Traffic System Forecasting using Activity Recognition

James Howard, William Hoff
Center for Automation, Robotics, and Distributed Intelligence
Colorado School of Mines

Motivation

Using a collection of small anonymous sensors we look to recognize and predict human behavior within a building. Accurate behavior prediction will allow for the creation of building environmental control schemes designed to reduce energy consumption.

Methodology

Using a hierarchical approach allows us to recognize activities at different time scales. First we use local sensor information for 10-20 second length activities. We then use this information as the basis for global activity prediction at the range of 5-10 minutes.

System Design

We designed a sensor network consisting of wireless computer "motes" and passive infrared (PIR) motion sensors [1]. These were mounted in hallways and rooms in a large campus building (Fig 1).

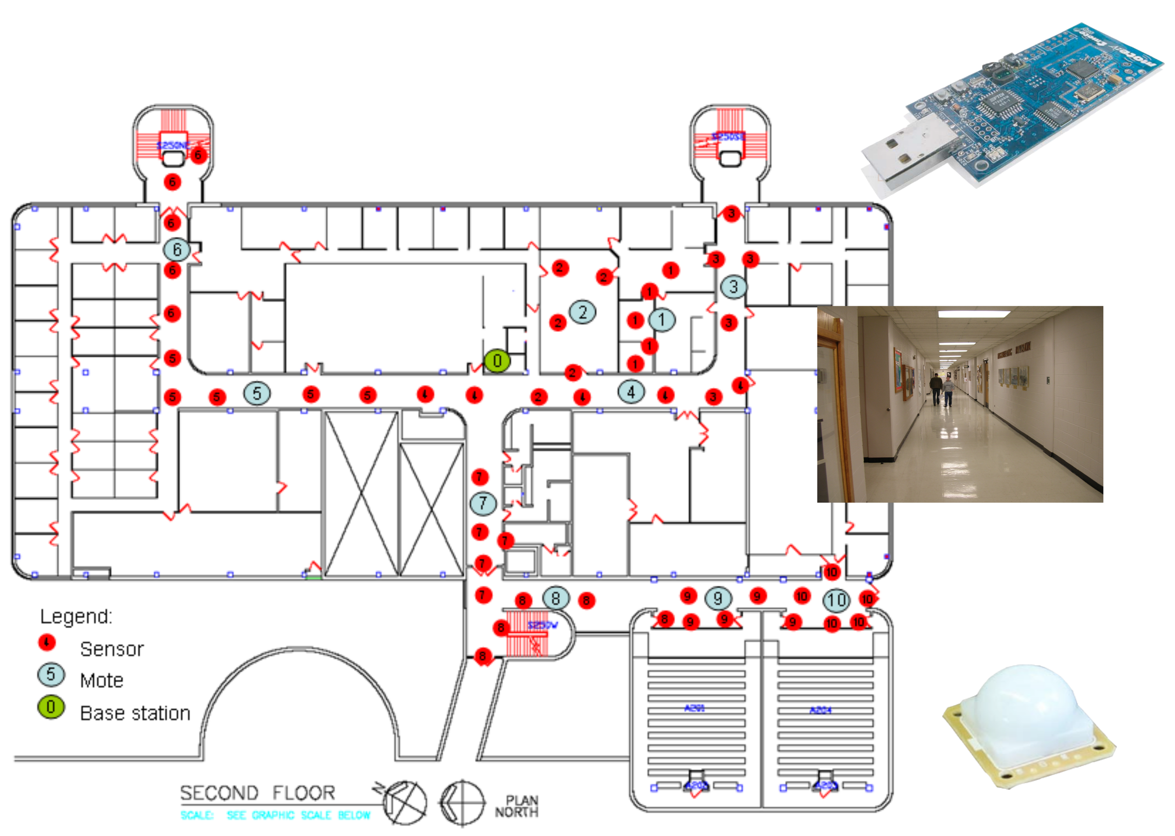


Figure 1. Sensor network; small dots are the PIR sensors; larger dots are motes.

