Tutorial on Smartphone App Usage, Understanding, Modelling, And Prediction

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http://fi.ee.tsinghua.edu.cn/UbiCompTutorial.html

Outline

1. Background, App Data Collection and Datasets
2. Smartphone App Usage Modelling
3. App Usage Prediction and Recommendation
4. User Profiling from the App Usage
5. Concluding Remarks & Future Directions

Who we are

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Background, App Data Collection and Datasets

Background, App Data Collection and Datasets

Background and Motivation

Scope and Research Questions

App Data Collection: Carat Case

Other Available App Datasets

What is App Usage?

Understanding the long-term evolution of mobile app usage is critical for industries by exploring which mechanisms can effectively improve user experience, enhance apps' competitive power, and grasp market opportunities during developments.

Insights for service providers, application developers, device manufacturers for improving user experience and app markets.

Smart device data provides a rich basis for multidisciplinary research.

Privacy is a very important requirement for data gathering, processing and disclosure. Smart device data typically requires ethical review board (IRB) approval.

Heather O'Brien and Elaine Toms. **What is user engagement? A conceptual framework for defining user engagement with technology.** JASIST, 2008.

Trends in mobile app usage?

The usage of smartphones has evolved significantly since 2007 when iPhone was released.

Diverse demands are mainly supported by mobile apps. Mobile apps reflect the daily work and leisure activities of people.

The number of apps in app markets has reached 2.7 million. The app economy is estimated to be worth 6.3 trillion dollars.

This vast market attracts and motivates app developers, market intermediaries, and service providers to develop, disseminate, and deliver better mobile apps.

Mobile advertisement has become a very significant industry.

Mobile app data sources

Mobile app data can be obtained from

- Smart devices through an instrumented app or library
- Network traces when application can be identified based on the traffic
- Controlled experiments in the lab or small-scale in the wild experiments

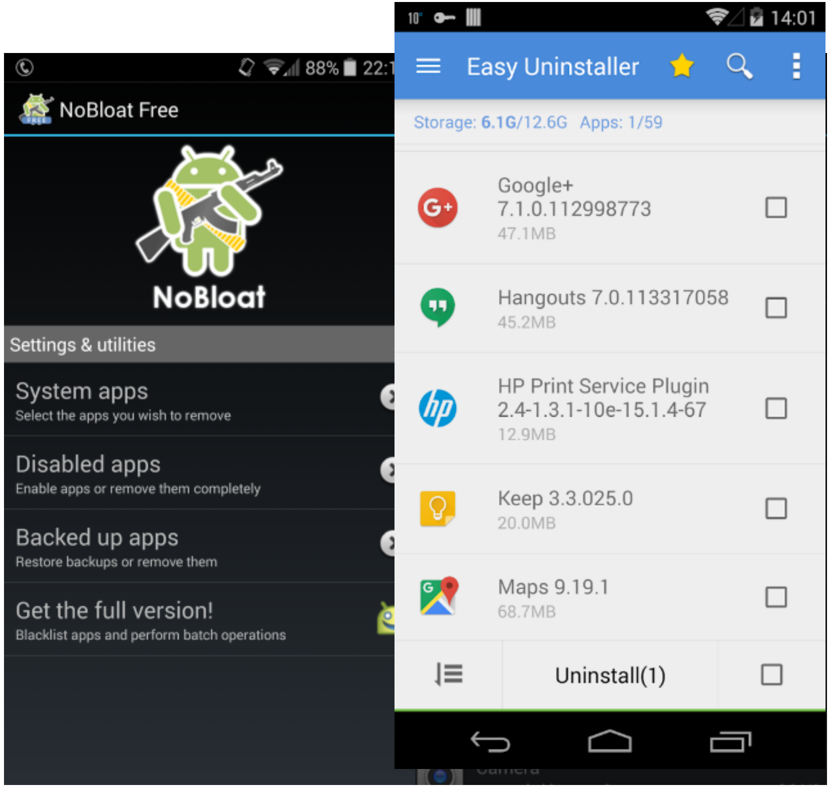
Mobile app data is typically difficult to obtain

- High cost in mobile app development and deployment
- Network data is very restricted
- Privacy concerns

Obtaining Real-life Usage Data: Challenges

- Crowdsourcing: access to real-life contexts
  - Subject to user activity
  - Sparse, incomplete data
  - Application could be closed
  - Could be uninstalled at any time
  - Network conditions, locations vary

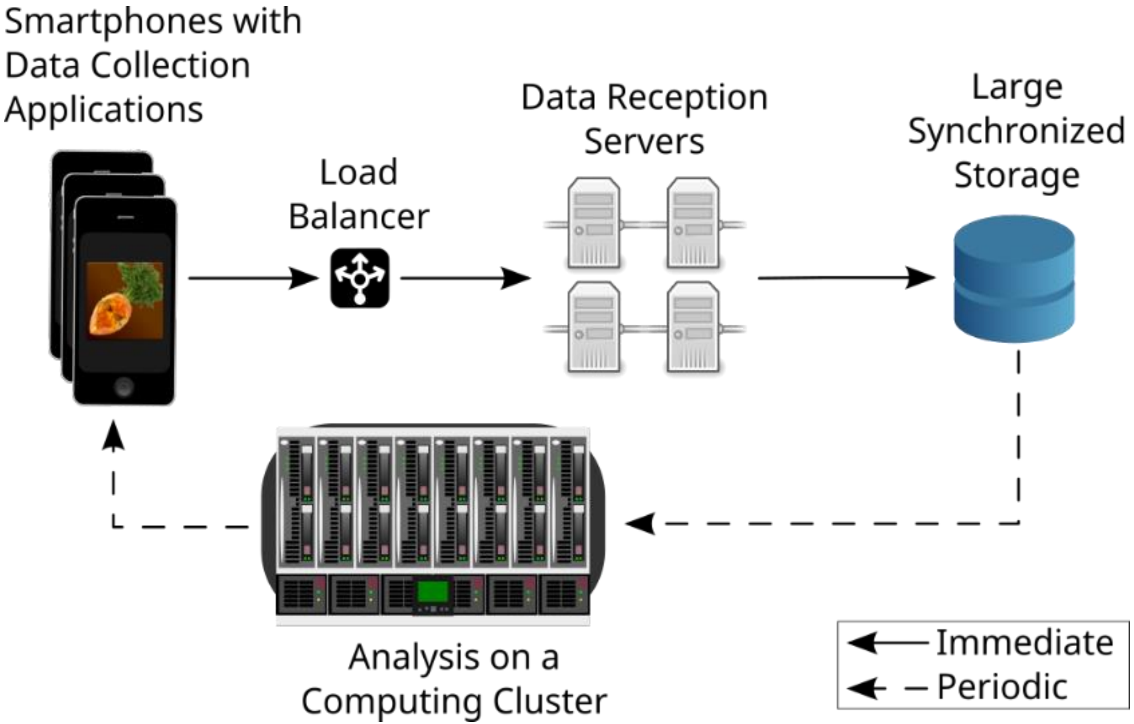
→ Application needs to be useful and popular



Crowdsourcing Benefits

- Prospect of building a large dataset that accumulates over time
- Contexts not possible to capture in a lab
    - Moving devices between cities, countries
    - Greatly varying network connections, technologies
    - Various ambient temperatures
    - Real-life interaction, games, users completing daily tasks
    - Passive monitoring: Users “act natural”

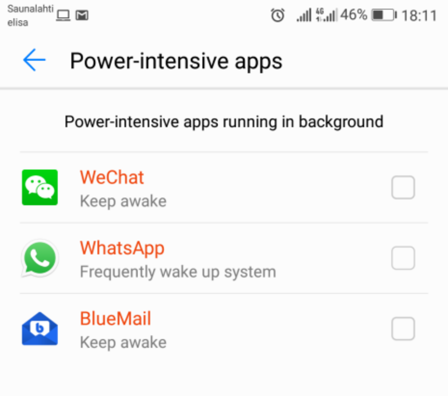
An example of a crowdsourcing system

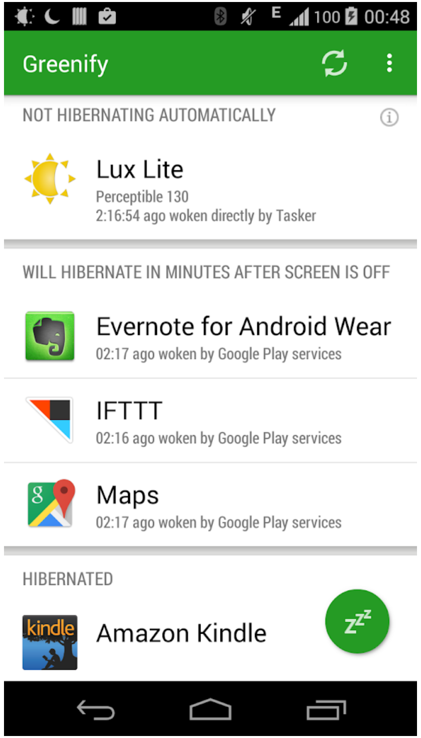


Obtaining Real-life Usage Data: Challenges

- Battery life impact of monitoring
- Metered data connections

→Application needs to be lightweight





Example: Carat

- Originated in UC Berkeley, in collaboration with University of Helsinki
- Mobile app for Android and iOS
- Currently over 850 000 users
- >2.5 TB of data, > 250 million measurements
- Research project with many directions
- Publications and info: http://carat.cs.helsinki.fi

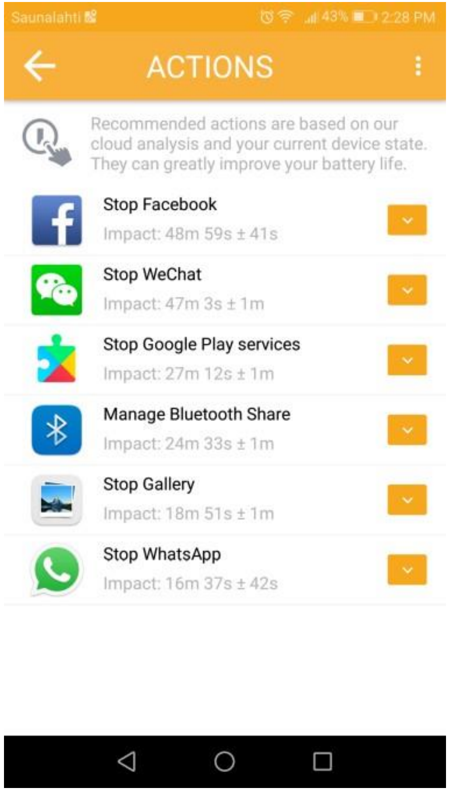
Dataset August 2018

Property	Quantity
Unique measurements	361,769,494
Registered devices	885,311
Devices with data	802,308
Size (compressed json)	683 GB
iOS devices	50.8%
Android devices	49.2%
Measurements / user	274
Unique iOS apps	167,482
Unique Android apps	603,854

- Carat is the first system to use the device community to detect and correct energy problems
- Our method for diagnosing energy anomalies uses the community to infer a specification (expected energy use), and we call deviation from that inferred specification an anomaly
- A. J. Oliner, A. P. Iyer, I. Stoica, E. Lagerspetz, S. Tarkoma. Carat: Collaborative energy diagnosis for mobile devices, In Proceedings of ACM SenSys ‘13.

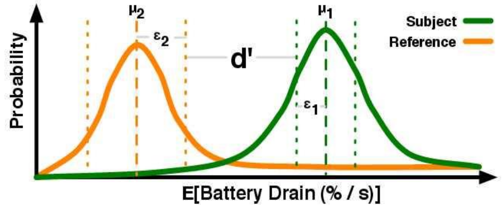
Carat app

- Carat App on Google Play and AppStore
- Informs the user of apps with abnormally high energy use
- Quickly received over 100,000 users
- Also collects data for research purposes
- Sparse data: measures only when battery life changes by 1%
- May be closed by the OS or user
- Lightweight: only communicates with server when opened by the user

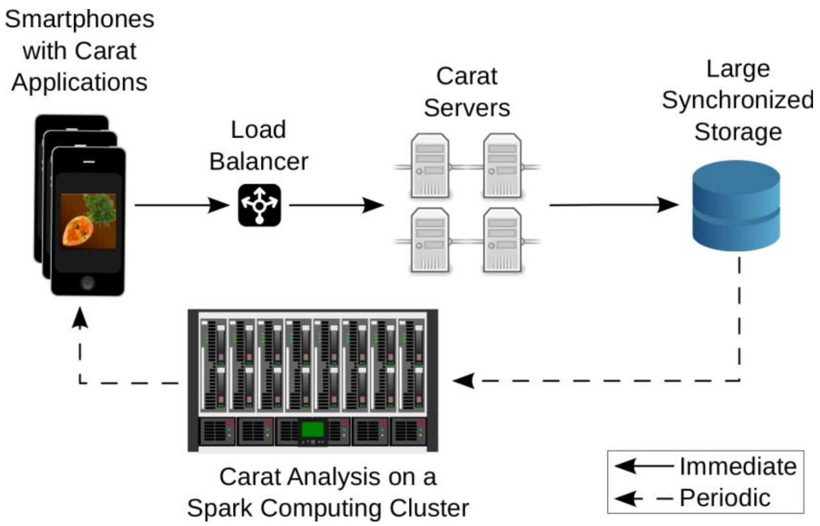


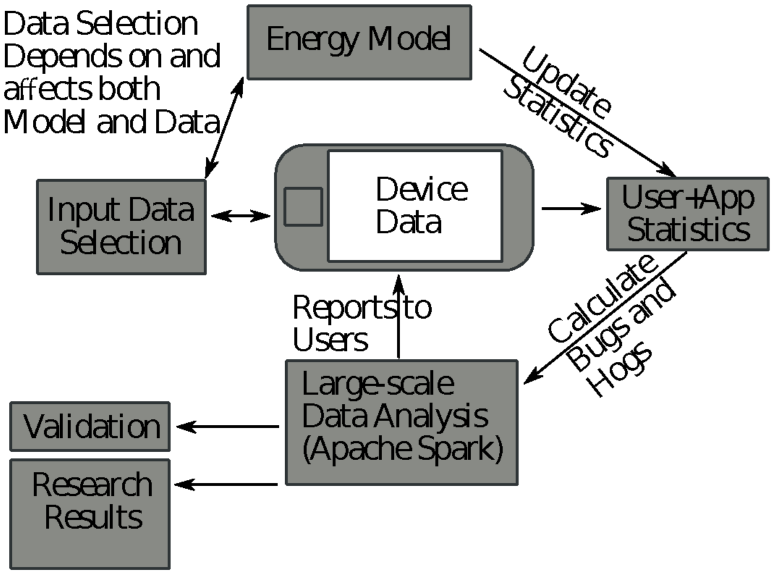
Collaborative data gathering

- Each device collects: Battery life, timestamp, running apps, context/system settings
- The data is combined and the results for your apps and your device are sent back to you
- Context feature analysis: how various context features affect the energy consumption of the device
- Collaborative aspect: analysis across devices
    - Samples are combined to obtain energy drain probability distributions (with features)
    - Users, Apps, App and User pairs, OS versions, Device models



The Carat project: System

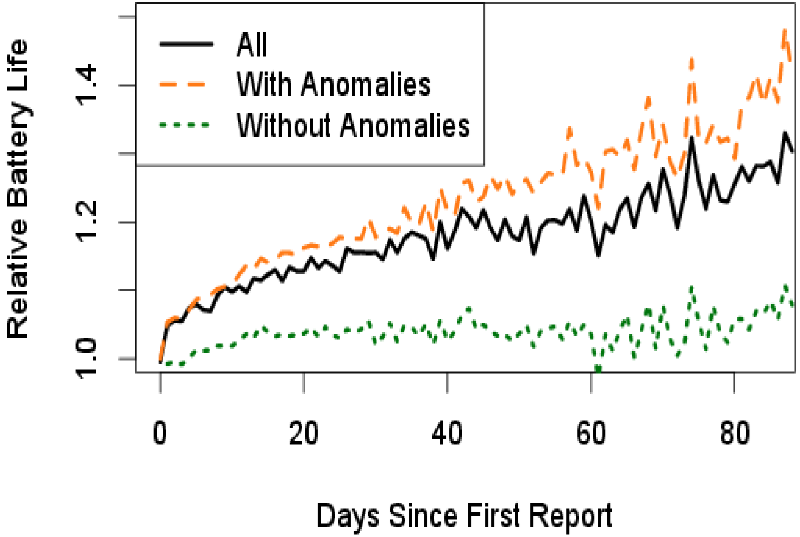




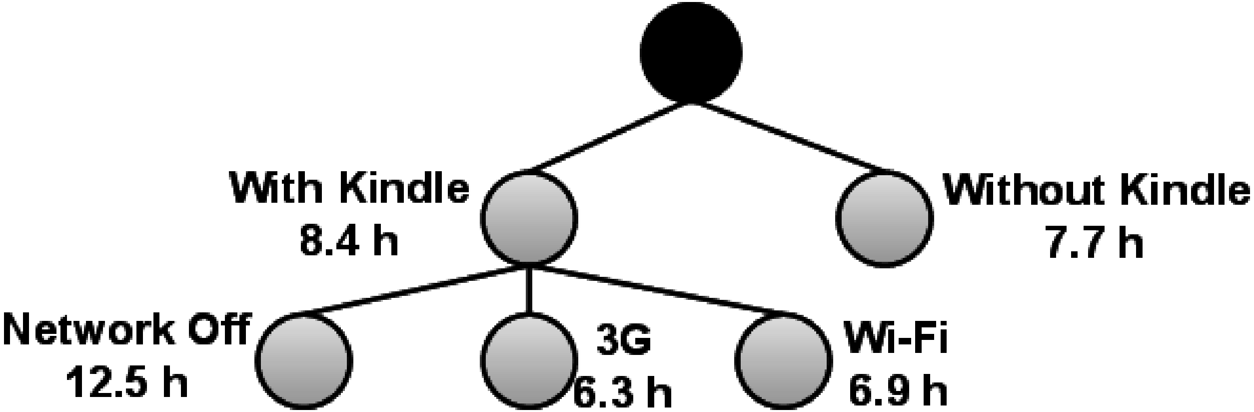
Carat energy hogs and bugs

- Users see Hogs, high energy use apps
- And Bugs that use energy faster on THEIR device than on others
- Users with these issues quickly see battery life benefits once they are addressed

- Average improvement 20%
- Those with energy anomalies can improve 41%



Example energy debugging with smartphone data



Kindle whispersync bug diagnosed with a decision tree.
The decision tree allows ”what-if” analysis and the generation of recommendations.

Infrastucture

Version	Run Time	Users	Samples	€/Month
2011	10 h	10,000	100,000	1,000
2012	10 h	100,000	2,000,000	10,000
2013	10 h	500,000	16,500,000	2,000
2014	4 h	700,000	20,000,000	1,000
2015	4 h	800,000	25,000,000	1,500
2017	4 h	Dynamic	Dynamic	1,000

- Data Analysis: Amazon EC2
- 10 x X-Large VM (4 cores, 15G memory)
- Server facing mobile devices: Amazon EC2
- 4 x medium VM (1 core, 4G memory)
- Load balancer, independent DNS name for easy changing of infrastructure when required
- Amazon S3
- Storage of data (incoming 0.5-1.0 GB / week)

Release history

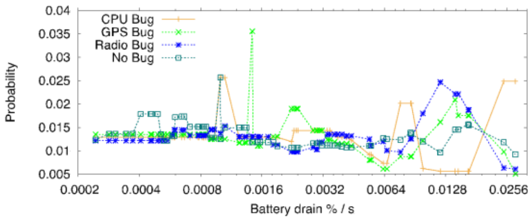
Date	Release Summary
2012, June	Stopped recording battery-related events that did not include battery level changes, as some Android devices had hundreds of battery-related events with unchanged battery levels.
2013, early	Added tracking of various system settings.
2013, end	Added application install, update, and remove events tracking, as well as application developer signature hash for anti-malware work (Android only)
2015, Nov	Completely new UI 2.0, iOS and Android.
2016	Added tracking of more system settings on iOS and Android.
2017	Working around iOS application list issues
2017	iOS no longer gets application info
2018, early	Android no longer gives full process list on new devices. Carat is using AppUsageStats [13] with user permission to gather app info on Android.

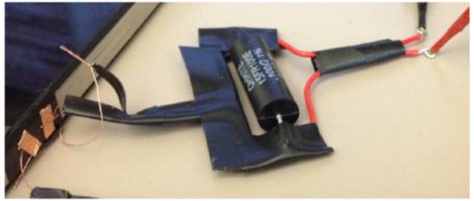
Mobile application

Date	Release Summary
Early 2012	Used Amazon DynamoDB for storage. Single threaded.
Updated 2012	Multi-threaded, DynamoDB. Able to process the user base much faster. Proved to be expensive.
Late 2012	Reduced operating costs by 90% at the expense of having to manage files manually. Collects username/timestamp files to a new RDD, combines the resulting RDD with existing data, creating a large single dataset for analysis.
2013	Used a union of raw data RDDs for analysis, as the copying into a large RDD slowed down the backend as data amount increased.
2014 to present	The analysis generates and updates statistics of new raw data at the beginning of the analysis. Analysis is done based on the statistics. Reduces the amount of data required to process by 100x.
2017	Data format changes from binary to JSON on the research side. The operative system still uses binary RDDs.
2019	Planned data format change of the server+backend.
2019	Planned migration of the whole backend from Amazon EC2 to the internal cluster.

Backend

Lessons Learned





- Research prototype != product
    - It is not easy to scale
    - 100 000 users in one day when we launched
    - Scaling will cost, cloud is not free
    - Mobile OS have significant restrictions for background processes
- Design system so that it can evolve (no hardcoding, extensible formats)
- Validation is not easy
    - Ground truth
    - Injected bugs, validated bugs

Use case: Malware

- We studied malware based on the dataset
- McAfee, Mobile Sandbox, MalGenome, ...
- Malware infection rates are higher than conservative estimates (0.26% of devices)
- Google says 0.12% of manually installed packages are malware, not very far from this number
- Lookout Antivirus predicts >1%

Our infection estimate is higher than previous research, but lower than some AV vendors.

H. T. T. Truong, E. Lagerspetz, P. Nurmi, A. J. Oliner, S. Tarkoma, N. Asokan, S. Bhattacharya. The Company You Keep: Mobile Malware Infection Rates and Inexpensive Risk Indicators, In Proceedings of WWW ‘14.

Privacy leaks and Carat results

- Recent studies have found that it is possible to have **side-channel attacks** based on simple network flow level information exposed by the mobile systems through proc file systems, and therefore, both iOS and Android are restricting this information to third-party applications. Similarly, third-party applications are not getting access to the system process list.
  - X. Zhang, X. Wang, X. Bai, Y. Zhang, and X. Wang, “OS-level Side Channels without Procfs: Exploring Cross-App Information Leakage on iOS,” in NDSS, 2018.
- **Smartphone app fingerprinting:** Using Carat data it has been shown that knowing the presence of four randomly chosen applications on a device are enough to re-identify users in a dataset of 54,893 users
  - Gábor György Gulyás, Gergely Acs, and Claude Castelluccia.Near-Optimal Fingerprinting with Constraints. Proceedings on Privacy Enhancing Technologies, 2016 (4):1-18.

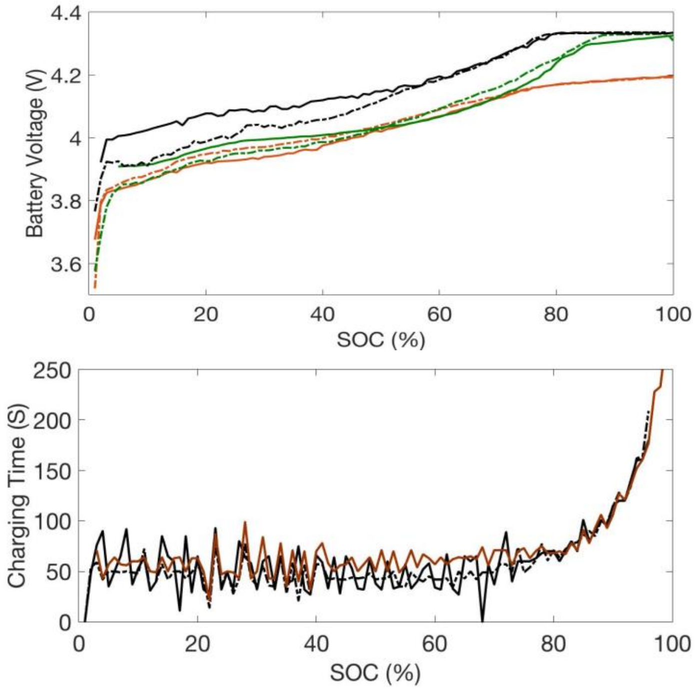
Use case: Power management

Constructing Charging Events.

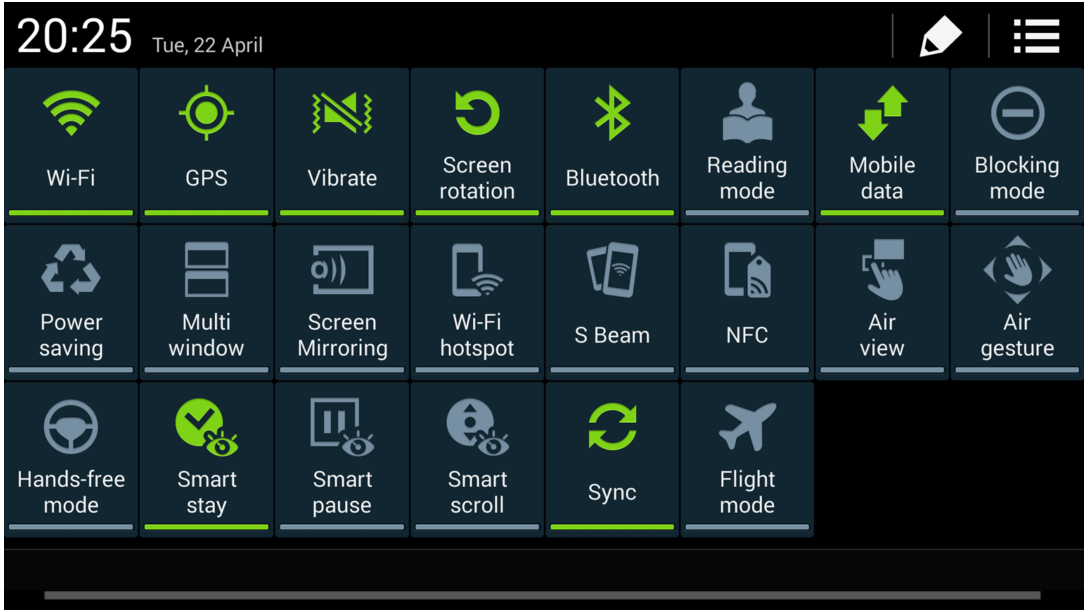
- ➔ **Battery Voltage Curves** Battery Voltage Per Battery Level.
- ➔ **Charging Time Curves** Time to charge one percent of the battery.
- ➔ **Battery Temperature** Battery temperature per SOC while charging.

Sparse sampling can provide a lot of information about the smartphone power management techniques and user charging behavior.

Mohammad Ashraful Hoque, Matti Siekkinen, Jonghoe Koo, Sasu Tarkoma: Full Charge Capacity and Charging Diagnosis of Smartphone Batteries. IEEE Trans. Mob. Comput.16(11): 3042-3055 (2017)



Use case: smartphone configuration



Studying the impact of context and system settings to device performance and battery

Use case: optimizing battery life

→ 98% better expected battery life through settings and context

Battery Temperature	Distance Traveled	CPU Use Level	Screen Brightness	Estimated Battery Life (h)
Under 30°C	>0	Low	Automatic	8.83 – 9.12
Under 30°C	>0	Low	Manual	8.49 – 8.82
Under 30°C	>0	High	Automatic	8.09 – 8.24
Under 30°C	>0	Medium	Automatic	7.65 – 7.89
Under 30°C	>0	Medium	Manual	7.34 – 7.60
Under 30°C	>0	High	Manual	7.27 – 7.41
Under 30°C	None	Medium	Automatic	6.57 – 6.64
Under 30°C	None	Low	Automatic	6.28 – 6.35
Under 30°C	None	Medium	Manual	6.13 – 6.20
Under 30°C	None	Low	Manual	5.88 – 5.96
Under 30°C	None	High	Automatic	5.78 – 5.82
Over 30°C	>0	Low	Automatic	5.08 – 5.22
Under 30°C	None	High	Manual	5.00 – 5.04
Over 30°C	>0	Low	Manual	4.73 – 4.88
Over 30°C	>0	High	Automatic	4.62 – 4.69
Over 30°C	>0	Medium	Automatic	4.59 – 4.70
Over 30°C	>0	Medium	Manual	4.28 – 4.39
Over 30°C	None	Medium	Automatic	4.25 – 4.29
Over 30°C	>0	High	Manual	4.08 – 4.14

Ella Peltonen, Eemil Lagerspetz, Petteri Nurmi, and Sasu Tarkoma. Energy Modeling of System Settings: A Crowdsourced Approach. PerCom '15. Best Paper Award.

Use case: optimizing battery life

- Wi-Fi signal strength dropping one bar can result in over 13% battery loss
- High temperature can cause 50% battery loss, and high temperature is not always related to high CPU load
- Automatic screen brightness is, in the most cases, better than manual setting
- In addition to CPU, battery temperature and distance traveled are useful in predicting battery lifetime

Carat Top 1000 Users Long-Term App Usage Dataset

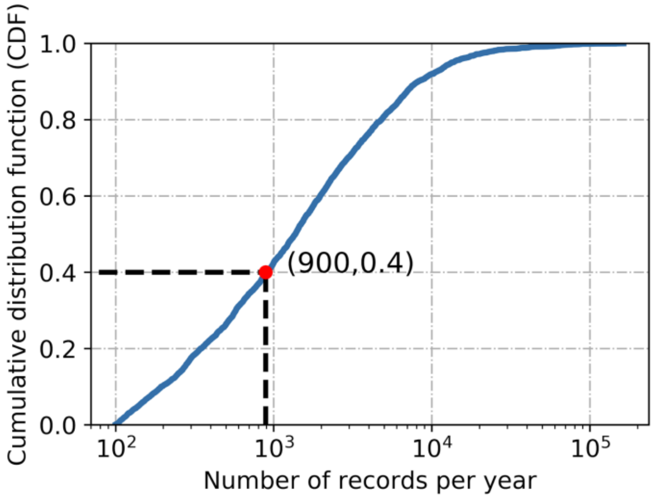
- Available at: https://www.cs.helsinki.fi/group/carat/data-sharing/
- The dataset contains three facets of data:
  - Time series of app usage data (only the top 10000 apps based on occurrence count in our data are included)
  - User registrations with OS and device Model history of users
  - App category information crawled from Google Play
  - The list of the top 10000 apps that are available in the dataset.
- The first contains the top 1000 users ranked by the total duration using Carat since the beginning of 2014. There are 18,146,042 time series records spanning 4.65 years for the longest duration users, and over 2 years even for the 1000th. The records are from over 100 countries, and 315 timezones.

