"What Apps Did You Use?": Understanding the Long-term Evolution of Mobile App Usage

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ABSTRACT

The prevalence of smartphones has promoted the popularity of mobile apps in recent years. Although significant effort has been made to understand mobile app usage, existing studies are based primarily on short-term datasets with limited time span, e.g., a few months. Therefore, many basic facts about the long-term evolution of mobile app usage are unknown. In this paper, we study how mobile app usage evolves over a long-term period. We first introduce an app usage collection platform named carat, from which we have gathered app usage records of 1,465 users from 2012 to 2017. We then conduct the first study on the long-term evolution processes on a macro-level, i.e., app-category, and micro-level, i.e., individual app. We discover that, on both levels, there is a growth stage enabled by the introduction of new technologies. Then there is a plateau stage caused by high correlations between app categories and a pareto effect in individual app usage, respectively. Additionally, the evolution of individual app usage undergoes an elimination stage due to fierce intra-category competition. Nevertheless, the diverseness of app-category and individual app usage exhibit opposing trends: app-category usage assimilates while individual app usage diversifies. Our study provides useful implications for app developers, market intermediaries, and service providers.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

App usage; App categories; Google play; Long-term evolution

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1 INTRODUCTION

Since the introduction of the first Android-based smartphone the 'HTC Dream' in 2007 [28, 29], the usage of smartphones has significantly evolved over the last ten years, extending from essential communications to various applications, e.g., ordering food, shopping online, and managing health [1, 10, 19, 20]. Such diverse demands are supported by mobile apps, i.e., software applications designed to run on mobile devices [30]. To satisfy various user requirements, Google Play and Apple Store, i.e., the official Android and iOS app markets, provide a wide range of apps for mobile users. As of 2019, the number of apps in app markets has reached 2.7 million [21], and the app economy is estimated to grow to 6.3 trillion dollars by 2021 [25]. Such a vast market attracts and motivates app developers, market intermediaries, and service providers to better develop, disseminate, and deliver mobile apps.

In recent years, countless efforts have been made to study mobile app usage. Existing studies principally explore users' static behavior based on short-term datasets collected in a given time window ranging from one week [5, 23, 26], several months [6, 14, 15, 27, 32], and up to one year [18]. However, existing research falls short in studying the long-term evolution of users' app usage since they are limited by the short time span of their datasets.

Every year, mobile users will acquire new generations of smartphones, technologies, and apps. Both smartphone hardware and software are significantly advancing over time. As a result, users' mobile app usage will correspondingly evolve. The evolution of app usage makes some previous findings based on short-term datasets out-of-date and no longer applicable. Hence, in this dramatically changing world, studying evolutionary trends and extracting general laws behind mobile app usage enables us to gain insight beyond short-term observations. However, up to now, *many basic facts about the long-term dynamics of mobile app usage are unknown.* Therefore, exploring the long-term evolution of mobile app usage is essential.

Understanding the long-term evolution of mobile app usage is critical for industry because understanding such mechanisms can enable companies to effectively improve user experience, enhance apps' competitive power, and grasp market opportunities during development. For instance, for market intermediaries and service providers, analyzing the evolution processes can help with tracking app preferences of users, monitoring the maturity of different app categories, and forecasting the future flourishing apps. They can further draw upon such insights to optimize the decisions for maintaining and improving the entire app market. Moreover, the long-term evolution study can help app developers grasp general laws behind the long-lived app categories and apps. In this way, app developers can make better decisions for developing and releasing apps and improving the competitive power of their apps.

In this paper, we make the first effort towards understanding the long-term evolution of mobile app usage. Specifically, our study details how users' usage changes over time at both s macro-level and micro-level, i.e., app categories and apps, respectively. To this end, we have collected a long-term app usage dataset by leveraging an Android-based platform called Carat. The dataset covers around 1,500 users in over 80 countries and their app usage records for six years from 2012 to 2017 (Section 2). We first use the dataset to make a macro-level analysis on the evolution of app-category usage in terms of four metrics, i.e., the number of used app categories, the diversity of app-category usage, the popularity of app categories and the correlations of app categories (Section 3). Next, we extend our analysis to the micro-level, i.e., individual app granularity. We characterize the evolution of app usage based on similar metrics. Comparing the evolving trends between the macro-level and micro-level, we delve into the reasons and summarize the general laws of long-term usage evolution (Section 4). At last, we explore the implications of our findings for app developers, market intermediaries, and service providers (Section 5). Among the many insightful results and observations, the following are the most prominent.

- The long-term usage evolution of app-categories and apps exhibits different processes. A complete usage evolution of an app-category undergoes two stages, i.e., a growth stage and a plateau stage. However, apart from the above two stages, apps have one more additional stage, i.e., an elimination stage.
- The diversity of app-category usage declines over time due to non-decreasing usage evolution processes. However, the diversity of app usage increases greatly, showing large differences between mobile users at the app level.
- The app usage shows a typical *Pareto effect*. A small group of apps dominate usage in both the entire app market and individual app categories. Also, we identify 12 essential apps of different functionality for smartphones.
- The release of new technologies will trigger the growth stage for both app categories and apps. This increasing trend will not be influenced by the maturity of app categories and the *Pareto effect*.
- The fierce intra-competition of apps results in an elimination stage of app usage and the decrease in correlations between apps in the same category. Also, the evolution of app usage will be affected by the degree of maturity of the app's category.

2 LONG-TERM MOBILE APP USAGE DATASET

2.1 Data Collection and Basic Analysis

It is difficult to collect a long-term app usage dataset for two main reasons. 1) For privacy and safety concerns, mobile users are hesitant to let a third party collect their data, especially for long-term collection. 2) In the research community scholars can recruit volunteers and use a monitoring app to collect app usage records. However, executing such a long-term study is costly in terms of both human labor and capital.

