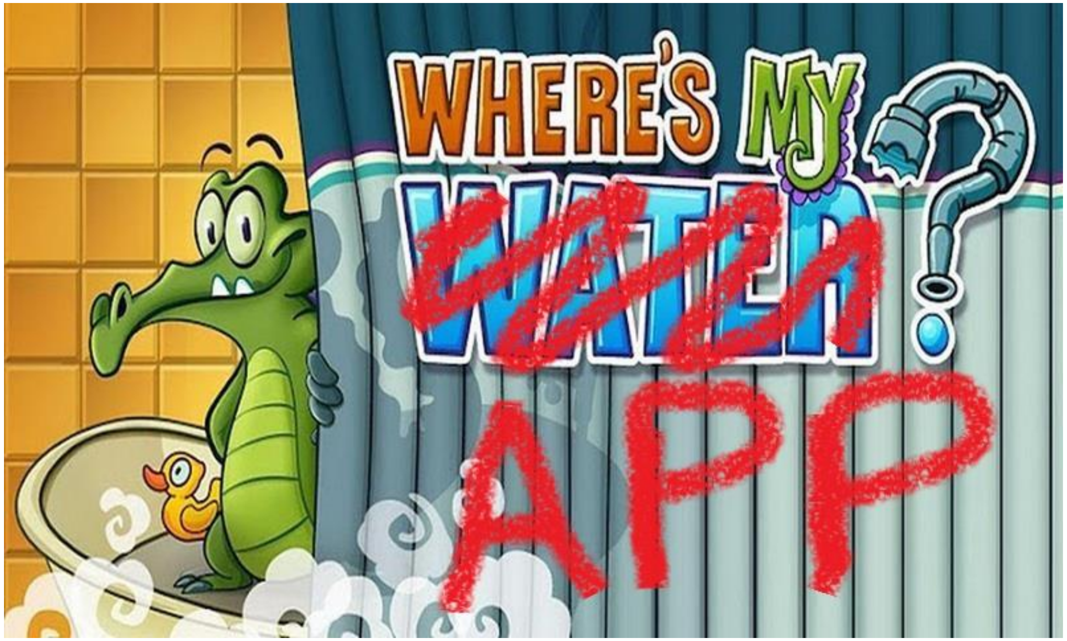
Where's my app?



…. seriously, where is it?

Ranveer Joyseeree

Who has a smartphone?

Who DOESN'T have a smartphone??

Who DOESN'T have a smartphone??

- Almost no-one!

How many of them do you have?

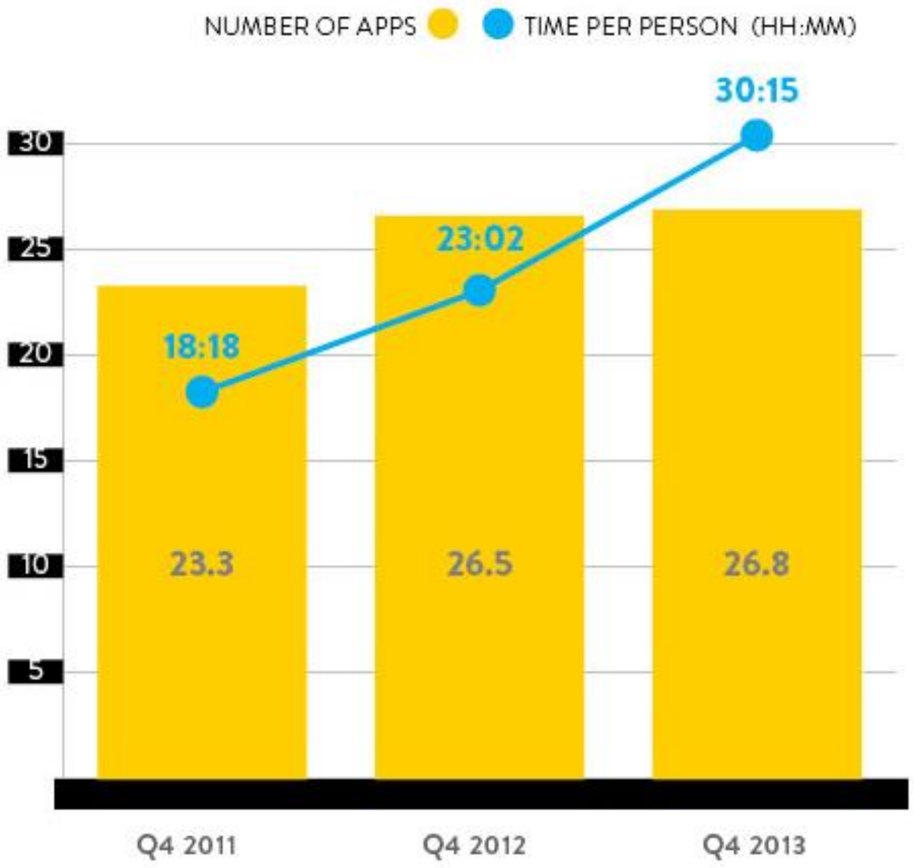
How many of them do you have?

Too many!

How much time do you spend on them?

How much time do you spend on them?

- Too much!



http://www.nielsen.com/us/en/insights/news/2014/smartphones-so-many-apps--so-much-time.html


1980
2010


ebay
amazon
smule
urbanspoon
ORACLE
32

KEEP
CALM.
THERE'S
AN APP
FOR THAT

Too many apps!

Too many apps!

Getting worse!

Too many apps!

Getting worse!

Too many apps!

Getting worse!


TIME

TECH VIDEO GAMES

Nintendo Announces Plans to Expand Into Mobile Gaming

Rishi Iyengar @iyengarrishi

SHARE

TAP

March 17, 2015

NATIONAL

Phone battery life 'causing stress' for millions

A dead battery in a smartphone would cause stress for nine out of 10 Britons, as daily activities hinge on a single factor "having enough juice to keep the phones running," says a report by smartphone case maker mophie.

1:40 am, Mon 12 May 2014

More than 70% would 'give up dessert' for battery life

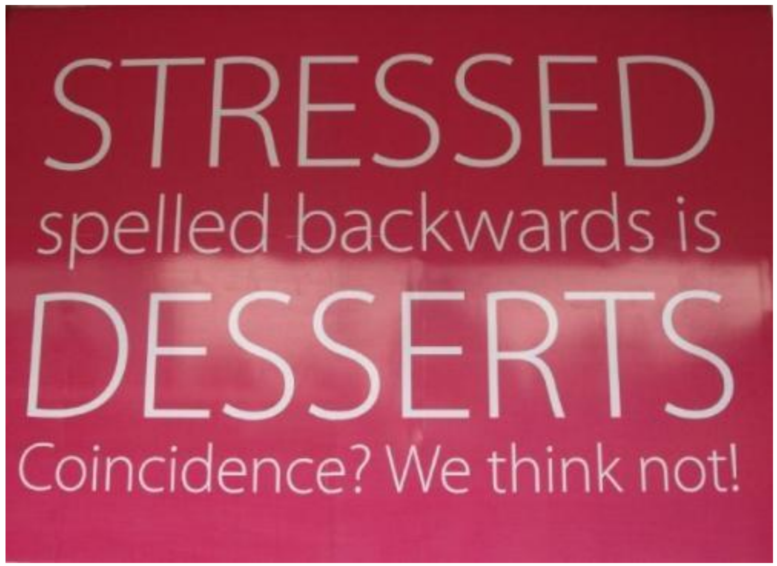
Almost half of those surveyed said that if their mobile phone died they would only be able to remember three phone numbers - and more than 70% said they would give up having pudding after a meal in order to have a fully charged smartphone for a month.

Kevin Malinowski, a spokesman for mophie, said:

> *Millions of people rely on their smartphones daily to stay in touch with loved ones and do work on the move.*

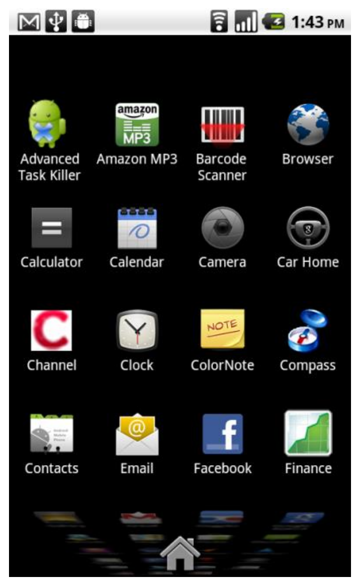

YOU
Y U NO GET OFF INTERNET AND DO SOMETHING


FREE TIME
FREE TIME EVERYDAY
makeameme.org


STRESSED
spelled backwards is
DESSERTS
Coincidence? We think not!

Existing solutions

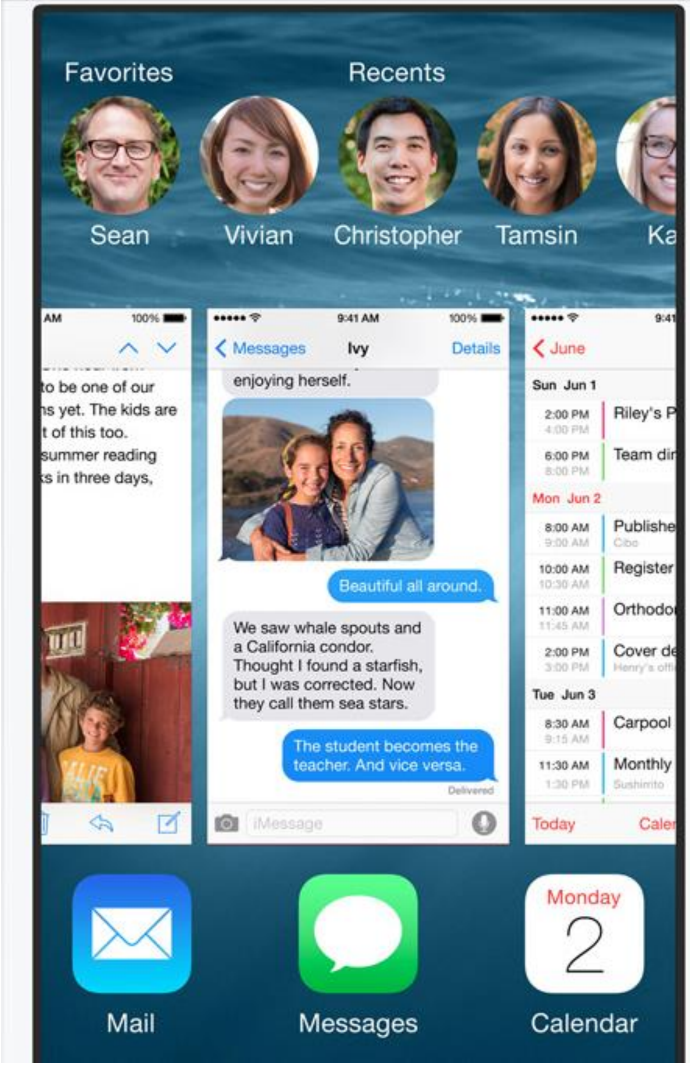
Home screens



MFU

Nokia Z Launcher app

MRU


Favorites
Recents
Sean
Vivian
Christopher
Tamsin
Messages
Ivy
Details
enjoying herself.
Beautiful all around.
We saw whale spouts and a California condor. Thought I found a starfish, but I was corrected. Now they call them sea stars.
The student becomes the teacher. And vice versa.
Delivered
iMessage
June
Sun Jun 1
Mon Jun 2
Tue Jun 3
Carpool
Today
Monday
2
Mail
Messages
Calendar

Time still lost!