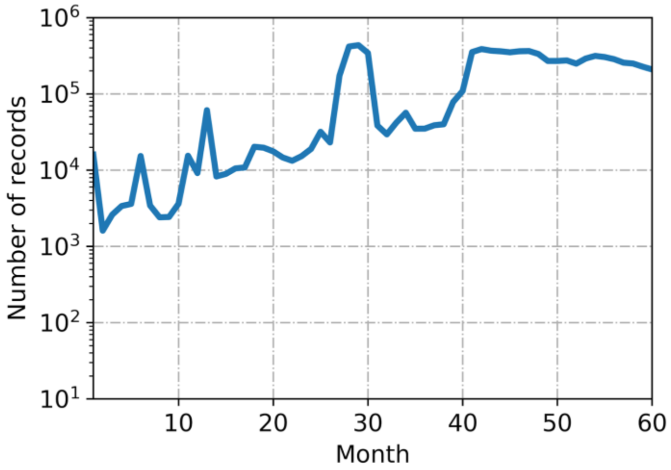
JSON Format

- JSON format
  - uuid (unique user id, anonymized)
  - timestamp (UNIX UTC timestamp of when sample was taken. Depends on phone's clock.)
  - batteryLevel (67%, etc)
  - batteryStatus (discharging, charging, etc)
  - timeZone (the user's time zone in text form)
  - mobileCountryCode (the MCC of the mobile network the user was connected to.)
  - apps (app usage data, see below)
- OS and model history
  - uuid (unique user id, anonymized)
  - timestamp (UNIX UTC timestamp of when the registration was done. Depends on phone's clock)
  - model (the Android device model code that Carat was installed on)
  - osVersion (the current OS version number at time of installation)

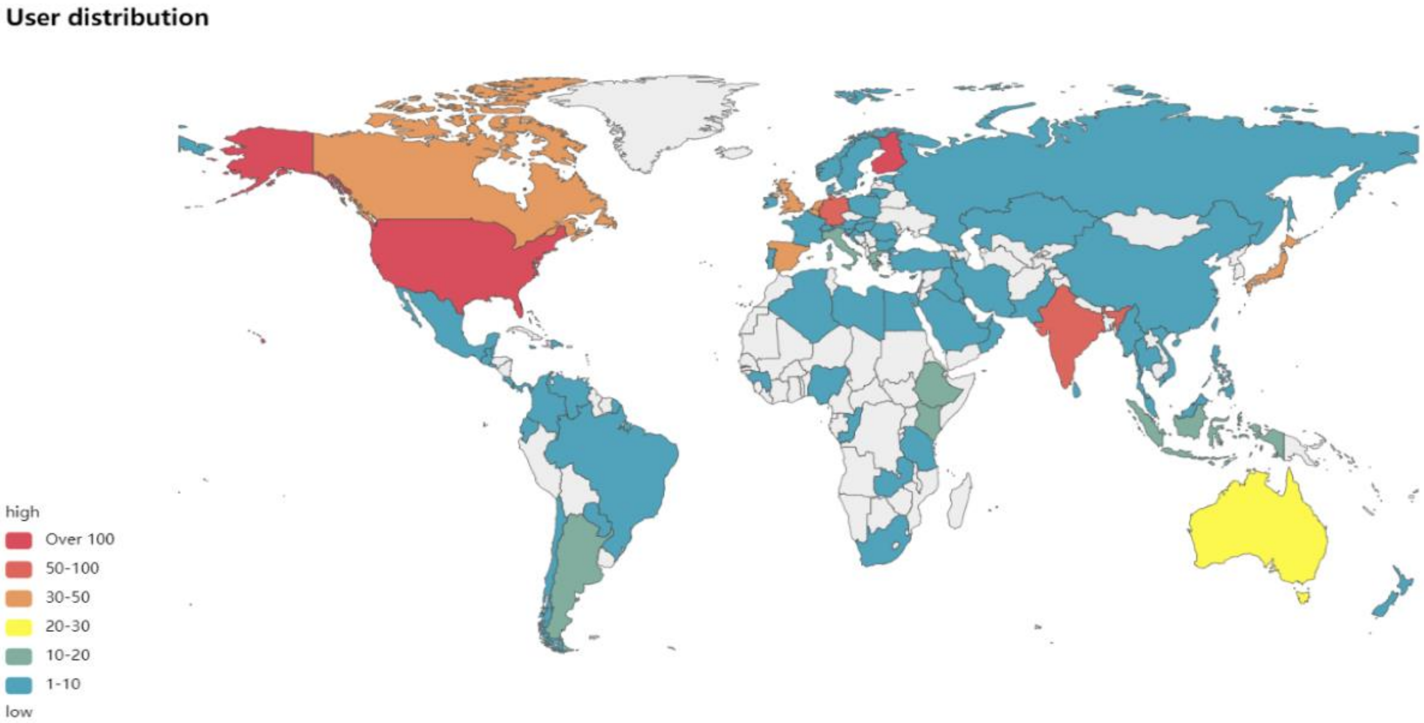
Longitudinal view to Carat data (with full data)

# of Users	# of Records	# of Apps	# of App Categories	Attributes	Date	Area
1,465	12,457,867	110,932	32	User ID, apps, time zone, timestamp, mobile network type	01/2012 -12/2017	Worldwide (over 80 countries)





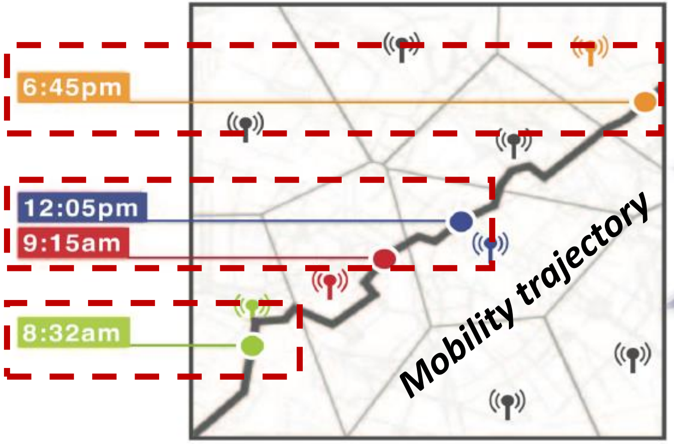
Longitudinal view to Carat data



The continuity of data collection and the diversity of user distribution guarantee the quality and representativeness of our long-term app usage dataset.

Context-aware App Usage Dataset

- **Who, When, Where and Which Apps**



$$(l_1,t_1)\,||\,(l_2,t_2)\,||\,(l_3,t_3)\,||\ldots$$

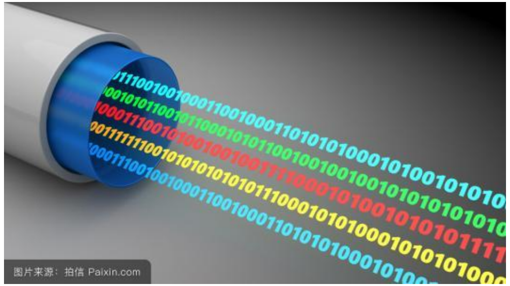
App usage trace

http://fi.ee.tsinghua.edu.cn/appusage/

Context-aware App Usage Dataset

- **User Profile**

description, followers, gender, verified reason, etc.



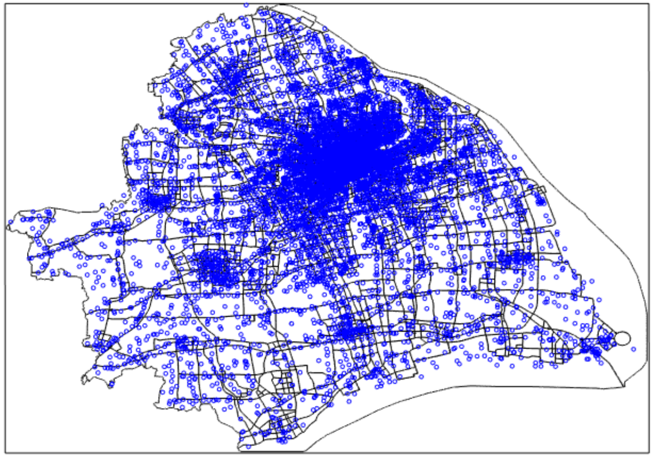
Key	Type	Size	Value
avatar_hd	unicode	1	https://wx3.sinaimg.cn/orj480/5f…
close_blue_v	bool	1	False
cover_image_phone	unicode	1	https://tva1.sinaimg.cn/crop.0.0…
description	unicode	1	脸叔的脑残粉，保罗的小迷弟
follow_count	int	1	374
follow_me	bool	1	False
followers_count	int	1	220
following	bool	1	False
gender	unicode	1	m
id	int	1	1608241353
like	bool	1	False
like_me	bool	1	False
mbrank	int	1	4
mbtype	int	1	2
profile_image_url	unicode	1	https://tvax3.sinaimg.cn/crop.0.…
profile_url	unicode	1	https://m.weibo.cn/u/1608241353?uid=1608241353&luicode=20000174
screen_name	unicode	1	桃子栗_
statuses_count	int	1	596
urank	int	1	32
verified	bool	1	True
verified_reason	unicode	1	中国图库签约摄影师
verified_type	int	1	0
verified_type_ext	int	1	0

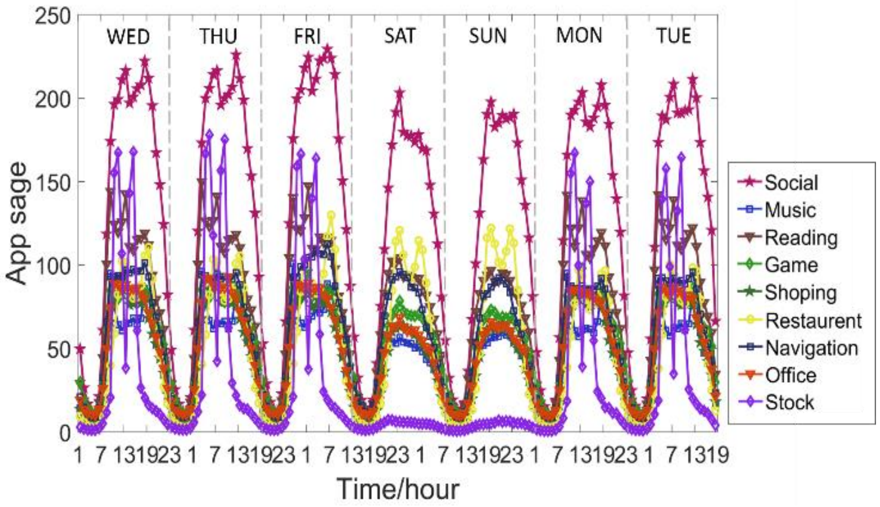
Context-aware App Usage Dataset

- **Overview**

  ✔ 30,685 users with Sina Weibo, we crawled their user profiles
  ✔ nearly 1W base stations in Shanghai
  ✔ 2,000+ APPs
  ✔ during a period of 2016.4.20-2016.4.26
  ✔ among weibo users, 1239 users provide their career

Details Are Here
http://fi.ee.tsinghua.edu.cn/appusage/

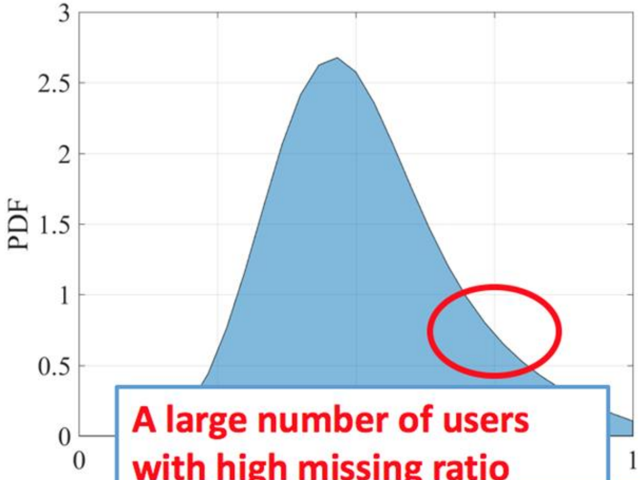




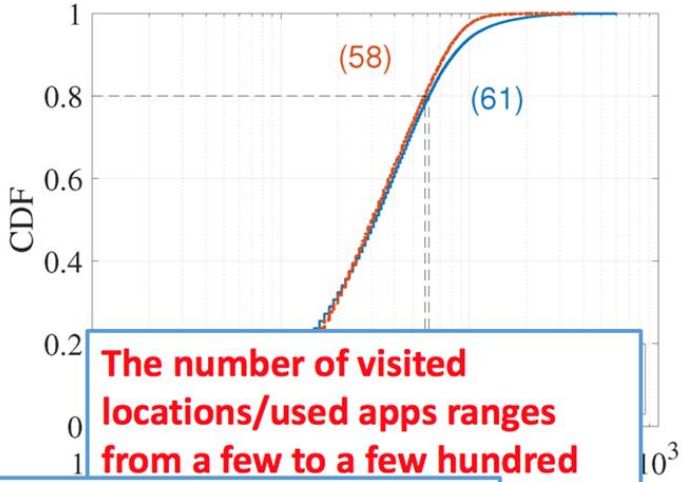
Context-aware App Usage Dataset

User ID||Time||Location (BS ID)||App ID

Source	#Records	#Users	Duration	#Locations (BSs)	#Apps
ISP	1,548,972,010	1,731,070	20th-26th , April, 2016	10,875	3,503



A large number of users with high missing ratio



The number of visited locations/used apps ranges from a few to a few hundred

Heterogeneous app usage across a large user population

Distrib … without app usage records

… nd #app visited/used by each user

http://fi.ee.tsinghua.edu.cn/appusage/

Context-aware App Usage Dataset: Limits

- **Apps without network requests**
  - natural limitation of using ISP datasets
- **Limited identified apps**
  - Apps out of the 3,503 apps
  - Included the most popular iOS apps and Android apps
- **Apps with HTTPS**
  - These apps still partially use HTTP

http://fi.ee.tsinghua.edu.cn/appusage/

Smartphone App Usage Modelling

Modelling smartphone use

Vassilis Kostakos
University of Melbourne

Tutorial given at UbiComp 2019
September 10
London, UK

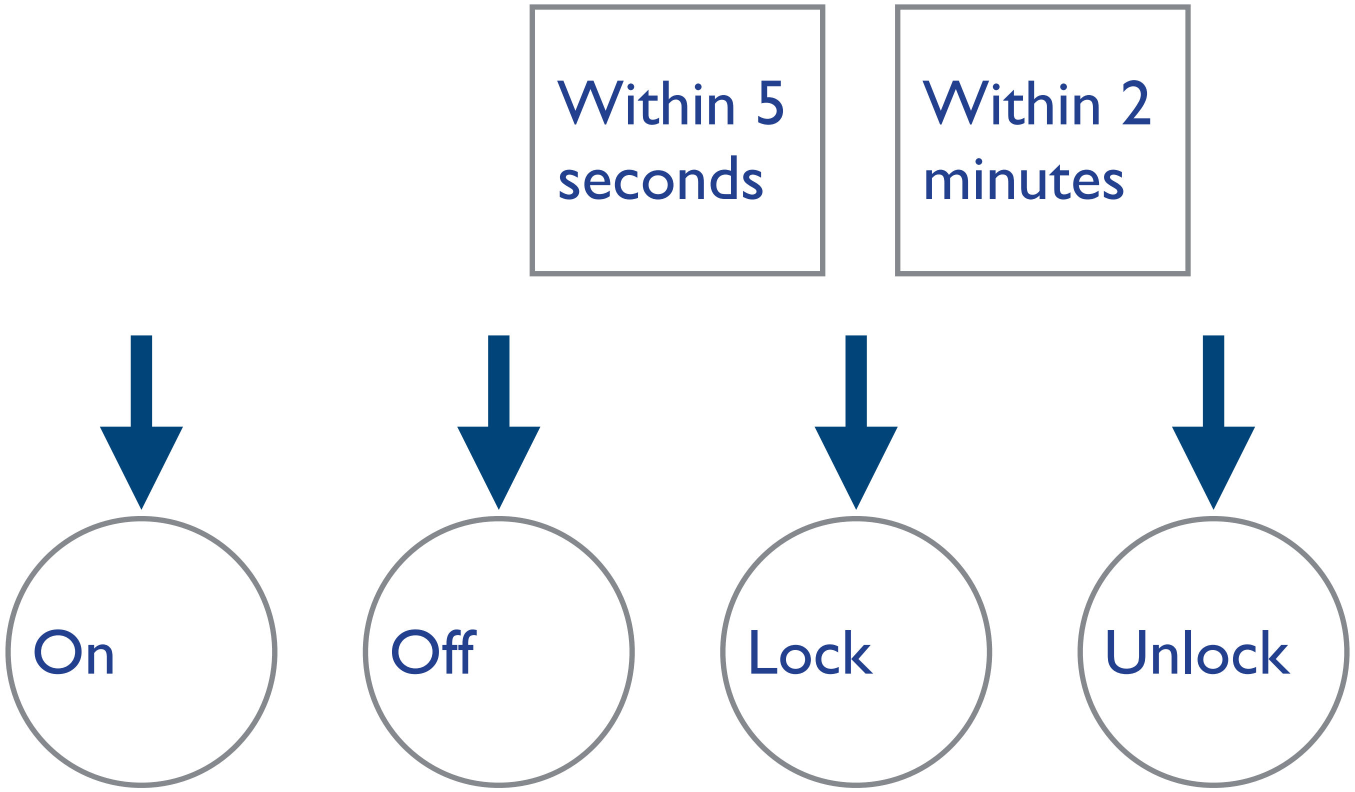
Summary of techniques

- V. Kostakos, D. Ferreira, J. Goncalves, S. Hosio. 2016. "Modelling Smartphone Usage: A Markov State Transition Model", Proc. International Joint Conference on Pervasive and Ubiquitous Computing (**UbiComp**), pp. 486-497.

- S. L. Jones, D. Ferreira, S. Hosio, J. Goncalves, V. Kostakos. 2015. "Revisitation Analysis of Smartphone App Use", Proc. International Joint Conference on Pervasive and Ubiquitous Computing (**UbiComp**), pp. 1197-1208

Motivation

- Model smartphone use
- Make predictions about next "screen event"
- In realtime and ongoing



Some prior work in HCI (Usability)

Markov modeling (variant)

- Probability of transitioning to a "state"
  - Given current state
  - Given elapsed time

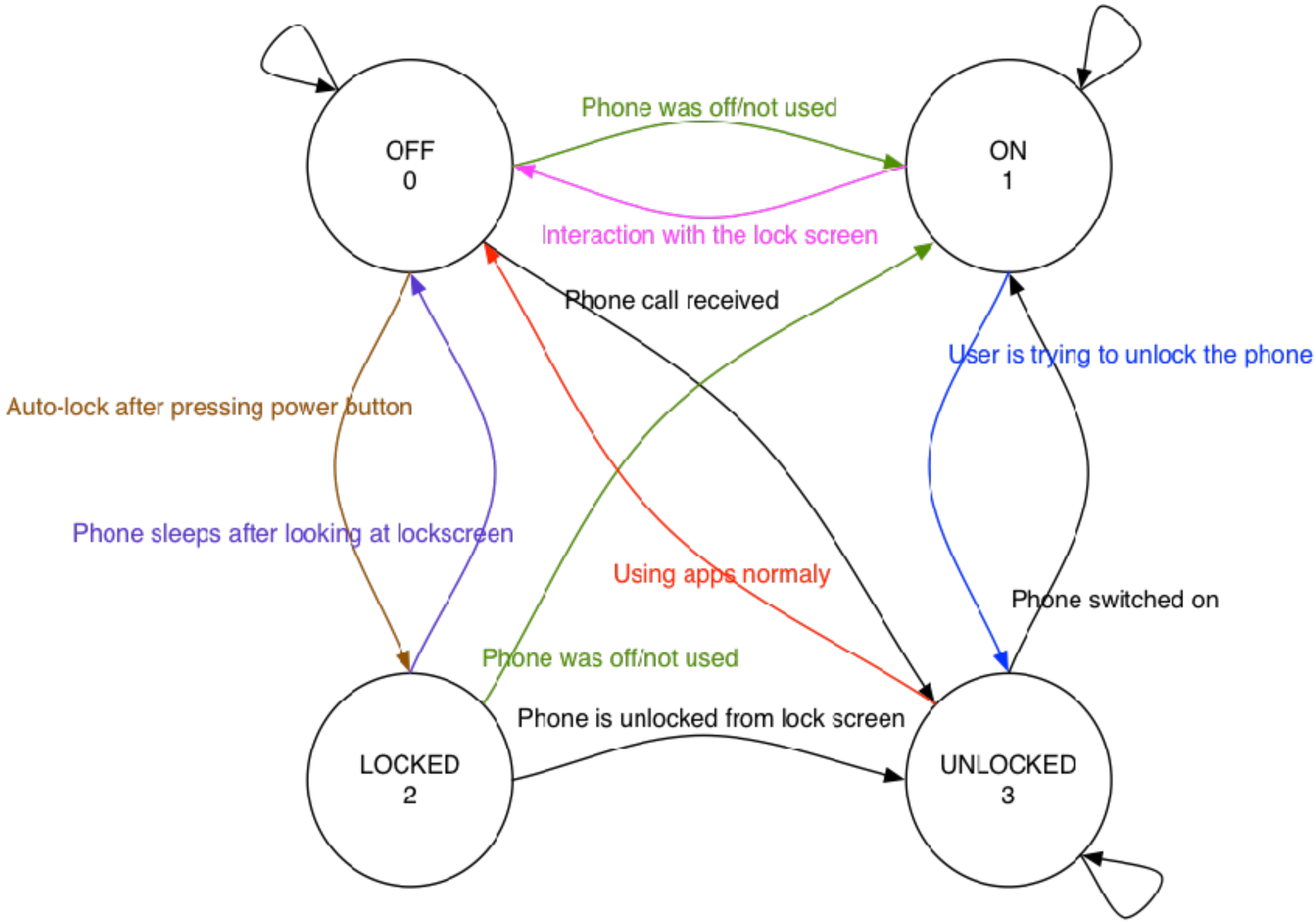
Android Event	Description
0: **Off**	Power to the screen has stopped
1: **On**	Power to the screen has been activated
2: **Lock**	Screen locked (to avoid accidental input)
3: **Unlock**	Screen unlocked (input is enabled)

Method

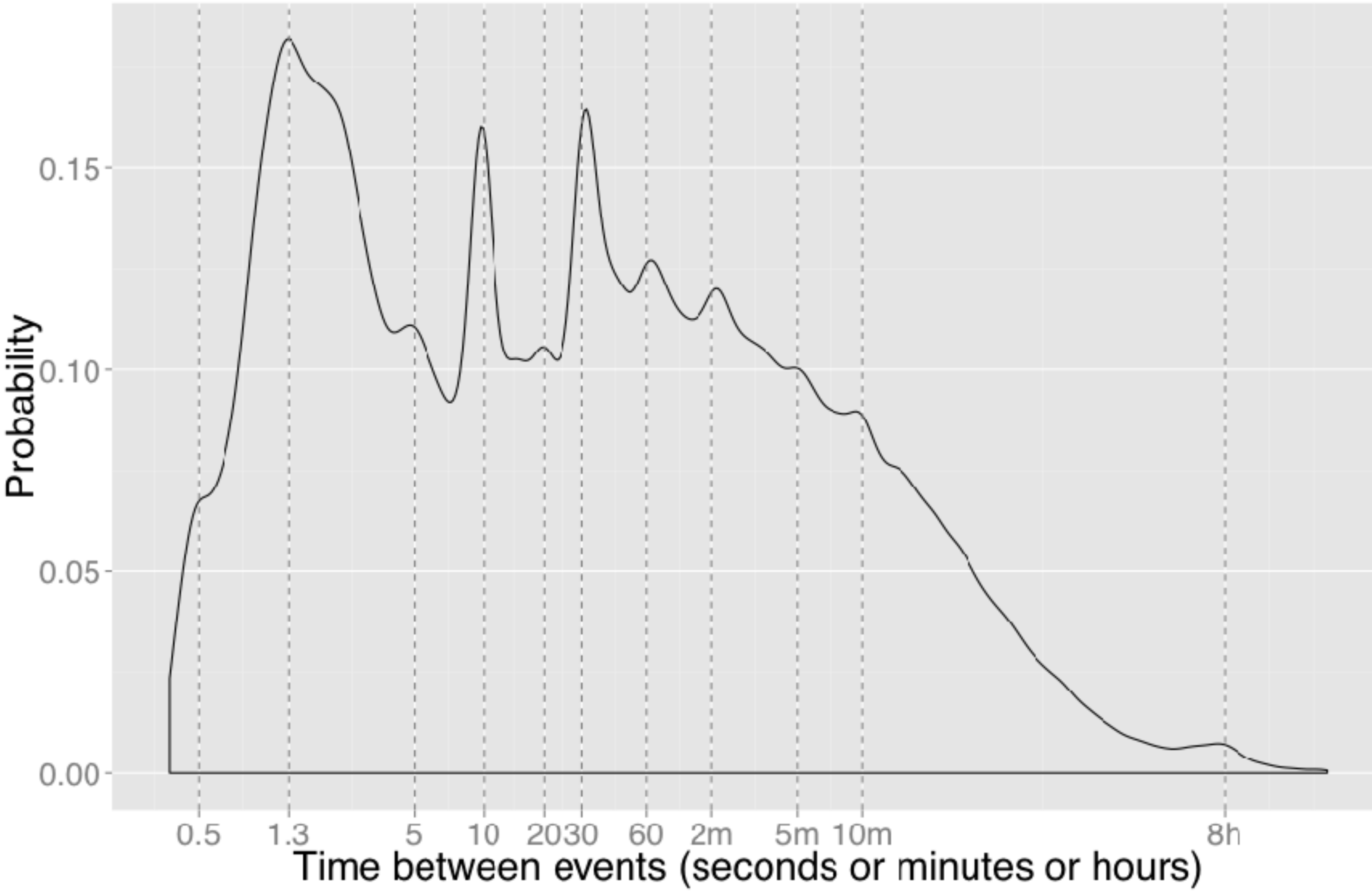
- Re-analyse an existing dataset
  - 271,832 screen events
  - 90 days
  - n=218
  - Securacy: An Empirical Investigation of Android Applications' Network Usage, Privacy and Security (WiSec 2015)
- Validate with another dataset
  - 34,169 screen events
  - 30 days
  - n=17
  - A Systematic Assessment of Smartphone Usage Gaps. (CHI 2016)

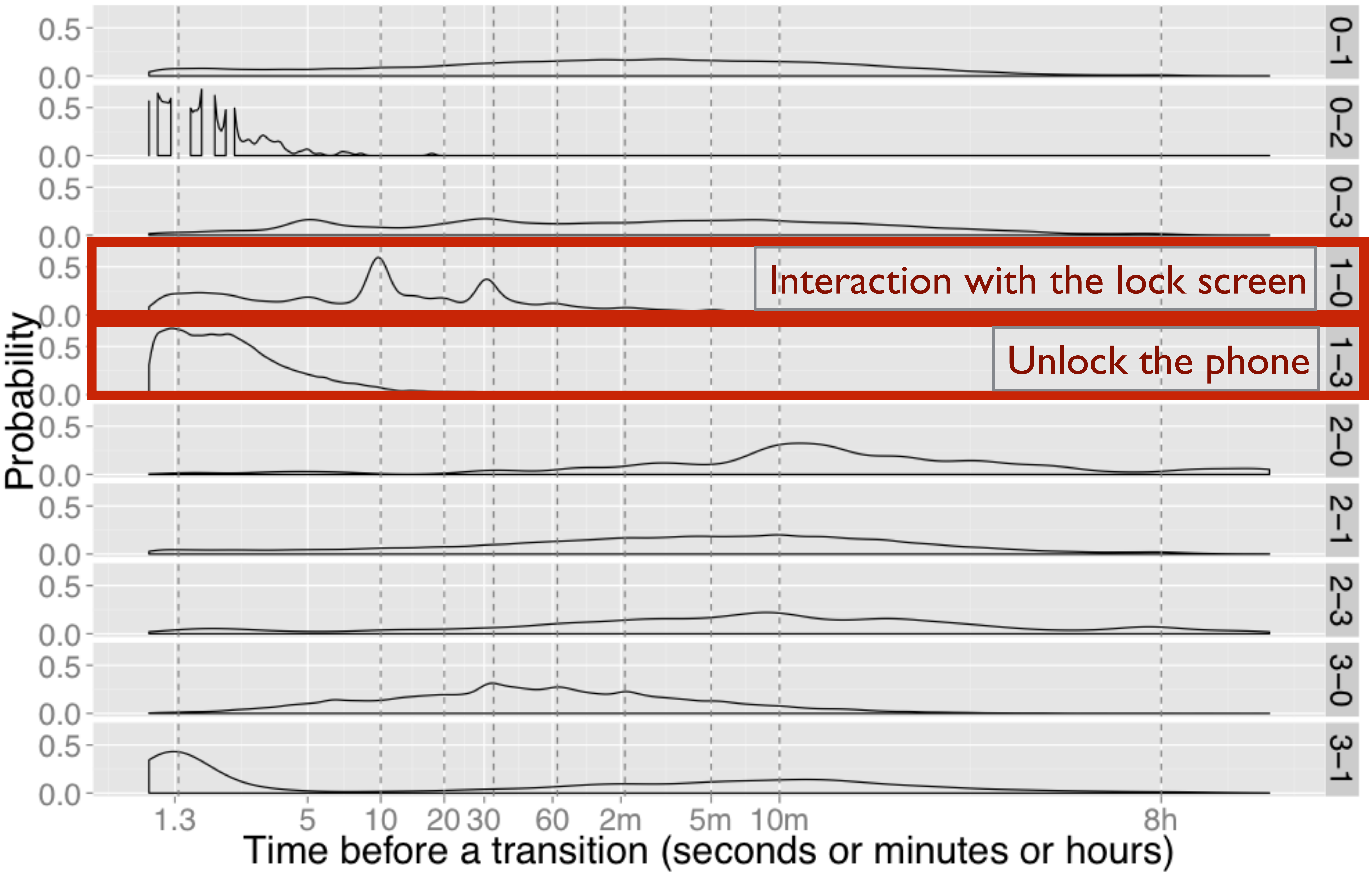
Results

		To			
		0: Off	1: On	2: Lock	3: Unlock
	0: Off	0.50%	33.03%	59.4%	7.05%
From	1: On	45.32%	2.03%	0	52.64%
	2: Lock	2.83%	95.64%	0	1.53%
	3: Unlock	80.5%	13.58%	0	5.92%


OFF
0
ON
1
LOCKED
2
UNLOCKED
3
Phone was off/not used
Interaction with the lock screen
Phone call received
User is trying to unlock the phone
Auto-lock after pressing power button
Phone sleeps after looking at lockscreen
Using apps normaly
Phone switched on
Phone was off/not used
Phone is unlocked from lock screen

