of cost and paid apps. To make paid apps gain familiarity developers offer a free trial version of their apps. Freemium strategy is positively correlated to high sales volume and revenue of the paid version of their apps [2] [14]. Optimal price of a commercial app can be improved with augmenting users by offering free trials [15]. A study was conducted on user purchase intention and concluded that purchase intention is influenced by app rating, currency value and free alternatives to paid apps [16].

User reviews are a very rich data source for understanding user reported issues to improve the quality of apps and get higher ratings [17]. According to a study, reviews and ratings are not static, developers response to reviews can lead to the constructive outcome on the rating of the app [19]. User feedback can be interpreted using different approaches, one such approach is CRISTAL proposed by Fabio Palomba et al. According to them, developers who update their apps rendering user feedback rewarded with higher ratings [13]. Due to noisy app reviews, direct parsing is mostly ineffective and inflexible to a large number of reviews. To overcome this issue, phrase-based extraction (PUMA) system is proposed, an automated technique which can extract user opinions from app reviews [20]. Most common complaints among user reviews are functional errors, requests for additional features and app crashes [18].

III. Procedure

This study contains both quantitative and qualitative data. The approach used in this paper is exploratory data analysis. Data for different variables are aggregated and visualized to understand the properties of the Google Play Store. EDA assists us to understand characteristics that can be effective to capture the Android market.

All this work is done in python Jupyter Notebook. Datasets are handled with the help of the Pandas library. Statistical analysis is performed using the NumPy library, and then data is visualized using Matplotlib and Seaborn library to get useful insights from data. In this paper, the correlation between ratings, no of installs and no of reviews are evaluated w.r.t. app size, price and category. To do analysis on user reviews, word clouds are built to get the top frequency words for different sentiments. Upon the frequency of these words, reviews are manually studied to get information about the common good and bad reviews.

A. Data

Proposed Sample has data about 10840 apps and contains and 64296 users review. The sample is taken as a dataset from kaggle.com [27]. It has two files. The 1st file contains parameters about apps info as mentioned in Table I:

2nd file contains parameters about user reviews and sentiments analysis as mentioned in Table II:

B. Preprocessing

Original Records were 10841, after removing duplicate and noisy data 9658 records remained. Further, convert app “Size” to MB, remove ‘+’ , ‘,’ from “Installs”, create classes for “Content Rating” (Everyone, 10+, 13+, 17+, 18+), Convert data types of all columns:

C. Statistical Description

Stats are calculated about each numerical and descriptive parameter in data. Statistics for variables in App Info file is presented in Table III and Table IV.

TABLE I. App Info

Name	**Depiction**
App	App name
Category	App category name
Rating	User rating in the range of [1,5]
Reviews	Quantity of user reviews
Size	Size of the app
Installs	Number of user downloads or installs
Type	Paid or Free
Price	App price
Content Rating	Age group the app is targeted on
Genres	Apart from the main category an app can belong to multiple genres
Last Updated	Last time the app was updated
Current Ver	Latest version of the app
Android Ver	Minimum required Android version

TABLE II. App Reviews

Name	**Depiction**
App	App name
Translated Review	Translated user feedback
Sentiment	Feedback sentiment analysis
Sentiment Polarity	Feedback Sentiment polarity score
Sentiment Subjectivity	Feedback Sentiment subjectivity score

TABLE III. App Info: Numerical Data Statistics

	Rating	**Reviews**	**Size**	**Installs**	**Price**
Count	8196	9658	8432	9658	9658
Mean	4.2	216615	20.4	7778312	1.1
Std	0.5	1831413	21.8	53761004	16.9
Min	1	0	0	0	0
25%	4	25	4.6	1000	0
50%	4.3	967	12	100000	0
75%	4.5	29408	28	1000000	0
Max	5	78158306	100	1000000000	400

TABLE IV. APP INFO: DESCRIPTIVE DATA STATISTICS

	Count	**Unique**	**Top**	**Freq**
App	9658	9658		
Category	9658	33	FAMILY	1831
Type	9658	2	Free	8902
Content Rating	9658	6	Everyone	7903
Genres	9658	118	Tools	826
Last Updated	9658	1377	3 Aug, 2018	252
Current Ver	9650	2817	Varies with device	1054
Android Ver	9656	33	4.1 and up	2202

TABLE V. APP REVIEWS: NUMERICAL DATA STATISTICS

	Sentiment_Polarity	**Sentiment_Subjectivity**
Count	37427	37427
Mean	0.0	0.0
Std	0.0	0.0
Min	-1.0	0.0
25%	0.0	0.0
50%	0.0	1.0
75%	0.0	1.0
Max	1.0	1.0

TABLE VI. APP REVIEWS: DESCRIPTIVE DATA STATISTICS

	App	**Translated_Review**	**Sentiment**
Count	37427	37427	37427
Unique	865	27994	3
Top	Bowmasters	Good	Positive
Freq	312	247	23998

Statistics for parameters in App Reviews file is presented in Table V and Table VI.

