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BEHAVIOUR RECOGNITION IN SMART HOMES

A DISSERTATION PRESENTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS
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Abstract

In the context of this thesis, behaviour recognition aims to infer the particular behaviours of the inhabitant of a smart home from a series of sensor readings from around the house. This thesis views the behaviour recognition problem as a task of mapping the sensory outputs to a sequence of activities performed by the inhabitant. The main focus is the development of machine learning methods to find an approximation to the mapping between sensor outputs and behaviours.

While there have been many supervised machine learning methods for identifying behaviours from a sensor stream, they generally assume that the behaviours are either segmented or perform segmentation and behaviour recognition separately. In order to be used in the real world, segmentation and behaviour recognition should not be treated separately. This thesis addresses this problem based on a set of hidden Markov models (HMM) and a variable window length.

As the majority of the methods reported in the literature are based on supervised learning approach, they generally rely on a labelled dataset, where the behaviours of the inhabitant have to be manually labelled. This is often not practical in the real world. Most current unsupervised methods are not suitable for behaviour recognition as they are based on inputs of fixed dimensionality. In the smart home, the behaviours that are to be recognised are variable in length. This thesis introduces an unsupervised learning method that addresses this problem, which is based on compression and the edit distance between words. This includes both the segmentation of the sensor stream into suitable patterns and identification of patterns that correspond to human behaviours. This thesis also shows that the resulting method can be used to provide labels to training data for a supervised method.

However, training a learning algorithm on sensors that are irrelevant and/or redundant becomes crucial as they may affect the recognition performance. This thesis addresses the sensor selection problem for behaviour recognition through an

information-theoretic approach, which is based on information gain, modelled in the form of a decision tree. The main idea is to identify the set of informative sensors that are highly correlated with the behaviours. This thesis also presents solutions to address the ‘generalisation’ issues of the informative sensors identified across the different trees.

To evaluate the effectiveness of our proposed methods, we use a real smart home dataset obtained from the MIT PlaceLab and compare the labels produced by our methods with the labels assigned by a human to the activities in the sensor stream. We also validated our methods on other benchmark datasets and learning algorithms.

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