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Mobile Applications Usage Prediction for Enhanced User Experience

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Abstract:

Smartphones are no doubt, one of the most essential accessories as these phones have taken over almost every solution of our everyday operations. Achieving their goals comes with a cost. The variety of Apps and increase in mobile Apps are consistently trying to make smartphones obsolete. The user experience is affected by the mass of Apps and the performance and efficiency are affected by the occupation of memory. Especially in Android OS, the inbuilt low memory killer, which is responsible for freeing memory, is obsolete. For it does not consider user needs information and frequently kills Applications that are going to be launched. In this paper, we propose an Approach of machine learning to develop a system that predicts the upcoming Apps and prelaunch them as well tweak the android User Interface with bringing predict Apps forward for usability and better user experience. We use Scikit-learn; a machine learning library for Python and implement a Decision tree classifier; a machine-learning algorithm to trained models on the previous App usage data provided by google from a smartphone. Later on, through experimentation, the results demonstrate the accuracy of the model and its feasibility to be implemented as a real-world system into an App usage manager for Android operating system.

Key words: User Experience, Mobile Applications Usage, Machine Learning, UX, Prediction,

الملخص:

أن الهواتف الذكية هي من أهم الملحقات التي نعتمد عليها لحل جميع العمليات اليومية و لتحقيق الاهداف هنالك تكلفة معينه. التطبيقات المتنوعه وزيادتها في الاجهزه المحمولة باستمرار جعل من الهواتف الذكية متروكة تجارب المستخدمين تتأثر بكمية التطبيقات والأداء والكفاءة وكذلك من حيث استخدام الذاكره. خاصة في نظام التشغيل Android ، القاتل المدمج للذاكرة المنخفضة ، التي هي المسؤولة عن توفير الذاكرة متروكة ايضاً لعدم اخذها بالاعتبار احتياجات المستخدم من المعلومات وغالبًا ما تقتل التطبيقات التي سيتم إطلاقها. في هذا البحث، تم اقتراح نهج للتعلم الآلي لتطوير نظام يتنبأ بالتطبيقات القادمة والقيام بتشغيلها مسبقًا بالإضافة إلى تعديل واجهة مستخدم android مع تطوير تطبيقات التنبؤ و سهولة الاستخدام وتجربة خدمة المستخدمين بشكل افضل. نحن نستخدم Scikit-Learn ؛ مكتبة للتعلم الآلي لـ Python و تنفيذ مصنف القرار؛ خوارزمية التعلم الآلي للنماذج المدربة على بيانات استخدام التطبيقات السابقة المقدمة من Google من الهواتف الذكية. في وقت لاحق، من خلال التجارب، توضيح دقة وجودة النتائج تمكننا من استخدامه بشكل حقيقي في ادارة التطبقات لنظام التشغيل Android.

الكلمات الرئيسية: تجارب المستخدمين، استخدام تطبيقات الهواتف الذكية، التعلم الآلي، التنبؤ.

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پوخته:

ئامێرە زیرەکەکان بوونەتە یەکێک لەپێداویستیە سەرەکییەکانی ڕۆژانەی هەموو تاکێک لەبەڕێکردنی زۆرینەی ئێش و کارەکانی ڕۆژانە، بەجێهێنانی ئەمە تێچوی دیاریکراوی خۆی هەیە. هەمەجۆری بەرنامەکان و زیادبونی بەردەوامی ژمارەیان وایکردووە ئامێرە زیرەکەکان ئەرکی خۆیان بەباشی جێبەجێ نەکەن. ئەزمونی بەکارهێنەران کارتێکراوە بە ژمارەی بەرنامەکان و گورجی و چوستیان لەڕوی بەکارهێنانی میمۆریەوە، بەتایبەتی لە سیستەمی ئیشپێکردنی ئەندرۆید، بەرنامەی تەرخانکراو هەیە بۆ لەکارخستنی بەرنامەکان بۆ زیادکردنی میمۆری ئازادکراو و بەردەستخستنی بۆشاییەکی زیاتر لە میمۆری (یادگە) بەڵام زۆربەی کات ئەو بەرنامانە دادەخات کە بەکارهێنەر بەتازەیی بەکاریهێناوە و گوێ نادات بە پێداویستی بەکارهێنەر، وەدواجار دەبێتە هۆی بێزارکردنی بەکارهێنەر، لەم توێژینەوەیەدا شێوازێک لە فێربونی ئامێریی پێشنیارکراوە بۆ بەرەوپێشبردنی سیستەمێک کەپێشبینی بکات خودکارانە بۆ داخستنەوەی بەرنامە ناپێویستەکان بۆ فەراهەمکردنی بڕێکی زیاتر لەمیمۆری، سەرەڕای چێکردنی ڕوکاری بەکارهێنەر لە ئەندرۆیدا، هاوشانی ئاسان بەکارهێنان و خزمەتکردنی بەکارهێنەر بەشێوازێکی باشتر. سایکیت-لێرن وەک کتێبخانەی فێربونی ئامێریی لە پایثن و پۆلێنکاری درەختیی بڕیار وەکو ئەلگۆریزمی فێربونی ئامێریی بەکارهێنراوە بۆ ڕاهێنانی مۆدێلە پێشنیارکراوەکە لەسەر بەرنامە بەکارهاتووەکانی پێشووتر، کەلەڕێگەی گوگڵ فۆرمەوە دەیتاکانی بەدەست هاتووە ڕاستەوخۆ لە ئامێرەزیرەکەکانەوە وەرگیراوە. پاشان ئەنجامەکان لە تاقیکردنەوەی مۆدێلە پێشنیارکراوەکە وردی و چوستی و گورجی پێشان دەدات لەڕوی بەڕێوەبردنی بەکارهێنانی بەرنامەکان بۆ یادگە.

کلیلە وشەکان: ئەزمونی بەکارهێنەران، بەکارهێنانی بەرنامەکانی مۆبایلە زیرەکەکان، فێربونی ئامێریی، پێشبینیکردن.

1. Introduction

In the present age where smartphones are ubiquitous not only as phones but personal computers. They are used not just for calling but messaging, or entertainment, make presentations with, edit word files and even write articles. Artificial Intelligence (AI) integrated Apps have made it easy for solving everyday problems more efficiently and in less time. Hence, enabling the smartphone to do more and more tasks as an all-in-one pocket solution costs increasing the number of Apps as there are different Apps for different real-world problems and often different Apps for the same set of tasks. These Apps have to occupy the space and RAM of the smartphone devices to run simultaneously for achieving multitasking. This need for multitasking has also made both the resource usage and user experience of smartphones an area of concern. According to an empirical study of Yahoo people have 95 plus Apps on average and this is a large number of Apps. The two problems that are been identified by us, with having a large number of Apps are: The First one is the user must have to find Apps through a large list or grid of Apps from the user interface. Secondly, launching the App often has increased latency and results in a bad user experience. This is caused by the heavy usage of Apps leading to large sets of data collected in the App's cache that is removed from the RAM (fast memory) by the phone's conventional memory freeing tool and on launching the App is reloaded to the memory from storage (slow memory). This is a very unoptimized method and badly affects user experience sometimes even causing a loss in scenarios where time is important e.g. transactions, trading, emergency calls, and other real-time critical tasks. etc. Our solution for these problems is twofold. We propose a method in which we deploy an App that acts as an alternate launcher to the system's main launcher, been authorized mobile App usage data, giving better control over tweaking the UI. The launcher will gather data both based on App usage in a contextual and non-contextual manner. Then machine learning will be based on the probability to predict the next most probable App user is going to switch to and run in a given time. This will tweak the UI dynamically bringing the most used Apps to the front in the UI based on the context and allowing the launcher to help manage the

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resources reducing the App loading latency significantly by preloading their data to Fast memory and where in most cases Apps are online and need refreshing the content, it will also be able to perform a background content refresh based on practical predictions. This will ultimately enable a better overall user experience and efficient day-to-day tasks using smartphones.