IV. EVALUATION

The success of an app can be measured by its rating, no of installs and reviews. In this paper, success parameters are evaluated according to their distribution in different categories. 33 categories are found in the data. Average no. of apps in each category is 292.

The top five categories contain the most active apps in the market are Family, Game, Tools, Business and Medical.

The family contains 19% of apps available in our data. The bottom five categories containing the least apps are Arts & Design, Events, Parenting, Comics and Beauty as visible in Fig. 1.

A. *Rating*

According to word-of-mouth literature, for open platforms like Google Play Store rating is an important success factor [23]. Rating is measured as the star rating, ranging from 1 to 5. Naive users use this rating system to perceive app satisfaction [7]. Generally, most of the apps are performing well with an average rating of 4.17. Rating pattern across each category is shown in Fig. 2.

To get useful insights, in this paper only those categories are considered in which no. of apps are more than 292. Categories are filtered that has more than average no. of apps.

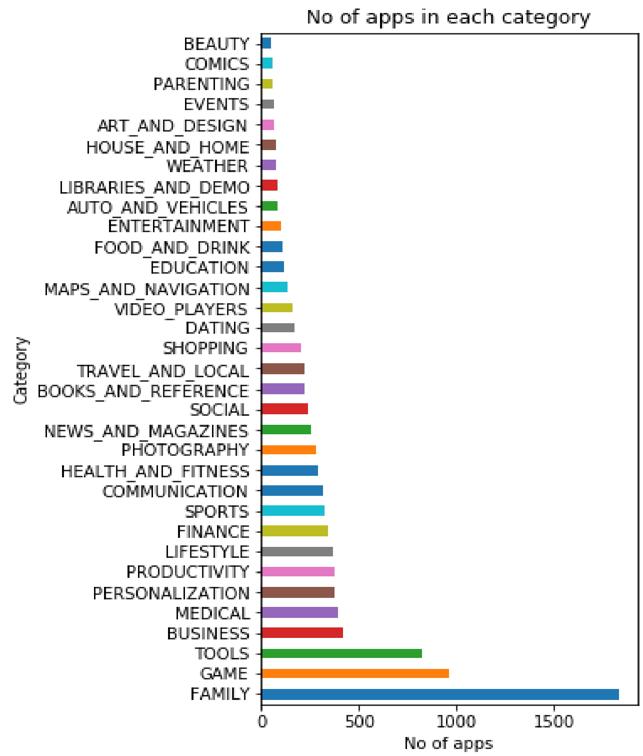

Fig. 1. No of Apps in each Category.

Fig. 2. Rating Pattern in each Category.

Upon drilling down, we found out that the Personalization category has the highest average rating i.e. 4.33, 4% apps in our data belong to Personalization, distribution of rating in Personalization can be visualized in Fig. 4. The family category is on 5th position and Tools is on 11th position, so Apps in Tools needed more attention from developers as highlights in Fig. 3.

B. Installs

No. of Installs is considered to measure the success of an app. In this data no. of installs range from 0 to 1 billion. No. of installs are grouped and their frequency and percentage is obtainable in Table VII. Average installs are 7778312. Only a few apps have more than 100 million installs and they are free apps as shown in Fig. 5.

If more no. of installs is considered as success criteria then results are very different across categories w.r.t. ratings. Average installs are very good across the Communication category. Fig. 6 shows that Productivity is also performing better than many high rating categories.

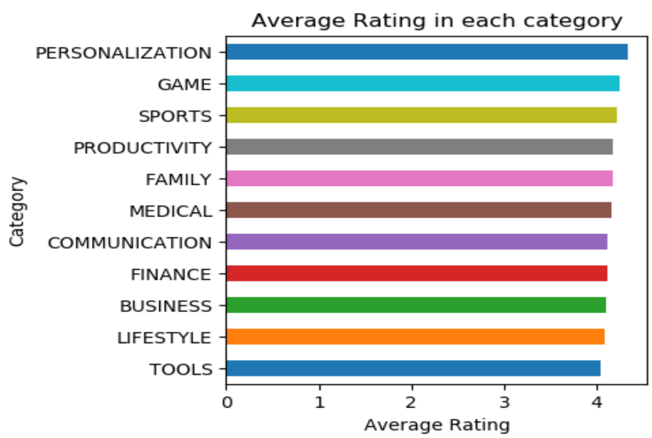

Fig. 3. Average Rating in each Category where no of Apps ≥ 292.

