University of Glasgow | School of Computing Science

Probabilistic Formal Analysis of App Usage to Inform Redesign

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School of Computer Science Seminar, University of St Andrews
9 February 2016

Installing and using an app

Installing and using an app

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ANDROID APP ON Google play

Installing and using an app

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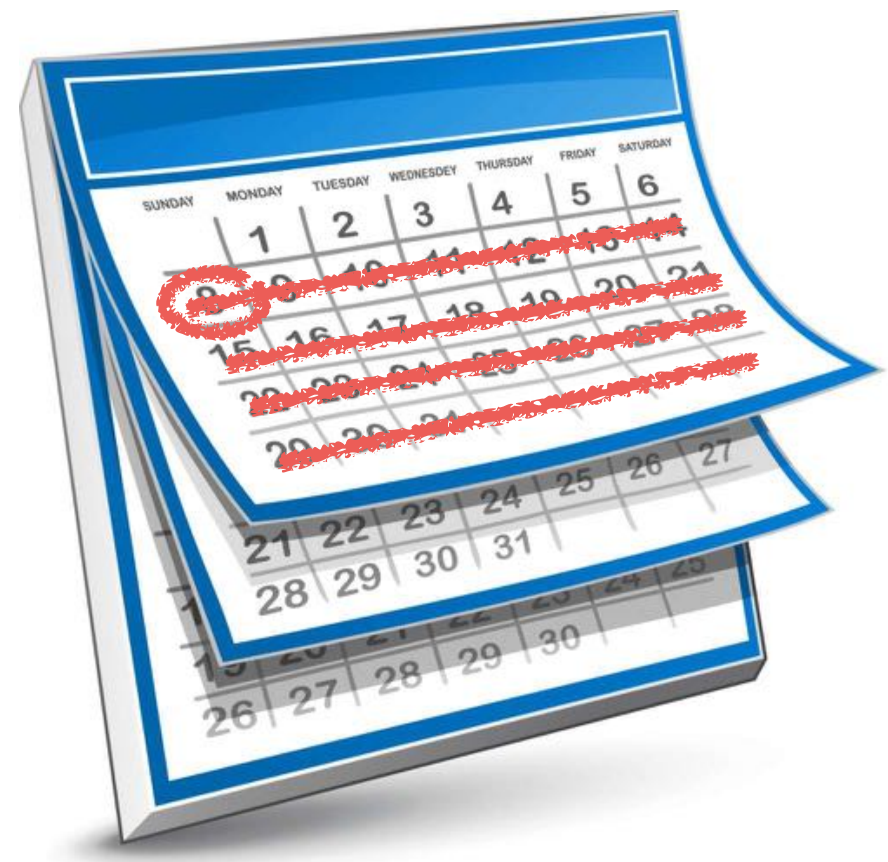

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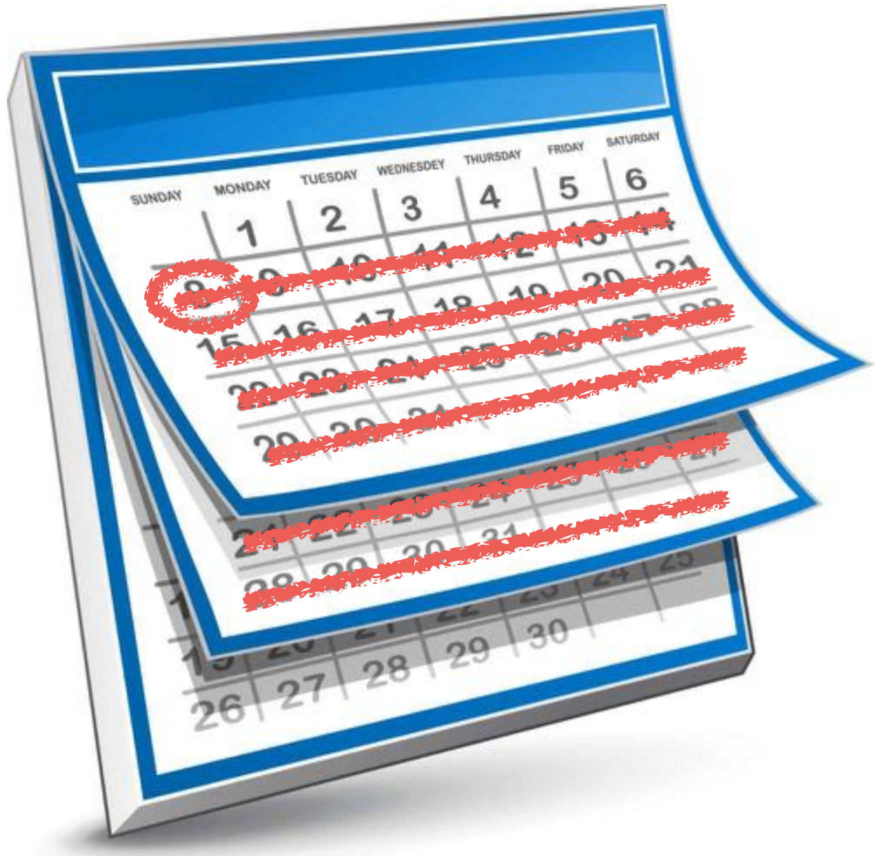
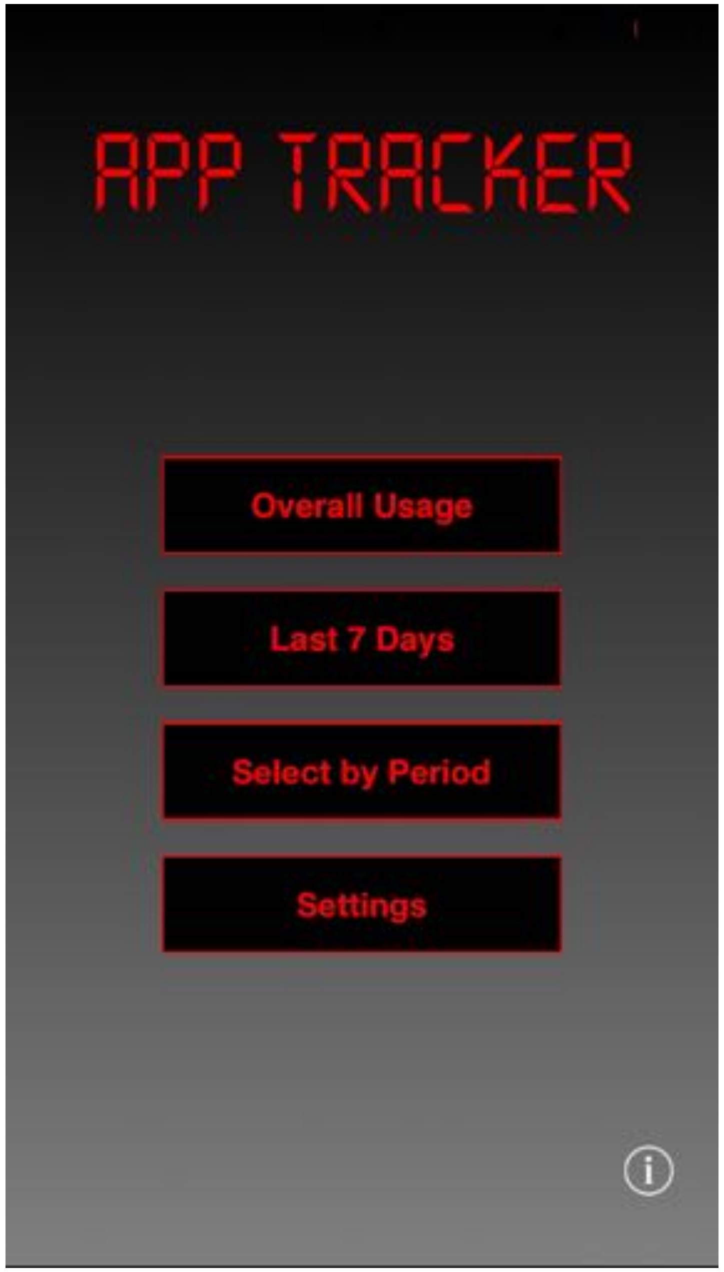


Our motivation

- Users engage with an app in different ways — understand them and use them to inform the app redesign.
- How should we identify and characterise the different styles of use within a population of users?
- How does such characterisation evolve:
    - over an individual user trace?
    - over a number of sessions?
    - over days and months?

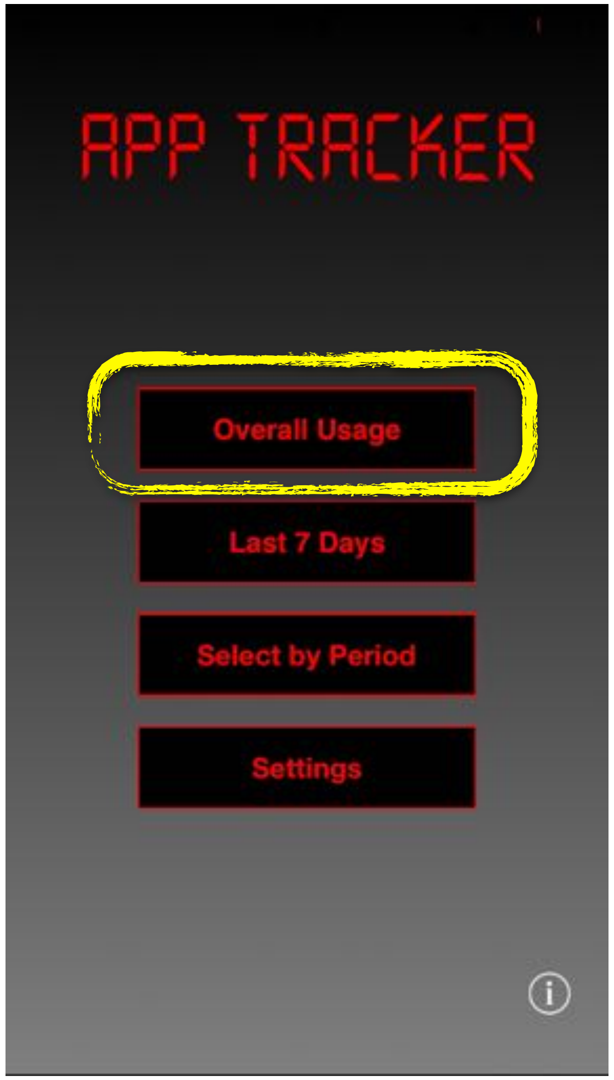
Case study: the **AppTracker** app

- Runs in the background
- Records opening and closing of apps, locking and unlocking the device
- Provides charts and statistics about the device usage
- Over 35K downloads



