# Prediction of passenger density in underground Systems

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## ABSTRACT

This paper provides a provides a comparison between several prediction accounts in the area of the underground stations.

## 1. INTRODUCTION

Underground transportation systems are big energy consumers and have significant impacts on energy consumptions at a regional scale [2]. Approximately 30% of the required energy is needed for operating the metro stations and surroundings, such as ventilation, vertical transportation and lighting [1].

To realize energy saving in this area already an intelligent control system for metro stations was developed. The control system is adaptive on the basis of environmental factor forecasts and occupancy flow patterns [5].

Changing the parameter doesn't have an immediate effect. Therefore it would the number of passenger needs to be predicted.

This paper focuses the prediction of number of passenger in the station.

## 2. STATE OF THE ART

Context prediction breaks the border from reaction on past and present stimuli to proactive anticipation of actions. Initiated by the pioneering work ofMayrhofer et al. [9], researchers have for about one decade now considered the prediction of context to enablepro-active context computing. Research directions spread from applications for context prediction [7] over event prediction [18], architectures for context prediction [8, 11, 14], data formats [3] and algorithms [6]. Recent work focuses on three main challenges:

1. Prediction mostly limited to location
2. No benchmarks and common data sets
3. No common development framework

While there have been contributions targeting some of these challenges, we still see them as unsolved and in the following will further elaborate on these challenges. First, several authors have studied aspects of future context with the aim of enabling proactive behaviour in applications. Applications considered are diverse and range across basically all aspects of daily life. Still, the survey of Voigtmann and David shows that a great share of context prediction research so far concentrates on location prediction [17]. Recently the research on location prediction tends to focus on new approaches for indoor location, e.g. [12, 10] and the use of social networks as data source [19]. We see a great potential for the use of context prediction in applications to enable sustainability, e.g. applications for energy efficiency. An important building block for this is the prediction of user preferences. Since preference settings in many applications tend to be complicated and have important implications, for example on the user's privacy, predicting the user's preferences was shown to solve the problem of too lax preference settings [4]. Also, important to enable applications for sustainability and energy efficiency, is the prediction of user routine, e.g. [13].

Secondly, regarding missing benchmarks and data sets, although utilized by numerous algorithms, a comprehensive comparison of their strengths and weaknesses on benchmark data sets is yet missing. To raise context prediction to a professional level at which it might be integrated in commercial applications, we need to establish common, widely accepted data sets, develop and disseminate accepted benchmarks and provide more general description of algorithmic performance not only restricted to specific applications but to a whole class of applications utilising input data with similar properties. One promising approach is to utilize data that users share over social networks [19].

And last, although, several authors have considered architectures for context prediction [8, 14], a common methodology or platform has not yet crystallised. Application developers are forced to start from scratch. One reason for this is that previous authors seldom provided usable sources of their applications that could be extended. In order to foster the integration of context prediction into applications, support for application developers has to be greatly improved.

[16, 15]



## 3. DATA ACQUISITION

### 3.1 Metro Station

Metro Station Passeig de Gracia - Line 3 form now on PdG-L3

### 3.2 Data Acquisition

Metro Station Passeig de Gracia Line 3 (PdGL3).

Data are gathered via CCTV. The images are processed. Out of each image the number of passenger is gathered. In this way a database was filled which contains for each data set the time, location and value. Data Acquisition...

# 4. RESULTS

Results

# 5. CONCLUSION

Conclusion

# 6. ACKNOWLEDGEMENTS

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