Data Representation

Sensor data is represented in the form of a two dimensional matrix H (t,s), where the columns are sensors and the rows are time intervals (Fig 2). Local movement patterns appear as structures in the matrix. For example, a person walking down the hall causes consecutive hits in adjacent sensors, which appears as a diagonal streak.

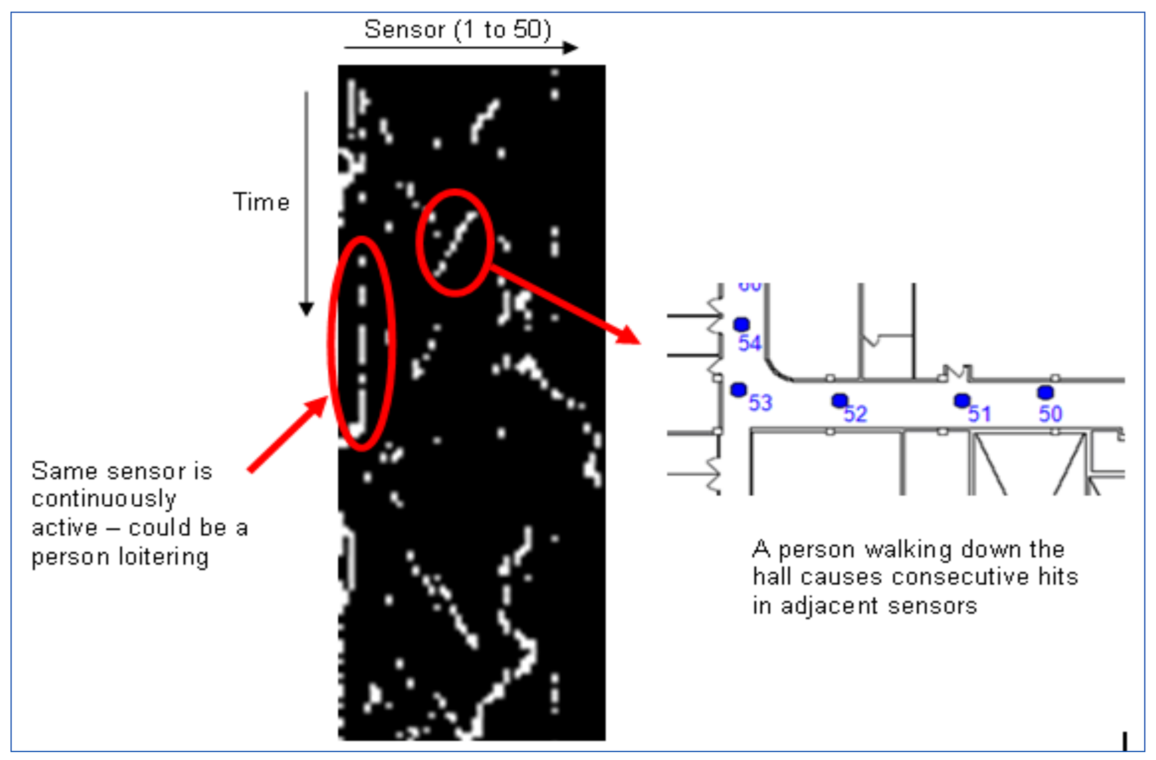


Figure 2. Example of sensor data in the form of a two dimensional matrix.

Local Activities

Network topology is inferred from the sensor data. Strong correlation scores define the local neighborhood for each sensor.

High activity data sensed from local neighborhoods is then clustered using a k-means clustering algorithm. The resulting cluster is then represented by a Hidden Markov Model trained on all data within that cluster. Figure 3 shows some of these trained Hidden Markov Models.

