Google Play Is Not A Long Tail Market

An Empirical Analysis of App Adoption on the Google Play App Market*

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ABSTRACT

Distributions of popularity of many online markets have long tails. However, the profitability of the long tail remains in dispute among researchers. With an analysis of an extensive dataset of Google Play transactions, this work first examine the long tail of the mobile application market. Our results suggest that Google Play is more of a "Superstar" market strongly dominated by popular hit products than a "Long-tail" market where unpopular niche products aggregately contribute to a substantial portion of popularity. Blockbuster apps have more downloads, higher ratings and satisfaction ratio. Additionally, we investigate the impact of price on sales of paid apps and find that certain expensive professional apps constitute disproportional large sales. Our findings reveal the unique market structure of the mobile app market, under which the discovery of niche apps is still an intractable task.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioural Sciences

General Terms

Economics; Measurement

Keywords

Mobile application market; long tail; popularity distribution; electronic commerce; mobile commerce

1. INTRODUCTION

Nowadays many online retailers are providing consumers with innumerable products to choose from. In these markets, distributions of popularity are usually found to be long-tailed such that a small number of popular hit products make up the "head" and the great many unpopular niche products constitute the "tail". A number of markets, such as Amazon.com, the online retailing giant, are claimed to be "Long Tail" markets where aggregated sales of the countless niches contribute a significant fraction of the total revenue [3,5,7]. Nevertheless, some other markets, such as Rhapsody, an online music subscription service, are discovered to be "Superstar" markets where the blockbusters strongly dominate the revenue [9]. Many works have been devoted to examining these competing perspectives on the profitability of the long tail, this work further brings the examination to the emerging mobile application (app) market.

Being a rapid growing market with immense demand, the mobile app market is considered to be the future of software industry. For instance, the Google Play (the rebranded Android Market) has 300 million users, over 600,000 listed apps, and 20 billion cumulative downloads since Google launched Android in 2009 [2]. Some anecdotal sources estimated that the whole mobile app market generated revenue surpassing 15 billion$ in 2011 [1]. Besides, this market has naturally a long-tailed sales distribution. Among the tens of thousands of apps listed in Google Play, Angry Bird, perhaps the most successful blockbuster app, has more than 50 million downloads, while numerous unknown niche apps have only dozens of downloads.

Given such a market with huge contrast between the hits and niches, a key question for developers is where should they focus: the superstars or the niches? In other words, should developers concentrate on creating tomorrow's superstars or try their luck with many different niches? This question is of strategic importance for developers to stand out in the fierce competition on app market. The examination of the long tail of mobile app market could therefore provide insights in understanding the market structure and evaluating profitability of the long tail.

Despite the interest, lack of data in sufficient size hinters research in mobile app market, since market operators, such as Apple and Google, are reluctant to disclose detailed operational data. Apart from the work based on limited data [13], this research, to our knowledge, is the first to examine popularity distribution of a mobile app market at a large scale. In particular, we analyze an extensive dataset of transactions of Google Play for Android apps and examine popularity distributions of paid and free apps. We find that user consumption of apps is limited and hit apps largely meet this demand. The dominance of hit apps are reflected by that hit apps make up a disproportionately large fraction of popularity and have higher ratings. Our results indicate that Google Play, whose downloads and sales distributions are largely concentrated on hit apps, is more of a Superstar market than a Long Tail market. Besides, we also discover that, though most paid apps are cheap, some expensive apps account for disproportionately large revenue.

In the remainder of this paper, we proceed as follows. In Section 2 we review related work on the Long Tail theory of digital

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markets. Section 3 and 4 describe the dataset we use and methodology of research. Then we present and analyze our results in Section 5. We conclude with a summary of this work and the discussion of implications of our findings to strategies in Section 6.

2. RELATED WORK

In traditional market, best-selling hit products strongly dominate the market and the contribution of niches are negligible. This phenomenon of sales concentration is termed as the Pareto principle by Economists. The Pareto principle, also known as the 80/20 rule, states that a small proportion (e.g., 20%) of products in a market often generate a large proportion (e.g., 80%) of sales [4].