Time between events





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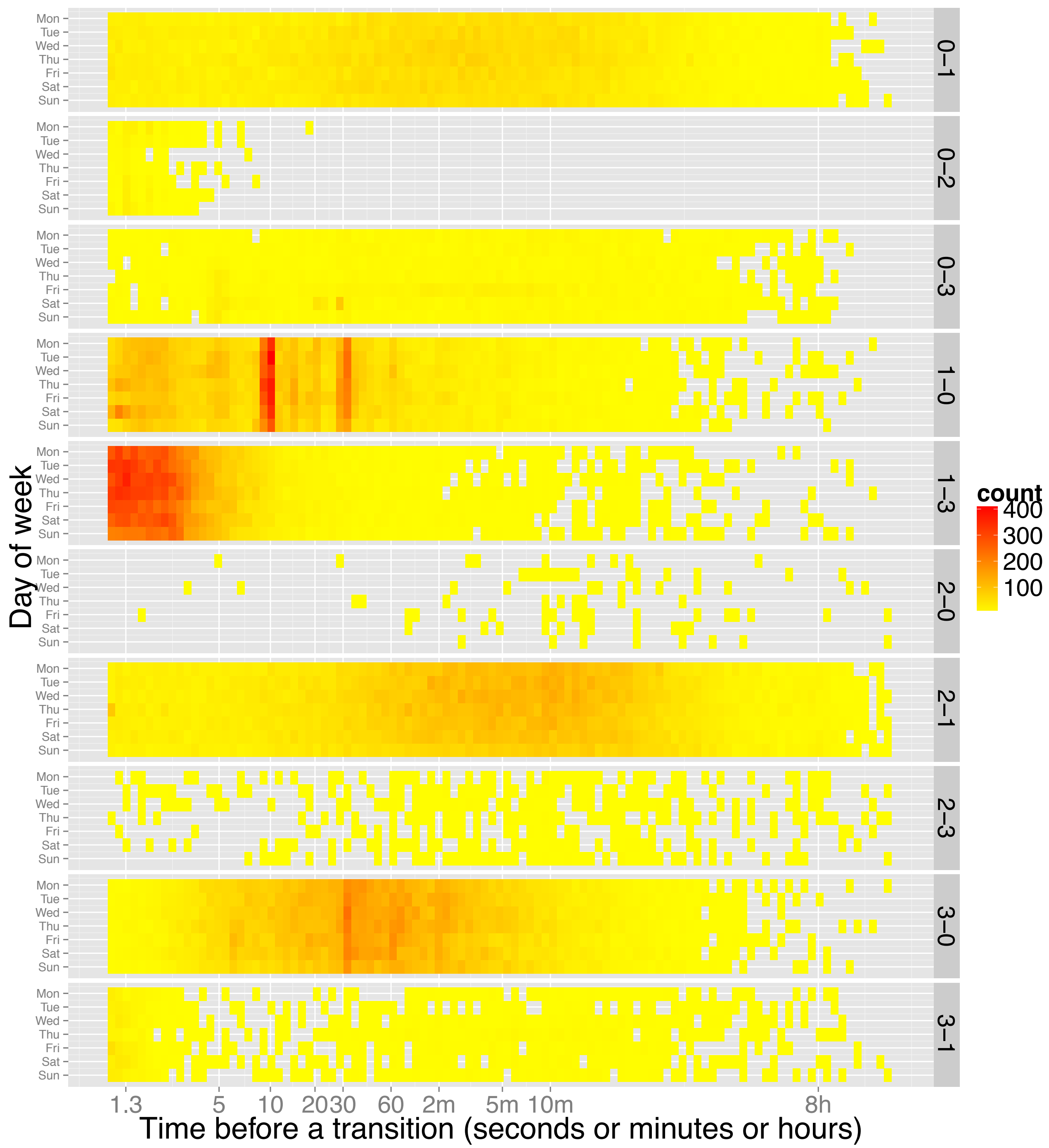
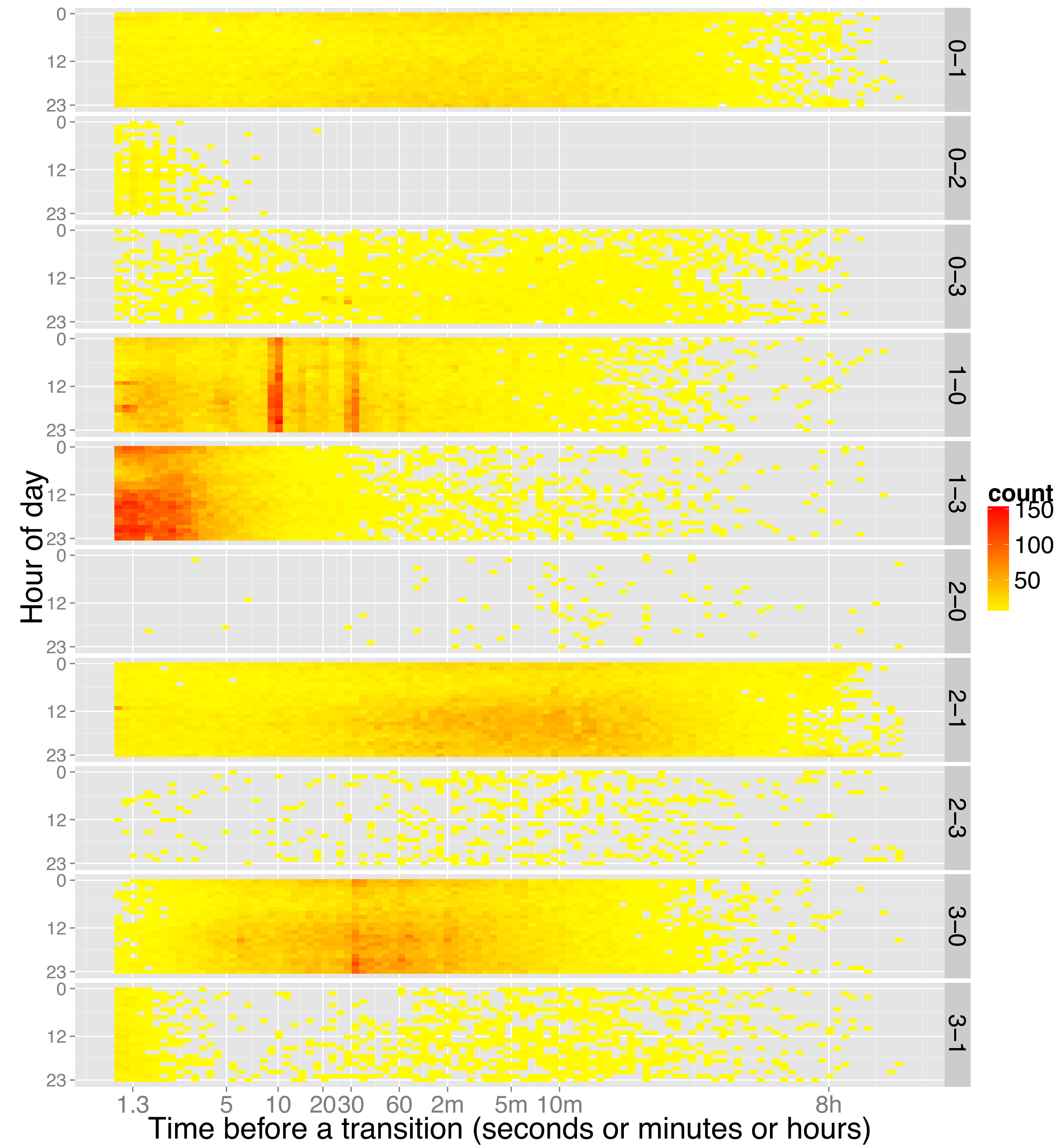
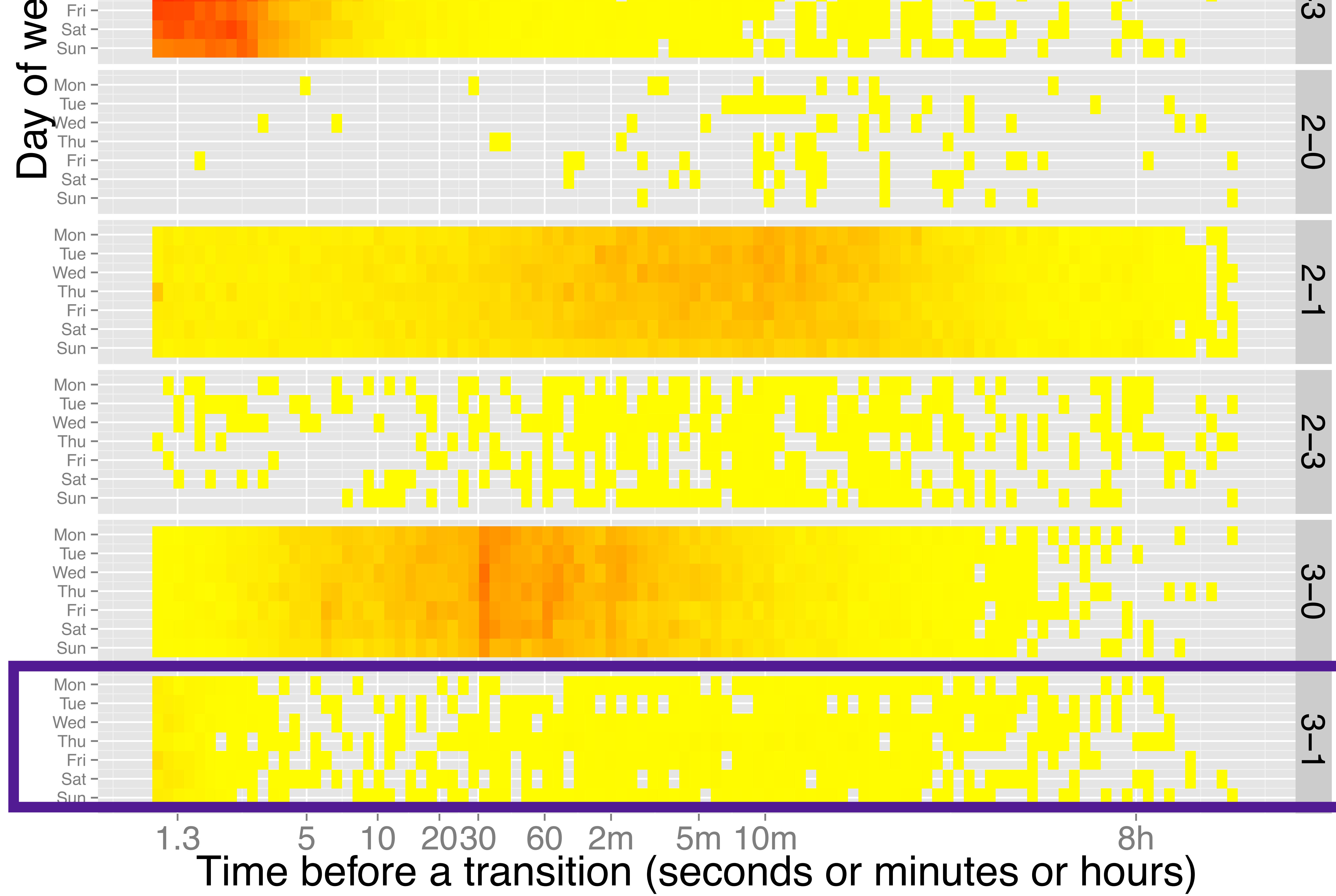
Account for context

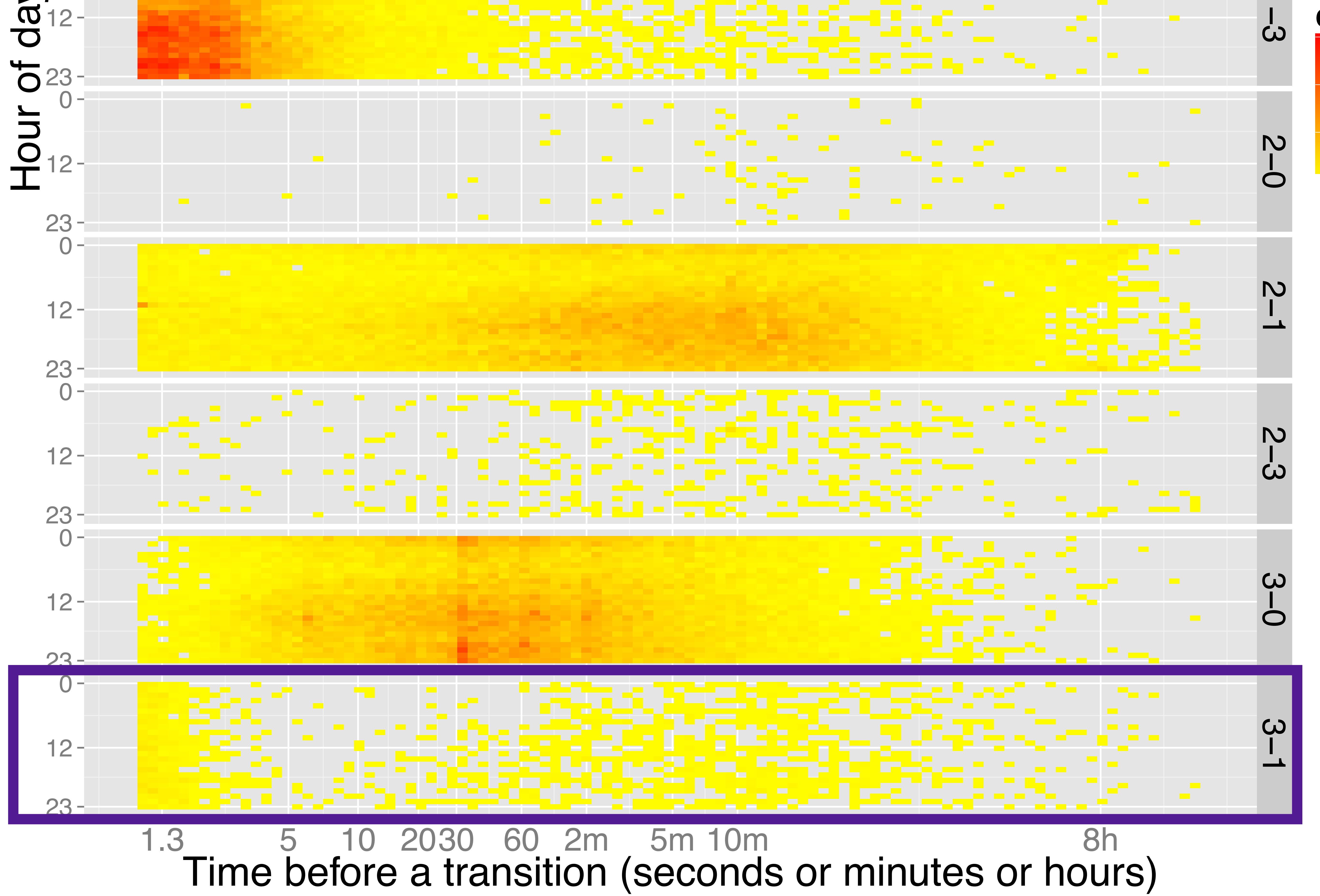
- Day & time
- Battery level
- User "type"

Context: day & time

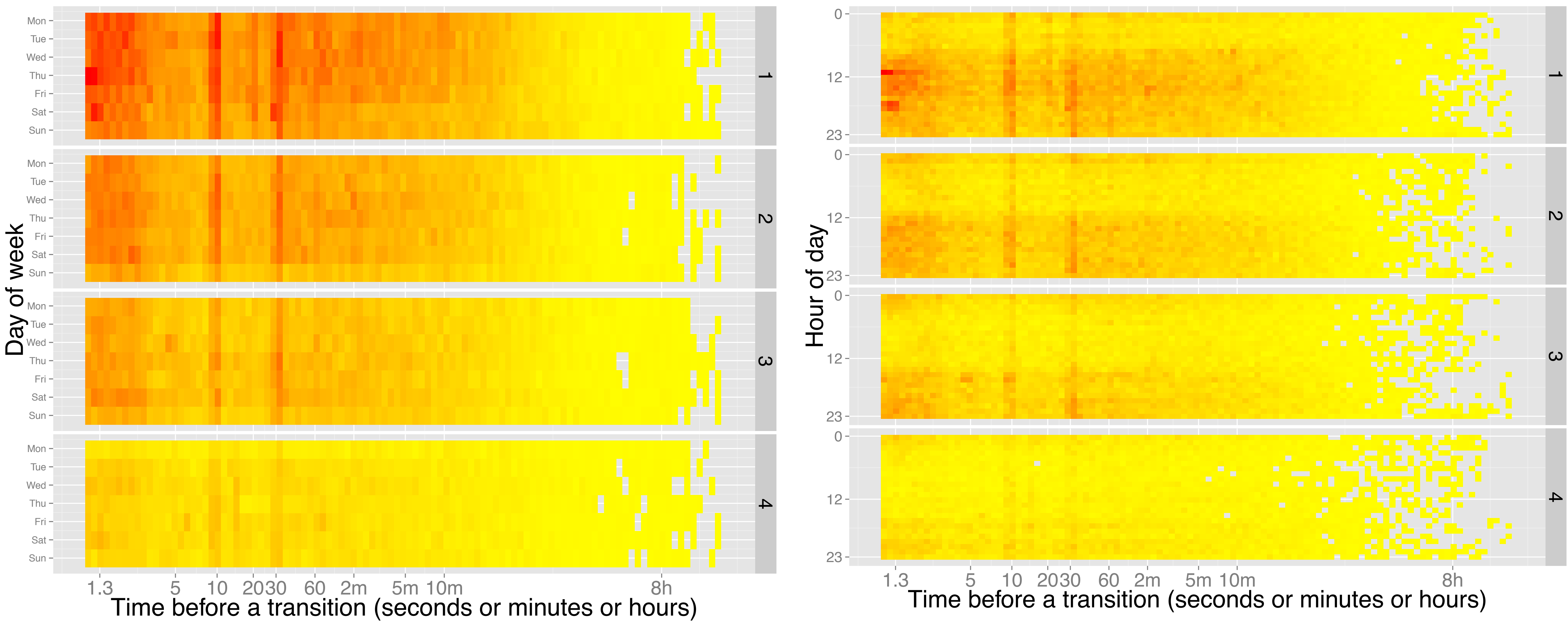




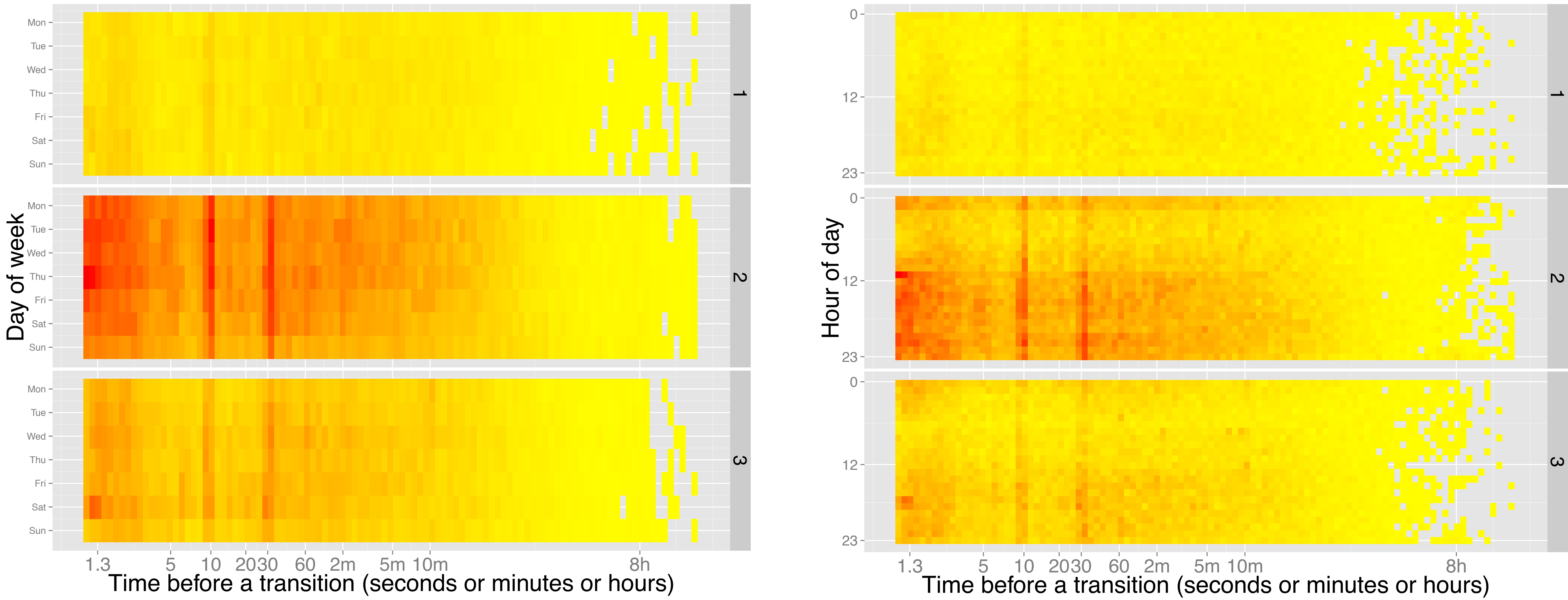

Day of we
Mon
Tue
Wed
Thu
Fri
Sat
Sun
3
2–0
2–1
2–3
3–0
3–1
1.3
5
10
20
30
60
2m
5m
10m
8h
Time before a transition (seconds or minutes or hours)


Hour of day
0
12
23
–3
2–0
2–1
2–3
3–0
3–1
1.3
5
10
20
30
60
2m
5m
10m
8h
Time before a transition (seconds or minutes or hours)

Context: battery level



Context: user "type"



OS can "Interrogate" the model

- How much time do we spend at each state?
- Starting in state 3, how much time (on average) does it take to reach either state 2 or 1?
- If the user turns on the phone (state 1), what is the probability that the phone remains in that state for 20 seconds?
  - For 120 seconds?
  - How does this change with context?

A worked example

- If we arrive to state 1 (screen ON), what is the probability that we are still in state 1 after 20 seconds?

= 1 - (

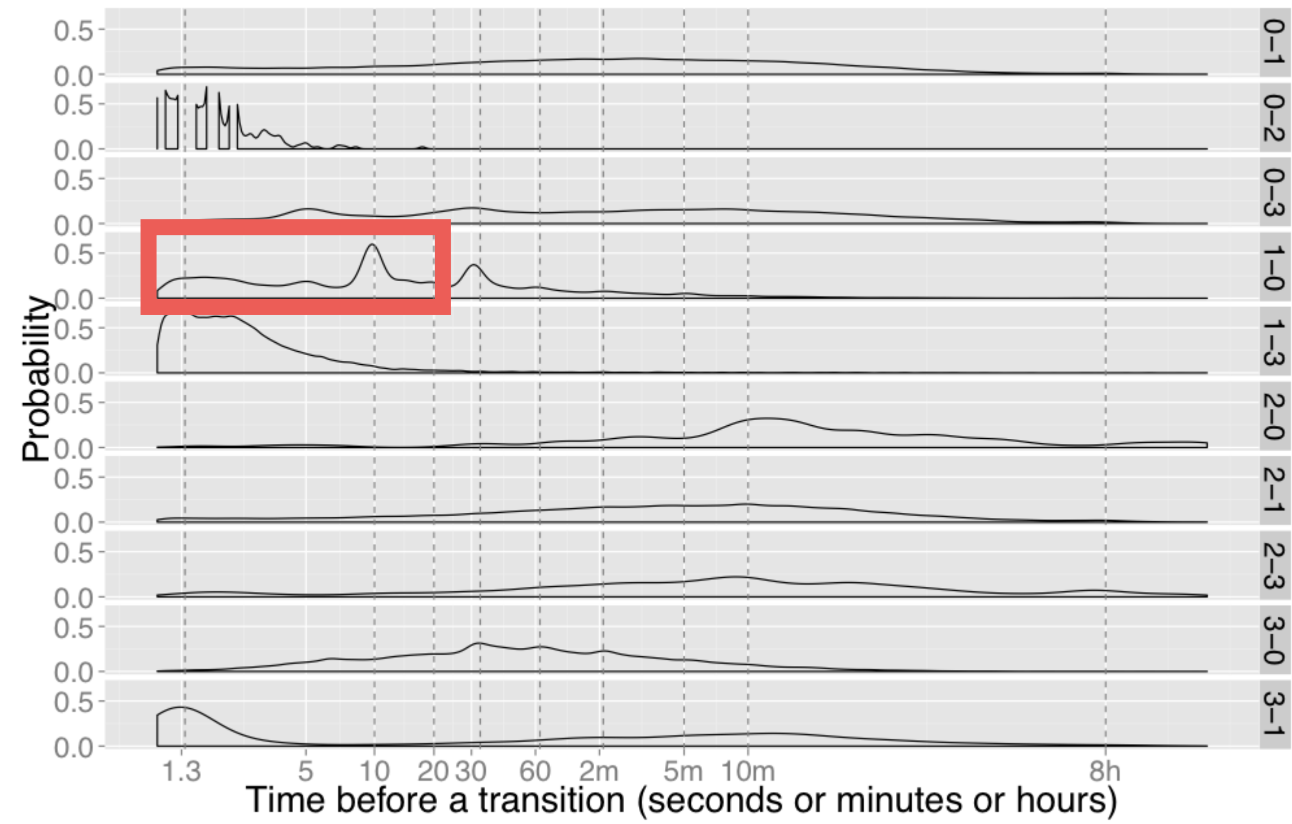
probability we move to state 0 in less than 20 seconds +

probability we move to state 2 in less than 20 seconds +

probability we move to state 3 in less than 20 seconds

)

		To			
		0: Off	1: On	2: Lock	3: Unlock
From	0: Off	0.50 %	33.03 %	59.4 %	7.05 %
	1: On	45.32 %	2.03 %	0	52.64 %
	2: Lock	2.83 %	95.64 %	0	1.53 %
	3: Unlock	80.5 %	13.58 %	0	5.92 %



= 1 - (

prob. we move to state 0 * (integral 0<t<20 for 1➡0) +

prob. we move to state 2 * (integral 0<t<20 for 1➡2) +

prob. we move to state 3 * (integral 0<t<20 for 1➡3)

)

$$
= 1 - \Big(0.4532 * (\text{integral } 0<t<20 \text{ for } 1 \Rightarrow 0) + 0 * (\text{integral } 0<t<20 \text{ for } 1 \Rightarrow 2) + 0.5264 * (\text{integral } 0<t<20 \text{ for } 1 \Rightarrow 3) \Big)
$$

= 1 - (

0.4532 * 0.6659034 +

0 +

0.5264 * 0.9705692

)

= 0.187 i.e. 18.7%

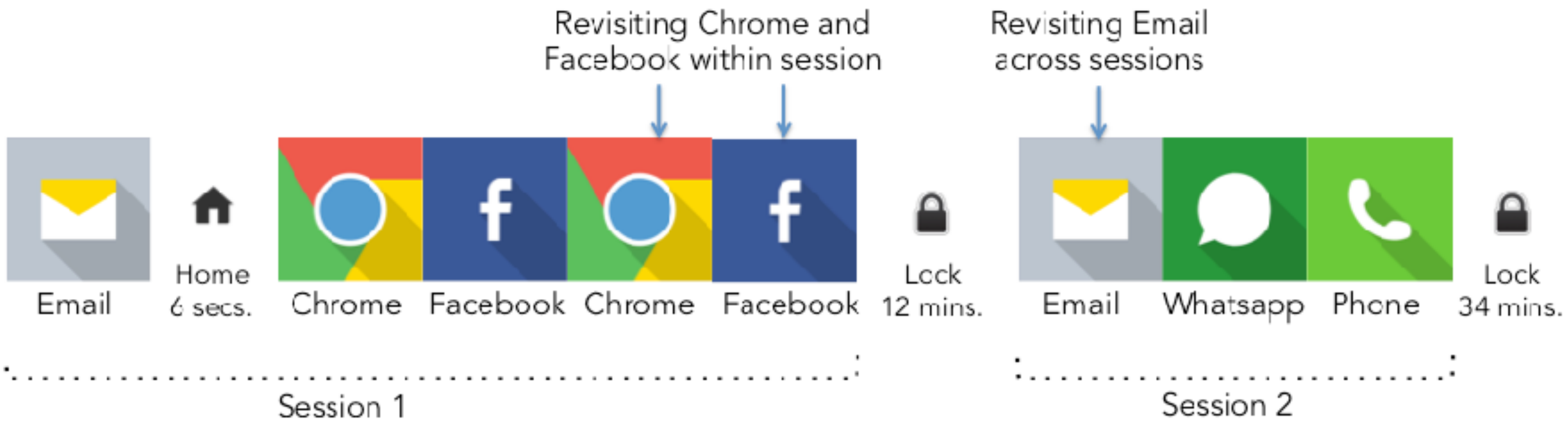
Hence:

	Model	**Dataset**
• Staying in state 1 for at least 20 sec:	18.7%	10.5%
• For 120 sec:	6.9%	4.5%
• For 20 sec & battery > 75%:	19.0%	10.9%
• For 20 sec & battery < 25%:	17.7%	10.8%
• For 20 sec & 2pm:	17.5%	10.8%
• For 20 sec & 4am:	18.4%	6.6%

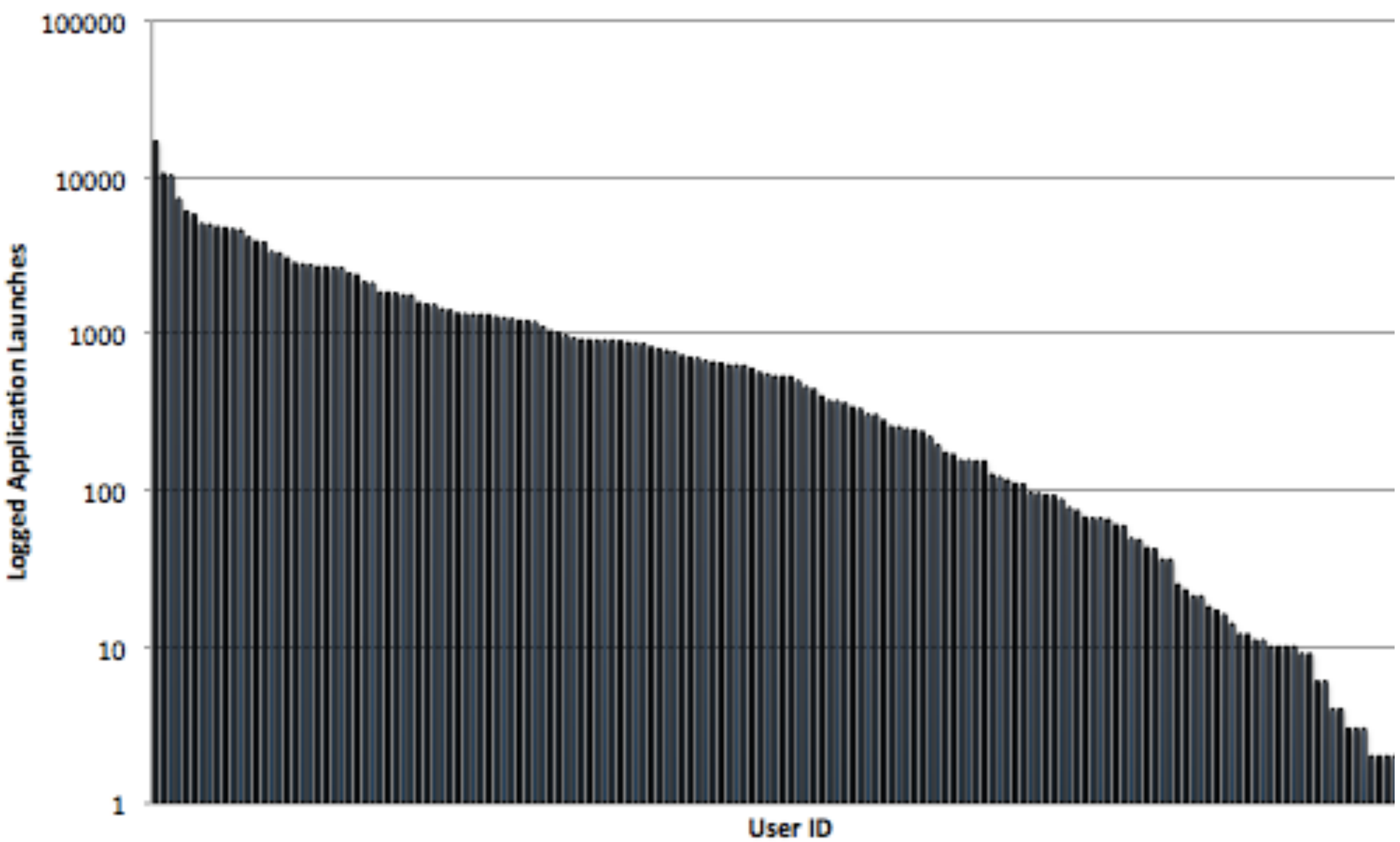
Error (RMSE) = 7.8%

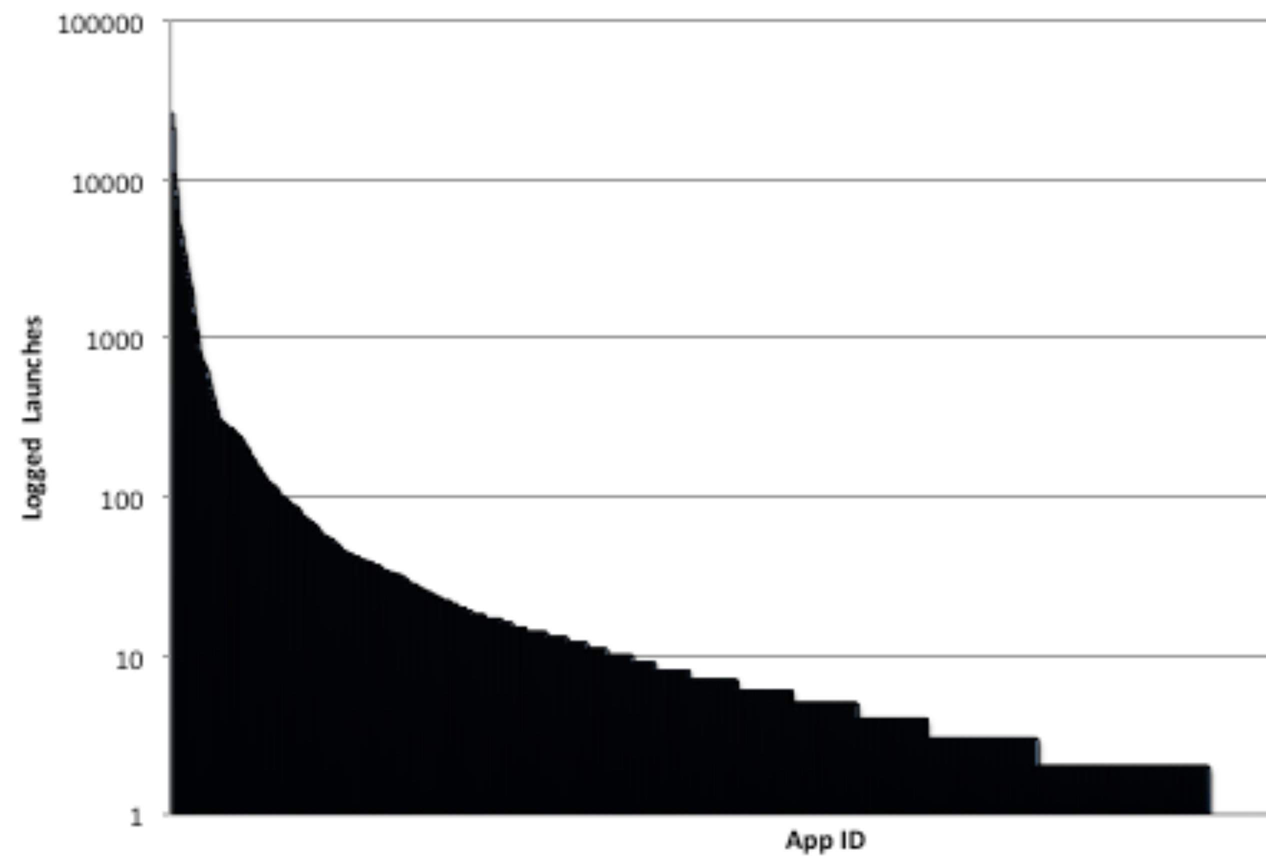
Revisitation analysis:
Do smartphones create habits?

We built an app and deployed to an appstore. The app collects data.