AppTracker main menu

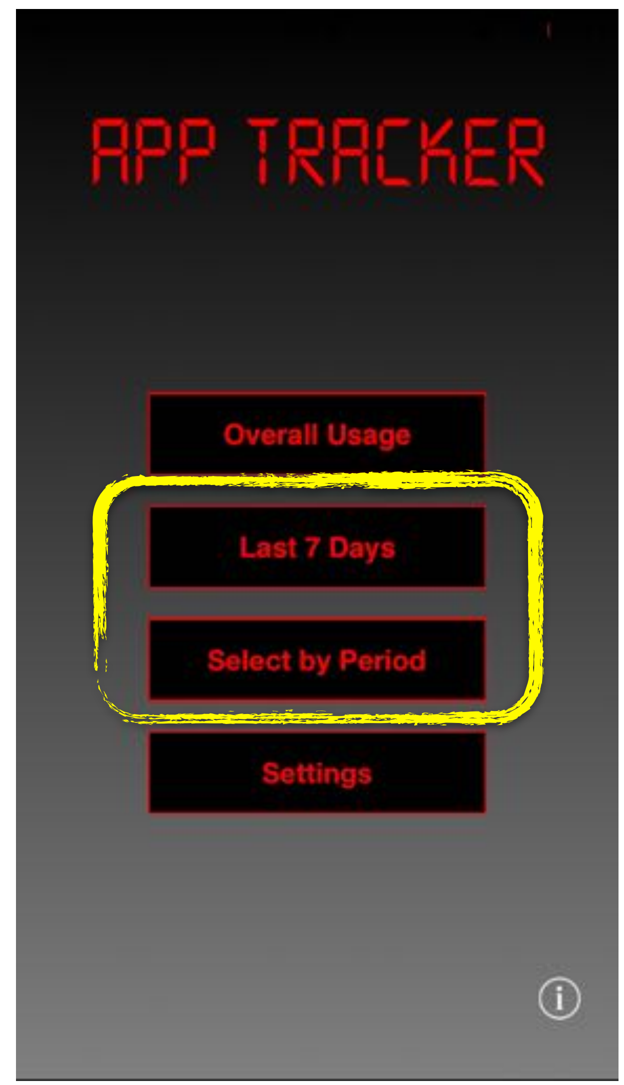
- ***Overall Usage*** provides a summary of all the data recorded since AppTracker was installed:
    - ✦ ***Most Used Apps (Top Apps)***
    - ✦ ***Stats***

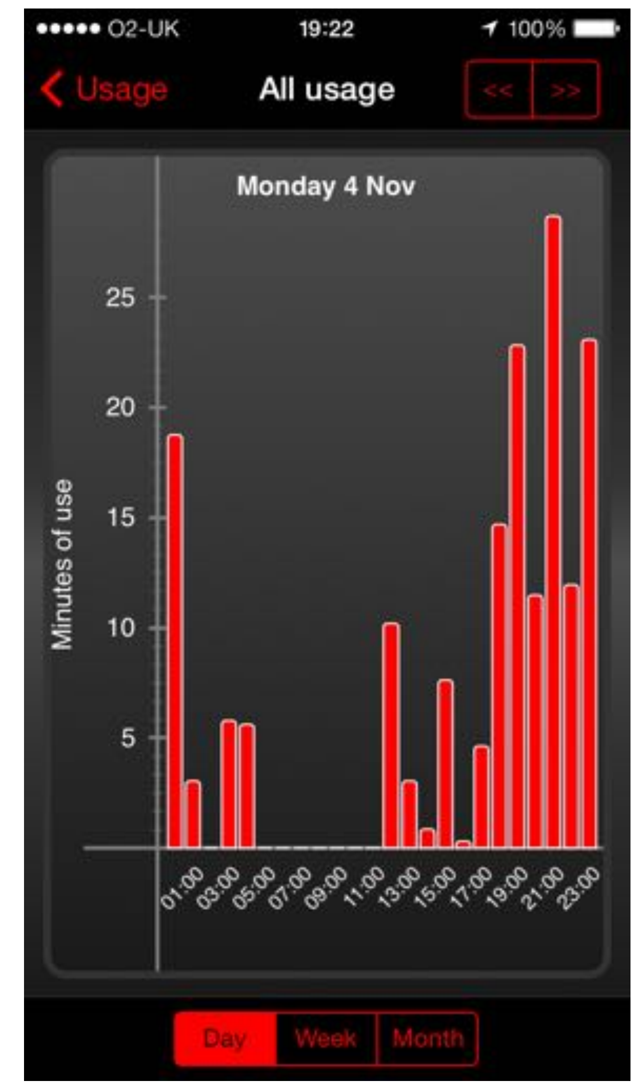


AppTracker main menu

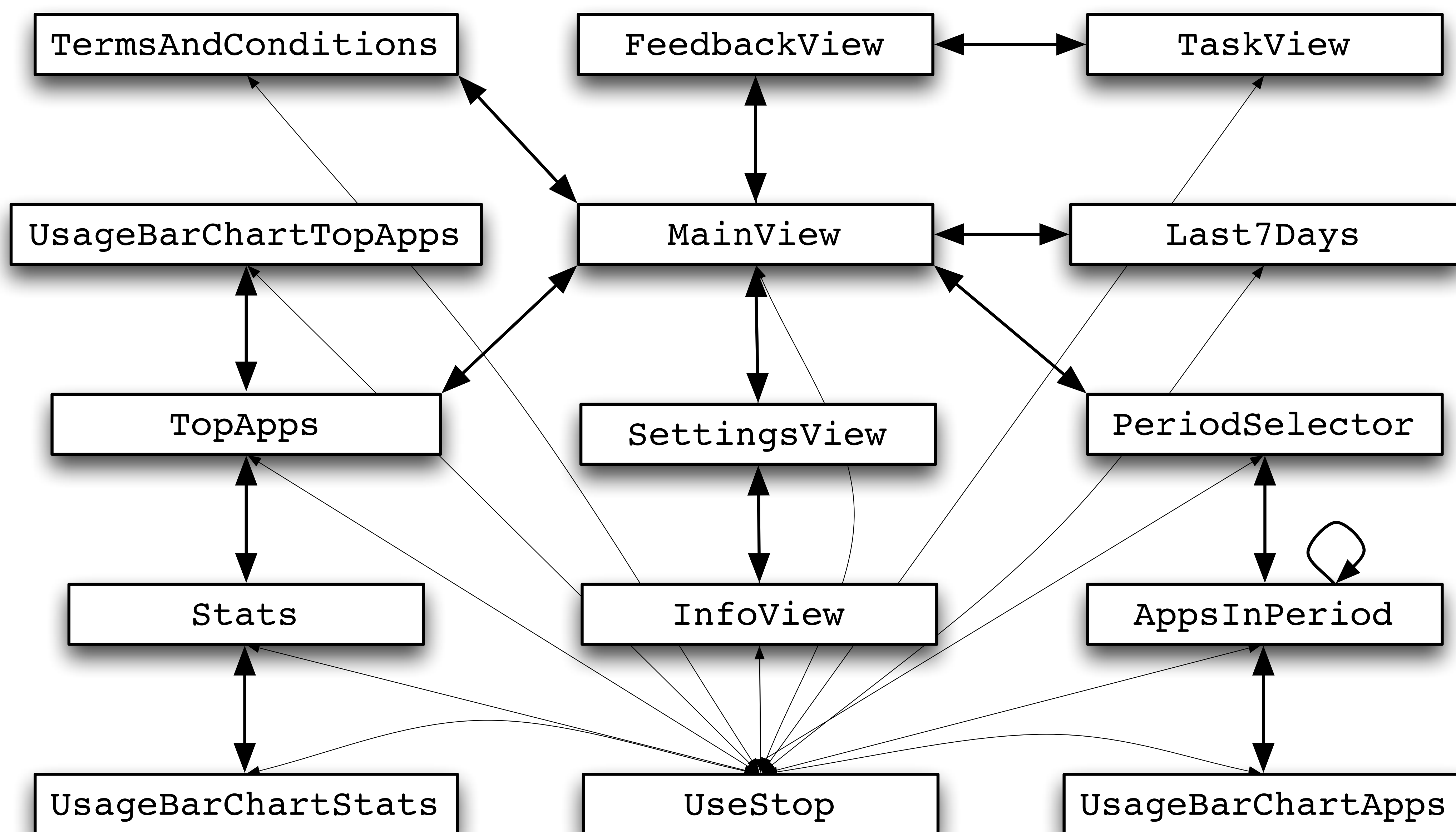
- ***Last 7 Days*** shows a stacked bar graphs of usage of the top 5 apps during the last 7 days of usage.

- ***Select by Period*** shows statistics by any period of interest, e.g.
  - ✦ most used app last Monday
  - ✦ time spent on Facebook last week
  - ✦ device usage over a day

