Rhythm

Overview

Rhythm is not only a personalized home lighting application, but a platform on which other 1^{st} or 3^{rd} party applications could be built upon to control and personalize other home systems such as heating and cooling or media outputs such as multi-room stereo systems.

Rhythm Lighting Application

Moving to the rhythm of your family, this application offers personalized, predictive lighting throughout the home. The Rhythm lights are personalized, learning the lighting preferences of individual household members. The lights are predictive, illuminating areas ahead of you as you move about the house. The benefits of Rhythm Lighting are:

- Comfort – offering different levels and CCT mixture of illumination to match the individuals and activities of the home.
- Safety – automatically illuminating areas ahead of you can prevent potential injures due to stairs and obstacles.
- Secure – informing you about unexpected activity in the home and offering automatic vacation lighting so that the home appears occupied.

A companion smartphone/web application allows users to control lighting and also to access information about the home. The application could provide additional benefits such as per fixture usage, information about when and how long people spend time in different areas of the home. This would be useful for time management and monitoring children. For example, how much time do I spend a week in my office? How late are my kids staying up? etc.

Rhythm Platform

The platform provides essential data about the rhythm of the home that can be integrated with other systems, automating home management. The platform provides data along three key dimensions:

- Who is in the home
- What they are doing
- Where they are in the home

Not only does the system provide the current Who, What, and Where, but it learns the typical patterns of these over time to provide predictive information about the immediate next state and various future time points such as +30, +60, +90 minutes.

Product Integration

The Rhythm platform has potential for integration with other GE product lines. All appliances can provide input to the system that would better inform the activity in the home (e.g. cooking appliances relate to meal times) and can be tracked to provide per appliance energy usage information. The platform could also be used to control some appliances like water heaters based on usage patterns.

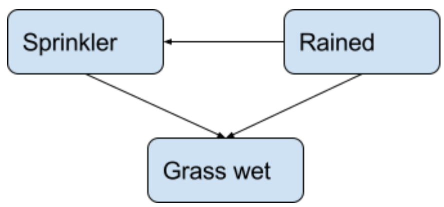
Background

The Rhythm platform is based on probabilistic graphical models (Koller). You can skip this section if you are familiar PGMs.

Probabilistic Graphical Models

The probabilistic graphical model (PGM) is an intuitive formalism for building machine-learned models that predict any number of unknown variables based on observed variables. This brief introduction is not a tutorial but will hopefully provide enough information to understand the Rhythm design.

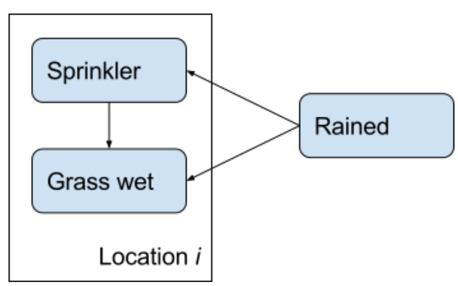
A PGM is described graphically as shown in this classic example:



Each oval represents a variable (an input value or output value) and the arrows describes how variables causally affect each other. Rain influences whether the grass is wet and if the sprinkler will come on. The sprinkler also may cause the grass to be wet.

There are coefficients associated with the arrows that can be learnt by training the model. During training, a number of examples are given which provide the values for some or all of the variables. Once trained, the model can be used to predicate any unknown variables based on any known values. The output is a set of probabilities that the variables will take on any particular value. For example, given that the grass is wet we can calculate probabilities that it rained or that the sprinkler was on.

The Rhythm design also uses so-called plate models like the one below:



A plate model is just a graphical short hand. The parts of the diagram in boxes represent multiple copies of the same variables/influences. The box label “Location *i*” means for each location *i*. In this example there are several sprinklers, each with its own variable, and the grass near each sprinkler may or may not be wet. Each sprinkler is influenced by whether it rained or not. Whether the grass is wet or not depends only on the sprinkler at that location and generally whether it rained or not.

Methods

This section describes the methodology used to provide the platform functionality described above.

The Rhythm platform uses data collected from the fixtures to train three different PGMs (described below) that learn the typical patterns of movement and usage of the home. The PGMs are used to provide the platform's service which is to predict current state, next state, and future state. The following sections describe more detail about the PGMs used to predict each of these states.

Current State

Rhythm makes use of audio and WiFi signals to determine who is in the home, where they are and what they are doing.

