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Intelligent Agents for Mobile Location Services

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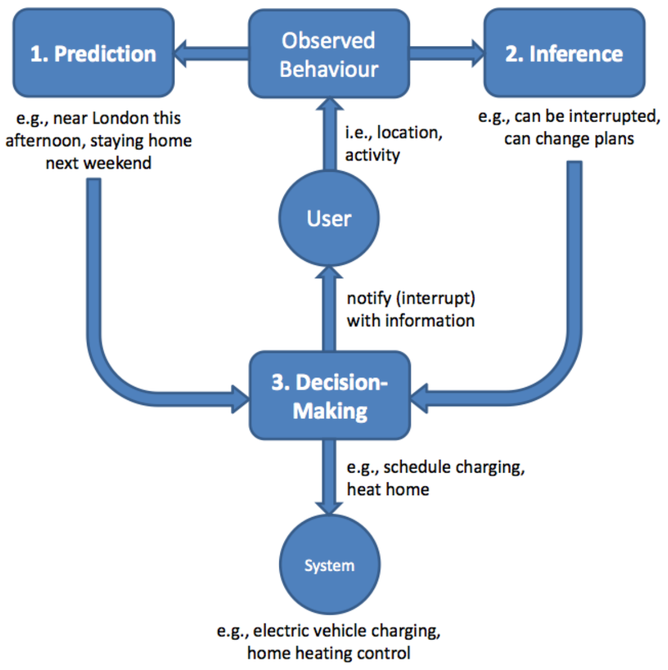
Workflow for Intelligent Assistance

To provide background services to users of mobile devices in daily life



Validated with Nokia Dataset

Data type	Quantity
Calls (in/out/missed)	240,227
SMS (in/out/failed/pending)	175,832
Photos	37,151
Videos	2,940
Application events	8,096,870
Calendar entries	13,792
Phone book entries	45,928
Location points	26,152,673
Unique cell towers	99,166
Accelerometer samples	1,273,333
Bluetooth observations	38,259,550
Unique Bluetooth devices	498,593
WLAN observations	31,013,270
Unique WLAN access points	560,441
Audio samples	595,895

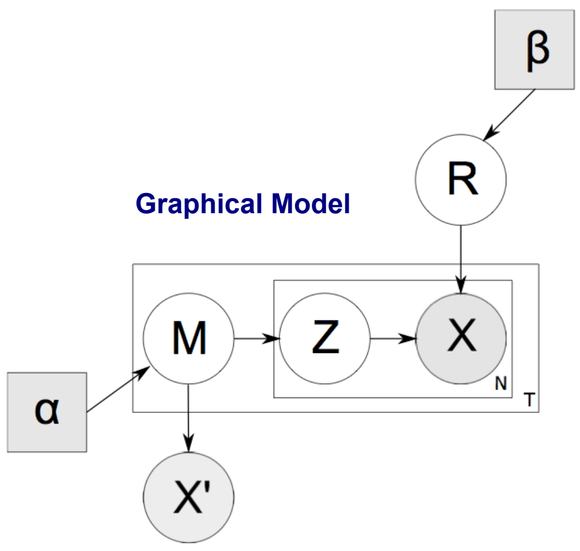
- Recorded daily life mobility and phone actions of 152 people [1]
- Approximately 2 years' worth of data

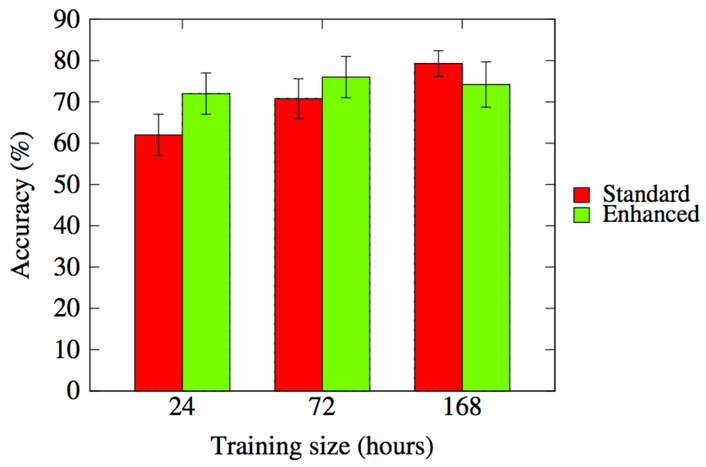
1. Realistic Location Prediction

Goal: generate accurate predictions for **new users** of location prediction services

- Assume set of observations **X'** of *established* user, each row is a 1-of-K vector indicating location presence for each time step
- **M** is a set of Dirichlet distributions (one for each time slot) generating **X'**
- **X** is another set of location observations of *new user*
- **R** maps the latent variables **Z** to observations of new user **X**
- Can use expectation maximization to find maximum *a posteriori* of this location transformation matrix **R**
- Model similar to latent Dirichlet allocation [2]

Graphical Model





- Tested approach by simulating arrival of new users through truncation of location histories
- Approach demonstrates improvement in prediction for new users when only (up to) 1 week of history has been gathered