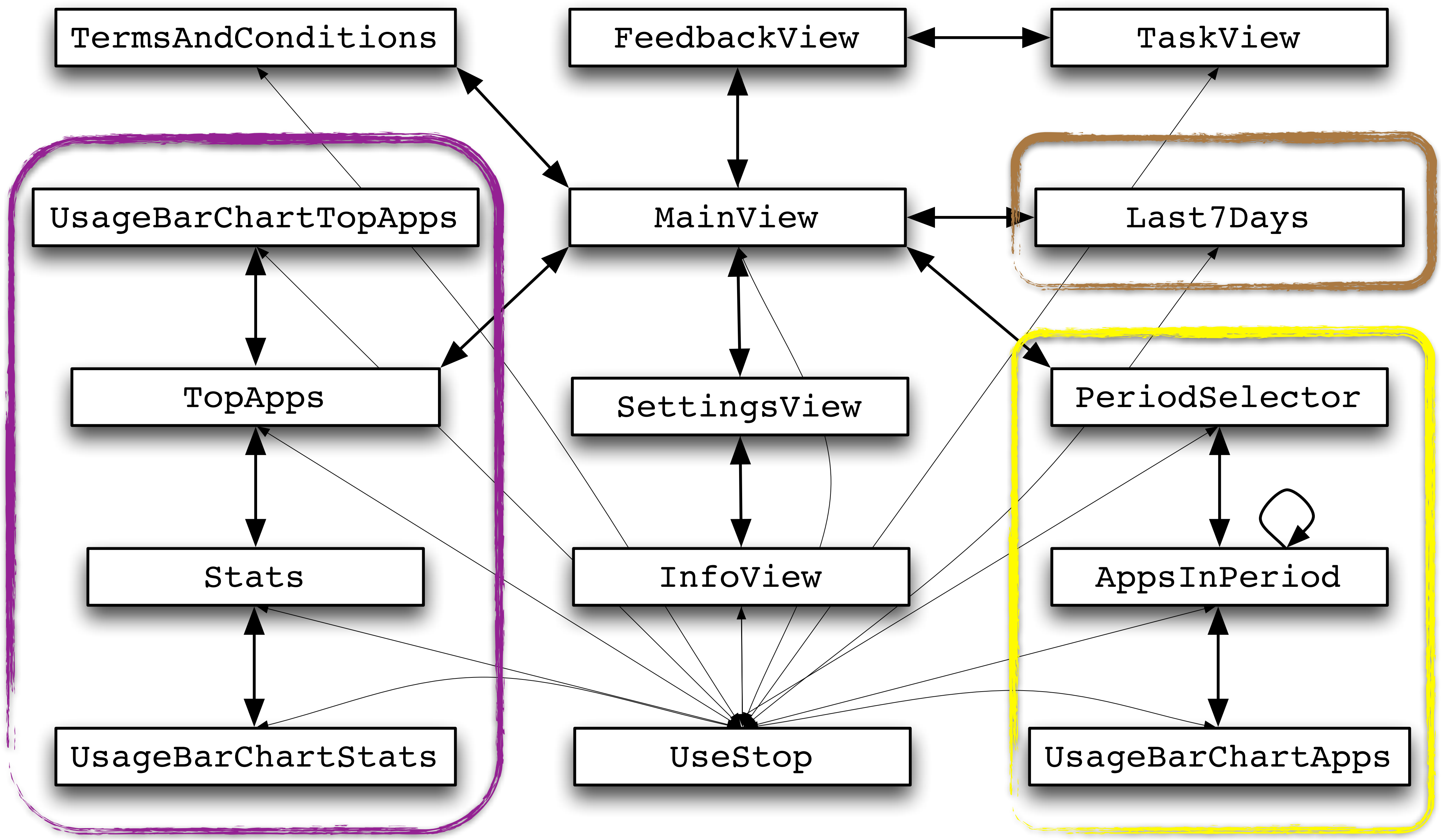




AppTracker state diagram



AppTracker hypothesised behaviour (frequent)



Overview of the analysis

- Instrument the app
- Clean and prepare the raw logged data
- Infer activity patterns and user weightings for given parameters and data sets
- Ask questions about the patterns using probabilistic temporal properties and model checking in PRISM
- Compare user weightings / patterns distributions
- Discuss with developers to inform redesign

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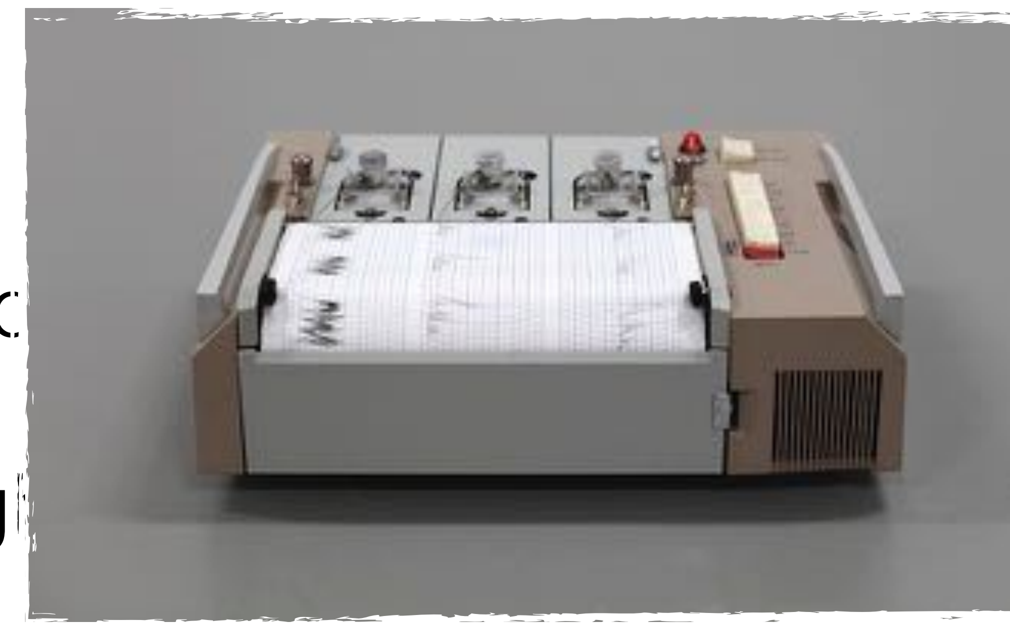

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Not sequential!

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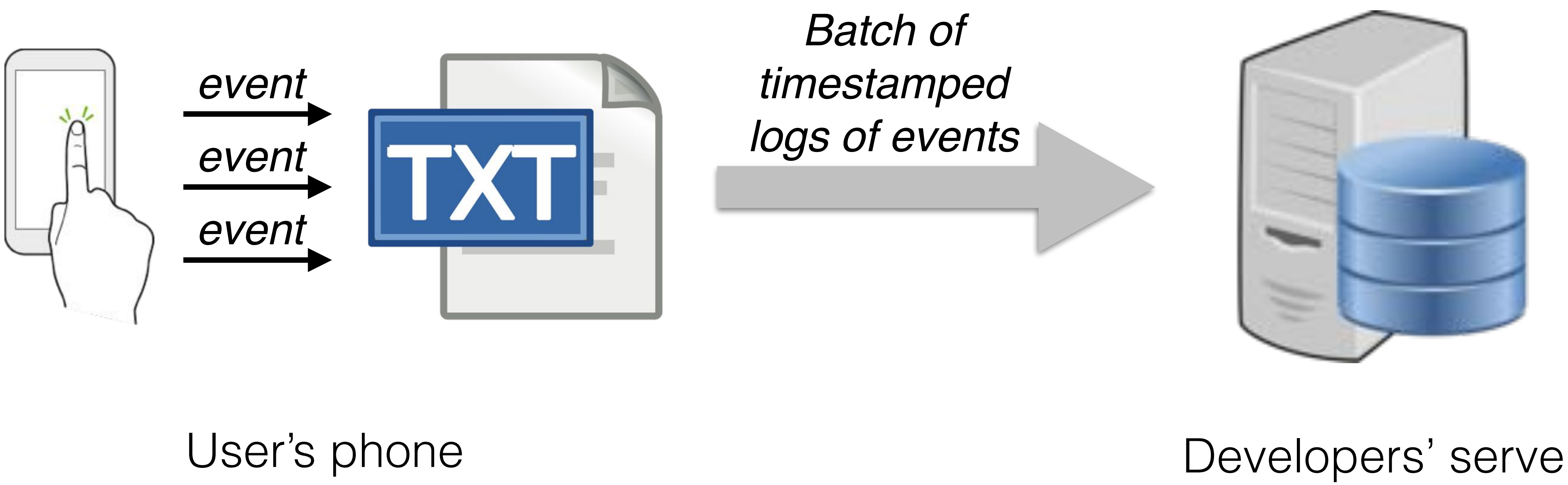
Complementary to other data analytics methods

(e.g., SQL queries, visualisations)

Instrument the app



SGLog data logging infrastructure (SUM group@GU)

Prepare the raw logged data

- User traces based on 15 selected state abstractions:


```
[{"deviceid":"xx:xx:xx:xx:xx:xx","totalevents":230,"firstSeen":"2013-08-20
09:10:59","lastSeen":"2014-03-24 09:57:32","sessions":[[{"timestamp":"2013-08-20
09:11:02","data":"TermsAndConditions"},{"timestamp":"2013-08-20 09:11:23",
"data":"Main"},{"timestamp":"2013-08-2009:11:46","data":"TopApps"},
{"timestamp":"2013-08-20 09:11:50”,"data":"Main"},
{"timestamp":"2013-08-2009:11:52","data":"Last7Days"},{"timestamp":"2013-08-20
09:11:56", "data":"Main"},{"timestamp":"2013-08-20:11:59", "data":"PeriodSelector"},
{"timestamp":"2013-08-20 09:12:04","data":"Main"},{"timestamp":"2013-08-20
09:12:06","data":"UseStop"}],...
```


- Clean up the data: 489 user traces between Aug. 2013 - May 2014
- Segment the session data: intervals of days of usage [0,1), [1,7), [7,30), [0,30), [30,60), [60,90)
- Compute the 15x15 transition-occurrence matrix for each trace in a given data set

Infer activity patterns

- Look for $\mathcal{K}$ distinct behaviours
  - Run a non-linear optimisation algorithm for parameter estimation to learn $\mathcal{K}$ admixture bigram models from transition-occurrences matrices
  - $\mathcal{K}$ discrete-time Markov chains Φ_k — **activity patterns**: $\Phi_k[i,j]$ is the probability of moving from state i to state j while in Φ_k
  - for each user trace, a weight vector $(\Theta_1, \ldots, \Theta_{\mathcal{K}})$ with Θ_k the probability of using the k^{th} activity pattern

About PRISM

Probabilistic model checker (Birmingham & Oxford)

- probabilistic models expressed in a high-level state-based language (DTMC, MDP, CTMC, etc.)
- model checking quantitative properties expressed as temporal logic formulae (PCTL, CSL, PCTL*, etc.), extensions with costs/rewards
- exhaustive analysis of all possible executions of the model

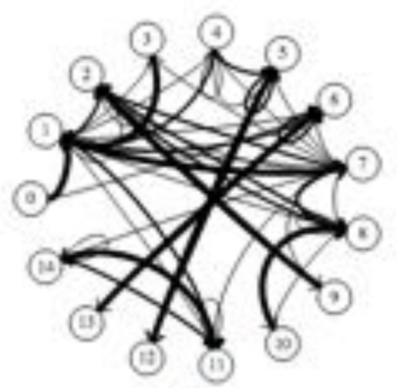
Activity patterns in PRISM

- Generate a PRISM model for each activity pattern
  - 15 states — one for each view, including `UseStop`
  - reward structures for:
    - visiting a specific screen view (state) — reward value 1
    - counting button taps (steps/transitions) — reward value 1
- What can we say about each activity pattern?

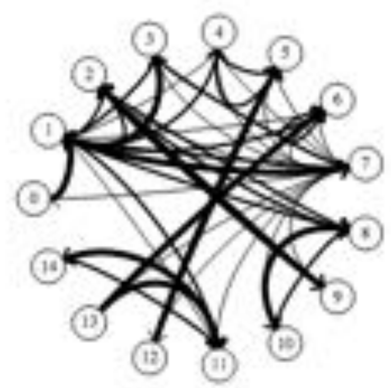
Activity patterns for the first 30 days

Activity patterns for the first 30 days

2 patterns



AP1



AP2

Discrete-time Markov chains: the arrows are probabilistic transitions.