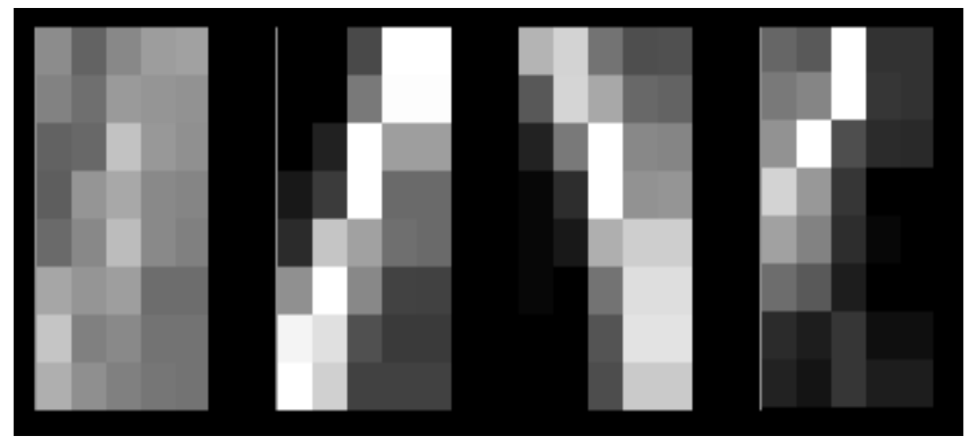


Figure 3. Representative Hidden Markov Models trained from local neighborhood data

Global Activities

We analyze the large scale distribution of local patterns over time using the method of probabilistic latent semantic analysis [2]. The method discovers a small number of latent or "hidden" classes in the distribution of detected local events.

We divide the local patterns into fixed length time periods, and find latent classes in the distributions. For any new period of time, we can represent it as a combination of latent classes. Applying k-means clustering on this latent class space allows us to assign a class label to any new activity (Fig 4).

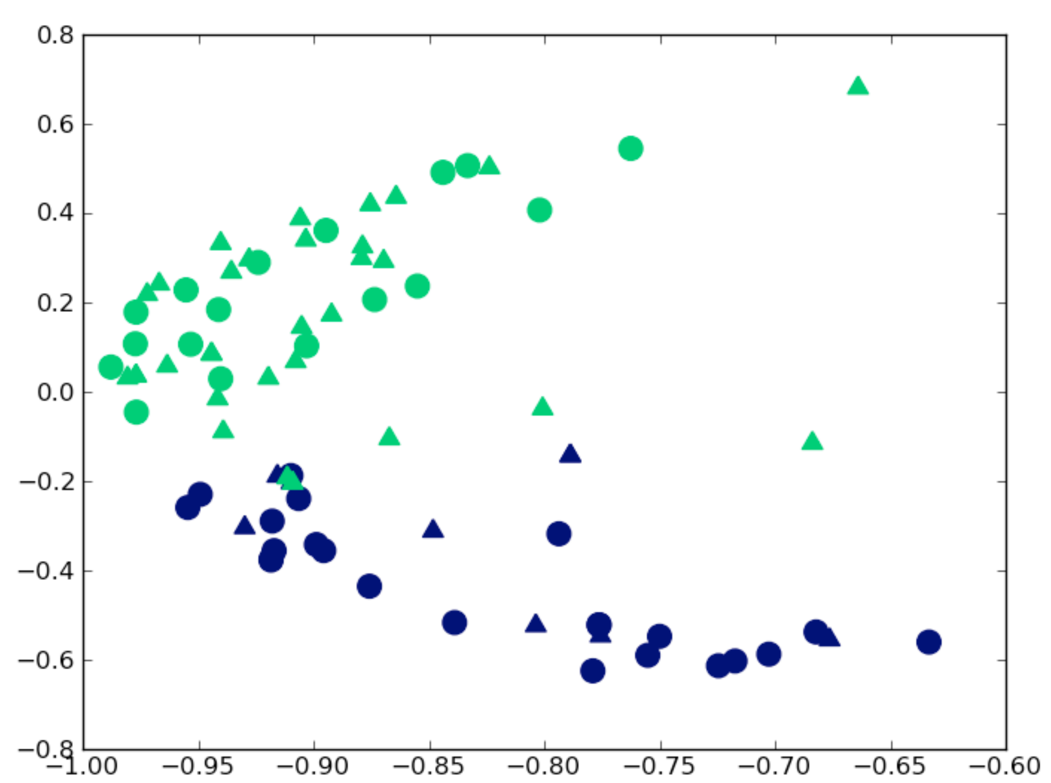


Figure 4. Clustering of latent class projected data. Early Morning (o) and evening (triangle)