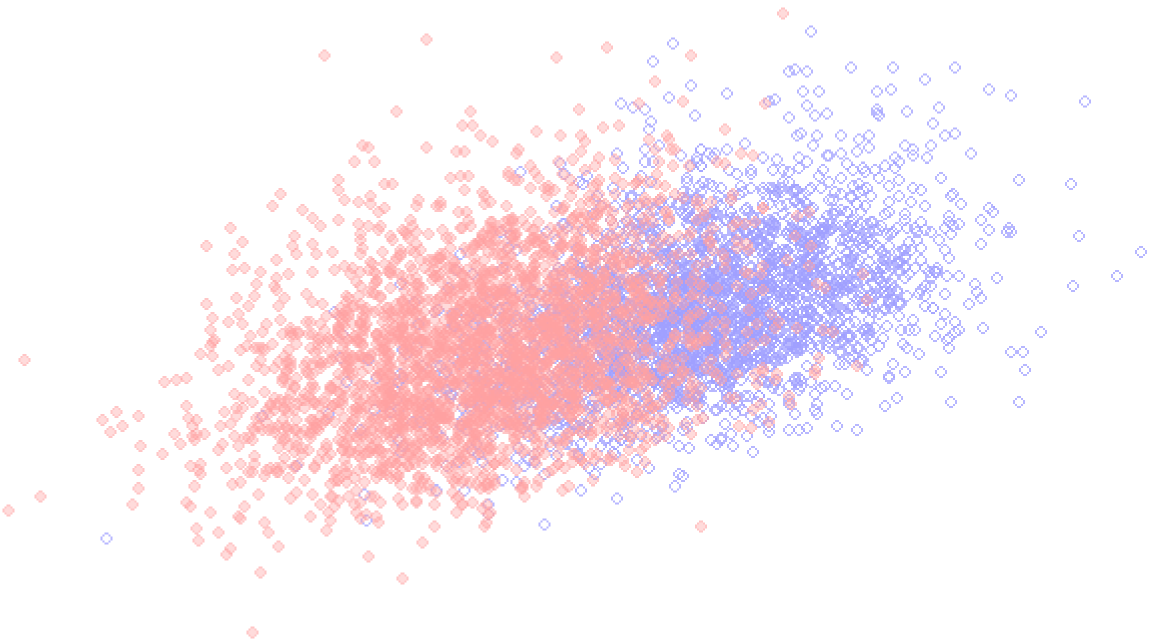
Time still lost!

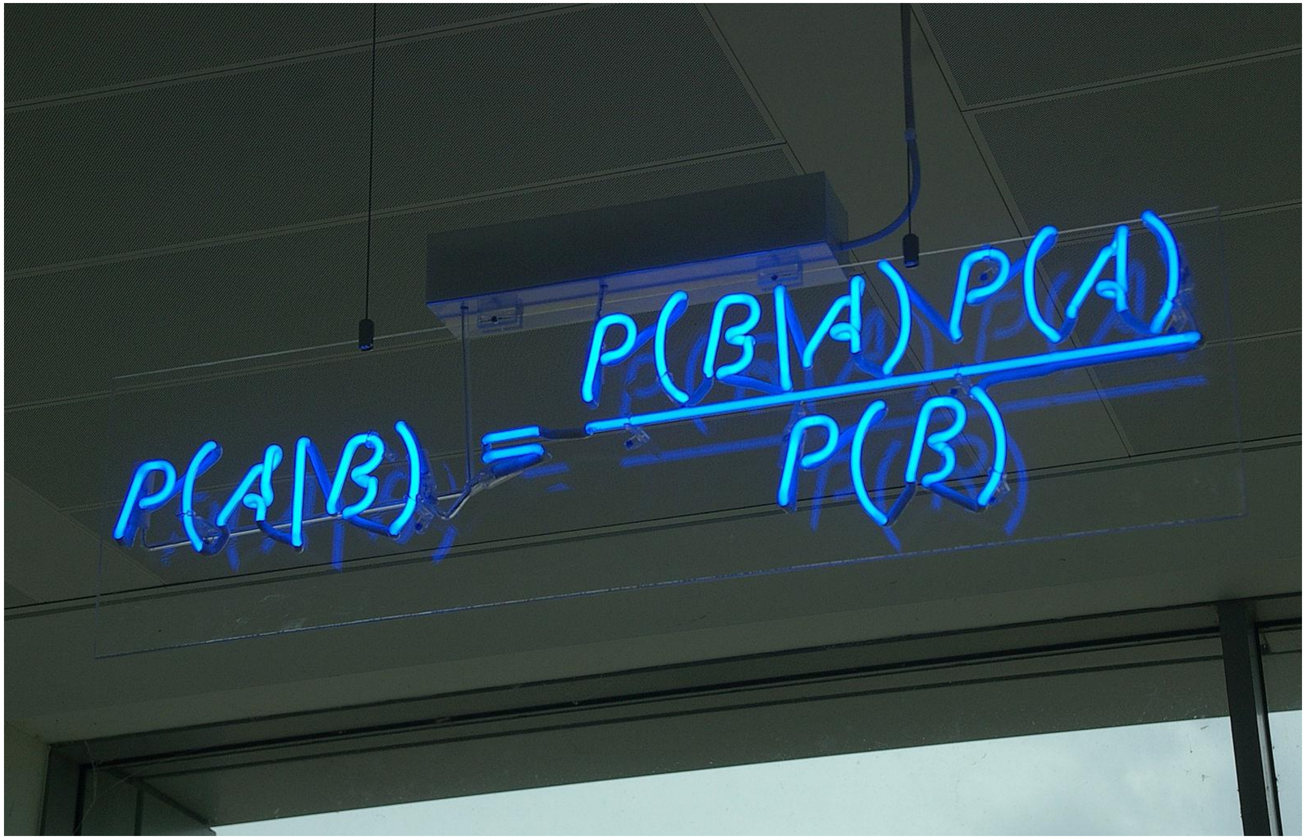
General methods do not suit everyone

Solution

Predict next used app using current context

Current research

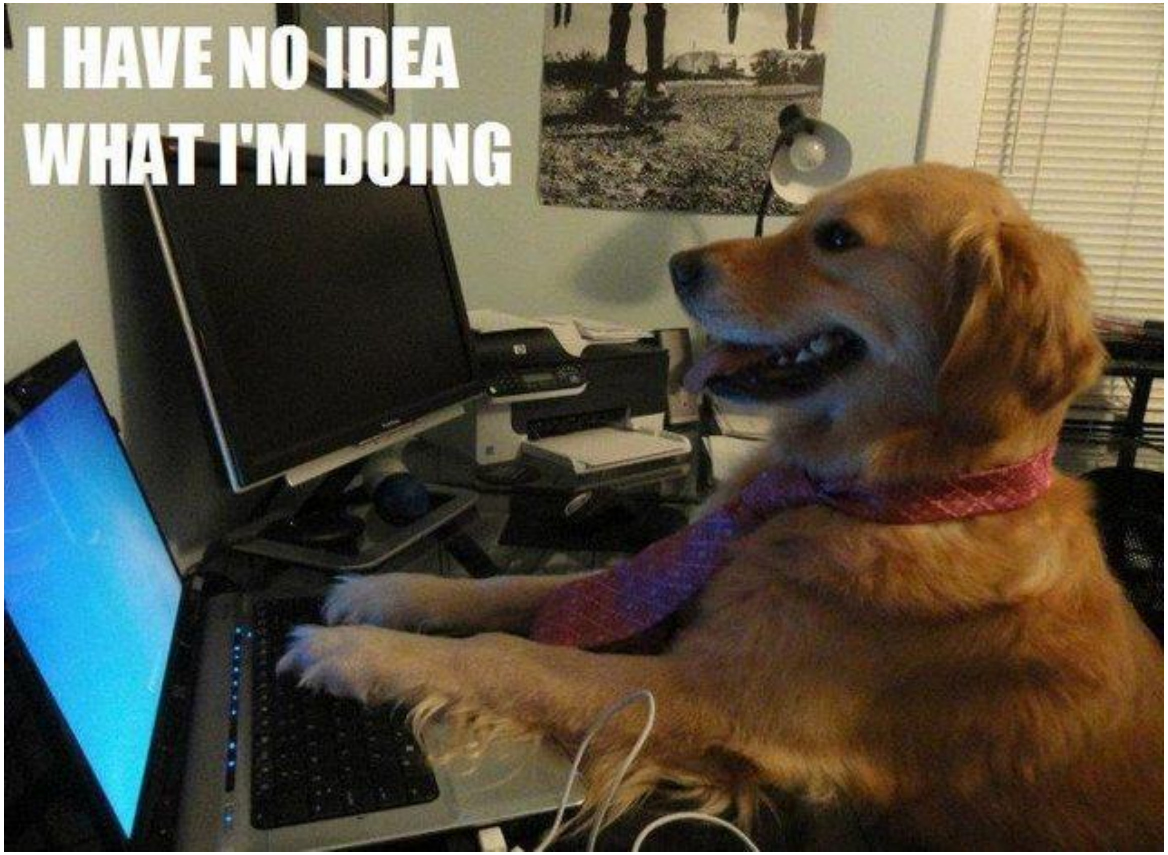



P(A|B) = P(B|A) P(A) / P(B)

Remaining issues

Limited number of applications developed

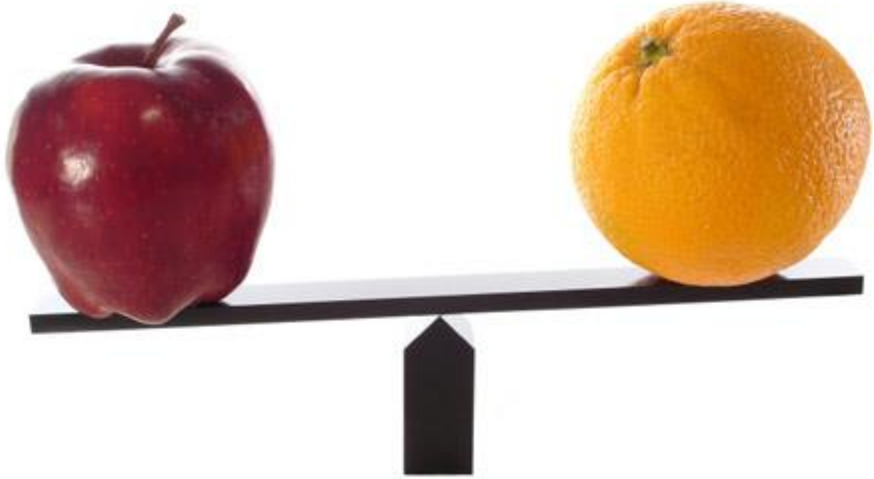
No analysis of how end-users utilized them



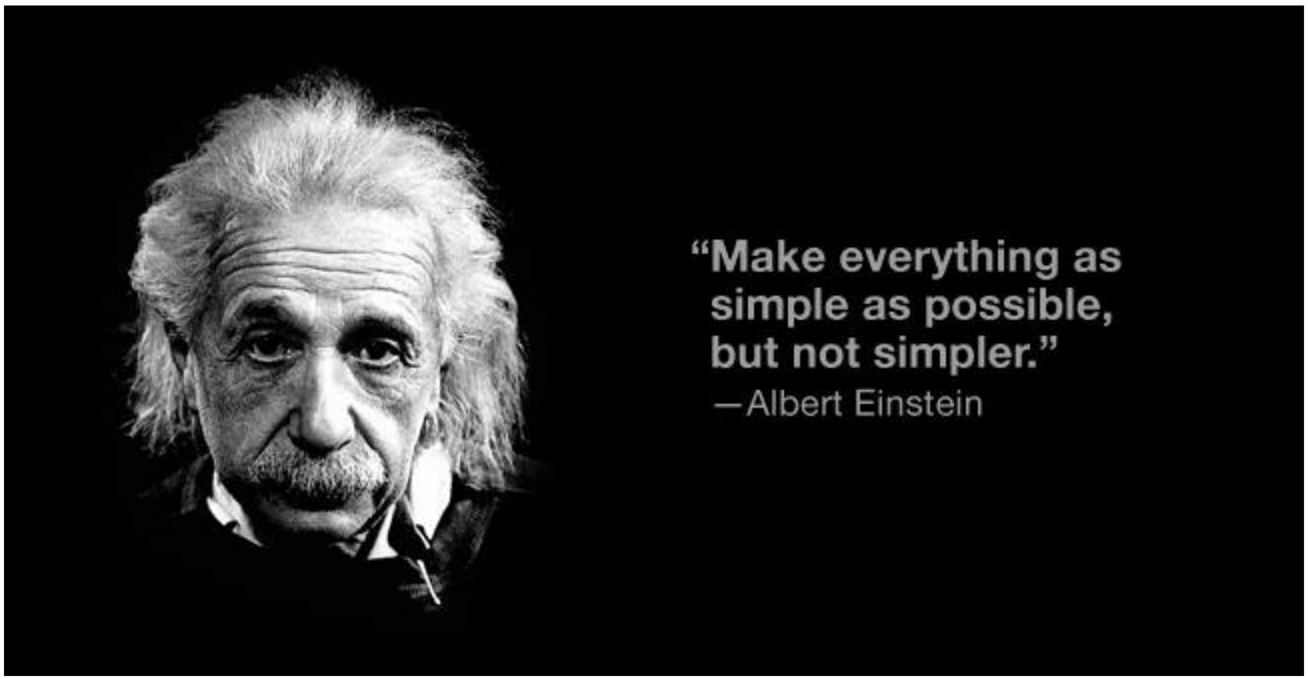
Unreliable performance:

- High with few candidate apps
- Low with many candidate apps

Little comparison with other approaches



Insufficient study of other contextual information



Overview

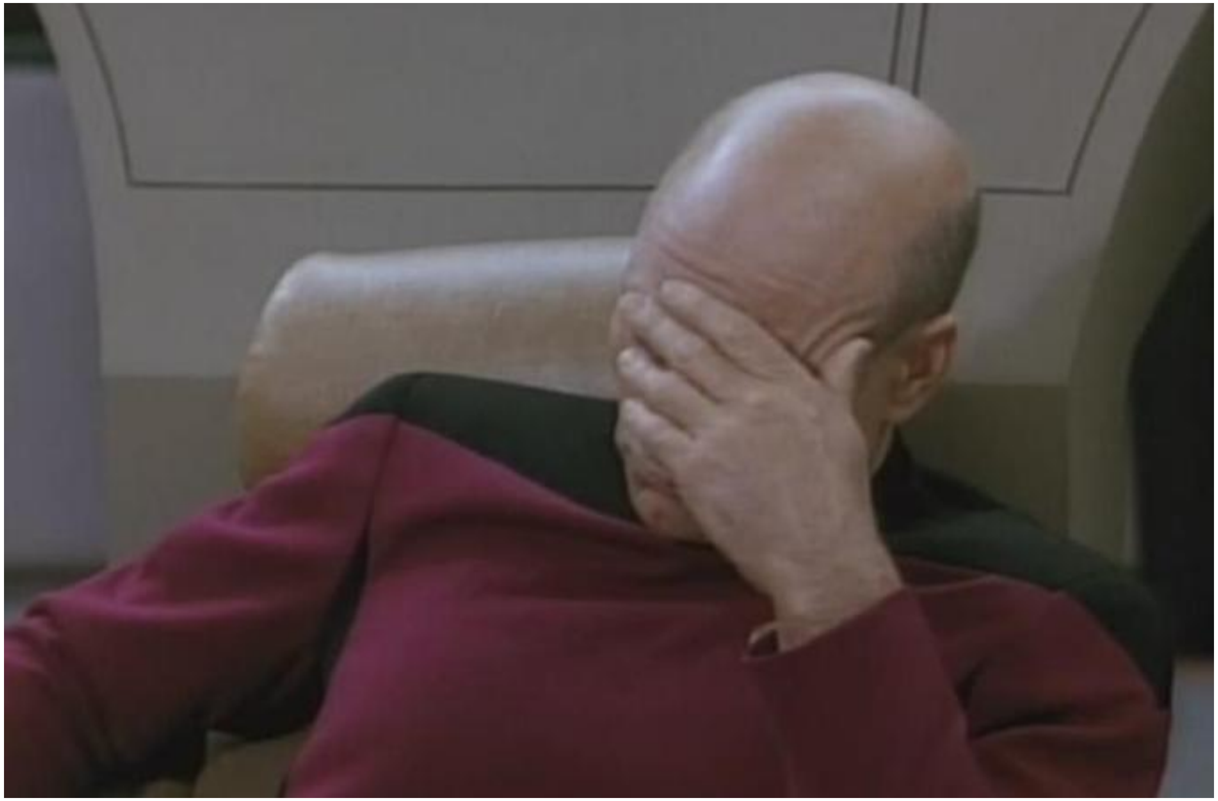
- 3 mining applications
- Discussion and conclusion
- Questions

MINING APPLICATION 1

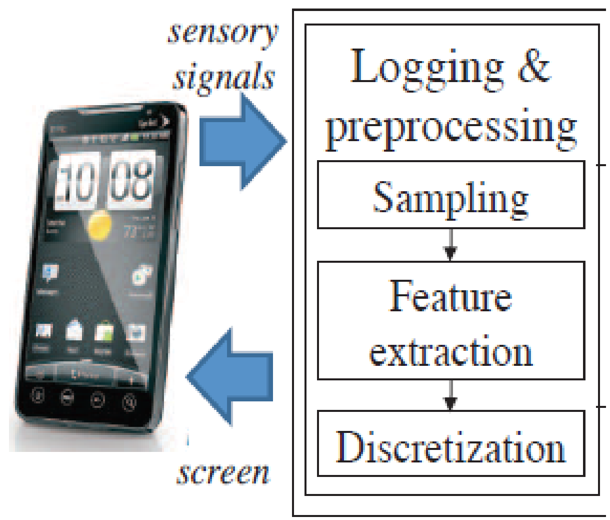
Shin, C., Hong, J. H., & Dey, A. K. (2012, September). Understanding and prediction of mobile application usage for smart phones. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing* (pp. 173-182). ACM.

Dynamic home screen app

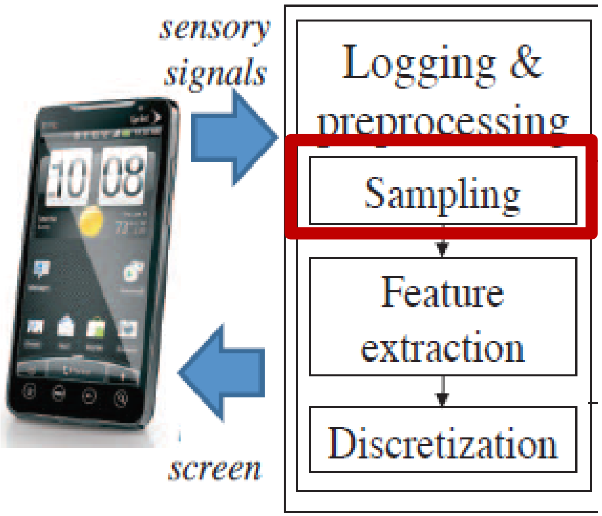
Yet another app!



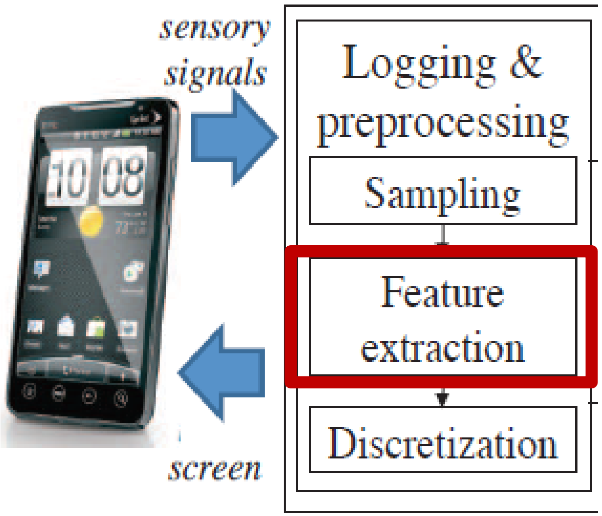

sensory
signals
screen



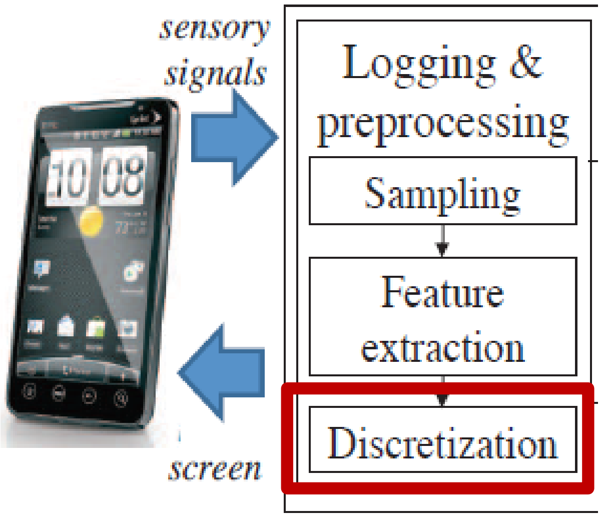
sensory
signals
screen
Logging &
preprocessing
Sampling
Feature
extraction
Discretization



- GPS, calls, SMS, accelerometer, …
- illumination, battery status, Wi-Fi, …
- running apps, active app, app status.

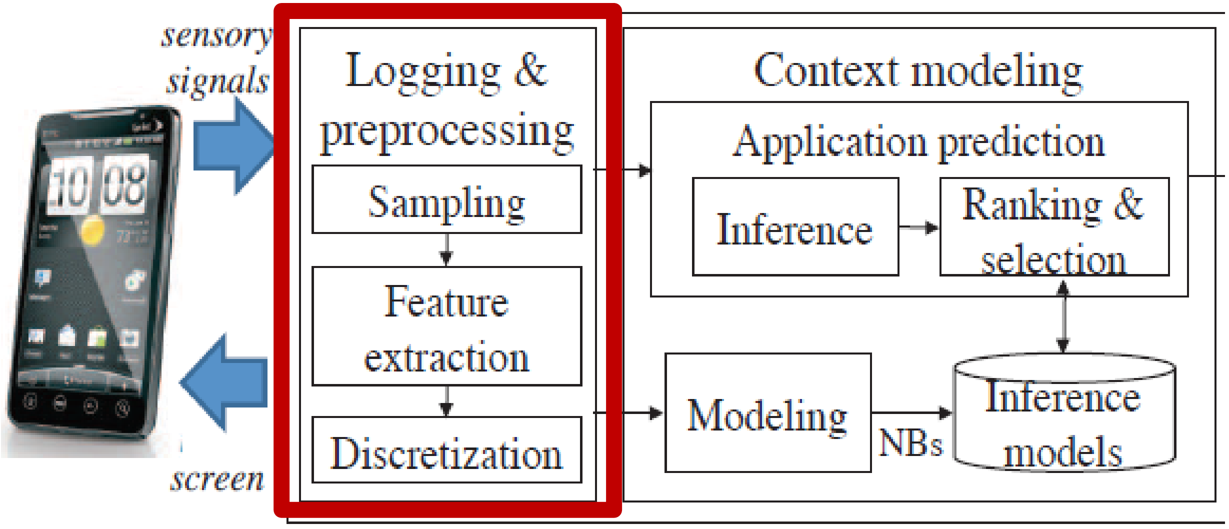


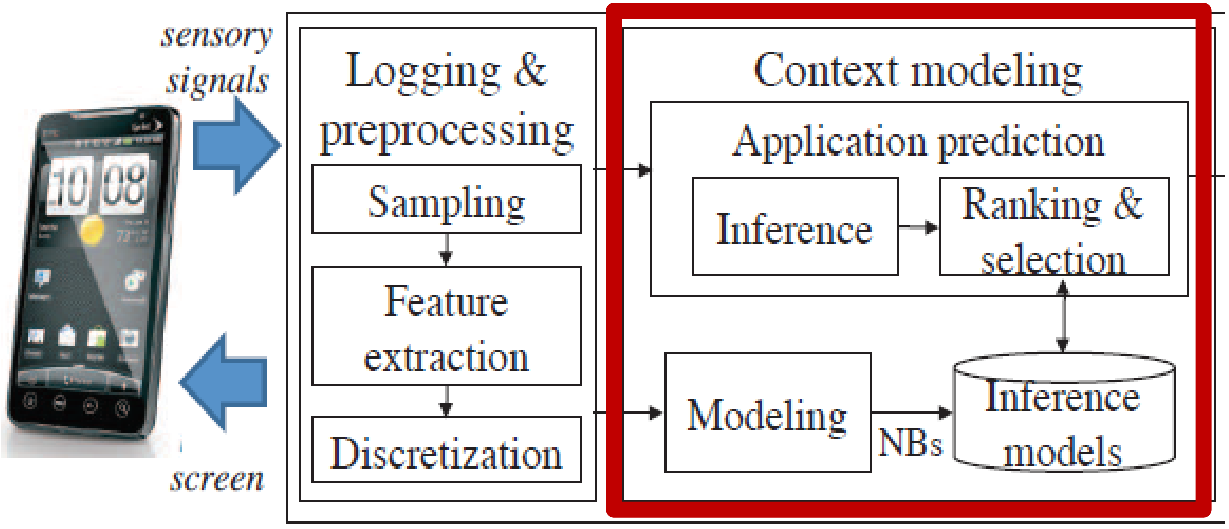
- *loc_gpsx, acc_avgx, event, net_status, …*
- *ill_level, wifi_status, bat_level, …*
- *last_app, last_appcnt, app_pkgchange, …*