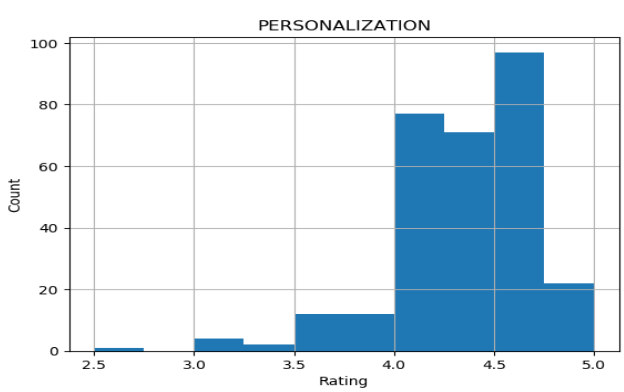

Fig. 4. Distribution of Rating Across Personalization Category.

TABLE VII. INSTALLS STATISTICS

Installs	Count	Percent
I>0 & I <= 10e8	9614	99.5%
I> 10e8 & I<= 50e8	24	0.25%
I> 50e8 & I<= 10e9	20	0.21%

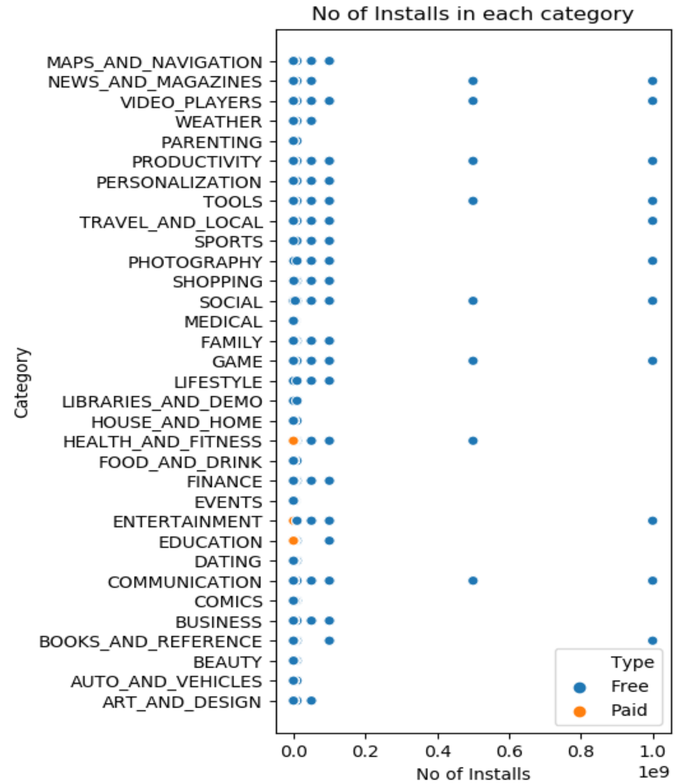

Fig. 5. No of Installs Pattern in each Category.

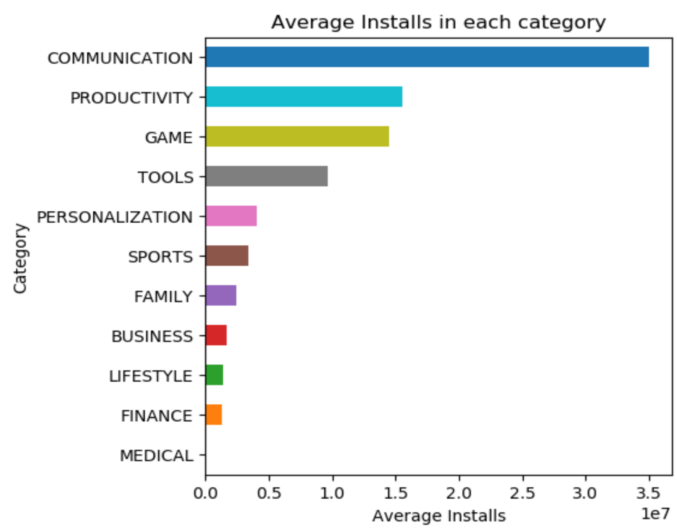

Fig. 6. Average Installs in each Category where no of Apps ≥ 292.

By plotting ratings versus installs, we can see that high rated apps have more installs. Fig. 7 indicates that users tend to install apps that have good reviews and high ratings.

C. Price

To prevent consumer negative attitude specialists must develop specific strategies for pricing; failure on pricing will result in the customer losing interest in other app features [26]. There are two types of apps: Free and Paid. Frequency of each type is presented in Table VIII. Frequency distribution for paid apps is obtainable in Table IX.