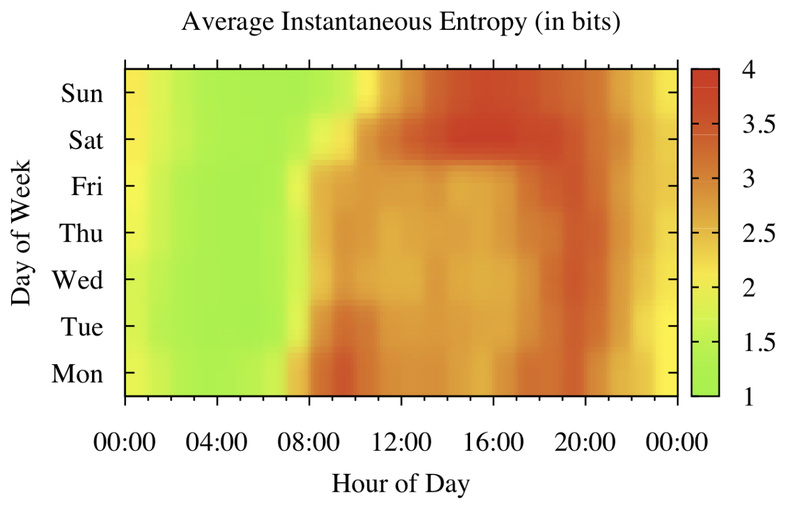
2. Inference of Departure from Routine

Goal: measure the extent to which user behaviour is currently following routine

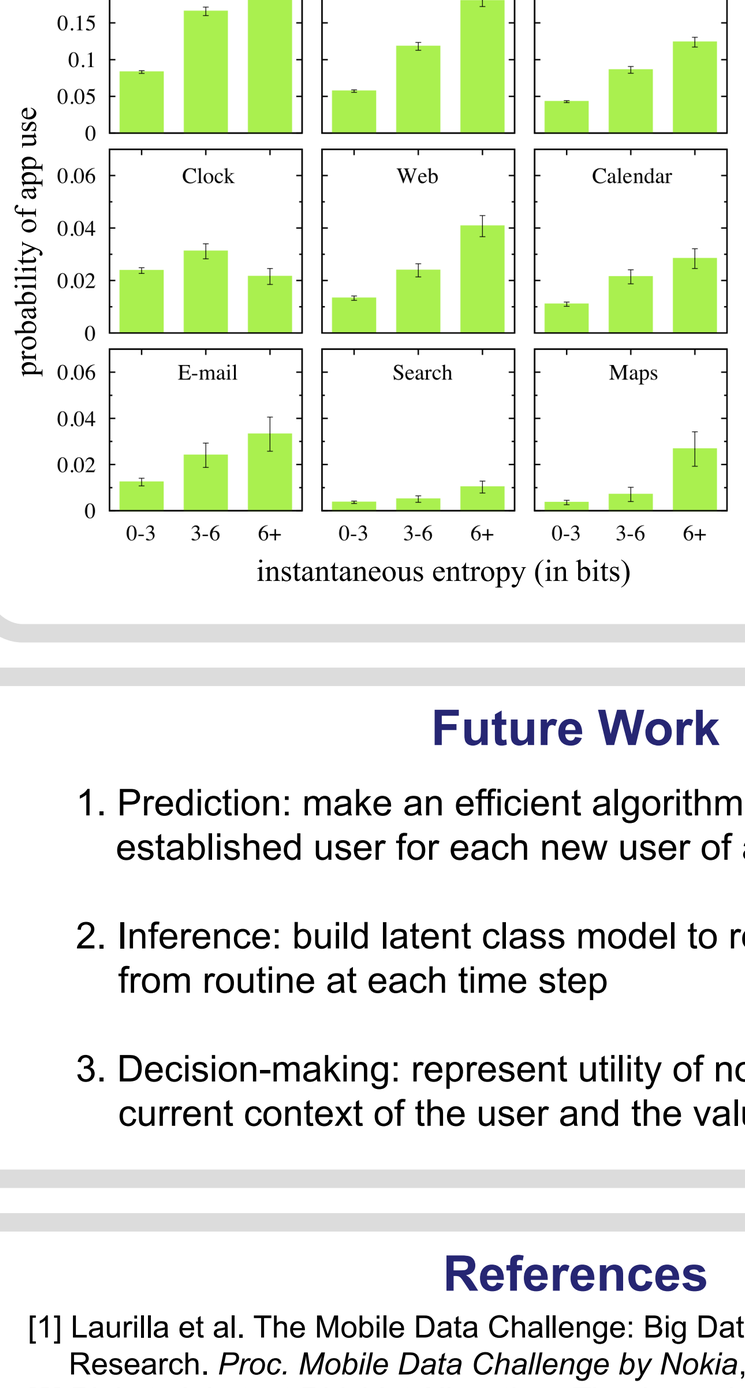
In collaboration with Sebastian Stein

- Existing work treats predictability as feature of individual [3]
- But, arguably, *periods* of low predictability are most interesting times for the user, when they are departing from routine
- Can use entropy estimator to find the information rate of the time series
- We modified the Lempel-Ziv estimator to work in real-time on mobile device:

$$\hat{H}_N := \left(\frac{1}{N} \sum_{i=2}^{N} \frac{\Lambda_i}{\log_2 (i)} \right)^{-1}$$



- Estimator agrees with intuitions about when departures from routine happen in daily life



- Departure from routine correlates with app use
- Biggest increases occur with maps and search
- Interpretation: the user seeks out information and functionality usually when they are breaking from routine

Future Work

1. Prediction: make an efficient algorithm to find best matching established user for each new user of a prediction system
2. Inference: build latent class model to represent departure from routine at each time step
3. Decision-making: represent utility of notifications given the current context of the user and the value of information

References

[1] Laurilla et al. The Mobile Data Challenge: Big Data for Mobile Computing Research. *Proc. Mobile Data Challenge by Nokia*, 2012.
[2] Blei et al. Latent Dirichlet Allocation. *The Journal of Machine Learning Research*, 3:993-1022, 2003.
[3] Song et al. Limits of Predictability in Human Mobility. *Science,* 327(5968):1018-1021, 2010.

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