To overcome the above difficulties, we designed an Android-based long-term data collection platform called Carat. Carat is a mobile app that can record users' smartphone usage data automatically. First, to eliminate user privacy concerns, the user will be informed of all data collection items when installing Carat in the End-user License Agreement (EULA). We will not collect any personal information. Furthermore, the data-gathering part of the platform is open-source[1] thus users can examine it easily. Second, to reduce the expense of long-term data collection, we motivated users to keep using Carat for long time periods. To this end, we designed Carat as not only a simple data collection app but also a collaborative energy diagnosis app. Carat can provide personalized recommendations for improving smartphone battery life. Carat gathers a data sample every time the battery level changes by 1%, as allowed by the Android system. Each data sample contains a list of apps being used, a user-specific identifier, battery level, timestamp, time zone, mobile country code, and mobile network type. As of now, the Carat platform has gathered data from over 30,000 mobile users from over 100 countries[2].

As our focus is on studying the long-term evolution of mobile app usage, we select users with more than three years of records and define them as long-term users. In the end, we obtain 1,465 long-term users with 12,457,867 records starting from January 2012 to December 2017. Since the user may uninstall and reinstall Carat during the data collection period, the number of long-term users changes over time, i.e., 2012 (965 users), 2013 (836 users), 2014 (1,010 users), 2015 (1,197 users), 2016 (1,114 users), 2017 (916 users). Also, we crawl the apps' category information directly from Google Play. Table 1 summarizes the dataset used in our analysis.

Unlike previous works whose mobile app usage datasets are collected only from one city [8, 23, 32] or one country [31], our users are distributed across the world. The long-term users are from 87 countries. We use both time zones and mobile country codes to determine the country of users. The majority of the users are based in the USA (360 users). Also, there are many users in Finland (278 users), India (60 users), Germany (52 users), and the UK (49 users). The diversity of the Carat dataset enables us to capture the evolving trends of the worldwide app market, improving the representativeness of our analysis results.

2.2 Ethical Considerations

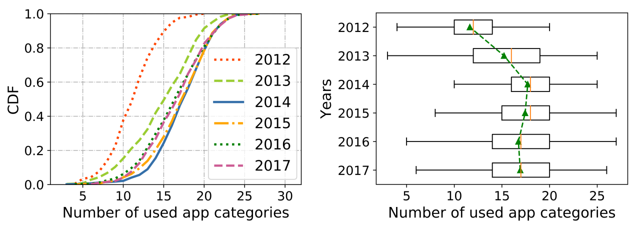
We are very aware of the privacy implications of using the collected data for research. We have taken adequate measures to safeguard the privacy of the involved mobile users. As mentioned, we do not collect any personal information from users. Also, the data-gathering part of Carat is open-source. The mobile users are informed of the data collection and management procedures and grant their consent from their devices. The dataset is stored in a secure local server protected by strict authentication mechanisms

[1] http://carat.cs.helsinki.fi/

[2] Sample of our collected data available at https://www.cs.helsinki.fi/group/carat/data-sharing/.

Table 1: Summary of our dataset.

# Users	# Records	# Apps	# App Categories	Attributes	Date	Area
1,465	12,457,867	25,068	32	Apps, time zone, timestamp, mobile network type	01/2012 - 12/2017	Over 80 countries



(a) CDF of the number of app categories used by each unique user.

(b) Distribution of used app categories across different years.

Figure 1: Evolution of app-category usage across six years.

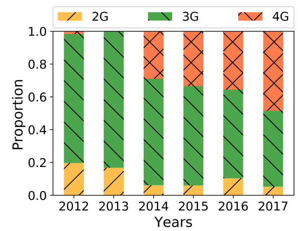


Figure 2: Proportions of mobile network types.

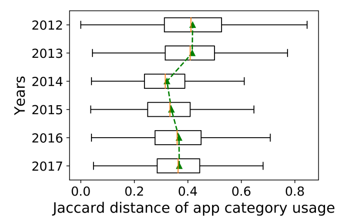


Figure 3: Jaccard distance of app-category usage.

and firewalls. A user-specific identifier is randomly generated when a user first installs Carat. We only have users' mobile country codes rather than sensitive location information. Hence, we cannot associate user-specific identifiers with physical users. All researchers are regulated by a strict non-disclosure agreement to access the data. This work has received approval from all authors' local institutions.

3 EVOLUTION OF APP-CATEGORY USAGE

3.1 Number of App Categories

We begin our analysis by investigating the most intuitive metric of app-category usage, i.e., the number of app categories used by each user during a given year. Figure 1(a) presents the Cumulative Distribution Function (CDF) of the number of used app categories for all long-term users from 2012 to 2017. We observe that the evolution of app-category usage undergoes two stages.

- **Stage one (2012 - 2014).** In this stage, the number of app categories used by each user increased significantly. The increasing trend suggests that during this stage, *smartphones were endowed with more functions, and people started using smartphones in more diverse activities.* In 2012, over 80% of users used less than 14 app categories, while the number increased to 20 by 2014. Moreover, the average number of used app categories expanded from 12 in 2012 to 17 in 2014.
- **Stage two (2014 - 2017).** During this stage, the number of used app categories remained stable over time, which implies that *both smartphones' functions and users' usage at the app-category granularity became steady.* As depicted in Figure 1(a), the CDF curves for years from 2014 to 2017 are very close to each other. The average number of used app categories was around 17.

Alternatively, to better illustrate the changes in the number of used app categories, we depict the distributions across different years using box-plots in Figure 1(b). Compared with CDF curves, box-plots describe data through their quartiles, enabling us to observe the changes in different groups of data [17]. In the box-plot, candlesticks represent the minimum and the maximum values of the data, while the boxed area contains the values between the 25% and 75% quatiles. The horizontal line depicts the median. The green upper triangle denotes the mean. From 2012 to 2014, the values in the interquartile range, i.e., the boxed area, increased significantly, reinforcing Figure 1(a). However, after 2014, the third quartile is constant, implying the group of users who use relatively more app categories remained stable. Although the first quartile dropped slightly until 2016, there was no discernible change in terms of the average value. Especially in 2016 and 2017, the interquartile range was the same, representing a steady state in users' app-category usage.

