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Towards Understanding iOS App Store Search Advertising: An Explorative Study

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***Abstract*—With millions of apps competing in the market, one major issue for app developers is to get their apps discovered by intended users. iOS App Store Search Advertisement (ASA) is a mechanism that provides app developers a chance to increasing the awareness of their apps within the iOS App Store by bidding related searching keywords. However, as one of the most efficient methods to promoting apps, ASA has not been touched by our research community, to the best of our knowledge. To fill the void, in this paper, we present the first large scale explorative study on understanding iOS app store search advertising. Specifically, we have created the first dataset on ASA promotion, covering over 47K popular apps across 22 categories and over 2.8 million ASA bidding keywords during the first week of 2021. Based on this dataset, we investigate the adoption of ASA in the wild and the characteristics of the bidding keywords. Furthermore, we created a large-scale app-keyword relation graph, based on which we infer the app competitive relations. We observed two types of app competitive relations, i.e., explicit competition that the advertised apps intended to attract users who search the corresponding target apps by embedding their names into the ASA keywords, and implicit competitions that apps share a large portion of bidding keywords with others. Our efforts reveal interesting implications to stakeholders in the mobile app ecosystem, including app markets and app developers, etc. our study is the first step towards understanding and improving the in-market mobile app promotion mechanisms.**

***Index Terms*—Mobile advertising, App Store Search, iOS App, App Promotion**

I. Introduction

The mobile app ecosystem has shown increasingly popular in recent years [1]. With millions of apps competing in the market, one major issue for app developers is to getting their apps discovered by intended users [2]. Thus, *app promotion* is one of the key steps to app success. Kinds of app promotion methods and tools are available to increasing the visibility of mobile apps. For example, app developers can rely on mobile ad networks (e.g., Google Admob) to deliver advertisements [3], or they can take advantage of App Store Optimization (ASO) techniques to boost their exposure during users searching related keywords in app markets [4], [5].

Apple announced iOS ***App Store Search Advertising*** (ASA) launched along with iOS 10 emergence in 2016 [6]. App developers finally got a chance to increase the awareness of their apps within the iOS App Store. According to the official statistics [7], 70% of iOS App Store visitors use search to find apps, and over 65% of app downloads in iOS app store come directly from user searches. Thus, ASA seems to be a promising way to promote apps within the app store. Taking advantage of ASA, mobile app ads are shown on the top of App Store search results by bidding related keywords. Figure 1 shows an example. When mobile user searches keywords like “hook up” (we choose this keyword as it is one of the most popular ASA keywords, see **Section V**), the advertised app would be shown first with light-blue background and an Ad logo, and then followed by the normal search results.

ASA operates on a bidding system, which means that developers should place bids to run ads for certain keywords. Then Apple puts all relevant bids into an auction. For each keyword, one or more apps would win the auction to placing ads for the keyword. Apple claims to use advanced algorithms to determine how relevant the advertisement of an app is to the search query of a given keyword, mainly based on the metadata of the app (e.g., app name, category and description).

App store mining is a hot topic [8]. A number of studies have characterized the mobile app ecosystem by analyzing large-scale apps [1], [9], [10], and their related meta information on the market, including app description [11], [12], privacy policy [13], [14], app reviews [15], [16], etc. However, to the best of our knowledge, *App Store Search Advertisement*, as one of the most efficient ways to promoting apps, has not been touched by the research community. *We are unaware the status quo of ASA adoption in the wild, and whether we can gain insights based on mining the usage of ASA.*

One major challenge to study ASA is *how to collect a comprehensive dataset of ASA promotions in the wild*. It is certainly that only iOS app store can access to a complete dataset of app bidding and ASA advertising information. Nevertheless, as ASA is a huge market which requires sophisticated methods for selecting and bidding keywords, there are some leading app intelligence companies around the world who keep tracking of ASA promotions in the wild. In general, they usually take advantage of a large number of smartphones or hire a lot of users to collect their keywords searching results in iOS app store for automatically collecting the related promoted apps (like Figure 1) for given keywords. The ASA dataset created by app intelligence companies, although cannot be as complete as the one maintained by the market, is sufficient for us to perform an explorative study to disclosing the mysterious nature of iOS App Store search Ads.

This Work. In this work, we take the first step to understanding iOS app store search advertising. Specifically,

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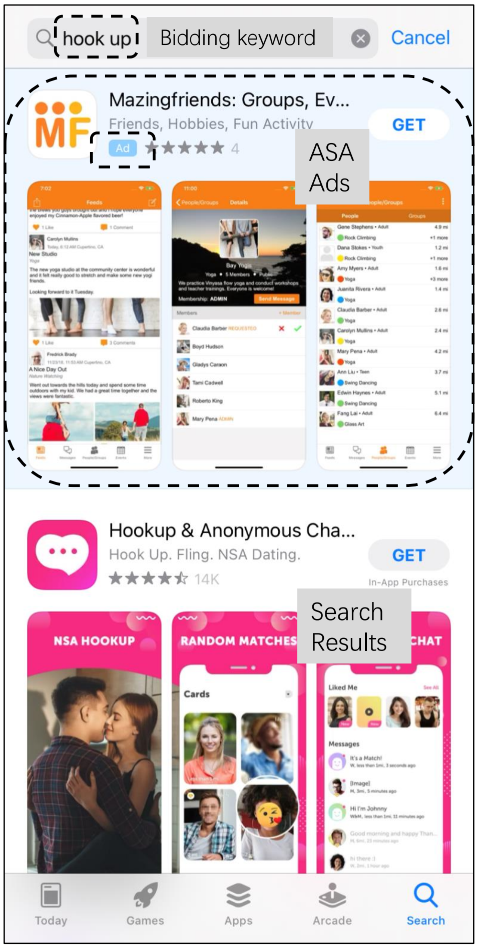

Fig. 1. An example of an App Store Search Advertisement.

we first harvest a large-scale ASA promotion dataset (**see Section III**) covering the most popular apps (over 47K apps) across 22 categories in iOS App Store and their successfully bid keywords within the period from 1st January 2021 to 7th January 2021, by collaborating with a leading mobile app intelligence company. Our dataset covers the result of roughly 3 million bidding keywords. Based on this dataset, we further investigate the adoption of ASA in the wild (**see Section IV**) by analyzing the proportion of apps that use ASA across categories, the number of keywords they bid, and the correlation of the number of ASA keywords with app popularity. We next study the characteristics of the bidding keywords (**see Section V**), towards understanding what kinds of keywords are favored by app developers. At last, we are interested in app-keywords relation analysis, seeking to reveal both explicit and implicit app competition relations from the ASA bidding keywords (**see Section VI**). Among many interesting findings, the following are the most prominent:

- *Although the ASA advertising mechanism has been officially launched over 4 years, the advertising market is not as competitive as we expected*, i.e., only 7.5% of apps have delivered ASA ads in our dataset. However, app competition varies greatly across categories. To reach to more potential users, apps usually bid thousands of keywords, especially the apps with high rankings.
- *App developers seem to be inclined to bid on dating or social networking related keywords such as"ins tracker" and "hookup", even if these keywords are irrelevant to the functionalities of their apps*. Although most of the keywords are *discovery-centric*, over 10% of them are brand-specific that contain the names of other apps or developers.
- *We have created a large-scale app-keyword graph, which can be used to infer the app competitive relations*. We observed two types of app competitive relations, i.e., *explicit competitions* that the advertised apps intend to attract users who search the corresponding target apps, and *implicit competitions* that apps share a large portion of bidding keywords with others.