This imbalance may have been changed by the Internet. Some digital markets have deviated from traditional markets. Chris Anderson, the editor in chief of the Wired Magazine, coined the term "Long Tail " to describe the observation that aggregated sales of niche products which are usually unavailable in brick-and-mortar stores constitute a sizable portion of sales of some online retailers [3]. For example, 30% of Amazon's sales of books and 20% of Netflix revenue of movies come from titles unavailable in largest offline stores [3]. Low stocking and distribution costs that enable abundant supply, and easy searching tools with smart recommender systems that allow users to access otherwise unnoticed niche products are regarded as key factors to the formulation of the long tail [5, 6]. Some researchers further claim that, when compared to brick-and-mortar counterparts, the concentration of sales distribution in online markets would shift away from homogenized hits to heterogenized niches that are more appealing to consumers' different individual tastes, and consequently, producers and retailers should put more emphasis on niche products [3, 4].

Though acclaimed by the business world, the value of long tail is in dispute in academia. Researchers find evidences from video [8, 9, 14] and music markets [10] that online market sales concentrate further on hit products, therefore retailers should continue emphasizing the hit products. Particularly, in her influential work [8], Elberse reviews the sales data from Nielsen VideoScan, Nielsen SoundScan, Quickflix, and Rhapsody, and points out that the long tail is actually overvalued: "the tail is likely to be extremely flat and populated by titles that are mostly a diversion for consumers whose appetite for true blockbusters continues to grow. It is therefore highly disputable that much money can be made in the tail."

Regarding the long tail of mobile app market, a previous work based on cross-sectional data of top sellers in Apple App Store claims that app portfolio diversification to be positively correlated with sales performance suggesting the advantage of exploiting the long tail [13]. Rather than being limited by data merely from the top runners, our work firstly examine the sampled data of sales distribution of the whole market using an extensive dataset collected directly from users.

3. DATA

To obtain operational data of mobile app markets directly from market operators is very hard. We are fortunate to get an extensive dataset of Google Play from *42matters AG* through its Android app *Appaware*, which captures installations, updates and removals of apps in real time and shares this information among its users [11]. Its central database receives records of transactions from Appaware clients running in users' Android phones. The transfer of these records is authorized in the terms of use when users install Appaware. A record contains user id, time, type of transaction (install, removal, and update), app name, app price, app rating, and etc. The dataset is part of those records and Table 1 shows some statistics. In general, this dataset consists of 208000 anonymous users' 84.1 million transactions from March 2011 to November 2011. During this period Appaware was focused on aggregating data, and its social features that allows interaction among users and app recommendation features were not activated thus having little impact on user behaviors. The dataset is one of the few sources that are statistically large enough for studies in sales distortion and user consumption patterns in mobile app markets.

Users	208 187
Paid Apps	16 214
Free Apps	175 087
Transactions	17 609 041
Paid App Sales	1 887 175$
Paid App Downloads	530 168
Free App Downloads	6 079 398

Table 1: Statistics of dataset.

To show the representativeness of this dataset, namely, the the users of Appaware is a representative sample of the whole Android user group, we conduct an evaluation by comparing rankings of downloads in our data with those available in Google Play. Intuitively, if an app x has a higher ranking of downloads than y in Google Play, then x should also have more downloads recorded than y in our data. With comparison of all possible combinations of two-app pairs, we could examine how much the dataset accords with Google Play available data.

In detail, for a given app, although the ground truth (precise number of downloads) is inaccessible, the range that how many downloads it has is listed in Android Market. These ranges are given by an ascending sequence of predefined consecutive intervals: $[1, 5], [5, 10], [10, 50], [50, 100], \cdots$. Every app x fits in a range $r(x)$ and all the apps share the same sequence of ranges.