One possible reason for the increase in used app categories in stage one is the development of mobile networks. From 2012 to 2014, many countries, including the USA, Finland, the UK, etc., started to deploy fourth-generation mobile networks (4G) [16]. By 2014, 4G mobile networks had been commercialized and used on a large scale. In terms of the mobile network types in our dataset, we present how the proportions of different mobile network types changed from 2012 to 2017 in Figure 2. In our case, 2G and 3G refer to second-generation and third-generation mobile networks, respectively. We can observe that by 2014, around 30% of collected users were using 4G networks, and the fraction grew steadily after that, corresponding to the commercialization of 4G networks. Compared to 3G providing up to 21.6 Mbit/s download rate, 4G networks can support 1 Gbit/s or about 50 times that of 3G. As a result, mobile networks no longer inhibit the usage of latency-sensitive apps and data consuming apps, e.g., online gaming apps, online video apps, and map apps. Therefore, more app categories are widely used by mobile users to facilitate and color their lives. The details of the changes in popularity across different app categories will be discussed in Section 3.3.

3.2 Diversity of App-category Usage

We next study the diversity of app-category usage across different users. In 2010, Falaki *et al.* [7] first demonstrated the diversity of smartphone usage and strongly motivated the need for customizing smartphones to different mobile users. Zhao *et al.* [32] illustrated diversity in mobile app usage as well. Hence, we are interested in analyzing how the diversity of app-category usage changes over time.

We apply Jaccard distance [13] to measure the difference in app-category usage between two users. Jaccard distance is a commonly used metric to measure the similarity between two sets. Denoting C_a and C_b as the sets of app categories used by user A and user B, respectively, the Jaccard distance is computed as,

$$J(A,B) = \frac{|C_a \bigcup C_b| - |C_a \bigcap C_b|}{|C_a \bigcup C_b|}. \tag{1}$$

If the two users use the same app categories, i.e., $C_a = C_b$, $J(A,B) = 0$. On the contrary, if the two users use completely different app categories, i.e., $C_a \bigcap C_b = \emptyset$, $J(A,B) = 1$.

For each year, we compute the Jaccard distance between every two users and illustrate the distributions using box-plots, as shown in Figure 3. We notice that the average pairwise distance, denoted as the green triangle, shows a downtrend. Especially from 2013 to 2014, the average value dropped dramatically from 0.42 to 0.32. Although there was a slight increase after 2014, the average pairwise distance was still much lower than that of 2013. Also, the distribution did not significantly change from 2014 to 2017. The decaying distance reflects that *the diversity of app-category usage declined, and users' requirements for smartphone functions tend to be consistent.* We infer that two reasons led to a decrease in the diversity of app-category usage. First, the development of technologies, including in mobile networks, smartphone hardware, and software, etc., caused more app categories to become popular, and mobile users use similar app categories. For instance, because of the low network throughput and low quality of experience for online gaming, in 2012, only a small group of game fans would use online gaming apps. However, after the large-scale deployment of 4G networks, the quality of experience of mobile online games improved significantly. People become eager to download and play mobile online games. This inference is supported by the increasing popularity of game apps and will be discussed in detail in Section 3.3. Therefore, in this way, users tend to use similar app categories. Second, the app ecosystem pushes mobile users to use similar app categories. With the widespread adoption of mobile apps, a robust app ecosystem has formed, and the correlations of different app categories has become stronger (detailed in Section 3.4). For example, mobile users may share music, games, or books with their friends through social and communication apps. Therefore, their friends have to install the corresponding app categories if they want to open shared content. As time goes by, people will gradually use similar app categories.

3.3 Popularity of App Categories

To understand which app categories are more competitive and explore general laws in usage evolution, we next investigate how the popularity of each app category changes over time. In our case, we measure the popularity in terms of unique users, which is the ratio of the users who used that app category to all long-term users. For instance, if one app category has a popularity of 0.9, it means that 90% of long-term users have used at least one app belonging to that app category. Figure 4 shows the popularity of each app category across different years. From 2012 to 2014, there were 26 app categories. In 2015, three new app categories were introduced, i.e., 'Art and design', 'Food and drink', and 'Maps and navigation'.

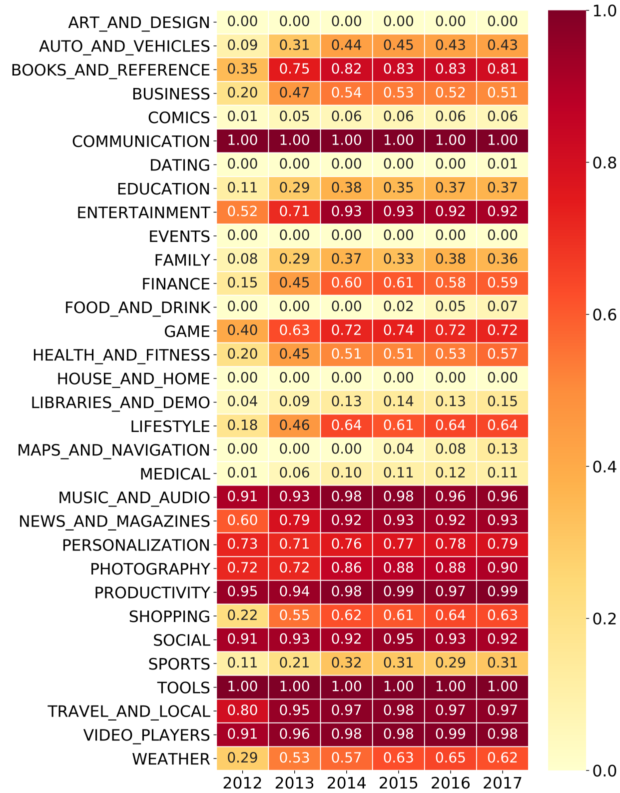


Figure 4: App category popularity across different years.

In 2016, there were two new categories, i.e., 'Events' and 'House and home'. In 2017, one new category, 'Dating' appeared. Therefore, in total, we have 32 app categories.

We first focus on the prevalent app categories. We define an app category as prevalent if its popularity is higher than 0.9. The prevalent app categories represent the critical requirements and preferences of mobile users. We discover that there are two types of prevalent app categories distinguished by their evolution processes.

- **Prior prevalent app category**. This type refers to the category whose popularity has exceeded 0.9 since 2012. There are six prior prevalent categories, including 'Communication', 'Music and audio', 'Productivity', 'Social', 'Tools', and 'Video players', which suggests smartphones have already acted as communication devices and multimedia players since 2012.
- **Posterior prevalent app category**. This type refers to the category whose popularity reached 0.9 after 2012, which suggests changes in smartphone roles. There are four posterior prevalent categories, i.e., 'Entertainment', 'News and magazines', 'Photography', and 'Travel and local'.