To the best of our knowledge, this is the first explorative study of iOS App Store Search Ads based on large-scale data collected in the wild. Our results motivate the need for more research efforts to illuminate this widely unexplored direction. To boost following research, we have released our dataset to the research community at:

https://zenodo.org/record/4661000

II. Apple App Store Search Advertisement

Apple Search Advertisement (ASA) is an acquisition channel that connects advertisers with a relevant target audience. By bidding to appear when a user enters a particular keyword in the App Store, developers can share their app with users that have a proven interest in specific terms.

A. The process of using ASA

For developers who want to promote their apps through ASA, Apple provides them with two versions of ASA: *Basic* and Advanced [17]. For ASA basic, after the developer sets the relevant information of the app to be promoted, Apple will automatically find the best keywords that match the app. But developers have no right to choose keywords by themselves and this ASA payment model is based on `CPI` (cost per installation) up to $10,000 per app per month, which means that all developers need to do is to provide information of the promoted app to Apple, then only pay for the installation. The Advanced ASA provides developers with more options, i.e., developers can choose keywords by themselves and Apple also provides them with detailed reports on all indicators and APIs to measure value and manage at scale. The Advanced ASA has two keyword matching modes [18]. One is broad match, which is the default matching mode of the ASA. When developers add a keyword with broad match, Apple may display the ad if the user searches for this keyword or its related words (i.e., if developers add "Youtube" as a keyword, Apple may deliver the ad to users searching for "video apps" or "Twitch"). Apple decides whether to display ads when users search for related words and variations, which means there may be unexpected query requests and developers need to bid for these unexpected keywords separately. The second mode is exact match. If the developers add a keyword with square brackets, it will only deliver accurate exact results to the user (i.e., if developers add "[Youtube]" as a keyword, Apple may deliver ads for users who look for "Youtube" or its slight typo word "Youtude"). Each of these two matching modes has its advantages. Exact match means that the number of ad impressions will be reduced, but there will be higher `TTR` (Tap-Through Rate, the rate of the number of ad impressions converted to the number of user clicks) and `Conversion` (the number of downloads generated by the ad within the specified time), because the requirements for displaying ads are more precise and strict. Promotional apps that use broad match may have more traffic, but there will be a considerable amount of invalid taps (users click on ads but do not download them), which means more budget as ASA Advanced charges based on CPT (cost per tap). In addition, Advanced ASA also has a search matching function. Apple's algorithm will automatically match some users' search terms based on app titles and keywords, even if developers do not bid on these words, their ad can be matched. Search matching is a good tool for mining new related keywords [18].

B. Advantage of ASA

Ideally, ASA shows several advantages compared to traditional mobile advertising. *(1) Flexible keyword selection.* App developers/marketers can freely choose ASA keywords according to their needs to promote their apps. They can adjust bids based on performance, such as increasing bids for exact match keywords or defining which terms are negative keywords to ensure not bidding for them. *(2) Reasonable bidding rules.* The key factors that affect ASA's ranking are not just bids but also relevance, which means that blindly bidding on keywords is useless, requiring advertisers to find matching keywords. *(3) Reasonable payment model.* There are two payment models: basic and advanced. The basic model is based on `CPI` (cost per installation) which would not require marketers to set audience refinements or relevant keywords. Instead, Apple matches ad to potential customers themselves and end at anytime marketers want. This kind of ASA is suitable for those advertisers who want to increase the installation volume with limited time and budget. The advanced model is more complex as it expands upon options and gives advertisers greater control of their targeting capabilities. With the advanced model, advertisers can select their own keywords, control when ads are exposed to users, and utilize their own creative assets. The advanced ASA is based on `CPT` (cost per tap), which is suitable for advertisers with advertising experience and sufficient budget.

III. Study Design

A. Research Questions

Our study is motivated by the following research questions:

RQ1 *How many apps have adopted the Apple Search Ads for promotion?* As one of the most effective ways to promote apps within the market, it is unknown to us how many apps are taking advantage of ASA to increase the awareness of their apps.

RQ2 *What kinds of search keywords are most favored by developers?* Keyword selection is the key process to make the app promotion more effective. Thus, it is thus interesting to study what kinds of keywords are most popular, and whether there are difference across diverse categories of apps.

RQ3 *Can we identify app relations (e.g., potential competitors) from the ASA bidding keywords?* The bidding keywords can reflect the intended users of the corresponding apps. Thus, we want to further investigate the app relations based on the bidding keywords.

B. Dataset Collection

As no available dataset on ASA has be released for research, we decide to collect such a dataset and release it to the research community. However, it is non-trivial to know the keywords bid by each app, as no public information on the official iOS app market could be collected. Thus, we collaborate with an anonymous leading mobile app intelligence company to collect this dataset. The company has maintained the daily bidding keywords and their corresponding apps, based on massive information collected from a great number of smartphones. We collected the most popular apps in the 22 mainstream categories and their information from iOS App Store[1] for a week, i.e., from 1st January, 2021 to 7th January, 2021. As iOS App Store provided the daily top-1500 apps for each category, we collected the daily top apps and finally created a dataset with a total number of 47,378 popular apps. We further collected their bidding keywords during the span of one week, with 2,827,437 unique bidding keywords and 13,512,438 app-keyword relations in total, as summarized in Table I. Note that, if one app has successfully bid a keyword (i.e., there exist ads of this app when users search the keyword), we regard there is a mapping between this app and the corresponding keyword. One keyword may correspond to more than one app (i.e., the advertised apps may vary across users).

TABLE I
A Summary of our collected ASA dataset.

Country	Days	Unique Apps	Keywords	App-Keyword Relations
The US	7	47,378	2,827,437	13,512,438

IV. Adoption of ASA in the Wild

In this section, we analyze the adoption of ASA in the wild.

[1]Note that the apps and ASA ads are different across regions, our dataset collection is based on the US App Store.

TABLE II
THE DETAILS OF TOP 10 APPS WITH THE MOST NUMBER OF ASA

App ID	Application Name	Developer	Category	The Highest Ranking	The Number of ASA
891132290	Simple Radio	Streema, Inc.	Music	29	112,088
1115120118	Klarna Shop now. Pay later.	Klarna Bank AB	Shopping	14	83,727
549750492	Dino Fun	Avocado Mobile Inc	Education	202	70,052
920161006	Breethe: Meditation & Sleep	OMG. I Can Meditate!	Health & Fitness	28	67,591
510873505	Secret Photo Vault	KeepSafe Software, Inc	Photo & Video	88	64,038
1473574597	PowerDirector Video Editor App	CyberLink	Photo & Video	115	63,977
317469184	ESPN: Live Sports & Scores	ESPN	Sports	1	63,416
530621395	Wish	ContextLogic Inc.	Shopping	6	62,531
290638154	iHeart: Radio, Music, Podcasts	iHeartMedia Manageme	Music	9	61,360
1473551769	Slide Show Maker?	Maple Labs Co., Ltd	Photo & Video	120	58,300

A. Proportion of Apps that use ASA

Overall, among the 47,378 popular apps we collected, only 3,540 of them (7.5%) have delivered ASA ads during our one week analysis. It suggests that, *although ASA mechanism has been launched over 4 years, the market is not as competitive as we expected.* The main reason might be that the cost of ASA is not free, and many developers have no budget for ASA advertising. However, subtle differences arise when looking in detail on a per-category basis. Figure 2 shows the proportion of apps that take advantage of ASA for promotion, across the 22 categories (sorted by the proportion). For popular apps in the “Health&Fitness” category, 333 of them (18.3%) were found being advertised in the market. While as to apps in “Magazine & Newspaper” category, only 2.2% of them adopted ASA promotions. *The diverse distribution across categories could reflect the degree of app competition within each category.* In general, the per-category market (e.g., health and fitness apps) is highly competitive if many apps within the corresponding category (i.e., these apps are highly possible to share same/similar functionalities) distribute ASA ads to their intended users. Thus, it is reasonable to summarize that, during the time of our study, apps in categories including “Health&Fitness”, “Photo & Video” and “Social Networking” are more competitive than apps in other categories.