Revisiting Chrome and
Facebook within session
Revisiting Email
across sessions
Email
Home
6 secs.
Chrome
Facebook
Chrome
Facebook
Lock
12 mins.
Email
Whatsapp
Phone
Lock
34 mins.
Session 1
Session 2

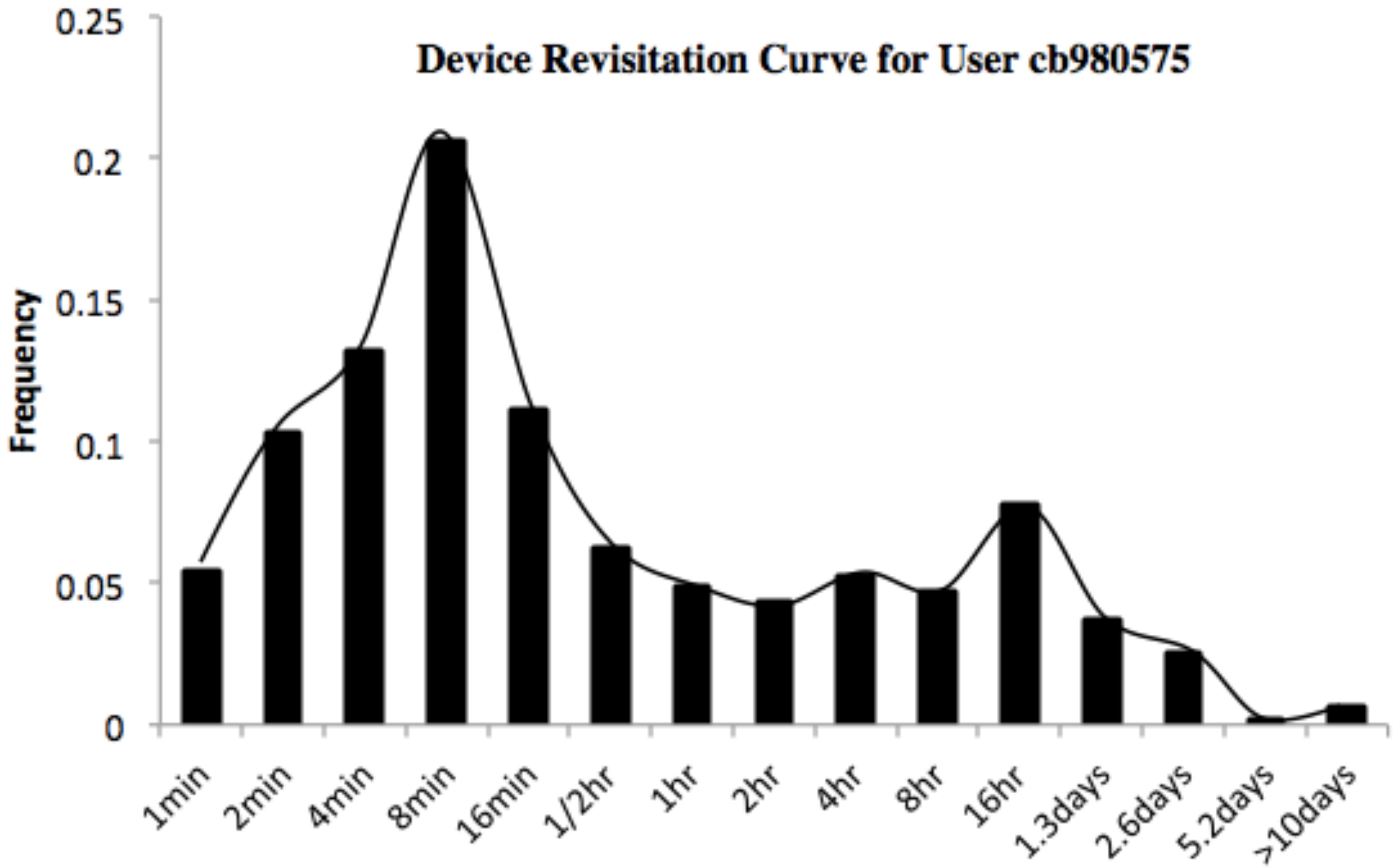
Differences in launching



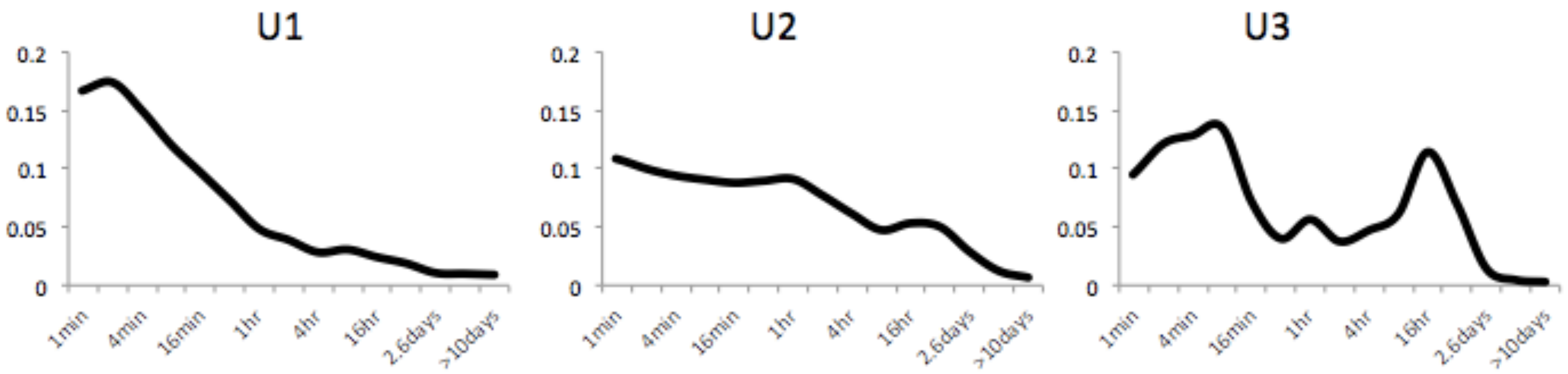


Y-axis is LOGARITHMIC!

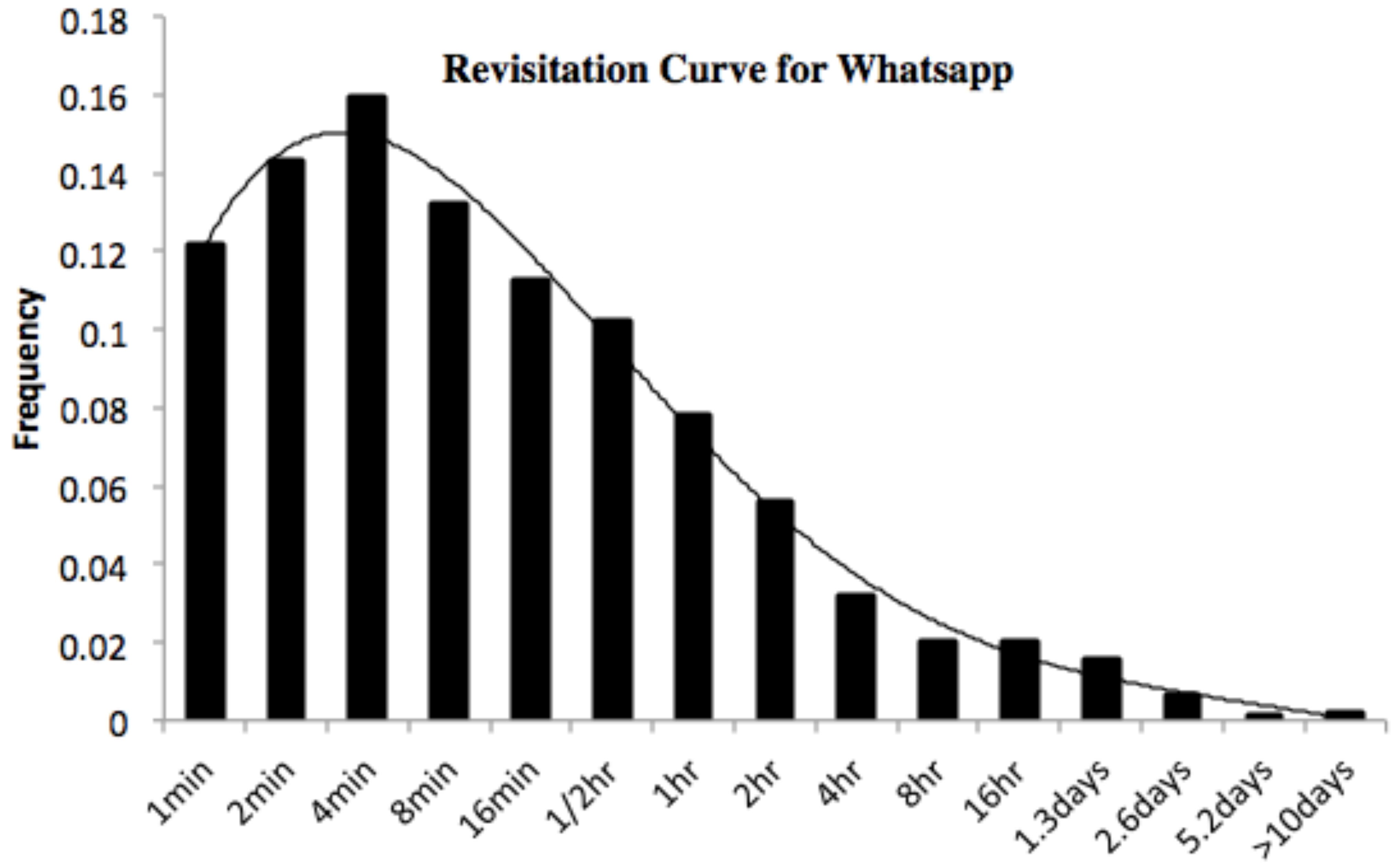
Histograms per user



Patterns emerge (users)



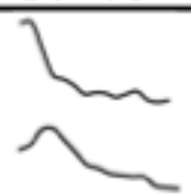
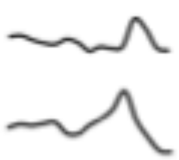
Histograms per app



Patterns emerge (apps)

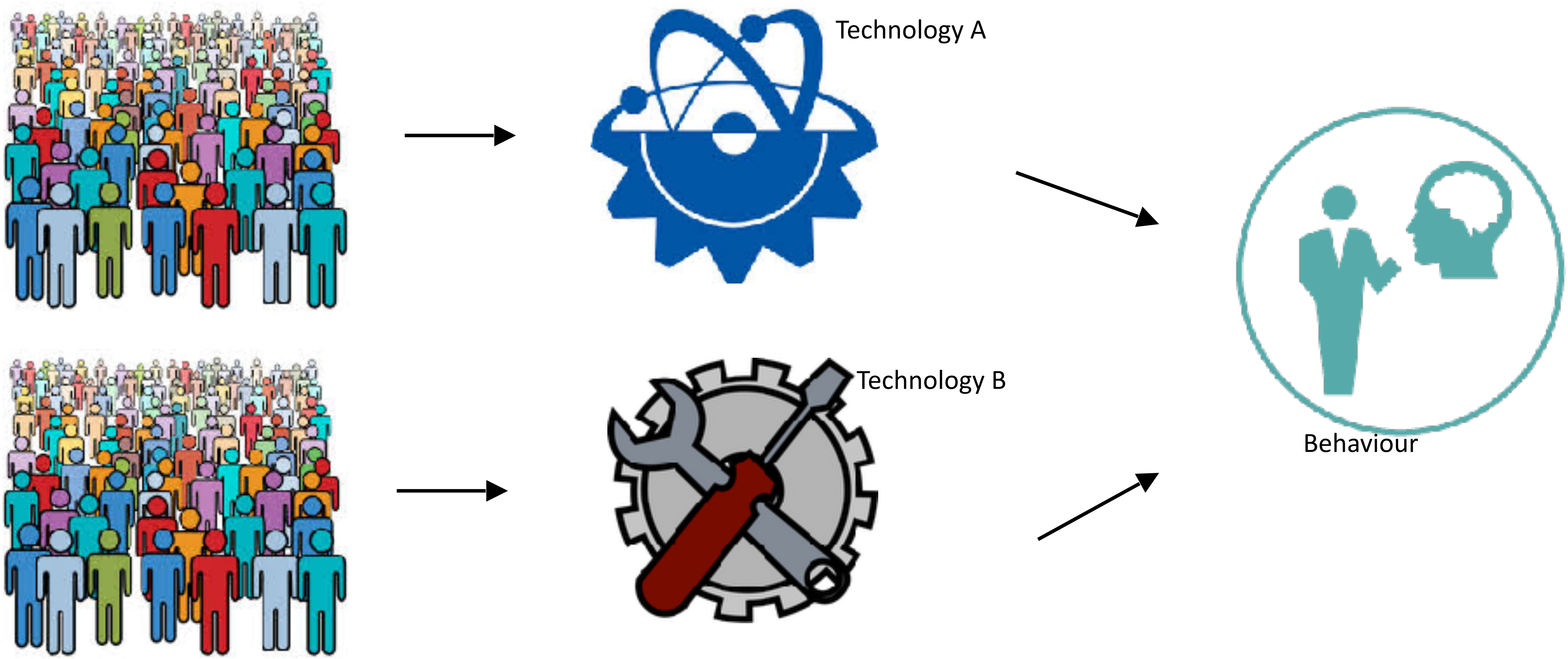
Cluster Label	Description	Centroid Revisitation Curve	Example Apps	Cluster Size (# Apps)
F1	Fast		Google Play Store, Facebook Messenger, InoReader, Chrome Beta, BlackBerry Messenger, Reddit, Okcupid	32 (13%)
F2	Fast		Chrome, Whatsapp, Facebook, Google Hangouts, SMS/MMS, Viber, Youtube, Contacts+, Google Maps, Firefox, Spotify, Skype, Snapchat, Xperia Conversations, Line, Reddit News, Telegram Messenger, Music, Falcon Pro	82 (33%)
M1	Medium		Phone, Gmail, Contacts, Email, Dialer, Clash of Clans, Instagram, Outlook, Yahoo Mail, Opera Browser	47 (19%)
S1	Slow		Gallery 3D, Calendar, Camera, Twitter, Calculator, Clean Master (Speed Booster) Runkeeper Pro, Flipboard, Google Play Services, Mobile Bank, Mobile Weather, Flickr, Google Doc Editor, Tumblr, Quick Office, Google Translate	30 (12%)
S2	Slow		Settings, Desk Clock, Organiser, Tinder, Plants vs. Zombies 2, Clash of Lords, Titanium Backup, Hot or Not, Control Panel, Candy Crush Saga, Castle Clash	40 (16%)
H1	Hybrid		Evernote, Google+, Google Docs, MusicBox, Adobe Reader, 9gag, Video Player, Meo Remote, Waze, Dictionary, Opera Mini	21 (8%)

Compare to Web revisitaton (2000's)

Cluster Group	Centroid Curve	Description	Corresponding cluster group descriptions from Adar *et al.* [1]
Fast (F1,F2)		Instant Messaging, Browser, Social Media	Hub & Spoke, Shopping & Reference, Auto refresh, Fast monitoring, Pornography & Spam.
Medium (M1)		Email and Phone Communication	Popular homepages, Communication, .edu domain, browser homepages.
Slow (S1,S2)		Utilities, Multimedia, Health and Fitness, Games, Dating, Phone Settings	Entry pages, Weekend activity, Search engines used for Revisitation, Child-oriented content, Software updates
Hybrid (H1)		Documents, Notes, Video, Satnav	Popular but infrequently used, Entertainment & Hobbies, Combined Fast & Slow.

Similar patterns.
What does this mean?

Do phones create habits?



The end

Prof. Vassilis Kostakos
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School of Computing and Information Systems
University of Melbourne

App Usage Prediction and Recommendation

App Usage Prediction and Recommendation

Prediction

- Problem definition and Related Work
- Context-aware App usage prediction
- Deep learning for App usage prediction

Recommendation

- Problem definition for App recommend.
- Methods overview for App recommend.
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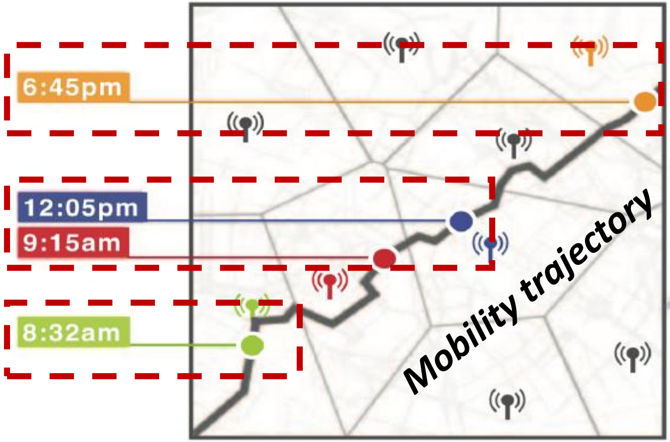
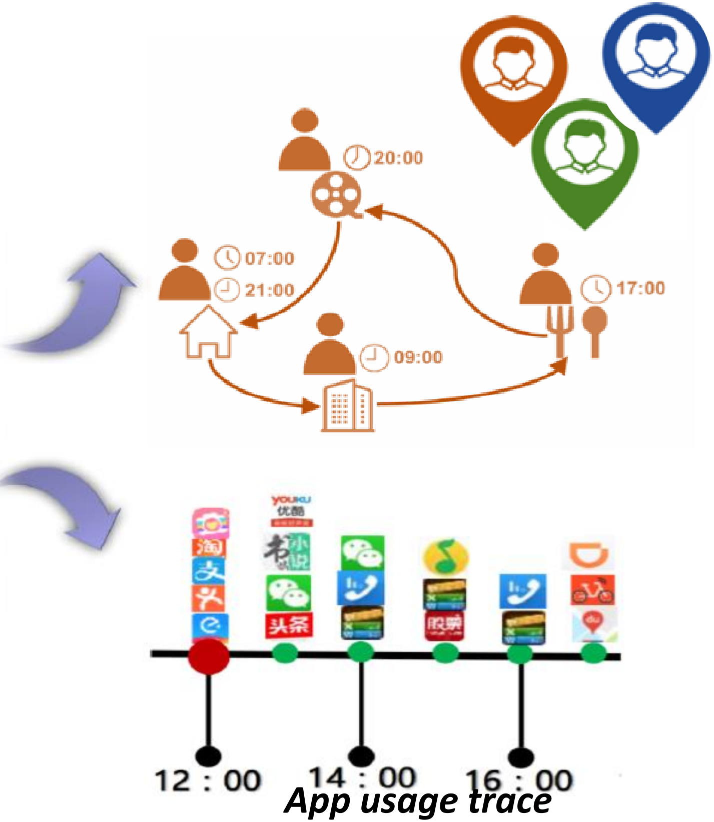
Problem Definition:

Which kind of information we need to consider in App usage prediction?

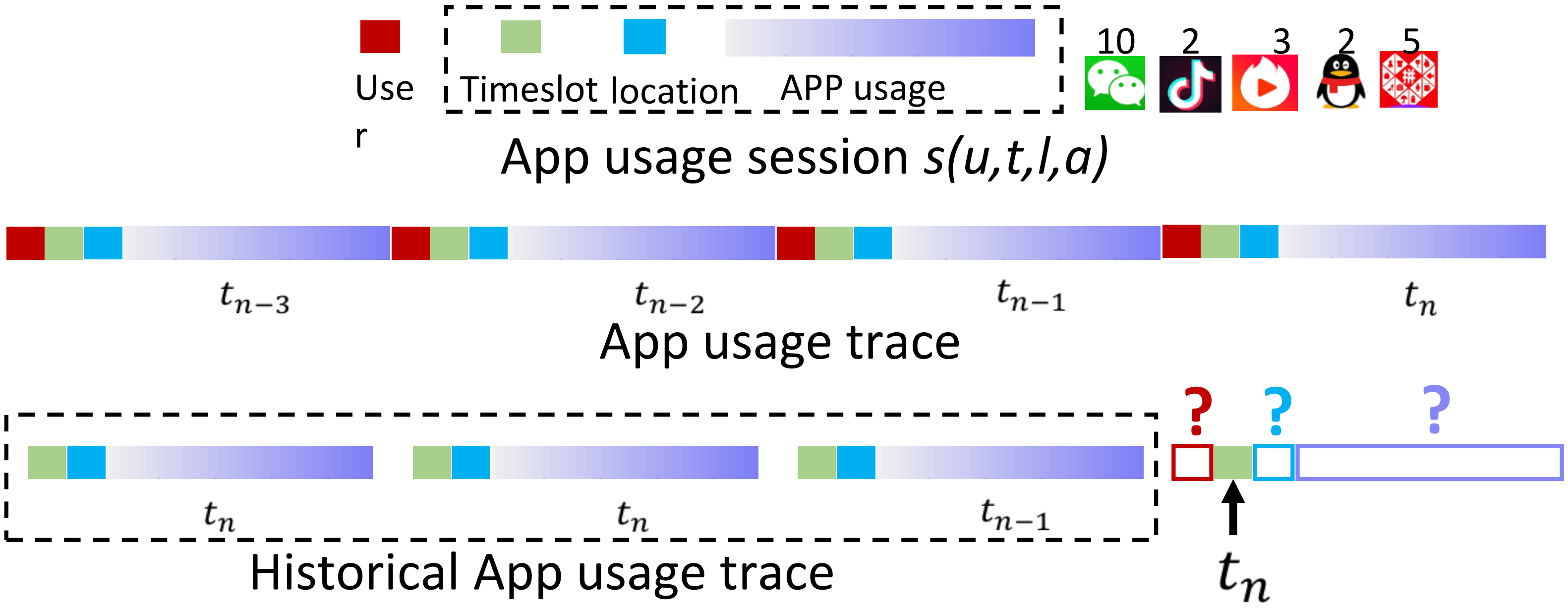
1. ***Sequential and Periodical***
2. ***Spatial–temporal Correlation***
3. ***User preferences***



$$(l_1,t_1)\,||\,(l_2,t_2)\,||\,(l_3,t_3)\,||\ldots$$



Problem Definition



Task：

1. Predict his next App usage in given t_n;
2. Predict his next location in given t_n;

App Usage Prediction Related Research

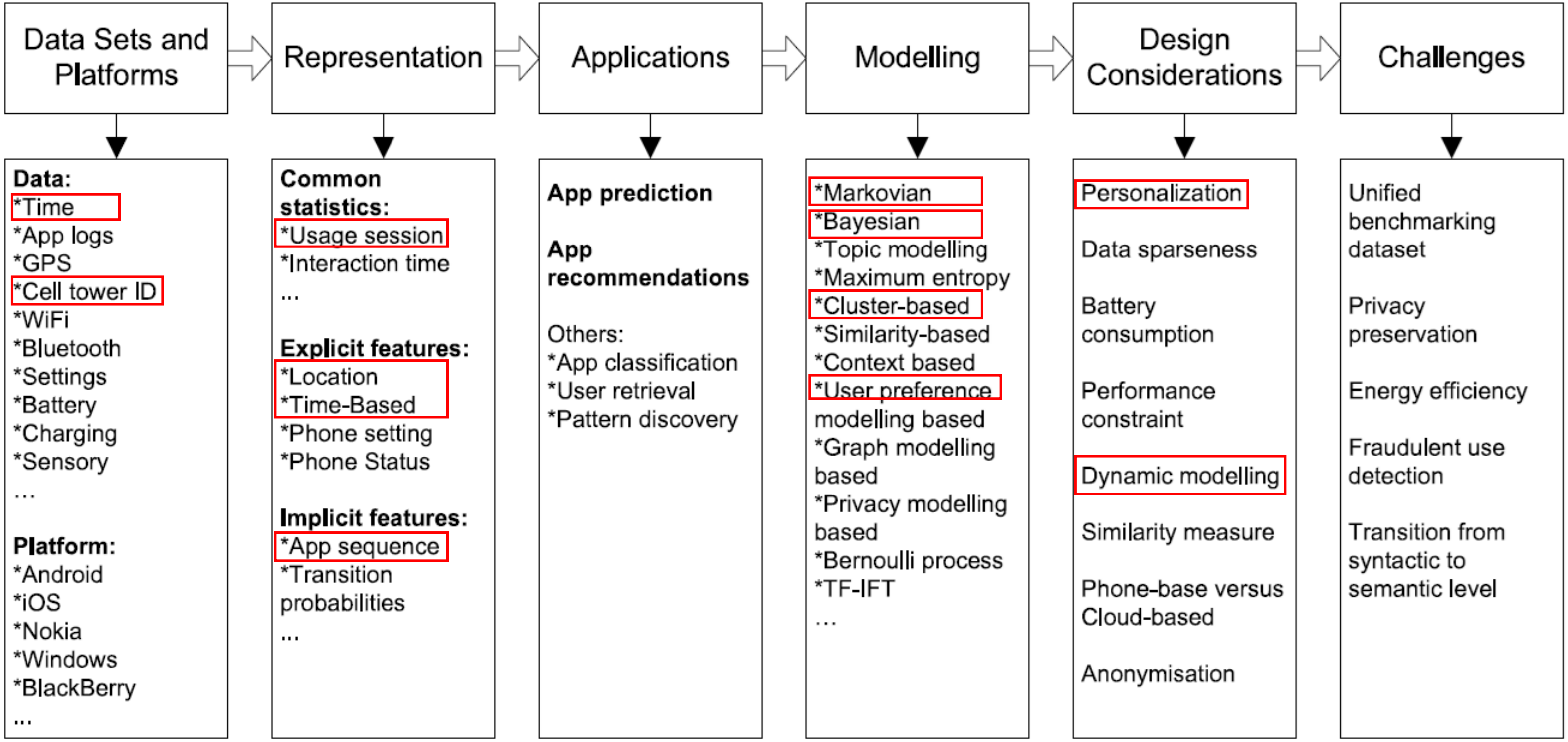
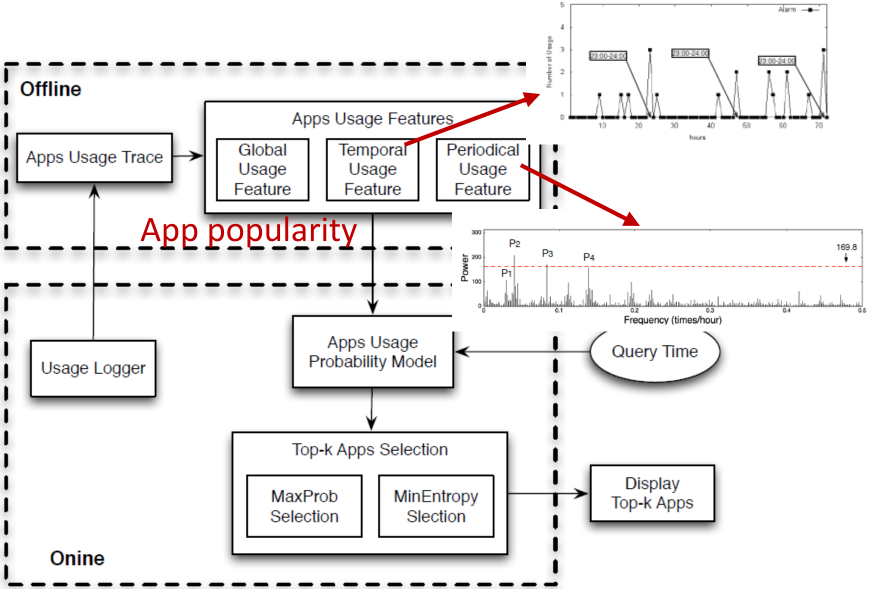


Fig. 1. Overview of our survey, where app prediction and recommendations in bold are our focused application topics.

Related works of sequence prediction

On Mining Mobile Apps Usage Behavior for Predicting Apps Usage in Smartphones



The accuracy reaches to 80% when k is 5
(Average number of Apps of a user 53)

Figure 1: An overview of Temporal-based Apps Predictor (TAP).

Zhung-Xun Liao, Yi-Chin Pan, Wen-Chih Peng, and Po-Ruey Lei. 2013. *On mining mobile apps usage behavior for predicting apps usage in smartphones.* In Proceedings of the 22nd ACM international conference on Information & Knowledge Management **(CIKM '13**). ACM, New York, NY, USA, 609-618

DeepMove: Predicting Human Mobility with Attentional Recurrent Networks

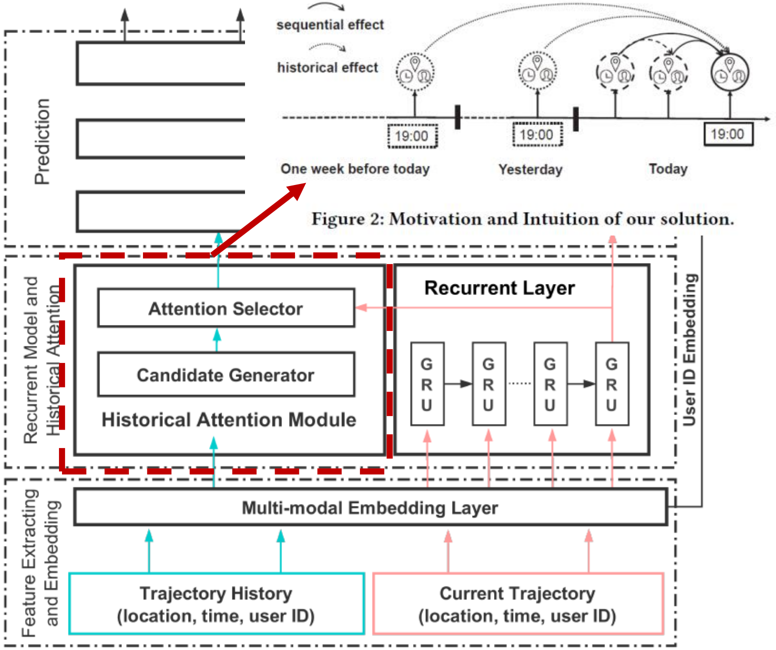


Figure 3: Main architecture of DeepMove.

Feng, Jie, et al. "*DeepMove: Predicting Human Mobility with Attentional Recurrent Networks*." Proceedings of the 2018 World Wide Web Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 2018.

Related works of Spatial-temporal Prediction

Understanding and Prediction of Mobile Application Usage for Smart Phones

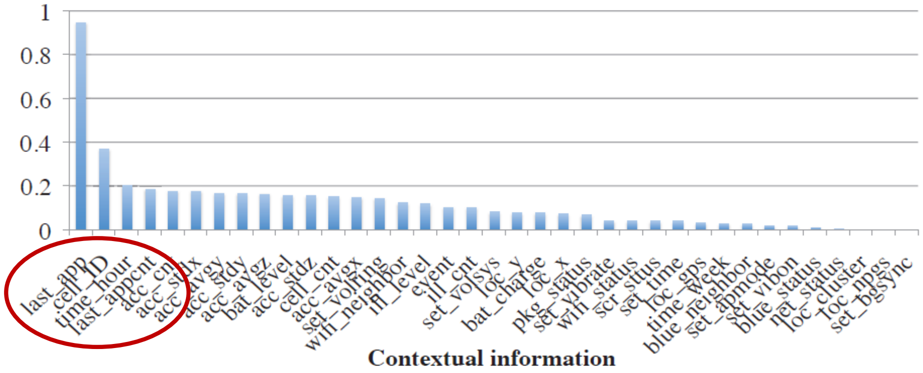


Fig. 3. Average information gain of context features across all users.

- **last_app** was very important for app prediction followed by **cell_ID** and **time_hour**, while other contextual features, such as bat_state and illumination were quite poor for predicting app usage.

Choonsung Shin, Jin-Hyuk Hong, and Anind K. Dey. 2012. *Understanding and prediction of mobile application usage for smart phones*. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing (**UbiComp '12**). ACM, New York, NY, USA, 173-182.

Predicting Activity and Location with Multi-task Context Aware Recurrent Neural Network

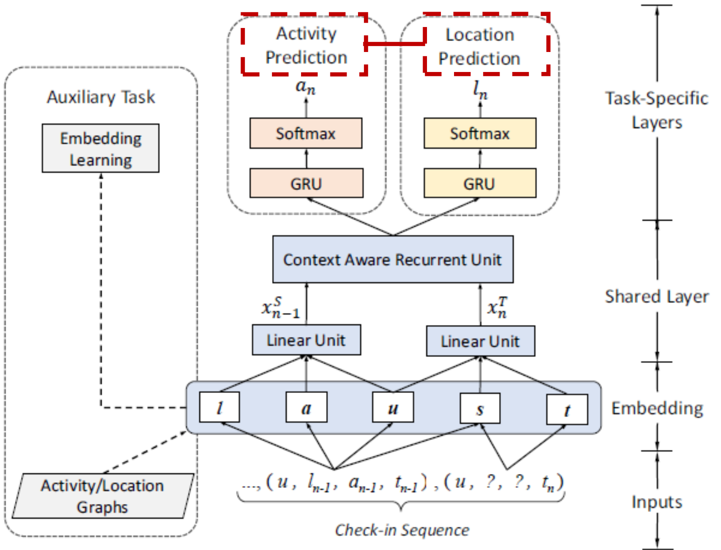


Figure 1: The overall framework of MCARNN

Liao, Dongliang, et al. "Predicting Activity and Location with Multi-task Context Aware Recurrent Neural Network." IJCAI. 2018.

Related works of Context-aware Prediction

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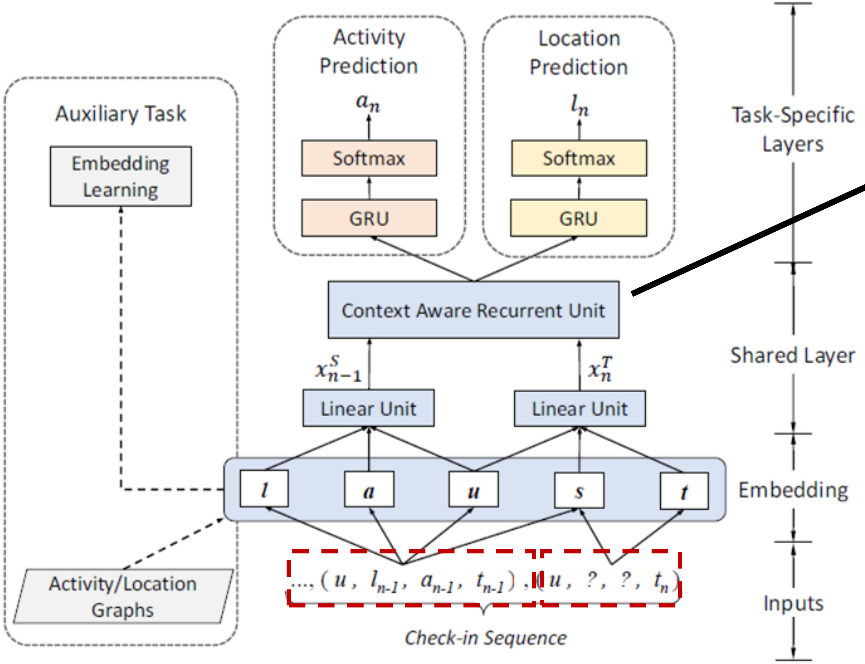

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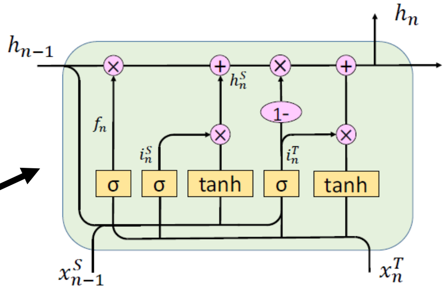

Figure 2: Context Aware Recurrent Unit

fined as a quadruple
t user u visits location l
goal is to predict user u's
tivity a_n , given the
e historical check-in
$\ldots, r^u_{n-1}\}$

Liao, Dongliang, et al. "Predicting Activity and Location with Multi-task Context Aware Recurrent Neural Network." IJCAI. 2018.