Compared to prior prevalent categories, posterior prevalent categories are more relevant to life services. The emerging of posterior prevalent categories implies smartphones changed from communication tools to life assistants coloring users' daily lives. This shifting may be caused by the development of technologies in mobile networks, smartphone hardware, and software. For example, as analyzed in Section 3.1, the prevalence of 'Entertainment' might

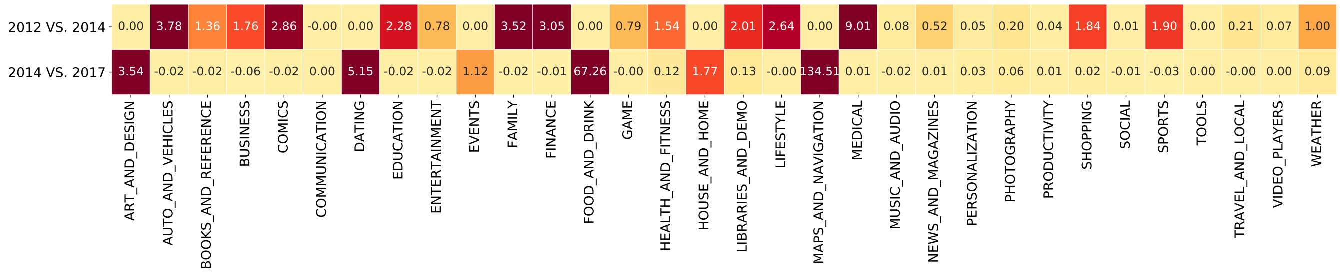
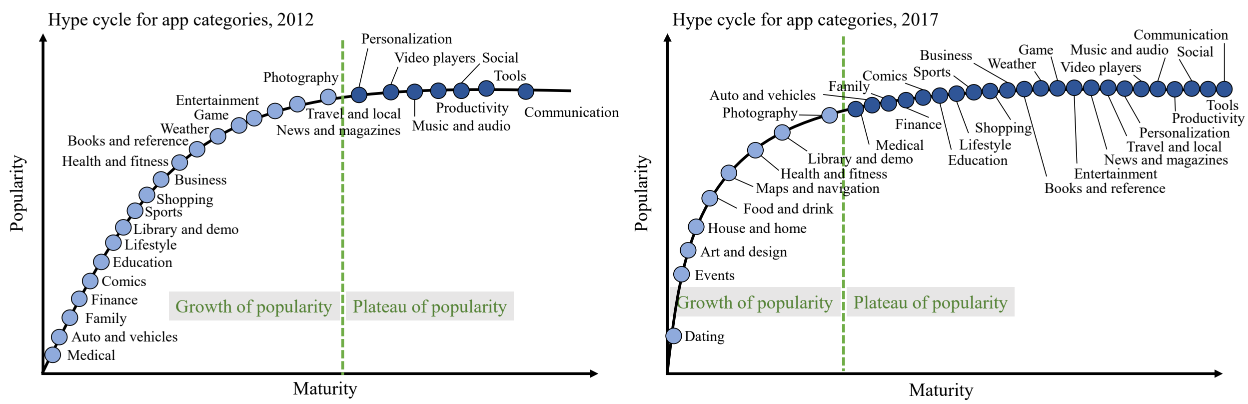


Figure 5: The growth rates of popularity across different app categories.



(a) The hype cycle of popularity for different app categories in 2012.

(b) The hype cycle of popularity for different app categories in 2017.

Figure 6: The evolution of app category popularity.

be caused by the upgrade of mobile networks. The increment in smartphone screen size may be responsible for the rise in the usage of 'News and magazines' due to the improved reading experience. 'Photography' apps also benefit from the upgrade of smartphone hardware. More powerful CPU and high-resolution cameras enable 'Photography' apps to process and render photos in real-time. Also, we infer that 'Travel and local' apps became prevalent due to the improvement in software services, like recommendations and visualizations.

It is of great importance to study the growth rates of popularity across different app categories for capturing users' preferences during the evolution of the app market. For each app category, we compute its growth rate of popularity during two stages, i.e., 2012-2014 and 2014-2017, respectively. Figure 5 shows the results. From 2012 to 2014, except for prior prevalent app categories, the popularity of other app categories increased. This trend suggests that *the app market for prior prevalent app categories has been mature since before 2012, and the entire app market experienced a boom period from 2012 to 2014*. The 'Medical' category had the highest growth rate during stage one, growing more than nine times. Such a high growth rate for the 'Medical' category verifies our previous inference that smartphones are turning into users' life assistants. Additionally, the popularity of other life-related app categories, like 'Finance', 'Family', 'Shopping', 'Education', and 'lifestyle', increased significantly as well. During stage two, i.e., from 2014 to 2017, newly added categories are concentrated in life services, and their popularity also underwent a significant increase. Especially for 'Food and drink' and 'Maps and navigation', their popularity grew over 67 times and 134 times, respectively. However, with the exception of the newly added categories, the popularity of other app categories stopped rising and became relatively stable during this stage. The stable popularity indicates the app category has become mature and also illustrates users' high reliance on that app category.

In terms of the popularity growth rates across diverse app categories, we present the hype cycles of popularity for app categories in Figure 6. The hype cycle shows the relationship between the maturity of app categories with their popularity. In the hype cycle, we only focus on depicting changes in popularity rather than exact values. Generally, if the app category is more mature then its popularity is more stable. As shown in Figure 6, the evolution of app category popularity undergoes two stages, i.e., growth of popularity and plateau of popularity.