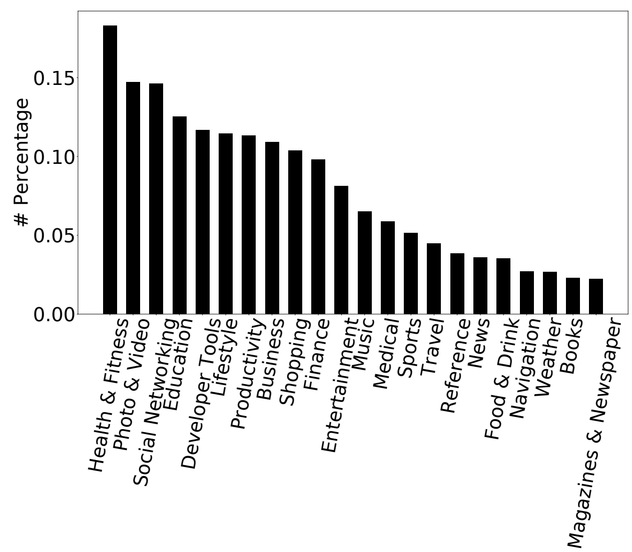

Fig. 2. The proportion of apps that use ASA for promotion across categories.

B. The Number of Bidding Keywords

1) Overall Distribution: We next analyze the number of bidding keywords covered by each app. Figure 3 shows the overall distribution for all the 3,540 apps with ASA promotions. On average, each app has bid 3,818 keywords. Roughly 24% of the apps bid less than 100 keywords, while over 88% of the apps bid less than 10K keywords. Notably, over 11% of apps have bid over 10K keywords. In our dataset, the most aggressive app, “Simple Radio”, has bid over 112K keywords during the time of our study. The top-10 apps ranked by the number of bid keywords are shown in Table II.

2) The number of ASA keywords across categories: Figure 4 shows the total number of ASA bidding words in each category. This distribution is roughly in line with the proportion of apps that adopted ASA (see Figure 2). For the most competitive categories, the number of corresponding keywords is generally higher than those of the less competitive categories. Education category shares the most number of

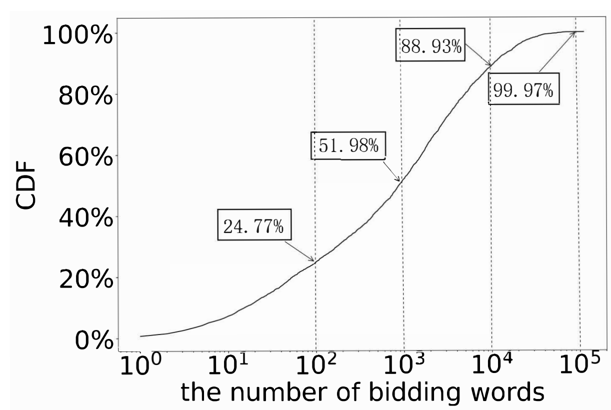

Fig. 3. The CDF distribution of the number of ASA bidding words.

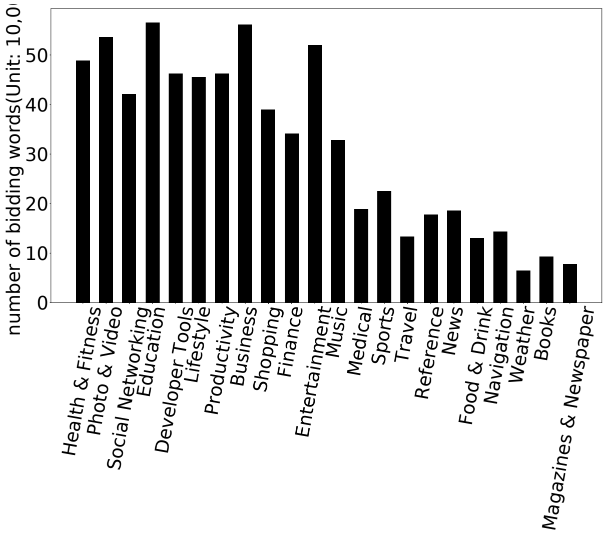

Fig. 4. The number of keywords for each category.

keywords, with 565,242 in total, while Weather category shares the least number of keywords, with only 64,962 in total.

C. The number of ASA Keywords VS. App Popularity.

Figure 5 reflects the relationship between the number of ASA bidding words and the ranking of the app in its corresponding category. Note that, as the app ranking fluctuates during the one week of our dataset collection, we use the highest app ranking for each app. As expected, there is an overall slightly positive correlation between the number of bidding words and app popularity, i.e., the more popular the app (i.e., the higher the ranking), the more bidding keywords they have covered. It is no doubt that increasing the number of bidding keywords would enlarge the exposure of the app, whose ranking would be potentially promoted. It is worth noting that, we observe some most popular apps like `Netflix`, `Google` and `Youtube` did not bid ASA keywords. We speculate that, as these apps are long-lasting popular apps that almost everyone has these apps installed on his/her smartphones, it is unnecessary for them to bid ASA keywords for promotion.

Answer to RQ1: *Although ASA advertising mechanism has been launched over 4 years, the market is not as competitive as we expected, i.e., only 7.5% of apps have delivered ASA ads in our dataset. However, app competition varies greatly across categories. To reach to more potential users, apps usually bid thousands of keywords, especially the apps with high rankings.*

V. Characterizing the ASA Keywords

Next, we study the characteristics of the bidding keywords.

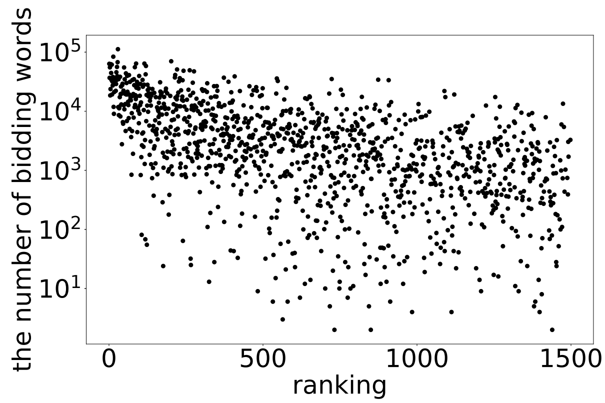

Fig. 5. The number of bidding words VS. app ranking.