Figure 4 shows an example of latent class projected data that has been clustered into two clusters, green and blue. The green cluster consists of data that primarily came from late afternoon periods (triangles), and the blue cluster consists of data that primarily came from early morning periods (circles). Thus, the algorithm has distinguished morning activities (i.e. many building entrance events) from afternoon activities (i.e. exit events).

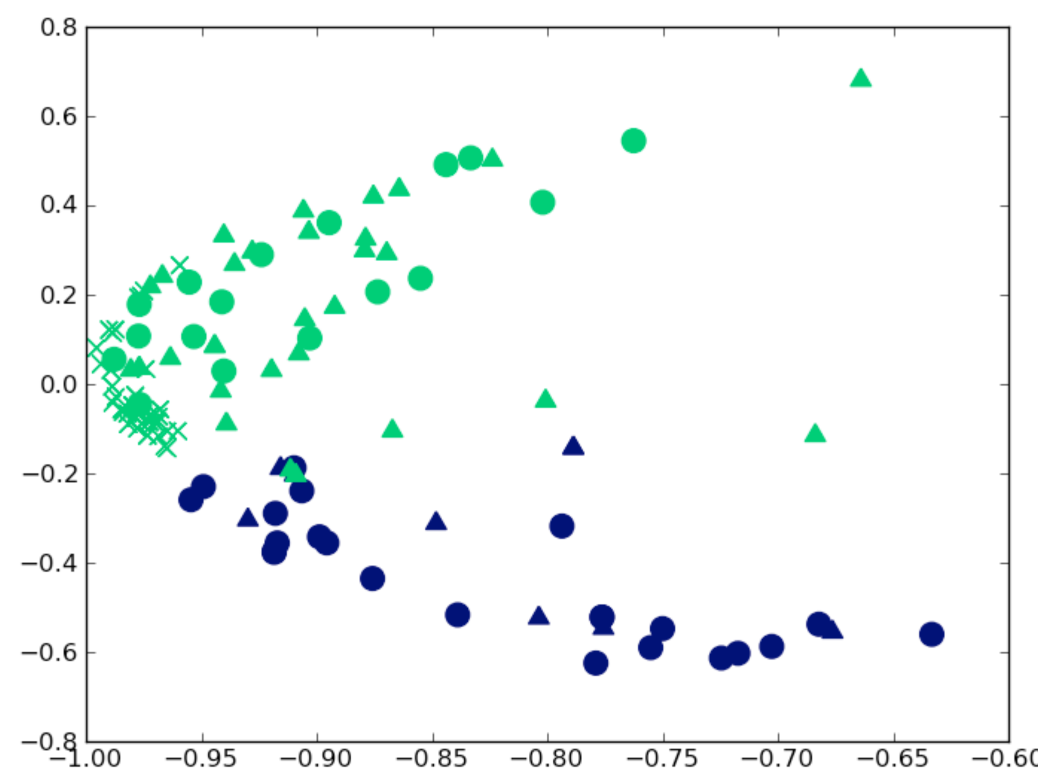


Figure 5. Classifying lunch time (x) data onto early/late split

Projecting data extracted from the beginning of typical lunch times (12:05 pm - 12:20pm), we see in figure 5 that all data is projected to our cluster associated with building exit.