Activity patterns for the first 30 days

Discrete-time Markov chains: the arrows are probabilistic transitions.

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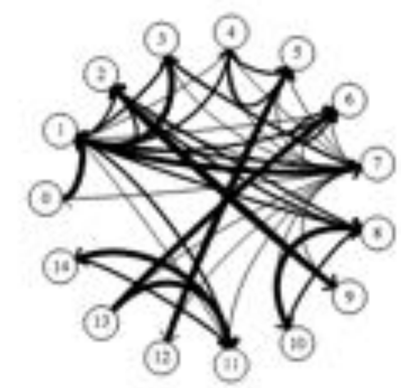
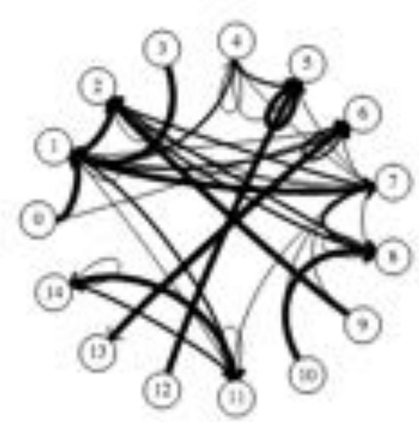


AP2

3 patterns



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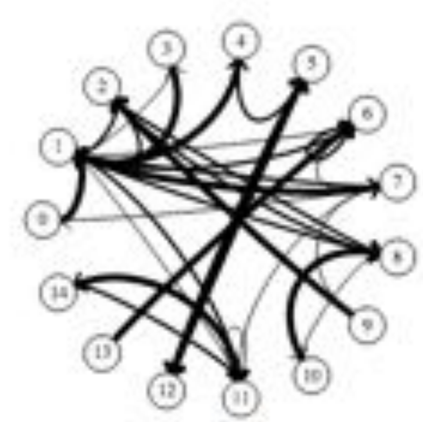

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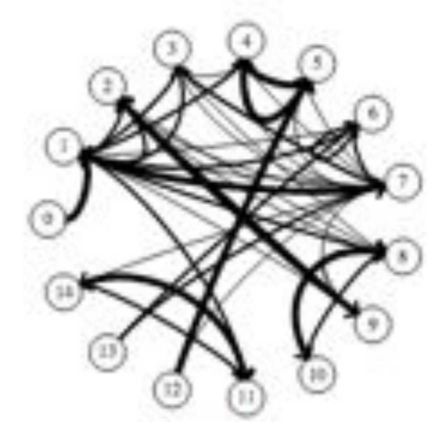
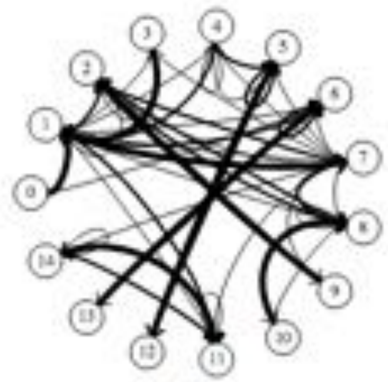


AP3

Activity patterns for the first 30 days

Discrete-time Markov chains: the arrows are probabilistic transitions.

2 patterns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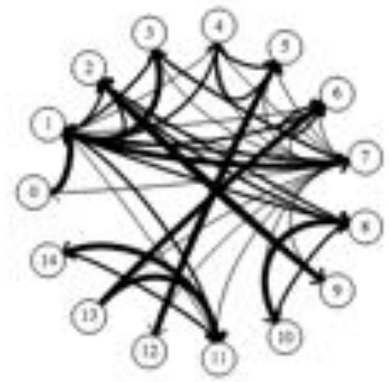
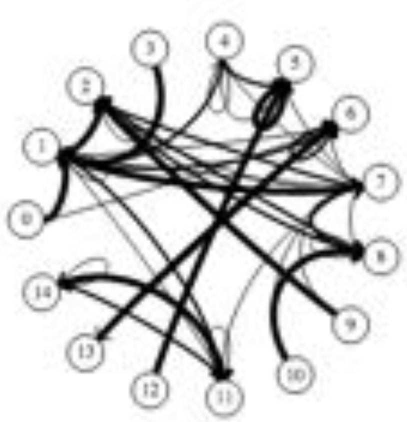

AP2

3 patterns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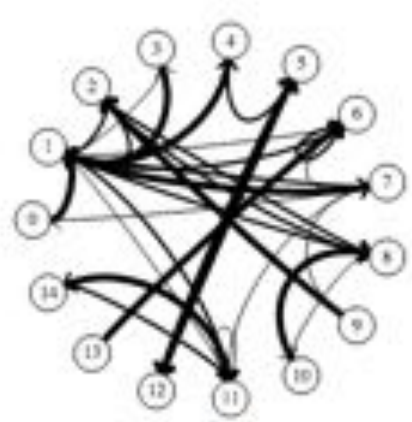
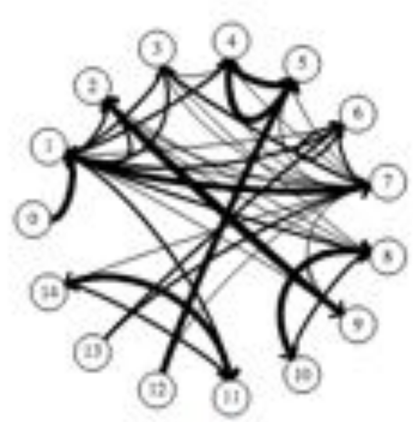
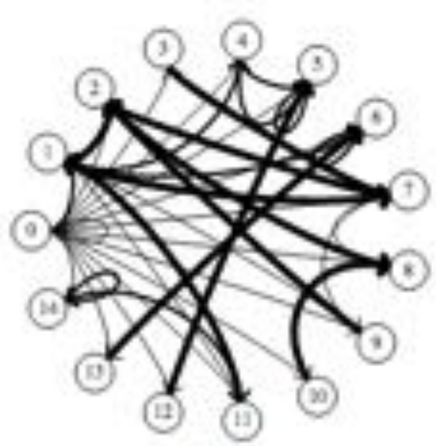

AP2


AP3

4 patterns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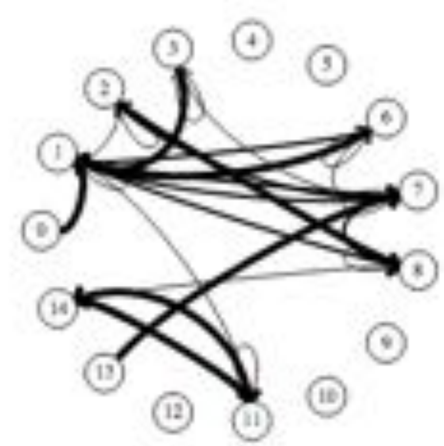
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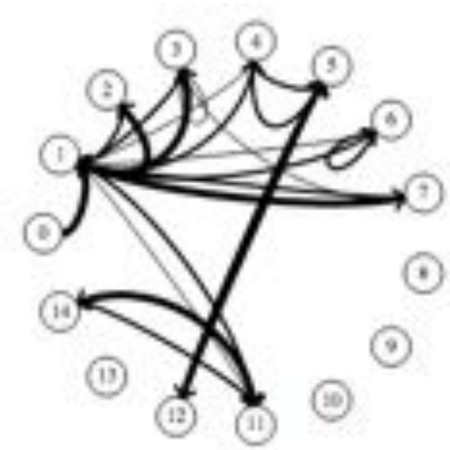
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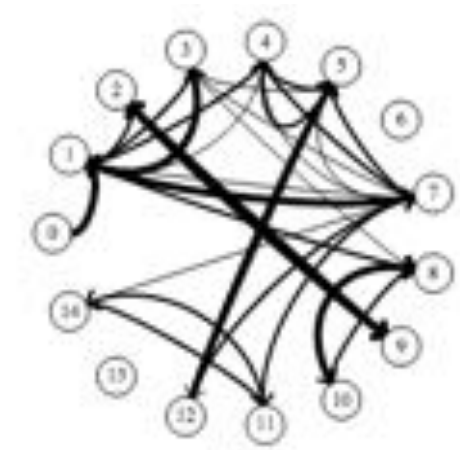
AP4

What questions can we ask?

- An exploratory process of identifying the “good” questions:
  - ✦ any type of app
  - ✦ a particular type of app (e.g. goal-oriented apps)
  - ✦ a particular app
- Find experiential questions in order to identify:
  - ✦ more relevant questions to ask and
  - ✦ most relevant states to query

Formulate temporal properties

(PCTL with rewards)

- General questions:
  - Likelihood of viewing a particular screen for the first time within 100 taps.
  - Average number of views of a particular screen within 20 button taps.
  - Average number of button taps to reach a particular screen view, etc.
- More app-specific questions:
  - Probability to perform an event if always reading ***InfoView*** within 25 steps.
  - Average number of button taps to go to screen view s_2 from s_1.
  - Probability of repeating a specific event *50* times, etc.

Formulate temporal properties

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- General questions:
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    - Average number of views of a particular screen within 20 button taps.
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    - Probability of repeating a specific event *50* times, etc.

Compare the results across all patterns!

