



Probabilistic Formal Analysis of App Usage to Inform Redesign

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Installing and using an app



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How does your style of using the app changes in time?



Installing and using an app



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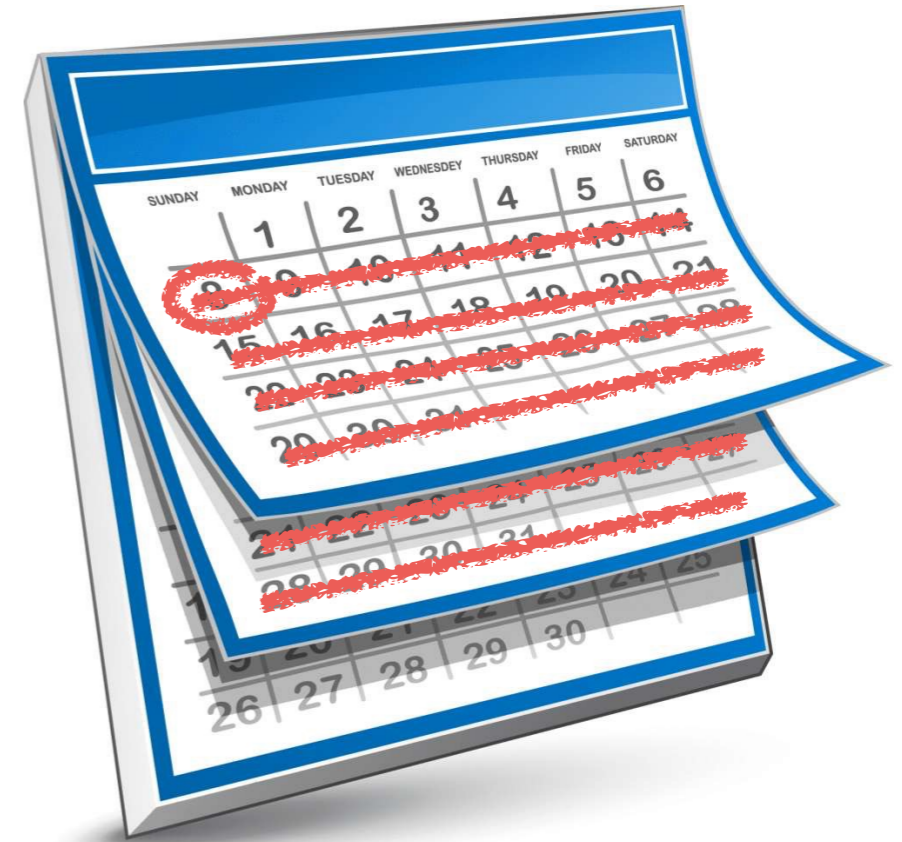
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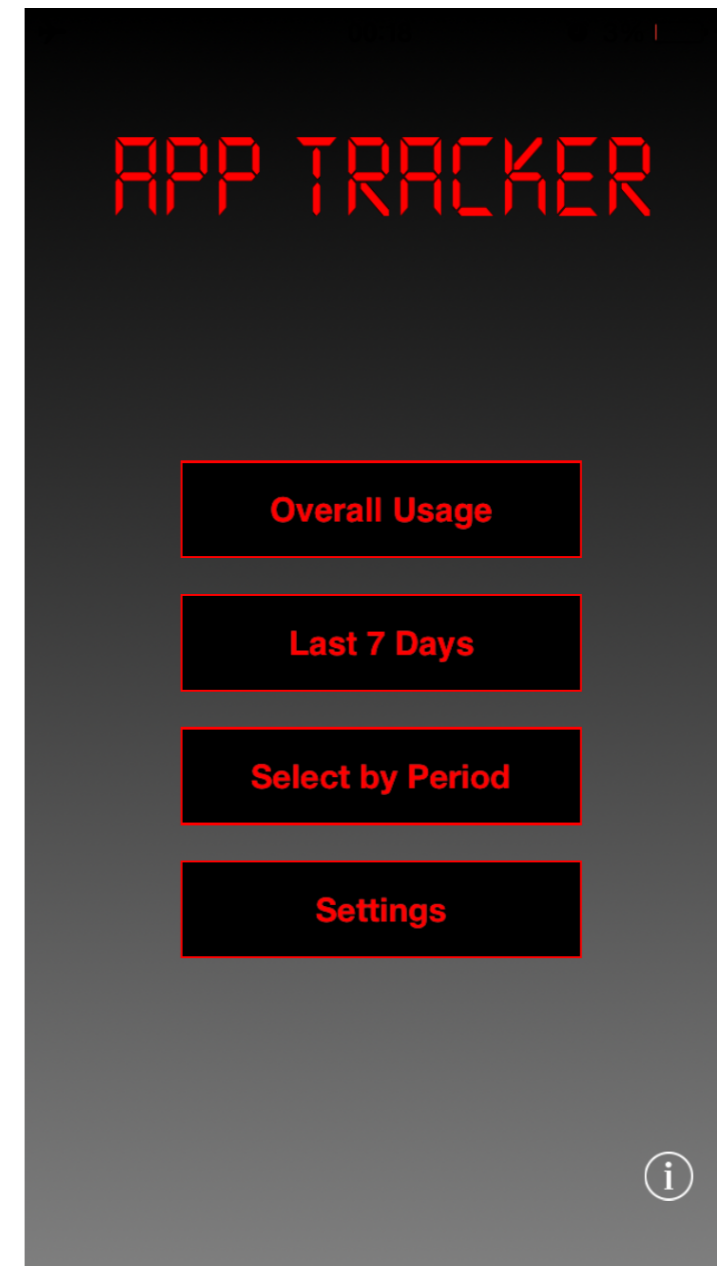


Our motivation

- 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?

