Predicting Object Locations using Spatio-Temporal Information by a Domestic Service Robot: A Bayesian Learning Approach

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Motivation

One of the ways domestic service robots can better assist humans is by providing personalized, predictive and context-aware services. Robots can observe human activities and work patterns and provide time-based contextual assistance. This thesis aims to enable domestic robots to empirically learn about human behaviour and preferences. In the current literature, user preferences are learned for a generic home environment, on the contrary we learn preferences over a specific home. The developed approaches in this thesis cover the following two knowledge generation topics:

- learning user preferences in object placement
- learning user location preferences

Fig. 1: Robot recording different locations of the cup.

Approach

Robots generate a lot of information using the raw data from their sensors, which is often discarded after use. If this information is recorded, it can be used to generate new knowledge[4]. The thesis proposes models to generate knowledge about user preferences using stored information in the robot memory.

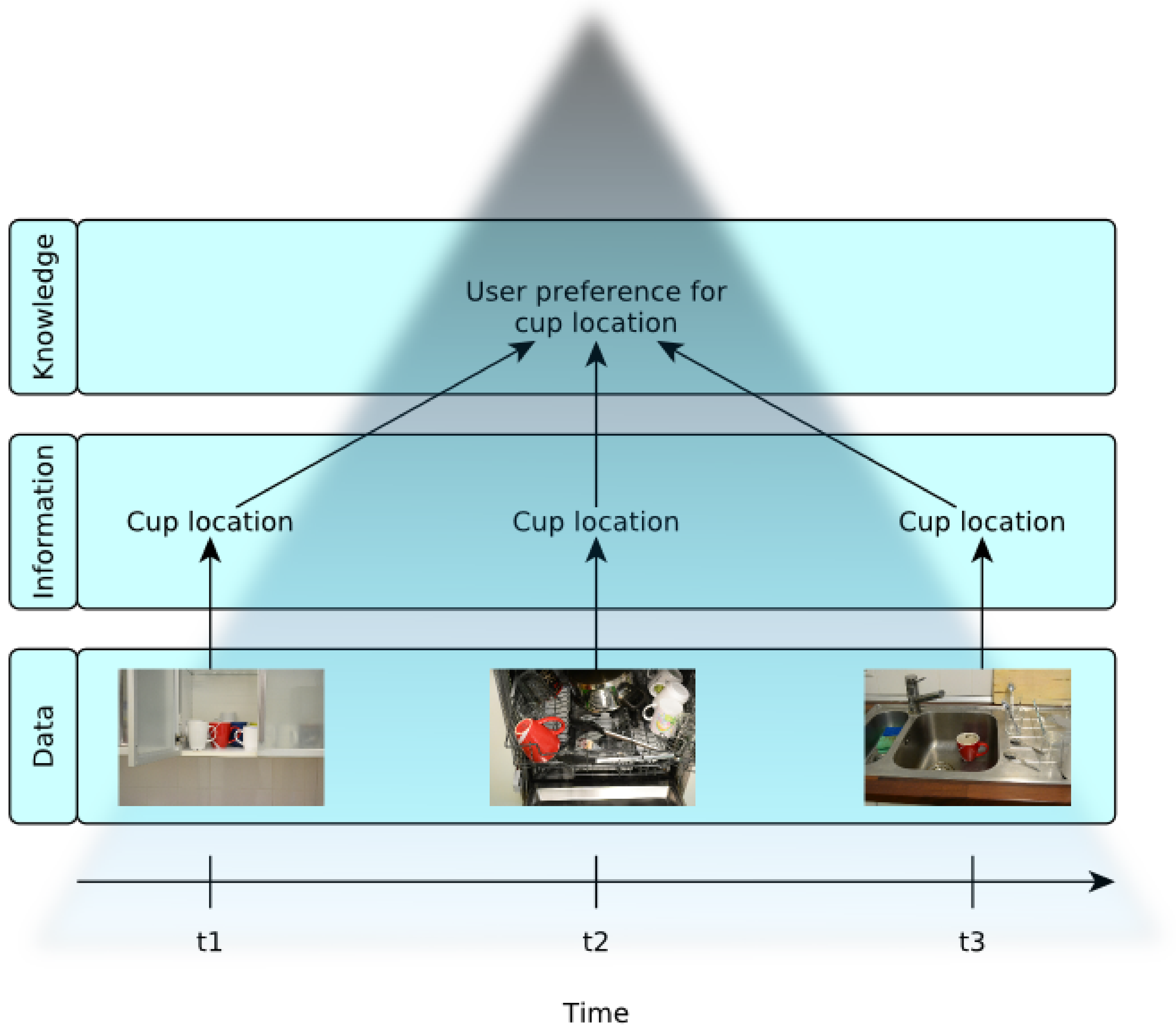


Fig. 2: Knowledge Pyramid

Bayesian Machine Learning

- Human behaviour and preferences are based on time of the day.
- The problem of learning preferences from previous information in robot memory, is formulated as a Bayesian inference problem

$$p(\theta|D,t) = \frac{p(t|\theta,D)p(\theta|D)}{p(D)} \quad (1)$$

where θ represents the user preferences, t represents the time of the day and D represents the previous information of the object location or the person location.