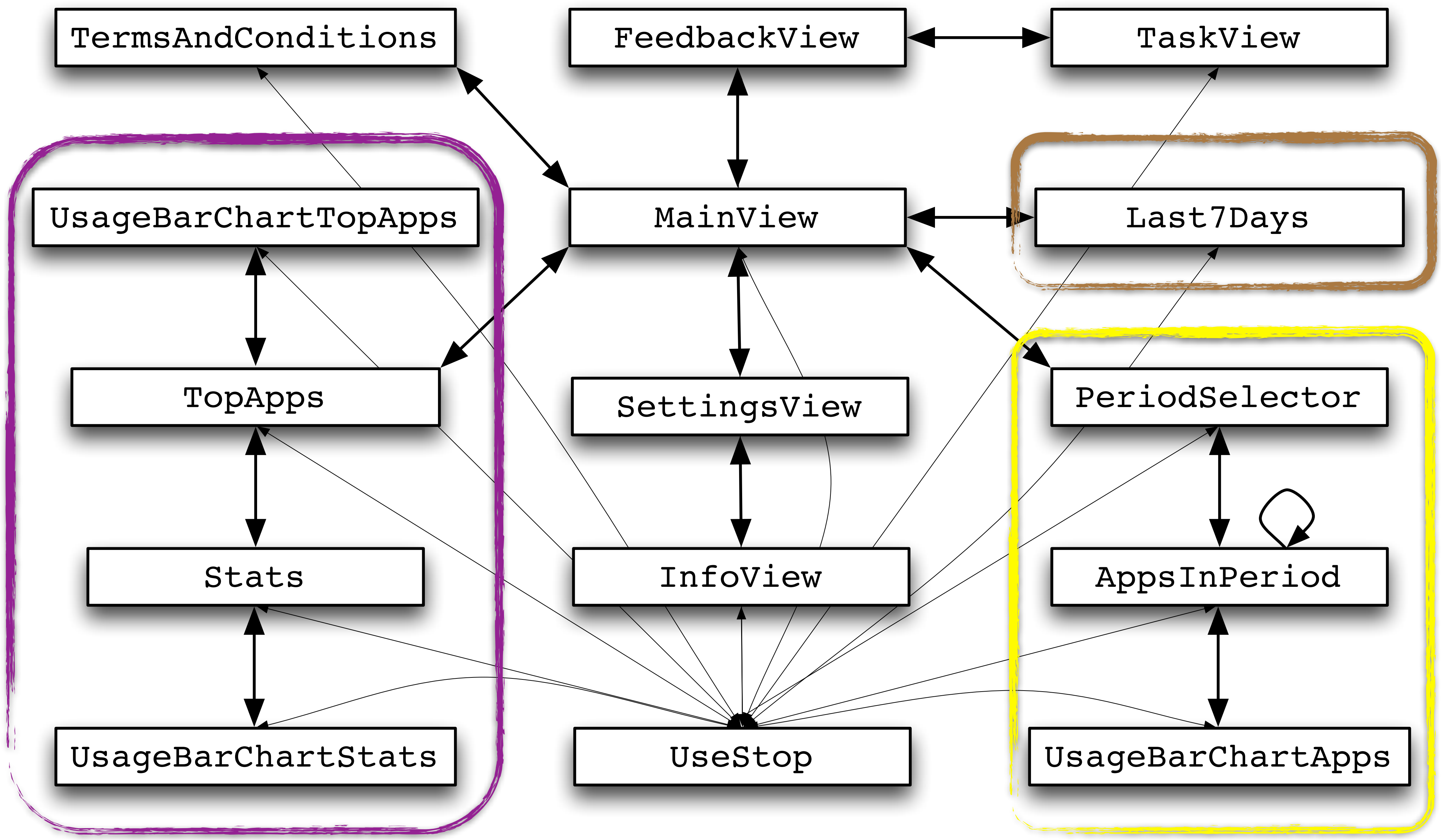
Formulate temporal properties

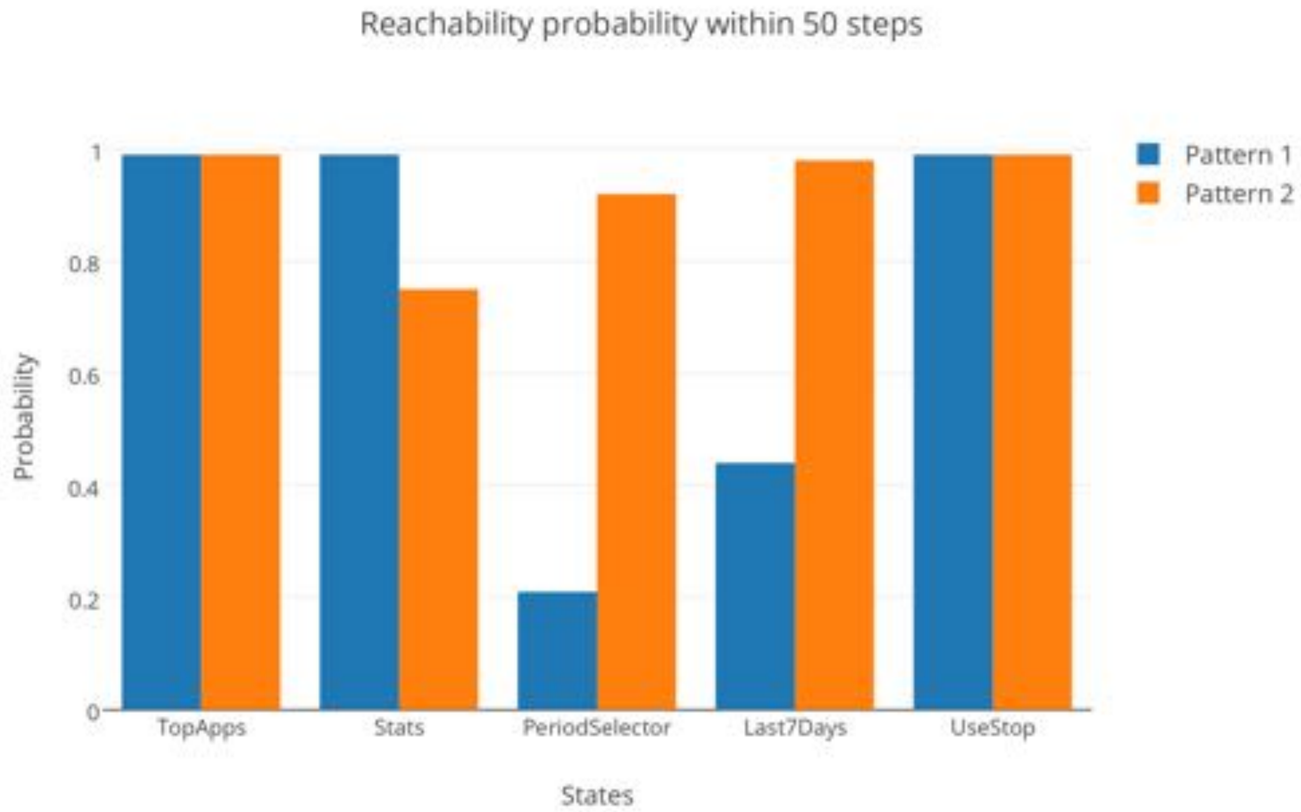
- Probability to reach the state **`s`** for the first time within **`N`** steps:
  - `P=? [!s U<=N s]`
- Expected number of visits to the state **`s`** within **`N`** steps:
  - `R{“r_s”}=? [C<=N]`
- Expected number of steps to reach the state **`s`**:
  - `R{“r_Steps”}=? [F s]`