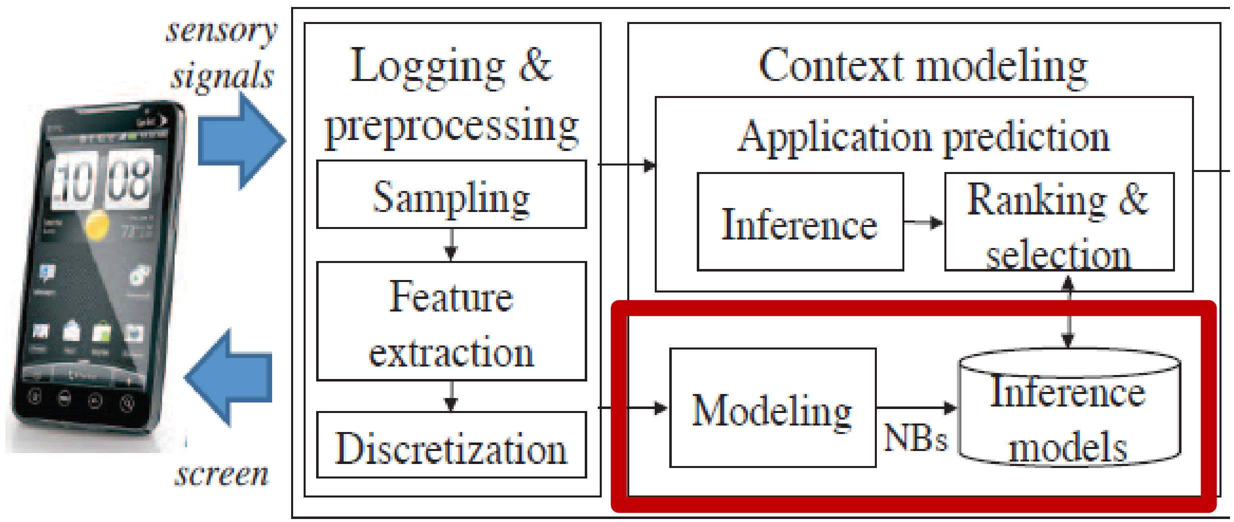


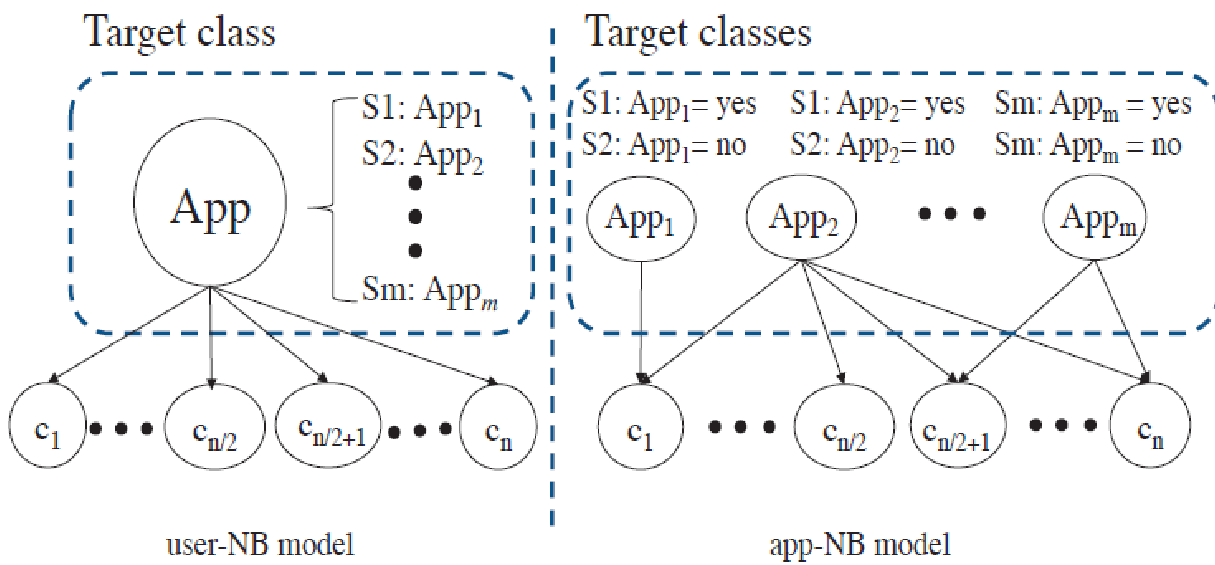
- Continuous -> {verylow, low, medium, large, verylarge}

Sensor	Contextual information	Possible values
Illumination	Level (*ill_level*) Illumination changes (*ill_cnt*)	{verylow to veryhigh} {verylow to veryhigh}
Screen	Status (*scr_status*)	{on,off}
Call-SMS	Event (*event*)	{call, sms, none}

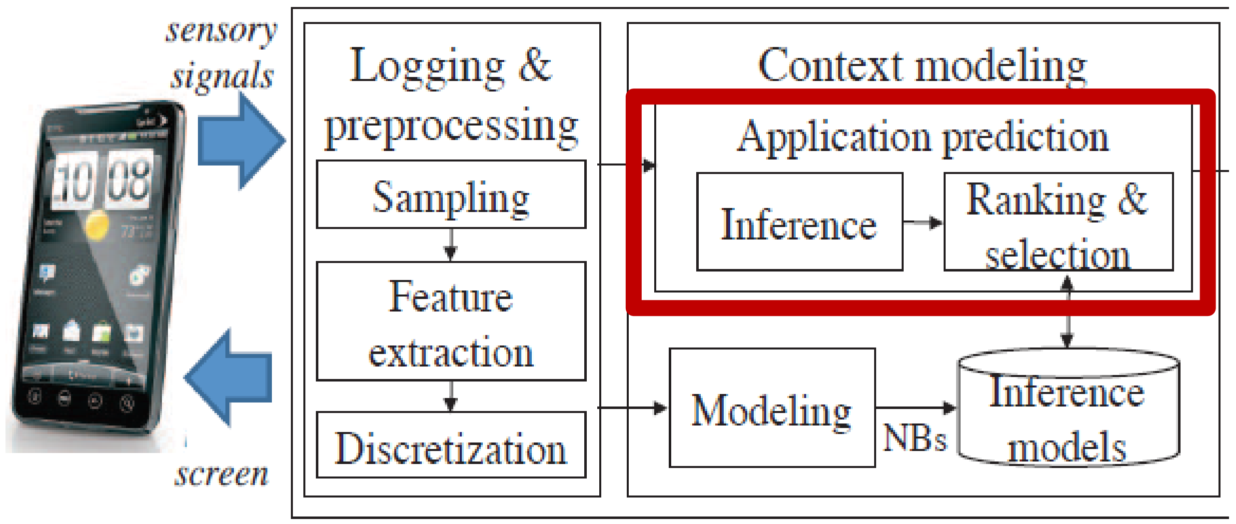

sensory
signals
screen
Logging &
preprocessing
Sampling
Feature
extraction
Discretization
Context modeling
Application prediction
Inference
Ranking &
selection
Modeling
NBs
Inference
models


sensory
signals
screen
Logging &
preprocessing
Sampling
Feature
extraction
Discretization
Context modeling
Application prediction
Inference
Ranking &
selection
Modeling
NBs
Inference
models

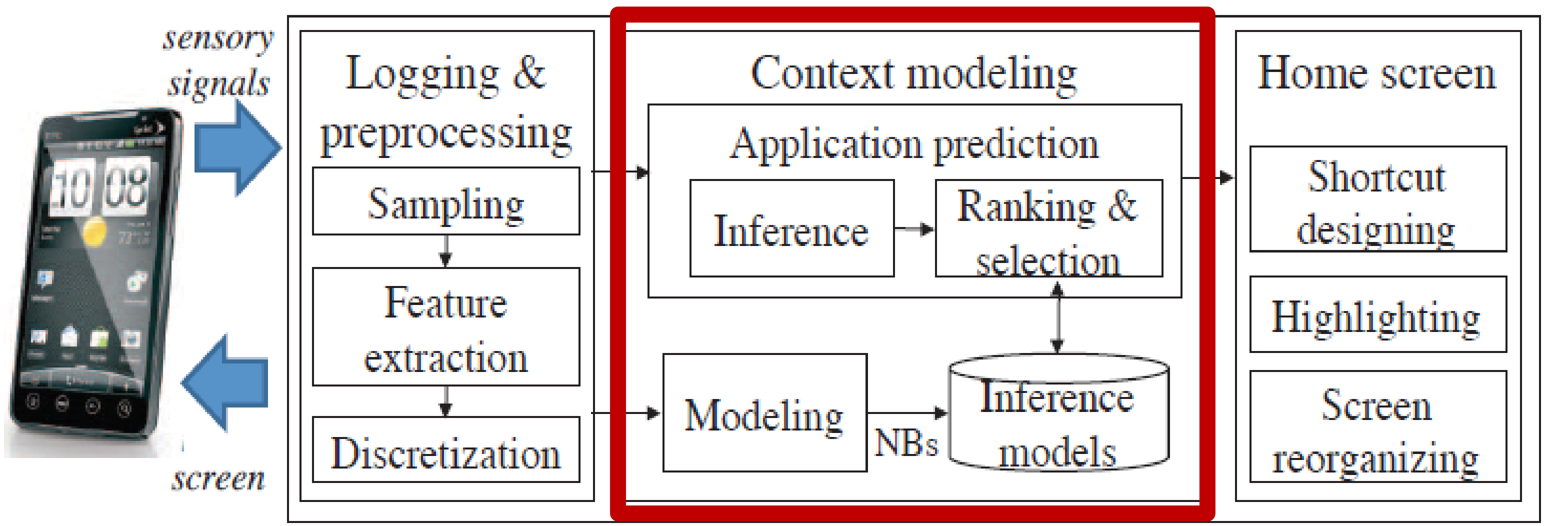

sensory
signals
screen
Logging &
preprocessing
Sampling
Feature
extraction
Discretization
Context modeling
Application prediction
Inference
Ranking &
selection
Modeling
NBs
Inference
models

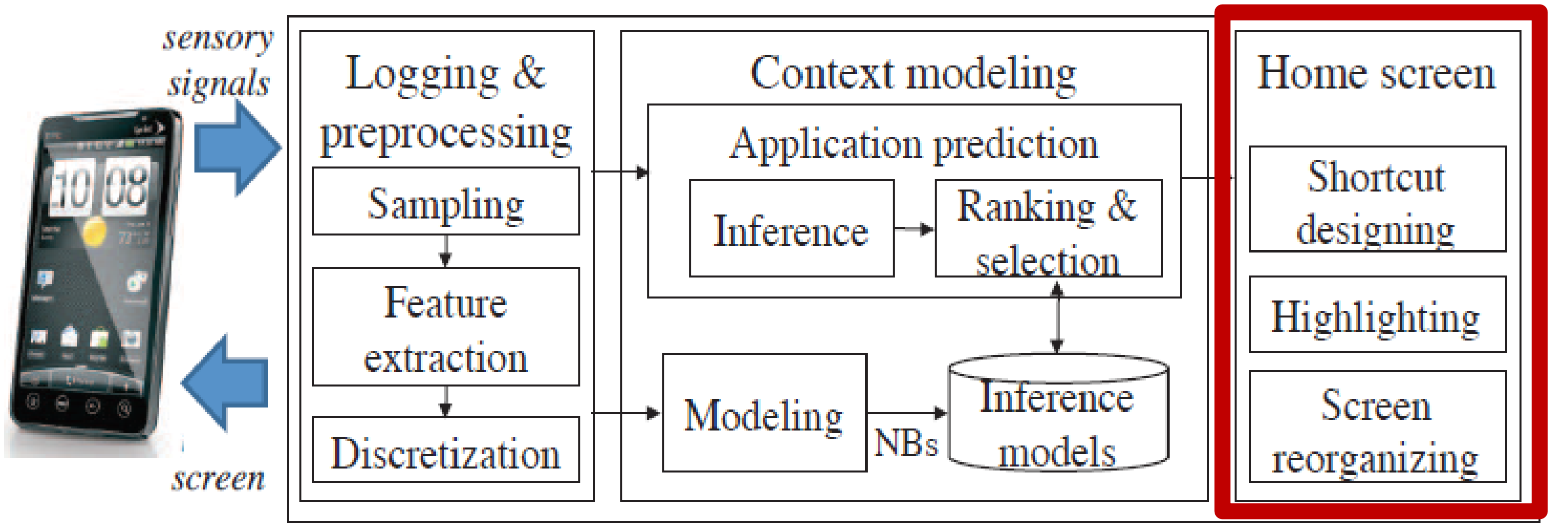


Target class
App
S1: App1
S2: App2
Sm: Appm
c1
cn/2
cn/2+1
cn
user-NB model
Target classes
S1: App1= yes
S2: App1= no
S1: App2= yes
S2: App2= no
Sm: Appm = yes
Sm: Appm = no
App1
App2
Appm
c1
cn/2
cn/2+1
cn
app-NB model


sensory
signals
screen
Logging &
preprocessing
Sampling
Feature
extraction
Discretization
Context modeling
Application prediction
Inference
Ranking &
selection
Modeling
NBs
Inference
models

