Semantic Anomaly Detection in Daily Activities

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ABSTRACT
We monitor activities of daily living of smart home residents to detect anomalies in their behavior. Unlike traditional anomaly detection systems, we aim to reduce false positives in anomaly detection with the help of semantic rules. Some of these rules are predefined based on expert knowledge and the rest are learned by the system with the help of resident/expert feedback. We also correlate trend of change in different activities to improve anomaly detection. In addition to monitor statistical deviation from regular behavior, we also detect deviation from healthy and social norms (defined by experts) as anomalies.

Author Keywords
Daily activities, anomaly detection, activity monitoring.

ACM Classification Keywords
H.3.4 Systems and Software: User profiles and alert services.

General Terms
Algorithms, Human Factors, Performance.

INTRODUCTION
Advances in sensing technologies enable us to recognize daily activities in home settings. It is now possible to learn models for daily activities for a resident in smart home that facilitates long-term monitoring to detect deviation from normal behavior i.e., anomalies ([4, 2, 3]). However, existing anomaly detection systems suffer from generating numerous false positives that makes them unreliable. The main reason for the false positives is treating each activity instance and day independently ignoring the correlation among them ([1]). Another reason is the lack of semantic rules to filter out false positives as logical deviation from normal behavior.

We propose a semantic anomaly detection system that uses semantic rules to define logical deviations from regular behavior. Our system starts with an initial set of predefined rules defined from domain knowledge. As the system runs, newly detected anomalies are verified by the resident / experts to be included as new rules if appropriate. Our system also combines activities from multiple days to better understand trend of change in behavior. In addition, we develop models for correlations among multiple activities so that change in one daily activity can be explained by changes in one or more other activities.

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DESCRIPTION
Abnormal behavior can occur in countless forms and it therefore appears problematic to be able to build a good generic model of abnormality. Initially, we plan to develop models from the training data that represent normal behavior. Note that based on the training data, there may be multiple models for normal behavior (e.g., weekdays, weekends, Fridays). Based on these models, we detect statistical deviation from normal behavior in testing data. Thus we find abnormal behaviors that never happened in the training data.

Figure 1 shows our semantic anomaly detection framework. The 'Anomaly Detector' module detects anomalies in the testing data. However, some of these anomalies may be explained by user feedback and / or expert knowledge. For example, the user may be recovering from a major operation, or there may be a power outage. The 'Anomaly Filters' module detects such scenarios and do not report them as behavioral anomalies. If there is significant number of instances of a particular scenario, a new behavioral model is developed for this scenario and stored in the 'Normal Behavior Models' so that in future such scenarios are not detected as anomalies. In this way, the set of normal behavior models keeps getting enriched.

The 'Explainable Scenarios' may contain the following rules: 1) Watching a pet for a few days 2) Entertaining visitors 3) Power outage 4) Recovering from major medical operation 5) Sensors died 6) Extreme weather: cold/heat wave 7) Social security check did not arrive: cannot purchase food or medication 8) Major medication change 9) Life changing events e.g., sibling died, new grandchild 10) The list is extensible over time

NOVELTY
The main novelty of our system is the set of semantic rules that will help to reduce false alarms in anomaly detection. Current sensor based systems for home health care collect information and some apply simple statistical based anomaly

represent normal behavior. Note that based on the training data, there may be multiple models for normal behavior (e.g., weekdays, weekends, Fridays). Based on these models, we detect statistical deviation from normal behavior in testing data. Thus we find abnormal behaviors that never happened in the training data.

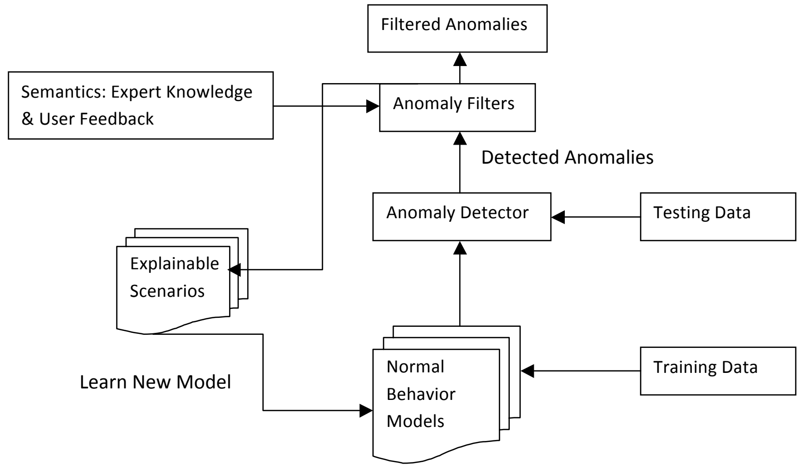

Figure 1: Anomaly Detection Framework

Figure 1. Framework for Semantic Anomaly Detection

Figure 1 shows our anomaly detection framework. The 'Anomaly Detector' module detects anomalies in the testing data. However, some of these anomalies may be explained by user feedback and / or expert knowledge. For example, the user may be recovering from a major operation, or there can be severe knowledge. The 'Anomaly Filters' module detects such scenarios and do not report them as behavioral anomalies. If there are significant number of instances of a particular scenario, a new behavioral model is developed for this scenario and stored in the 'Normal Behavior Models' so that in future such scenarios are not detected as anomalies. In this way, the set of normal behavior models keeps getting enriched.

detection. They suffer from the problem of too many false alarms that makes them unreliable. For example, if our system detects that the user is out of house for more than a day, it does not look for anomalies in other activities e.g., eating, sleeping. It only reports that user is not in house and thus reduces false positives that may be generated due to irregularity in other activities.

Existing anomaly detection systems consider each instance of each activity independently and decide whether that instance is normal or not (point anomalies). However, considering each instance of each activity independently and looking for an anomaly in one single instance is not enough for detecting behavioral anomaly. In contrast, in addition to point anomalies, our system detects the following kinds of collective anomalies:

1) Look at the instances of the same activity for **N** days collectively and detect anomalies. We need to combine instances of multiple days to capture any trend of change in behavior. For each activity, we combine its instances for **N** consecutive days and define some features that will be representative of normal behavior. From the training data, we need to take all data points consisting of all instances of an activity for **N** consecutive days and develop models of normal behavior using these. After training, each testing data point consists of all the instances for **N** consecutive days. For different activities, there may be different features used in the models.

2) Look at the instances of all activities for **N** days collectively and detect anomalies. We need to look at different activities collectively to find if there is any regularity/correlation among them. If there is, then we develop models with them representing normal behavior and find deviation from these models to detect anomalies. Some features that can be useful in this case are relative order of activities, causal relationships (e.g., activity A happens before/after/during activity B), interval between activities.

Another novelty of our system is that, we do not only detect statistical deviations from regular behavior. We also detect behaviors that are against social and healthy norms as anomalies. For example, if the resident does not brush teeth in a day, or does not wash hand before or after a meal, it may be part of his behavior, but we still report such unhealthy habit as anomalous behavior. A set of such social and healthy norms is defined by experts.

FUTURE DIRECTION

The first step is to develop statistical models to represent regular behavior and to detect point and collective anomalies. We also need to define the set of semantic rules used to filter false positives in anomaly detection. We need to design detailed evaluation plan to show that our system can significantly reduce number of false alarms and at the same time can detect real anomalies. We will also develop tools to take feedback from users and experts, and use them in defining new semantic rules.

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