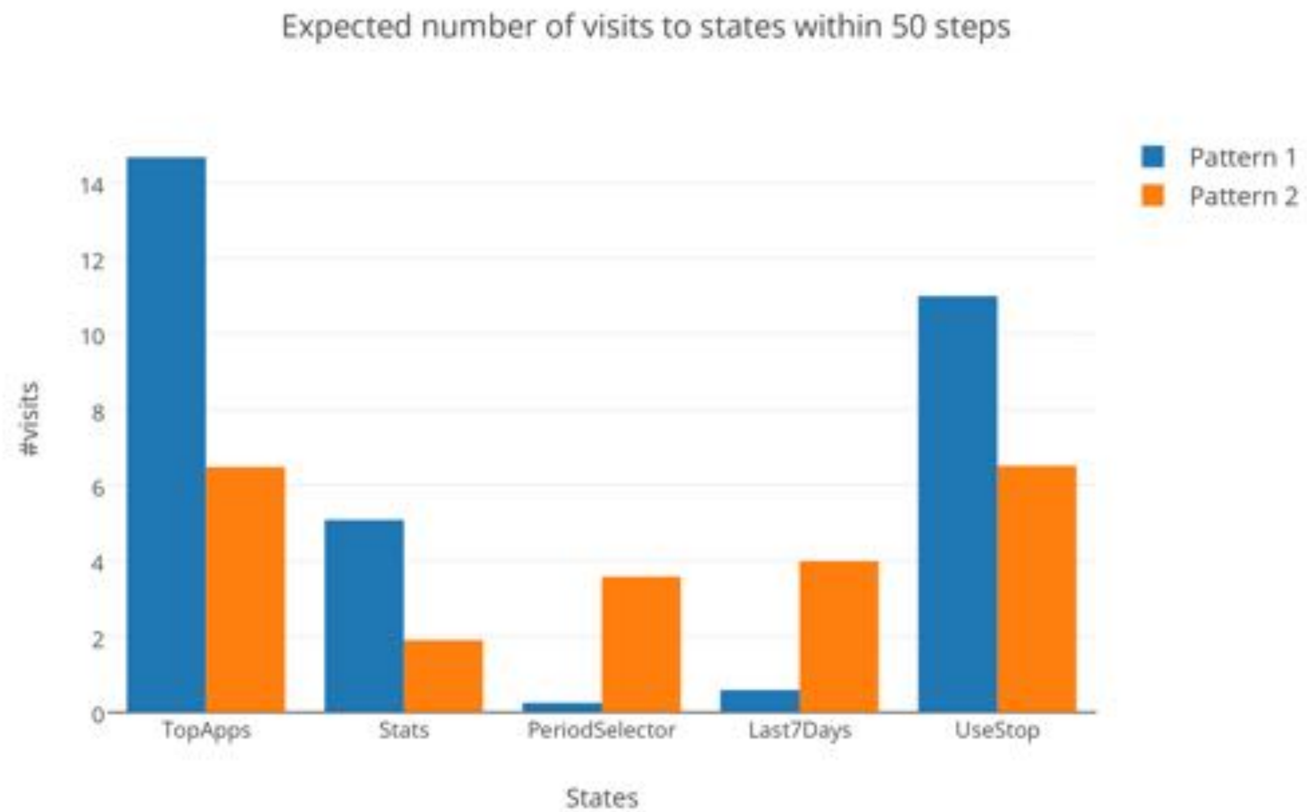
Probabilistic model checking

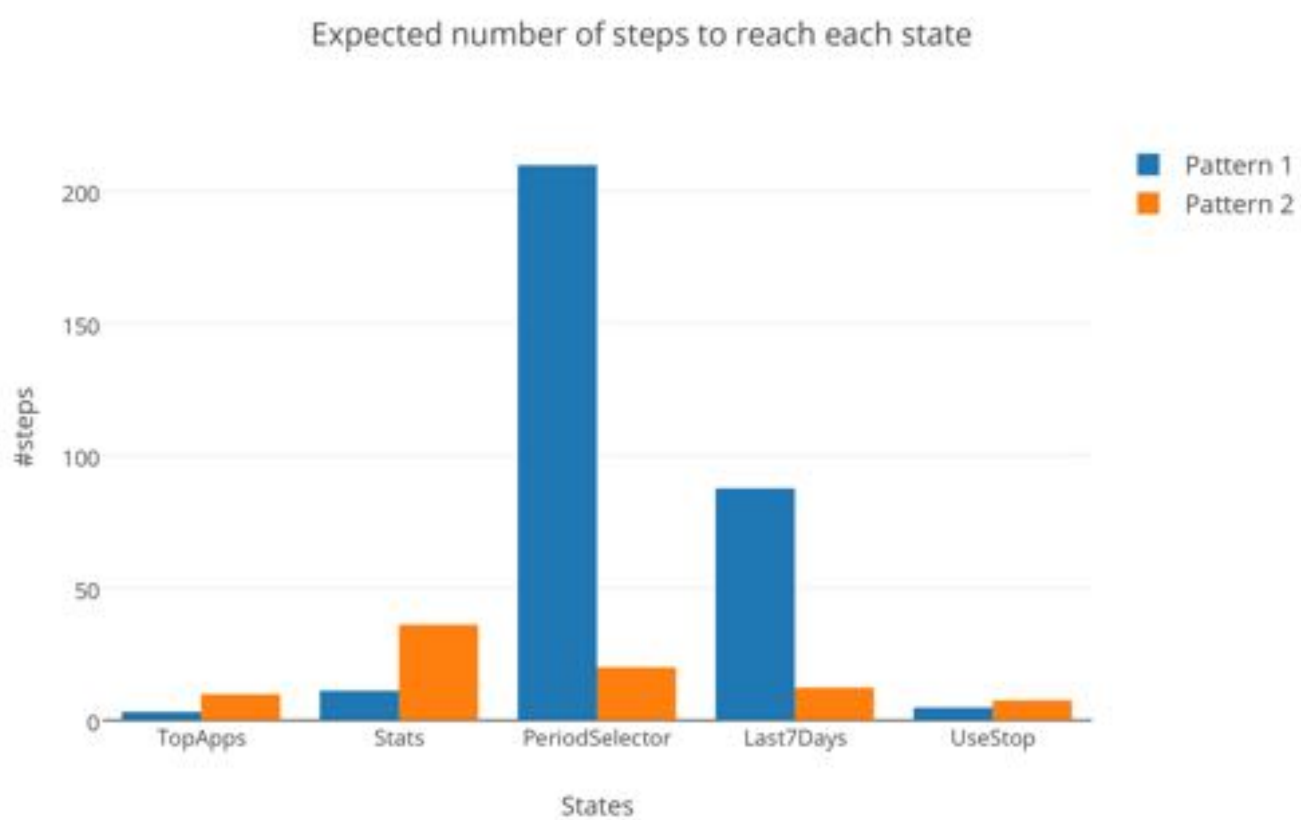
- Probabilistic Computation Tree Logic (PCTL) with rewards in PRISM
- Compare the results across:
    - all activity patterns,
    - states: `TopApps, Stats, PeriodSelector, Last7Days, UseStop,`
    - intervals of days of usage [0,1), [1,7), [7,30), [0,30), [30,60), [60,90)

AppTracker hypothesised behaviour









First month analysis:

- two activity patterns ($\mathcal{K}$=2)
- Pattern 1
  - Higher `TopApps` and `Stats`
  - Shorter and more frequent sessions
- Pattern 2
  - Significant results for `Last7Days` and `PeriodSelector`
  - Longer and less frequent sessions

Table 2: **Property 1** (the probability of reaching a given state for the first time within N steps), **Property 2** (the expected number of visits to a given state within N steps), and **Property 3** (the expected number of time steps to reach a given state) checked for different states and time cuts, and for $N = 50$ steps

Prop.	Time cut	TopApps		Stats		PeriodSelector		Last7Days		UseStop	
		AP1	AP2	AP1	AP2	AP1	AP2	AP1	AP2	AP1	AP2
Property 1	$[0, 1)$	0.99	0.99	0.99	0.83	0.47	0.79	0.49	0.96	0.99	0.99
	$[1, 7)$	0.99	0.99	0.98	0.80	0	0.93	0	0.98	0.99	0.99
	$[7, 30)$	0.99	0.99	0.99	0.64	0.01	0.94	0.84	0.96	0.99	0.99
	$[0, 30)$	0.99	0.99	0.99	0.75	0.21	0.92	0.44	0.98	0.99	0.99
	$[30, 60)$	0.99	0.99	0	0.90	0.73	0.83	0.56	0.98	1	0.99
	$[60, 90)$	1	0.95	0.96	0.72	0	0.94	0	0.97	1	0.99
Property 2	$[0, 1)$	13.94	7.44	7.63	2.15	0.79	1.82	0.70	3.13	11.41	6.17
	$[1, 7)$	17.22	5.77	4.00	2.31	0	3.97	0	4.03	12.91	6.30
	$[7, 30)$	14.93	7.15	5.43	1.47	0.01	4.61	1.78	3.41	12.86	5.74
	$[0, 30)$	14.67	6.48	5.08	1.90	0.24	3.58	0.58	3.99	11.00	6.51
	$[30, 60)$	13.40	6.83	0	3.76	4.41	2.04	0.85	4.54	12.46	5.61
	$[60, 90)$	17.30	5.83	2.94	2.60	0	3.26	0	4.43	13.96	5.63
Property 3	$[0, 1)$	3.31	8.41	8.18	28.67	79.32	32.46	74.87	15.56	4.86	7.88
	$[1, 7)$	2.05	10.70	12.44	31.90	∞	19.12	∞	12.38	3.85	7.55
	$[7, 30)$	2.52	9.68	9.70	48.61	∞	17.78	26.61	14.58	3.88	8.44
	$[0, 30)$	3.05	9.73	11.01	36.03	209.68	19.94	87.54	12.19	4.67	7.43
	$[30, 60)$	4.04	10.34	∞	22.33	38.21	28.28	61.74	11.08	1	8.82
	$[60, 90)$	2.02	15.28	16.53	39.68	∞	17.41	∞	11.56	3.57	8.90

Table 2: Property 1 (the probability of reaching a given state for the first time within N steps), Property 2 (the expected number of visits to a given state within N steps), and Property 3 (the expected number of time steps to reach a given state) checked for different states and time cuts, and for $N = 50$ steps

Prop.	Time cut	TopApps		Stats		PeriodSelector		Last7Days		UseStop	
		AP1	AP2	AP1	AP2	AP1	AP2	AP1	AP2	AP1	AP2
Property 1	$[0,1)$	0.99	0.99	0.99	0.83	0.47	0.79	0.49	0.96	0.99	0.99
	$[1,7)$	0.99	0.99	0.98	0.80	0	0.93	0	0.98	0.99	0.99
	$[7,30)$	0.99	0.99	0.99	0.64	0.01	0.94	0.84	0.96	0.99	0.99
	$[0,30)$	0.99	0.99	0.99	0.75	0.21	0.92	0.44	0.98	0.99	0.99
	$[30,60)$	0.99	0.99	0	0.90	0.73	0.83	0.56	0.98	1	0.99
	$[60,90)$	1	0.95	0.96	0.72	0	0.94	0	0.97	1	0.99
Property 2	$[0,1)$	13.94	7.44	7.63	2.15	0.79	1.82	0.70	3.13	11.41	6.17
	$[1,7)$	17.22	5.77	4.00	2.31	0	3.97	0	4.03	12.91	6.30
	$[7,30)$	14.93	7.15	5.43	1.47	0.01	4.61	1.78	3.41	12.86	5.74
	$[0,30)$	14.67	6.48	5.08	1.90	0.24	3.58	0.58	3.99	11.00	6.51
	$[30,60)$	13.40	6.83	0	3.76	4.41	2.04	0.85	4.54	12.46	5.61
	$[60,90)$	17.30	5.83	2.94	2.60	0	3.26	0	4.43	13.96	5.63
Property 3	$[0,1)$	3.31	8.41	8.18	28.67	79.32	32.46	74.87	15.56	4.86	7.88
	$[1,7)$	2.05	10.70	12.44	31.90	∞	19.12	∞	12.38	3.85	7.55
	$[7,30)$	2.52	9.68	9.70	48.61	∞	17.78	26.61	14.58	3.88	8.44
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	$[60,90)$	2.02	15.28	16.53	39.68	∞	17.41	∞	11.56	3.57	8.90

Probabilistic model checking

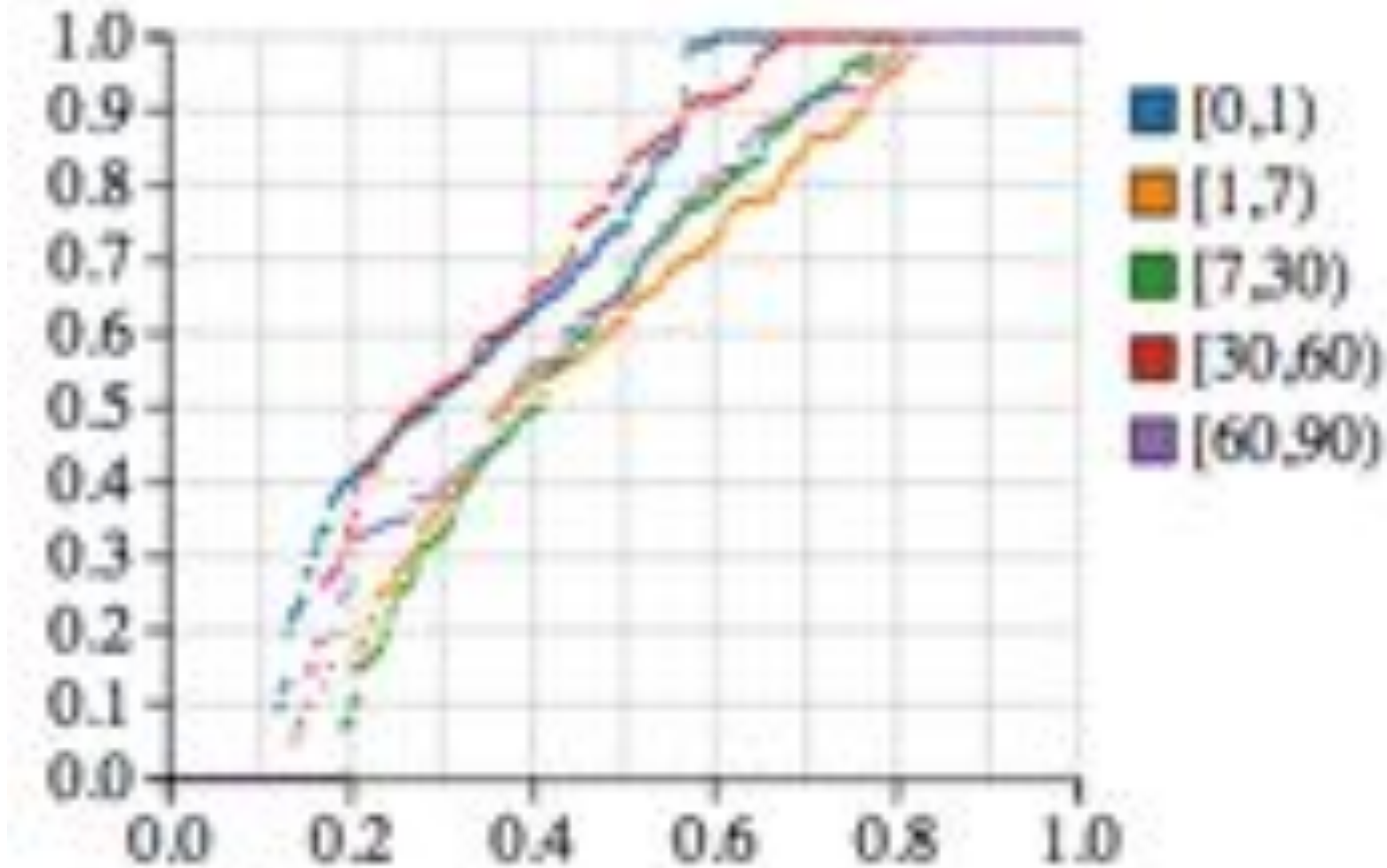
- For the second month data, [30,60), we need more discriminatory properties
- More app-specific questions:
  - Probability to reach `s` from `t` during the same session:
    - `filter(state, P=?[(!s & !"UseStop") U<=N s], t)`
      - for `(s, t)` ∈ $\{$`TopApps, PeriodSelector, Last7Days`$\}^2$
  - Expected number of steps to reach `s` from `t`:
    - `filter(state, R{"r_steps"}=?[F s], t)`
      - for `(s, t)` ∈ $\{$`TopApps, PeriodSelector, Last7Days`$\}^2$
      - for `(s, t)` ∈ `{TopApps, PeriodSelector, Last7Days}` × `Main`
      - for `(s, t)` ∈ `UseStop` × `{TopApps PeriodSelector, Last7Days}`

