

# A context-aware Notification Service

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## **ABSTRACT**

This paper discusses the principles of making inferences about a user's context from location time-series. These principles have been implemented and embedded in a statistical model, used in a Sentient [1] Notification Service. This model makes estimates about the probability of a situation occurring in the future, based on users' locations and past behavior and using methods such as Bayesian inference [2]. This information is then used by a Context-Aware Notification Service [10] to notify all registered users who are interested in the particular activity.

## **Keywords**

Context-Aware, notification service, activity modeling, Bayesian inference, Hidden Markov models

## **INTRODUCTION**

Imagine the following scenario: at 8.15 am, on a Thursday morning, in an IT company, a visitor wishes to meet the Director of Finance. The director's secretary, queries the system for the probability that the Director will be in his office shortly.: "What is the likelihood that the Director will be in his office within half an hour?" The system returns an encouraging probability of 85% and the secretary types in her PDA "notify me as soon as the Director of Finance appears anywhere on the premises." Meanwhile, the Director has just arrived and enters the building by the garage. Immediately a notification is sent to his secretary of his arrival.

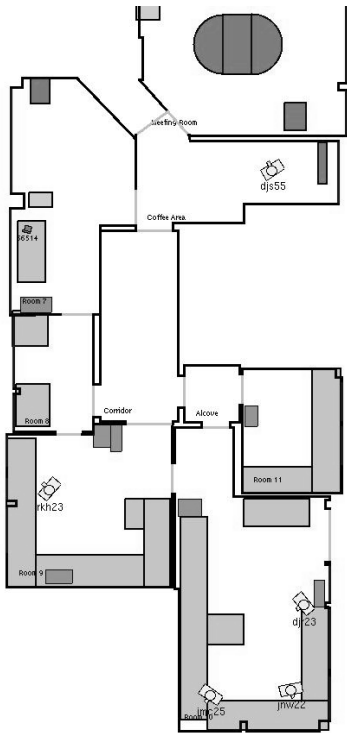
## **Activity modeling and likelihood estimations**

Current location platforms [4], [7] and context-aware systems [5], [6] do not provide any likelihood estimation of a situation of interest that allows decision making. E.g. requests similar to "I want to be registered for notification about whether Person X is in his office, only if there is a strong possibility that Person X will come in the office today" are unfeasible.

## **Statistical Modelling: Bayesian Predictive Discriminant analysis**

An analysis of sightings in the Laboratory for Communications Engineering (LCE) [8] over a period of 72 hours using Bayesian Predictive Discriminant Analysis has produced a set of predictions of people's movements.[11] Discriminant analysis is a tool that aims to construct a model for predicting the value of one discrete variable using other variables. The predictions use infinitively many models weighted by their probabilities to do the prediction. In this experiment, the data were produced by the Active Bat system [4]. Each of 16 lab members has been assigned a identifier from A to P and each person's position returned from the Active has been aggregated to form a dataset, whereupon the analysis is based. The data set can be seen in Table 1.

The layout of the rooms in the LCE lab can be seen in Figure 1. An interesting case is to determine the locations where people are most "likely" to be "seen" by the location system. Since the LCE is a working environment, we expect each person to be spending most of his/her time at the workplace.

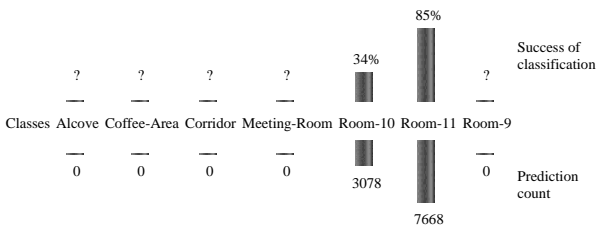


**Figure 1:**The LCE lab layout (upper floor)

Name	Location	Timestamp
Person A	Room-10	416.531330
Person M	Room-11	417.542323
Person M	Room-11	418.654543
Person M	Room-11	419.987987
Person P	Meeting-Room	421.567291
.....		
Person M	Coffee-Area	452.984925
.....		
Person P	Room4	489.981384

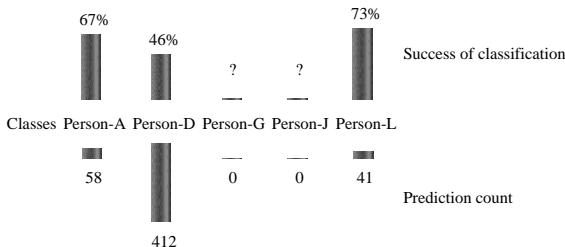
**Table 1:** The dataset for the Bayesian Discriminant Analysis

Indeed, looking at the following figure which was produced by the BAYDA tool, and which depicts a prediction of where Person M is more likely to be “seen”, there is a distinctively high probability that Person M, will be seen at Room 11 which is his office. The second peak in the predicted probabilities is at Room10, which is the office that Person M was moving into at the time of the experiment. The fact that Person M can only be associated with these two areas from the available data, suggests that his movement inside the rest of the LCE locations (for the duration of the experiment) are not regular enough to place him anywhere else except Room11 and Room 10, with even small probability.