Acknowledgments

National Science Foundation (grant CNS-0931748), The Lockheed Martin Corp. and Northrop Grumman

References

[1] W. Hoff, J. Howard, "Activity recognition in a dense sensor network," 1st Int'l Conf on Sensor Networks & Applications, 2009

[2] T. Hofmann, "Probabilistic Latent Semantic Indexing", Int'l SIGIR Conf on Research & Development in Information Retrieval, 1999

Traffic System Forecasting using Activity Recognition

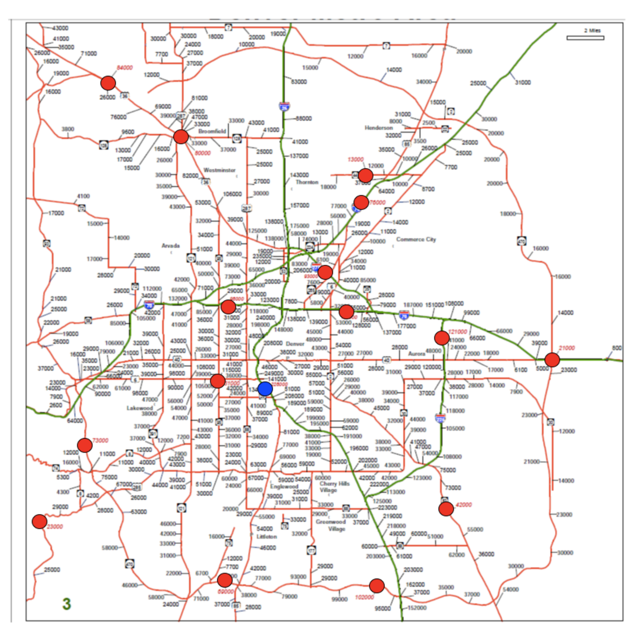
James Howard, William Hoff
Center for Automation, Robotics, and Distributed Intelligence
Colorado School of Mines

Motivation

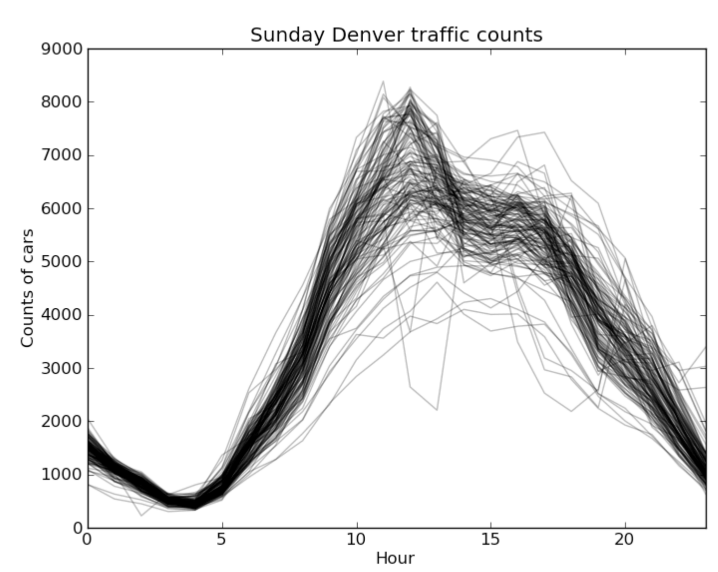
According to a 2005 study by the US Department of Transportation [1], optimal timing of traffic lights on major roadways across the United States could account for approximately a 22% reduction in emissions along with a 10% reduction in fuel consumption. The total estimated fuel savings would amount to approximately 17 billions gallons of motor fuels annually. Accurate estimates of traffic density allows modern traffic light control systems to dynamically change timings and thus increase overall traffic flow.

Data

Roadway data collected as counts of vehicles over time at various positions along a traffic system. The time resolution of traffic density is an important factor in our work. Results shown here are based on total counts per 15 minutes.