We define $r(x) \succ r(y)$ if left bound of $r(x)$ is greater than or equal to right bound of $r(y)$. Let A be the set of all apps in the dataset, and $d(x)$ number of downloads of an app $x \in A$. We calculate:

$$C = \frac{|\{(x, y) \mid x, y \in A, r(x) \succ r(y), d(x) \geq d(y)\}|}{N}$$

$$U = \frac{|\{(x, y) \mid x, y \in A, r(x) = r(y)\}|}{2N}$$

$$W = 1 - U - C$$

where (x, y) is an ordered pair of apps and $N = \binom{|A|}{2}$ is the total number of possible pairs. C represents the percentage of correct pairs, U unclear pairs, i.e. the ones are in the same range, and W wrong pairs.

From Table 2 we could see that more than 70% of pairs have correct orderings in both paid and free apps. Additionally, we find that for popular apps which have bigger range and more recorded downloads, C is even higher around 80%. In short, the dataset preserves the ordering between apps in the Google Play fairly well, and we could analyze the general Android user behavior using this dataset.

	Paid Apps	Free Apps
C	71.5%	76.0%
U	15.9%	14.3%
W	12.6%	9.7%

Table 2: Evaluation of dataset representativeness.

4. METHODOLOGY

When analyzing the data, we partition apps into two categories: paid and free, taking account of intrinsic differences between paid apps and free apps. An app is defined as free if it never charges users for downloading. Table 1 already indicates the difference: there are a lot more free apps than paid apps, and free apps also have much larger total number of downloads than paid ones. In addition to that, top downloaded free apps has around 10 times more downloads than top paid apps recorded.

For paid apps, we unify the local payment currency used in Google Play of different countries by converting all payments to US dollar using the exchange rates listed in Google Currency on May 1, 2012. We believe this has minor impact on the calculation of total sales. Also, Google Play has a return time for paid apps, within which a payment could be refunded if the purchased app is deleted. Since late December 2010, this return time has been set to 15 minutes. Spurious downloads that were removed within 15 minutes after download are neglected accordingly.

Finishing these preparations, following [7, 8, 12], we focus the analysis of sales distribution of paid apps and downloads distribution of free apps.

5. RESULTS

5.1 User Consumption

To begin with, we find user consumption of apps to be rather limited. Figure 1 depicts the consumption where for a given number of downloads x in the horizontal axis, the corresponding y value is its percentile rank, i.e. the percentage of users downloading less than or equal to x apps. For example, 72% of users have not downloaded any paid apps and only 2% not any free app[1]. Most users (80^{th} percentile) download no more than 1 paid apps and 43 free apps. Low number of downloads of paid apps may be caused by the fact that most apps in Google Play are free and, as some business observers speculate, users in Android market are less willing to pay than in other mobile markets.

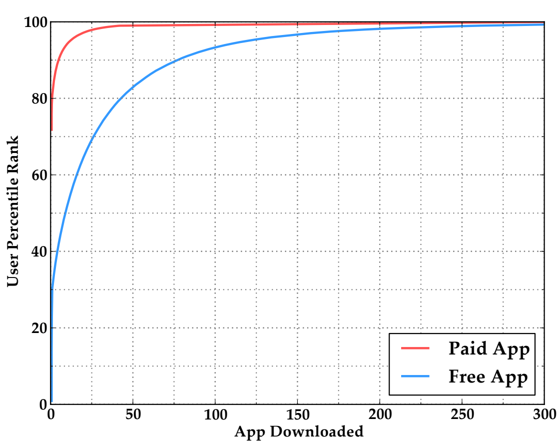

Figure 1: User percentile of downloads.

5.2 The Long Tail

[1]Due to the design of Appaware, users not downloading any apps cannot be recorded.