Sensor data

Microphones are used to capture audible range sounds in the environment as well as movement characterization based on the Doppler Effect. Fixed pre-trained machine-learned models are used to characterize the activity near the fixture based on the frequency components of the audible sound environment and the frequency shift due to the Doppler Effect on an inaudible transducer source. These inputs are sufficient to categorize activity into broad categories such as reading, watching TV, listening to music, etc. There are a number of published techniques for categorizing sound such as artificial neural networks (Mökinen), support vector machines (Chu), and decision tress (Wang).

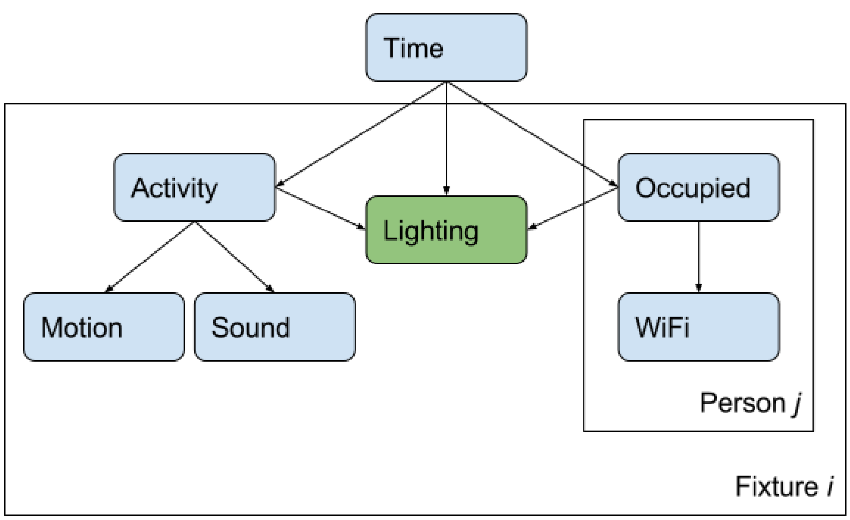
I did some experimentation with convolutional neural networks and an inexpensive MEMS microphone:

https://www.youtube.com/watch?v=oRvMJZxruP8

Additionally, the strength and device ID obtained from a WiFi receiver are used to identify who is in the home and in what area. It is not necessary to associate IDs to names, but that could be useful for smartphone-based applications.

Learning

The current state is modeled using the following PGM:



- Time is the time of day

- Activity is the activity happening in the room (TV, reading, etc.) of fixture *i*
- Occupied is true/false if person *j* is present at fixture *i*
- Lighting is the desired setting of fixture *i* (light level/mixture)
- Motion is the type of motion near fixture *i* (frequency and magnitude)
- Sound is the type of sound at fixture *i* (noise, music, TV)

The primary purpose of this model is to predict the desired light setting from the current sensor data. The light setting consists of two level settings, one for each of the color temperatures. The light setting is a function of the time of day, who's present and what the activity is. Who is present and the activity are not directly observable but predicted based on the observable data from the sensors, *i.e.* motion in the room, type of sound and WiFi signals.

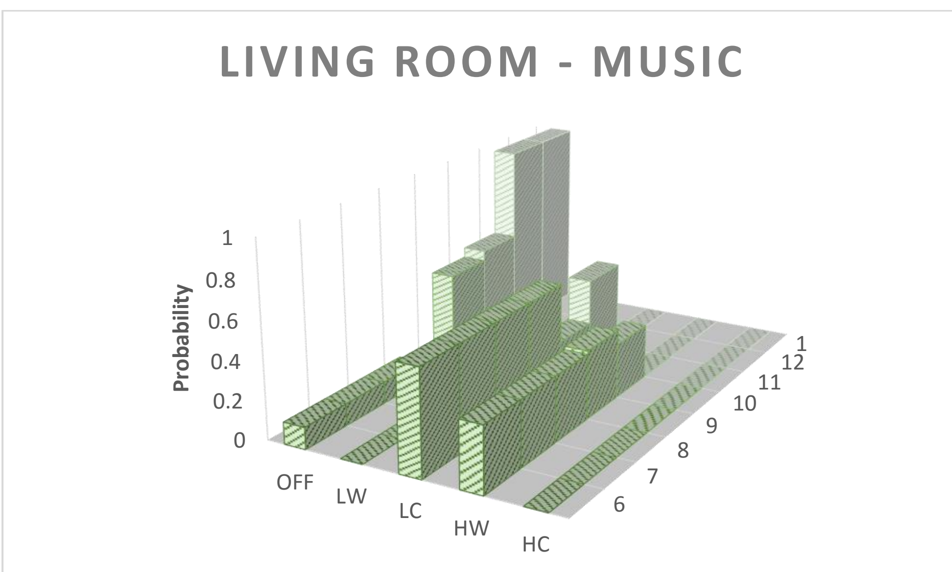
Validation

To validate this approach, sample data was generated by simulating the behavior and usage of two people for a living room and a bedroom. The simulated people had the following lighting preferences:

Person/Location	Reading	Music	Movie/TV
A – living room	High/cool	Low/cool	Off
B – living room	High/cool	High/warm	Low/warm
A – bedroom	High/cool		
B – bedroom	High/warm		

These preferences and an arrival model were used to generate when person A/B used the living room/bedroom and the activity. This data was used to generate hourly light settings for each room for 28 days. When both people were in a room person A's preference was chosen over person B's.