- **Growth of popularity.** In this stage, the popularity of the app category increases. When an app category is newly introduced, it will be at this stage initially. Furthermore, as previously discussed, the development of technologies and smartphone designs, like 4G networks and larger screen sizes, will trigger an increase in multiple app categories' popularity.
- **Plateau of popularity.** In this stage, the popularity of the app category tends to be stable, which suggests that the

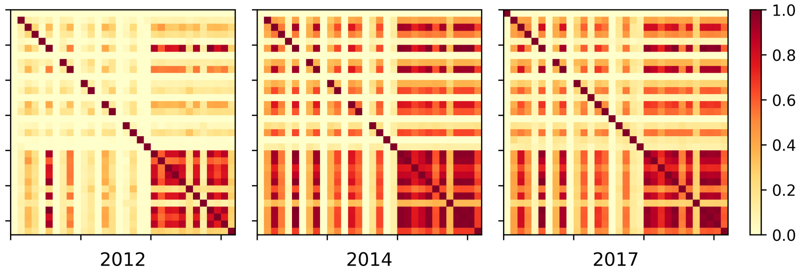


Figure 7: The correlations of app categories across different years.

market in this app category is mature. For different app categories, their steady popularity is different because they have different potential customers. For instance, the steady popularity for 'Communication', designed for almost all smartphone users, is around 1, while the steady popularity for 'Education' mainly used by students, is only 0.37.

Surprisingly, *there is no discernible decline stage during the popularity evolution of app categories*. We infer that there are three factors that inhibit the formation of a decline stage, i.e., user habits, user communities, and an app ecosystem. **First**, nowadays, people are accustomed to using diverse apps to facilitate their daily lives, e.g., ordering food and shopping online. Meanwhile, an app category contains a group of apps with similar functionality that typically differ from other app categories. Hence, it is hard for one app category to substitute for another. As a result, users' reliance and a category's irreplaceability will push users to continue to use that app category. **Second**, for one app category, its users will form a user community. The community will encourage users to keep using that app category. Taking 'Communication' as an example, if others are used to using 'Communication' apps, like Skype and Whatsapp, to contact you, it is difficult for you to get rid of 'Communication' apps and switch to make phone calls and sending SMS messages. **Third**, with the development of the app market, a stable and highly correlated app ecosystem has been formed (detailed in Section 3.4). Various app categories are connected with and reliant on others. Due to the high correlations among app categories, users have to keep using multiple app categories together. For example, for online shoppers, apart from 'Shopping' apps, they have to use 'Finance' apps for online payment as well.

3.4 Correlations of App Categories

To validate the previous inference about the app ecosystem, we then study the correlations of app categories. In our case, we use the co-usage of app categories for unique users to represent their correlations. Given two app categories C_A and C_B, we denote the number of unique users using an app either in category C_A or C_B as $\mathscr{D}(C_A \bigcup C_B)$, and the number of unique users using apps from both categories C_A and C_B as $\mathscr{D}(C_A \bigcap C_B)$. The correlation between categories C_A and C_B is computed as,

$$Corr(C_A, C_B) = \frac{\mathscr{D}(C_A \bigcap C_B)}{\mathscr{D}(C_A \bigcup C_B)}. \tag{2}$$

The correlation $Corr(C_A, C_B)$ represents the probability that one user uses both categories C_A and C_B.

Figure 7 displays the correlations of app categories in 2012, 2014, and 2017, respectively. In the heatmap, each row or column represents one app category. The categories are sorted in descending order by their first letter (the same as Figure 4). From Figure 7, we can observe that the strength of correlations between app categories generally increased from 2012 to 2014. Comparing the heatmaps in 2014 and 2017, *the correlations across various app categories were high and tended to be stable, suggesting that a robust app ecosystem had formed*. In that app ecosystem, all app categories are closely related to each other. 'Communication' and 'Social' have the highest correlations with other app categories. As the most popular app categories, 'Communication' and 'Social' act as the bases of the app ecosystem and the bridge to connect different categories. For example, users may recommend useful apps or share interesting content like news, music, and videos via 'Communication' and 'Social' apps to others. Meanwhile, others may try the recommended apps or use a viewer app to open the received content. Therefore, the fragmented and independent app categories are closely interconnected and form a robust ecosystem.

3.5 Summary

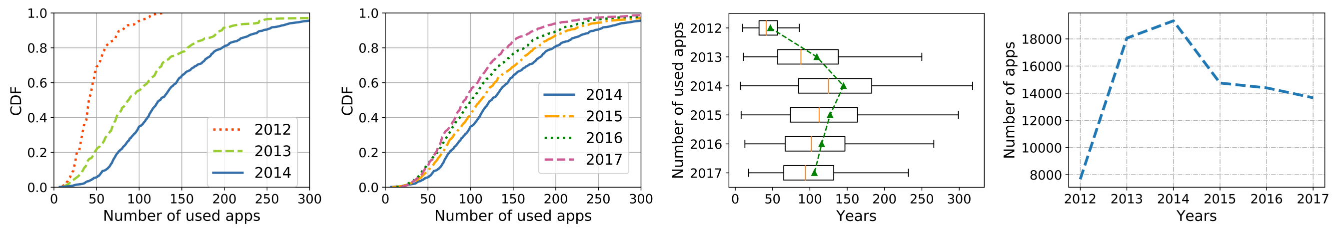
From the macro-level analysis, we can conclude that mobile app-category usage has indeed changed over the six years from 2012 to 2017. The functionality of smartphones has broadened from fundamental communication needs to life assistants. Generally, the evolution of app-category usage has two stages, i.e., a growth stage and plateau stage. The growth stage is triggered by the release of new technologies in multiple fields, including mobile networks, smartphone hardware, and software. The plateau stage is caused by both user factors, including user habits and user communities, and app factors, including the high correlated app ecosystem. Due to the stable evolution processes, users' app-category usage tends to be consistent, i.e., the diversity decreases, over time.

4 EVOLUTION OF APP USAGE

4.1 Number of Used Apps

We first analyze the number of apps used by each unique user. As shown in Figures. 8(a) and 8(b), similar to app categories, the evolution of app usage is also separated into two stages by the year 2014.

- **Stage one (2012 - 2014).** During this stage, *users increased the number of apps used on their smartphones*. In 2012, a user used up to 120 apps in one year, which is consistent with the



(a) CDF of the number of used apps for each user from 2012 to 2014.
(b) CDF of the number of used apps for each user from 2014 to 2017.
(c) Distribution of the number of used apps for each user across different years.
(d) The total number of used apps across different years.

Figure 8: The evolution of app usage from 2012 to 2017.

finding in previous work by Falaki *et al.* [7]. Nevertheless, in 2013, over 20% of users used at least 150 apps. In 2014, that proportion rose significantly to around 40%. This boosting period at the micro-level is consistent with the macro-level. As analyzed before, the occurrence of this stage should be motivated by the release of new technologies.