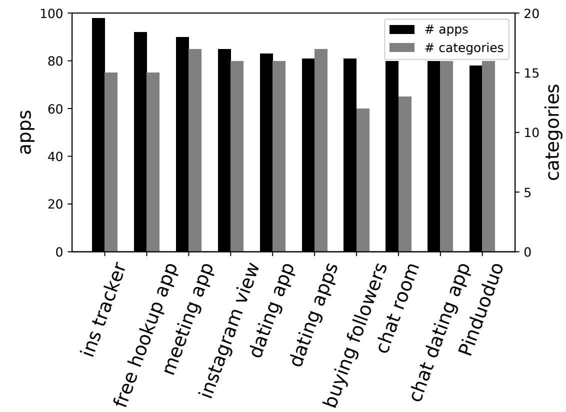

Fig. 6. Top 10 most competitive ASA keywords ranked by the number of advertised apps.

A. Most Popular ASA Keywords

Figure 6 presents the top-10 most competitive ASA bidding keywords that were successfully bid by most number of apps. 90 apps win the auction to placing ads for the keyword "ins tracker", including "TikTok", "Ins Analyzer: Tracker Report" and "Life360: Find Family & Friends". Notably, except for the 10th keyword "Pinduoduo" which is the name of a popular

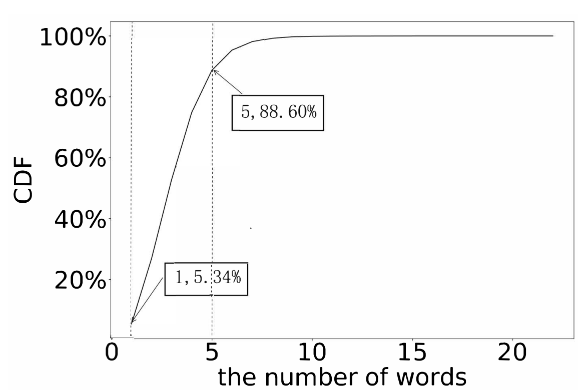

Fig. 7. The distribution of the length of bidding keywords.

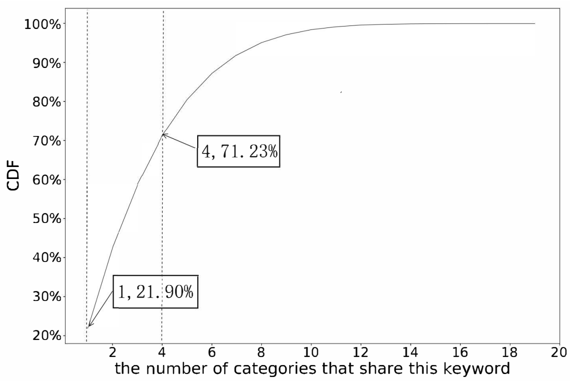

Fig. 8. The CDF distribution of keywords shared by categories.

TABLE III
THE NUMBER OF KEYWORDS FOR EACH CATEGORY.

Category	# keywords	# exclusive (%)
Health & Fitness	488,803	80,810 (16.53%)
Photo & Video	536,318	110,378 (20.58%)
Social Networking	421,240	37,328 (8.86%)
Education	565,242	169,020 (29.90%)
Developer Tools	463,019	35,160 (7.59%)
Lifestyle	455,191	33,950 (7.46%)
Productivity	462,419	24,367 (5.27%)
Business	560,979	48,551 (8.65%)
Shopping	389,856	61,723 (15.83%)
Finance	341,005	63,634 (18.66%)
Entertainment	520,095	81,337 (15.64%)
Music	328,347	45,459 (13.84%)
Medical	189,511	21,484 (11.34%)
Sports	225,011	59,193 (26.31%)
Travel	133,091	19,268 (14.48%)
Reference	178,097	9,063 (5.10%)
News	186,478	12,925 (6.93%)
Food & Drink	130,539	34,250 (26.24%)
Navigation	143,725	14,231 (9.90%)
Weather	64,962	9,555 (14.71%)
Books	92,870	6,917 (7.45%)
Magazines & Newspaper	78,350	3,673 (4.69%)
Total	2,827,437	-

Chinese shopping app, all the top-9 bidding keywords are dating and social networking related. We further analyze the app categories for the apps that have successfully bid these keywords, and observe that almost all of them were bid by apps from over 12 categories. For example, even for the apps from "Weather" categories, they bid to placing ads for the keyword "ins tracker".

B. The Length of the Bidding Keywords

As shown in Figure 7, roughly 21% of bidding keywords contain a single word, while over 71% of bidding keywords contain less than 5 words. However, we observe that some bidding keywords are quite long. For example, the keyword "7 min sixpack workout & abs core exercises videos" bid by "Fitbod Workout & Fitness Plans" and the keyword "collage para fotos y videos instagram gratis" bid by "Collage Maker", are two of the quite long bidding keywords. Actually, we observe that most of the long keywords contain the names of other popular apps, which will be detailed in the following. It suggests that *some app developers are seeking to expand the bidding keywords aiming to reach to more potential users*.

C. Classification of the Keywords

We first perform a manual analysis of the top 2,000 most popular keywords (based on the number of unique advertised apps), trying to explore how app developers set and expand the keywords. In general, we categorize the keywords into two main types [19].

- **Branded Keywords**, which means using the well known brand names or app/developer names as keywords, such as "Google" and "Youtube". If users want to download an app, they usually search for the name of the app directly. In this way, bidding branded keywords can lead to more potential users. We did not emphasize that keywords contain exactly a certain brand name, but as long as they are closely related to a certain brand, they are considered as branded keywords.
- **Generic Keywords**, which are related to general query requests. When the user does not have a clear target app, they may search for keywords based on the functionality of the app, e.g., "Live apps" or "Dating apps".

Based on our manually analysis of the top-2,000 apps, branded words accounted for 10.70% (214 out of 2,000), and generic words accounted for 89.30% (1,786 out of 2,000). It is inline with our expectation, as the generic keywords have a much larger keyword base than the branded keywords. We will further study the implication of keywords selection on app competitors in Section VI.

D. Representative keywords for each category

Here, we define the *exclusive keyword* of each category as the keyword that only bid by the apps within one specific category, otherwise the keyword would be regarded as the shared keywords (i.e., bid by apps from more than one category). The proportion of exclusive keywords across categories is shown in Table III. The proportion of exclusive keywords is quite low, ranging from 4.7% (category `Magazines & Newspaper`) to 29.9% (category `Education`).

1) Shared Keywords Across Categories: For all the 2.8 million bidding keywords, over 78% of them are shared by more than one category, and over 28% of them are shared by at least 5 categories, as shown in Figure 8. Table IV lists the top-5 keywords and top-5 exclusive keywords for each category, ranked by the number of corresponding advertised apps. Interestingly, almost all the top bidding keywords across categories are *dating-related*, which are definitely to be shared keywords. It suggests that, *although Apple App Store claims that they have adopted advanced techniques to determine how relevant the app is to the search query of a given keyword, the regulation seems to be not quite promising, i.e., the most popular keywords are always not category-specific*.

Fig. 9. Word Cloud of the Exclusive Keywords for Six Representative Categories.

2) Exclusive Keywords for each category: We further analyzed the exclusive bidding words of each category, as shown in Table IV (see Column 3) and Figure 9 (the word cloud of the exclusive bidding words for 6 example categories). Most of the exclusive bidding words are related to the functions of the corresponding category. For example, "fitness", "workout", "yoga" and "sleep" are most popular exclusive keywords in the `Health & Fitness` category, while "Pizza", "food", "Cooking" and "Chocolates" are the most representative keywords in the `Food & Drink` category.