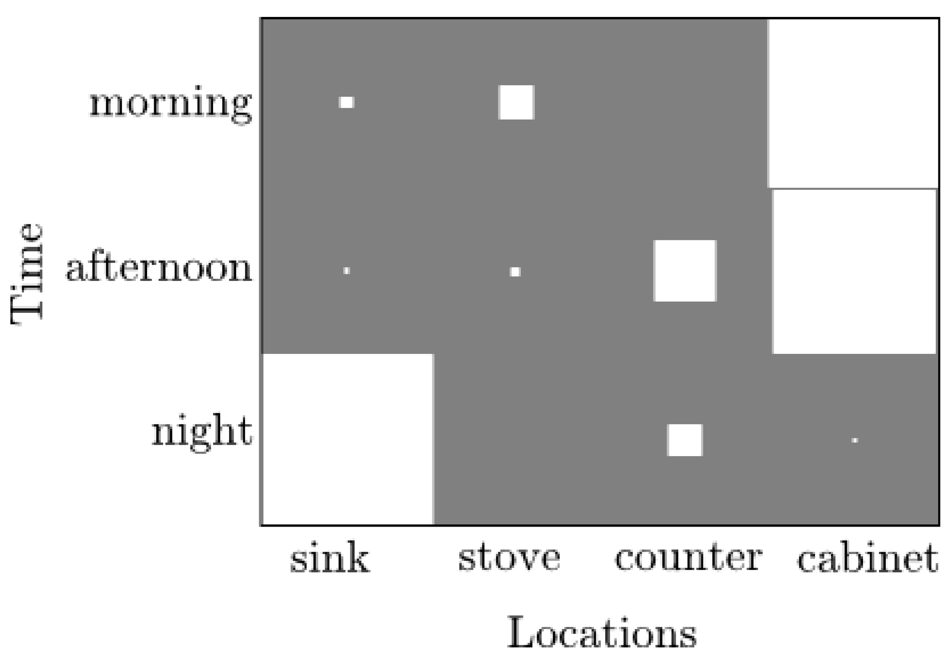
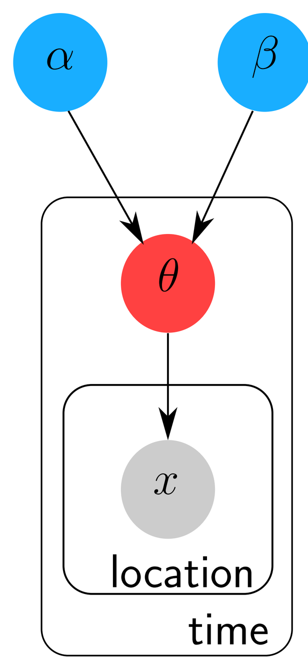


Fig. 3: Probability distribution of user preference in placing cup at different locations.

Probabilistic Graphical Models

Based on the problem type and the input datatype, different models were developed to represent the user preferences. Bayesian models are represented using probabilistic graphical models.

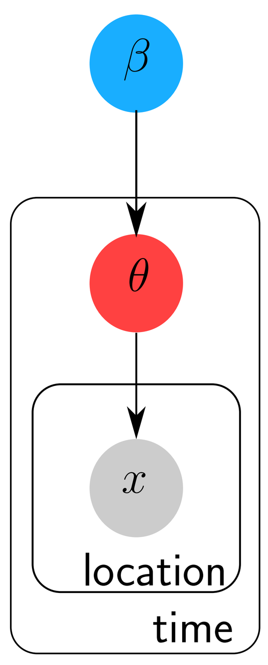
- **Hierarchical Beta Bernoulli model (HBB)**



$\alpha \sim Beta(2,2)$
$\beta \sim Beta(2,2)$
$\theta \sim Beta(\alpha,\beta)$
$x \sim Bernoulli(\theta)$

- modelling **single** location preference.
- data type is **boolean**.

- **Hierarchical Dirichlet Categorical model (HDC)**



$\beta \sim Dirichlet(1,..1)$
$\theta \sim Dirichlet(\beta)$
$x \sim Categorical(\theta)$

- modelling **multiple** location preferences.
- data type is **discrete** categories.

The models were implemented using **Probabilistic Programming languages** BayesPy [3] and PyMC3 [5]

Results

- The HBB model was evaluated on **KTH dataset**[2], which contained locations of 37 objects in an office for a duration of 5 weeks, collected by a mobile robot. The learning on this dataset showed the model could predict locations of 26 objects with 70% accuracy.
- The HBB model was evaluated on a **Brayford dataset** [2] which contained human presence information of 6 locations in an office, collected by a mobile robot. Evaluation results showed that the robot was able to learn with more than 60% accuracy for all the rooms.
- HDC model for learning the user location preferences was evaluated in the **Aruba dataset**[1]. The evaluation results showed that the model was consistently predicting user location with 63% accuracy.

Conclusions

- The Bayesian models were able to learn user preferences to a large extent. Regular patterns were learned, while objects/persons that followed no observable pattern were not predicted well.
- We hope that our approaches will set up service robots into the existing household by knowing what and who are there in a home and adapting to them.
- These service robots will grow and change with the users, with a greater awareness of the world around them.

References

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Acknowledgements

We gratefully acknowledge the continued support by the b-it Bonn-Aachen International Center for Information Technology, Rheinisch-Westfalische Technische Hochschule Aachen University and the Bonn-Rhein-Sieg University of Applied Sciences.

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