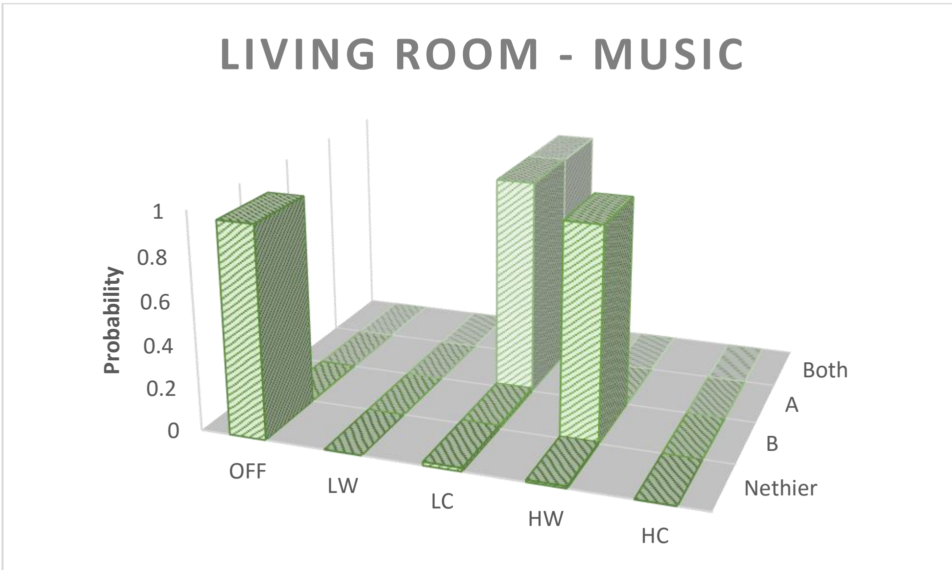
The simulated lighting data was used to train the PGM described above. The following shows some sample output of the PGM:



LW – low/warm, LC – low/cool, HW – high/warm, HC – high/cool

This graph shows the probability that the light setting is in any given settings per hour, given that the activity detected is music and the people in the room is unknown. These results validate the expected behavior of the predictive model. The OFF column demonstrates the probability of the lights being off increases by hour near the time occupants retire to the bedroom. It also shows how, without knowing who is in the room, the probability is weighted towards the preference of the dominate person A which was low/cool.

Of course, if we actually know the people in the room based on WiFi traffic the probabilities are almost certain:



LW – low/warm, LC – low/cool, HW – high/warm, HC – high/cool

When no one is present the lights are off, A's preference (low/cool) when only A or both are present, and B's preference (high/warm) when only B is present.

Next State

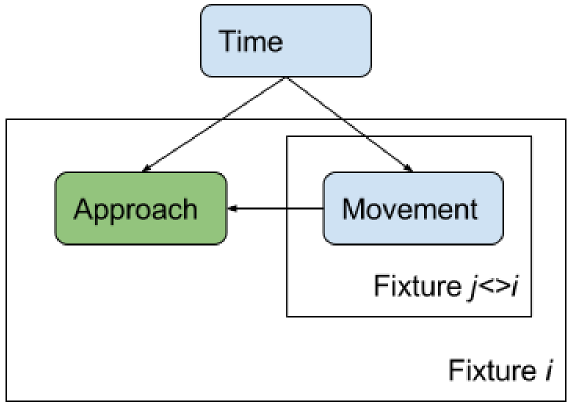
The Rhythm platform uses Doppler Effect data from each fixture to detect when people leave an area and predict the area they are about to enter.

Sensor data

The Doppler Effect of sound from an in-fixture transducer is used to identify when someone is leaving or entering the area. Doppler Effect has both magnitude and direction (towards or away), but only the direction is used for next state prediction.