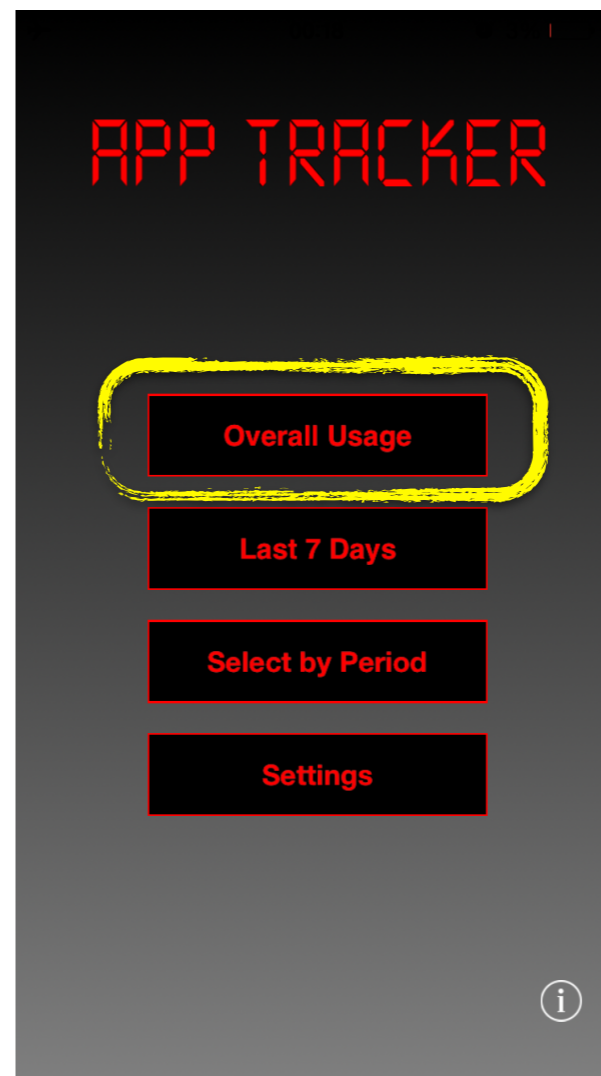
Case study: the **AppTracker** app

- 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



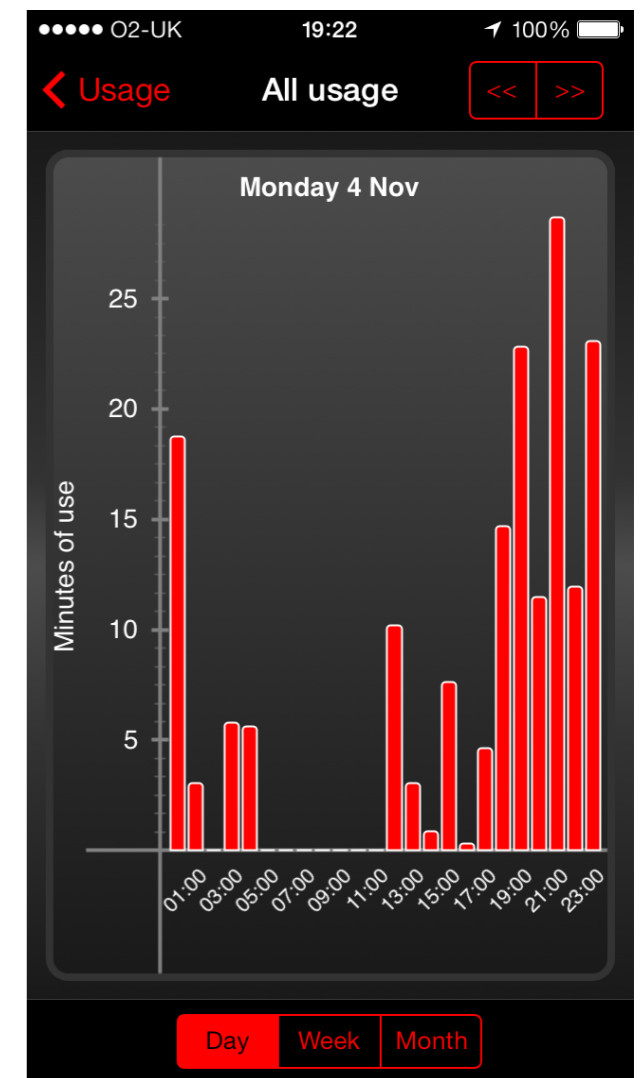
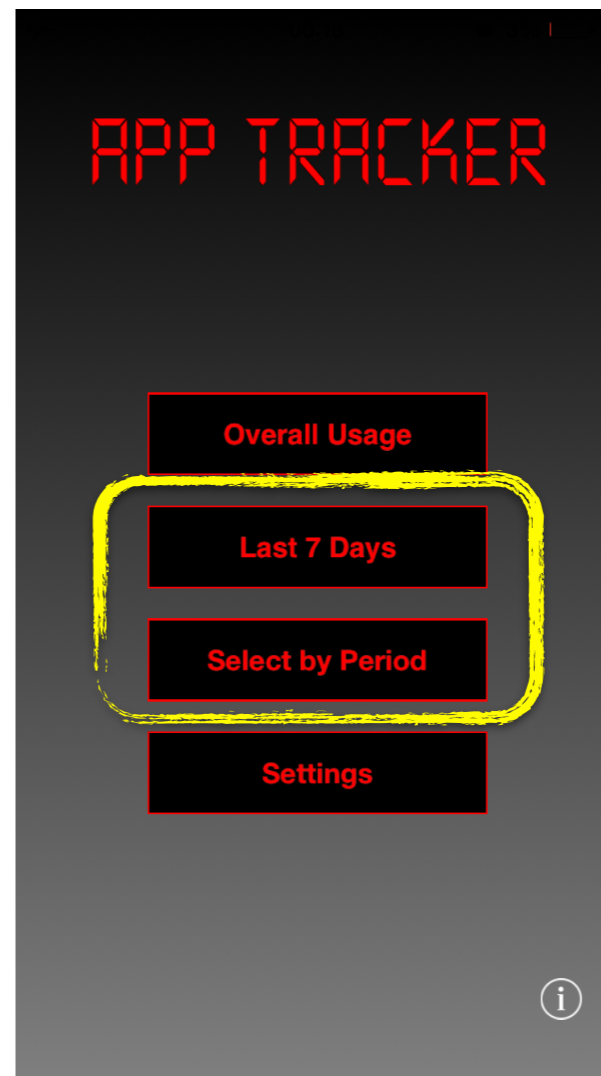
AppTracker main menu

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

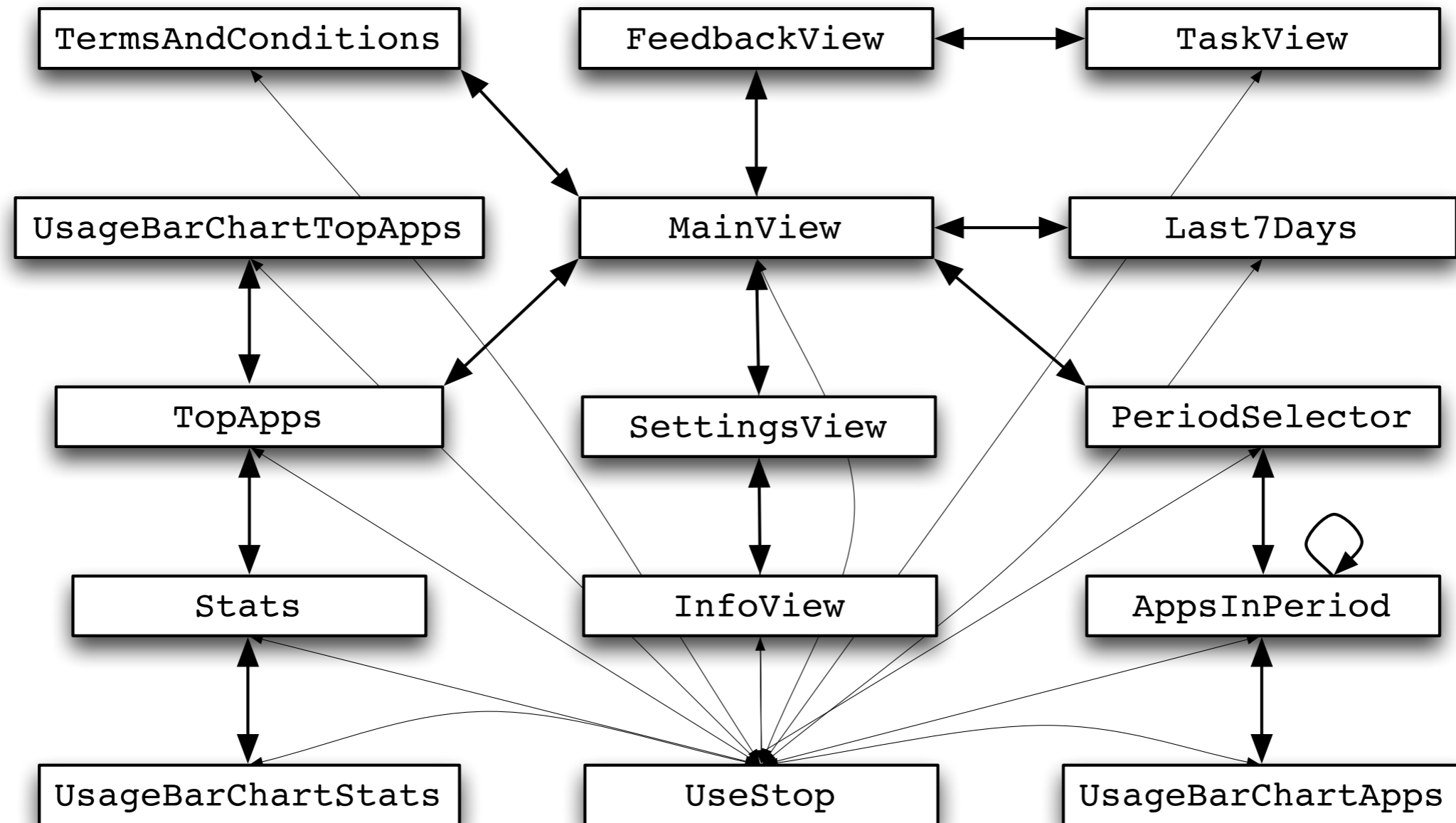


AppTracker main menu

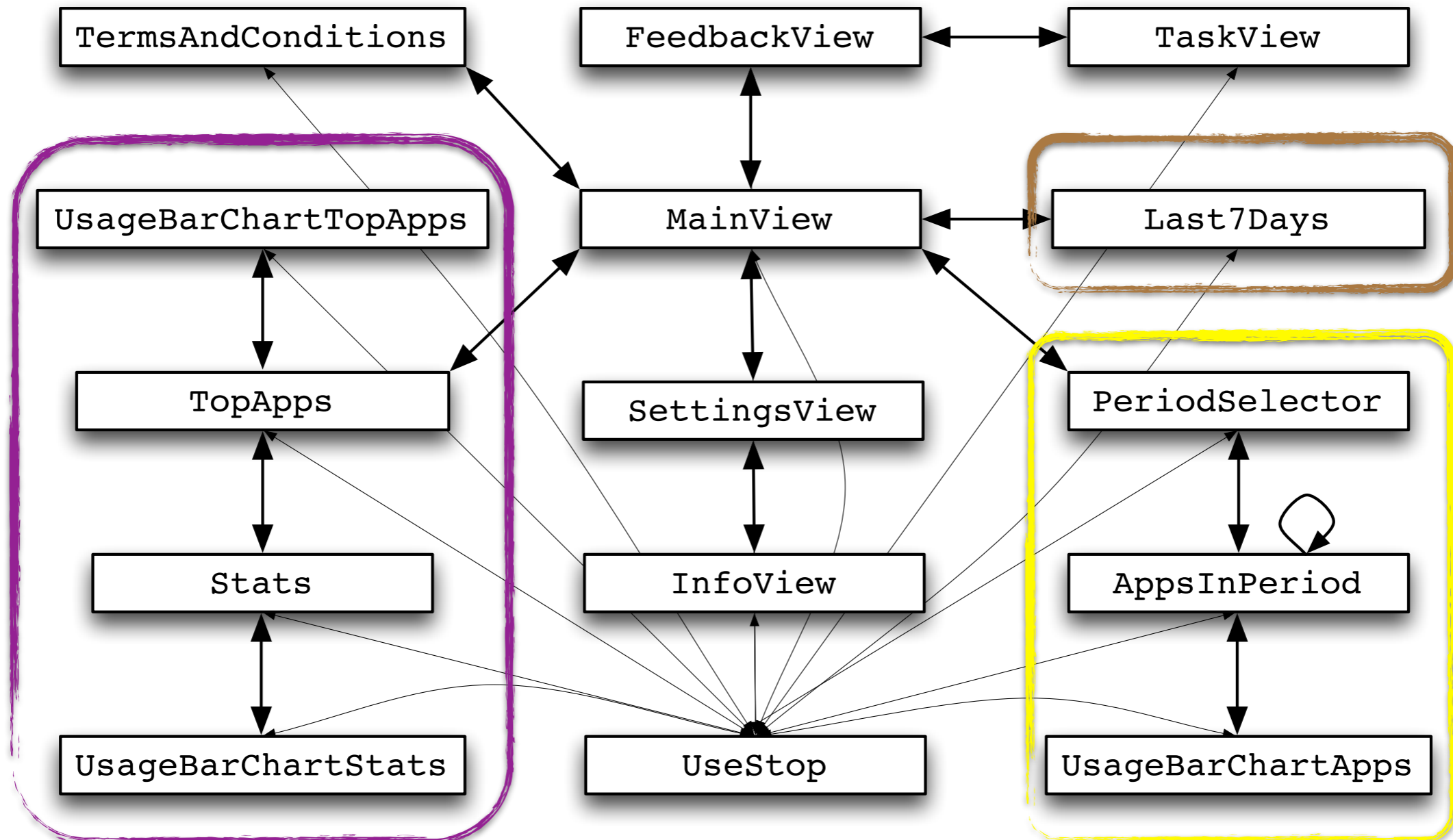
- **Last 7 Days** shows a stacked bar graphs of usage of the top 5 apps during the last 7 days of usage.
- **Select by Period** shows statistics by any period of interest, e.g.
 - ◆ most used app last Monday
 - ◆ time spent on Facebook last week
 - ◆ device usage over a day