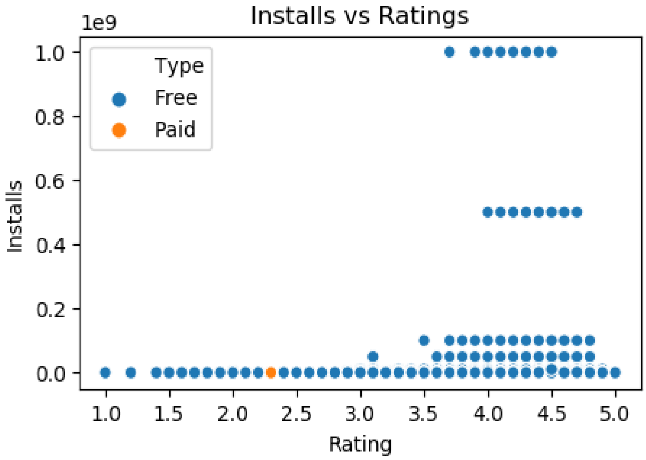

Fig. 7. Correlation between Installs and Ratings.

TABLE VIII. PRICE STATISTICS

Type	Count	Percent
Free	8902	92%
Paid	756	8%

TABLE IX. PAID APPS STATISTICS

Paid	Count	Percent
P>0 & P<=50	733	97%
P>50 & P<=350	7	1%
P>350 & P<=400	16	2%

In Fig. 8, we can see that average Price for Finance, LifeStyle and Medical is fairly high while in rating they stand on 8th, 10th and 6th position respectively. Interestingly, Game apps are reasonably priced below ~20$.

To understand the impact of price on rating and no. of installs, we plotted price w.r.t. rating and installs in Fig. 9 and Fig. 10, and found out that apps with high price do not deliver high ratings or more installs. Most of the top rated apps are priced between ~1$ to ~30$.

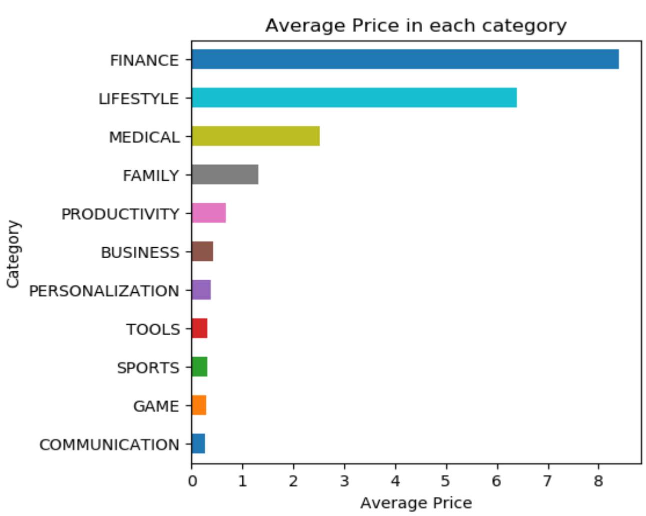

Fig. 8. Average Price in each Category where no of Apps ≥ 292.

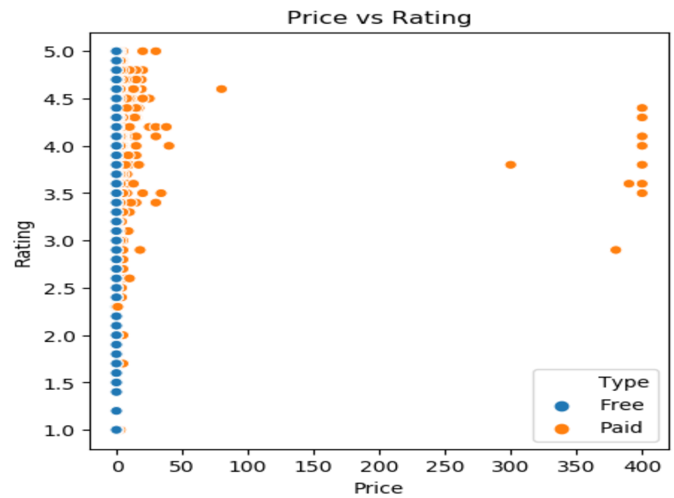

Fig. 9. Correlation between Price and Rating.

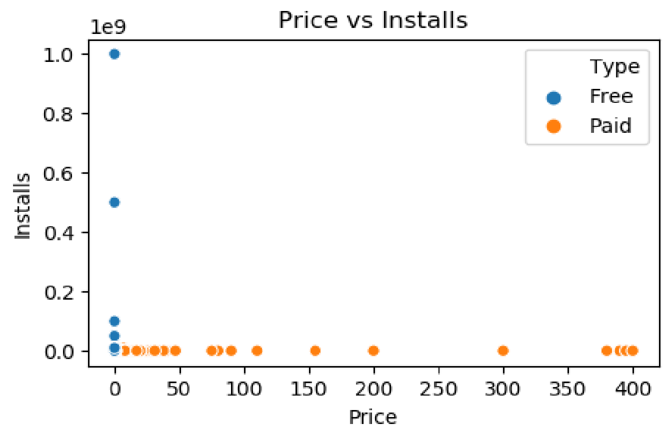

Fig. 10. Correlation between Price and Installs.