Probabilistic model checking

- Conclusions for $\mathcal{K}$=2 — two distinct activity patterns labelled:
    - Overall viewing pattern (pattern 1) — higher level stats visualisations
    - Time-partitioned viewing pattern (pattern 2) — in-depth stats visualisations

Comparing pattern distributions $\mathcal{K}$=2

- First day dominated by app exploration
- Interval [30,60) sees a rise in app exploration
- Intervals [1,7), [7,30), [60,90) — more settled usage behaviour



Probability of a user trace to behave according to the Time-partitioned viewing pattern

Analysis for $\mathcal{K}$=3, first month data

1. Overall Viewing pattern:
   - `TopApps` and `Stats` have best results for all three general properties,
   - `PeriodSelector` and `Last7Days` are absent,
   - twice as short and twice more frequent sessions than for pattern #3.
2. 'weaker' Overall Viewing pattern than pattern #1:
   - `TopApps` has poorer results than #1, and better results than `Stats` and `Last7Days` in #2,
   - `PeriodSelector` is absent.
3. Time-partitioned Viewing pattern:
   - `PeriodSelector` has the best results, followed closely by `TopApps` and `Last7Days`.

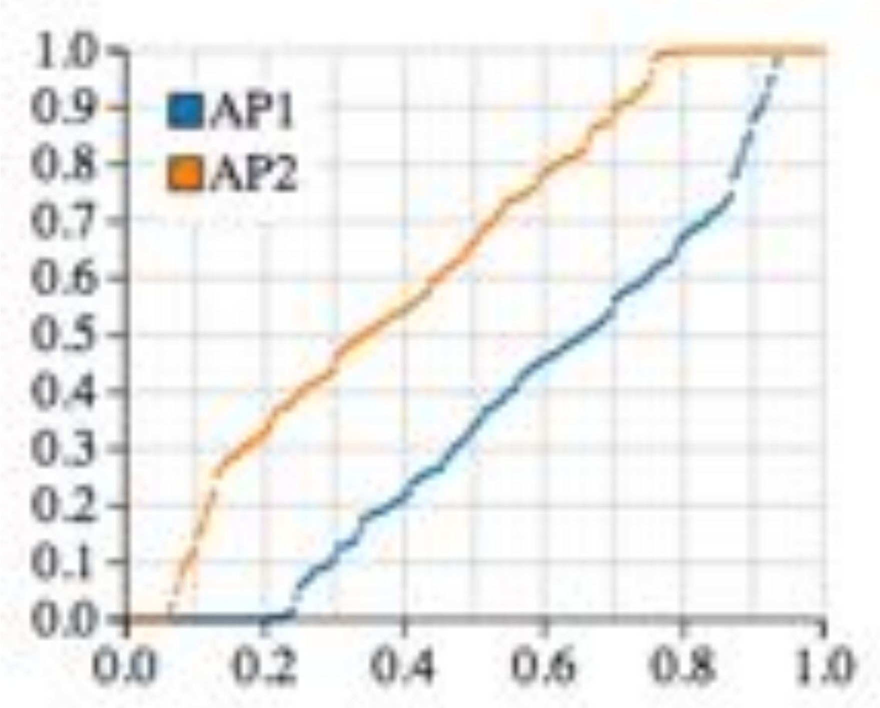
Analysis for $\mathcal{K}$=4, first month data

- Activity patterns:
  1. mainly **`TopApps`** Viewing
  2. mainly **`Stats`** — **`TopApps`** Viewing
  3. Time-Partitioned Viewing
  4. exclusive **`TopApps`** — **`UsageBarChartTopApps`**
- Shorter and more frequent sessions for #1 than for #2 and #3