2. Literature Review

Abhinav Parate et al. Proposed a solution that makes App prefetch practical on mobile phones. Their contributions are two-fold. First, they design an App prediction algorithm, APPM, that requires no prior training, adapts to usage dynamics, predicts not only which App will be used next but also when it will be used, and provides high accuracy without requiring additional sensor context. Secondly, they perform parallel prefetch on-screen unlock, a mechanism that leverages the benefits of prediction while operating within the constraints of mobile operating systems. Trinh-Minh-Tri Do et al. aims at mining usage patterns from Apps data recorded continuously with smartphones. A new probabilistic framework for mining usage patterns is proposed. That based on probability gives predicts the pattern of App you are going to use based on the App you start. Ke Huang et al proposed a method to optimize the resource management of a smartphone by predicting the contextual data of App usage pattern. Which means time, location, etc. The data was taken from the dataset of MDC. Choosing Shin Et al. Proposes a method in which data taken from phone's sensor and App usage from smartphones is collected, to perform a comprehensive analysis of the context related to mobile App usage and build prediction models that calculate the probability of an App in the current context (The context is decided by the sensory data). Shreenath Acharya et al. proposed a mechanism named Analysis and Prediction of Application Usage (APAU) in Android Phones for providing recommendations to a smartphone user while selecting Applications of their interest like mail checking, messaging, and making calls. APAU mainly focuses on identifying usage patterns and investigating human behavior during Application selections by extracting the generic behavioral patterns to predict and provide a useful set of recommendations. PAUL BAUMANN et al., Proposed EBC, a novel algorithm to schedule Application prefetches and overcome their drawbacks. EBC calculates Application usage probabilities and traffic volume estimates to decide when and for which Applications prefetches should be activated. Thus, it Applies different policies depending on whether a cellular or Wi-Fi connection is available. Ricardo Baeza-Yates et al. proposed a method to improve home screen Apps usage experience through a prediction mechanism that allows showing to users which App someone is going to use in the immediate future. The prediction technique is based on a set of features representing the real-time spatiotemporal contexts sensed by the home screen App. Andre Luiz Nunes Martins et al., proposed context-based launcher using recurrent neural network (RNN), a special branch of neural networks capable of remembering dependencies, taking in consideration the even the old outputs with inputs, providing highly accurate data without any extra sensor context.

3. Methodology

To investigate the problem of App usage, data gathered from a volunteer's smartphone. This data was collected by downloading App-usage data from myactivity.google.com authorized by the volunteer's Google Account. This data contains the logs of every App launched relative to the time

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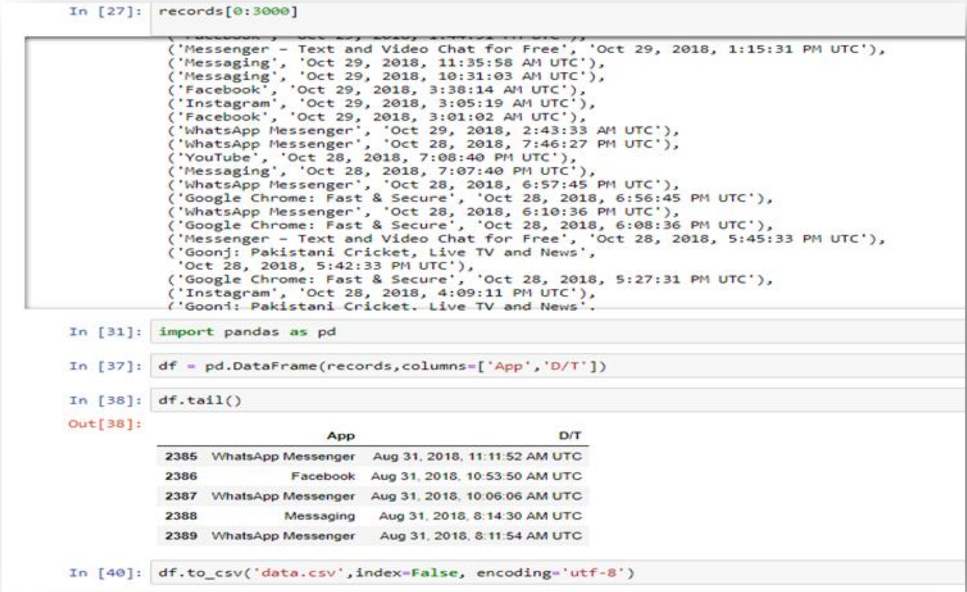
of launch represented in an HTML file. And needs some measures to be extracted. The file contained data from August 2018 to Oct 2018 which is our data of interest for analysis and learning.