D. Size

Despite the known fact that app size increases with app functionality, it can also bound users to install apps with greater size due to limited storage capacity [24]. Apps average size is 20 MB and has a range of up to 100 MB. Frequency distribution of app size is given in Table X.

After plotting size and rating in Fig. 11, paid apps appeared to be bulkier relative to free apps. Apps with greater size have low ratings. User likes light and less expensive apps and rates them higher because most of the top-rated apps are neither too heavy nor too light, ranging between ~2MB to ~40MB.

TABLE X. SIZE STATISTICS

Size	Count	Percent
S>0 & S<=20	5465	57%
S>20 & S<=40	1660	17%
S>40 & S<=60	707	7%
S>60 & S<=80	328	3%
S>80 & S<=100	272	3%
nan	1226	13%

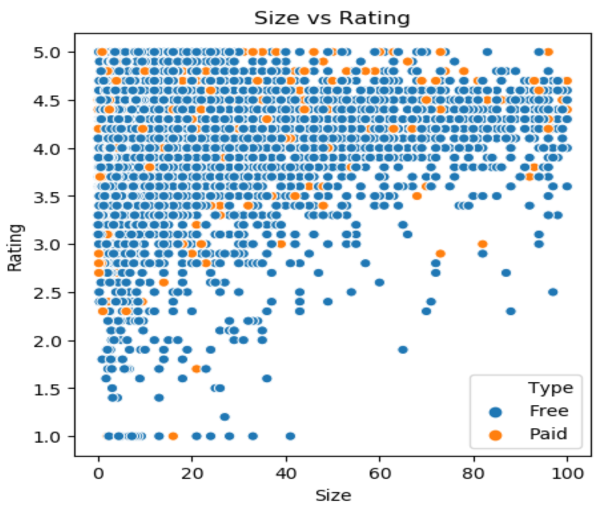

Fig. 11. Correlation between Size and Rating.

Upon drilling down to categories as visualized in Fig. 12 we find out that, average size is higher for Game and Family but these bulky apps are fairly high rated which means that they are bulky for a purpose. To provide better and interactive features in Games developers can enhance its Size. But higher size limits the audience with users that have more space in their smartphones. It's a tradeoff that developers need to balance, for selecting the size of an app, developers should consider its category and respective audience.

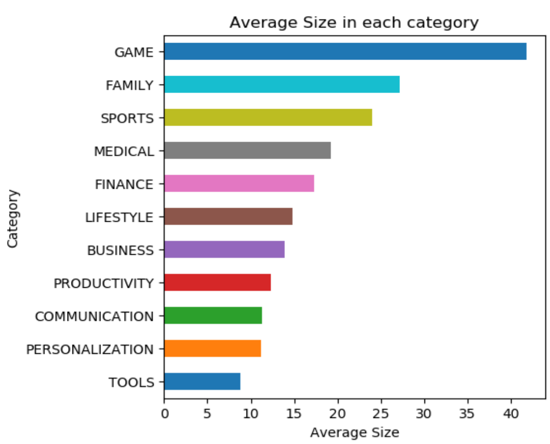

Fig. 12. Average Size in each Category where no of Apps ≥ 292.

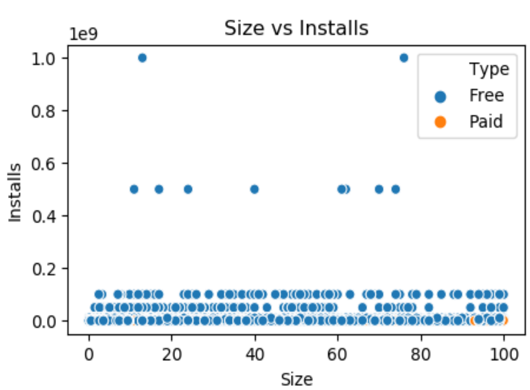

Fig. 13. Correlation between Size and Installs.

No. of Installs is higher for low to medium size apps as plotted in Fig. 13.

E. No. of Reviews

No. of reviews ranges up to 800 million. Average reviews are about 0.2 million. No of reviews are grouped and their grouped frequency is presented in Table XI. No of reviews for Social is at the top as visible in scatter plot of reviews in each category in Fig. 14.

If we compare the average no of reviews for categories in which apps is more than 292, we can see in Fig. 15 that Communication has high average no. of reviews and no. of installs.

F. Reviews

Reviews file has 37,427 translated reviews of 865 unique apps and their calculated sentiment analysis. Sentiment categories and their statistics are presented in Table XII. Sentiment analysis is an automated process of understanding the opinion of a person about a particular subject. Sentiment analysis provides information about polarity and subjectivity. Sentiment count is highlighted in Fig. 16.