AppTracker state diagram



AppTracker hypothesised behaviour (frequent)

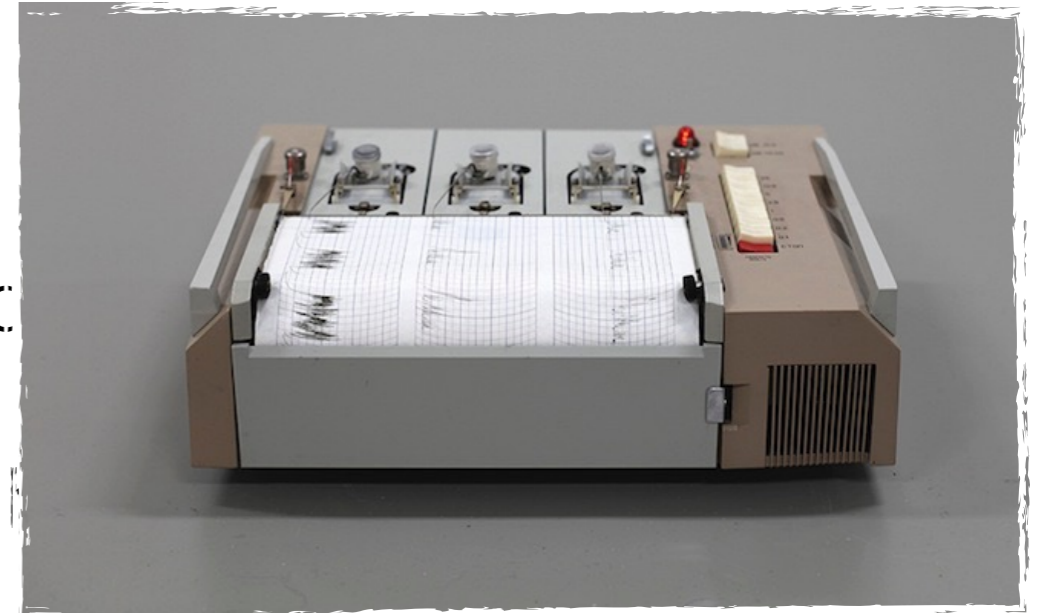


Overview of the analysis

- 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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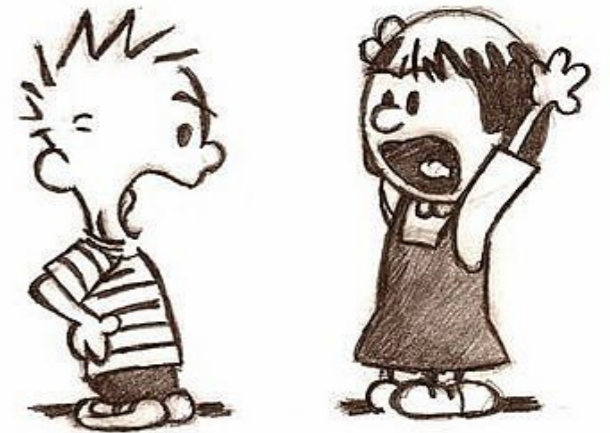
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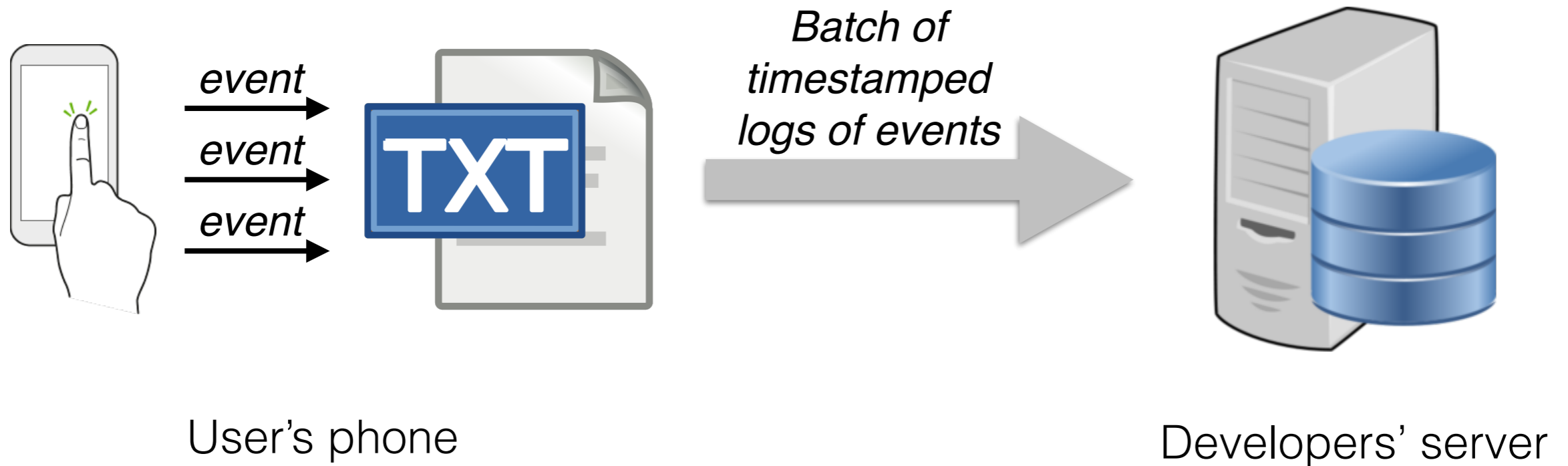
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Not sequential!

Overview of the analysis

- Instrument the app
- Clean and prepare the raw logged data
- **Complementary to other data analytics methods**
(e.g., SQL queries, visualisations)
- 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

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": "2013-08-20 09:11:46", "data": "TopApps"}, {"timestamp": "2013-08-20 09:11:50", "data": "Main"}, {"timestamp": "2013-08-20 09:11:52", "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

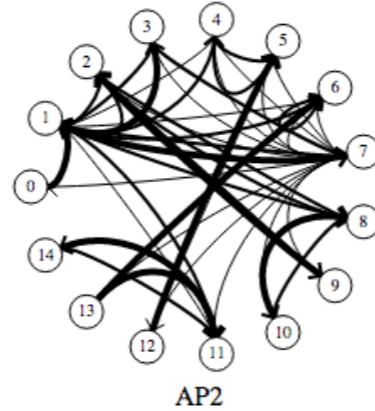
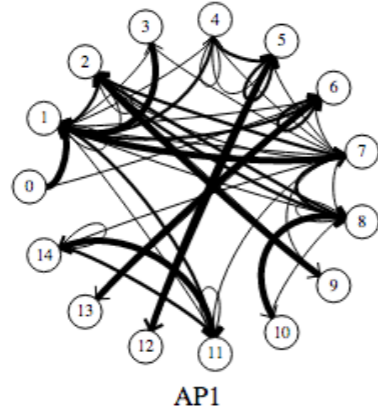
Infer activity patterns

- 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 $(\Theta_1, \dots, \Theta_{\mathcal{K}})$ with Θ_k the probability of using the k^{th} activity pattern

Activity patterns for the first 30 days

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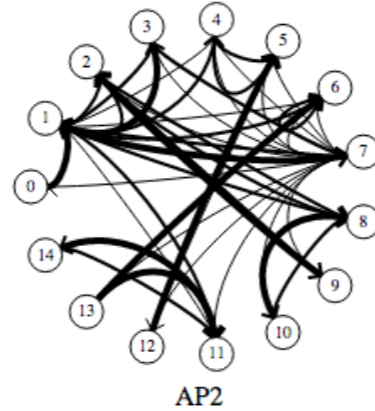
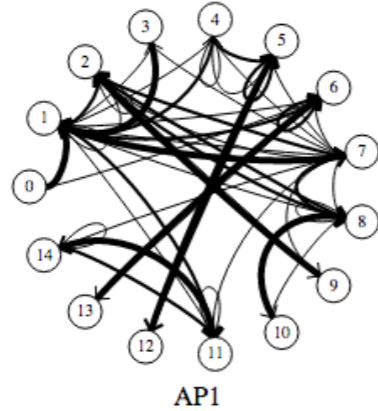
2 patterns



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

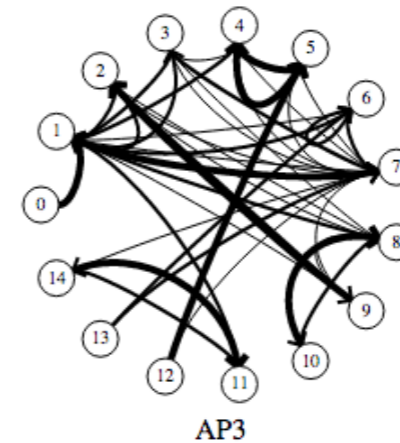
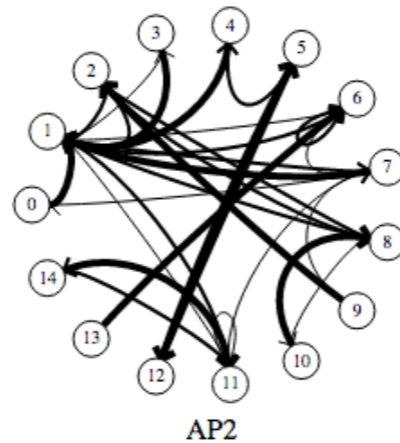
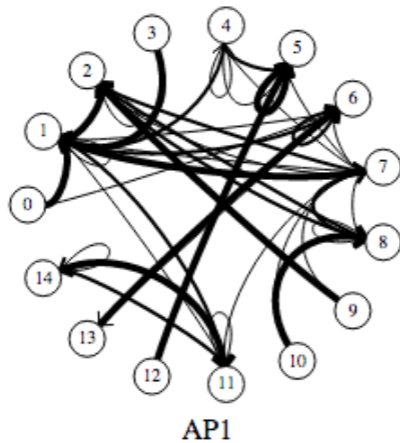
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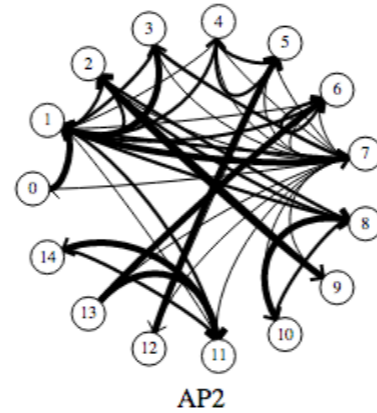
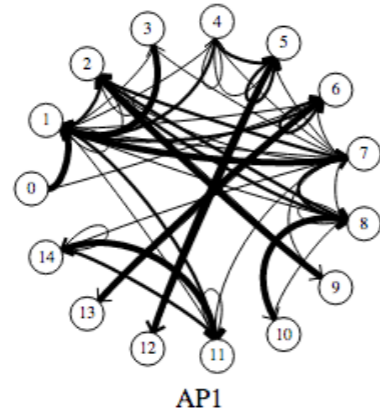
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3 patterns