Answer to RQ2: *App developers seem to be inclined to bid on dating or social networking related keywords such as"ins tracker" and "hookup", even if these keywords are irrelevant to the functionalities of their apps. Although most of the keywords are discovery-centric, over 10% of them are brand-specific, which can reflect the competitive relationship.*

VI. App-Keywords Relation Analysis

The bidding keywords can reflect the intended mobile users of the corresponding apps, which naturally forms a relation graph. Thus, in this section, we first create an app-keyword graph. Then, based on this graph, we propose to infer the app competitive relations.

A. App-Keyword Graph

App-keyword graph (AKG) is uniformly defined as a *undirected graph*: $AKG = (A, K, E)$, where A is a set of app nodes, K is a set of keyword nodes, and E is a set of bidding records. Specifically, our constructed AKG has 3,540 app nodes (i.e., apps that have ASA records), 2,827,437 keyword nodes, and 13,512,438 bidding relations. Interestingly, for the constructed graph, there are 4 connected components. The largest connected component contains 3,536 apps (99.9%) and 2,827,431 keywords (99.9%), the remaining three are separate apps. It suggests that almost all apps are in a state of being connected by bidding keywords together. Figure 10 shows a sampled AKG based on 198 apps and 5,567 keywords. Information presented on this graph can provide insights on the similarity/competitiveness of apps. For example, if two app nodes share many `app-keyword-app` paths, their targeted mobile users are definitely similar. Furthermore, nodes with high degree represent the most popular keywords or the most

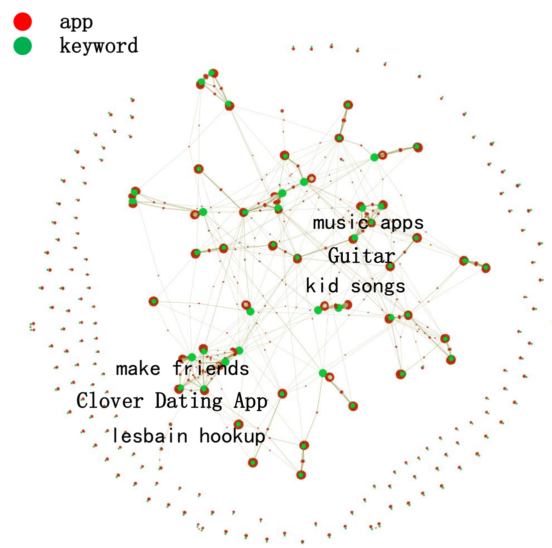

Fig. 10. The relationship between app and bidding words.

TABLE IV
MOST POPULAR ASA KEYWORDS FOR EACH CATEGORY.

Category	Top 5 keywords	Top 5 exclusive keywords
Business	ins tracker, free hookup app, meeting app, instagram view, dating app	invoice, proposal, invoice ninja, labor ready, invoice2go.com
Weather	ins tracker, dating apps, magic likes, followers insight, find my airpods	weather forecast, apple weather, doppler radar, dtn weather, dark weather
Developer Tools	ins tracker, free hookup app, meeting app, instagram view, dating app	switch data, lux meter, sapphire app, qwerty, pink keyboard
Travel	ins tracker, buying followers, one night hookup dating, hookup apps, buy tiktok followers	air travel, wyndham, skiplagged, marriott, hostel
Sports	ins tracker, meeting app, instagram view, dating app, dating apps	bovada, myscore, volleyball score, handicap, golf handicap
Social Networking	ins tracker, free hookup app, meeting app, instagram view, dating app	twitter bot, lovoo gmbh apps, justalk, gaze,mewee
Reference	ins tracker, meeting app, instagram view, dating app, dating apps	tureng, leo geomatch, pi family day, god's word, grace bible church app
Productivity	ins tracker, free hookup app, meeting app, instagram view, dating app	raft calendar, caleb, awesome note, personal assistant, nordpass
Photo & Video	ins tracker, free hookup app, meeting app, instagram view, buying followers	videoleap, blur photo, vintage photo, photofox, kine
News	free hookup app, meeting app, instagram view, dating app, dating apps	sacramento news, trending politics, nuevo dia, khabar, reno
Navigation	ins tracker, free hookup app, meeting app, instagram view, dating app	smart compass, speedy, psta, lei seca, garmin drive
Music	meeting app, chat room, chat dating app, buy tiktok followers, status download	mixer box 3, battle me, online music, drum machine, dj mixer
Lifestyle	ins tracker, free hookup app, meeting app, instagram view, dating app	thumper, pattern app, guardian app, zapp, zap
Health & Fitness	ins tracker, free hookup app, meeting app, dating app, dating apps	tabata, 30 day butt, fit app, tabata workout, 7 minute
Finance	ins tracker, free hookup app, instagram view, dating app, dating apps	litecoin, td ameritrade, share, bitpay, bitfinex
Entertainment	ins tracker, free hookup app, meeting app, instagram view, dating app	starz encore, starz go, hbo latino, amc stubs a list, starz free
Education	free hookup app, meeting app, dating app, dating apps, buying followers	math learner, educational, kids academy, math facts, learning letters
Books	free hookup app, meeting app, instagram view, dating app, dating apps	harlequin, bookshout, novel updates, ireader, book shout
Medical	ins tracker, meeting app, instagram view, chat dating app, random chat app	pepid, mybmgchart, sanford health, nch mychart, mychart froedtert
Magazines & Newspaper	instagram view, chat dating app, buy tiktok followers, instagram unfollwers, music apps	cosmopolitan, cosmopolitan magazine us, fast company, zee news, smithsonian networks
Food & Drink	free hookup app, dating app, dating apps, buying followers, dating apps for couples	hungry howies, marcos pizza, pizza hut delivery, food service, pizza bolis
Shopping	free hookup app, meeting app, instagram view, dating app,dating apps	zaful, revolve, victoria secret, uo, raulph lauren

aggressive apps. The AKG can be used for supporting search keywords recommendation and app competitor analysis, etc.

B. Explicit App Competition

As aforementioned, we observed a portion of the sampled keywords are brand-specific, and most of the names are popular app names (i.e., target apps), which could reflect the explicit app competition. That is to say, the advertised apps intend to attract users who search the target apps.

To measure to what extent this kind of competition exists in the wild, we match the 47,378 app names with all the bidding keywords in our dataset. Here, we enforce strict matching, i.e., the keywords have to be identical with the app names. At last, 3,540 app names were found in the keywords dataset, bid by 1,090 apps. Figure 11 shows the competition graph. App "thermometer app for fever", which belongs to category "Medical", has the largest degree, 60 apps bid advertisements on its app name. Interestingly, 19 (31.67%) of them belong to the same category "Medical" and all the other apps share different categories with it.

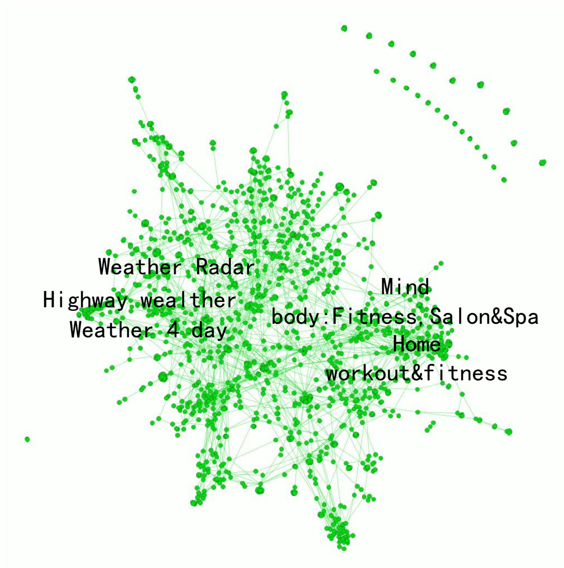

Fig. 11. A sampled AKG based on 198 apps and 5,567 keywords.