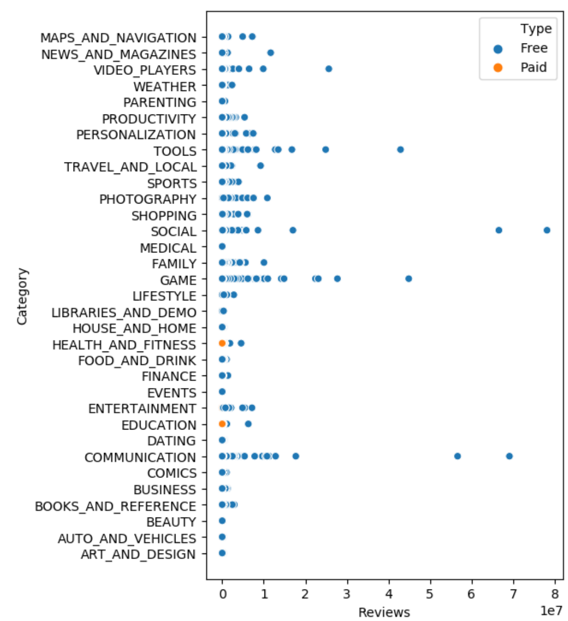

Fig. 14. Reviews Pattern in Each Category.

TABLE XI. REVIEWS STATISTICS

No. of Reviews	Count	Percent
R>0 & R<=10e7	9628	99.7%
R>10e7 & R<=50e7	26	0.3%
R>50e7 & R<=80e7	4	0.04%

TABLE XII. SENTIMENT STATISTICS

Sentiment	Count	Percent
Positive	23998	64%
Negative	8271	22%
Neutral	5158	14%

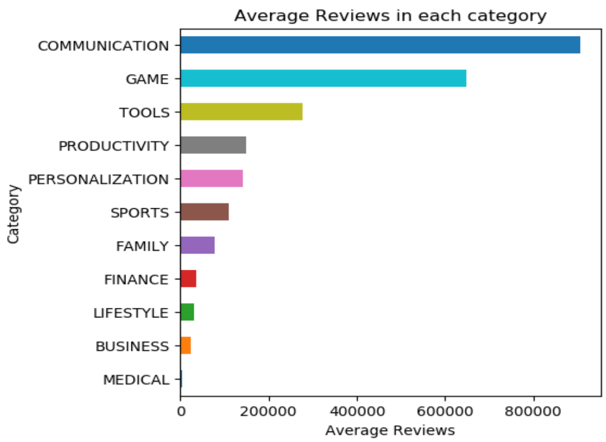

Fig. 15. Average Reviews in each Category where no of Apps ≥ 292.

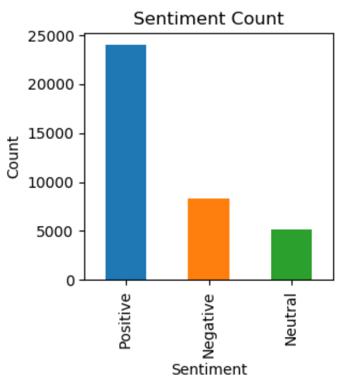

Fig. 16. Sentiment Count for Positive, Negative and Neutral.

The polarity of sentiment lies between -1 to 1, where 1 means positive and -1 means negative. Frequency distribution for sentiment polarity is given in Table XIII. In this data, the polarity of most reviews lies in the range of [-0.25, 0.5] as can be seen in polarity distribution in Fig. 17.

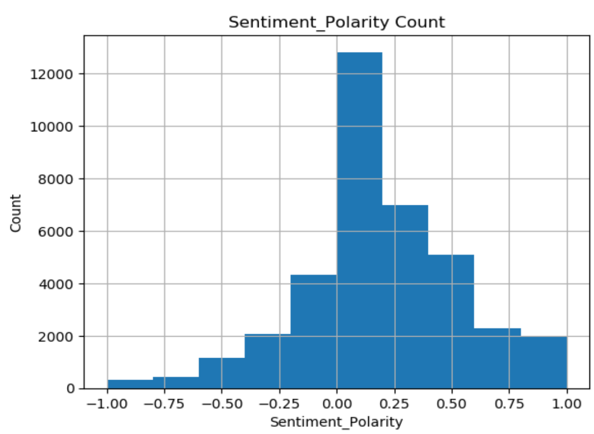

Fig. 17. Distribution of Sentiment Polarity.

TABLE XIII. SENTIMENT POLARITY STATISTICS

Sentiment Polarity	Count	Percent
SP>-1 & SP<=0	13429	36%
SP>0 & SP<=1	23998	64%

Subjectivity lies in the range of [0, 1] representing 0 as an objective view or factual information and 1 as a subjective view. Frequency distribution for sentiment subjectivity is given in Table XIV. The subjectivity of most reviews lies in the range of [0.4, 0.8] as plotted in subjectivity distribution in Fig. 18.

Word cloud for top words in reviews is provided in Fig. 19. The most common words in reviews are game, good, app, time, and great.