MINING APPLICATION I

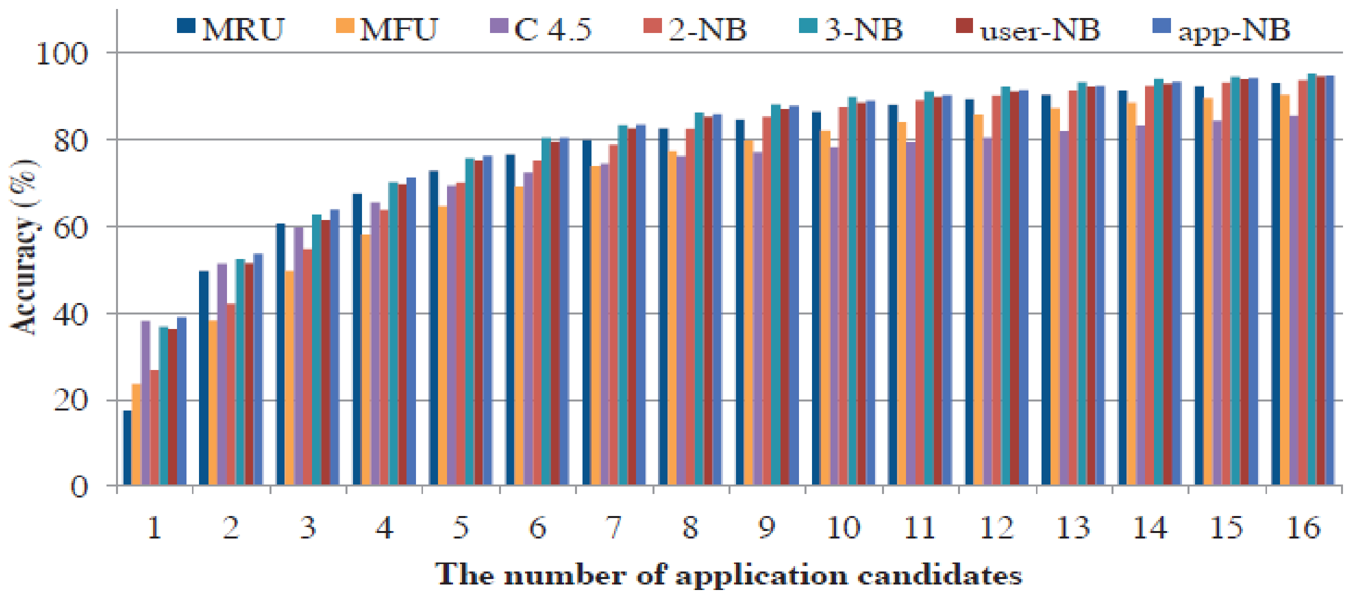



sensory
signals
screen
Logging &
preprocessing
Sampling
Feature
extraction
Discretization
Context modeling
Application prediction
Inference
Ranking &
selection
Modeling
NBs
Inference
models
Home screen
Shortcut
designing
Highlighting
Screen
reorganizing

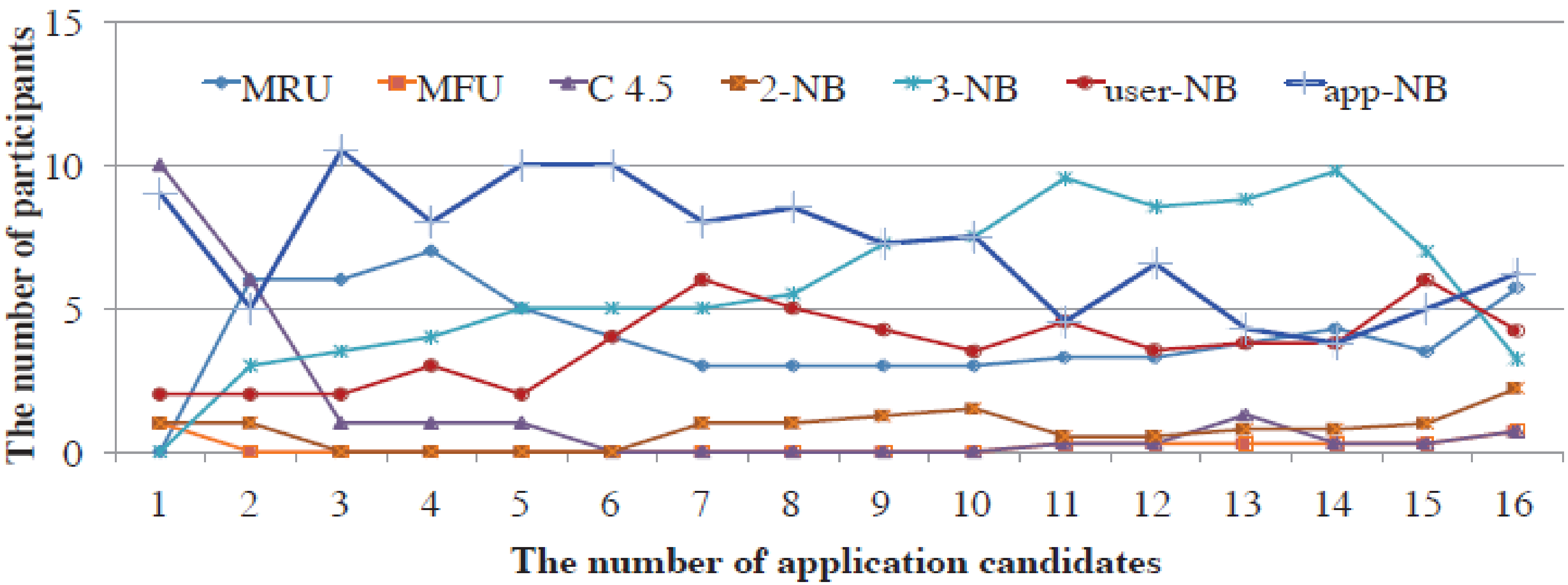

9:48
Phone
Browser
Clock
Settings
Messaging
Gmail


9:48
Phone
Browser
Clock
Settings
Messaging
Gmail

Performance assessment

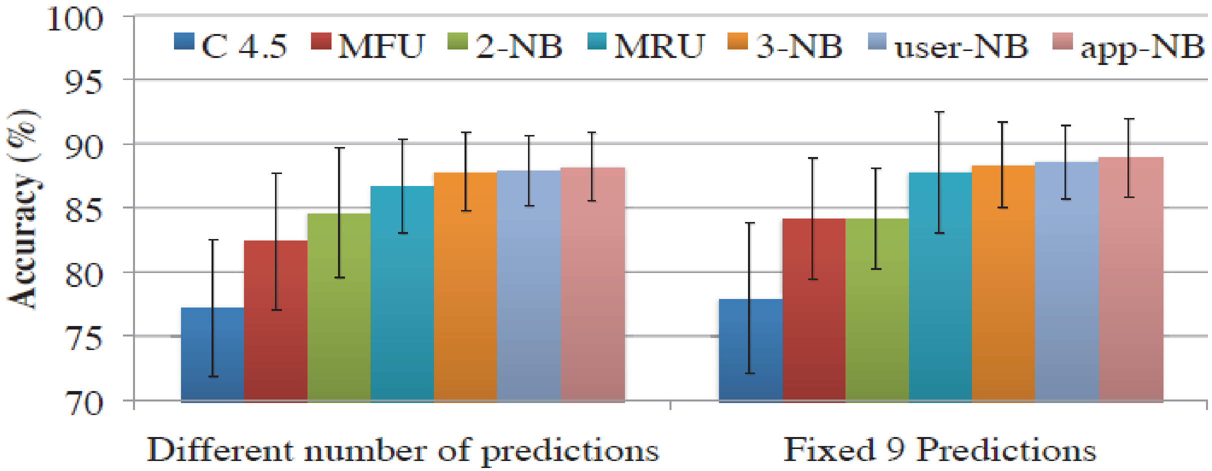


- C4.5 = decision tree strategies
- 2NB = 2-feature-based NB model (location and hour of day)
- 3NB = 3-feature-based NB model (location, hour of day, last_app)

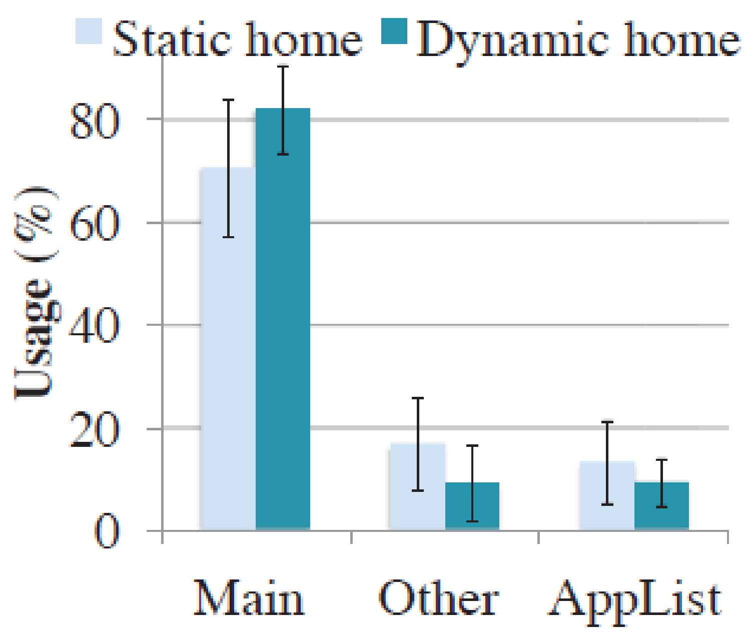


The number of participants
0
5
10
15
MRU
MFU
C 4.5
2-NB
3-NB
user-NB
app-NB
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
The number of application candidates

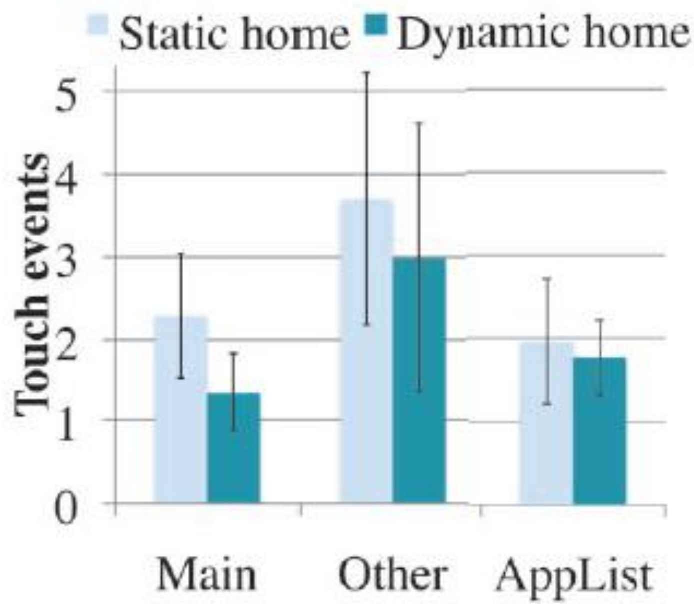
EVALUATION

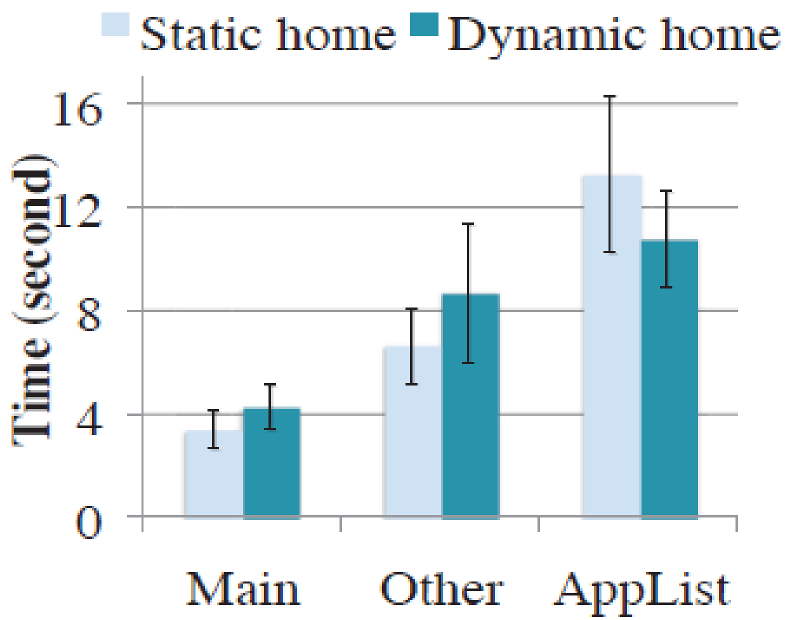


100
95
90
85
80
75
70
Accuracy (%)
C 4.5
MFU
2-NB
MRU
3-NB
user-NB
app-NB
Different number of predictions
Fixed 9 Predictions