Related works of Context-aware Prediction

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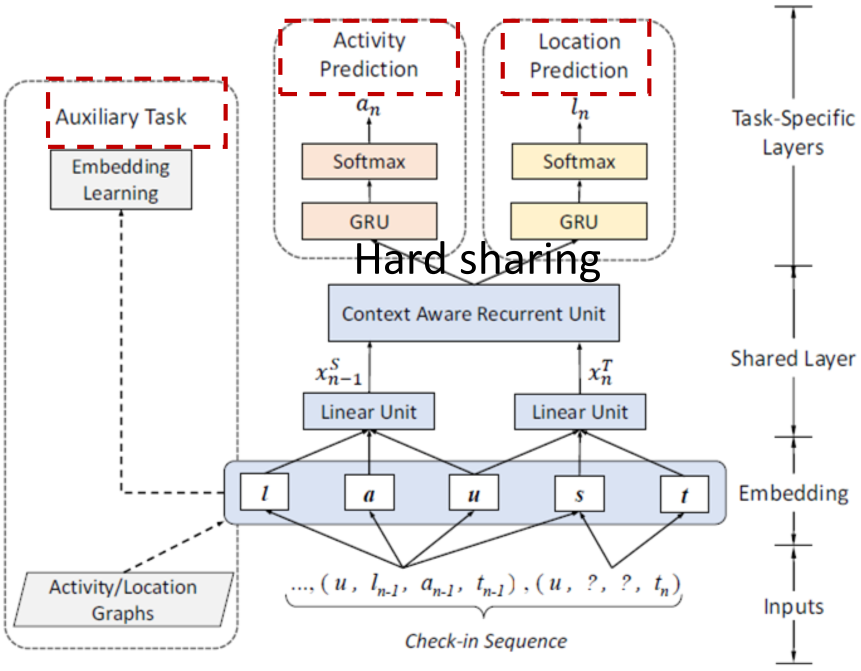
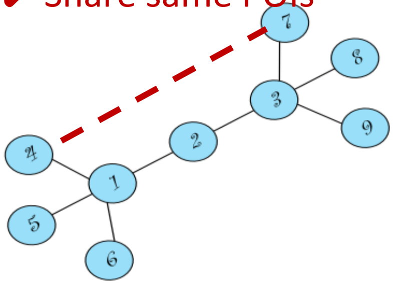
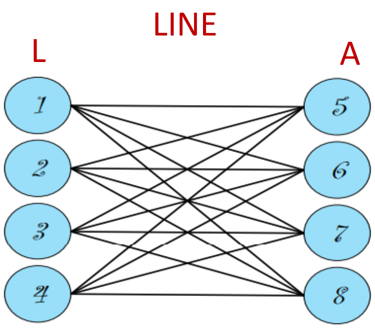


Figure 1: The overall framework of MCARNN

✔ Closer than threshold
✔ Share same POIs



location-location graph



location-activity graph

The overall loss of MCARNN is the total loss of the activity prediction, location prediction and embedding learning.

$$J = \lambda_1 J_a + \lambda_2 J_l + \lambda_3 (J_{G_l} + J_{G_a}) \quad (6)$$

Predicting App

Predicting location

Embedding

Liao, Dongliang, et al. "Predicting Activity and Location with Multi-task Context Aware Recurrent Neural Network." IJCAI. 2018.

Related works of Context-aware Prediction

Predicting Activity and Location with Multi-task Context Aware Recurrent Neural Network

Dataset	Method	Location Prediction					Activity Prediction				
		Acc@1	Acc@10	Acc@20	NLL	MAP@100	Acc@1	Acc@3	Acc@5	NLL	MAP@20
NYC	MF	0.0774	0.1788	0.1957	8.3399	0.4005	0.1739	0.3008	0.3980	4.0183	0.6393
	CAH	0.1328	0.3521	0.4179	7.0680	0.5331	0.2338	0.3825	0.4481	3.7882	0.6716
	ST-RNN	0.1663	0.4126	0.4671	6.7701	0.5632	-	-	-	-	-
	SERM	0.1480	0.3731	0.4386	7.0104	0.5395	0.2240	0.3905	0.4624	3.7406	0.6788
	MTGRU	0.1640	0.4128	0.4688	6.6957	0.5722	0.2310	0.3912	0.4665	3.7134	0.6925
	SCARNN	0.1743	0.4268	0.4911	6.5869	0.5836	0.2393	0.3847	0.4697	3.7239	0.6859
	MCARNN	**0.2011**	**0.4601**	**0.5198**	**6.2961**	**0.6092**	**0.2572**	**0.4217**	**0.5032**	**3.5740**	**0.7058**
TKY	MF	0.1021	0.2041	0.2536	6.6641	0.6018 1	0.2322	0.3672	0.4345	3.6191	0.6871
	CAH	0.1728	0.3877	0.4551	5.9137	0.6662	0.3455	0.5006	0.5690	3.0173	0.7511
	ST-RNN	0.2033	0.4904	0.5703	5.5774	0.7033	-	-	-	-	-
	SERM	0.1796	0.4271	0.4862	5.8377	0.6726	0.3863	0.5840	0.6730	2.6706	0.7892
	MTGRU	0.2000	0.4948	0.5619	5.6804	0.6823	0.4047	0.6062	0.6786	2.5937	0.8129
	SCARNN	0.2431	0.5289	0.6037	5.3974	0.7035	0.4463	0.5709	0.6347	2.5031	0.8248
	MCARNN	**0.2829**	**0.5807**	**0.6391**	**5.0057**	**0.7425**	**0.4706**	**0.6599**	**0.7332**	**2.3320**	**0.8739**

Table 2: Performance comparison with baselines

Existing representative APP usage prediction works.

Method	Paper	Context	Performance	Shortage & features
Markov	[Natarajan *et al.*, 2013]	App sequence	Recall of 67% at top 5 Apps on a dataset of over 17,000 users and 9,000 Apps	Not using location context, simply modeling the sequence
	[Parate *et al.*, 2013]	App sequence, time and location	Accuracy of 80.85% and 81.35% at top 5 Apps without and with time and location context for 34 users	Insufficient evaluation of limited users, inadequate utilization of context
Bayesian	[Shin *et al.*, 2012]	App sequence, time, location and phone states	Accuracy of 87.8% for 9 Apps for 23 users	Inadequate utilization of context, insufficient evaluation
	[Huang *et al.*, 2012]	App sequence, time and location	Accuracy of 69% at top 5 Apps for 38 users with a maximum App number of 43	Independent hypothesis, insufficient evaluation with limited users and Apps
Deap learning	[Zhao *et al.*, 2018]	App sequence, time	Recall of 54.83% at top 1 Apps for more than 10,000 users and 2000 Apps	Inadequate utilization of context, simply modeling the sequence, weakly personalized
	Our **DeepApp**	App usage history, time and location	Recall of 64.05% at top 5 Apps for thousand of users and 2000 Apps	Better modeling the sequence by GRU, better modeling the complex relation of different context via multi-task learning, strong personalized

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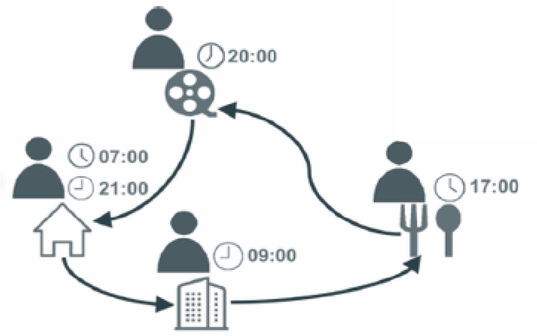
Context-aware App Usage Prediction



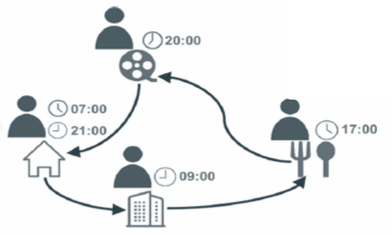
What is the context?

- Time, Location, Environment, related POI, etc.
- Most important: spatio-temporal context

Challenging for context-aware prediction:

- The intrinsic randomness of human behaviors introduces large noise to app usage data
- There are hidden semantics in app usage traces
- App usage data is highly skewed, where a small number of apps contribute to most of the usage data

Key Problem: How to Capture the Context?



Solution 1: Embedding the context

- Graph Embedding

X. Chen, Y. Wang, S. Pan, **Yong Li**, P. Zhang. CAP: Context-aware App-usage Prediction, ***in ACM UbiComp 2019 (IMWUT).***

- Reconstruction Embedding

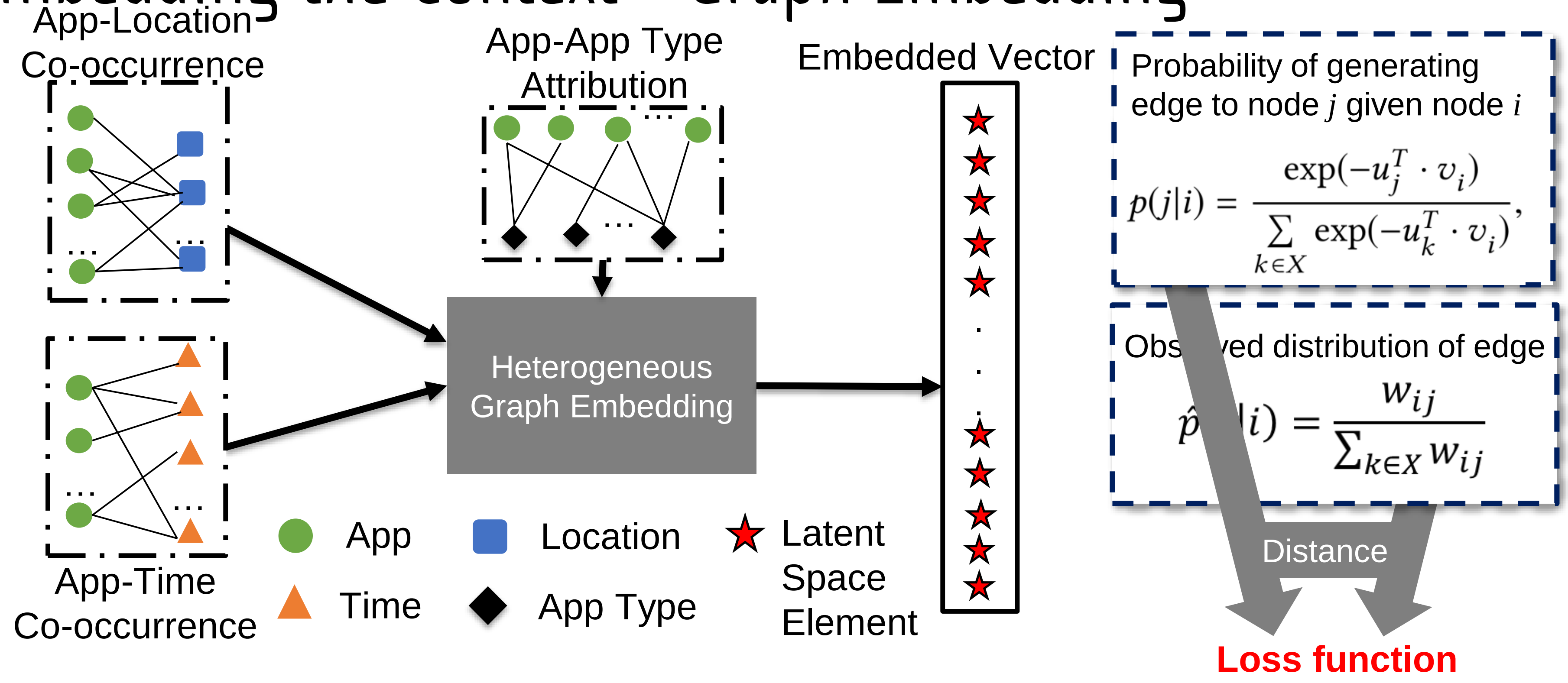
H. Wang ,***Yong Li***, M. Du, Z. Li, D. Jin. App2Vec: Context-Aware Application Usage Prediction, ***submitted to IEEE TMC***.

Solution 2: Modeling the context

- Probabilistic Graphical Models (PGMs)

H. Wang, Yong Li, S. Zeng, G. Wang, P. Zhang, P. Hui, D. Jin. Modeling Spatio-Temporal App Usage for a Large User Population, ***in ACM UbiComp 2019 (IMWUT).***

Embedding the Context - Graph Embedding



X. Chen, Y. Wang, S. Pan, Yong Li, P. Zhang. CAP: Context-aware App-usage Prediction, ***in ACM UbiComp 2019 (IMWUT)*.**

Embedding the Context - Graph Embedding

Summary over history records

Time-variant user profile $\vec{u}_\tau = \sum_{(u,\vec{c}_i,\tau_i)\in\Re^u_\tau} e^{-(\tau-\tau_i)}\vec{c}_i + (1-\beta) \sum_{(u,\vec{a}_i,\tau_i)\in\Re^u_\tau} e^{-(\tau-\tau_i)}\vec{a}_i$

Location

Time decay

App

Predictor: $S(q,a) = \vec{u}_\tau \cdot \vec{a}_j$

prediction score

user profile

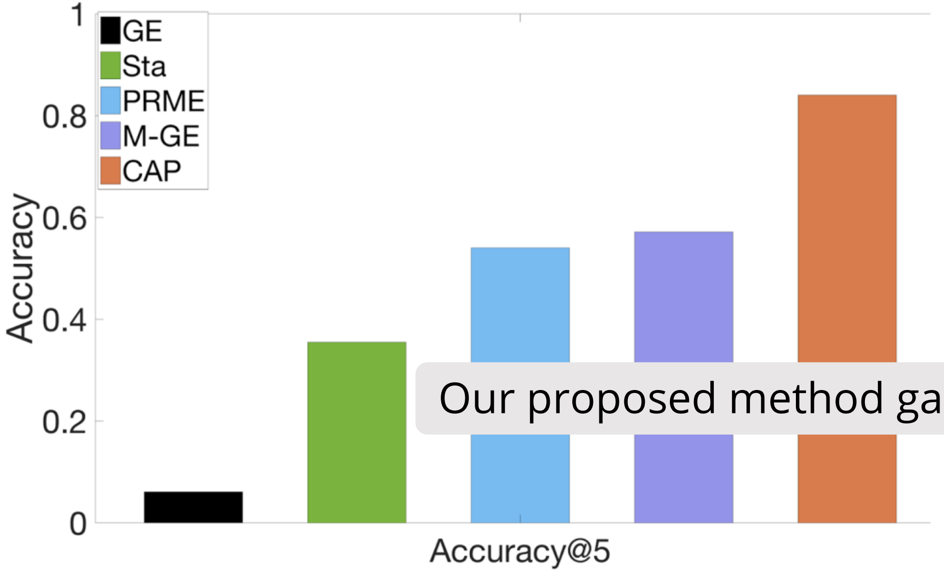
possible mobile App

X. Chen, Y. Wang, S. Pan, Yong Li, P. Zhang. CAP: Context-aware App-usage Prediction, ***in ACM UbiComp 2019 (IMWUT)*****.**

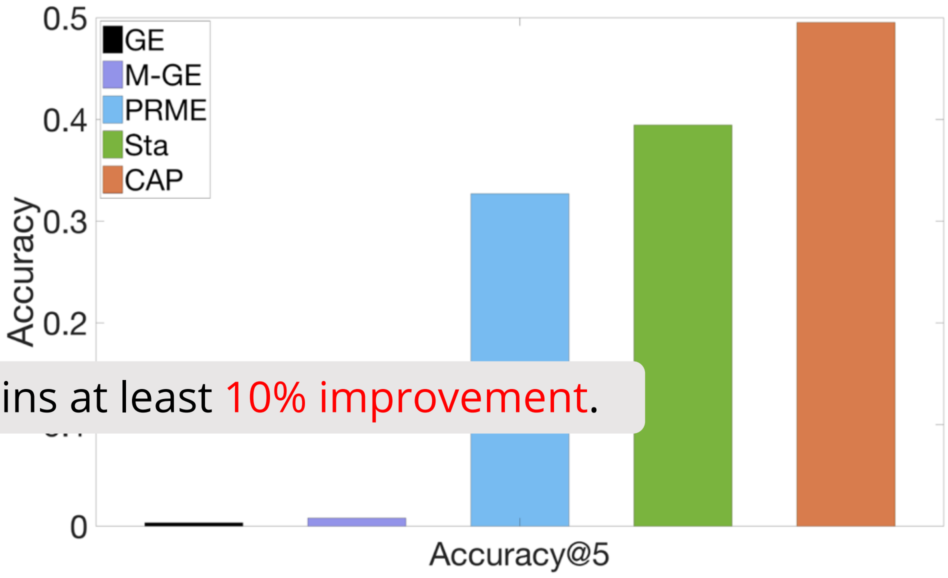
Embedding the Context - Graph Embedding

30% higher

10+% higher



China Telecom Dataset

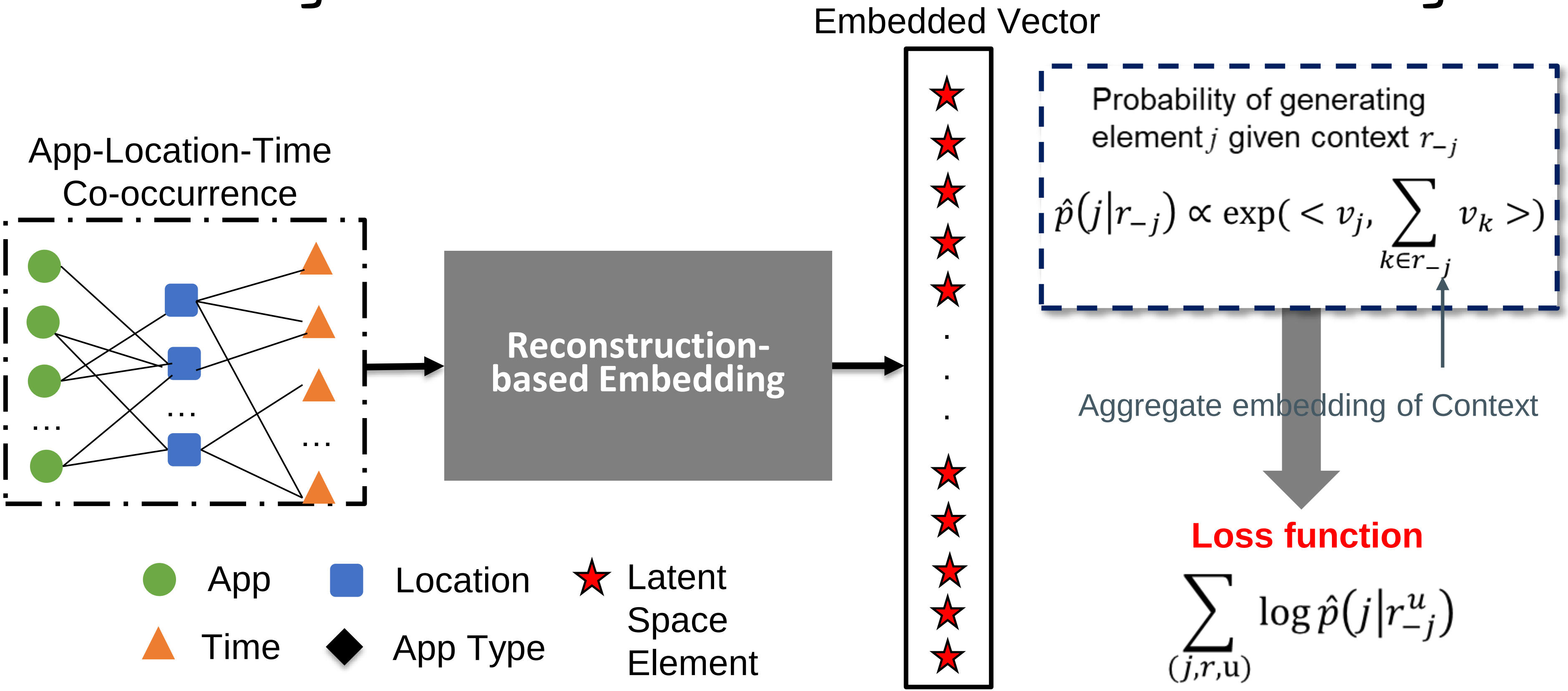


TalkingData Dataset

Our proposed method gains at least 10% improvement.

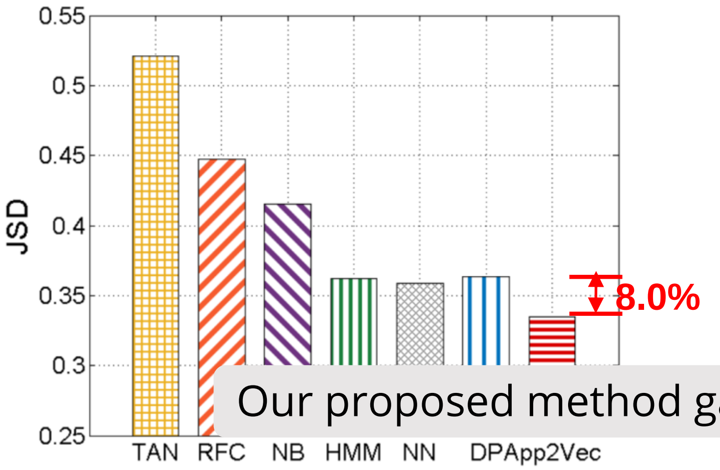
X. Chen, Y. Wang, S. Pan, Yong Li, P. Zhang. CAP: Context-aware App-usage Prediction, ***in ACM UbiComp 2019 (IMWUT)*.**

Embedding the Context - Reconstruction Embedding

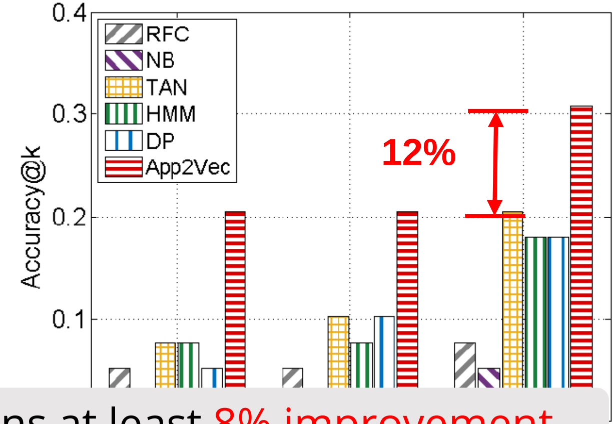


H. Wang ,***Yong Li***, M. Du, Z. Li, D. Jin. App2Vec: Context-Aware Application Usage Prediction, ***submitted to IEEE TMC***.

Embedding the Context - Reconstruction Embedding



All apps

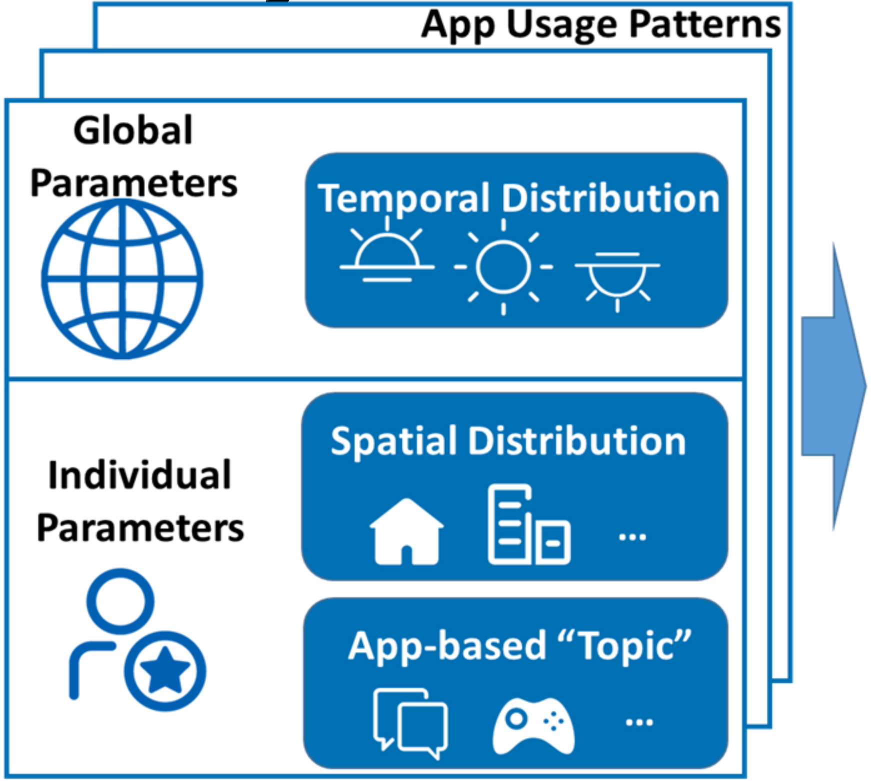


Rarely-used apps

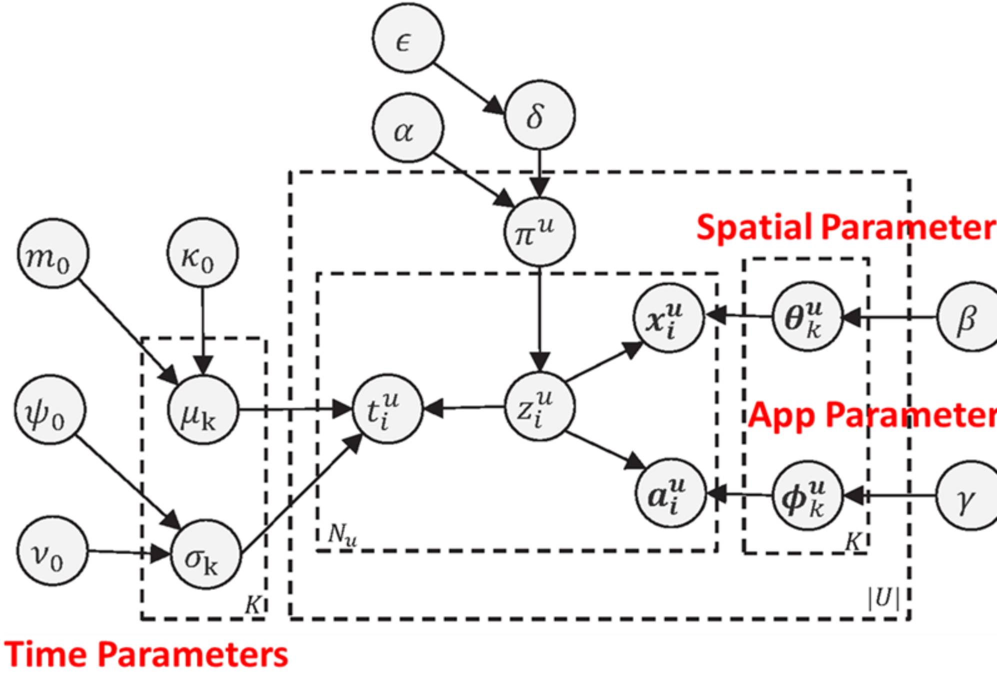
Our proposed method gains at least 8% improvement.

H. Wang, Yong Li, S. Zeng, G. Wang, P. Zhang, P. Hui, D. Jin. Modeling Spatio-Temporal App Usage for a Large User Population, in ***ACM UbiComp 2019 (IMWUT)***.

Modeling the Context - PGMs



App Usage Model



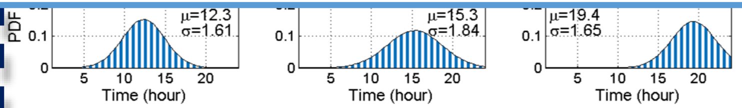
Probabilistic Graphical Model

H. Wang, Yong Li, S. Zeng, G. Wang, P. Zhang, P. Hui, D. Jin. Modeling Spatio-Temporal App Usage for a Large User Population, in ***ACM UbiComp 2019 (IMWUT)***.

Modeling the Context - PGMs

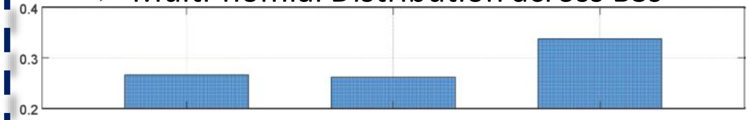
Use multiple appropriate probability distribution to model app with multi-dimensional context

■ **Temporal Distribution**



■ **Spatial Distribution**

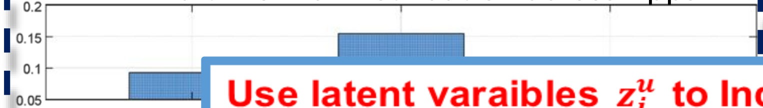
➢ Multi-nomial Distribution across BSs



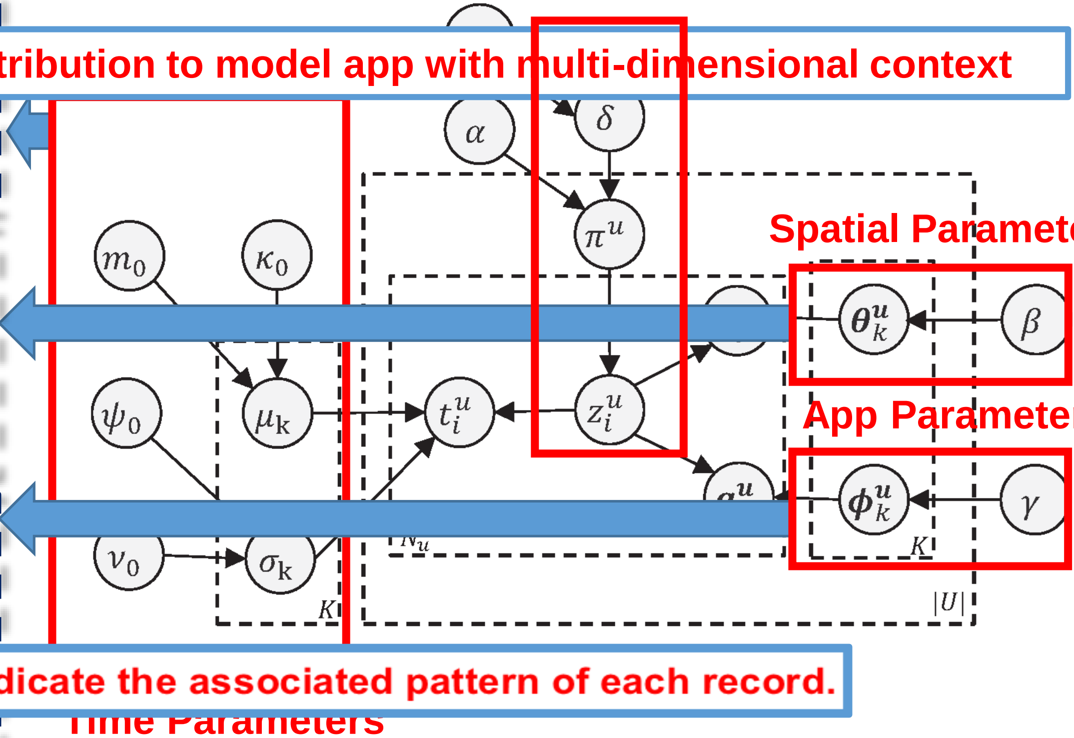
Normalized PoI Distribution (Residential)

■ **App Distribution**

➢ Multi-nomial Distribution across Apps



Normalized App Category Distribution (Maps)

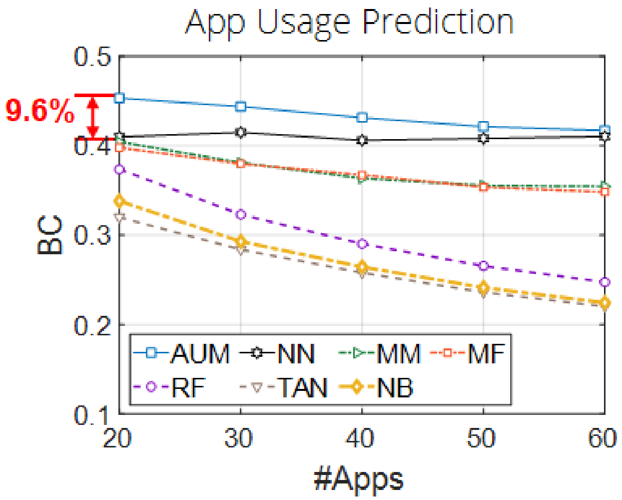


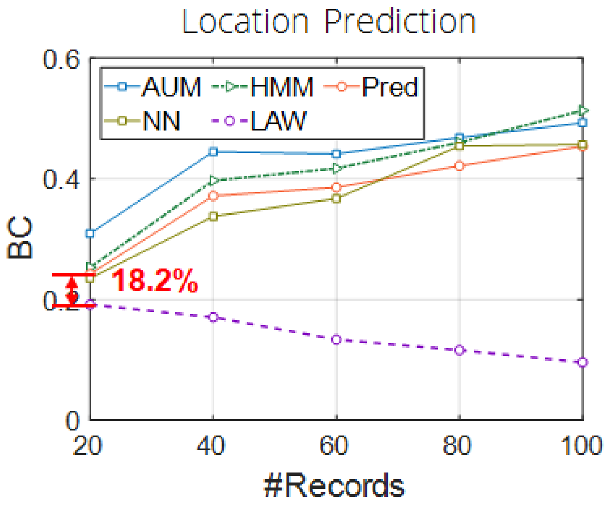
Use latent varaibles z_i^u to Indicate the associated pattern of each record.