Now we move on to the central question, namely, is the Google Play a long tail market, by examining the distortion of *popularity*. For paid apps, popularity is defined as total value of sales, and free apps total number of downloads. In Figure 2, we use the Lorenz Curve and Gini Coefficient to study the concentration of consumption where Apps are ranked ascendingly by its popularity. The Lorenz Curve depicts the ratio of cumulative popularity of the bottom x percent apps to the total popularity. The line of equality is Lorenz curve for the case that every app has the same chance of being downloaded, thus making the curve a 45-degree line. The Gini Coefficient g represents the deviation of a Lorenz Curve to the line of equality. In detail:

$$g = 1 - \frac{\text{Area under the Lorenz Curve}}{\text{Area under the line of equality}}$$

A big Gini Coefficient indicates a Superstar market dominated by the hits, and a small Gini Coefficient shows a Long-tail market characterized by the long tail.

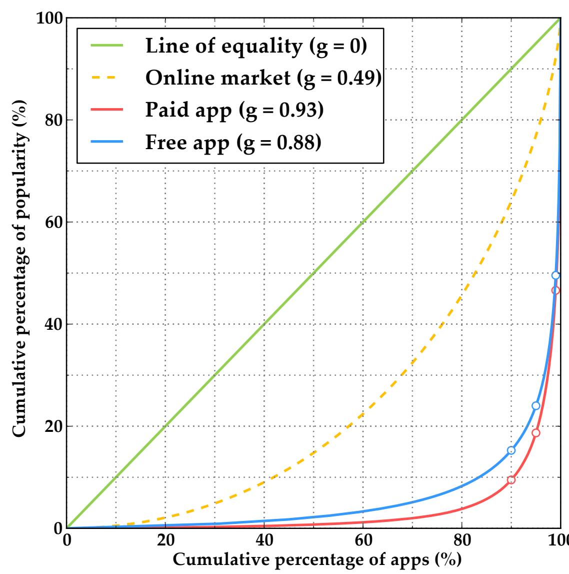

Figure 2: Lorenz Curve and Gini Coefficient.

Hits are clearly dominating in Figure 2. For both sales of paid apps and downloads of free apps, top 1%, 5% and 10% most popular apps make up approximately 50%, 80% and 90% percent cumulative popularity. This dominance of hit products is even stronger than the well known Pareto Principle which claims that 20% most popular products possess 80% of popularity. These curves are also far different from Lorenz Curve of the typical online market [7] whose Gini coefficient is around 0.5. With such a large Gini Coefficient, the Google Play market is substantially unbalanced towards the hits.

These patterns are depicted in absolute terms in Figure 2 and Figure 4, where apps are ranked by popularity descendingly in x-axis, and its popularity value is in y-axis. Figure 3 shows that the popularity decreases sharply as the rank increases. The diminishing of popularity is so fast that we have to take logarithmic scale in y-axis. Instead of having a long tail, the Google Play has a tall head and a flat tail.

Taking logarithmic scales in both axes, Figure 4 reveals the power law of popularity. In studies of other online markets, a presumed power law distribution is used to estimate the structure of the market [5, 7]. Though we do not observe a global power law in the data, a piecewise power law is found using two linear regressions segmented at roughly $x = 1600$. Both regressions fit the curve nicely with coefficients of determination (R^2) as 0.9998 and 0.9967 respectively.

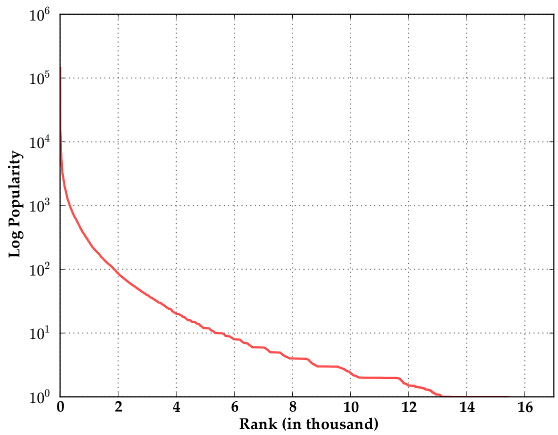

Figure 3: Tall head and flat tail.