- **Stage two (2014 - 2017).** During this stage, *the number of apps used by each user decreased year by year, which is significantly different from the trend at the macro-level.* In 2017, the proportion of users who used over 150 apps fell to 20%.

To examine the changes in detail, we depict the distribution across different years using box-plots in Figure 8(c). We observe that the minimum number of used apps almost did not change over the six years and always stayed at around 12. The 12 app limit suggests that one smartphone has at least 12 essential functions. We will determine these 12 essential apps in Section 4.3. Moreover, from 2014 to 2017, compared with the minimum value and first quartile, the third quartile and maximum value dropped more sharply. That means the people who use many apps were significantly influenced and tended to use fewer apps. We then compute the total number of used apps across different years and present the results in Figure 8(d). However as opposed to Figures 8(a), 8(b), and 8(c), we aggregate all apps used in that year by all long-term users. As shown in Figure 8(d), the total number of apps used per year peaked in 2014 and then gradually declined. The decreasing trend implies that low-quality apps started to be discarded by users after the boosting period, i.e., stage one.

Because of the difference in trends during stage two at the macro-level and the micro-level, we next study the relationship between the numbers of apps and app categories used by each user. We show the data in Figure 9, where each dot represents one unique user. Generally, people who use more apps also use more app categories. From 2013 to 2014, the data points moved to the right and down, indicating that users started to use more apps and app categories simultaneously. Interestingly, we discover a phase change in Figure 9(b). When the user used more than 15 app categories, the number of used apps would increase dramatically. The different degrees of maturity across app categories may cause this phase change. In 2014, there were around 15 developed app categories with high degrees of maturity, and their markets were dominated by three to five apps in each category. As a result, users would focus on a small group of governing apps when they used these app categories. Conversely, when users utilized developing app categories lacking the governing apps, they would try many of the apps in that category and then select several high-quality apps. Thus, the number of used apps would increase suddenly. Compared with 2014, the data points in 2015 and 2017 moved to the left, suggesting users used fewer apps, but the distribution of the number of used app categories did not change. Moreover, in Figure 9(d), we discover the phase change faded, implying that governing apps have appeared in the previous developing app categories.

4.2 Diversity of App Usage

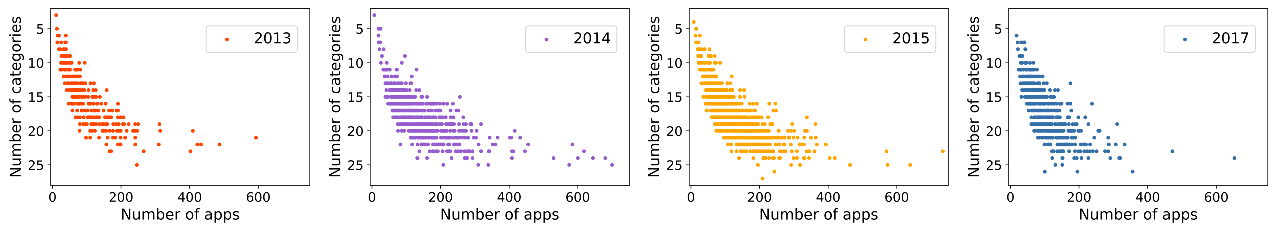
We next explore a question: how the diversity of app usage changes over time and whether the trend is consistent with app categories. By applying Jaccard distance to measure the difference of app usage between every two users, we depict the distribution of pairwise Jaccard distances across different years in Figure 10. From 2012 to 2013, the average distance between two users jumped from 0.75 to 0.85, implying the diversity of app usage increased. The trend is contrary to that at the macro-level in Figure 3. After 2013, the distribution became stable, i.e., the strength of diversity stopped increasing. However, users' used apps were still extremely different from others considering the minimum distance is nearly 0.7.

In summary, *the diversity between users exhibits two opposite evolutionary trends at the micro-level, i.e., apps, and the macro-level, i.e., app categories, respectively.* At the macro-level, mobile users fully explore the functionality of smartphones and tend to use more and similar app categories. On the other hand, at the micro-level, mobile users have different preferences and use a diverse array of apps.

4.3 Distribution of App Popularity

We further study the distributions of app popularity from 2012 to 2017. Figure 11 reports the CDF of app popularity (the ratio of app users to all users). Our results reveal a typical *Pareto effect* for app usage. Over 80% of apps have less than 0.01 popularity in 2012, while this number increased to 90% by 2017. The Pareto effect suggests that although the set of apps used by one user are quite different from others, the app market is still governed by a small number of dominating apps. This observation is consistent across all six years.

We next rank apps in terms of their popularity and select the top 20 apps for each year. We then discover that there are 16 dominating apps that repeatedly appeared in the top 20 list every year. We post the 16 apps and their rankings across different years in Figure



(a) The number of used app categories and apps across different users in 2013. (b) The number of used app categories and apps across different users in 2014. (c) The number of used app categories and apps across different users in 2015. (d) The number of used app categories and apps across different users in 2017.

Figure 9: The relationship between the number of used app categories and apps in different years.

Table 2: Twelve essential apps and their functionality.

App	Functionality	App	Functionality	App	Functionality
com.sec.android.inputmethod	Keyboard input	com.sec.android.gallery3d	Image and video viewing	com.sec.android.app.launcher	Home screen application
com.google.android.apps.plus	Google+, socializing	com.google.android.talk	Message contacts, video or voice calls	com.google.android.music	Music palyer
com.google.android.apps.maps	Maps and navigation	com.google.android.gms	Google play services	com.google.android.gm	Gmail
com.google.android.youtube	Watching videos	com.google.android. googlequicksearchbox	Google search	com.android.chrome	Web browsing

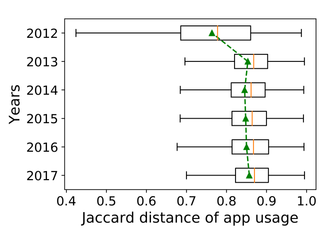


Figure 10: Jaccard distance of app usage.

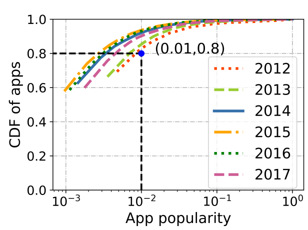


Figure 11: CDF of the popularity of apps.