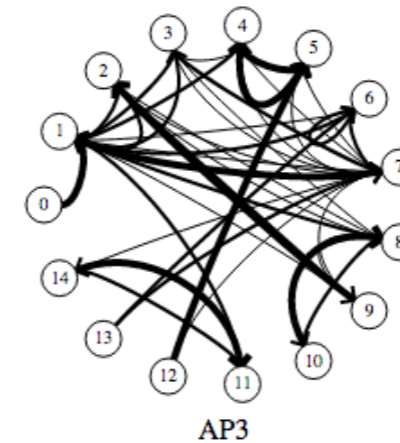
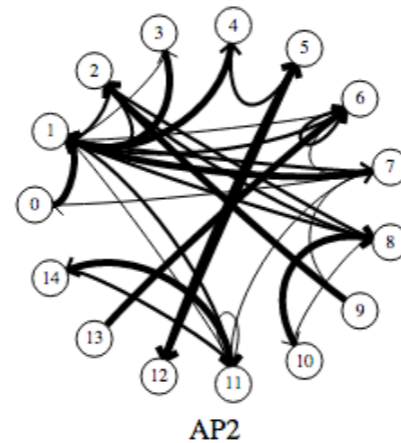
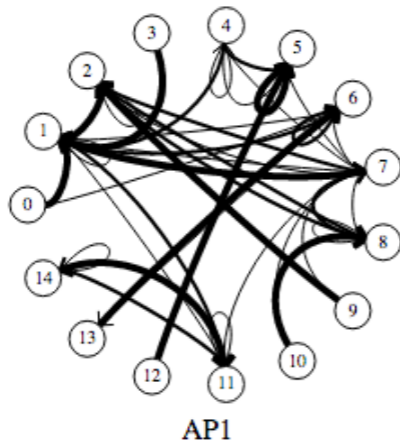
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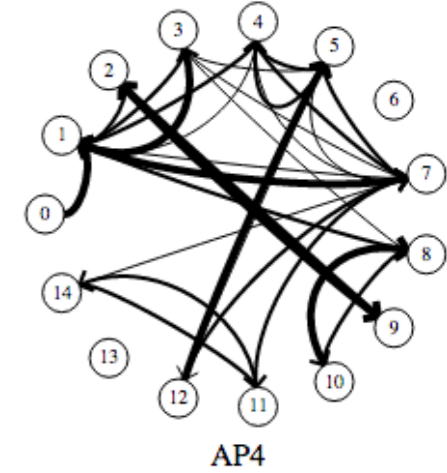
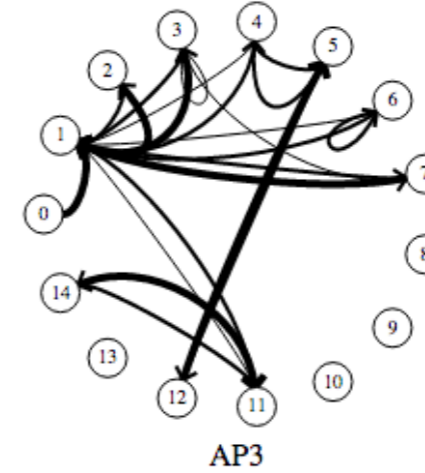
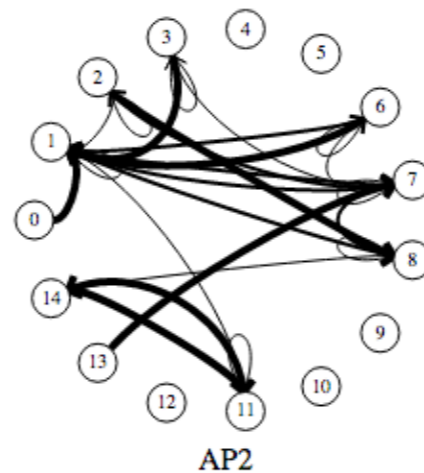
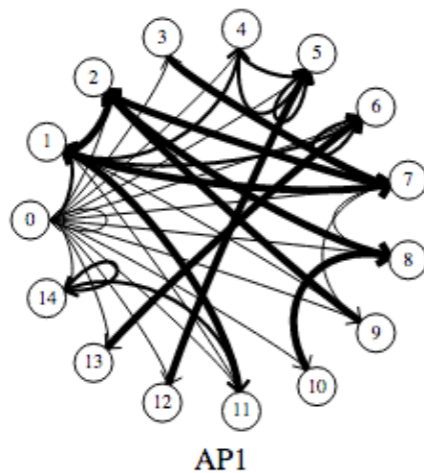


*Discrete-time Markov chains:
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3 patterns



4 patterns



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

Probabilistic model checking

- Ask questions using Probabilistic Computation Tree Logic with rewards (rPCTL) and 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)`

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?

Temporal logic properties

- 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.

Temporal logic properties

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- More app-specific questions:
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 - Average number of button taps to go to screen view s_2 from s_1 .
 - Probability of repeating a specific event 50 times, etc.

Compare the results across all patterns!

Temporal properties in rPCTL

- ◆ Probability to reach the state s for the first time within N steps:

$$\rightarrow P=? [!s \ U \leq N \ s]$$

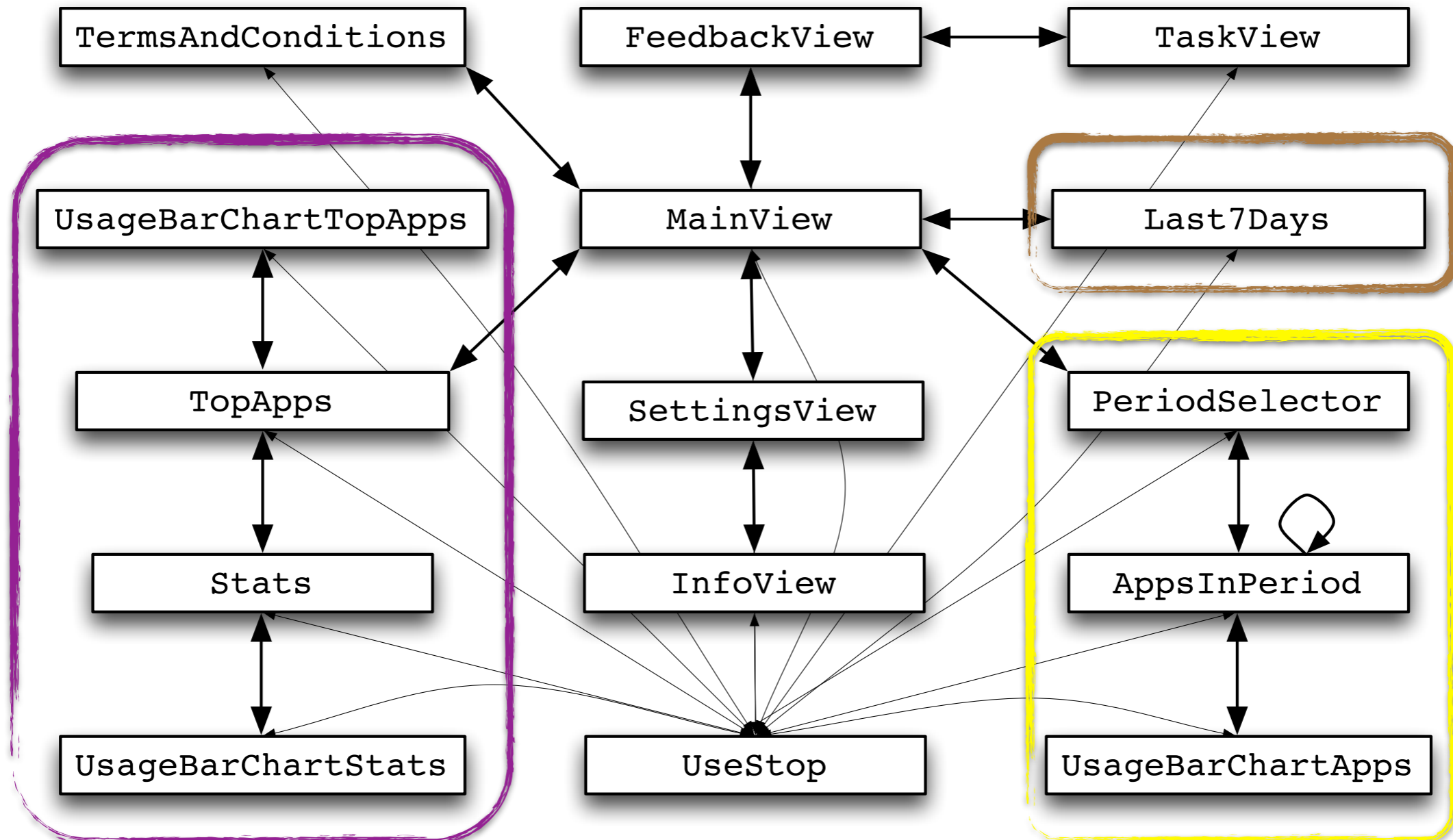
- ◆ Expected number of visits to the state s within N steps:

$$\rightarrow R\{ "r_s" \}=? [C \leq N]$$

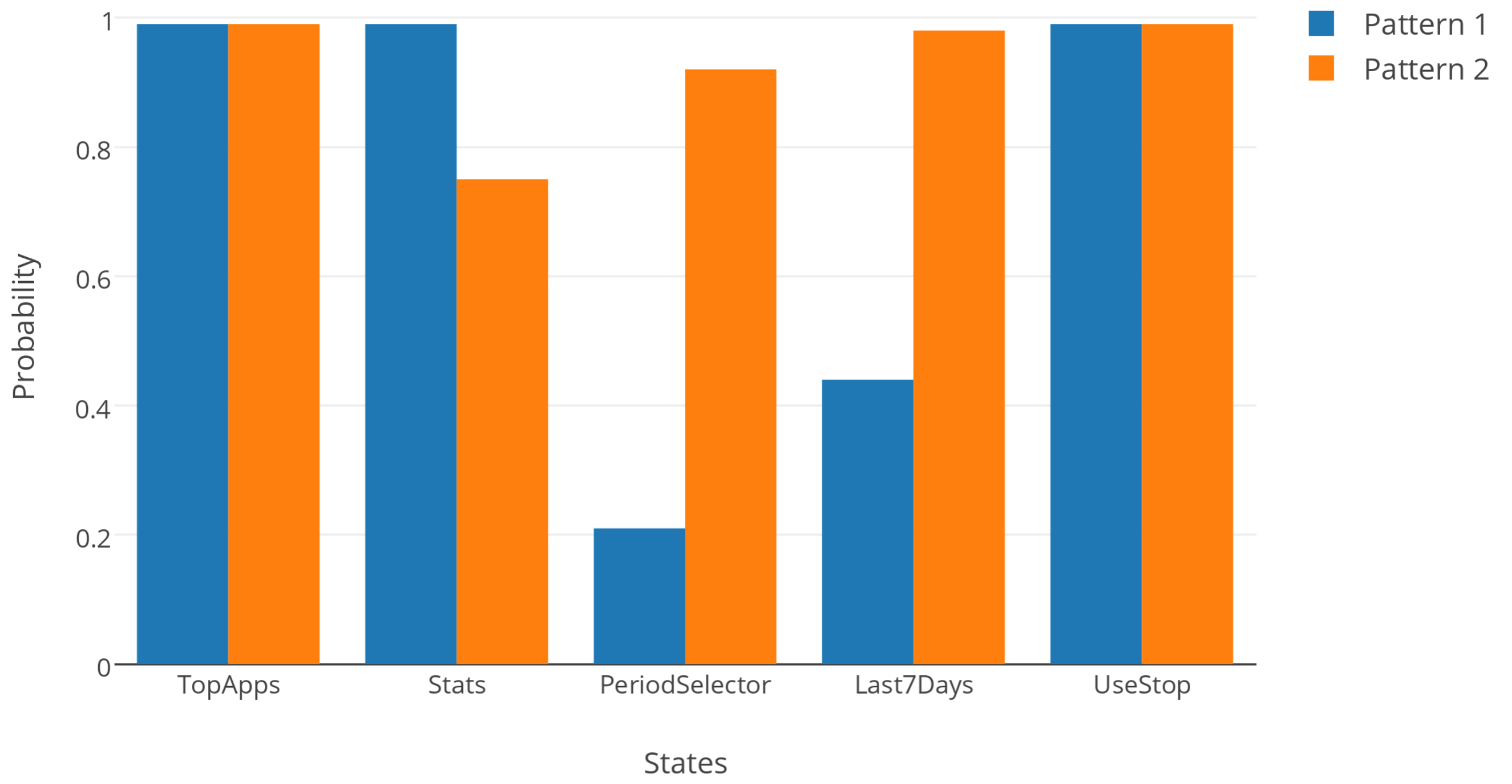
- ◆ Expected number of steps to reach the state s :