C. Implicit App Competition

We next inspect the implicit app competitions, i.e., apps share a large portion of bidding keywords. Thus, we represent each app as a vector, while each bit refers to whether the corresponding keyword is covered by the app. Then, we enforce a pairwise comparison of all the 3,540 apps, which forms over 10 million app pairs. Here, we use Jaccard distance [20] to measure the similarity. Note that, for each app pair (A, B), we calculate two similarity scores, i.e., $Sim_A(B)$ and $Sim_B(A)$, which represent the proportions of the shared keywords in all the bidding keywords of App A and App B, respectively.

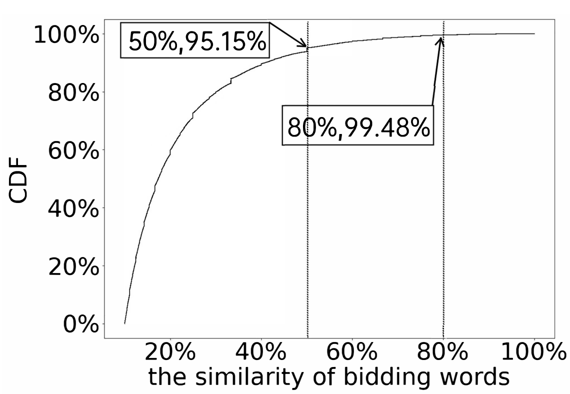

Fig. 12. Bidding keywords similarity for app pairs with over 10% of similarity.

As expected, most of the app pairs are quite different, with only 69,612 (0.56%) app pairs have a similarity score of over 10%. For app pairs with over 10% of similarity, the overall distribution is shown in Figure 12. Among the pairs with over 10% of similarity, over 4.85% of them have similarity scores over 50%, which we believe is the strong indicator of the app competition. It involves a total of 1,541 apps, which means that at least one of these 1,541 apps shares over 50% of the bidding keywords of it. For example, Figure 13 shows the top-5 similar apps related to "iHeartRadio Family", a popular Music app. Among these five apps, four belong to `Music` category ("iHeart: Radio, Music, Podcasts", "Pandora: Music & Podcasts", "Simple Radio", "RADIO.COM") and one belongs to `News` category ("Castbox").

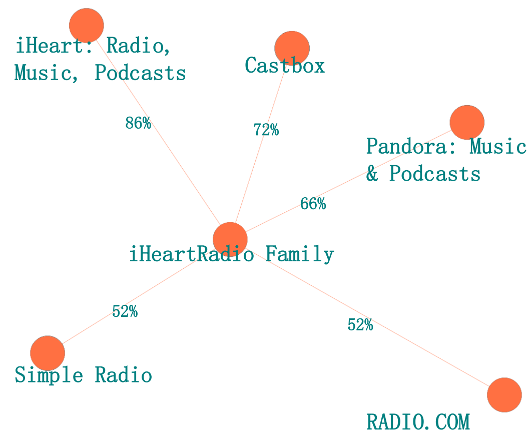

Fig. 13. Top-5 similar apps related to app "iHeartRadio Family".

Answer to RQ3: *We have created a large-scale app-keyword graph, which can be used to infer the app competitive relations. We observed two types of app competitions, i.e., explicit competitions that the advertised apps intend to attract users who search the corresponding target apps, and implicit competitions that apps share a large portion of bidding keywords with others.*

VII. Discussion

A. Implication

Our research efforts in this paper can contribute to different stakeholders of the mobile app ecosystem.

1) App Developers: The ASA keywords adopted are related to the business scope of the app. By comparing the similarity of ASA keywords covered by different apps, it is possible to discover potential competitive relationships between apps. To achieve the purpose of effective promotion with a reasonable budget, our study in this paper has the following implications. *(1) Choose a reasonable keyword coverage.* According to our data, different types of apps show a big gap in the scale of adopting ASA, which has a lot to do with the function of the app itself and the target users. Therefore, blindly increasing the coverage of keywords seems to be an inefficient and unwise way. To reduce the cost of adopting ASA, app developers need to keep the number of keywords within a reasonable range based on the types of apps they promote. *(2) Choose keywords truly related to the app.* According to Apple's official statement, the Tap-Through rate and Conversion rate are important criteria for the system to determine which app to display. When the user finds that the displayed ads are not related to their searched keywords, in general, the ads would not be clicked. Besides, according to our observation, most popular keywords are short-tail words and are shared by multiple categories which means the short-tail words are more competitive and expensive. Long-tail keywords are more specific. Comparing “sports” vs. “sports - yoga & dance”, the information contained in the second keyword is more specific, so the second one usually brings higher TTR (Tap-Through Rate) and conversion. *(3) Use branded keywords.* According to our data, we observed that only a portion of apps choose to bid branded words, which means that the bidding for branded word is not really fierce. Considering that most users will use branded keywords to find apps and most of the branded keywords are not competitive (except for some famous app names), it is an affordable and effective way to promote apps.

2) App Market Maintainers: Although Apple claims that they have adopted advanced techniques to determine how relevant the advertisement of an app is to the search query of a given keyword, we still observed a number of ASA ads that are totally irrelevant to the search keywords, especially for the dating related keywords. This, however, would decrease users’ experience when they search for desired apps. We argue that the ASA mechanism should be improved to provide truly related apps. Furthermore, we observe that ASA has not been widely adopted by app developers, we believe iOS app store should give publicity to ASA and provide more details on the benefit of ASA to attracting more developers and promoting high-quality apps to their intended users. This, will benefit the prosperous development of the overall mobile app ecosystem. At last, our study on iOS app store can also be brought by other app markets like Google Play and third-party app markets to develop/improve their own in-market app advertising.

B. Limitation

Our study carries several limitations. Although our work is the first explorative study of Apple ASA mechanism, our study is not comprehensive enough, as we cannot get the detailed information from either the app market or app developers. We only cover the top apps in the market, without considering the remaining millions of apps. Besides, we cannot measure the effectiveness of the ASA ads, thus we have to treat each keyword equally in our analysis. Moreover, although one keyword can correspond to more than one advertised apps, these apps may occupy different proportion of the ASA ads, which means that the edges in our constructed AKG graph should be weighted, which could enable fine-grained analysis. We leave these limitations for future study. Nevertheless, our study is the first step towards understanding and improving the in-market mobile app promotion mechanisms.

VIII. Related Work

A. App Promotion and Mobile Advertising

There are a number of ways for promoting mobile apps, including traditional mobile advertising, App Store Optimization (ASO), and in-market search ads (e.g., Apple Search Ads). A number of studies in our research community have analyzed the traditional mobile advertising, including mobile ad library (third-party library) detection [21]–[25], security and privacy analysis of mobile advertising [26]–[32], mobile ad fraud detection [32]–[36], mobile ad traffic analysis [3], etc. For the ASO techniques, several studies have characterized them [4], [5]. For example, Ranham et al. [4] have studied the Black Hat App Search Optimization (ASO) in Google Play, which is a kind of fraudulent behavior in the form of fake reviews and sockpuppet accounts, by recruiting ASO workers in the wild. However, to the best of our knowledge, this is the first paper on mobile in-market search ads.