**Figure 2:** Probability of Person M's sightings during the day

Similarly, using again the same methodology, we produced the following prediction of the probability of people’s sightings in the coffee-area during morning hours.



**Figure 3:** Probability of morning sightings in the coffee-area

This result can be interpreted as follows: In this case, while doing the cross validation, it was predicted 58 times that data item should belong to the class "Person-A" and 67.2% of these classifications were correct. So it is estimated that if the system predicts previously unseen data item to belong to the class "Person-A", there is 67.2% chance that this prediction is right. The reliability of this estimate can be rated by stating the fact

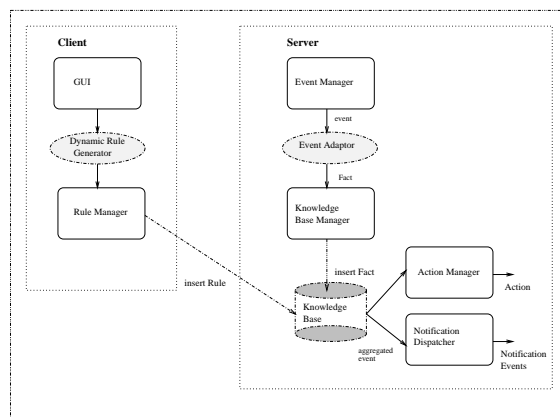
that the estimate is based on classifying 58 items (11% of the sample) as members of the class "Person-A". Below each estimate (fig2) a bar chart indicates the percentage of the sample size used to calculate this estimate.

## Preliminary Evaluation

We asked the people who were picked up by the system if they are frequently in the coffee area in the morning and both Person A and Person L confirmed that they regularly spend a considerable time in the coffee-area in the morning in order to prepare coffee. Person D, confirmed that although he doesn't drink coffee, he nevertheless makes tea regularly, and therefore is also often in the coffee area in the morning. Based on this inference, and by using the same methodology, the system could calculate the actual probability of coffee being prepared, by correlating the status of the coffee to the presence of the coffee-makers.

## THE PROCESSING ENGINE

We have implemented a rule-based notification server [10] which decides when the desired situation (such as the coffee-making) has been fulfilled in order to activate user rules, producing notifications. The Knowledge Base undertakes most of the cumbersome process of event aggregation and correlation. It is responsible for the management of location information as well as the production of inferences. It is built on an expert system engine implemented in Jess [9]. Jess implements a forward chaining rule interpreter that cycles through a match-execute cycle. During the matching phase, all rules are scanned to determine whose condition part is matched by the current state of the environment, i.e. contents of working memory. During the execute phase, the operation specified by the action part of the rule that has been found to match is executed. This cycle continues until either no rule matches or the system is explicitly stopped by the action part of a rule. A conflict resolution strategy is applied if more than one rule is found to match. The environment is modelled through a set of "facts" which are kept in a list in memory. Location information is received in the form of structured (CORBA) events by the Event Manager. The Event Adaptor is then responsible for mapping them into facts. When a "location" fact produced by the Event Adaptor gets asserted in the



knowledge base, the location management rules get activated, calculating the new track of the user's movements and the likelihood of the desired situation. Once the user-set conditions have been fulfilled,

**Figure 4:** Rule-based Notification Server Architecture.

the Action Manager triggers the appropriate predefined notification or other action. The Notification Dispatcher wherever appropriate, generates aggregated structured events can be fed back to the event service to be filtered by event consumers . The most straightforward actions involve sending email, SMS, executing a script, invoking a text-to-speech processor. The user can specify his own external functions. The Notification Dispatcher wherever appropriate, generates aggregated structured events can be fed back to the event service to be filtered by event consumers . .

## CONCLUSIONS

A Sentient Notification Service has been designed which achieves the following goals.

- It provides a model of producing logical abstractions over physical entities associated and their associating context.
- It reevaluates the state of the world and produces inferences that changes with respect to time and other variables of the environment.
- It provides a middleware component which features a powerful pattern matching ability for a large scale of events such as are typical in the case of location.

## ACKNOWLEDGEMENTS

I am grateful to Professor Andy Hopper for his precious guidance and support throughout this work. I would like to thank the University of Cambridge for supporting the funding of my PhD.

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