

Mapping users' checking habits in mobile app usage

Keywords: smartphones, mobile apps, digital behaviors, checking habits, complex networks

Smartphones have become an essential part of people's day-to-day life across the globe. There are more than 3 billion smartphone users worldwide, and this number is steadily growing. More than a third of smartphone owners report that the phone is the first thing they reach for when they wake up in the morning¹, and 81% of U.S. owners keep their phone nearby during nearly all waking hours². Individual smartphone usage vary widely, both within and across users [1]. Previous work mostly focused on describing aggregated usage patterns, while neglecting how app inter-dependencies and users' checking habits may induce characteristic app sequences. The available research exploring app sequences mainly focused on predicting the next used app [2] or describing transition probabilities between app categories [3].

Starting from a large-scale dataset, containing information on mobile app sequences of around 150k anonymized European users in 2017, we propose to study apps' inter-dependencies and their ecosystem via network analysis. We model the app ecosystem as a weighted directed network, whose nodes are apps and links represent users shifting between two apps. We weight any link $e_{i,j}$ by computing the median of the normalized number of shifts that occurred between apps i and j . Moreover, we choose to divide the year 2017 into quarters to trace the seasonality, building 4 different networks, whose summary statistics are shown in Figure 1a (original).

We propose to answer the following questions: *a) What is the overall structure of the app ecosystem? b) Which apps emerge from the cumulative checking habits of users and how do they shape the network connectivity? c) Is there seasonality in the observed behaviors? d) Is there a relationship between network components, user and app characteristics?*

We first analyze the degree distribution of the networks. We find exponential distributions, indicating that few nodes attract and release the majority of links. These nodes, which generate and receive the main flow in the network, are key components of users' checking habits. We then proceed to their detection, by leveraging the well-established *HITS* [4], that suits the directionality of our networks. Interestingly, we uncovered little to no differences when comparing the authority and hub rankings, with only some variation over time. We consistently find: 1) the most popular apps, e.g., Google Chrome, Facebook, Whatsapp, etc., in the top positions; 2) a similar distribution of app categories (according to the Google Play Store definition), with Communication and Social apps representing the majority in both rankings; and 3) small differences across time (see Fig. 1b). This result indicates that the most popular apps strongly influence the structure of the network, by acting as main connectors. This finding is also corroborated by studying the community structure of the network. By identifying the communities via *InfoMap* [5], we indeed find only a handful of communities with extremely low modularity, where the biggest one includes about 90% of the nodes in all quarters (Fig. 1a), making it difficult to relate any underlying structure to specific users' behaviors.

To overcome the influence of such apps and get a more meaningful representation of the network, we extrapolate the *metric backbone* [6]. The study of the backbone allows us to identify the underlying structure of the app ecosystem and have a better understanding of central nodes and communities. While the authorities are consistent with previous results, both in terms

¹https://www.huffpost.com/entry/smartphone-behavior-2015_n_7690448

²<https://news.gallup.com/poll/184046/smartphone-owners-check-phone-least-hourly.aspx>

of specific apps and category distribution (Fig. 1c), hubs now show a very different pattern. We find: 1) a lack of persistence of the same apps in time; 2) Games and News categories representing the majority of apps in the top 20; and 3) the presence of seasonal differences, e.g. more Weather apps in the last quarter of 2017 (not shown in the figure for brevity).

The number of meaningful communities and their modularity also increase (Fig. 1a - Backbone). Heuristically, through the cumulative degree distribution (Fig. 1e), we detect characteristic structures: *star or multi-star* communities and *network-like* communities (examples shown in Fig 1d). Star and multi-star communities are characterized by steeper increases in the cumulative normalized degree distribution, reflecting the large differences between the degree of focal apps and the rest of the nodes (Figure 1e). Figures 1d and 1e illustrate the results for the first quarter, but we have evidence that the same structures are consistent in all quarters.

Moreover, these findings suggest a relation with the users' online habits. We find that apps at the center of a star or a multi-star are most popular apps, connecting different areas of the network and describing more global behavioral patterns. Among stars in the first quarter, we have Whatsapp, Instagram, YouTube etc. As multi-star we retrieve related apps, such as Ebay and Amazon, Gmail and the phone email, calls and contacts. We also investigate the apps belonging to network-like communities and find that they are representative of local patterns. In particular, we find a relation to the country these apps belong to and to specific types of activity, i.e. app categories. Figure 1f displays the dual nature of each network-like community. Here, we highlight the percentage of nodes belonging to countries (top) and categories (bottom). While some communities are mostly explained by one or two types of activities/countries, others are related to both aspects. This suggests an inter-dependency between apps either related to their purpose (i.e. category of use) or to geographical areas (i.e. country specific apps).