Static home
Dynamic home
Usage (%)
80
60
40
20
0
Main
Other
AppList


Static home
Dynamic home
Touch events
0
1
2
3
4
5
Main
Other
AppList



Static home
Dynamic home
Time (second)
16
12
8
4
0
Main
Other
AppList

User Feedback

+ General satisfaction

- Lack of control
- Placement of apps changing

Contributions

+ Best performance for few apps to be predicted
+ All calculations on phone (privacy)
+ Reduced number of touch input events
+ Increased interaction with main home screen

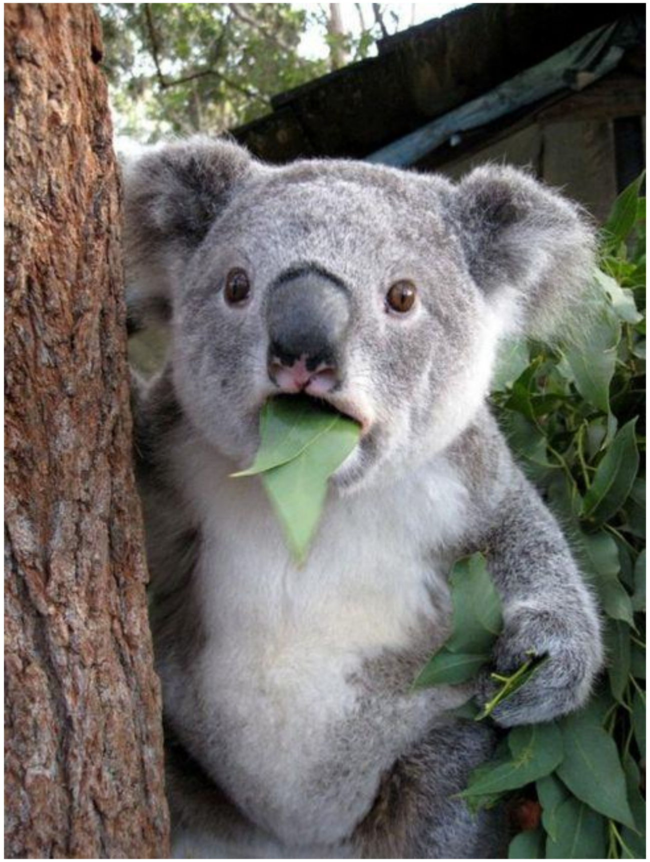
~ Battery life

- Slightly increased time to find app on home screens

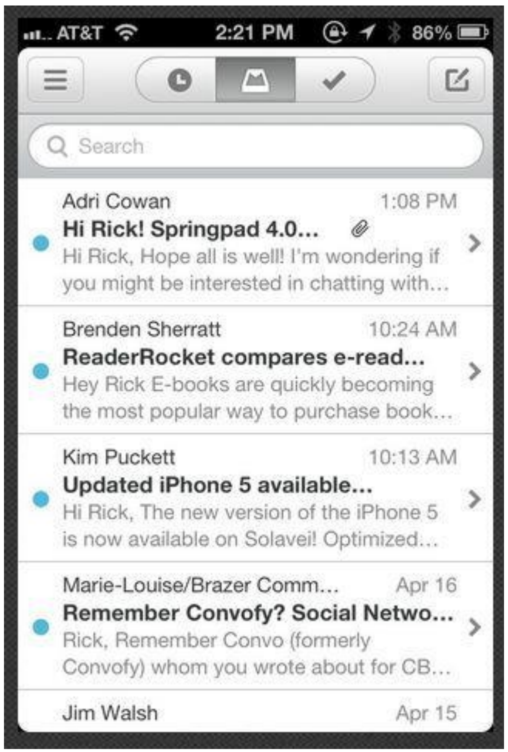
Next level – where's my content?

Prediction -> find app

User looking for **content**



Many apps -> real-time, content-driven



Average network latency: 11 s

Ideally -> BOTH prediction and app loading

MINING APPLICATION 2

Parate, A., Böhmer, M., Chu, D., Ganesan, D., & Marlin, B. M. (2013, September). Practical prediction and prefetch for faster access to applications on mobile phones. In Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (pp. 275-284). ACM.

Adaptive Shortcut Menu

Stock Android UI with user-configured shortcuts to apps

BOTH prediction and app loading:

- App Prediction by Partial Match (APPM)

- Time Till Usage (TTU)

APPM + TTU = PREeminently Practical approach to Prefetch (PREPP)

APPM

Text compression: Prediction by Partial Match (PPM)

APPM

Text compression: Prediction by Partial Match (PPM)

- “natio”

APPM

Text compression: Prediction by Partial Match (PPM)

- “natio”
- Next letter?

APPM

Text compression: Prediction by Partial Match (PPM)

- “natio”

- Next letter?

- “n”

Email, Facebook, twitter, ?

Low training overhead

Adapts to usage dynamics

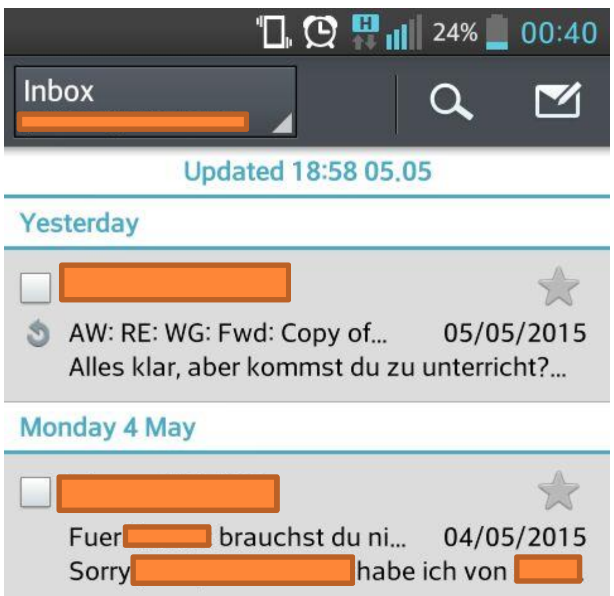
Calculations :

- when an app is opened
- for next app to be opened

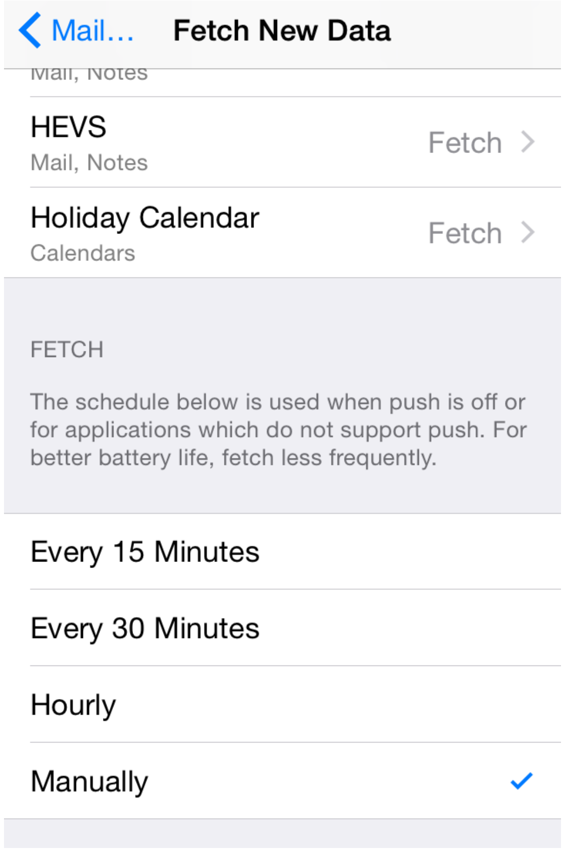
TTU

“Freshness” – how recently an app’s content was prefetched prior to application use

E.g. Email freshness

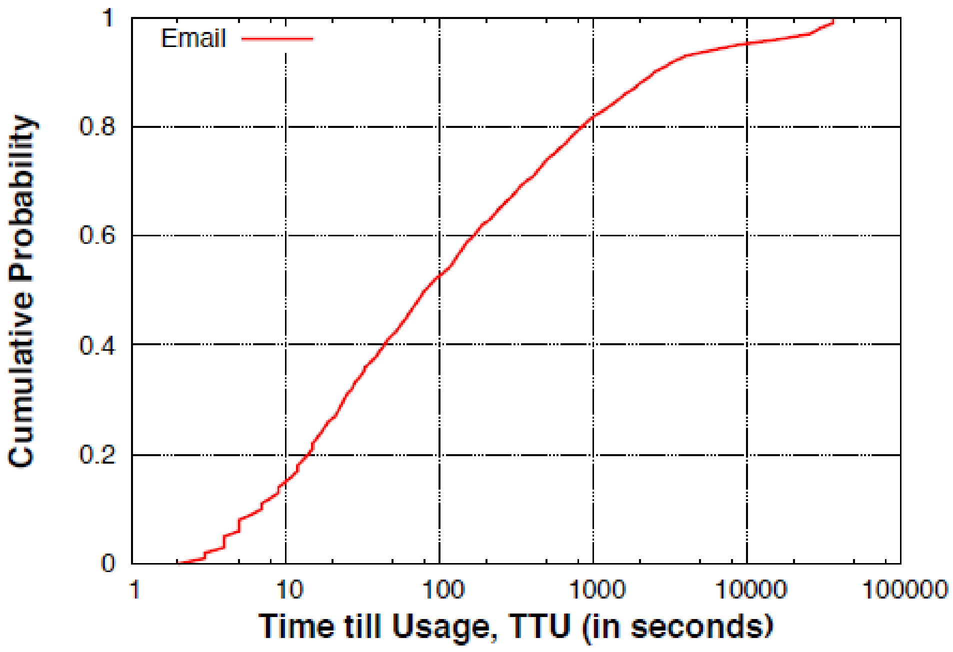


E.g. TTU versus polling



Cumulative Distribution Function (CDF) calculated

- CDF: $F_{TTU|nextapp=e}$, uses app usage history incl. timing



Need to predict WHEN app will be opened

Temporal modeling

APPM predicts next app

- Find Δt

Decision engine

Trade-off: freshness vs. bandwidth/battery cost

Prefetch considerations

Phone OS constraints: prefetch only when device is unlocked and in use

Prefetch considerations

Phone OS constraints: prefetch only when device is unlocked and in use

Minimal disruption: prefetch when user unlocks device for use

Prefetch considerations

Phone OS constraints: prefetch only when device is unlocked and in use

Minimal disruption: prefetch when user unlocks device for use

Saving energy: parallel prefetch on apps predicted to be used in quick succession

Adaptive Shortcut Menu

Stock Android UI with user-configured shortcuts to apps

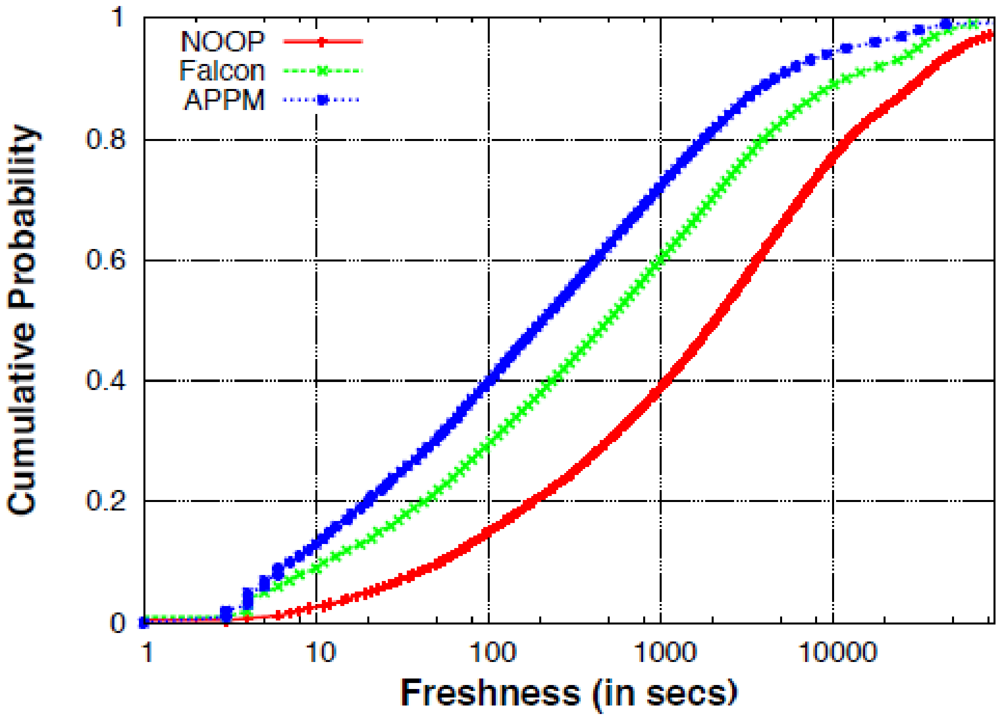
PERFORMANCE EVALUATION

Better prediction accuracy with fewer contexts esp. no location (privacy, energy constraints)