Sensor locations for denver traffic, blue sensor is used for future results

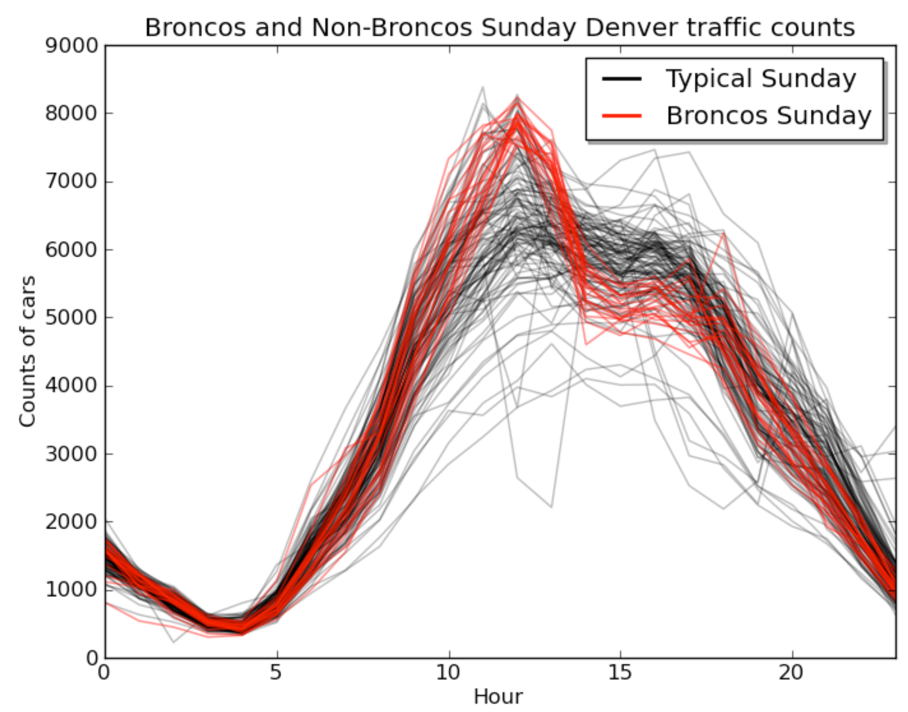


Counts of vehicles on Sundays in Denver

Methodology

Assumptions

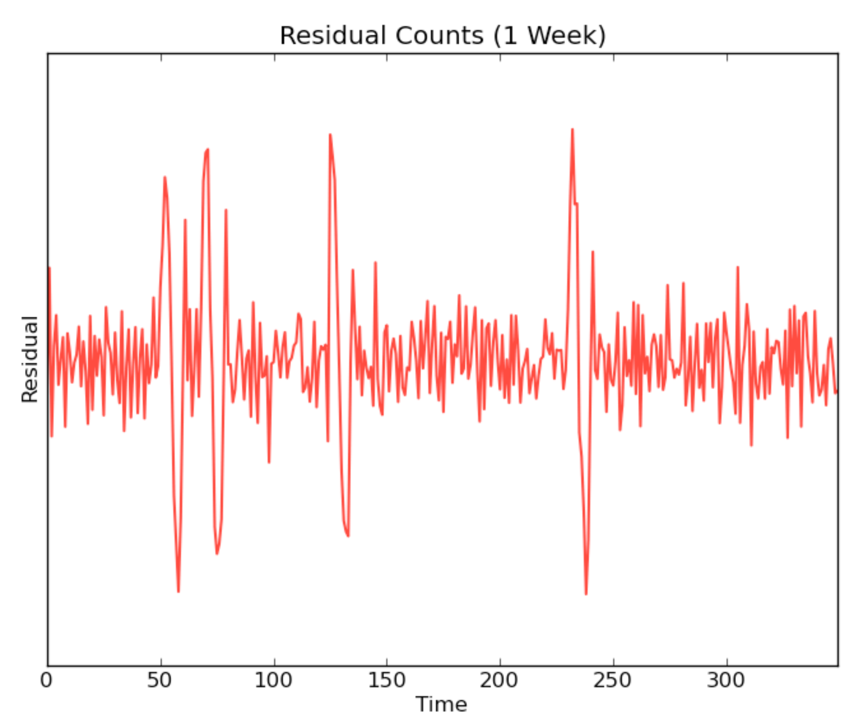
We assume that traffic is generated from a set of activities produced (e.g. Going to work, lunch, etc). Also we assume that forecasting deviations are the result of non-daily activities and not simply noise (e.g. Sports games)