This work presents a step forward in understanding our digital habits and characterizing the inter-connected nature of mobile apps and their ecosystem. Future work will be devoted to study more complex patterns of flow, by considering the concept of "memory" in the communities uncovered by InfoMap.

References

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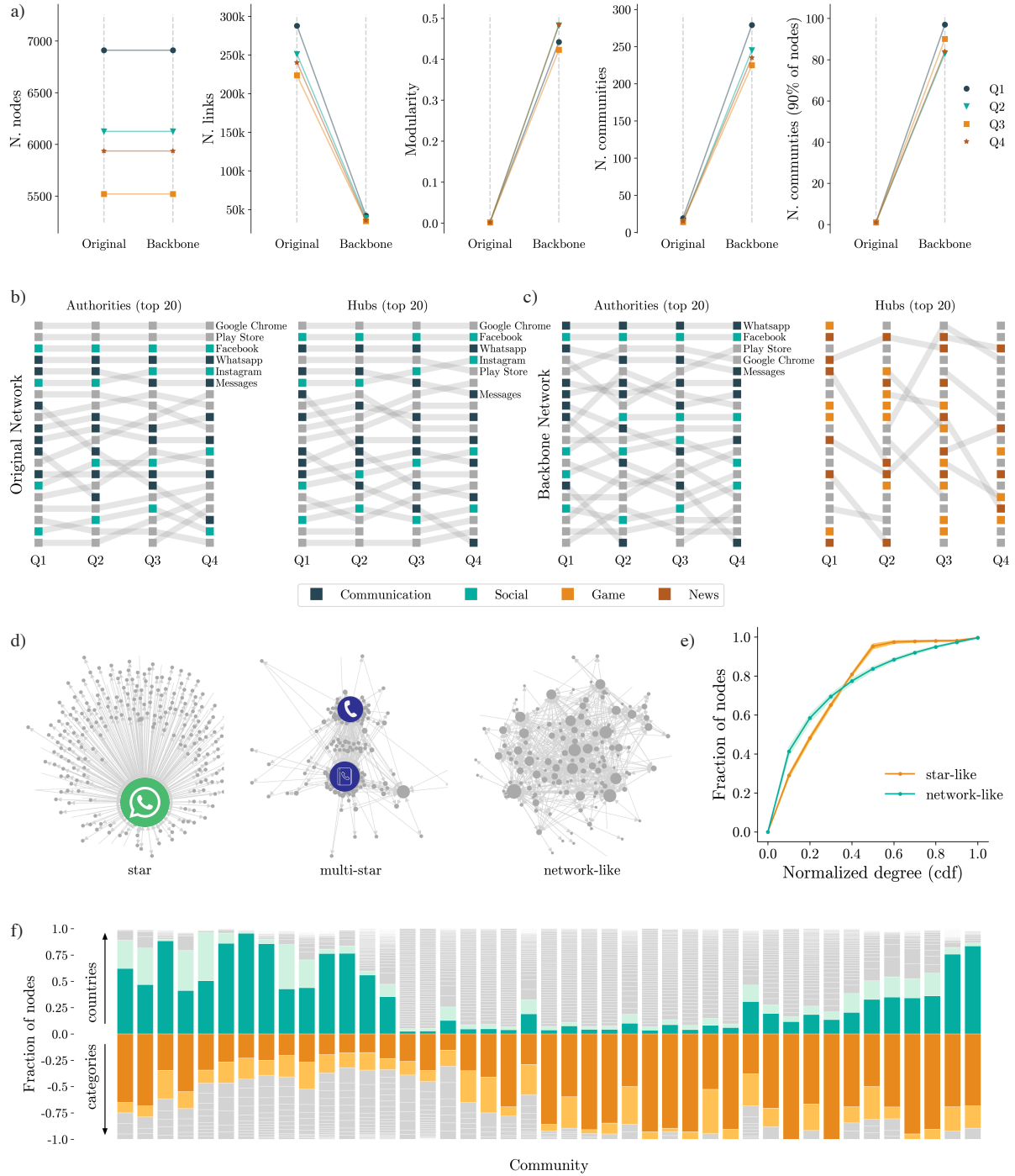


Figure 1: Result summary. a) Summary statistics comparing the original network and the backbone across quarters. b) Top 20 authorities and hubs of the original network. App names refer to apps that are either in the top 5 of Q1 or Q4 and never exit the top 20 across all quarters. Colors highlight the two most prevalent categories in the top 20. Links between quarters are present if the same app is also part of the following top 20 rankings and omitted otherwise. c) Top 20 authorities and hubs rankings of the backbone (analogous to b). d) Example of main types of communities: star – related to a single app (Whatsapp in this example), multi-star – related to two apps connected to each other (phone calls and contacts in this example), and network-like. e) Cumulative distribution function of the normalized degree for star-like and network-like communities. f) Comparison of network-like communities via Google Play Store categories and countries of users.