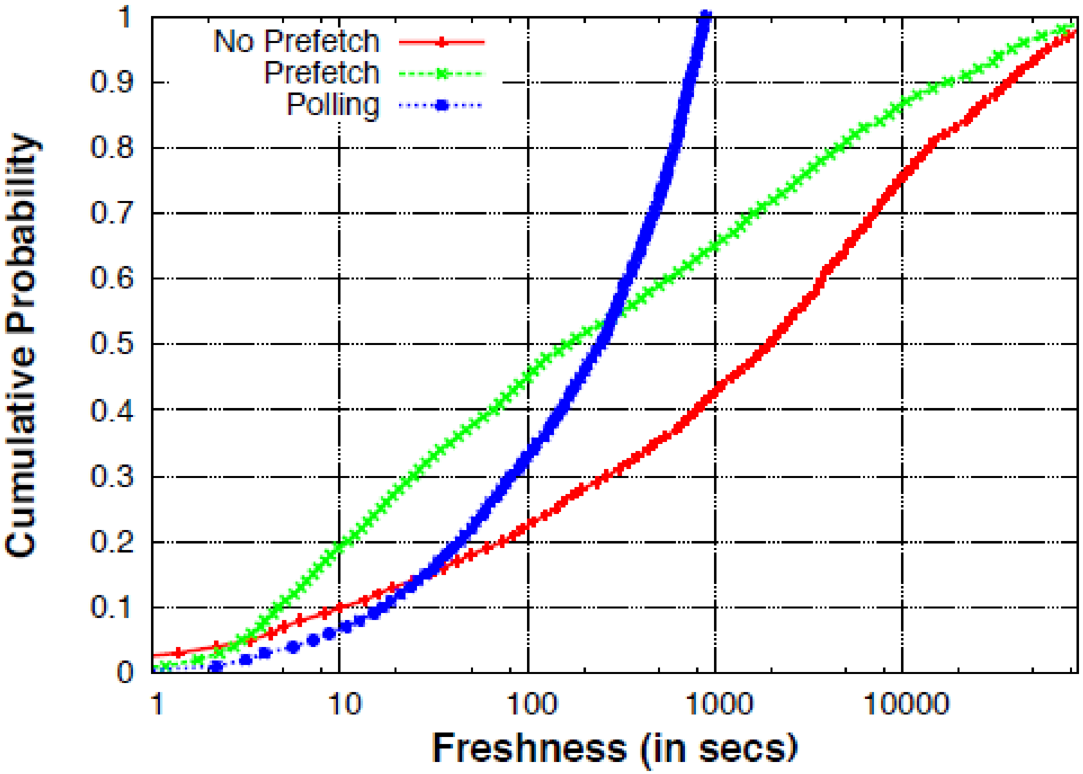
Algorithm	Prediction Accuracy
MFU	48.81±1.08 %
2-NB	74.87±1.60 %
3-NB	78.81±1.34 %
APPM	80.85±1.23 %

Algorithm	Prediction Accuracy
Falcon	70.16±1.56 %
APPM	74.37±1.41 %

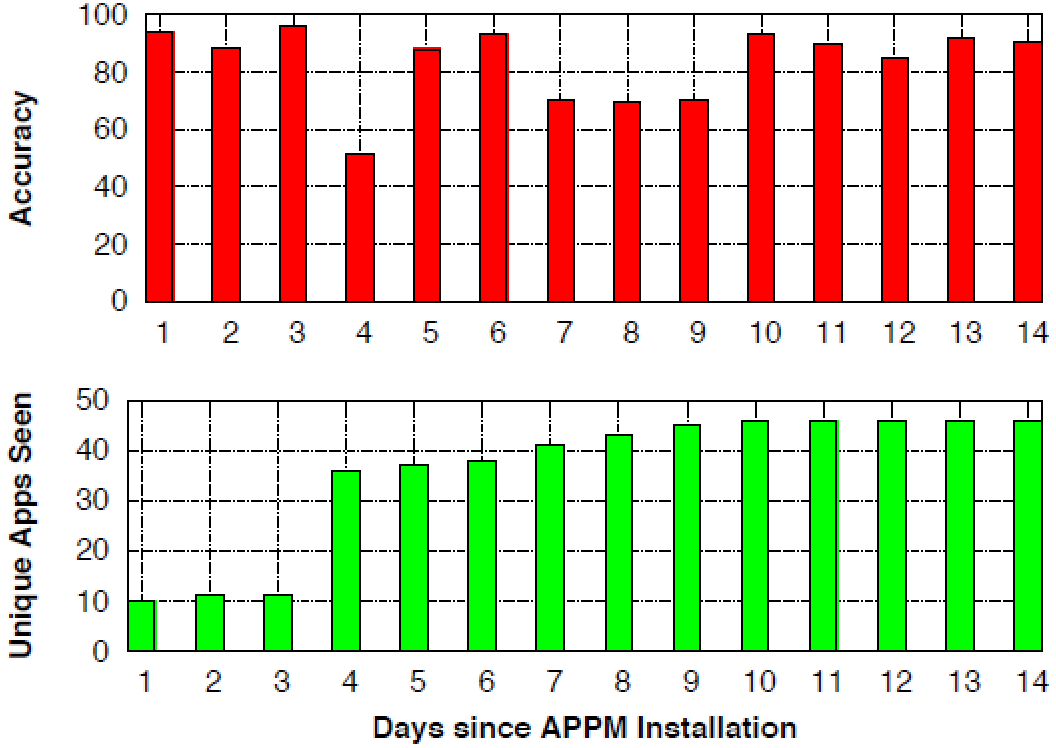
Better freshness vs. no-prefetch(NOOP) and Falcon e.g. for Email



Median: NOOP=32.6s, Polling=4.1, APPM=2.7



Little training and adaptable



Low system overhead

Binary Size	0.96MB
Memory	6.5MB
Time for prediction	$<250\mu s$
Time for prefetch decision	<5ms

Low battery use:

1875 = 0.13% of 1400mAh battery

	Energy Consumption(in μAh)	
	Data Transfer Phase	**Total**
Sequential	2320.04	3547.25
Parallel	1407.31	1875.00

Contributions

+ Best prediction accuracy vs. established methods
+ Location not needed
+ Better freshness
+ Little training and adaptable
+ Low system overhead

~ Battery life

Next level – improve my life!

Mining context data reveals user patterns

Chance to personalize/improve user experience!

MINING APPLICATION 3

Srinivasan, V., Moghaddam, S., Mukherji, A., Rachuri, K. K., Xu, C., & Tapia, E. M. (2014, September). Mobileminer: Mining your frequent patterns on your phone. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (pp. 389-400). ACM.

MobileMiner

Objectives:

- Finding co-occurrence patterns
- Improving overall user experience
- Enabling pattern mining entirely on device

Co-occurrence:

- {Morning, Breakfast, AtHome} -> {ReadNews}

Benefits:

- Preload content

Benefits:

- Provide useful shortcuts

Benefits:

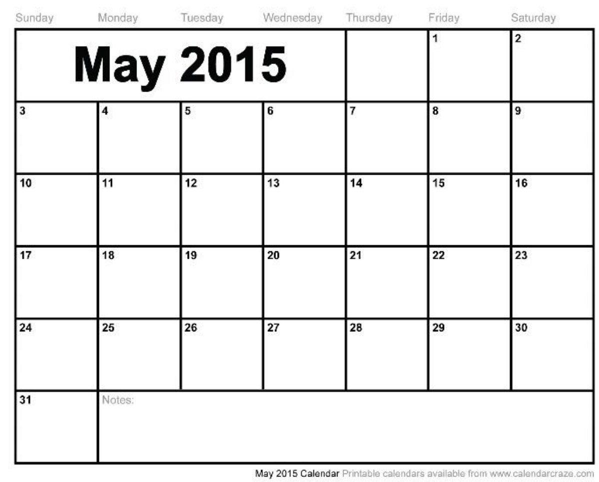
- Altering user habits

Benefits:

- If-then-else-type coding

Benefits:

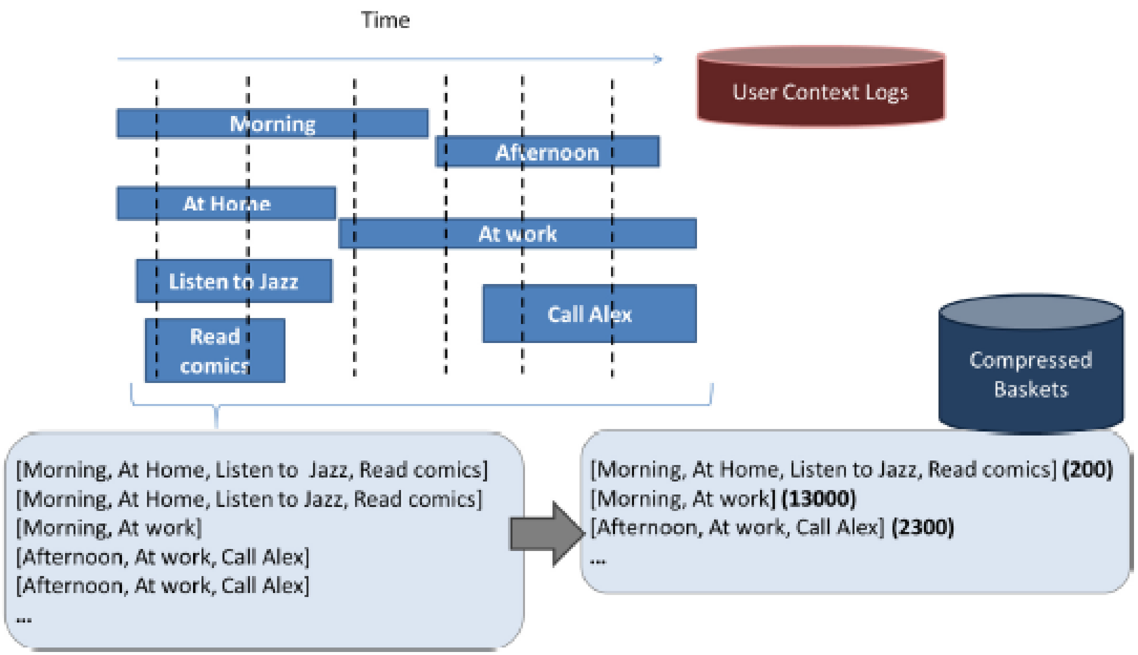
- Pattern mining service at multiple resolutions using limited resources



Benefits:

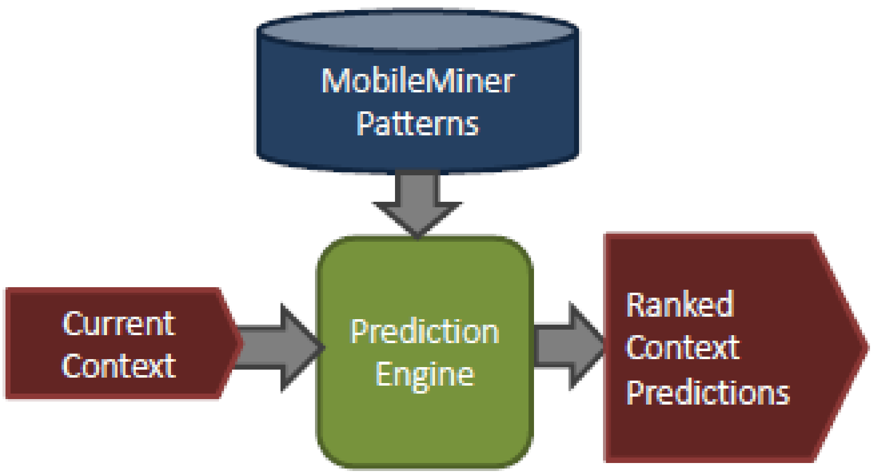
- Computations carried out during charging and when no app in use