Broncos and non-Broncos Sunday Counts of vehicles in Denver

Seasonal ARIMA Forecasting

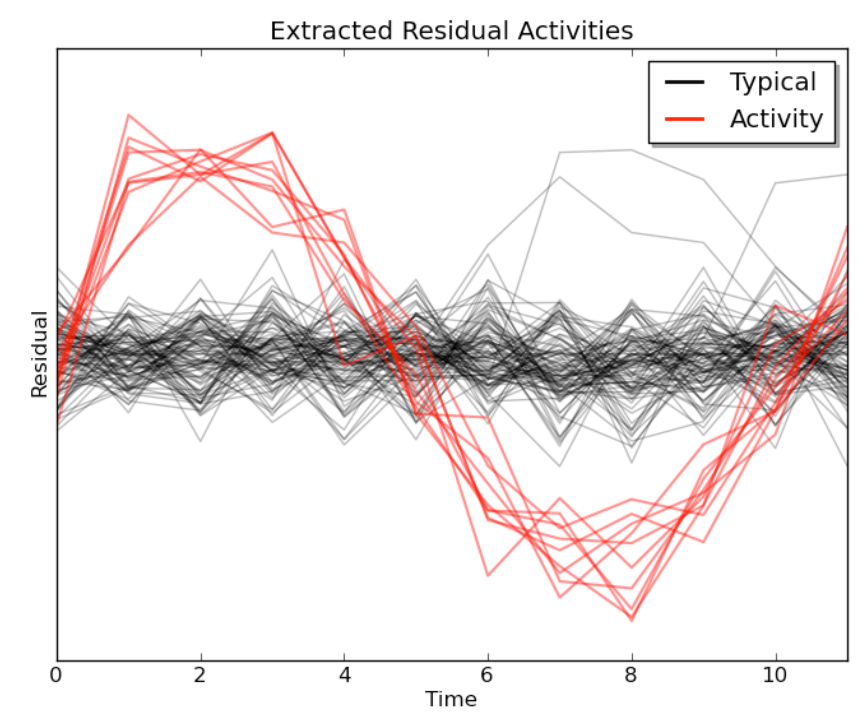
Conventional (Seasonal ARIMA model) forecasting will consistently mis-forecast such infrequent events. Such consistent mis-forecasting can be seen in the residual graph (Remaining results are simulated).



Residual data for one week. Spikes in the graph are likely due to unexpected activities.

Activity Modeling

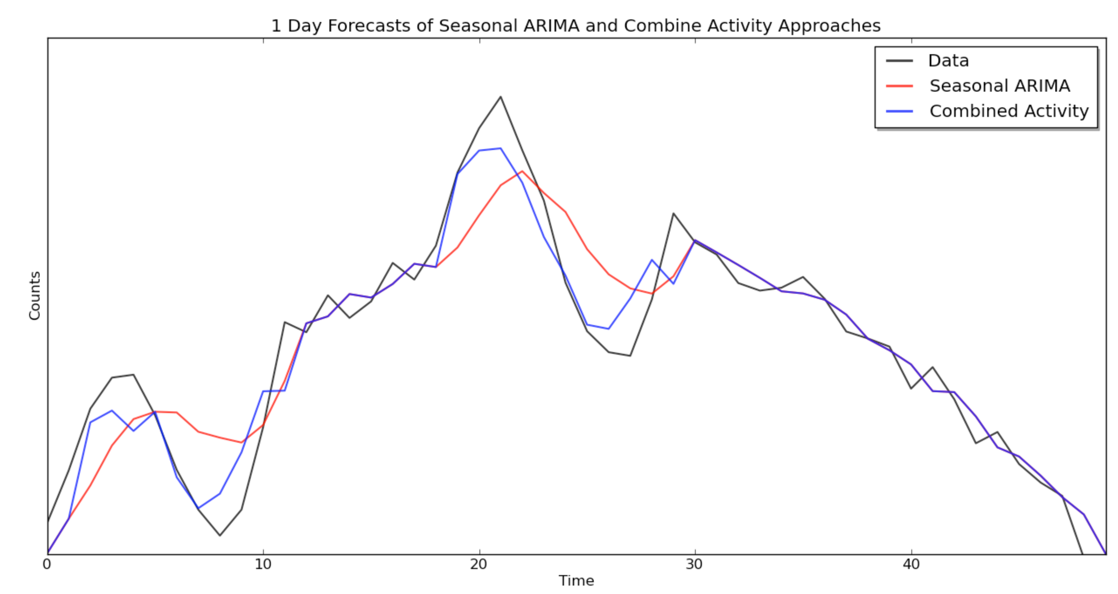
Large mis-forecasts are assumed to be activities. They are extracted using a fixed sliding window and applying Hotelling's T-square test. All such mis-forecasts are then clustered and modeled through a k-Means Hidden Markov Model algorithm. Note: we can model an arbitrary number of activities this way.