12. Twelve out of the 16 dominating apps are part of the Android operating system, and correspond to the 12 essential apps observed in Figure 8(c). We list the 12 apps and their functionality in Table 2. Apart from these 12 essential apps, there are also four dominating apps from three prior prevalent app categories. Whatsapp and Push service are from the 'Communication' category. Facebook is from the 'Social' category, and Dropbox is from the 'Tools' category. The rankings of dominating apps did not vary significantly during the period. Google quick search box and Google Play services had the most number of users. Also, the popularity of Chrome and Whatsapp rose steadily every year.

4.4 App Usage Within App Categories

Up to now, we have discovered that the evolutionary processes at the macro-level and the micro-level show considerable differences, especially during stage two, i.e., from 2014 to 2017. Therefore, we next delve into the reasons behind this phenomenon and investigate how app usage changes in a particular app category. For the sake

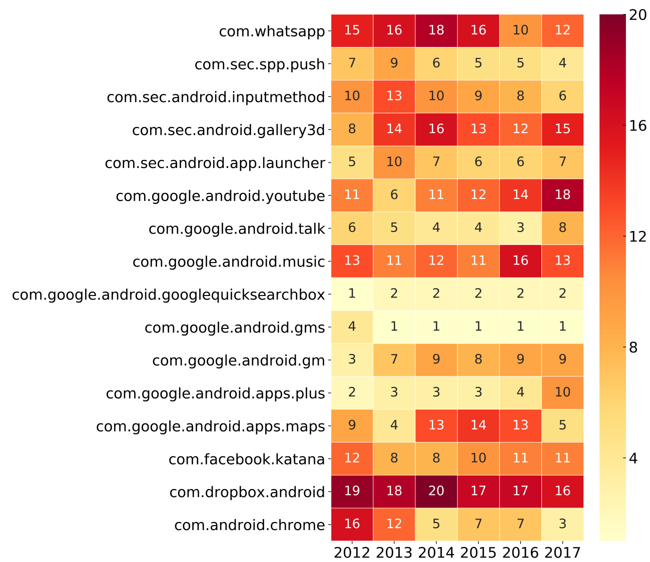
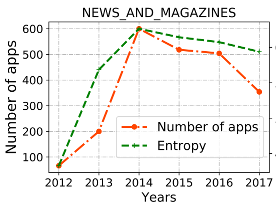


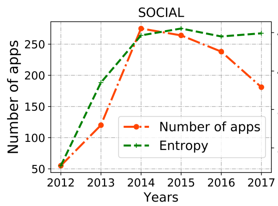
Figure 12: Rank of popular apps across different years.

of representativeness, we actually select two typical app categories, i.e., 'News and magazine' representing a posterior prevalent app category and 'Social' representing a prior prevalent app category.

In our case, we apply the number of apps and app usage entropy to measure the evolution processes. Figure 13 shows the results. The entropy is a common metric to measure the randomness of a system [9]. We use entropy to measure the centralization of app usage in one specific app category, i.e., whether app usage in that



(a) 'News and magazine' category.



(b) 'Social' category.

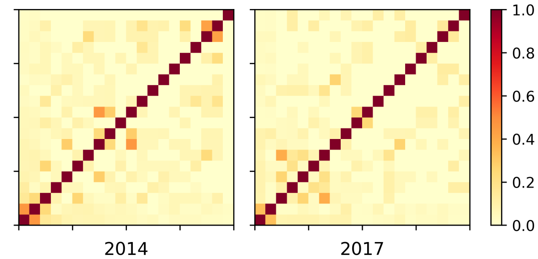
Figure 13: Evolution of app usage in 'News and magazine' and 'Social' categories.

category concentrates on a few apps. The lower the entropy, the higher the centralization of app usage.

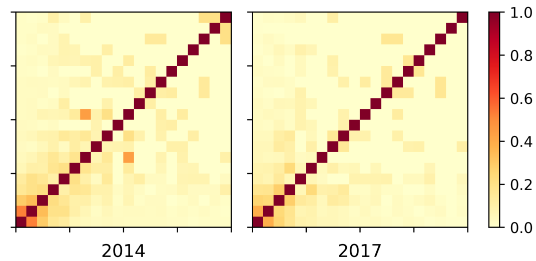
In terms of Figure 13, for both 'News and magazine' and 'Social' categories, the number of apps peaked in 2014 and then decreased. Their trends correspond to the trend for all apps, as shown in Figure 8(d). Additionally, we have also examined the other app categories and found their trends are consistent as well. Consequently, different degrees of maturity will not affect the evolution of the number of apps in different app categories. In terms of the number of intra-category apps, all app categories underwent two evolution stages, i.e., growth stage and elimination stage. We infer that the growth stage is caused by the release of new technologies, while the weeding-out of low-quality apps by users causes the elimination stage.

However, the evolution in entropy exhibits different trends in 'News and magazine' and 'Social' categories. For the 'Social' category, entropy first increased and then kept steady. The increase stage is caused by the growing number of apps in the category. New apps disperse users' concentration. On the other hand, the Pareto effect leads to the plateau stage. As a prior prevalent app category, 'Social' had a few governing apps dominating usage before 2012. Therefore, during the boosting period, the newly introduced apps would compete with these old governing apps, and some low-quality would be eliminated. Meanwhile, new governing apps would emerge. As a result, in 2014, apart from the increasing entropy, users' usage was also hugely dominated by both previous and new governing apps. Therefore, after 2014, the entropy did not change dramatically. For the 'News and magazine' category, the evolution in entropy still experienced the decrease stage. Since 'News and magazine' is a posterior prevalent app category, limited by its maturity, it had few governing apps before 2012. Hence, its entropy is deeply affected by the number of apps in the category.

In order to better understand the app elimination stage, we next investigate how the correlations of apps in the same app category changed from 2014 to 2017. Similar to Section 3.4, we use the co-usage of apps for unique users to represent their correlations. For consistency, we still use 'News and magazine' and 'Social' to represent posterior and prior prevalent app categories, respectively. In Figure 14, we depict the correlations of the top 20 popular apps in these two categories. In the heatmap, each row or column represents one app. The apps are listed in descending order in terms of their popularity. Compared with app categories, the correlations of apps in the same category is much lower, and most are below 0.2. Since the functionality of apps in the same category is similar,



(a) Correlations of apps in 'News and magazines' category.