H. Wang, Yong Li, S. Zeng, G. Wang, P. Zhang, P. Hui, D. Jin. Modeling Spatio-Temporal App Usage for a Large User Population, in ***ACM UbiComp 2019 (IMWUT)***.

Modeling the Context - PGMs

Evaluation Results





Our proposed algorithms outperform Competing algorithms with relative improvement over 9%.

H. Wang, Yong Li, S. Zeng, G. Wang, P. Zhang, P. Hui, D. Jin. Modeling Spatio-Temporal App Usage for a Large User Population, in ***ACM UbiComp 2019 (IMWUT)***.

App Usage Prediction and Recommendation

Prediction

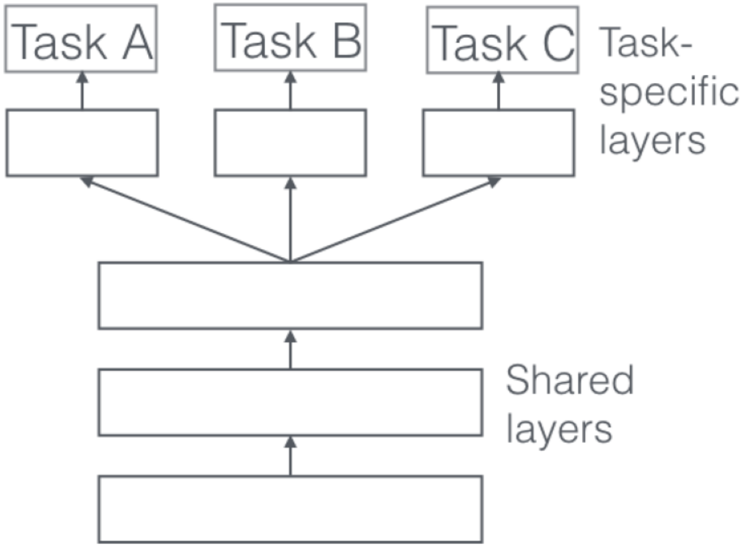
- Problem definition and Related Work
- Context-aware App usage prediction
- Deep learning for App usage prediction

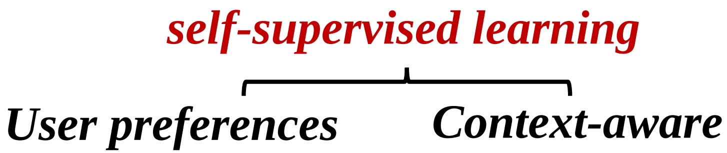
Recommendation

- Problem definition for App recommend.
- Methods overview for App recommend.
- Transfer learning for App recommend.

Deep Learning for App usage prediction

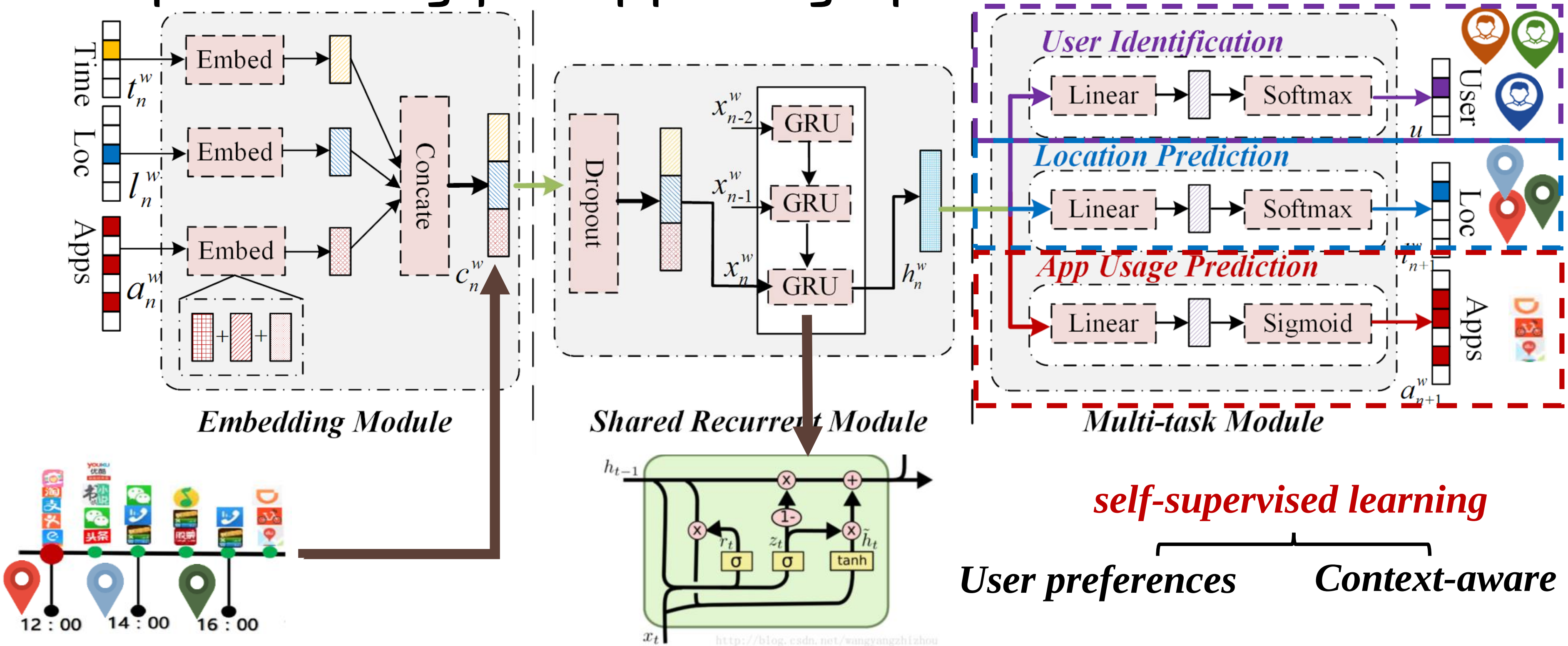
Multi-Task Learning





[3]Ruder, Sebastian. "An overview of multi-task learning in deep neural networks." *arXiv preprint arXiv:1706.05098* (2017).

Deep Learning for App usage prediction



Sequential regularity

self-supervised learning

User preferences

Context-aware

Deep Learning for App usage prediction

Model	R@5	AUC	MAP	ΔMAP
MRU	0.4272	0.7033	0.3832	-24.3%
MFU	0.5863	0.8041	0.3754	-25.8%
HA	0.5512	0.8003	0.4928	-2.6%
Bayes	0.5532	0.7901	0.5060	0
App2Vec	0.4534	0.9666	0.4046	-19.76%
RNN	0.5302	0.9702	0.4824	-4.7%
DeepApp(App)	0.4981	0.9619	0.4501	-11.0%
DeepApp(App+Loc)	0.5657	0.9750	0.5154	1.9 %
DeepApp(App+User)	0.6317	0.9802	0.5764	13.9%
DeepApp	**0.6405**	**0.9825**	**0.5862**	**15.8%**

Table 3: Comparison among different baselines with our model, where ΔMAP is compared with Bayes.

1. Improvement of 15% compared with competing methods
2. Improvement of 30.2% by multi-task learning

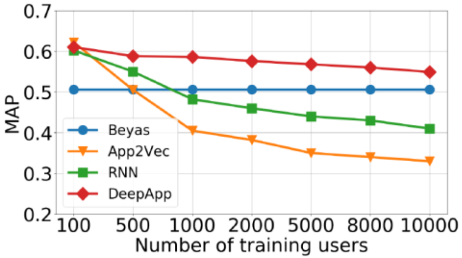


Figure 2: Performance vs. user number.

Robustness of user scale

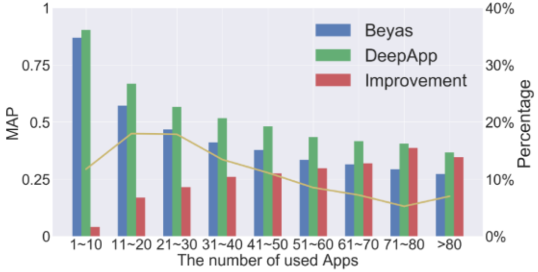


Figure 3: Performance vs. App number.

Robustness of App diversity

App Usage Prediction and Recommendation

Prediction

- Problem definition and Related Work
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Recommendation

- Problem definition for App recommend.
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- Transfer learning for App recommend.

Problem Definition for App Recommend.

Background

- App recommendation aims to infer user's preferences towards unobserved new apps and then recommend favorable ones to targeted users.

App Install.

App Usage

App Ratings

- App Recom.
  - General Recommend.
  - User/App Cold-start Recommend.
  - Privacy Preserving Recommend.
  - Novel And Diversity Recommend.

Problem Definition for App Recommend.

Problem 1.1 General-installation Recommend.

- Given a user's historical app installation records, it tries to pick new apps that the user is likely to install and recommend them to him/her.

Problem 1.2 General-usage Recommend.

- Given a user's historical app usage records, it tries to pick new apps that the user is likely to use and recommend them to him/her.

Problem 1.3 General-rating Recommend.

- Given a user's ratings towards some observed apps, it predicts the user's ratings towards other unobserved apps so as to recommend those apps with the highest ratings by that user.

Problem Definition for App Recommend.

Problem 2 User/App Cold-start Recommend.

- User cold-start: recommend apps to newly coming users.
- App cold-start: recommend users to newly released apps.

Problem 3 Privacy Preserving Recommend.

- It needs to consider both app privacy permissions and user preference to make the final app recommendation.

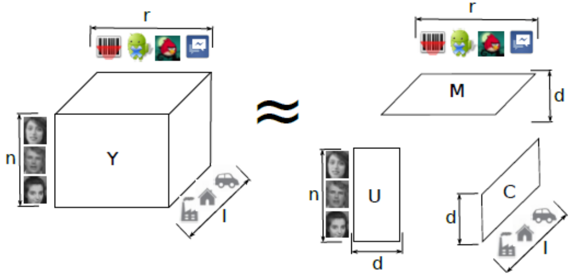
Problem 4 Novel And Diverse Recommend.

- It requires to provide novel and diverse app recommendations to users, *i.e.*, recommending apps from new categories or with complementary functions those already installed ones.

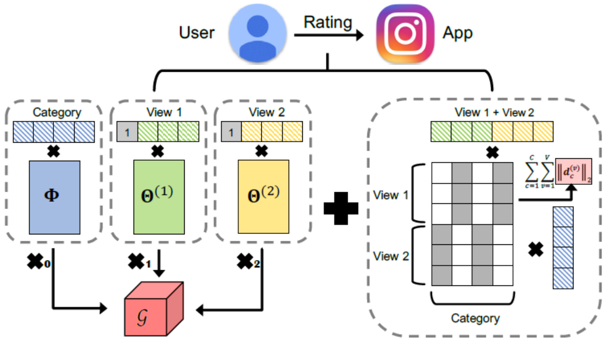
Method overview for App recommend.

Solutions for general recommendations (1)

- Collaborative Filtering (CF)
  - **item based:** Yan et al.@MobiSys'11[22], Shi et al.@KDD'12[31]
- Context Aware Filtering (CAF)
  - **location/POI:** Woerndl et al.@ICDE'07[26], Kaji et al.@UbiComp'11[37], Yu et al.@UbiComp'18[80]
  - **location & time:** Girardello et al.@MobileHCI'10[43], Montenegro et al.@ESA'12[25], Bohmer et al.@IUI'13[34]
- Tensor Factorization (TF)
  - **extra domain of spatiotemporal features:** Karatzoglou et al.@CIKM'12[32], Shi et al.@SIGIR'12[33]
  - **extra domain of app features:** Liang et al.@ICDM'12[49]



Karatzoglou@CIKM'12



Liang@ICDM'12

Method overview for App recommend.

Solutions for general recommendations (2)

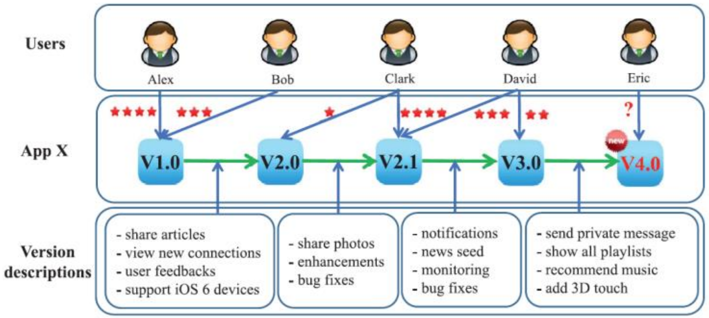
- Topic Model [40,27,41,45,51]
  - Yu et al.@PAKDD’12[27], Zhu et al.@ICDM’12[45], Lin et al.@SIGIR’14[40], Jang et al.@BIGCOMP’15[41], Han et al.@IPL’17[51]
- Graph Model
  - **app co-occurrence graph:** Bae et al.@BIGCOMP’15[36], Yankov et al.@SIGIR’13[47]
  - **social graph:** Wei et al.@AAAI’11[44]
- Hidden Markov Model (HMM)
  - Zhu et al.@TOC’15[46]

Bae@BIGCOMP’15

Method overview for App recommend.

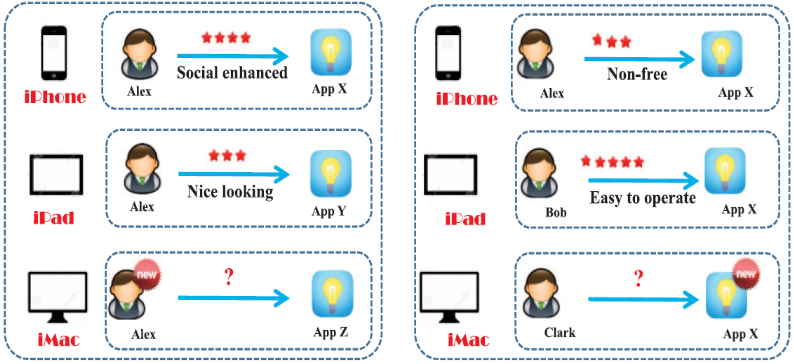
Solutions for user/app cold-start recommendations

- Collaborative Filtering (CF)
  - Davidsson et al.@IUI'11[38],
    Cao et al.@TOIS'17[48],
    Tu et al.@TMC'18[0]



Cao et al.@TOIS'17

- Topic Model
  - Lin et al.@SIGIR'13[29],
    Cao et al.@IS'17[50]



(a) new-user cold-start. (b) new-App cold-start.

Cao et al.@IS'17

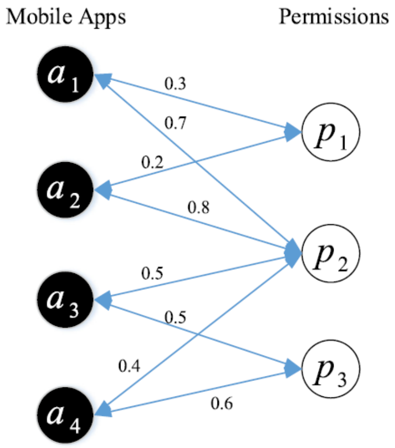
Method overview for App recommend.

Solutions for privacy preserving recommendations

- Collaborative Filtering (CF)
  - Peng et al.@WWW'18[38]
- Graph Model
  - Zhu et al.@KDD'14[42]

Solutions for novel and diverse recommendations

- Content based Filtering (CBF)
  - Bhandari et al.@IRT'13[28]
- Graph Model
  - Wang et al.@IAT'13[35]



Peng et al.@WWW'18

App Usage Prediction and Recommendation

Prediction

- Problem definition and Related Work
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- Deep learning for App prediction

Recommendation

- Problem definition for App recommend.
- Method overview for App recommend.
- Transfer learning for App recommend.

Transfer learning for App recommend.

Background

- Due to privacy concerns, app usage data is hard to obtain, which makes it hard to understand user interests and personalized app recommend..
- **Transfer Learning**: User profiles in social network (e.g., tweets) is abundant and easy to obtain, which may help to understand user interests.

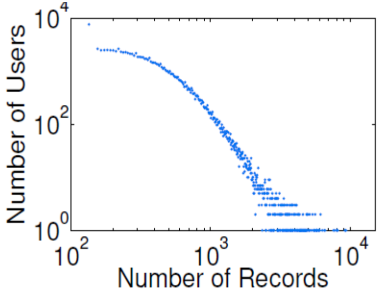
Zhen Tu, Yong Li, Pan Hui, Li Su, Depeng Jin, Personalized Mobile App Recommendation by Learning User’s Interest from Social Media, to appear in ***IEEE TMC 2019***.

Transfer learning for App recommend.

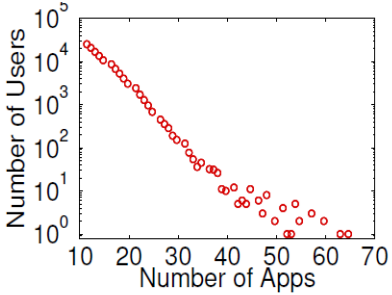
Datasets & Motivation

- app usage data

Location	Time Duration	Records	Users	Apps
Shanghai, China	20-26, April, 2016	9.4 billions	1.37 millions	2,000+



(a) Number of records per user

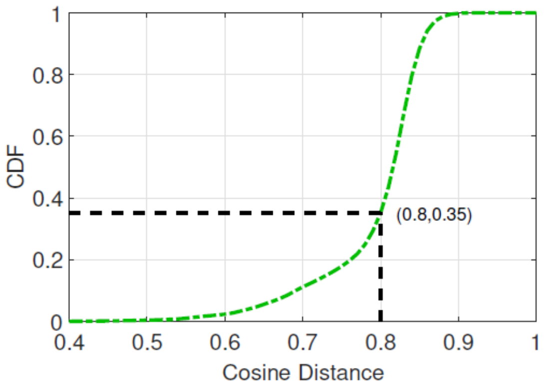


(b) Number of apps per user

- tweet info. by account linkage

Users	Tweets	Density
32,000	1.48 Million	46 tweets/user

- app sim. vector VS tweet sim. vector

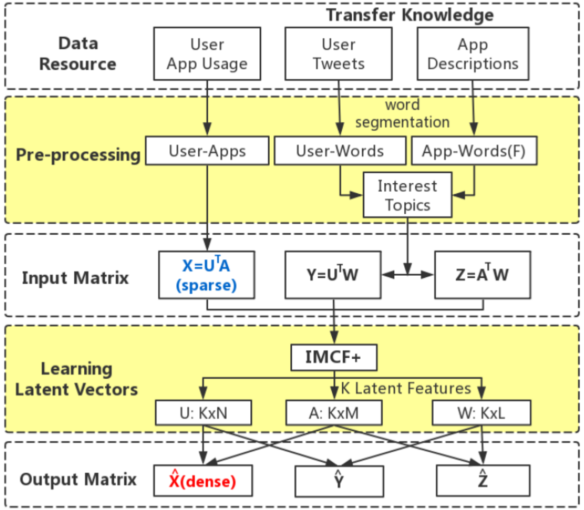


Individual app usage and their posted tweets are strongly correlated.
It is feasible to learn user interest from tweets to help personalized app recommendation

Transfer learning for App recommend.

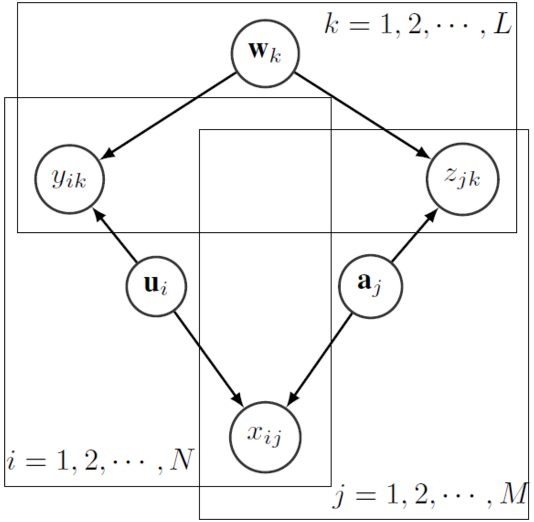
System Design

- Transfer Learning Framework



IMCF+: Interest-aware Matrix Co-Factorization Plus

- Generative Model

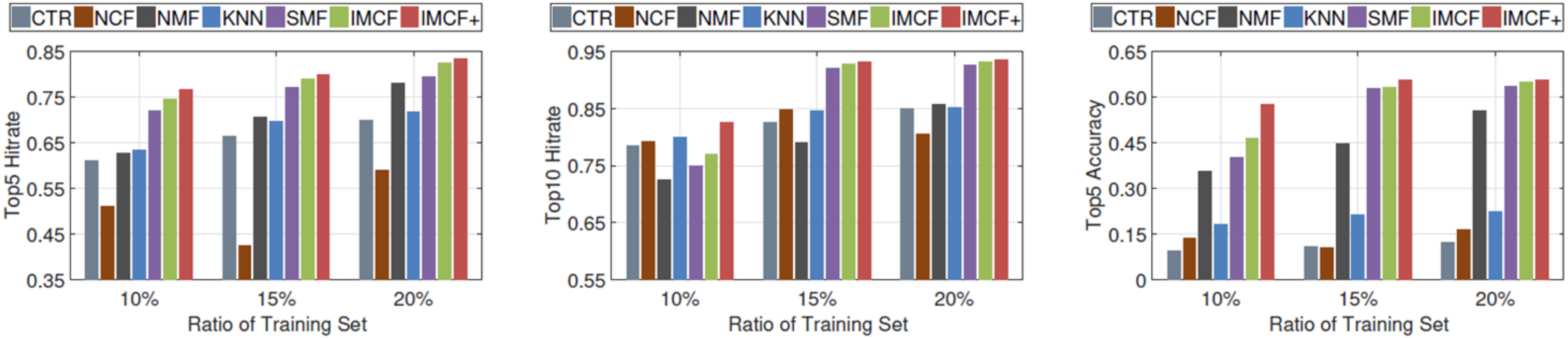


Graphical Representation

Transfer learning for App recommend.

Evaluation Results

- Performance in different sparsity levels



(a) Top5 Hitrate (b) Top10 Hitrate (c) Top5 Accuracy

Our IMCF+ system outperforms the other baselines under different sparsity levels. With 10% training data, our method gains at least 2.6% improvement in Top5 Hitrate than all the baselines.

Zhen Tu, Yong Li, Pan Hui, Li Su, Depeng Jin, Personalized Mobile App Recommendation by Learning User's Interest from Social Media, to appear in ***IEEE TMC 2019***.

Transfer learning for App recommend.

Evaluation Results

- Performance in solving user cold-start problems

Cold Start Problem		Top5 Hitrate			Top10 Hitrate		
Ratio of Training Users		10%	15%	20%	10%	15%	20%
Baselines	KNN	0.338	0.430	0.442	0.393	0.483	0.498
	CTR	0.445	0.447	0.445	0.625	0.588	0.62
Our Model	IMCF	0.493	0.540	0.577	0.600	0.636	0.673
	IMCF+	**0.527**	**0.587**	**0.629**	**0.649**	**0.717**	**0.773**

Our IMCF+ system performs very well in the cold start problem. With only 20% training users, our method achieves a 77.3% Top10 Hitrate, which gains at least 10% improvement.

Zhen Tu, Yong Li, Pan Hui, Li Su, Depeng Jin, Personalized Mobile App Recommendation by Learning User's Interest from Social Media, to appear in ***IEEE TMC 2019***.

User Profiling from the App Usage

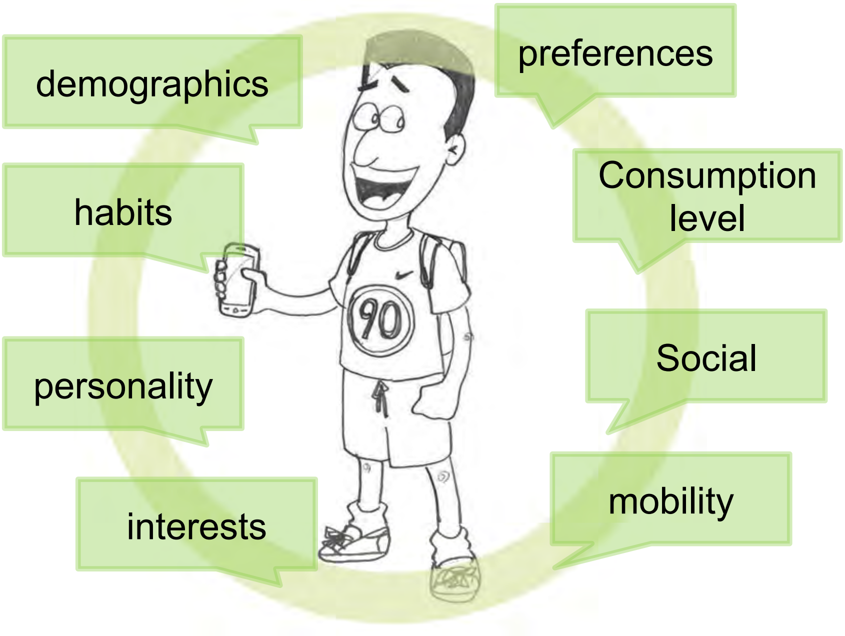
User Profiling from Their Use of Smartphone Applications

Sha Zhao
Zhejiang University
szhao@zju.edu.cn
http://www.shazhao.net

User profiling

- **What is user profiling?**
  - A process of analyzing user sensing data, exploring how data correlated with user personal information, and extracting key features to describe or infer user characteristics

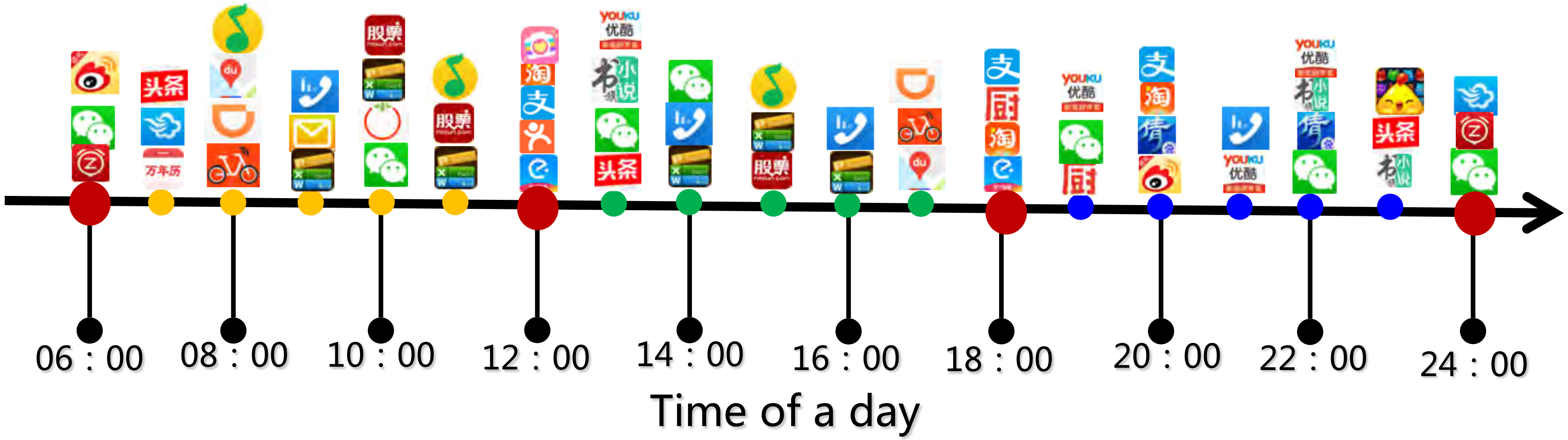
Smartphone apps



User profiles

Ubiquitous smartphones, ubiquitous apps

- **Apps：entry to access everyday life services**
  - Vast volume
  - Various types
  - Diverse usage



Apps provide us a new lens for user profiling

- **Apps convey rich personal information**
  - Users install and use apps depending on their needs and interests
  - A smartphone is tightly associated with a same person
  - Smartphones accompany users almost everytime and everywhere

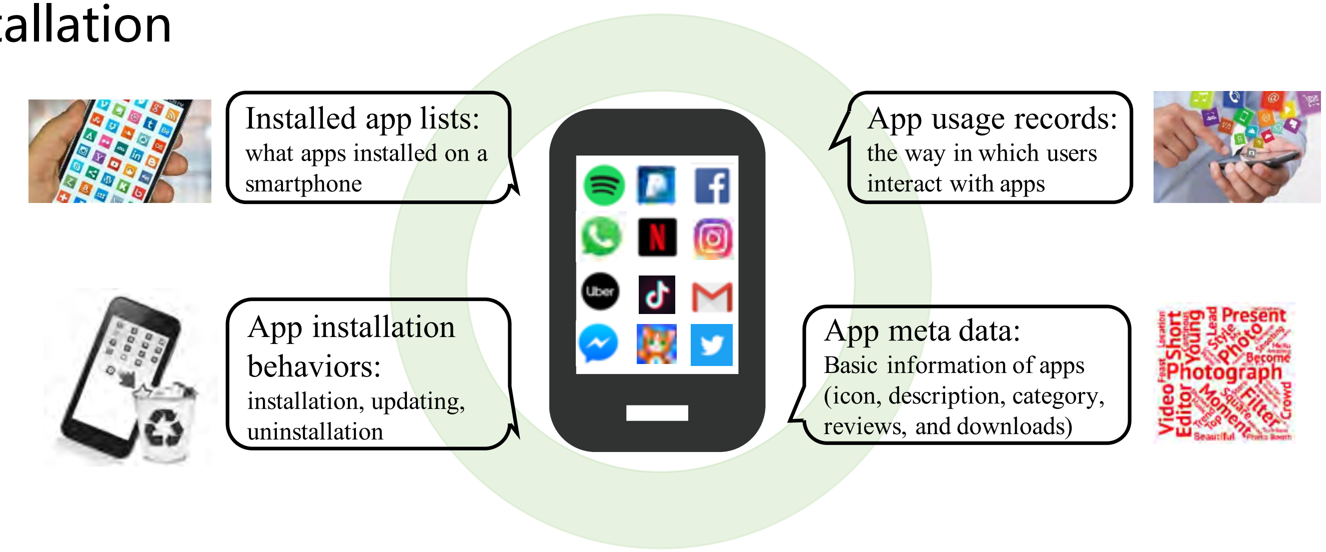
RoadMap

- App information for user profiling
- User information to profile
- User profiling framework
- Implications
- Challenges
- Several our research (Four work as examples)
- Future work and conclusion

Sha Zhao, et al. ***User Profiling from Their Use of Smartphone Applications: A Survey***. **Pervasive and Mobile Computing**, 101052, 2019

App information for user profiling

- **Roughly divide app data into four types:**
  - Installed app lists
    - What apps installed on a smartphone
  - App usage records
    - How users use apps
  - App installation behaviors
    - Installation, updating, uninstallation
  - App meta data
    - Basic information of apps



Some example app datasets

Table 1: Example app datasets

Type	Reference	Platform	#User	Duration	Description	Public
Installed app lists	Seneviratne et al. [48]	Android	231	-	Installed apps	N
	Wagner et al. [39]	Android	17,000	-	Installed apps	Y Device Analyzer[1]
App usage records	Kiukkonen et al. [34]	Nokia	200	1 year	App start and close events	Y MDC[2]
	Zhao et al. [13]	Android	106,672	1 month	Recent app task lists	N
App installation behaviors	Li et al. [20]	Android	0.8 M	1 month	Installation,update	N
	Frey et al. [29]	Android	2008	1 month	Installation logs	N
App description	Seneviratne et al. [7]	Android	218	-	App description	N
App categories	Zhao et al. [13]	Android	106,672	-	App categories	N

Some sensing framework:

Funf http://www.funf.org/about.html
AWARE https://awareframework.com
Carat project http://carat.cs.helsinki.fi/#

AppLens 2019 opens two datasets:

1) App usage dataset (Prof. Yong Li)
2) Long-term app usage: Carat (Prof. Sasu Tarkoma)

http://www.shazhao.net/applens2019/

[1] https://deviceanalyzer.cl.cam.ac.uk/collected.htm

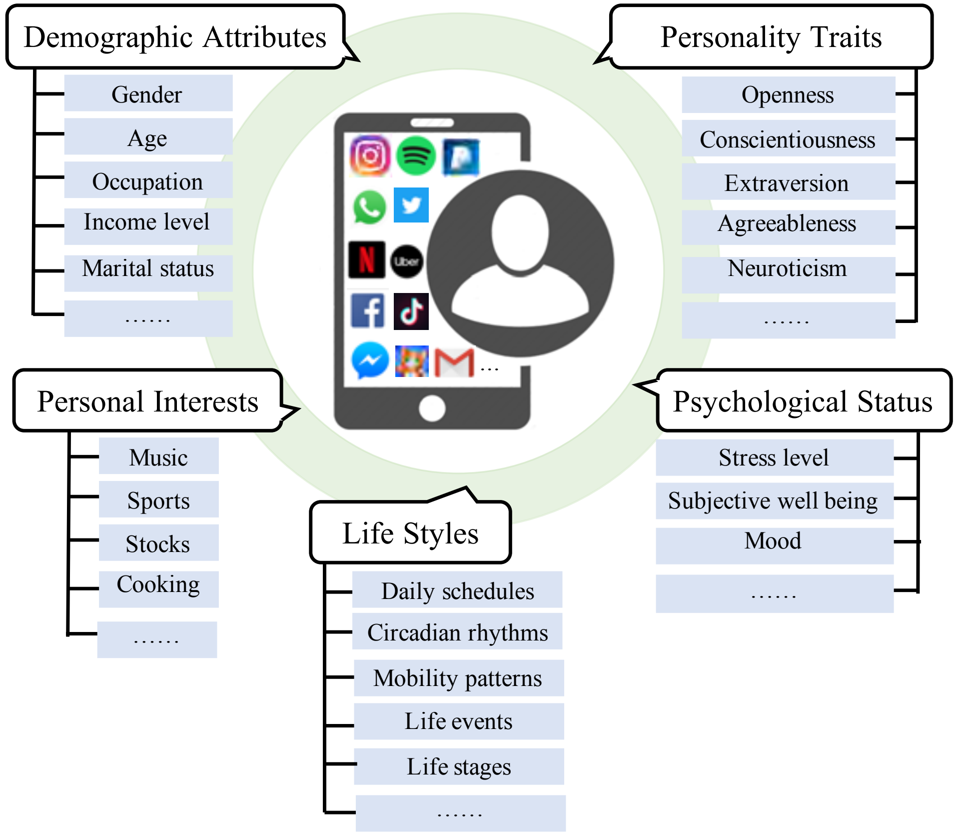
[2] https://www.idiap.ch/project/mdc/

Limitations of existing app datasets

- **Installed app lists**
  - Whether one user has installed an app may be a weak indicator of whether he/she really needs the app
- **App usage records**
  - Low sampling frequency, short duration, some apps (e.g. running in background, used offline or via WiFi network) are missed…
- **App installation behaviors**
  - Many users do not frequently update their apps or even let the OS automatically update apps
- **App meta data**
  - Reviews and rating can be quite sparse and even low-quality of some apps
  - The category assigned to the same one app may be different in different app stores
  - The description of some apps is rather limited

User information to profile

- **Based on the literature review, roughly summarize the types of user information into five categories:**
  - Demographic attributes
  - Personal interests
  - Personality traits
  - Psychological status
    - A state of psychological well being
  - Life styles



User profiling framework

- **Data collection**
- **Pre-processing**
  - Noise cleaning, data transformation, dimensionality reduction, user representation
- **Methods**
  - Descriptive statistics, regression, clustering, classification
- **User profiles**

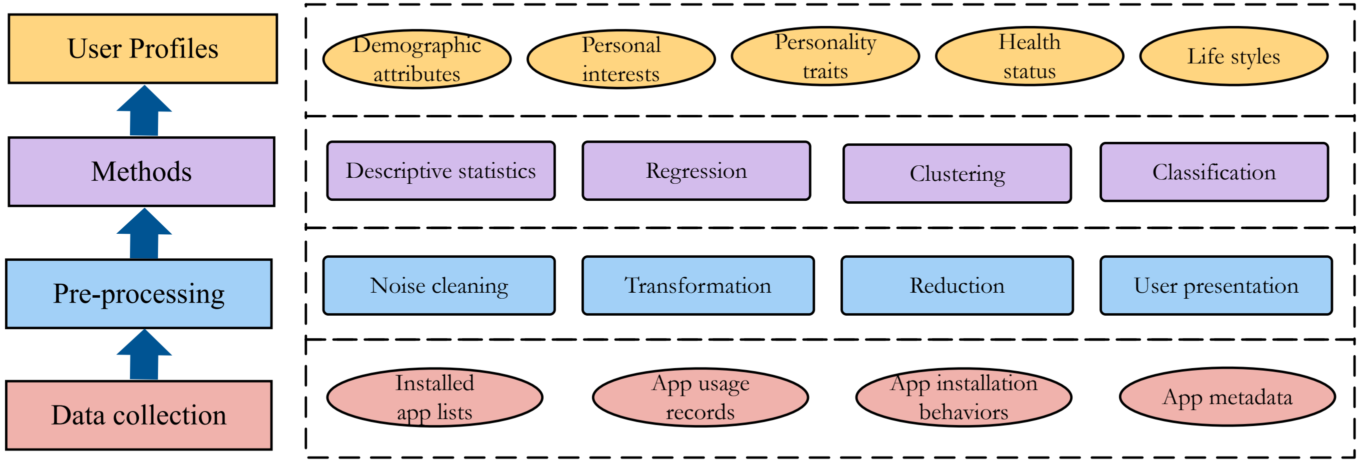


Fig. 1: A generic framework for user profiling from smartphone apps

Data collection

- **Three ways**
  - Designing specific collection tools, e.g., AppSensor [Bohmer et al, 2011], AppJoy [Yan et al, 2011]
    - Most on Android system
    - Distributed in app markets (e.g., Google Play)
    - Difficult to be widely applied by a variety of crowds
  - Sensing framework, e.g., Funf, AWARE [Ferreira et al, 2015], Carat project [Oliner et al, 2013], Device Analyzer [Wagner et al, 2014]
    - Relatively large-scale, and long duration
    - Data quality depending on how users use the collection tools
  - Data management platform developed by companies, to improve commercial services accordingly
    - Relatively large-scale

Pre-processing

- **Noise cleaning**
  - removes the noise that is irrelevant or meaningless to research goals
  - e.g., observation-based approach, distribution-based approach, and clustering-based approach
- **App data transformation**
  - Converts the raw data into understandable, unified, and ready-to-use form
  - e.g., extracting app usage records from recently task lists [Zhao et al, 2016], detecting app usage records from the internet entries [Qin et al, 2018]
- **Dimensionality reduction**
  - Reduces the number of variables input to minimize the data amount
  - e.g., using categories instead of apps, selecting top important apps or key words from app description

Methods

- **Summarize and roughly divide the methods into four categories:**
  - Descriptive statistics
    - Basic statistical assumptions (e.g., average, variance), to depict physical laws or patterns of user characteristics
  - Regression
    - Modeling the relationship between apps and users
      - Quantifying the strength of the relationship between apps and users
      - Fitting a predictive model to the given user characteristic using app data
  - Clustering
    - Discovering user groups based on their similarity
  - Classification
    - Identifying which category of a given user characteristic each individual belongs to
    - SVM, Bayesian models, Decision tree, kNN, Logistic regression, Neural networks, Ensemble learning (e.g., Random forest, GBDT)

Methods

Table 2: Literature survey in profiling users from smartphone apps

	Reference	Data	#User	Duration	User information	Method	Result
Descriptive statistics	Andone et al. [82]	AppUsage records	30,677	28 days	Differences in gender and age	Statistics	-
	Peltonen et al. [83]	AppUsage records	3,293	1 year	Country differences	Correlation	-
	Lim et al. [47]	Installation behaviors	4,824	2 months	Country differences	Correlation	-
	Murnane et al. [84]	AppUsage records	20	40 days	Circadian rhythms	Correlation	-
	Welke et al. [85]	AppUsage records	46,726	2 years	User differentiating	Hamming-distance	-
	Frey et al. [79]	App installation behaviors	2 008	1 month	life events	Keyword-based classifier	65%
	De Reuver et al. [41]	App usage records	233	28 days	Everyday routines	Correlation	-
Regression	Unal et al. [86]	AppUsage records	285	-	Big-Five personality	Regression Analysis	-
	Xu et al. [56]	App installation behaviors	22	1 month	Big-five personality	Linear regression	60%
	LiKamWa et al. [57]	AppUsage records	32	2 months	Mood	Linear regression	93%
	Gao et al. [58]	AppUsage records	106	-	Subjective well being	Linear regression	62%
Clustering	Zhao et al [13]	AppUsage records	106,762	30 days	User groups	k-means+ Meanshift	382 user groups
	Lee et al. [87]	AppUsage records	180	-	User groups	GMM	10 user groups
	Jesdabodi et al. [38]	AppUsage records	24	3 months	Users' current activity identifying	k-means	13 activities
	Amoretti et al. [60]	AppUsage records	100	2 months	Mobility	k-means	-
Classification	Seneviratne et al. [7]	Installed App lists	218	-	Gender	SVM	70%
	Seneviratne et al. [48]	Installed App lists	231	-	Religion, country...	SVM	Precision > 90%
	Zhao et al. [19]	Installed App lists	100,281	-	12 predefined traits	SVM	EER: 16.4%
	Ferdous et al. [88]	AppUsage records	28	6 weeks	5 stress levels	SVM	75%
	Malmi et al. [51]	UsedApp lists	3 760	1 month	Gender; Age(18–32 *vs.* 33–100) Race ...	Logistic regression	82% 77% 73% ...
	Chittaranjan et al. [52,89]	AppUsage records (MDC)	83	18 months	Big-Five personality	C4.5	76%
	Qin et al. [8]	AppUsage records	32,660	4 months	Gender 5 age groups	Bayes-based classifier	81% 74%
	Zhao et al. [90]	AppUsage records	10,000	3 months	Gender 3 Income levels	Neural networks	82% 64%
	Frey et al. [29]	InstalledApp lists	1,453	-	Life stages	Random forest	85%
	Mo et al. [16] Brdar et al. [73] Ying et al. [17]	AppUsage records (MDC)	83	1 year	Gender, Marital status, Age group, Job type	RandomForest, SVM, GBDT, KNN, multi-level classifier	88% 61% 81%

- Data scale varies from 20 users to over 100,000 users
- Data duration varies from 28 days to around 2 years
- App usage records have been used most (17 out 0f 28), and app description and categories
- Classification methods have been used most (13 out of 28)

Implications

- **Commercial services**
  - Targeted advertisement and smart services
  - Commercial user profiling services
    - Devoted to profile customers by leveraging their historical data, such as Data Management Platforms (DMPs)
- **Mobile apps and smartphones**
  - Design and popularity of mobile apps
    - From the view of app developers and designers
  - App store management
    - From the view of app store operators
  - Design and popularity of smartphones
    - From the view of smartphone manufacturers, mobile carriers
- **Mobile context-aware tools**
  - User characteristics learned from smartphone apps could be used by other mobile context-aware tools to improve users' life quality
  - E.g., health monitoring tools, analyzing health status and present feedback to users

Challenges

- Challenges in data
- Challenges in user representation and modeling
- Challenges in fusion of heterogeneous data
- Challenges in user privacy

Challenges in data

- **Data collection**
  - It is hard to collect a *large-scale dataset* in practice
  - The issue of *population bias*
  - Some datasets are based on *only one kind of operation system*
- **Groundtruth collection**
  - Difficult to collect *a large-scale groundtruth dataset* due to privacy concerns
- **Data processing**
  - Data noise, data redundancy, data sparsity, imbalanced data distribution

Challenges in user representation and modeling

- **To enhance the effectiveness of the models**
  - How to automatically find out key features
- **To determine the appropriate performance metrics**
  - How to make a good trade-off between different metrics?
  - How to measure the performance of unsupervised methods?
- **To interpret some results**
  - Many analyses have only correlation instead of causation
- **To generalize findings across studies**
  - Due to different populations, different OSes, different experiment environments

Challenges in fusion of heterogeneous data

- **Fusion of different types of app data**
  - Different app data in different format
- **Fusion of other sources and app data**
  - The data from different sources are stored in different structures, e.g., image, text, video, and audio
- **Difficulty in combining different data sources**
  - How to discover the relationship between different data sources?
  - How to combine one data type with other types?
  - How to decide which combined feature is more important?
  - ....

Challenges in user privacy

- **How to protect user privacy? Suggestions**
  - App publishers make the app transparent to corresponding app users
  - Users should be given rights to opt-in for providing the data
  - Phone systems provide user rights to control which capabilities or information that an installed app can access-known as permissions
  - App markets could reinforce policies for app publishers

Several Our Research

- **Discovering user groups**
  - UbiComp 2016
- **Mining individual user attributes**
  - IEEE Trans. On Industrial Informatics, 2019
- **Modeling app usage behaviors**
  - ICDE 2019

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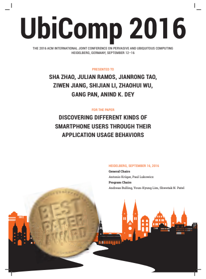
Work 1

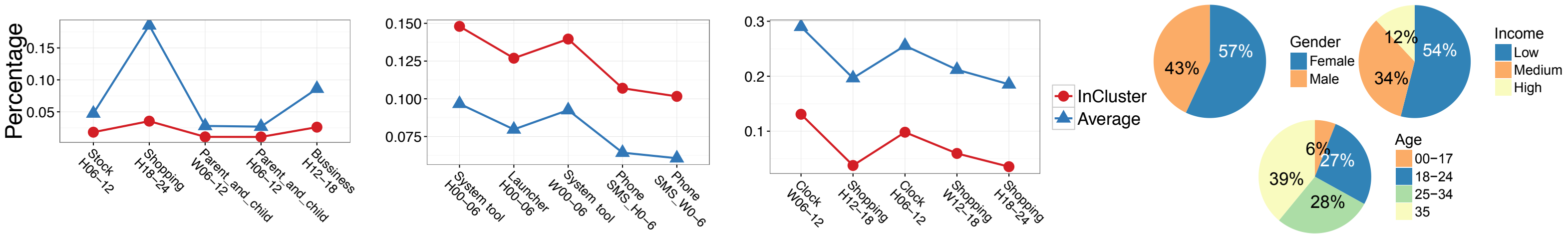
Discovering Different Kinds of Smartphone Users Through Their Application Usage Behaviors

Sha Zhao, Julian Ramos, Jianrong Tao, Ziwen Jiang, Shijian Li, Zhaohui Wu, Gang Pan, Anind Dey



ACM UbiComp 2016

Best Paper Award



(a)Top 5 general features

(b)Top 5 highest idiosyncratic features

(c)Top 5 lowest idiosyncratic features

(d) Proportion of users in each demographic attribute

App usage records

- **Which app is used**
- **When**
- **How often**
- **How long**

semantics

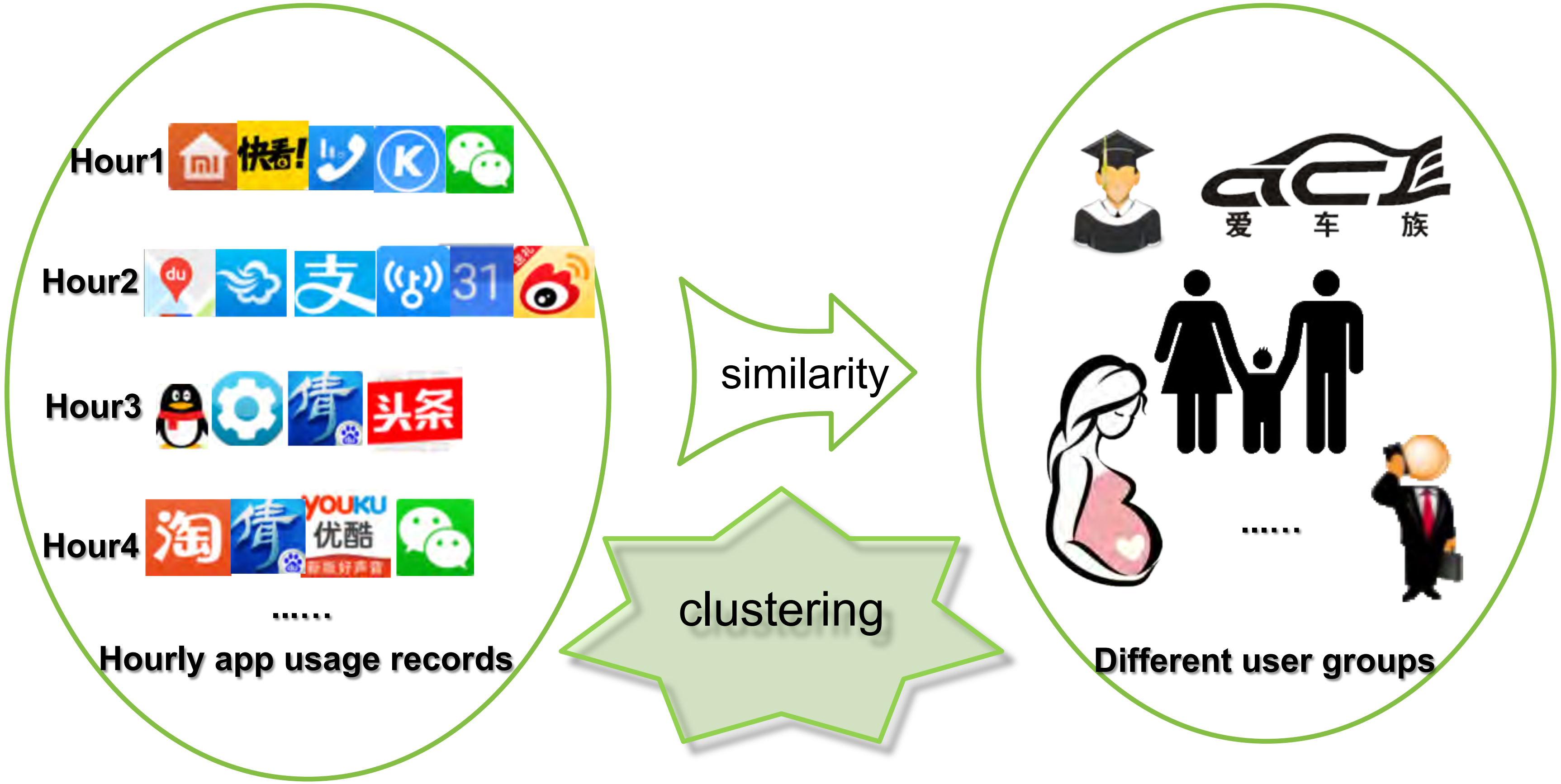
Temporal context

App usage records indicate the activities performed




Problem

- **To discover user groups from app usage records**



Dataset

- **The dataset contains lists of recent apps used on Android smartphones:**
  - Around 100,000 unique smartphones (users) from China, 80,000 unique apps
  - About 53 millions records
  - 30days : September 2015
  - Collected approximately every hour
  - Each user's gender, age range and income level

Table 5. Sample of lists of recent app tasks in the dataset

User ID	Time	The List of Recent App Tasks
0000751aecb005a2	2015/9/1 9:09	com.android.calendar, com.tencent.mobileqq, com.moji.mjweather
0000751aecb005a2	2015/9/1 10:09	com.miui.home, com.android.incallui, com.android.calendar, com.moji.mjweather

Table 6. User distribution in each demographic

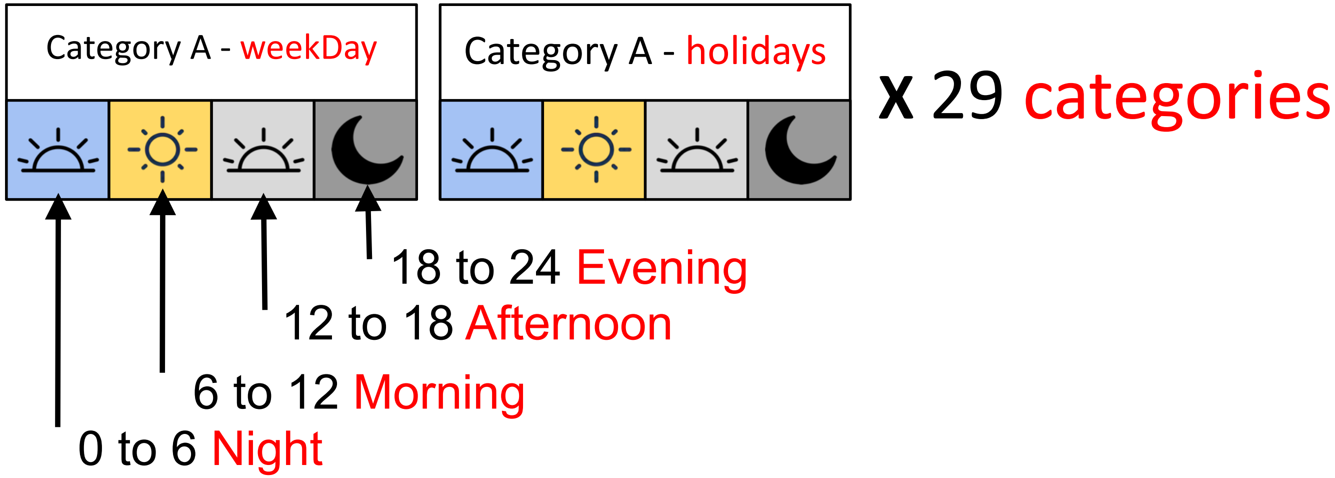
Proportion of users in each demographic attribute								
Gender		Age range				Income level		
Female	Male	0-17	18-24	25-34	35+	Low	Medium	High
0.59	0.41	0.05	0.37	0.36	0.22	0.31	0.38	0.31

Pre-processing

App **A** for user **C**

0.1	0.0	0.0	0.0	0.0		0.8
0 to 1	1 to 2	2 to 3	3 to 4	4 to 5	……	23 to 24

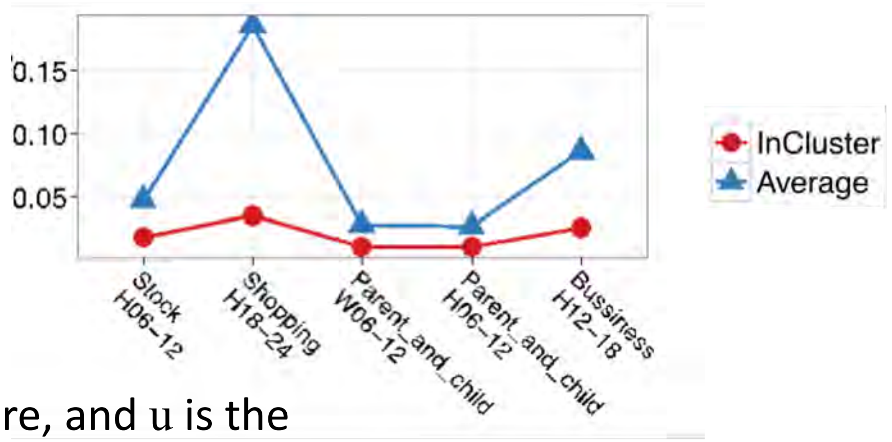
- **App usage weighting**
  - Compute app usage weight in each hour slot
- **App categorization**
  - Categories have an inherent semantic meaning (29 categories)
- **User representation**
  - Each dimension is the usage percentage of one category in a corresponding time periods (232 dimensions)



Clustering

- **Two-step clustering**
  - Cluster users using Kmeans
  - Take the centroids produced on the previous step and run Mean-Shift
- **Performance measure**
  - Considering clusters with uniform size, compactness and separation
- **Feature selection**
  - Help distinguish each cluster from the "average user" across all clusters

$$r_{ij} = \frac{c_{ij} - u_{ij}}{\max\limits_{j \in J}(|c_{ij} - u_{ij}|)}$$



Where c is the ***i***th centroid's value on the ***j***th feature, and u is the corresponding average value for all users

Results

- **382 user clusters**
  - Most clusters consist of 100-300 users
  - The centroids of clusters were nicely separated

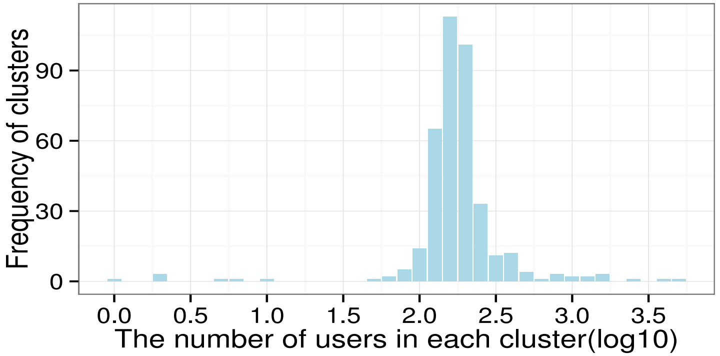


Fig. 13 Quantity of clusters with respect to number of users.

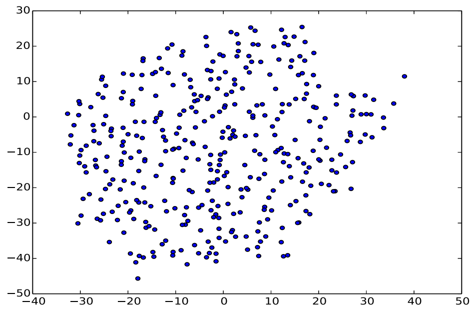
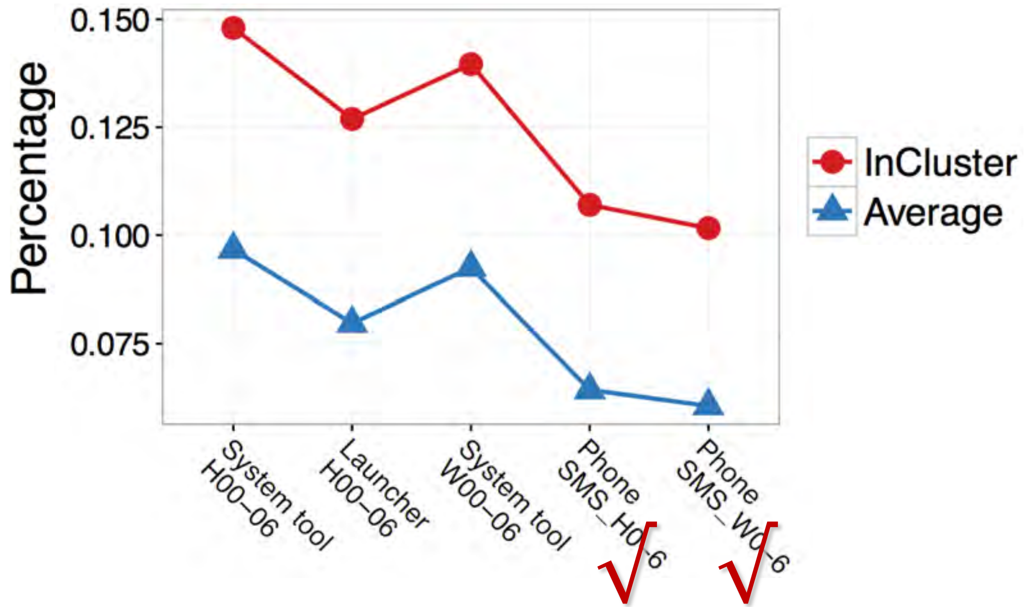
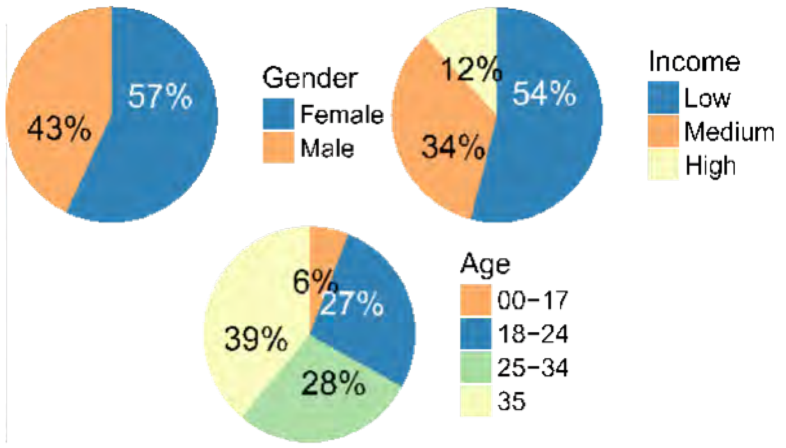


Fig. 14 t-SNE representation of the centroids

The biggest cluster (4981 users, Night communicators)



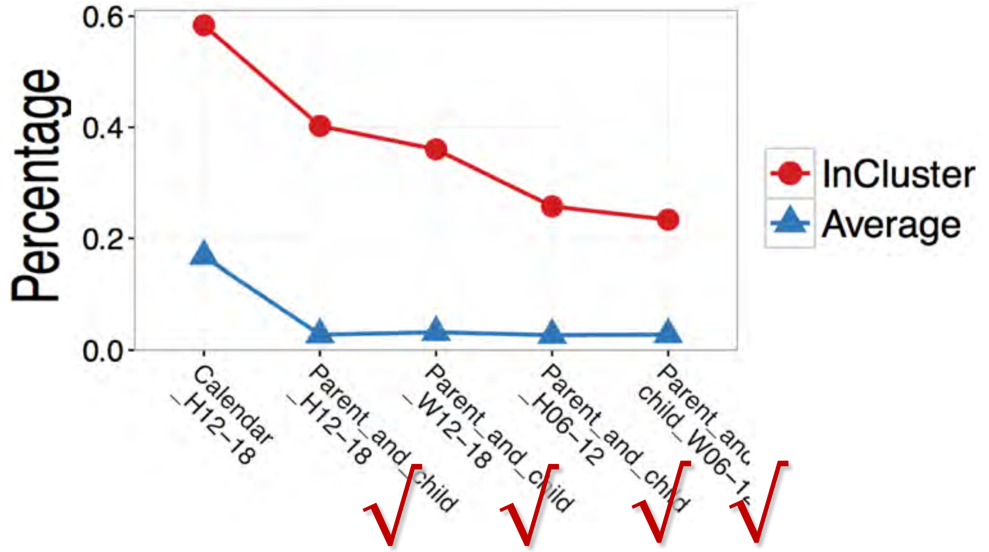
Top 5 highest idiosyncratic features



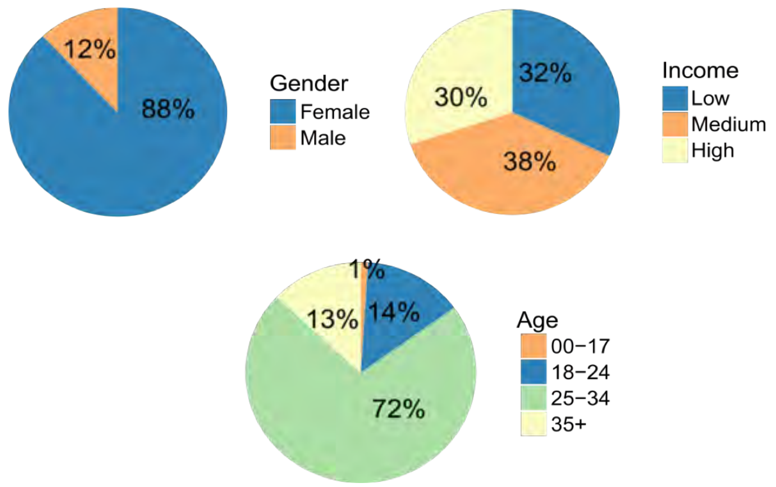
Proportion of users in each demographic attribute

Compared with "average user", the users in this cluster use Phone and SMS in from midnight to 6am more frequently

One small cluster (164 users, Young parents)



Top 5 highest idiosyncratic features



Proportion of users in each demographic attribute

Compared with "average user", the users in this cluster use apps related to parent and child more frequently

Several Our Research

- **Discovering user groups**
  - UbiComp 2016
- **Mining individual user attributes**
  - IEEE Trans. On Industrial Informatics, 2019
- **Modeling app usage behaviors**
  - ICDE 2019

Work 2

Gender Profiling from a Single Snapshot of Apps Installed on a Smartphone: An Empirical Study

Sha Zhao, Yizhi Xu, Xiaojuan Ma, Ziwen Jiang, Zhiling Luo, Shijian Li, Laurence T. Yang, Anind Dey, Gang Pan

IEEE Transactions on Industrial Informatics 2019

Research questions

- **To investigate the correlation between gender and apps installed on a smartphone:**
  - RQ1: what differences between females and males can be explored from installed app lists?
  - RQ2: Can gender be reliably inferred from a snap shots of apps installed? Which snapshot pictures are the most predictive? Which is the best combination of features?
  - What are the limitations of gender prediction model based solely on a snapshot of apps installed on a smartphone?

Installed app lists

- **15,000 smartphone users from China, 7,500 females and 7,500 males**
- **Each record consists of a:**
  - User ID (anonymized)
  - Gender
  - Installed app list: each list consists of app package names that are used to identify installed apps

Gender differences

- **The differences in the number and popularity**
  - Males install about 5 more apps than females on average
  - Beauty-related apps attract more female users, while users of system tool and car apps are mostly male.