B. App Store Mining and Mobile App Analysis

App store mining and mobile app anlaysis attract lots of efforts from our community in the last decade [8]. Some studies have analyzed millions of apps to understanding the overall mobile app ecosystem [1], [9], [10], [37], [38]. For example, Wang et al. [1] characterized the evolution of Google Play based on over 5 million app records collected from three snapshots of Google Play. Besides, a number of studies were focused on characterizing app developers [10], [38], [39], app market maintenance behaviors [40]–[42], app clone detection [24], [43], security [44]–[47], privacy issues [29], [48]–[50] and scams [33], [51], [52] in the ecosystem. Furthermore, a number of studies have combined various information crawled from the app market, including app description [11], [12], [53], privacy policy [13], [14], app reviews [15], [16], [54], app ratings and download [55], [56], etc. ASA promotion, as a new source of information to understanding the mobile app ecosystem, has not been touched by existing studies.

IX. Conclusion

App promotion is the key to the success of the app. App Store Search Advertisement, as the official way to promoting mobile apps within the market, has not been well studied in our research community. In this paper, we take the first step to characterize iOS app store search marketing. We first contribute to the community a large-scale dataset, consisting of over 2.8 million search keywords bid by the most popular apps across 22 categories in iOS app store. We then perform extensive analysis of the dataset from different perspectives, including the popularity of ASA, the characteristics of the keywords and the app relations mined from the ASA keyword bidding. Our work is of key importance to the community, our observations and insights gained are beneficial to the stakeholders in the mobile app ecosystem.

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REFERENCES

[1] H. Wang, H. Li, and Y. Guo, "Understanding the evolution of mobile app ecosystems: A longitudinal measurement study of google play," in *The World Wide Web Conference*, 2019, pp. 1988–1999.

[2] Q. Guo, H. Wang, C. Zhang, Y. Guo, and G. Xu, "Appnet: understanding app recommendation in google play," in *Proceedings of the 3rd ACM SIGSOFT International Workshop on App Market Analytics*, 2019, pp. 19–25.

[3] N. Vallina-Rodriguez, J. Shah, A. Finamore, Y. Grunenberger, K. Papagiannaki, H. Haddadi, and J. Crowcroft, "Breaking for commercials: characterizing mobile advertising," in *Proceedings of the 2012 Internet Measurement Conference*, 2012, pp. 343–356.

[4] M. Rahman, N. Hernandez, R. Recabarren, S. I. Ahmed, and B. Carbunar, "The art and craft of fraudulent app promotion in google play," in *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*, 2019, pp. 2437–2454.

[5] M. Karagkiozidou, C. Ziakis, M. Vlachopoulou, and T. Kyrkoudis, "App store optimization factors for effective mobile app ranking," *Strategic Innovative Marketing and Tourism*, pp. 479–486, 2019.

[6] A. Inc., "Search ads now available," https://developer.apple.com/news/?id=09282016a, 2016.

[7] ——, "Apple search ads," https://searchads.apple.com/, 2021.

[8] M. Harman, Y. Jia, and Y. Zhang, "App store mining and analysis: Msr for app stores," in *2012 9th IEEE working conference on mining software repositories (MSR)*. IEEE, 2012, pp. 108–111.

[9] H. Wang, Z. Liu, J. Liang, N. Vallina-Rodriguez, Y. Guo, L. Li, J. Tapiador, J. Cao, and G. Xu, "Beyond google play: A large-scale comparative study of chinese android app markets," in *Proceedings of the Internet Measurement Conference 2018*, 2018, pp. 293–307.

[10] H. Wang, Z. Liu, Y. Guo, X. Chen, M. Zhang, G. Xu, and J. Hong, "An explorative study of the mobile app ecosystem from app developers' perspective," in *Proceedings of the 26th International Conference on World Wide Web*, 2017, pp. 163–172.

[11] A. Gorla, I. Tavecchia, F. Gross, and A. Zeller, "Checking app behavior against app descriptions," in *Proceedings of the 36th international conference on software engineering*, 2014, pp. 1025–1035.

[12] R. Pandita, X. Xiao, W. Yang, W. Enck, and T. Xie, "{WHYPER}: Towards automating risk assessment of mobile applications," in *22nd {USENIX} Security Symposium ({USENIX} Security 13)*, 2013, pp. 527–542.

[13] L. Yu, X. Luo, X. Liu, and T. Zhang, "Can we trust the privacy policies of android apps?" in *2016 46th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN)*. IEEE, 2016, pp. 538–549.

[14] R. Slavin, X. Wang, M. B. Hosseini, J. Hester, R. Krishnan, J. Bhatia, T. D. Breaux, and J. Niu, "Toward a framework for detecting privacy policy violations in android application code," in *Proceedings of the 38th International Conference on Software Engineering*, 2016, pp. 25–36.

[15] N. Chen, J. Lin, S. C. H. Hoi, X. Xiao, and B. Zhang, "Ar-miner: Mining informative reviews for developers from mobile app marketplace," in *Proceedings of the 36th International Conference on Software Engineering*, ser. ICSE 2014. New York, NY, USA: Association for Computing Machinery, 2014, p. 767–778. [Online]. Available: https://doi.org/10.1145/2568225.2568263

[16] N. Genc-Nayebi and A. Abran, "A systematic literature review: Opinion mining studies from mobile app store user reviews," *Journal of Systems and Software*, vol. 125, pp. 207–219, 2017.

[17] A. Inc., "How apple search ads works," https://searchads.apple.com/help/basic/0035-how-apple-search-ads-works/, 2021.

[18] ——, "Add and manage keywords," https://searchads.apple.com/help/advanced/0014-add-and-manage-keywords/, 2021.

[19] M. Kamenkov, "Keyword expansion in apple search ads: Scale your profitability," https://splitmetrics.com/blog/keyword-expansion-apple-search-ads/, 2018.

[20] Wikipedia, "Jaccard index," https://en.wikipedia.org/wiki/Jaccard_index, 2021.

[21] X. Zhan, L. Fan, T. Liu, S. Chen, L. Li, H. Wang, Y. Xu, X. Luo, and Y. Liu, "Automated third-party library detection for android applications: Are we there yet?" in *2020 35th IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 2020, pp. 919–930.

[22] H. Wang and Y. Guo, "Understanding third-party libraries in mobile app analysis," in *2017 IEEE/ACM 39th International Conference on Software Engineering Companion (ICSE-C)*. IEEE, 2017, pp. 515–516.

[23] Z. Ma, H. Wang, Y. Guo, and X. Chen, "Libradar: fast and accurate detection of third-party libraries in android apps," in *Proceedings of the 38th international conference on software engineering companion*. ACM, 2016, pp. 653–656.

[24] H. Wang, Y. Guo, Z. Ma, and X. Chen, "Wukong: A scalable and accurate two-phase approach to android app clone detection," in *Proceedings of the 2015 International Symposium on Software Testing and Analysis*, 2015, pp. 71–82.

[25] M. Li, W. Wang, P. Wang, S. Wang, D. Wu, J. Liu, R. Xue, and W. Huo, "Libd: scalable and precise third-party library detection in android markets," in *Software Engineering (ICSE), 2017 IEEE/ACM 39th International Conference on*. IEEE, 2017, pp. 335–346.

[26] M. Backes, S. Bugiel, and E. Derr, "Reliable third-party library detection in android and its security applications," in *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, 2016, pp. 356–367.