The data that consisted of the "Name" and "Time of Launch" of the App, was parsed from the HTML file using HTML web parser "Beautiful soup" implemented in Python on the top of Jupyter IDE. The data was collected in a "Comma-separated values (.csv)" file format. Figure 1 depicts the form in which data has been collected.



```
In [27]: records[0:3000]

('Messenger - Text and Video Chat for Free', 'Oct 29, 2018, 1:15:31 PM UTC'),
('Messaging', 'Oct 29, 2018, 11:35:58 AM UTC'),
('Messaging', 'Oct 29, 2018, 10:31:03 AM UTC'),
('Facebook', 'Oct 29, 2018, 3:38:14 AM UTC'),
('Instagram', 'Oct 29, 2018, 3:05:19 AM UTC'),
('Facebook', 'Oct 29, 2018, 3:01:02 AM UTC'),
('WhatsApp Messenger', 'Oct 29, 2018, 2:43:33 AM UTC'),
('WhatsApp Messenger', 'Oct 28, 2018, 7:46:27 PM UTC'),
('YouTube', 'Oct 28, 2018, 7:08:40 PM UTC'),
('Messaging', 'Oct 28, 2018, 7:07:40 PM UTC'),
('WhatsApp Messenger', 'Oct 28, 2018, 6:57:45 PM UTC'),
('Google Chrome: Fast & Secure', 'Oct 28, 2018, 6:56:45 PM UTC'),
('WhatsApp Messenger', 'Oct 28, 2018, 6:10:36 PM UTC'),
('Google Chrome: Fast & Secure', 'Oct 28, 2018, 6:08:36 PM UTC'),
('Messenger - Text and Video Chat for Free', 'Oct 28, 2018, 5:45:33 PM UTC'),
('Goonj: Pakistani Cricket, Live TV and News',
 'Oct 28, 2018, 5:42:33 PM UTC'),
('Google Chrome: Fast & Secure', 'Oct 28, 2018, 5:27:31 PM UTC'),
('Instagram', 'Oct 28, 2018, 4:09:11 PM UTC'),
('Goonj: Pakistani Cricket, Live TV and News',

In [31]: import pandas as pd

In [37]: df = pd.DataFrame(records,columns=['App','D/T'])

In [38]: df.tail()

Out[38]:
```

	App	D/T
2385	WhatsApp Messenger	Aug 31, 2018, 11:11:52 AM UTC
2386	Facebook	Aug 31, 2018, 10:53:50 AM UTC
2387	WhatsApp Messenger	Aug 31, 2018, 10:06:06 AM UTC
2388	Messaging	Aug 31, 2018, 8:14:30 AM UTC
2389	WhatsApp Messenger	Aug 31, 2018, 8:11:54 AM UTC

```
In [40]: df.to_csv('data.csv',index=False, encoding='utf-8')
```

Figure 1: Hypertext Markup Language (HTML) data Parsed into comma-separated values (CSV) by Jupyter

This data enabled us to proceed to learn by feeding this data to a "Decision Tree Classifier"; a Machine Learning Algorithm based on which our implemented model learned and performed the predictions. The model was implemented in Scikit-learn; a Machine Learning Library for Python progRAMming language. The model learned on provided Data from two variables as inputs. 1) App Name 2.) App Launch time. The log consisted of information about a total of 56 Android Apps. Due to the limitation of environment variables and other effective factors not given as input to the system, we considered the top 10 frequently used Apps for the period mentioned above. These top 10 Apps were frequently used as well as covered the "most launch times of any App" for all the timeframes of the day. Figure 2 shows the graphical App usage data been analyzed and trained the model on.