TABLE XIV. SENTIMENT SUBJECTIVITY STATISTICS

Sentiment Subjectivity	**Count**	**Percent**
SS>0 & SS<=0.5	18151	48%
SS>0.5 & SS<=1	19276	52%

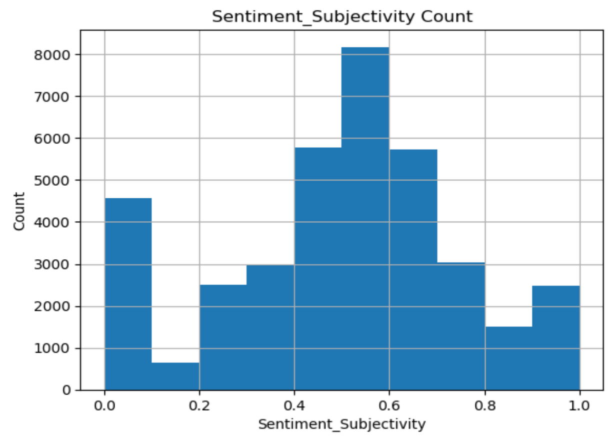

Fig. 18. Distribution of Sentiment Subjectivity.

Fig. 19. Word Cloud for Top 50 Words in Reviews.

Fig. 20. Word Cloud for Top 50 Words in Reviews with Positive Sentiment.

Word cloud for top words with positive sentiment in reviews is provided in Fig. 20. Top words for positive sentiment are great, good, time, love and game.

Customers mostly use simple and short response in positive reviews. Common positive reviews are:

- Great app, good app, killing time.
- Satisfying its purpose like Health apps keep people motivated to be healthy or regulate weight, Education helps in coaching, providing info and easy sharing in Communication apps.
- Appreciating updates.
- Backup and synchronization facilities help to retain the history of user profiles.
- Fewer ads.
- Useful reminders.

Word cloud for top words with neutral sentiment in reviews is plotted in Fig. 21. Most common words for neutral sentiment are work, app, need, phone and time.

Word cloud for top words with negative sentiment in reviews can be visualized in Fig. 22. Common words for negative sentiments are game, app, even, time and make.

Fig. 21. Word Cloud for Top 50 Words in Reviews with Neutral Sentiment.

Fig. 22. Word Cloud for Top 50 Words in Reviews with Negative Sentiment.

Negative reviews are commonly about the Game category and mostly highlight functional errors. Common complaints are:

- Functional errors like slow loading, hanging or freezing apps, utilizing too much memory and synchronization issues, frequently crashing apps.
- No updates and repairs.
- Excessive ads.
- High price with limited functionality
- Needs high bandwidth internet connection for the app to run properly.
- Forced purchases during games.
- Useless notifications.
- Poor navigation, buttons and links not working properly.
- Too much simple and dull apps.

V. Conclusion

High ratings and no. of installs are two success parameters considered in this study. After evaluation, we found out that free apps are performing better than paid apps. To get higher ratings, Personalization, Game and Sports are preferable categories with apps size ranging between 2MB to 40MB and priced below 30$. Exceptionally, bulky apps belonging to games are also getting higher ratings.

To get increased no of installs, Communication, Productivity and Games are preferable. Most of the blockbuster apps with increased installs has high ratings. This sample contains the largest proportion of Family Apps but they are not performing well either in terms of ratings nor installs.

No. of reviews increased with the increase in installs. Users tend to write a review either he is extremely satisfied or dissatisfied. Reviews, ratings and installs show that most of the users are satisfied with apps available on Google play store. Good reviews mostly contain short and simple words and highlight app usability, updates, history retainment and limited ads. User complaints are more elaborate and cover functional errors about the delayed response, frequent crashes, and issues like infrequent updates, excessive ads, limited functionality and high purchase price.

Sports, Tools and Medical categories have quite a potential for developers to work on.

References

[1] "Google Play Store: number of apps 2018 | Statista", Statista, 2019. [Online]. Available: https://www.statista.com/statistics/266210/number-of-available-applications-in-the-google-play-store/. [Accessed: 28- Apr-2019].

[2] Liu, Charles Z., Yoris A. Au, and Hoon Seok Choi. "An empirical study of the freemium strategy for mobile apps: Evidence from the google play market." (2012)

[3] Viennot, Nicolas, Edward Garcia, and Jason Nieh. "A measurement study of google play." In ACM SIGMETRICS Performance Evaluation Review, vol. 42, no. 1, pp. 221-233. ACM, 2014.

[4] Allix, Kevin, Tegawendé F. Bissyandé, Jacques Klein, and Yves Le Traon. "Androzoo: Collecting millions of android apps for the research community." In 2016 IEEE/ACM 13th Working Conference on Mining Software Repositories (MSR), pp. 468-471. IEEE, 2016.