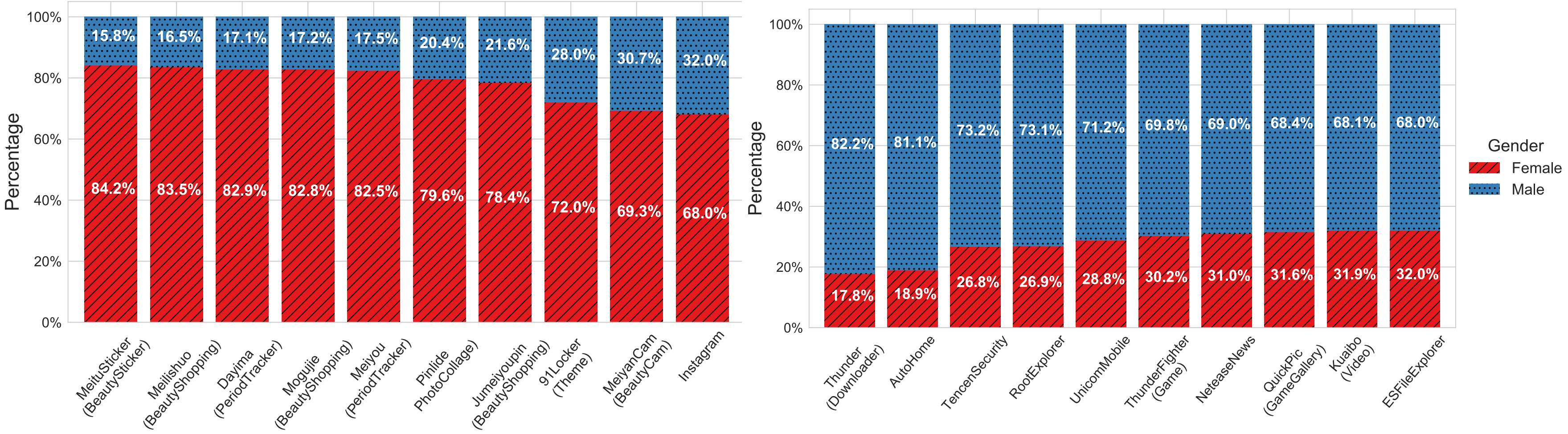


Fig. 8 The top 10 popular apps for (a) females and (b) males

Gender differences

- **The differences in app functions**
  - Apply LDA (Latent Dirichlet Allocation) to extract topics from app description text and each topic indicates a core function
  - Females are interested in apps that improve their look and feel, while males like apps that improve their access to the world

$p_M = 0.00765$, $p_F = 0.01629$ | $p_M = 0.00263$, $p_F = 0.01126$ | $p_M = 0.00614$, $p_F = 0.01454$ | $p_M = 0.00542$, $p_F = 0.01071$ | $p_M = 0.00159$, $p_F = 0.00653$

(a) The top 5 topics for female users.

$p_M = 0.06597$, $p_F = 0.01923$ | $p_M = 0.04529$, $p_F = 0.00105$ | $p_M = 0.01143$, $p_F = 0.00851$ | $p_M = 0.01134$, $p_F = 0.00855$ | $p_M = 0.01035$, $p_F = 0.00767$

(b) The top 5 topics for male users.

Fig. 9 The word clouds of the top 5 topics apps for (a) females and (b) males.

Gender differences

- **The differences in app functions**
  - Within the same app category, females and males have different preferences to apps

F

M

(a) Photography_and_Beauty (b) Health_and_fitness (c) Media_and_video (d) SON_and_IM (e) Shopping

Fig. 10 The word clouds of the 5 popular categories for (a) females and (b) males

Gender differences

- **The differences in app icons**
  - Females have more in pink, while males install more apps in different shades of blue.

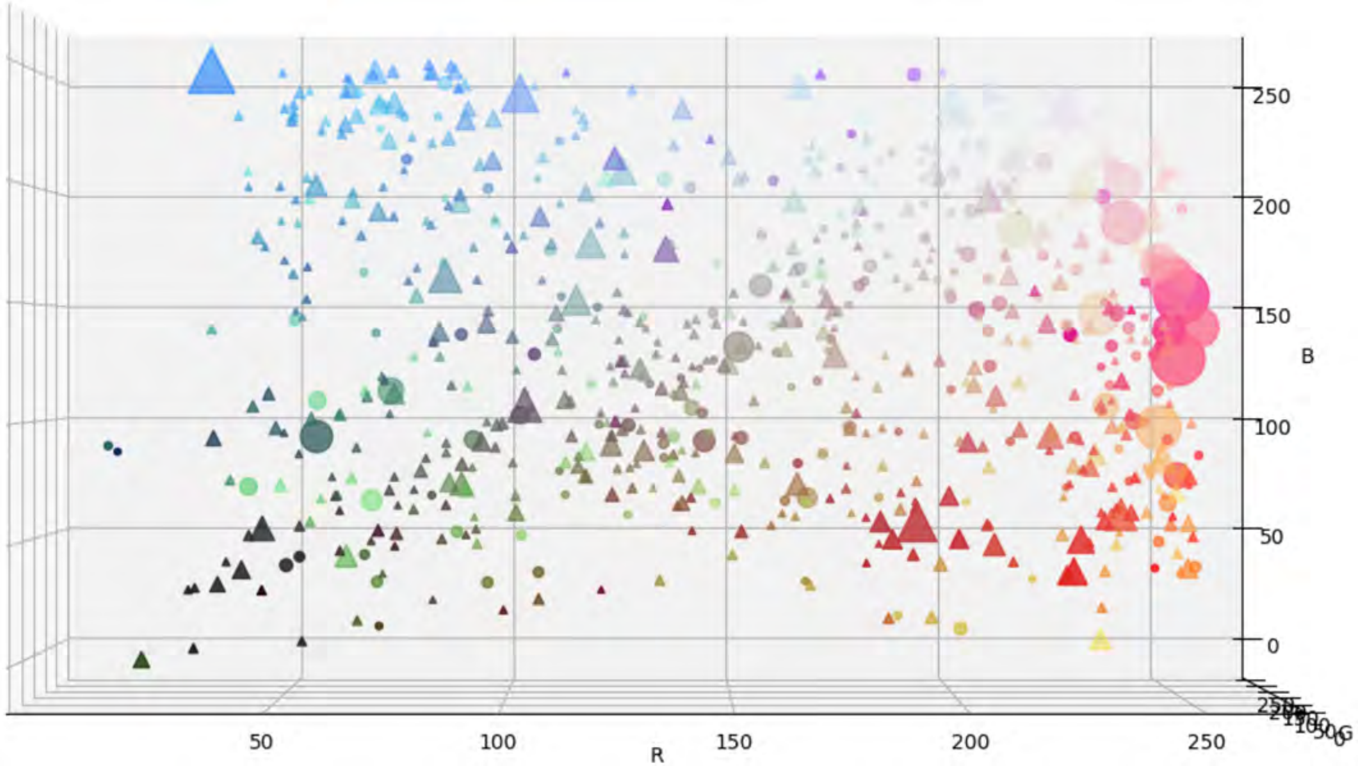


Fig. 11 The top 1000 apps mapped into RGB space (‘△’ : male, ‘o’: female)

Gender predictive ability

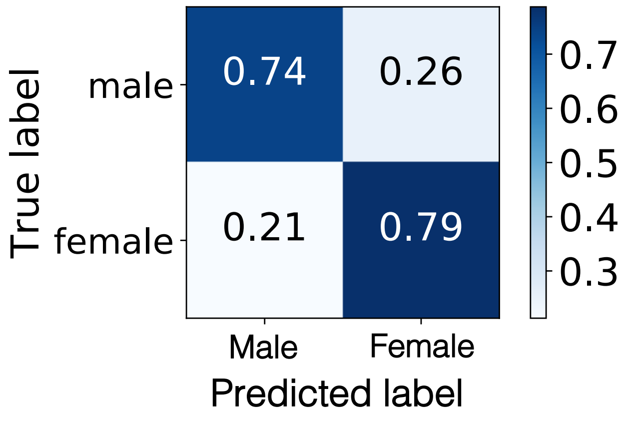
- **Extracting features based on the gender differences**
  - app-, topic-, category-, tag-, and icon-based features
  - Combination of any two feature types
- **Prediction results**
  - Accuracy: 76.62%, AUC: 0.84, F1: 0.77
  - Combination of app- and topic-based feature performs best, DNN model
  - Combination of features cannot contribute significantly

Table 4 Gender prediction results

Feature	Model	ACC	AUC	F1	Feature	Model	ACC	AUC	F1
App (1000)	SVM	0.7427	0.8202	0.7364	App+Icon (1064)	SVM	0.7419	0.8184	0.7383
	LR	0.7450	0.8213	0.7427		LR	0.7457	0.8212	0.7437
	GBDT	0.7470	0.8176	0.7341		GBDT	0.7421	0.8118	0.7323
	DNN	**0.7655**	**0.8424**	**0.7654**		DNN	0.7659	0.8414	0.7726
Topic (300)	SVM	0.7355	0.7969	0.7456	Topic+ Category (329)	SVM	0.7353	0.8039	0.7420
	LR	0.7306	0.7909	0.7392		LR	0.7357	0.7984	0.7404
	GBDT	0.7399	0.8034	0.7394		GBDT	0.7429	0.8072	0.7393
	DNN	0.7446	0.8122	0.7445		DNN	0.7411	0.8027	0.7338
Category (29)	SVM	0.6919	0.7580	0.6910	Topic+Tag (600)	SVM	0.7378	0.7963	0.7467
	LR	0.6907	0.7545	0.6828		LR	0.7361	0.7984	0.7404
	GBDT	0.6977	0.7594	0.6894		GBDT	0.7315	0.7945	0.7226
	DNN	0.6987	0.7432	0.6977		DNN	0.7187	0.7890	0.6994
Tag (300)	SVM	0.7240	0.7908	0.7231	Topic+Icon (364)	SVM	0.7378	0.7963	0.7467
	LR	0.7267	0.7965	0.7269		LR	0.7347	0.7965	0.7396
	GBDT	0.6881	0.7523	0.6812		GBDT	0.7443	0.8068	0.7362
	DNN	0.6987	0.7432	0.6977		DNN	0.7422	0.7992	0.7399
Icon (64)	SVM	0.6885	0.7412	0.6984	Category+ Tag (329)	SVM	0.7297	0.7984	0.7289
	LR	0.6927	0.7286	0.6912		LR	0.7318	0.8009	0.7305
	GBDT	0.6813	0.7470	0.6748		GBDT	0.7121	0.7730	0.7036
	DNN	0.6865	0.7357	0.6812		DNN	0.6901	0.7595	0.6923
App+Topic (1300)	SVM	0.7437	0.8194	0.7421	Category+ Icon (93)	SVM	0.7147	0.7762	0.7196
	LR	0.7453	0.8215	0.7438		LR	0.7096	0.7680	0.7098
	GBDT	0.7505	0.8181	0.7453		GBDT	0.7183	0.7820	0.7107
	DNN	**0.7662**	**0.8423**	**0.7661**		DNN	0.7081	0.7717	0.7211
App+ Category (1029)	SVM	0.7419	0.8174	0.7393	Tag+Icon (364)	SVM	0.7292	0.7968	0.7318
	LR	0.7446	0.8215	0.7419		LR	0.7290	0.7972	0.7304
	GBDT	0.7441	0.8126	0.7362		GBDT	0.7086	0.7734	0.7004
	DNN	0.7642	0.8424	0.7702		DNN	0.6964	0.7645	0.7056
App+Tag (1300)	SVM	0.7444	0.8181	0.7415	All (1693)	SVM	0.7445	0.8182	0.7437
	LR	0.7466	0.8217	0.7442		LR	0.7465	0.8217	0.7450
	GBDT	0.7323	0.7959	0.7186		GBDT	0.7423	0.8081	0.7335
	DNN	0.7630	0.8357	0.7696		DNN	**0.7655**	**0.8431**	**0.7653**

Error analysis

- **26% of males are misclassified as females, and 21% of females are misclassified as males**
- **The users that were classified as females install more female apps than the users inferred as males, and install fewer male apps**



	Apps	Proportion of the users in each predicted group installing the app			
		Male → Female	**Male → Male**	**Female → Male**	**Female → Female**
1	Mogujie-BeautyShopping	8.99%	0.50%	1.00%	16.21%
2	Meitu-Photography	37.67%	22.88%	19.42%	52.35%
3	Meilishuo-BeautyShopping	6.62%	0.25%	0.50%	12.08%
4	AutoHome-Car	1.60%	13.51%	7.21%	1.15%
5	Meiyou-PeriodTracker	5.63%	0.63%	1.25%	11.13%
6	Meiyan-BeautyCam	16.28%	6.11%	5.95%	23.41%
7	360-BeautyCam	18.04%	9.90%	9.77%	27.30%
8	Meipai-BeautyMV	16.69%	8.95%	6.83%	25.91%
9	Kuaibo-Video	5.94%	23.47%	16.10%	6.94%
10	Adobe FlashPlayer	12.45%	34.91%	21.67%	15.77%

Fig. 12 Error analysis: (a) confusion matrix, (b) Proportion of users in each predicted group installing the app

Several Our Research

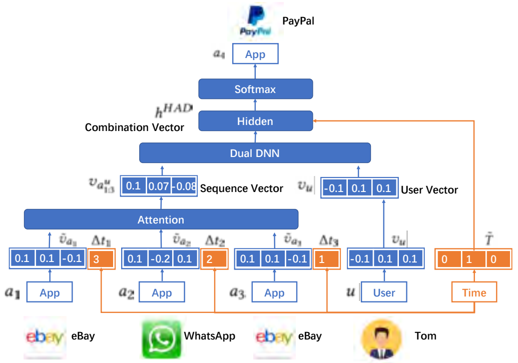
- **Discovering user groups**
  - UbiComp 2016
- **Mining individual user attributes**
  - IEEE Trans. On Industrial Informatics, 2019
- **Modeling app usage behaviors**
  - ICDE 2019

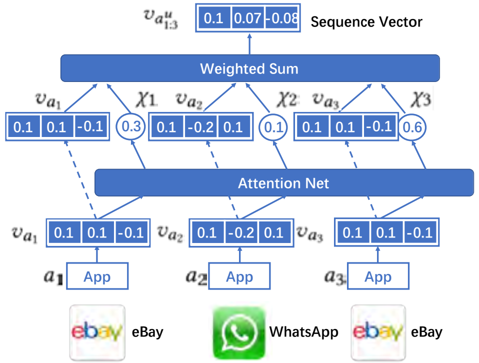
Work 3

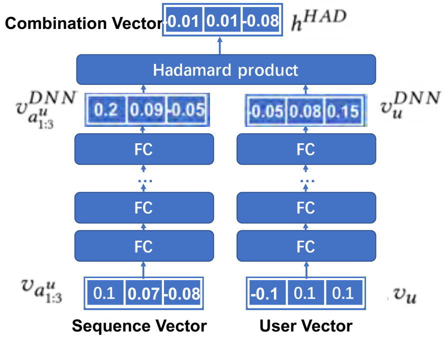
AppUsage2Vec: Modeling Smartphone App Usage for Prediction

Sha Zhao, Zhiling Luo, Ziwen Jiang, Haiyan Wang, Feng Xu, Shijian Li, Jianwei Yin, Gang Pan

The 35th IEEE International Conference on Data Engineering (ICDE2019)







Problem description

- **Given an observed sequence consisting of n most recently used apps, predict the next app that the user u most likely to use:**
  - outputs the probability distribution over all candidate apps

$$p(\cdot \mid a^u_{r-n}, a^u_{r-n+1}, \cdots, a^u_{r-1}, u)$$

- **Top k app**
  - Top k apps with the highest probability

44

Problem reduction

- **The next app depends on the sequence of recently used apps**
  - The correlation between sequentially used apps has a strong contribution to the accuracy of app prediction [6]
- **User personalization characteristics is important for app usage**
  - Preferences, needs, etc.

Reduce Doc2Vec to app usage prediction

Problem reduction

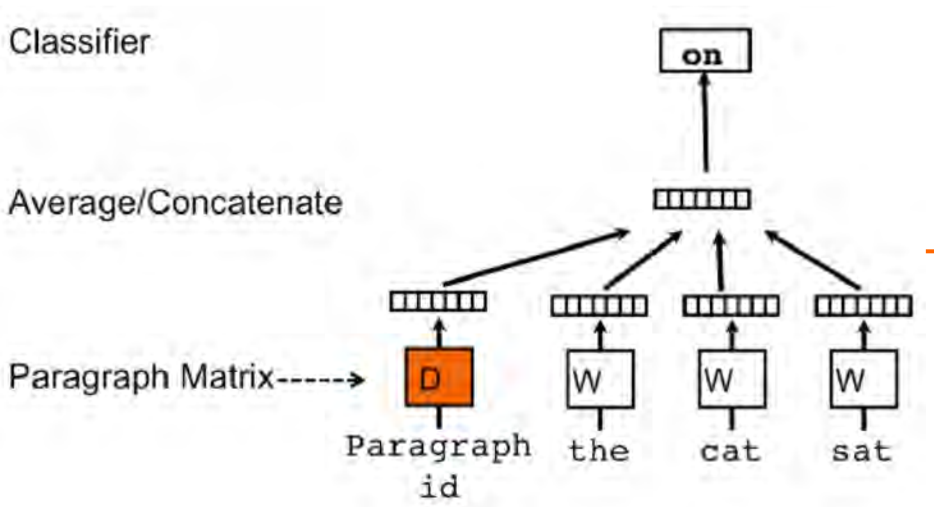


Fig. 15 Doc2Vec

- **Doc2Vec:**
  - Predicting the next word (app) by exploring a paragraph (user) and a sequence of words (apps) in a given context in the paragraph (user)

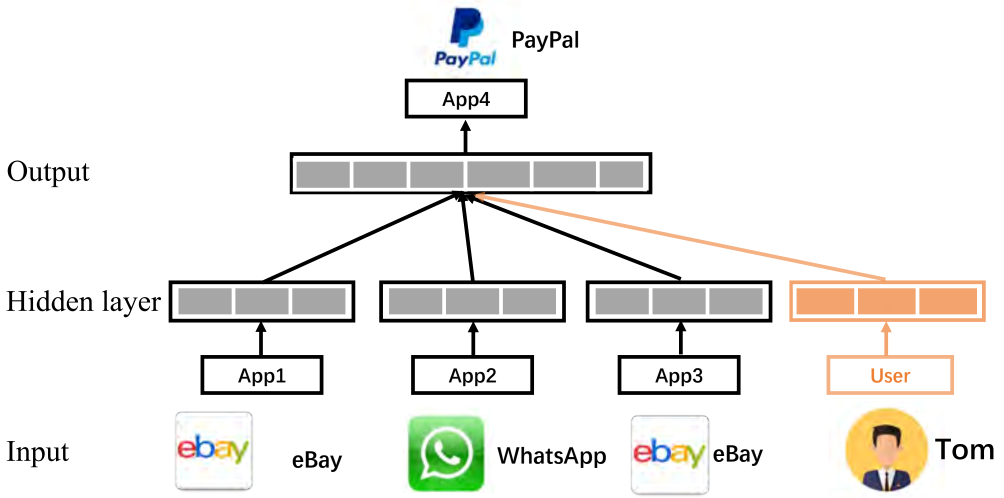


Fig. 16 Doc2Vec used in app usage

Major limitation of Doc2Vec

- **Apps in a given historical sequence are treated equally for the target app**
  - Drop-in apps are of less significance
  - Existing models hardly capture users' intention, especially in the scenarios of drop-in apps

AppUsage2Vec Overview

- **App-attention mechanism**
  - Measure the contribution of different apps to the target app
- **Dual-DNN module**
  - Deeply encode the user personalization characteristics
- **Temporal context**
  - Take the temporal context into account

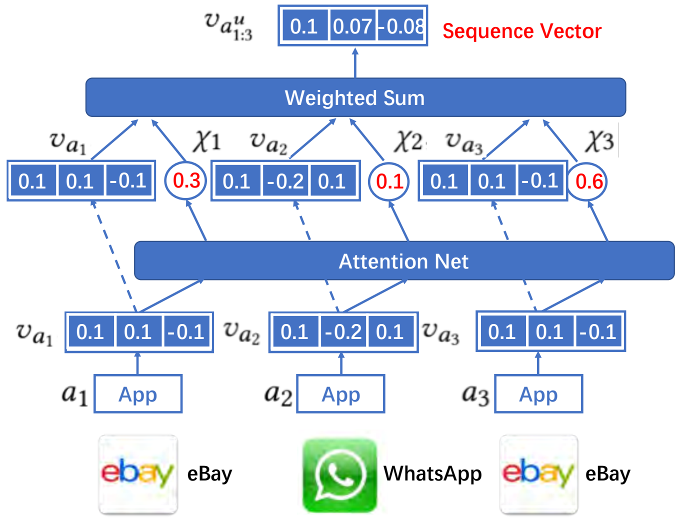


Fig. 17 App-attention mechanism

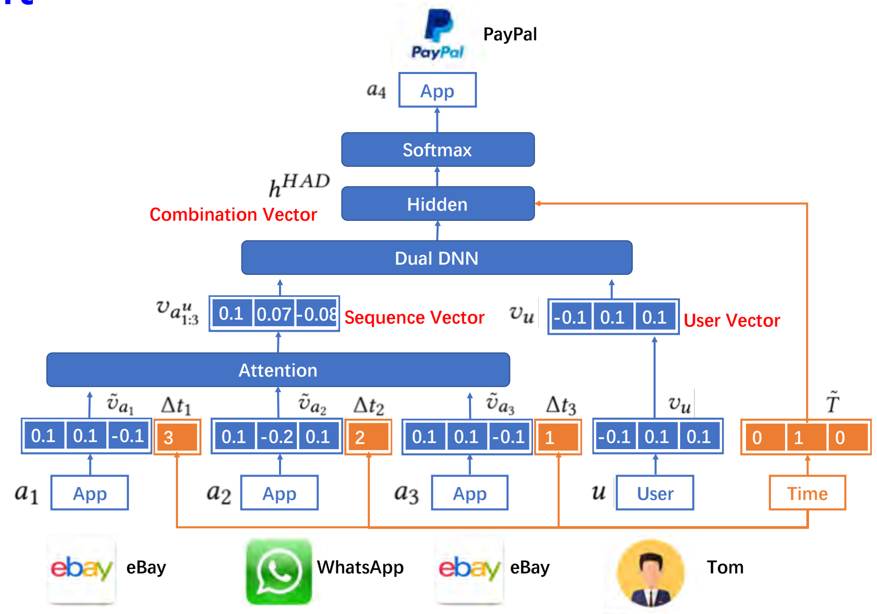


Fig. 18 AppUsage2Vec

Dataset

- **10,360 smartphone users from Zhejiang Province, China**
- **Aug. 23th, 2017 to Nov. 23th, 2017**
- **46,434,380 App usage records**
  - Anonymized ID of each smartphone
  - The start time stamp
  - The user-agent field of client
- **User privacy**
  - User ID was anonymized
  - Strict non-disclosure agreement
  - The dataset is located in a secure off-line server

Comparison with other approaches

Table 7 Performance comparison with other approaches.

Method	Recall@1	Recall @2	Recall @3	Recall @4	Recall @5
MRU	26.70%	41.15%	56.08%	62.37%	-
MFU	25.50%	45.58%	60.27%	62.37%	-
Naïve Bayes	7.88%	15.61%	22.28%	28.18%	33.54%
Markov chain	32.55%	55.00%	65.62%	72.52%	77.05%
Word2Vec	39.38%	62.81%	72.51%	78.39%	81.66%
Doc2Vec	39.91%	64.54%	73.23%	79.00%	82.76%
DNN	42.86%	66.36%	74.43%	78.79%	83.86%
HMM	48.81%	61.04%	66.26%	72.24%	76.16%
RNN-attention	51.26%	68.99%	76.43%	80.38%	83.36%
AppUsage2Vec	**54.83%**	**69.06%**	**77.63%**	**81.78%**	**84.47%**

Effectiveness of different components

- **Baseline: the original Doc2Vec**
- **Ours: AppUsage2Vec**

Table 8 Effectiveness of different components.

Baseline	Recall@1	39.91%
Baseline+Temporal context	Recall @1	43.39%
	Improvement	**3.48%**
Baseline+Attention	Recall @1	47.36%
	Improvement	**7.45%**
Baseline+dualDNN	Recall @1	44.25%
	Improvement	**4.34%**
Ours	Recall @1	54.83%
	Improvement	**14.92%**

RoadMap

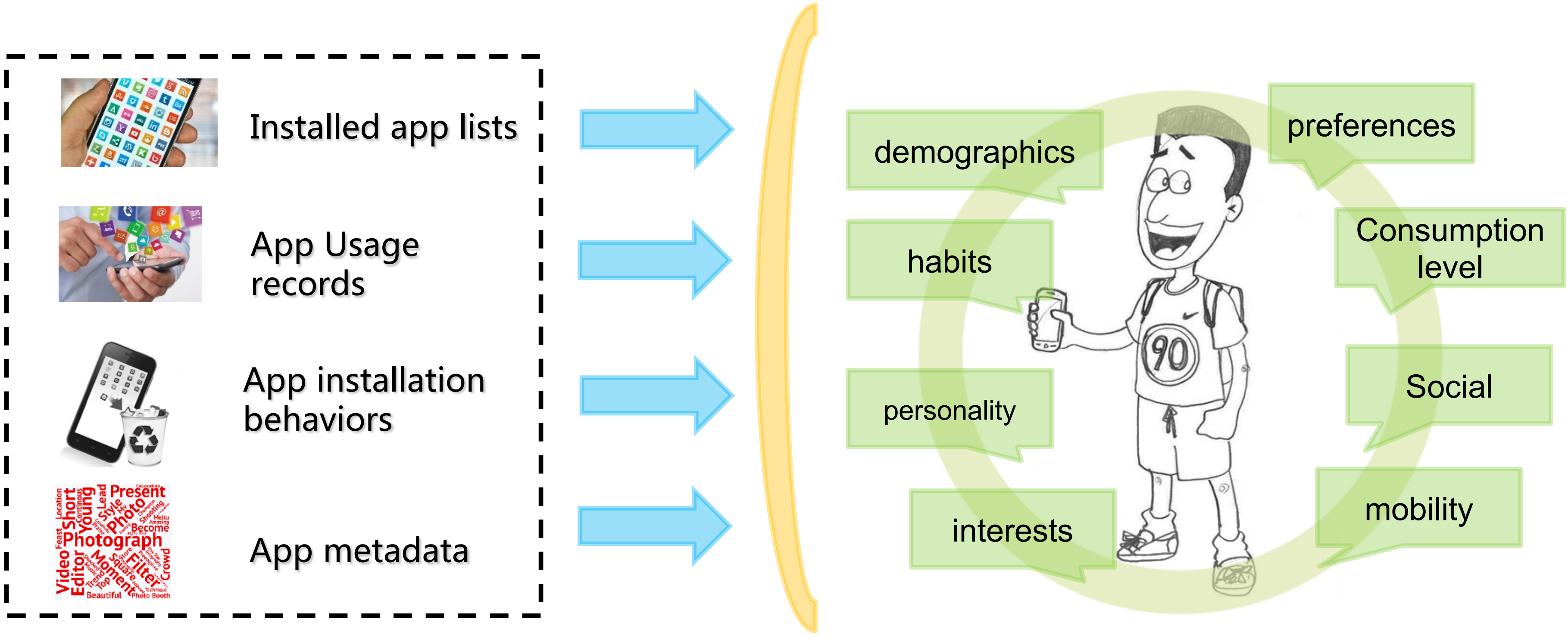
- App information for user profiling
- User information to profile
- User profiling framework
- Implications
- Challenges
- Several our research (Four work as examples)
- Future work and conclusion

Future work

- **To address the challenges**
  - Protecting user privacy
  - Taking the advantage of crowdsourcing techniques, collect data from different sources, and fuse the data to comprehensively profile users
  - Developing more sophisticated machine learning or deep learning methods to automatically find out key features
  - Developing general user representation
  - Learning more complicated user characteristics (e.g., values and social attributes)

Conclusion

- **User profiling from their use of smartphone apps**
  - App information for profiling, user information to profile
  - Methods, implications, and challenges



App data

User profiles

Related publications

1. Sha Zhao, Julian Ramos, Jianrong Tao, Ziwen Jiang, Shijian Li, Zhaohui Wu, Gang Pan, Anind Dey. Discovering Different Kinds of Smartphone Users Through Their Application Usage Behaviors. UbiComp 2016, 🏆Best Paper Award （国内第一个）, (CCF-A)
2. Sha Zhao, Zhiling Luo, Ziwen Jiang, Haiyan Wang, Feng Xu, Shijian Li, Jianwei Yin, Gang Pan. AppUsage2Vec: Modeling Smartphone App Usage for Prediction. ICDE 2019, (CCF A)
3. Sha Zhao, Shijian Li, Julian Ramos, Zhiling Luo, Ziwen Jiang, Anind Dey, and Gang Pan. User Profiling from Their Use of Smartphone Applications: A Survey. Pervasive and Mobile Computing, 2019 (IF = 2.769)
4. Sha Zhao, Yizhi Xu, Xiaojuan Ma, Ziwen Jiang, Zhiling Luo, Shijian Li, Laurence T. Yang, Anind Dey, Gang Pan. Gender Profiling from a Single Snapshot of Apps Installed on a Smartphone: An Empirical Study. IEEE Transactions on Industrial Informatics, 2019 (IF=7.377)
5. Sha Zhao, Gang Pan, Yifan Zhao, Jianrong Tao, Jinlai Chen, Shijian Li, Zhaohui Wu. Mining user attributes using large-scale APP lists of smartphones. IEEE Systems Journal, 2017 (IF=4.463)
6. Sha Zhao, Zhe Zhao, Runhe Huang, Zhiling Luo, Shijian Li, Jianrong Tao, Shiwei Cheng, Jing Fan, and Gang Pan. Discovering Individual Life Style from Anonymized WiFi Scan Lists on Smartphones. IEEE Access, 2019 (IF = 4.098)
7. Sha Zhao, Feng Xu, Yizhi Xu, Xiaojuan Ma, Zhiling Luo, Shijian Li, Anind Dey, Gang Pan. Investigating Smartphone User Differences in Their Application Usage Behaviors: An Empirical Study. CCF Transactions on Pervasive Computing and Interaction, 2019
8. Sha Zhao, Julian Ramos, Jianrong Tao, Ziwen Jiang, Shijian Li, Zhaohui Wu, Gang Pan, Anind K. Dey. Who Are the Smartphone Users? --Identifying User Groups with Apps Usage Behaviors. ACM SIGMOBILE Mobile Computing and Communications Review, 2017 (IF=1.33)
9. Sha Zhao, Zhe Zhao, Yifan Zhao, Runhe Huang, Shijian Li, Gang Pan. Discovering People's Life Patterns from Anonymized WiFi Scanlists. UIC 2014
10. Sha Zhao, Yifa ensed Data. UbComp
11. Sha Zhao, Fen Smartphones.
12. Sha Zhao, Yor d Learning from

AppLens 2019: The 2nd International Workshop on Mining and Learning from Smartphone Apps for Users, in conjunction with UbiComp 2019, Afternoon, September 10, Abbey

Thanks for Your Attentions

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Q&A

Concluding Remarks and Future Direction

Background, App Data Collection and Datasets

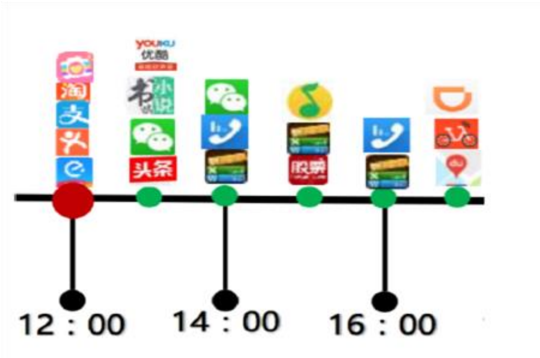
Obtaining real-life usage data: Challenges

- Subject to user activity
- Data quality: sparse, incomplete
- Uncertain issues: apps could be closed, uninstalled, and conditions of network and location
- Collection tools need to be lightweight

Crowdsourcing benefits:

- Prospect to build a large dataset
- Contexts covers a wide range: not limited to a specific context

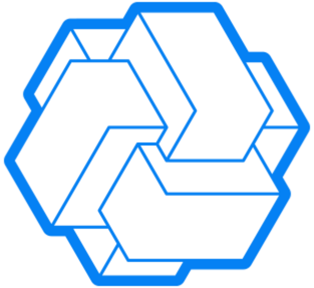
Prediction & Recomm.: Concluding Remarks



Challenges:

- Lack of large-scale app usage data
- Lack of efficient model & Privacy concern
- Cold-start & Privacy preserving app recommend.

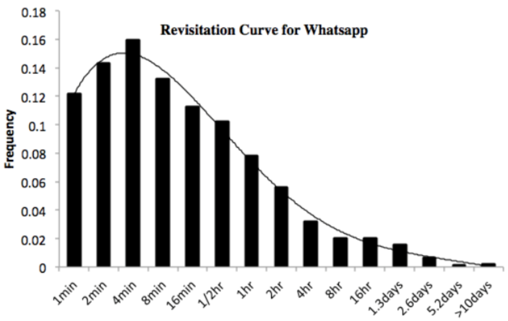
Opportunities:



- Big data era & AI techniques came of age
- Blockchain, federated learning techniques
- Need more available data to promote research; Desire deeper models to capture complicated user-app interactions

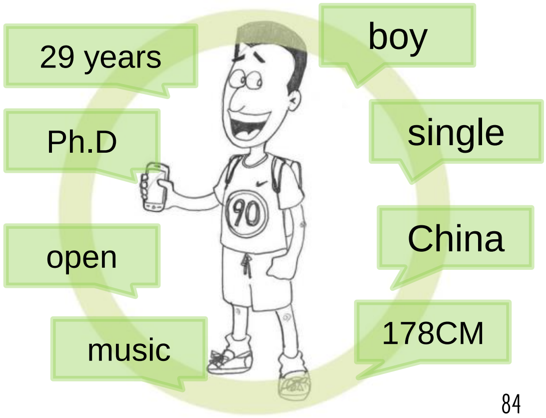
Modelling smartphone use

- The transition between smartphone usage events
    - On, off, lock, and unlock
- Context useful for modeling smartphone use
    - Day & time, battery level, user ”type”
- Smartphone usage habits
    - Usage patterns of apps
    - Usage patterns of users



User profiling of smartphone app usage

- App information for profiling
  - Installed app lists, app usage records, app installation behaviors, and app meta data
- User information to profile
  - Demographics, interests, personality, psychological status, and life style
- Methods for user profiling
  - Descriptive statistics, regress, classification, and clustering
- Challenges
  - Data, models, fusion of heterogeneous data, user privacy



Thank you

Website:

http://fi.ee.tsinghua.edu.cn/UbiCompTutorial.html