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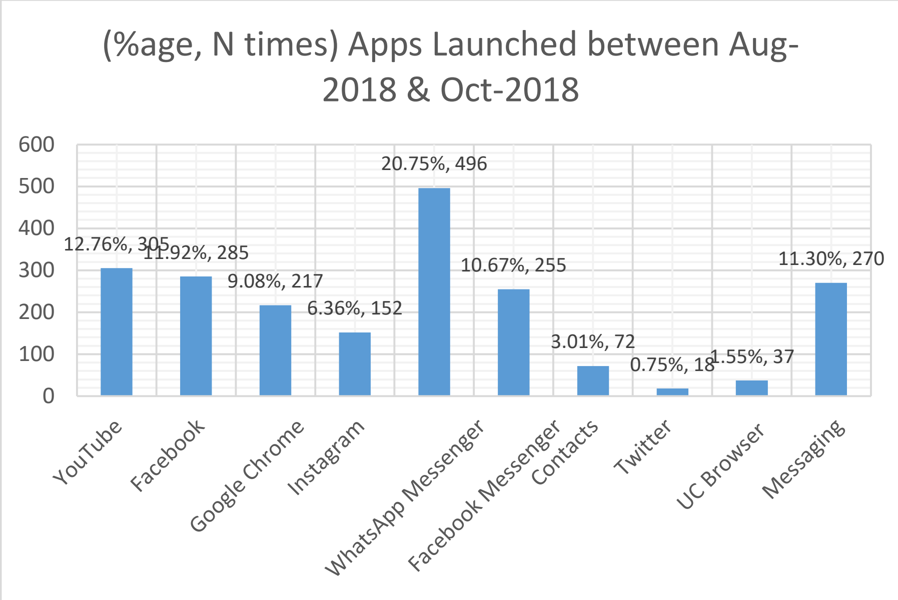

Figure 1: App usage data provided for the trained model

Once the Model learned on the data we developed an Android App around it. The Developed app was an App launcher in the mainstream of Android OS having "root access" and "App usage access" and recorded the Actual App launched by the user within a particular time relative to the Predicted App by the trained model and saved into a log file for every 30 minutes over a total period of 45 Days.

The results that were obtained from that log file over the period of 45 days were the milestone of this research. Using these results' accuracy, we were to decide to either finalized our model as an end product for prediction or needs further training.

4. Results

The deployed App launcher encompassing the trained model performed predictions and started managing resources. The App launcher used the UI and put forward the apps it predicted relative to that time on the smartphone of the volunteer and recorded the actual selection as compared to prediction in a log file. The results obtained over 45 days were then used to evaluate the accuracy of our model. Table 1 shows the results and Accuracy confusion matrix for the prediction model.

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Table 1: Confusion Matrix for Accuracy score

All occurrences of relative time/day (N) =45		45-Day logs of Classifier from App Launcher		
Time	**Predicted Launch**	**Actual TP (Yes)**	**Actual TN (NO)**	**Accuracy (%) = $\frac{(TP+TN)}{N} * 100$**
12:00 AM	WhatsApp Messenger	37	8	82.22%
12:30 AM	Google Chrome	34	11	75.56%
1:00 AM	Facebook	33	12	73.33%
1:30 AM	WhatsApp Messenger	35	10	77.78%
2:00 AM	WhatsApp Messenger	36	9	80.00%
2:30 AM	WhatsApp Messenger	37	8	82.22%
3:00 AM	WhatsApp Messenger	37	8	82.22%
3:30 AM	Messaging	37	8	82.22%
4:00 AM	Messaging	37	8	82.22%
4:30 AM	Messaging	36	9	80.00%
5:00 AM	Messaging	36	9	80.00%
5:30 AM	Messaging	37	8	82.22%
6:00 AM	Messaging	36	9	80.00%
6:30 AM	WhatsApp Messenger	36	9	80.00%
7:00 AM	WhatsApp Messenger	37	8	82.22%
7:30 AM	Messaging	36	9	80.00%
8:00 AM	WhatsApp Messenger	37	8	82.22%
8:30 AM	Facebook Messenger	33	12	73.33%
9:00 AM	Messaging	34	11	75.56%
9:30 AM	Messaging	34	11	75.56%
10:00 AM	Messaging	36	9	80.00%
10:30 AM	Messaging	34	11	75.56%
11:00 AM	WhatsApp Messenger	33	12	73.33%
11:30 AM	WhatsApp Messenger	33	12	73.33%
12:00 PM	Messaging	34	11	75.56%
12:30 PM	WhatsApp Messenger	33	12	73.33%
1:00 PM	WhatsApp Messenger	37	8	82.22%
1:30 PM	WhatsApp Messenger	37	8	82.22%
2:00 PM	WhatsApp Messenger	37	8	82.22%
2:30 PM	WhatsApp Messenger	35	10	77.78%
3:00 PM	WhatsApp Messenger	37	8	82.22%
3:30 PM	WhatsApp Messenger	34	11	75.56%
4:00 PM	WhatsApp Messenger	36	9	80.00%