[27] M. C. Grace, W. Zhou, X. Jiang, and A.-R. Sadeghi, "Unsafe exposure analysis of mobile in-app advertisements," in *Proceedings of the fifth ACM conference on Security and Privacy in Wireless and Mobile Networks*. ACM, 2012, pp. 101–112.

[28] P. Pearce, A. P. Felt, G. Nunez, and D. Wagner, "Addroid: Privilege separation for applications and advertisers in android," in *Proceedings of the 7th ACM Symposium on Information, Computer and Communications Security*. Acm, 2012, pp. 71–72.

[29] M. Liu, H. Wang, Y. Guo, and J. Hong, "Identifying and analyzing the privacy of apps for kids," in *Proceedings of the 17th International Workshop on Mobile Computing Systems and Applications*, 2016, pp. 105–110.

[30] L. Li, T. Riom, T. F. Bissyandé, H. Wang, J. Klein *et al.*, "Revisiting the impact of common libraries for android-related investigations," *Journal of Systems and Software*, vol. 154, pp. 157–175, 2019.

[31] T. Liu, H. Wang, L. Li, X. Luo, F. Dong, Y. Guo, L. Wang, T. F. Bissyande, and J. Klein, "Maddroid: Characterising and detecting devious ad content for android apps," in *Proceedings of the Web Conference 2020 (WWW'20)*, 2020.

[32] T. Liu, H. Wang, L. Li, G. Bai, Y. Guo, and G. Xu, "Dapanda: Detecting aggressive push notifications in android apps," in *2019 34th IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 2019, pp. 66–78.

[33] F. Dong, H. Wang, L. Li, Y. Guo, T. F. Bissyandé, T. Liu, G. Xu, and J. Klein, "Frauddroid: Automated ad fraud detection for android apps," in *The 26th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE 2018)*, 2018.

[34] B. Liu, S. Nath, R. Govindan, and J. Liu, "Decaf: Detecting and characterizing ad fraud in mobile apps." in *NSDI*, 2014, pp. 57–70.

[35] F. Dong, H. Wang, L. Li, Y. Guo, G. Xu, and S. Zhang, "How do mobile apps violate the behavioral policy of advertisement libraries?" in *Proceedings of the 19th International Workshop on Mobile Computing Systems & Applications*, 2018, pp. 75–80.

[36] J. Crussell, R. Stevens, and H. Chen, "Madfraud: Investigating ad fraud in android applications," in *Proceedings of the 12th annual international conference on Mobile systems, applications, and services*. ACM, 2014, pp. 123–134.

[37] L. Li, J. Gao, M. Hurier, P. Kong, T. F. Bissyandé, A. Bartel, J. Klein, and Y. Le Traon, "Androzoo++: Collecting millions of android apps and their metadata for the research community," *arXiv preprint arXiv:1709.05281*, 2017.

[38] H. Wang, X. Wang, and Y. Guo, "Characterizing the global mobile app developers: a large-scale empirical study," in *2019 IEEE/ACM 6th International Conference on Mobile Software Engineering and Systems (MOBILESoft)*. IEEE, 2019, pp. 150–161.

[39] W. Wang, G. Meng, H. Wang, K. Chen, W. Ge, and X. Li, "A3ident: A two-phased approach to identify the leading authors of android apps," in *2020 IEEE International Conference on Software Maintenance and Evolution (ICSME)*. IEEE, 2020, pp. 617–628.

[40] H. Wang, J. Si, H. Li, and Y. Guo, "Rmvdroid: Towards a reliable android malware dataset with app metadata," in *Proceedings of the 16th International Conference on Mining Software Repositories*, 2019, p. 404–408.

[41] H. Wang, H. Li, L. Li, Y. Guo, and G. Xu, "Why are android apps removed from google play? a large-scale empirical study," in *The 15th International Conference on Mining Software Repositories (MSR 2018)*, 2018.

[42] F. Lin, H. Wang, L. Wang, and X. Liu, "A longitudinal study of removed apps in ios app store," in *Proceedings of the 30th The Web Conference (WWW 2021)*, 2021.

[43] L. Li, T. F. Bissyandé, H.-Y. Wang, and J. Klein, "On identifying and explaining similarities in android apps," *Journal of Computer Science and Technology*, vol. 34, no. 2, pp. 437–455, 2019.

[44] Y. Zhou and X. Jiang, "Dissecting android malware: Characterization and evolution," in *2012 IEEE symposium on security and privacy*. IEEE, 2012, pp. 95–109.

[45] H. Zhou, H. Wang, Y. Zhou, X. Luo, Y. Tang, L. Xue, and T. Wang, "Demystifying diehard android apps," in *2020 35th IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 2020, pp. 187–198.

[46] Y. Tang, Y. Sui, H. Wang, X. Luo, H. Zhou, and Z. Xu, "All your app links are belong to us: understanding the threats of instant apps based attacks," in *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, 2020, pp. 914–926.

[47] H. Wang, H. Liu, X. Xiao, G. Meng, and Y. Guo, "Characterizing android app signing issues," in *2019 34th IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 2019, pp. 280–292.

[48] A. Razaghpanah, R. Nithyanand, N. Vallina-Rodriguez, S. Sundaresan, M. Allman, C. Kreibich, and P. Gill, "Apps, trackers, privacy, and regulators: A global study of the mobile tracking ecosystem," 2018.

[49] S. Xi, S. Yang, X. Xiao, Y. Yao, Y. Xiong, F. Xu, H. Wang, P. Gao, Z. Liu, F. Xu *et al.*, "Deepintent: Deep icon-behavior learning for detecting intention-behavior discrepancy in mobile apps," in *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*, 2019, pp. 2421–2436.

[50] H. Wang, Y. Guo, Z. Tang, G. Bai, and X. Chen, "Reevaluating android permission gaps with static and dynamic analysis," in *2015 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2015, pp. 1–6.

[51] Y. Hu, H. Wang, R. He, L. Li, G. Tyson, I. Castro, Y. Guo, L. Wu, and G. Xu, "Mobile app squatting," in *Proceedings of The Web Conference 2020*, 2020, pp. 1727–1738.

[52] Y. Hu, H. Wang, Y. Zhou, Y. Guo, L. Li, B. Luo, and F. Xu, "Dating with scambots: Understanding the ecosystem of fraudulent dating applications," *arXiv preprint arXiv:1807.04901*, 2018.

[53] C. Zhang, H. Wang, R. Wang, Y. Guo, and G. Xu, "Re-checking app behavior against app description in the context of third-party libraries." in *SEKE*, 2018, pp. 665–664.

[54] Y. Hu, H. Wang, T. Ji, X. Xiao, X. Luo, P. Gao, and Y. Guo, "Champ: Characterizing undesired app behaviors from user comments based on market policies," in *The 43rd ACM/IEEE International Conference on Software Engineering (ICSE 2021)*, 2021.

[55] M. Ali, M. E. Joorabchi, and A. Mesbah, "Same app, different app stores: A comparative study," in *2017 IEEE/ACM 4th International Conference on Mobile Software Engineering and Systems (MOBILESoft)*. IEEE, 2017, pp. 79–90.

[56] I. J. M. Ruiz, M. Nagappan, B. Adams, T. Berger, S. Dienst, and A. E. Hassan, "Impact of ad libraries on ratings of android mobile apps," *IEEE Software*, vol. 31, no. 6, pp. 86–92, 2014.