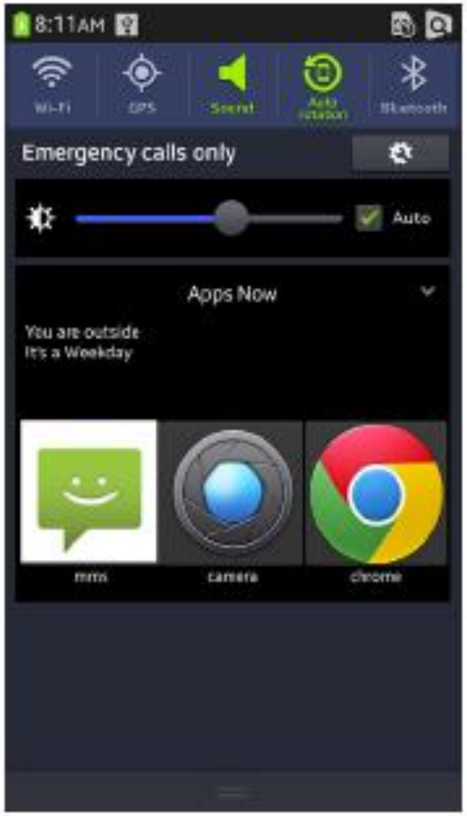
Rule/frequent itemset mining



Basket extraction + co-occurrence + filtering

Prediction pipeline



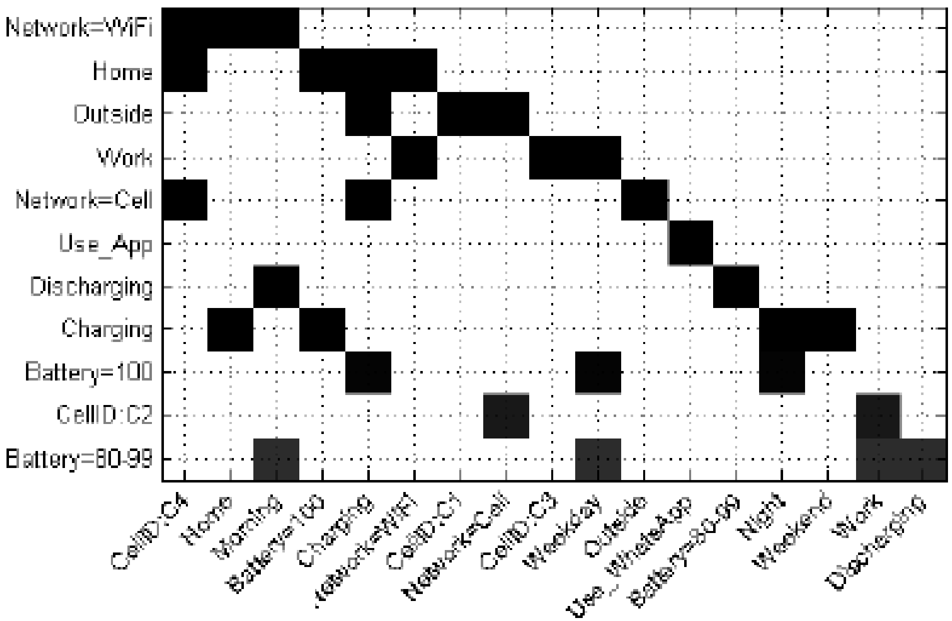

8:11AM
Sound
Emergency calls only
Auto
Apps Now
You are outside
It's a Weekday
mms
camera
chrome


4:20AM
Sound
Emergency calls only
Auto
Apps Now
You are at home
It's a Saturday
katana
whatsapp
chrome

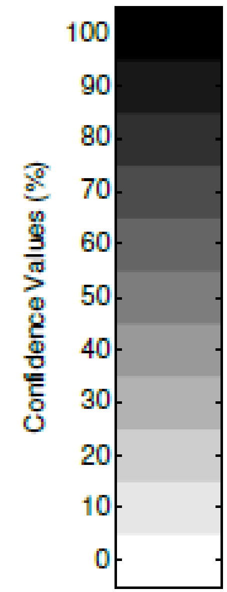
Performance evaluation

Performance Metric	Base Basket Extraction	Base Rule Mining	App Usage Filtering	App Usage Rule Mining
Execution time	1.7 seconds	16.5 minutes	1.4 seconds	21.2 seconds
Memory	9.9 MB	44.2 MB	11.6 MB	1.0 MB
CPU Utilization	22.9 %	24.3 %	20.8 %	21.9 %
Number of baskets or rules	114275 baskets 8559 compressed	46675 rules	752 baskets 327 compressed	1062 rules
Energy per day as % of full battery	<0.01 %	0.45 %	<0.01 %	0.01 %

CO-OCCURRENCES FOR ONE USER



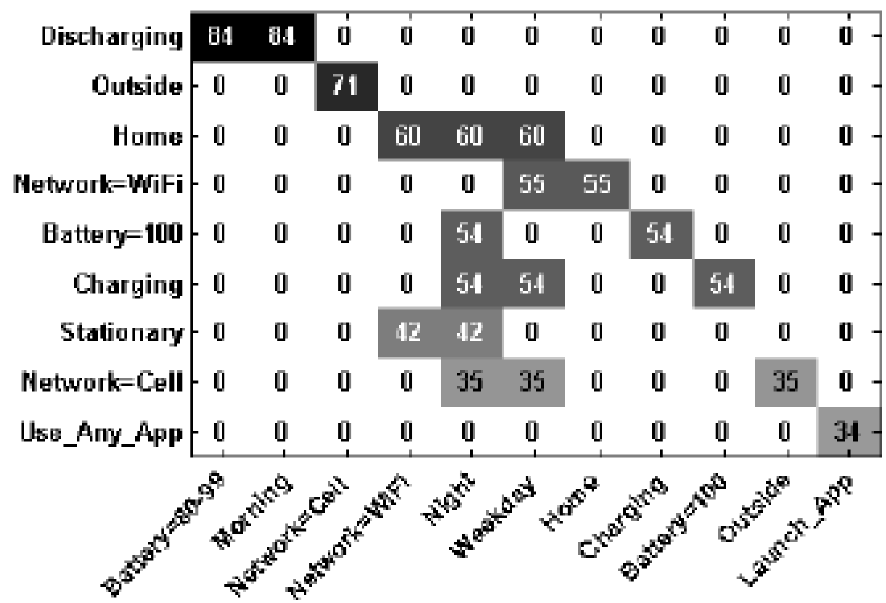
Overall patterns.



Key.

- Preload data intensive content before leaving home
- Provide reminders to switch to low power/charge phone

Co-occurrences for multiple users



All users.

- Group activity scheduling
- Recommendation services for groups of people

CONTRIBUTIONS

+ Effective reminders/recommendations
+ Computations on phone only (privacy, network)
+ Smart usage of limited resources
+ Battery life

DISCUSSION

Three approaches for improving user experience

Discussion

Three approaches for improving user experience

Measurable improvement

Discussion

Three approaches for improving user experience

Measurable improvement

People not always welcoming of such innovation

Conclusion

Undeniable usefulness

Conclusion

Undeniable usefulness

No guarantee that it will be used

Conclusion

Undeniable usefulness

No guarantee that it will be used

Would YOU use it?


That's all Folks!
Any Question ?

Mining application I

- Inference model infers posteriori probability of a target app $P(App_i \mid C_i)$, given sensory evidence C_i and prior probability $P(S_{Appi})$

$$P(App_i \mid C_i) = \frac{P(S_{App_i} = yes \mid C_i)}{P(S_{App_i} = yes \mid C_i) + P(S_{App_i} = no \mid C_i)},$$

where

$$P(S_{App_i} \mid C_i) = P(S_{App_i}) \prod_j P(c_{i,j} \mid S_{App_i}), \text{where } S_{App_i} \in \{yes, no\}.$$

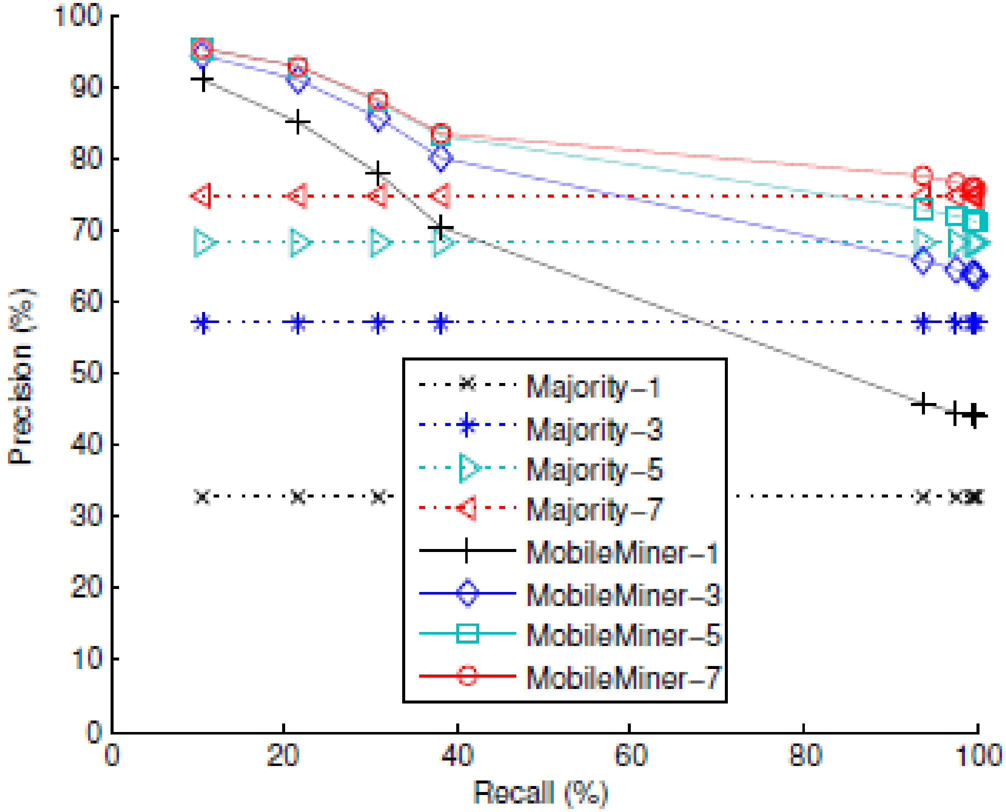
Mining application II

- Decision engine
  - Trade-off between freshness and bandwidth cost
  - Optimal refresh time for predicted app to be found

Algorithm 1 Compute Time To Prefetch

1. **Input:** Network Bandwidth Cost C; TTU distribution function for target app F_{TTU}; TTU probability history $d[1...L]$; Count of target app in user's history N.
2. **Output:** Time to wait for prefetch Δt.
3. Sort d in decreasing order.
4. $p = d[N_e * C]$ i.e. NC^{th} highest TTU probability.
5. $\Delta t = F^{-1}_{TTU}(p)$.
6. **return** Δt

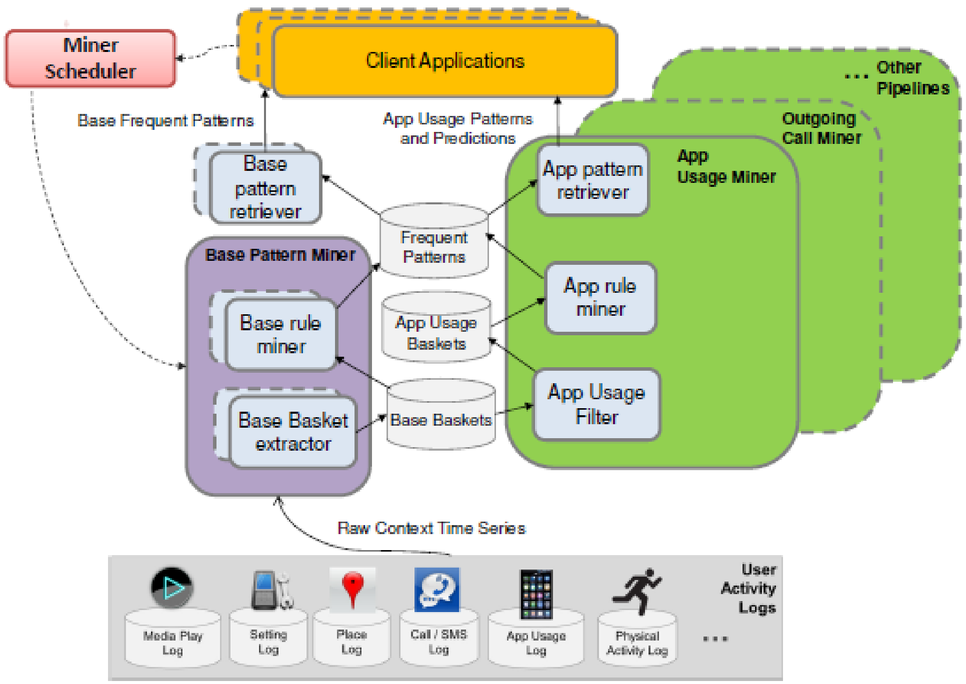
$$F_{TTU}(\Delta t) = p(nextapp = e) \times F_{TTU|nextapp=e}(\Delta t)$$



App prediction.

Mining application III

- System architecture



- Association rule-mining : Antecedent -> Consequent