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4:30 PM	WhatsApp Messenger	37	8	82.22%
5:00 PM	WhatsApp Messenger	37	8	82.22%
5:30 PM	WhatsApp Messenger	36	9	80.00%
6:00 PM	Facebook Messenger	35	10	77.78%
6:30 PM	WhatsApp Messenger	35	10	77.78%
7:00 PM	Facebook	34	11	75.56%
7:30 PM	Facebook	34	11	75.56%
8:00 PM	WhatsApp Messenger	37	8	82.22%
8:30 PM	YouTube	36	9	80.00%
9:00 PM	Instagram	34	11	75.56%
9:30 PM	YouTube	33	12	73.33%
10:00 PM	Facebook Messenger	36	9	80.00%
10:30 PM	WhatsApp Messenger	35	10	77.78%
11:00 PM	UC Browser	37	8	82.22%
11:30 PM	Google Chrome	35	10	77.78%
	Overall Accuracy			**78.80%**

The results shown are explained as follows into two paRAMeters.

- **TP –** True positive when the Predicted and Actual selection were an exact match.
- **TN** – True negative when the Predicted and Actual selection were a negative match.
- $\frac{(TP+TN)}{N} * 100$ is the Accuracy obtained by dividing total results of App launches relative to time by the total occurrences of that particular time during 45 days.

The overall accuracy of the system was 78.80%. It's important to note that the results contained only the Boolean information of the experimentation, that whether the Predicted Apps served the Actual cause or otherwise. Findings of which Apps were selected in case of a true negative result are out of the scope of this research.

5. Discussion

The problem identified in this research was solved by our implementation of this research and the results of its experiment, there are still a lot of considerable limitations to our research. One of the main of which comes with Android OS, for it doesn't allow permissions to any App launcher or App to manage resources until you have the root access. Secondly, managing the system resources includes the removal of unused and some of the unpredicted Apps if the memory is full to prefetch another App. This could result in deleting Apps from the Random-Access memory that was left to be continued by the user and will result in data and state loss, hence the worst user experience. Serious measures should be taken for critical problems like these until which this research is not implementable for real-world problems. However, it is a milestone toward along journey in this domain of Smartphones UX. The third limitation is with results; these results were only obtained from only one factor as input i.e. The App launch time and frequency. Various other significant

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factors result in App selection relative to a particular time of the day, also other factors can result in the need and mode of the user and nature of the Apps. Moreover, the results show that the system developed only managed resources for one App relative to a particular time. Giving any solution for sorting multiple Apps and predicting them according to other factors was out of the scope of this research. Lastly, indexing the installation of new Apps in the developed model and make it aware of the nature of Apps was also a limitation of our system.

6. Conclusion

This research paper proposes a solution to enhance App usage, resource usage, and ultimately User Experience of the smartphones by predicting the upcoming Apps relative to a particular time of the day and preloading them into RAM as well bring Apps forward into the main menu screen by tweaking the User Interface of the smartphone. The model is trained on the App usage behavior, App launch time, and frequency and predicts the Apps for the user to be preloaded. It's important to note that as we used our metrics to evaluate the result. It also creates a log file for Positive and negative results compare to predictions, based on which we can entirely improve our method of training model by introducing it into a reinforcement learning algorithm. The model can then use reinforced learning from log files every time a user launches or browse the menu for an App, the model would learn from the actual selections constantly and update its predictions. Another important future milestone is increasing the factors of Human usage of smartphones and introducing them as inputs to the algorithm for training such as user's behavior, mood, time spent over an App, usage patterns, frequency of switching between Apps. This will help us cope with the problem of dealing with users that often have complex requirements and expect performance-oriented solutions from their smartphones.

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