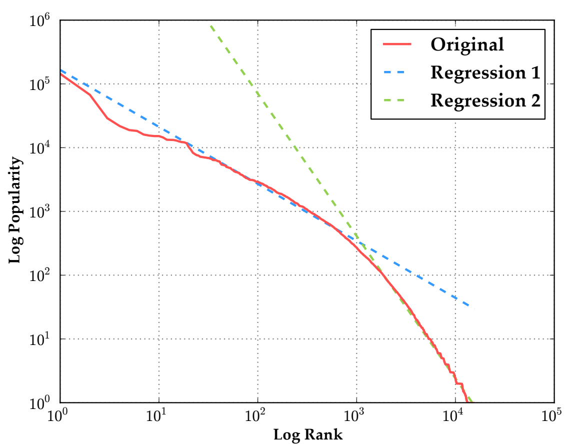

Figure 4: Piecewise power law.

The intersection point divides the apps into two parts: the top 10% hits and the bottom 90% niches. Unlike other online markets where the size of the head could be determined by titles available in biggest brick-and-mortar stores, the mobile app market does not have such a counterpart. This segmentation gives qualitative support to the conceptual notions of head and tail in the context of mobile app market. Also, the slope of the regression 2 is much steeper than that of regression 1, in other words, when compared to hits, popularity of niches drops much quicker. This suggests that for the niche apps, discovery is still an intractable task, especially in a market where most users download limited number of products.

5.3 Natural Monopoly and Double Jeopardy

The dominance of hit apps is further illustrated in the two phenomena of sales distribution: *natural monopoly* and *double jeopardy* which are also found in other superstar markets [8, 12].

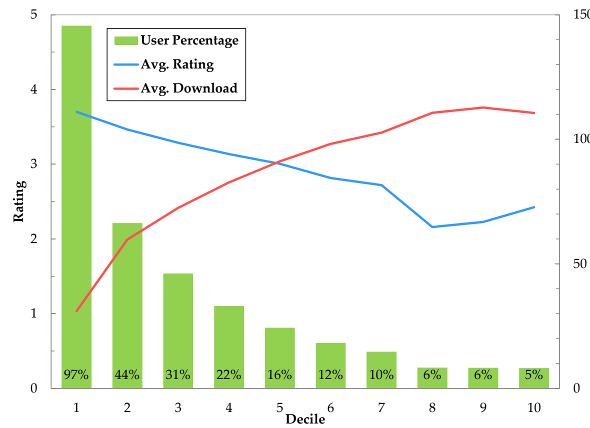

Figure 5: Natural Monopoly and Double Jeopardy

Natural monopoly claims that not only does popular products attract disproportionate share of customers, but also these customers purchase more popular products than unpopular ones. We find evidence supporting this theory. In Figure 5 and Figure 6, apps are sectioned into ten deciles where the most popular 10% apps are at leftmost and least popular 10% rightmost. The green bars in Figure 5 represent the percentage of users downloading at least one app in this decile[2]. Almost every user download the most popular apps while very few users download the least popular ones. Additionally, the red line shows the average number of apps downloaded by users downloading at least one app of a decile. It tells that, consumers of niche apps download more than those of hit apps.

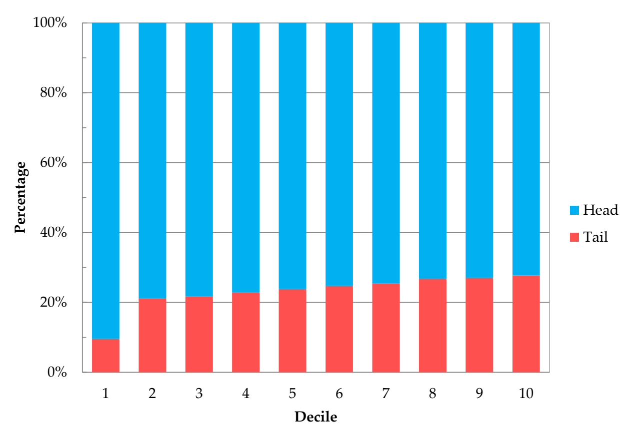

Figure 6: Distribution of downloads in tail and head.