$$\rightarrow R\{ "r_Steps" \}=? [F \ s]$$

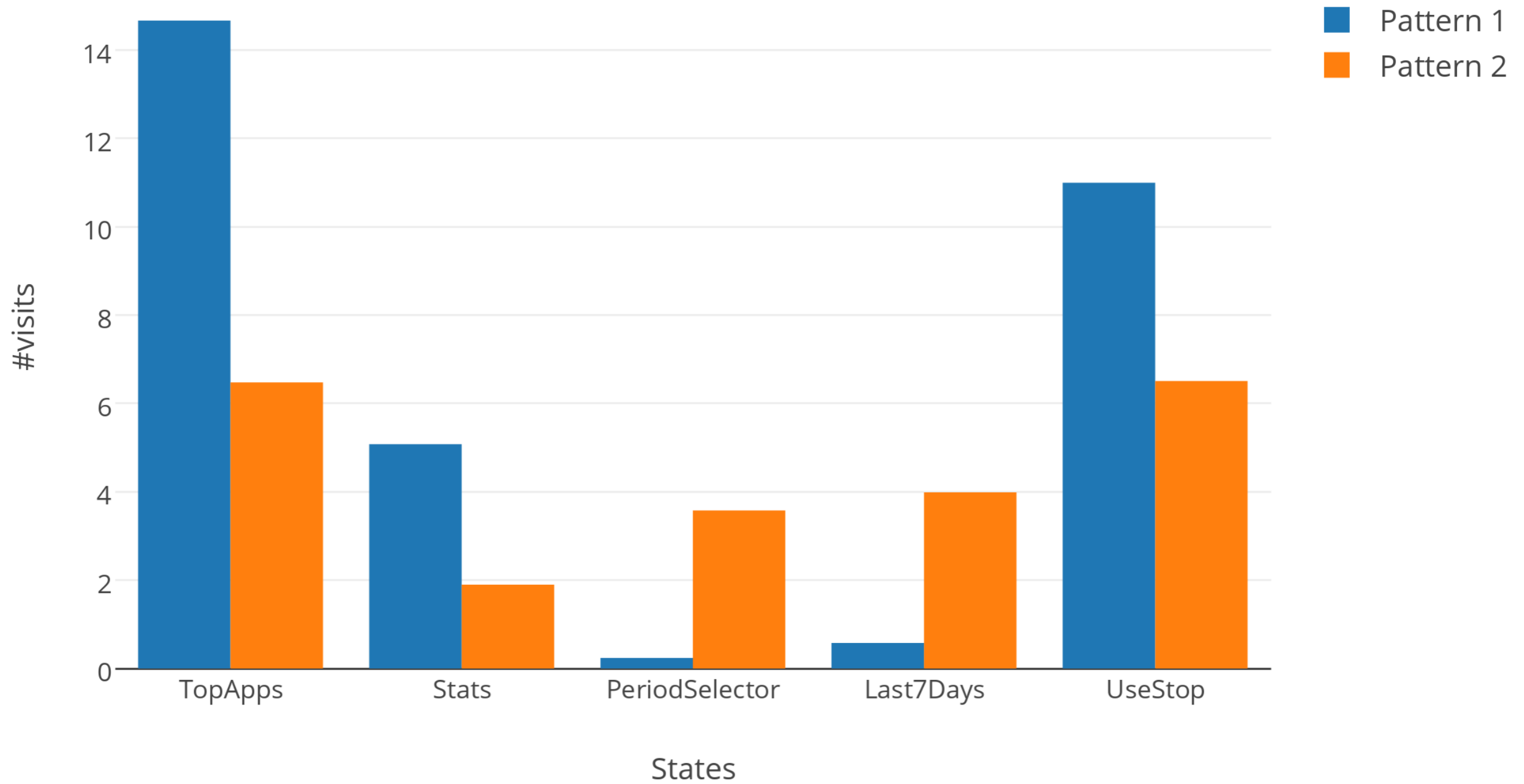
AppTracker hypothesised behaviour



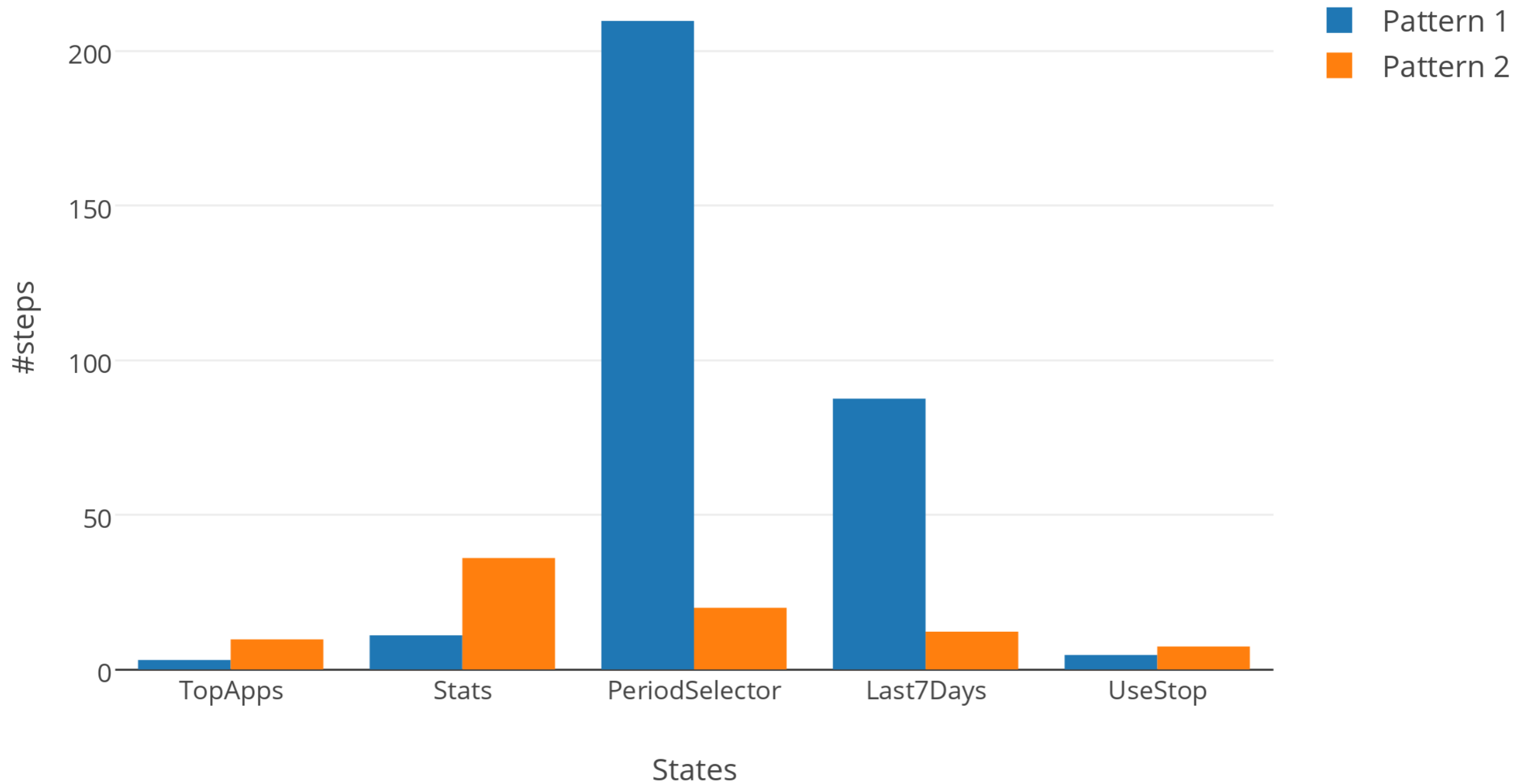
Likelihood of viewing a particular screen for the first time within 50 button taps in the first month of usage



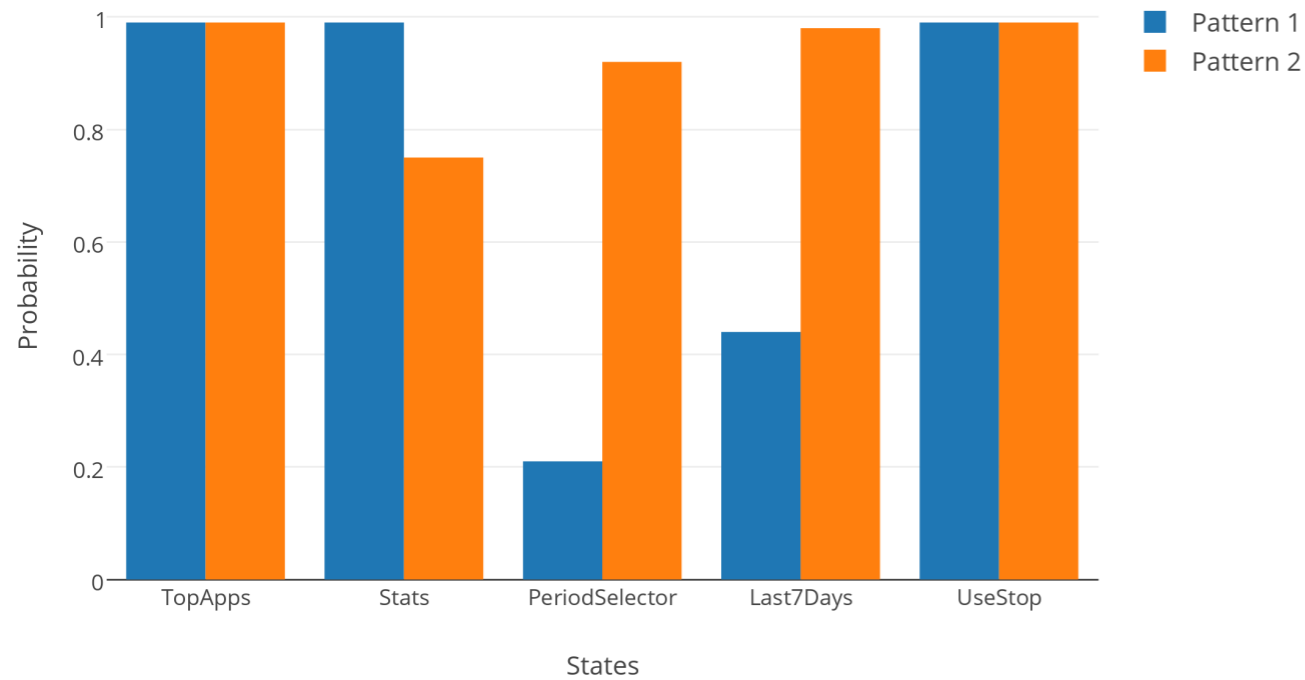
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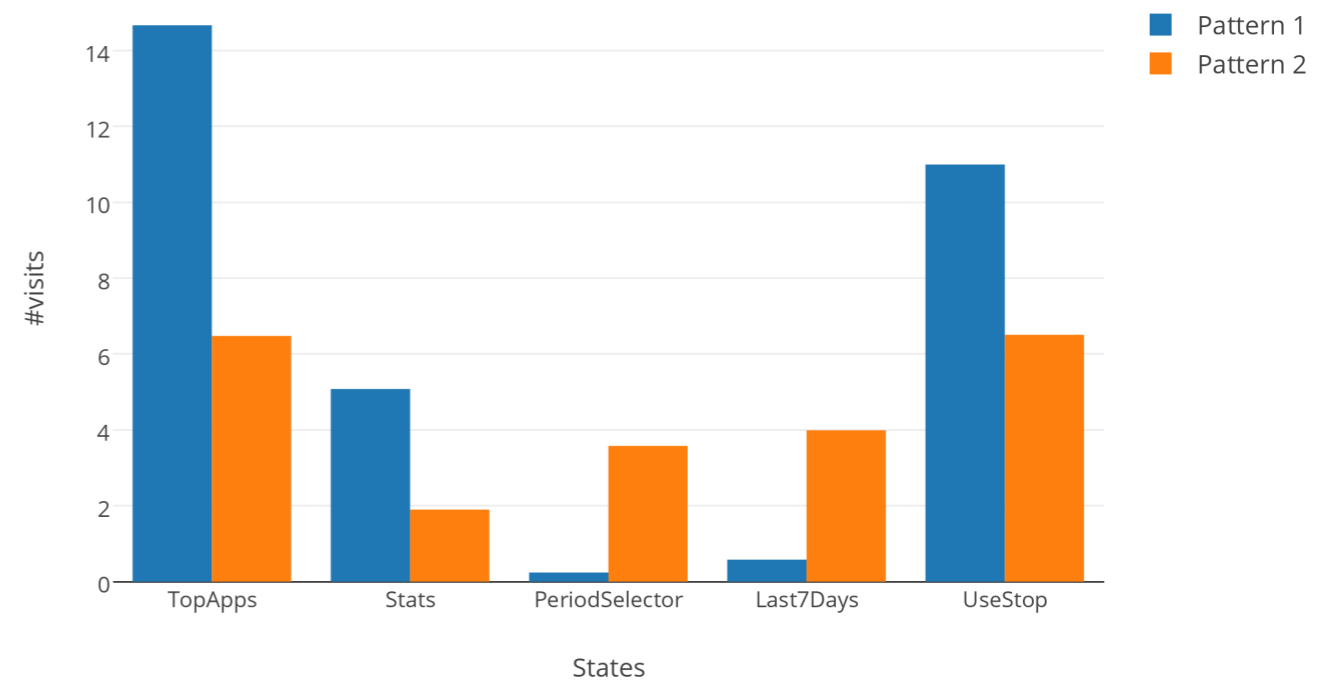
Average number of button taps to reach a particular screen view in the first month of usage



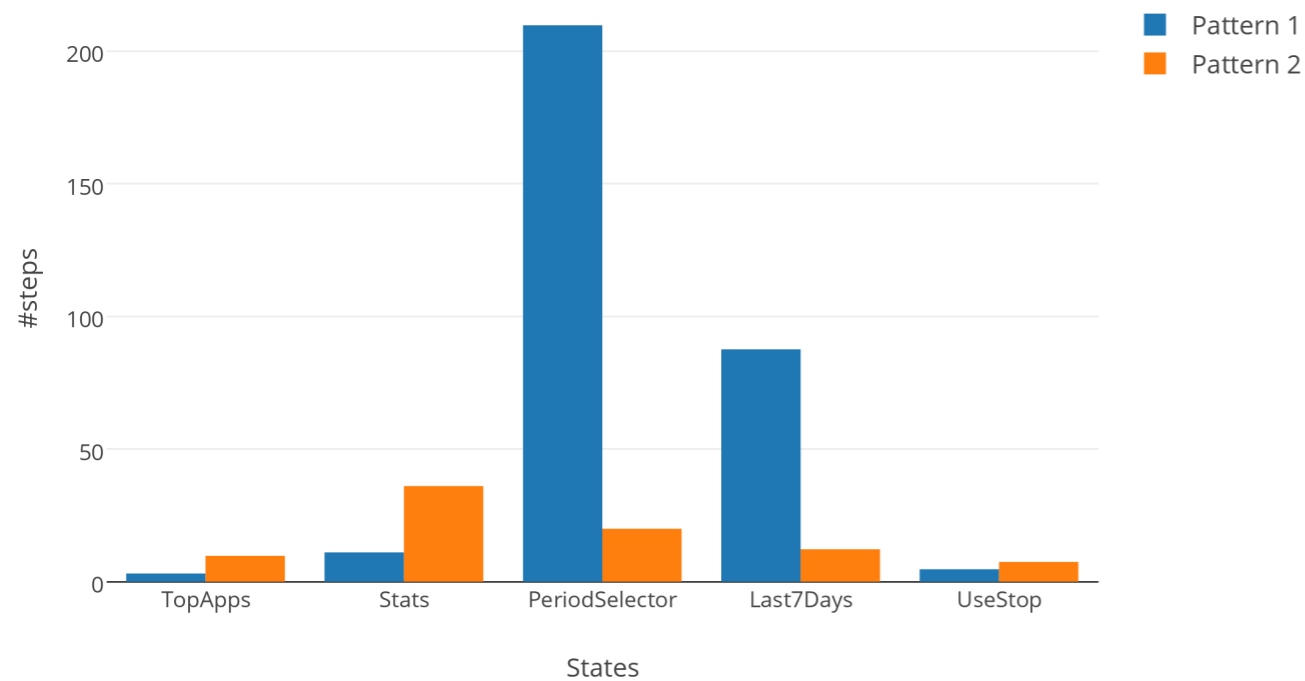
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Average number of views of a particular screen within 50 button taps in the first month of usage