Extracted mis-forecasts for an activity

Combined Forecasting

Final forecasting is then performed by using a bayesian combined forecasting model [2]. This model maintains a confidence of all trained activity models and forecasts based on the most likely model at each point in time.

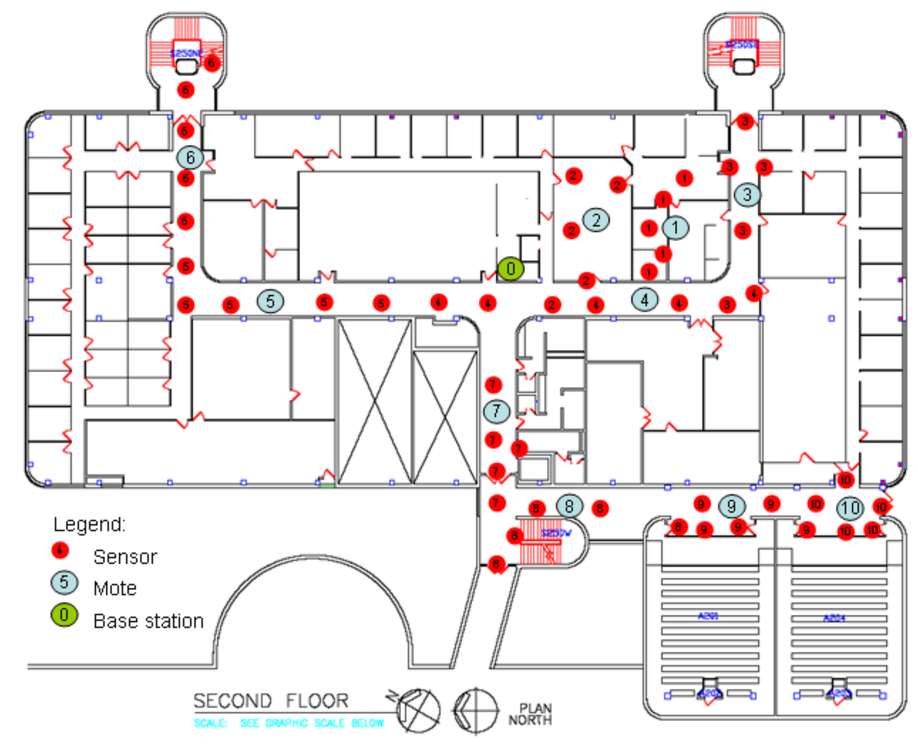


Combined forecasting for one day with 2 unusual activities

Building Traffic Systems

Building Forecasting

Our approach can be applied to building traffic systems through the use of passive infrared motion sensors to determine counts of people. Such motion sensors are inexpensive and may be deployed through the use of a sensor network.



Passive infrared sensor network place on the 2nd floor of Brown Hall

References

[1] US DOT. National Traffic Signal Report Card, 2007

[2] V Petridis, A Kehagias, L Petrou, A Bakirtzis, S Kiartzis, H Panagiotou, and N Maslaris. A Bayesian multiple models combination method for time series prediction. Journal of intelligent and robotic systems, 31(1):69–89, 2001

Acknowledgements

National Science Foundation (grant CNS-0931748), The Lockheed Martin Corp. and Northrop Grumman