We further drill down these downloads in Figure 6, in which the top 10% apps are entitled as Head and bottom 90% as Tail. Light users in 1[st] decile , i.e. those who download most popular apps, have larger portion of apps downloaded from most popular apps.

[2]Users who have not downloaded any paid apps cannot be observed in this chart.

Double jeopardy describes that the unpopular products have both less consumers and lower satisfaction rate, therefore in a “double jeopardy”. This is shown in Figure 5 by the descending bar chart and blue line, which represent number of consumers and their average rating of apps.

To sum up, the majority of users download hit apps and the few minority users download niche apps; all users consume much more hit apps than niche apps; and hit apps have higher user ratings than niche apps. This accords with the natural monopoly and double jeopardy observations, which clearly demonstrate the superiority of hit apps.

5.4 User Satisfaction

Having observed the dominance of the hit apps, we could further ask: to what extent do these hit apps satisfy individual customers? Do they meet the demands of most consumers or there are still a sizeable gap which needs the niches to fill?

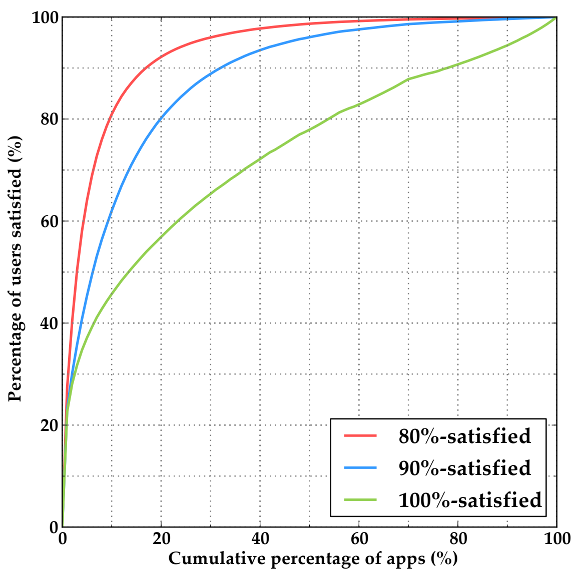

Figure 7: User satisfaction.

We answer this question by investigating the *user satisfaction ratio*. With an inventory of top x percent most popular apps, a user is *y-percent satisfied* if at least y percent of its demands of popularity are met by such inventory, and the satisfaction ratio z is the percentage of users that are y-satisfied among all the users.

In Figure 7, in order to grasp the users that are largely satisfied, we display the 80%-satisfied, 90%-satisfied and 100%-satisfied curves of users of free apps. Paid apps have similar curves, we omit these curves for simplicity of illustration. Generally, the 80%-satisfied and 90%-satisfied curves are increasing quickly before leveling off at a high satisfaction ratio, while the 100%-satisfied curve begin to increases steadily after the hit region. Still, with merely the top 10% most popular apps, namely the head, 80% of users are 80%-satisfied, 62% of users 90%-satisfied and 46% of users 100%-satisfied. In other words, the head itself can largely meet most users' demands. However, observing the gap between 90%-satisfied and 100%-satisfied curves, the niches have some room to meet users' eccentric demands.

5.5 Price Distribution

Finally, we analyse the distribution of sales and downloads of paid apps versus prices. In Figure 8, the height of a bar is the percentage of total apps in a section of prices, and corresponding percentages of total sales/downloads of all apps in this section are represented by the red and blue lines. Most apps are rather cheap, actually the average price of all paid apps is 2.6\$. Interestingly, among cheap apps which are below 3\$, the usual 1\$ apps have less aggregated downloads and sales than apps whose prices are ranging from 1\$ to 3\$. However, counter intuitively, a few expensive apps acquire disproportionate large revenue, whose price are dozens of times higher than cheap apps, thus a few downloads could contribute to a large profit. These apps are usually professional apps such as navigation, which may have different market position than games and daily apps.