Average number of button taps to reach a particular screen view in the first month of usage



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

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	[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
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	[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 $(s, t) \in \{\text{TopApps}, \text{PeriodSelector}, \text{Last7Days}\}^2$
 - ◆ Expected number of steps to reach s from t :
 - ➔ `filter(state, R{"r_steps"}=?[F s], t)`
 - ➔ for $(s, t) \in \{\text{TopApps}, \text{PeriodSelector}, \text{Last7Days}\}^2$
 - ➔ for $(s, t) \in \{\text{TopApps}, \text{PeriodSelector}, \text{Last7Days}\} \times \text{Main}$
 - ➔ for $(s, t) \in \text{UseStop} \times \{\text{TopApps}, \text{PeriodSelector}, \text{Last7Days}\}$

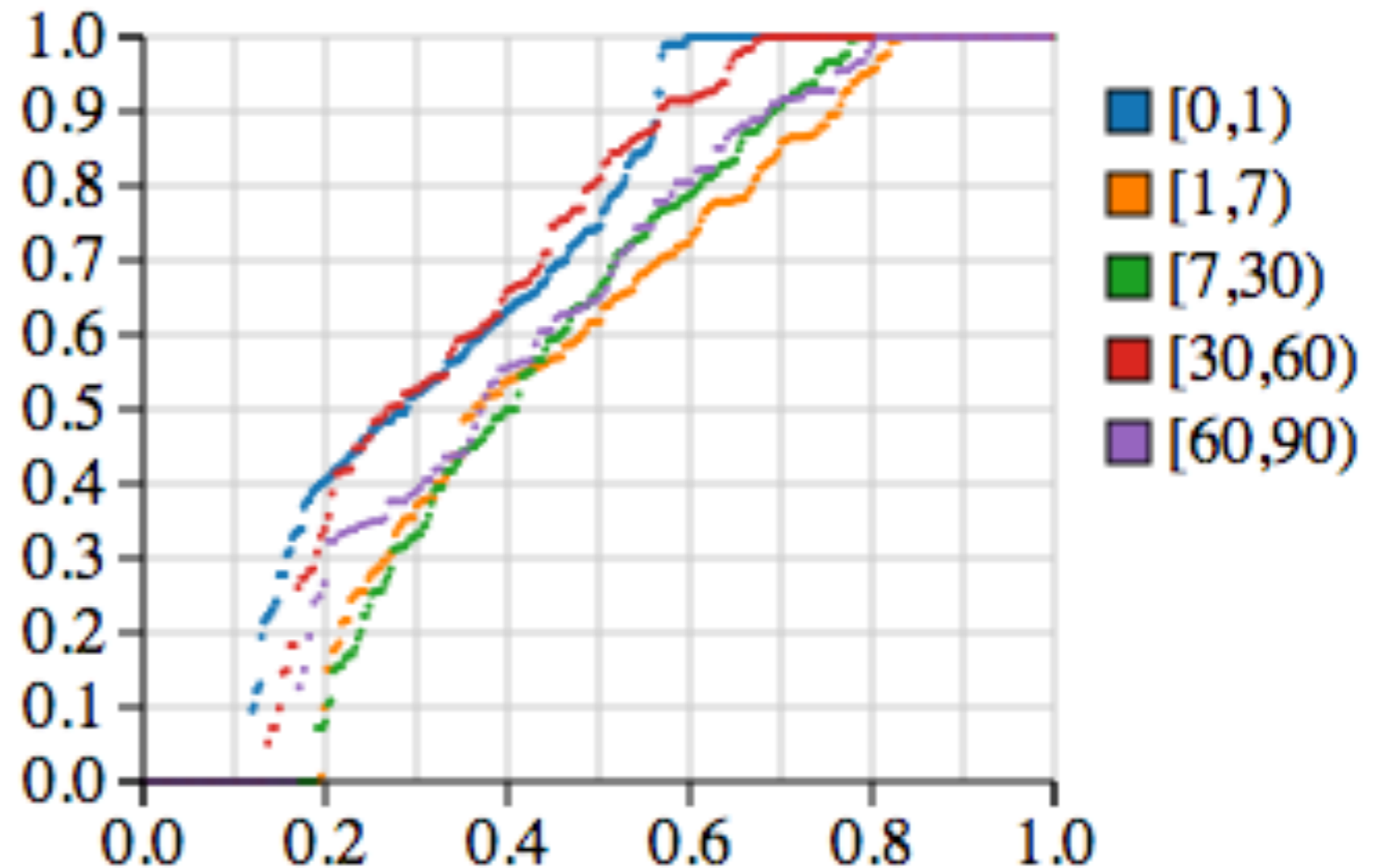
Probabilistic model checking

- 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`.

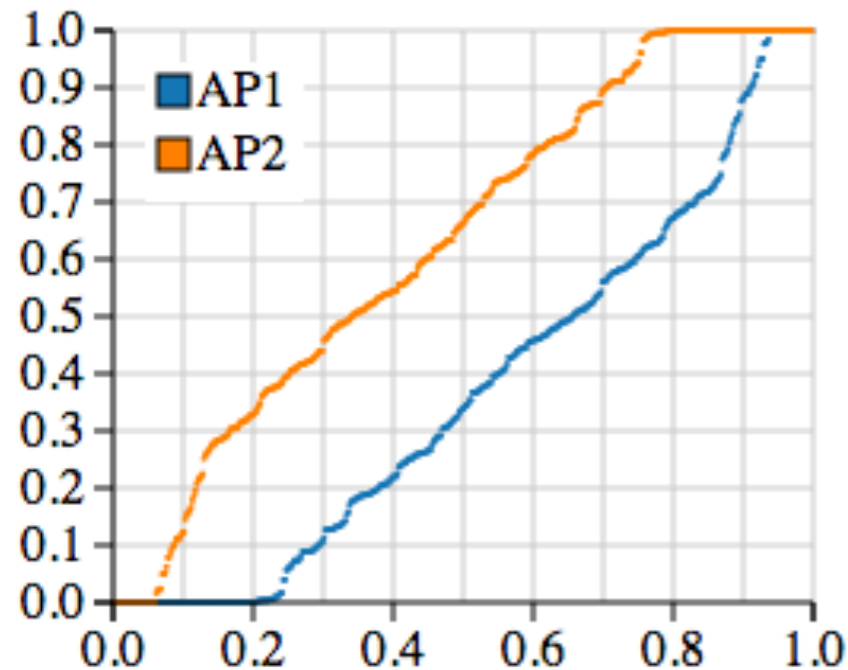
Analysis for $\mathcal{K}=4$, first month data