[5] Zhong, Nan, and Florian Michahelles. "Google play is not a long tail market: an empirical analysis of app adoption on the Google play app market." In Proceedings of the 28th Annual ACM Symposium on Applied Computing, pp. 499-504. ACM, 2013.

[6] Guzman, Emitza, and Walid Maalej. "How do users like this feature? a fine grained sentiment analysis of app reviews." In 2014 IEEE 22nd international requirements engineering conference (RE), pp. 153-162. IEEE, 2014.

[7] Ruiz, Israel J. Mojica, Meiyappan Nagappan, Bram Adams, Thorsten Berger, Steffen Dienst, and Ahmed E. Hassan. "Examining the rating system used in mobile-app stores." IEEE Software 33, no. 6 (2016): 86-92.

[8] Nayebi, Maleknaz, Bram Adams, and Guenther Ruhe. "Release Practices for Mobile Apps--What do Users and Developers Think?." In 2016 ieee 23rd international conference on software analysis, evolution, and reengineering (saner), vol. 1, pp. 552-562. IEEE, 2016.

[9] Martin, William. "Causal impact for app store analysis." In Proceedings of the 38th International Conference on Software Engineering Companion, pp. 659-661. ACM, 2016.

[10] McIlroy, S., Ali, N. and Hassan, A. (2015). Fresh apps: an empirical study of frequently-updated mobile apps in the Google play store. Empirical Software Engineering, 21(3), pp.1346-1370.

[11] Comino, Stefano, Fabio M. Manenti, and Franco Mariuzzo. "Updates management in mobile applications. iTunes vs Google Play." (2016).

[12] Martin, William, Federica Sarro, and Mark Harman. "Causal impact analysis applied to app releases in Google Play and Windows Phone Store." RN 15.07 (2015).

[13] Palomba, Fabio, Mario Linares-Vásquez, Gabriele Bavota, Rocco Oliveto, Massimiliano Di Penta, Denys Poshyvanyk, and Andrea De Lucia. "Crowdsourcing user reviews to support the evolution of mobile apps." Journal of Systems and Software 137 (2018): 143-162.

[14] Lee, Gunwoong, and T. S. Raghu. "Product Portfolio and Mobile Apps Success: Evidence from App Store Market." In AMCIS. 2011.

[15] Cheng, Hsing Kenneth, and Qian Candy Tang. "Free trial or no free trial: Optimal software product design with network effects." European Journal of Operational Research 205, no. 2 (2010): 437-447.

[16] Hsu, Chin-Lung, and Judy Chuan-Chuan Lin. "What drives purchase intention for paid mobile apps?–An expectation confirmation model with perceived value." Electronic Commerce Research and Applications 14, no. 1 (2015): 46-57.

[17] Khalid, Hammad, Emad Shihab, Meiyappan Nagappan, and Ahmed E. Hassan. "What do mobile app users complain about?." IEEE Software 32, no. 3 (2015): 70-77.

[18] Khalid, Hammad. "On identifying user complaints of iOS apps." In Proceedings of the 2013 International Conference on Software Engineering, pp. 1474-1476. IEEE Press, 2013.

[19] Hassan, Safwat, Chakkrit Tantithamthavorn, Cor-Paul Bezemer, and Ahmed E. Hassan. "Studying the dialogue between users and developers of free apps in the google play store." Empirical Software Engineering 23, no. 3 (2018): 1275-1312.

[20] Vu, Phong Minh, Hung Viet Pham, and Tung Thanh Nguyen. "Phrase-based extraction of user opinions in mobile app reviews." In Proceedings of the 31st IEEE/ACM International Conference on Automated Software Engineering, pp. 726-731. ACM, 2016.

[21] Picoto, Winnie Ng, Ricardo Duarte, and Inês Pinto. "Uncovering top-ranking factors for mobile apps through a multimethod approach." Journal of Business Research (2019).

[22] Wang, Shujun. "Determinants of mobile apps downloads: A systematic literature review." In The European Conference on Information Systems Management, pp. 353-360. Academic Conferences International Limited, 2017.

[23] Song, Chihoon, Kyungdo Park, and Byung Cho Kim. "Impact of Online Reviews on Mobile App Sales: Open Versus Closed Platform Comparison." In PACIS, p. 12. 2013.

[24] Dibia, Victor, and Christian Wagner. "Success within app distribution platforms: The contribution of app diversity and app cohesivity." In 2015 48th Hawaii International Conference on System Sciences, pp. 4304-4313. IEEE, 2015.

[25] He, Xiaoyun. "Understanding the mobile app markets: demand, supply, and value creation." (2018).

[26] Wan, Jinlin, Ling Zhao, Yaobin Lu, and Sumeet Gupta. "Evaluating app bundling strategy for selling mobile apps: an ambivalent perspective." Information Technology & People 30, no. 1 (2017): 2-23.

[27] "Google Play Store Apps". 2019. Kaggle.Com. https://www.kaggle.com /lava18/google-play-store-apps/activity.