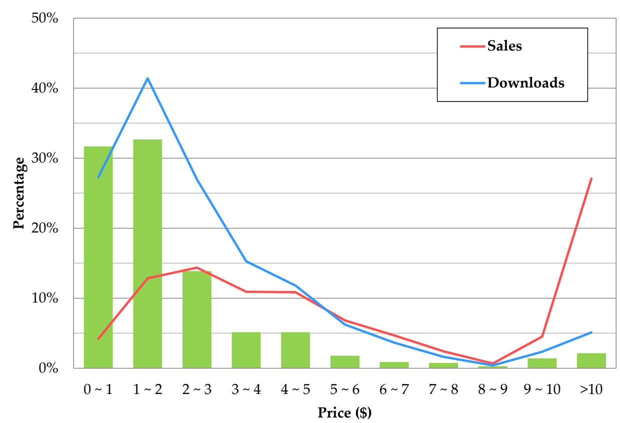

Figure 8: Distribution of sales and downloads of paid apps.

6. DISCUSSIONS

In this work we examine the distribution of sales and downloads in the Google Play using an extensive dataset. We find that the Google Play is a Superstar market largely dominated by hit apps. Among the limited number of apps downloaded or purchased by most users, hit apps make up the vast majority and achieve better user rating.

As mentioned in previous sections, the value of the long tail is in doubt. Although it matches the criteria of being a Long-tail market, the mobile app market is found to be a Superstar market. Developers should focus on hit apps to achieve a spot in the relatively small screen of smart phones which physically constraint user choices. Additionally, we also suggest developers to employ more flexible pricing policy. The cheap apps unnecessarily acquire more downloads and revenue. Surprisingly, we do not find any pattern of affection of discount promotion in the data.

Our findings suggesting that, mobile app market may follow a different market structure than the other online markets. First of all, in a highly connected world full of social networks and social apps, mobile market could be influenced by the tyranny of network effect which lead users tend to choose the same app. Studies investigating the impact of social features on the mobile app market would be beneficial. A second consideration is the diversity of user tastes. Do users really have diverse needs in choosing most apps? Unlike books or music whose perception is highly subjective, a user's need for an app, e.g. a navigation app, tends to be more objective. However, for different categories of apps, e.g. games, the perception may be subjective as well. Diversity of consumer needs of different categories of apps is another point of research. All these open research problems could help researchers and developers in understanding the underlying mechanism of mobile app market.

However, developers or market operators may have the chance to change the market structure by providing a smarter recommender system which better help consumers reach the niches. Existing recommender systems mostly take account of popularity, especially the collaborative filtering based methods, and contribute to the dominance of hit apps [10]. Though proven to be a non-trivial task, recommender system that is beneficial to niches in the long tail has been proposed [15]. How could recommender systems better enable users to explore the growing long tail where thousands of new apps are added to everyday? Is this able to change the market structure? Again, these remain open research questions which may make profound influence of the app market.

This work is also limited in two ways. Firstly, more sophisticated statistical analysis is needed to evaluate the soundness of data set. Records in the dataset are from users who have downloaded Appaware at first place, consequently these users are not necessarily a uniform sample of the total Android user population. We may extend our evaluation in Section 3 by using K-L divergence and other statistical techniques to estimate the deviation from the Google Play download distribution. Nevertheless, the lack of ground truth makes these analysis an intractable task. Secondly, due to limitation of data, we neglect the impact of in-app purchase nor revenue of advertisements, which have been important sources of revenue to developers. However, the objective obstacle is that these data are non-public to third party applications, and only Google and corresponding developers have access to these data.

Serving as a meta point of study in the sales distortion of mobile app market, this work could be further extended by building an analytical model of the user behavior in downloading mobile apps, and addressing the impacts of dynamic factors such as update of apps to user consumption.

7. ACKNOWLEDGMENT

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