- 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

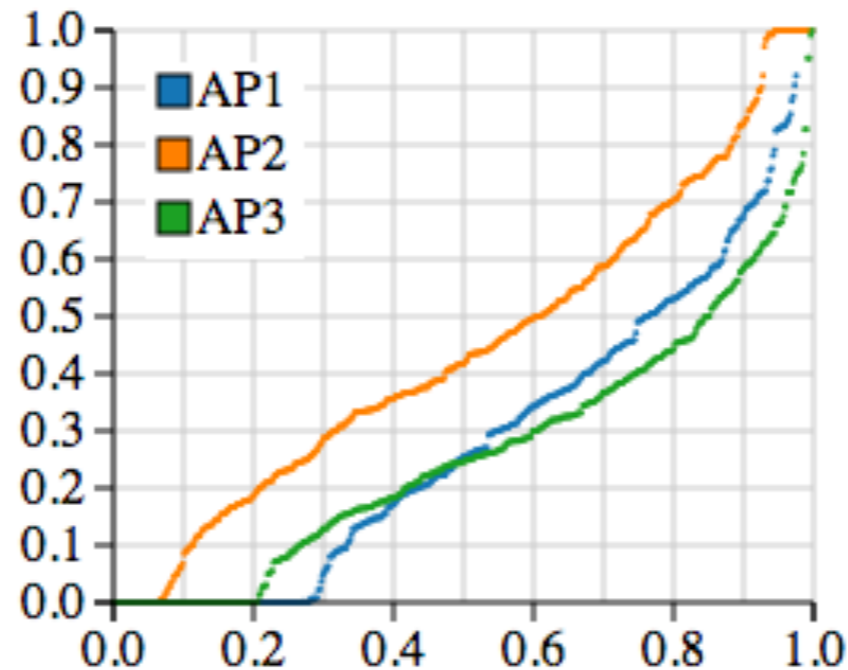
Comparing pattern distributions

First 30 days

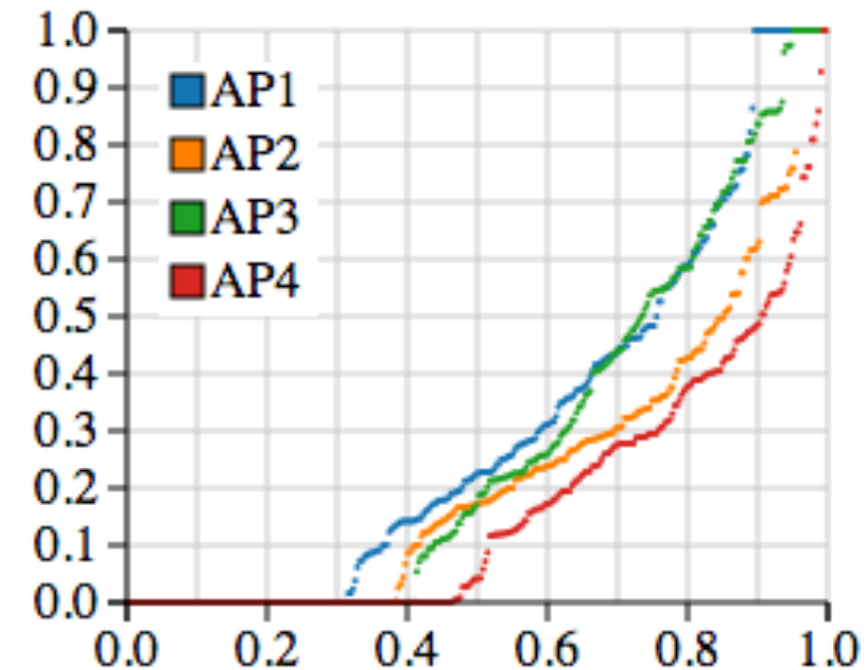
$\mathcal{K}=2$



$\mathcal{K}=3$



$\mathcal{K}=4$



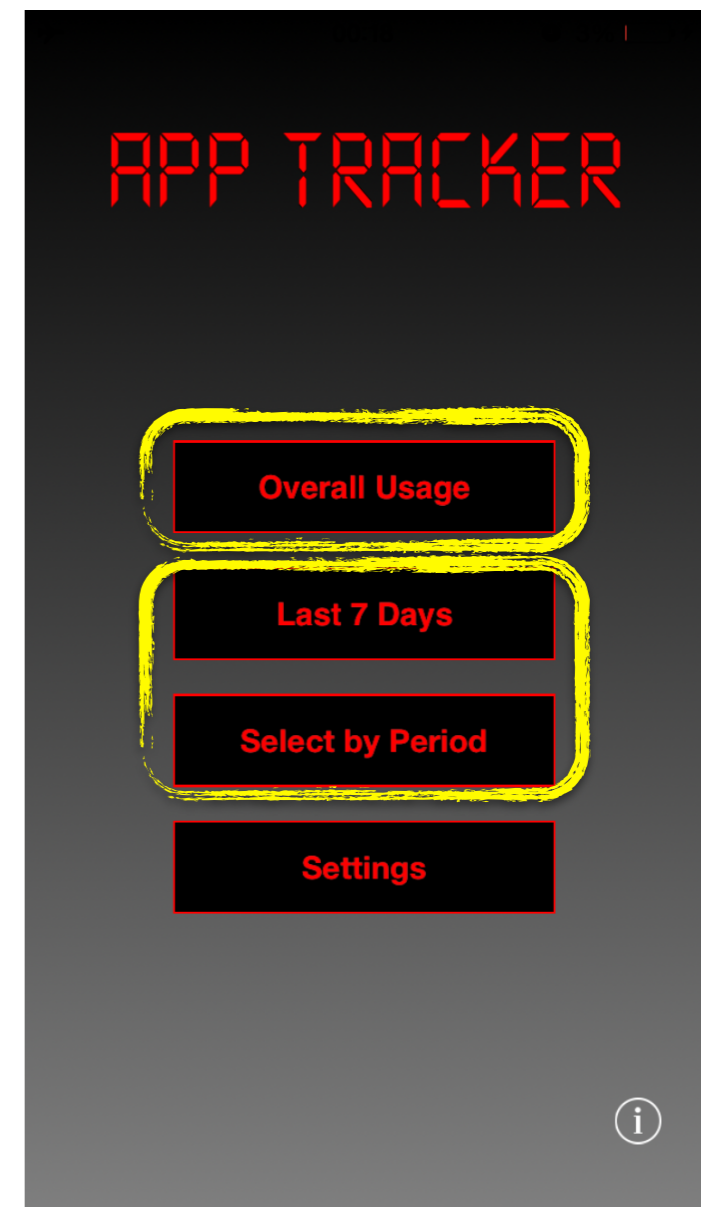
1. Overall
2. Time-partitioned

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

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

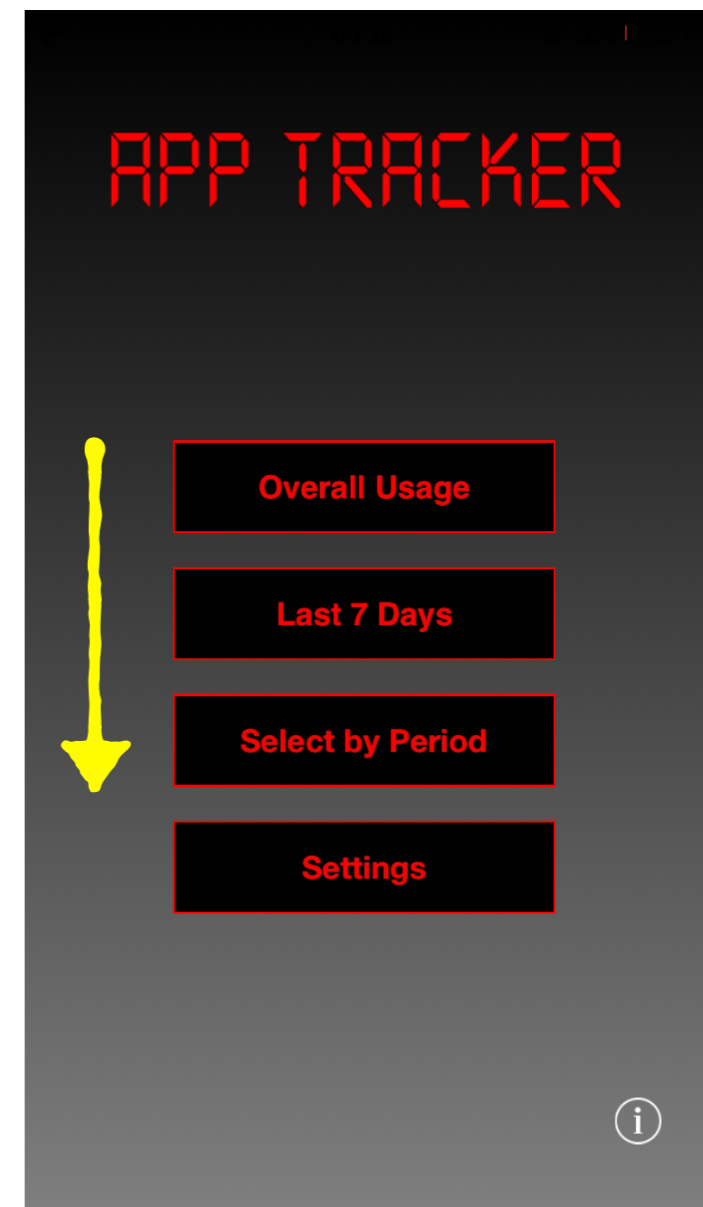
Inform the app redesign

- 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



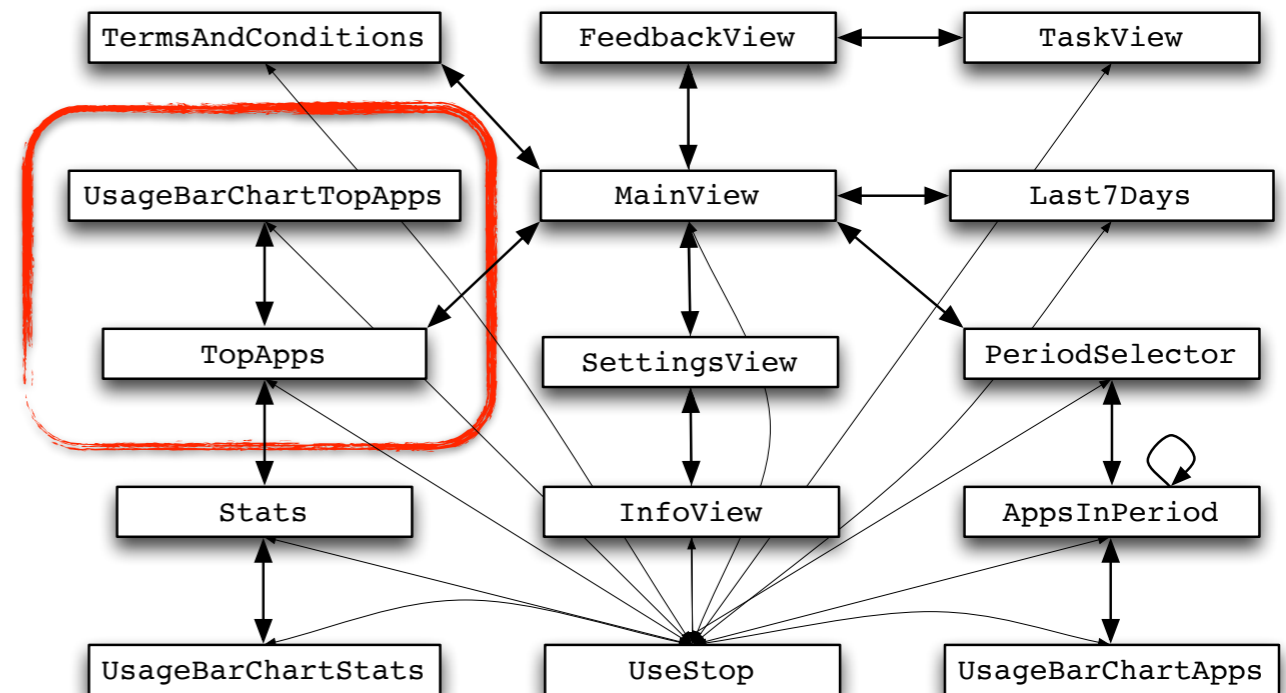
Inform the app redesign

- 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

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?