(b) Correlations of apps in 'Social' category.

Figure 14: Correlations of apps in 'News and magazine' and 'Social' categories.

installing multiple apps from the same category is often redundant. Also, due to intra-category competition, the correlations of apps shrank over time in both categories. We still observe that in the 'News and magazine' category, apps' correlations nearly followed a uniform distribution in 2014, suggesting that at the beginning stage, the correlations of apps are independent of their popularity. In 2017, with the increase in the degree of the app category's maturity, the apps with high correlations tended to have high popularity. By comparing the top 20 popular apps in both 'News and magazine' and 'Social' categories from 2014 to 2017, we then discover the relationship between correlations and popularity of apps. The apps with high correlations have a greater chance of gaining popularity in the future.

4.5 Summary

In terms of the micro-level observations, users' mobile app usage exhibits different evolution processes from the macro-level. The fierce intra-category competition leads to the occurrence of an elimination stage and a decrease in the correlations of apps. Moreover, because of the high overlapping functionality across apps and their often perfect substitutability, mobile users have less reliance on an individual app. Therefore, users' app usage diversity is vast. Nevertheless, due to the Pareto effect, the most popular apps across users are still consistent. Also, in terms of the entropy metric, the degree of app category maturity will affect the evolution of app usage in the category.

5 RELATED WORK AND DISCUSSIONS

5.1 Related Work

5.1.1 App Usage Analysis. Many previous studies have focused on how individuals use their smartphones and mobile apps [11, 12, 18, 24, 32]. Generally, they discovered people's app usage patterns by clustering users into groups and providing comprehensive descriptions of those groups. Zhao *et al.* [32] analyzed a short-term app usage dataset of one month covering 106,762 users. They grouped users into 382 clusters and gave a meaningful label to each cluster, such as Night communicators, Evening learners, and Financial users. In [12], Katevas *et al.* collected a four-week usage dataset from 340 users and revealed five user profiles, including limited use, business use, power use, and personality use. Jones *et al.* and Cao *et al.* [3, 11] analyzed users' app re-visitation patterns based on a three-month dataset covering 165 users and identified three distinct user clusters, i.e., checkers, waiters, and responsives. In [18], Peltonen *et al.* collected an one-year app usage dataset from 25,323 users distributed in 44 countries. They clustered users based on their cultural features and investigated how their cultural affiliations affect their usage behavior. However, existing studies only concentrated on a limited time span ranging from one week to one year, and did not investigate the long-term evolution of mobile app usage.

5.1.2 App Evolution Analysis. Also, some scholars worked on analyzing app evolution [2, 4, 22, 25]. Carbunar *et al.* [4] crawled an app dataset from Google Play including 160,000 apps over six months. They studied the evolution of app properties, like downloads, price, and update frequency. In [2], Calciati *et al.* studied how apps evolve in their permission requests. They tracked over 14,000 releases of 227 Android apps and discovered a common trend of apps requiring more permissions over time. Alternatively, in [22], Taylor *et al.* also took quarterly snapshots of Google Play over two years and investigated how permissions requested by apps changed over time. They analyzed over 30,000 apps and discovered that Android apps are not getting safer as they are updated. Wang *et al.* [25] crawled three snapshots of Google Play in 2014, 2015, and 2017, and explored the evolution of various app properties, including permission usage, privacy policy declaration, advertising libraries, updates, and malicious behavior. However, these studies only consider the evolution of apps' inherent properties instead of users' actual usage. Due to the lack of user involvement, it is hard for them to capture the real trends of the app market and the preferences of users. In contrast, our work is the first attempt to understand the evolution of users' mobile app usage through data collected on smartphones over the years.

5.2 Discussions

The most prominent discovery in our paper is that the usage evolution at different levels exhibits different processes. The relevant stakeholders should note this difference because they play different roles at different levels of the app market. For example, Google is responsible for maintaining the Android operating system. Market intermediaries are in charge of managing app platforms, while app developers should provide high-quality apps. The relevant stakeholders should focus on the evolution of their corresponding level and dynamically adjust their strategies to improve their services. Also, we discover that the release of new technologies will trigger increasing usage in both app categories and individual apps. Hence, when a breakthrough occurs, all relevant stakeholders can grasp the valuable opportunity to extend their market shares. One potential opportunity is the deployment of 5G mobile networks.

We also discovered opposing trends in usage diversity between app categories and apps. App category usage tends to be consistent, while app usage across mobile users becomes quite different. Therefore, the app market intermediaries, at a higher level, should focus on the consistent requirements across mobile users instead of customized services. However, as for app developers, seeking to develop a commonly popular app for all mobile users may be difficult. Instead, focusing on small groups of users and meeting their personalized needs is a better choice.

We also notice the fierce intra-category competition between apps causes an elimination stage of app usage, and different degrees of app category maturity will affect this competition. Hence, app developers have to improve the competitiveness of their apps, especially during the elimination stage. Also, when they design new apps, they can take the maturity of app categories into account and choose a newly introduced or developing app category. Additionally, we notice that correlation plays a vital role in app usage. The apps with high correlations with others will become more popular in the future. Hence, app developers can leverage this finding to improve their apps' competitiveness by adding both inter- and intra-app category cooperation functions into their app designs.

App usage shows a typical *Pareto effect* at all times. A small group of apps dominate usage in both the entire app market and individual app categories. We also identify twelve essential apps of differing functionality for smartphones. In terms of these observations, the market intermediaries can recognize a small group of popular apps and put their installation packages as close as possible to end-users. For example, with the help of network service providers, they can cache the .apk files at the edges of networks.

6 CONCLUSION

We conduct the first comprehensive study of the long-term evolution of mobile app usage. Specifically, our analysis covers about 1,500 Android users with six-year app usage records from 2012 to 2017. Overall, our findings indicate that users' app usage indeed changes over time. However, the evolution processes in app-category usage and individual app usage are different in terms of popularity distribution, usage diversity, and correlations. Our findings provide insights for app developers to make better decisions on developing apps and improve competitiveness. Also, our study can help market intermediaries to manage app platforms and supply high-quality services.

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