Machine Learning Smart Building

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Introduction

Maintaining a comfortable environment within a building such as a home or a school can often be a burden on homeowners and maintenance staff. Adjustment of the temperature and lighting in a room, for instance, is often a repetitive task which it would be convenient to automate.

This report contains a proposal for a project to eliminate these manual tasks. The objective of the project is to build a system to automate control of a building's environment, which uses machine learning algorithms to minimize manual configuration. The proposal presents several motivations for using the environmental control system, as well as a detailed description of the project's objectives. The proposal also includes a timeline for the completion of concrete milestones for the project as well as a technical summary of the proposed solution.

Background

Any home maintenance task which can be automated can save the owner a substantial amount of time and money. Automated environmental control is not a novel concept; devices such as light timers and programmable thermostats have existed for many years. Most of these common devices, however, must be configured manually. The system proposed in this report is able to configure itself based on normal actions taken by the user. By having the system learn the habits of the user dynamically, the configuration is essentially eliminated, leading to an ease of installation that does not currently exist.

One scenario in which a home automation system could be a significant help is in the case of a homeowner with physical limitations that prevent them from independently maintaining their house. A system which controls the living environment without requiring substantial configuration can give these people more independence, or allow their caregivers to focus on other priorities.

There is also a place for automated environment control in a commercial setting. An example of this is in educational buildings, where there are thousands of people in many different rooms at all times of day. Maintaining a single building in this situation requires full time staff. For example, during a lecture at sunset, an instructor may have to adjust the blinds and contact the maintenance staff to adjust the temperature at the same time each day. The cost and effort of this maintenance is multiplied for every building in a given institution. If a system could be installed in each building that learns to handle this activity automatically, it would help reduce the burden and cost of maintenance.

Another benefit of automated environment control is improved energy efficiency. It is not uncommon to leave a room forgetting to turn off a light, or to leave a building with the air conditioning still running. This leads to needless consumption of energy, again increasing the cost of maintaining the building. Removing this responsibility from the building owner also removes this waste of energy. An automated environment control can also improve energy efficiency beyond just removing negligence. Once the desired temperature of a room for a given time is known, options besides air conditioning or heating can be explored first. If the room temperature must be raised, and the temperature outside is warm enough, the system could open the room windows. Once the desired temperature has been reached, the windows could be automatically shut again.

Objectives

Currently, supervised learning algorithms require a complete input dataset and a meticulously configured output to train the system. We want to have the algorithm be trained in a real world environment where users perform live actions and the system determines relevant changes and environmental factors. This automated learning system will be generic and use only the categorical and numerical information provided by sensors and actuators.

Manual adjustment of a building's environment can be tedious. A goal of the project will be to create a system which uses automated learning to adjust the environment based on input from a number of sensors. The system should support simple configuration of any type of sensor, and should not contain detailed knowledge about any sensors or actuators.

This system will support dynamic updates to the configuration of sensors and actuators. Overhead for adding and removing new devices from the system will be minimal. The learning algorithm will then adjust to take these new devices into account when altering or maintaining the environment.

Technical Overview

This project consists of several smaller components that will be described in more detail in this section. The following is a list of the high level technical components of the system.

Machine Learning Algorithm

The machine learning algorithm will accept tables of categorical and numerical data which will be used to produce sets of decisions based on historical events. The implementation of this algorithm will be configurable and tunable for optimal output.

Training Method

The server will be trained using a watch and learn method. A user will train the system by using a web interface or manual controls. The user will enter the desired action, and the server will associate the current sensor information with the desired state. The server will have the following two modes: record and learn and assisted.

In record and learn mode, the server makes no decisions on its own. It records the user's interactions with the system and logs them in a database. It will then use this information to make future estimations about desired behaviour.

Assisted mode allows the server to make decisions, but will continue to receive user direction about expected behaviour. The system will record all user interactions, using them for behaviour prediction. The system makes its own decisions, while still accepting feedback from the user.

Central Control Server

This server will contain the machine learning algorithm as well as database management for logging device inputs and control events. These events will also be stored with the expected outputs so that they can be used for future decisions. The central server will also be responsible for communicating to the communication service.

Communication Service

The communication service is the central node for all communications in the network. It is responsible for forwarding all messages to the appropriate devices in the system. It is the only component that will communicate directly with the central server. All devices will communicate with the communication service using a special protocol that will be designed for this system.

Devices

To interact with the physical world, different embedded devices will be used in the system. These devices will use sensors and actuators to record different properties and interact with their environment. The devices will use a discovery protocol to automatically add themselves to the network. This will make configuration simple and dynamic. Once the device is connected, it will be added to the machine learning server and be logged and controlled with the other devices.

HTTP Gateway

The gateway is a thin HTTP wrapper around the communication interface's API and acts as a bridge between the web client and the core services. The gateway will serve the web pages for the web client and provide a RESTful API for interacting with the communication protocol.

Web Interface

The web interface provides direct user interaction through a graphical user interface. This interface will communicate through the HTTP gateway using a RESTful API. The web client will provide remote control capabilities, allow for device simulation, and provide overall information monitoring.

Schedule

ID	Milestone	Date
1	Machine Learning Server Prototype	September 25th, 2016
2	Communicating Protocol and Service	October 16th, 2016
3	Sensor Communication and Discovery	November 6th, 2016
4	Sensors and Actuators; Inputs and Control	November 6th, 2016
5	Gateway and Web Client	January 29th, 2017
6	Remote Record and Learn	February 12th, 2017

Milestones

1. Machine Learning Server Prototype

This will include the central server as well as the machine learning algorithm. This will use sample data for inputs and output. All learning will be simulated for tuning and testing.

2. Communication Protocol and Service

By the end of the milestone the protocol will be defined and the communication service will be running using simulated data. The service will only be communicating with the machine learning server at this time.

3. Sensor Communication and Discovery

Sensor communication will all be routed through the communication service. This will use the communication protocol from the previous milestone. To aid in usability, when a new device is added to the network, it will follow a discovery protocol to add itself to the machine learning server's system. The discovery protocol and implementation will be completed in this milestone.

4. Sensors and Actuators; Inputs and Control

During the development of milestone 3, sensor reading and actuator control will be programmed. This can be done concurrently with the development of the communication of the sensors themselves. Data values will be read from sensors while control signals will need to be sent to actuators. The system must log both data values and control values so they can be used to learn the patterns of a user and apply them to the system

5. Gateway and Web Client

The system will have a user interface for a high level user remote control. This remote will be controlled by a web client. This client will be served through a simple web gateway that will provide a simple REST API for interacting to the communication service.

6. Remote Record and Learn

By the end of the milestone, the three modes will be added to the machine learining server. The server will also use training data from a recording session instead of simulated data.

Required Facilities

This project will require access to a variety of sensors and actuators which can be manipulated using a microcontroller such as an Arduino or Raspberry Pi.