Comparing pattern distributions

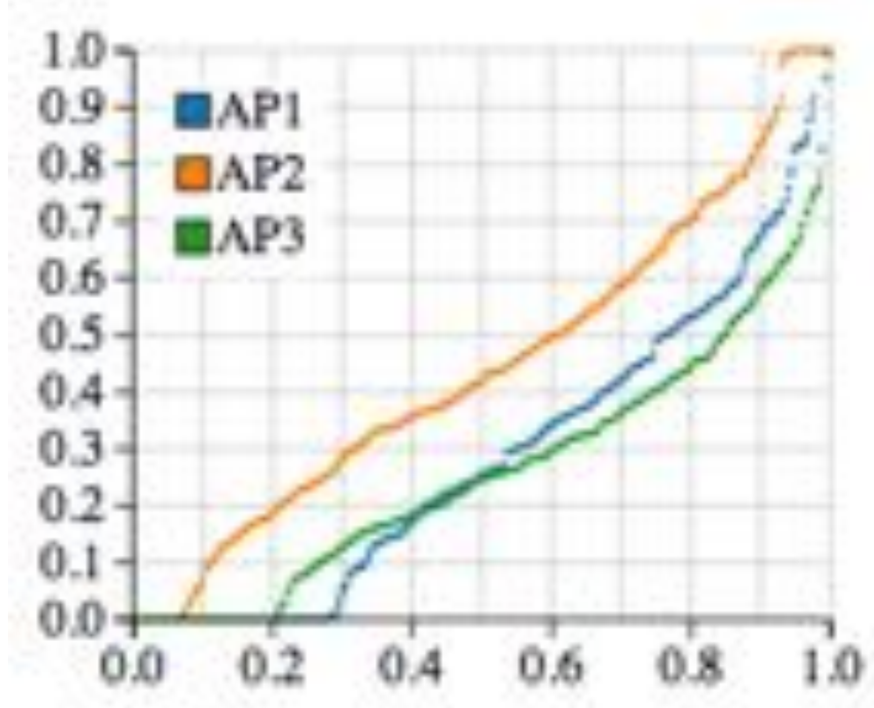
First 30 days

$\mathcal{K}=2$



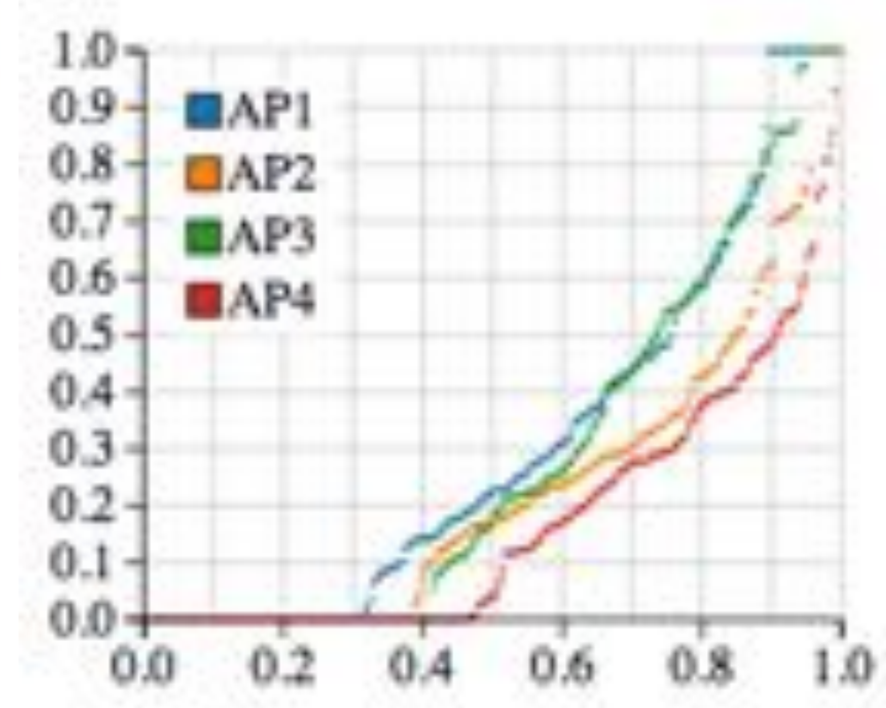
1. Overall
2. Time-partitioned

$\mathcal{K}=3$



1. Overall
2. weaker Overall
3. Time-partitioned

$\mathcal{K}=4$

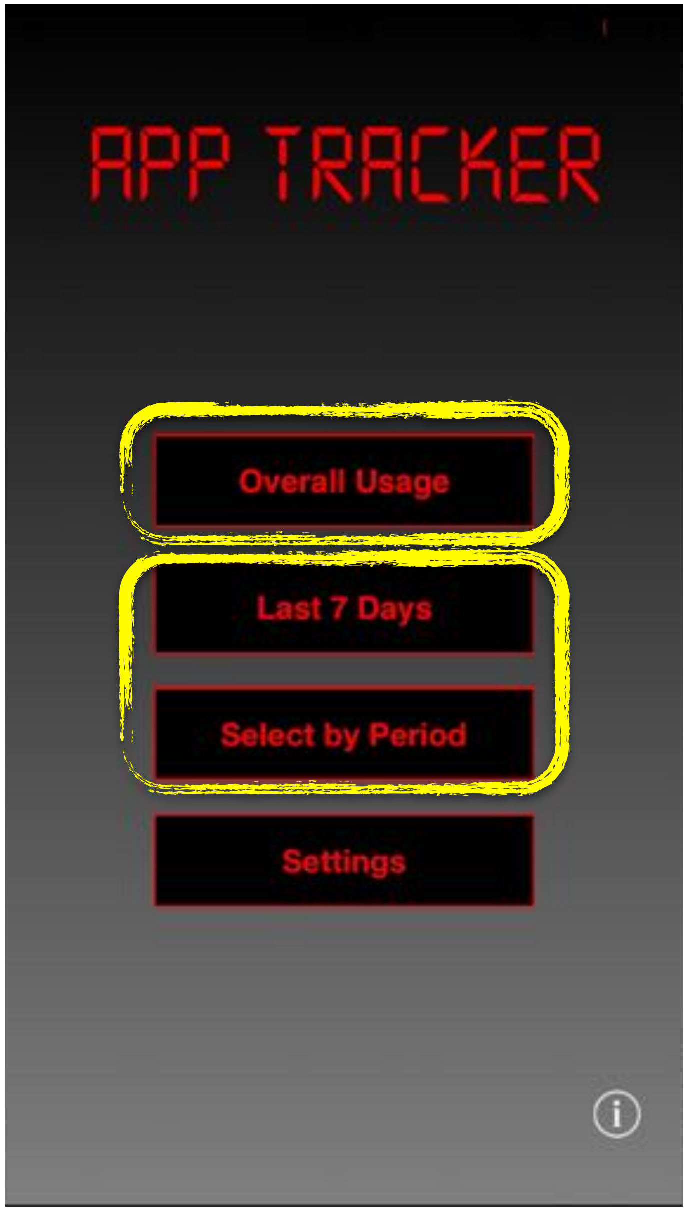


1. mainly `TopApps`
2. `Stats` - `TopApps`
3. Time-partitioned
4. exclusive `TopApps` and `UsageBarChart`

Inform the app redesign

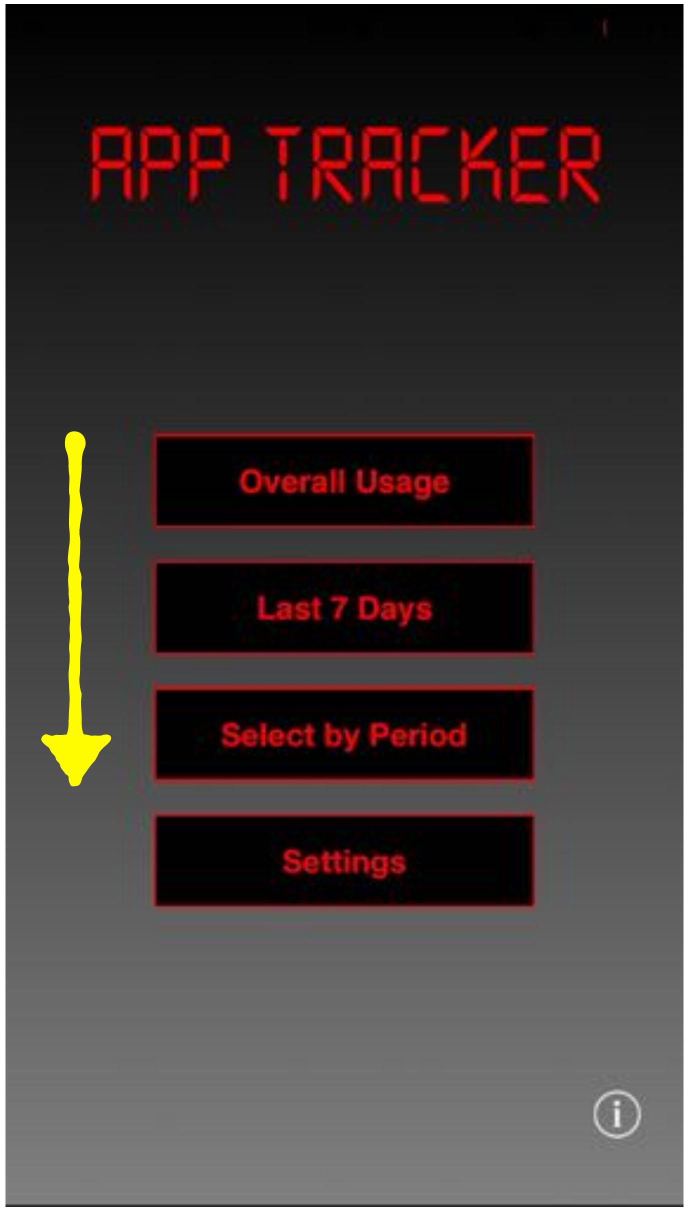
- For $\mathcal{K}$=2 no pattern is significantly dominant, usage is fairly distributed between the two patterns.
- Session length indicative of a more suitable glancing-like view.
- From 3 to 2 main viewing options ?

    1. glancing-like short interactions in a new *Overall Usage* screen
    2. longer interactions in a new ***Select by Period***, including ***Last 7 Days*** and more filtering and querying tools



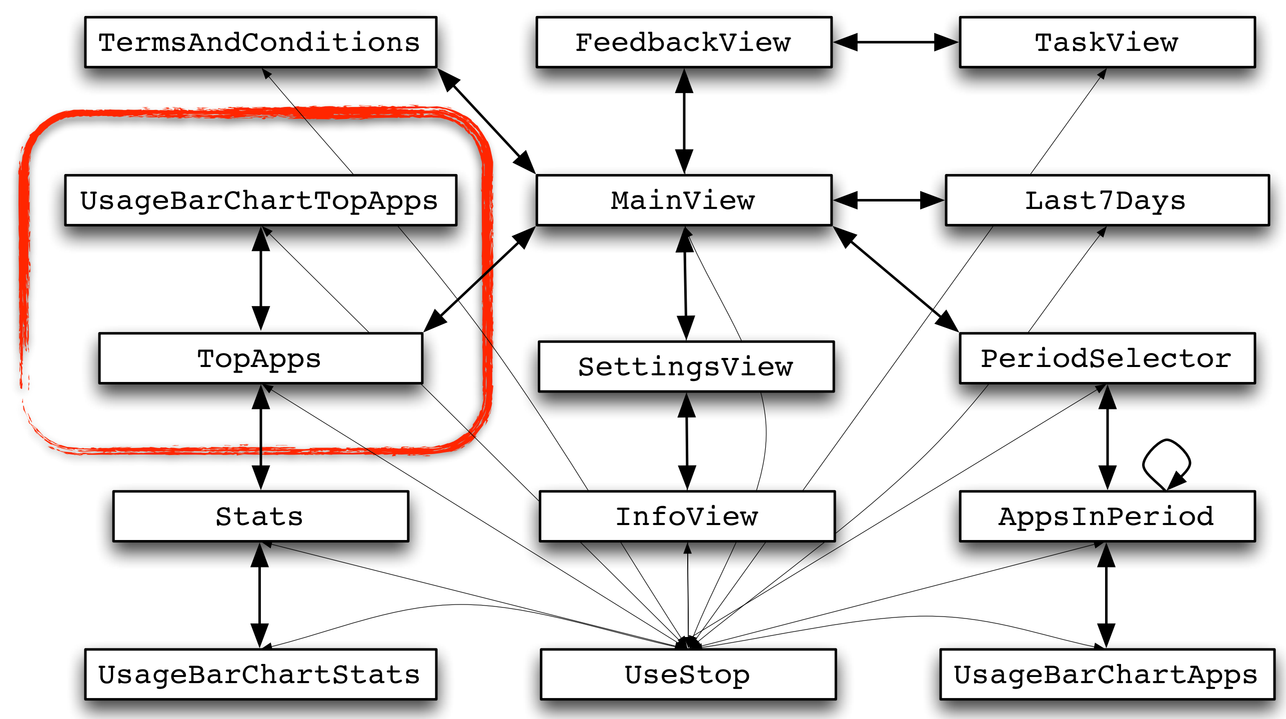
Inform the app redesign

- Are users merely following the suggested paths defined by the interface?
  - For $\mathcal{K}$=3 there is no pattern centred uniquely around ***Select by Period***, but one centred around ***Last 7 Days***, and one around both.
  - For $\mathcal{K}$=4 ***Last 7 Days*** and ***Select by Period*** always go together, the same is true for $\mathcal{K}$=5.



Inform the app redesign

- For $\mathcal{K}$=4 and $\mathcal{K}$=5 we uncover repeated switching between **`TopApps`** and **`UsageBarChartTopApps`**
  - more investigatory than glancing behaviour
  - not just uncovering the menu structure, but finding unexpected behaviours
  - move this loop from ***Overall Usage*** to ***Select by Period***?



Inform the app redesign

- Discovering glancing activity patterns for **widget** extensions on iOS8 and iOS9, or **glances** on the Apple Watch

- Typical glancing patterns for AppTracker are Overall Viewing and `TopApps`-centred patterns

Glances. You can provide users with timely read-only information that they care about with a Glance — a quick and lightweight view of your app.

Conclusion — our contribution

- Populations of users characterised by inferred temporal behaviours rather than user attributes
  - ✦ Inference of Markov models of usage patterns from logged user sessions — activity patterns
  - ✦ Characterisation the activity patterns by probabilistic temporal properties using model checking
- Analysis of a mobile app to inform developers about the actual use and future redesign

Ongoing and future work

- Developing a code environment for the analysis — Blocks
- More apps to analyse and properties to identify:
  - ✦ Activity patterns combined with user attributes (timezone, device type)
  - ✦ Different probabilistic models, e.g., Hierarchical Hidden Markov models
  - ✦ Game app: Hungry Yoshi — for a richer dataset of user traces
  - ✦ Activity tracking/health apps: MatchFIT, Quped — to be released soon

A POPULATION APPROACH TO UBICOMP SYSTEM DESIGN

A Population Approach to Ubicomp System Design is a five year research programme working towards a new science of software structures.

The Populations research programme is funded by an EPSRC Programme Grant (EP/J007617/1). It is a collaboration between the University of Glasgow and the University of Warwick.

Drawing metaphorically from biological concepts of species and evolution, *The Populations Programme* accepts and takes advantage of the scale, variety and dynamism possible in contemporary software. We treat software class as a varied and changing population of software instances in use.

www.softwarepopulations.com

Thank you!

Questions?