Learning

The current state is computed using the following PGM:



- Time is the time of day
- Approach is true/false if anyone is approaching fixture *i*
- Movement is the direction of movement seen an fixture *j*

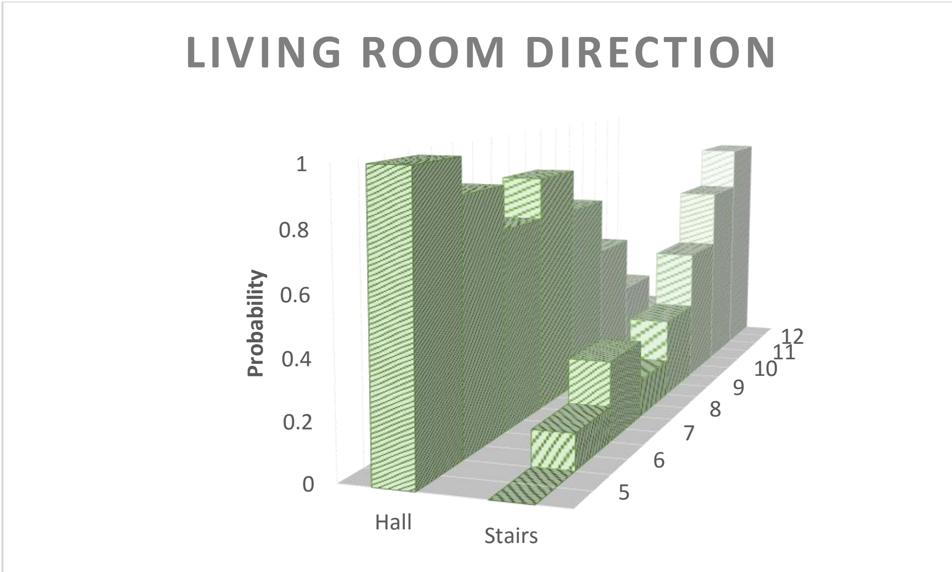
Approach is the unknown we wish to predict here. Without knowing the layout of the home, this network will quickly learn where people are likely headed based on their current movement.

Validation

As for the current state model, simulated data is used to validate the next state PGM. In this case, movements are randomly generated for a home with a kitchen and living room on one floor separated by a hall, and a bedroom on a second level.

When someone moves between the kitchen and the living room, they turn on the hall light as they pass through. When they move from either room to the bedroom they turn on the stair lights. Movements between the living room and kitchen are more likely early in the evening and more likely to the bedroom later.

After training with the randomly generated movements, the trained model was used to predict whether someone leaving the living room would pass through the hall or stairs for each hour of the evening. The results are shown below.

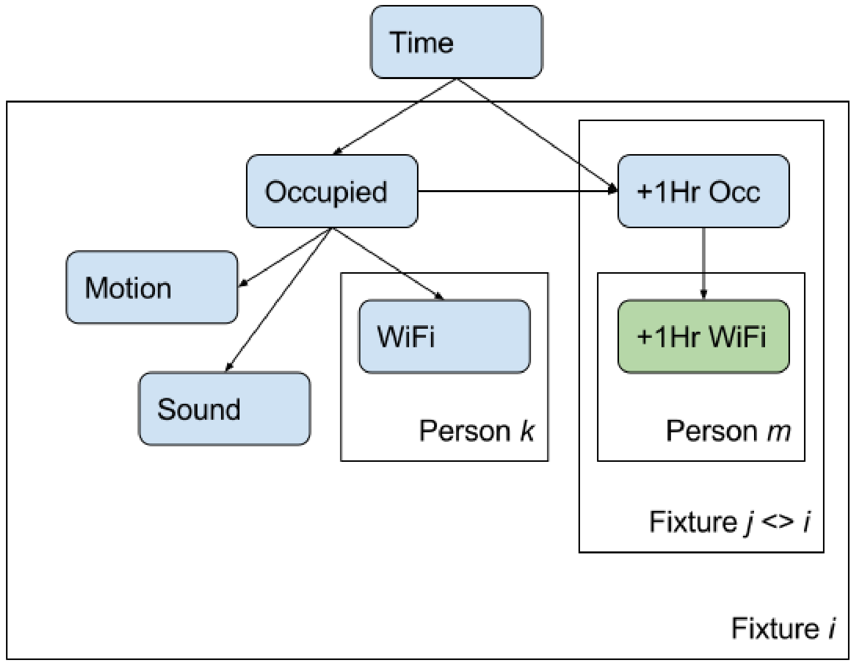


The results are as expected. The probability of going to the kitchen fall off rapidly from 10 – 12PM and the probability of going up stairs increase rapidly during the same timeframe.

Future State

Although the Rhythm lighting application does not use the future state, this is an important part of the platform for other applications such as automatically establishing schedules for heating or cooling various zones in the home. Setting up programming schedules is tedious for homeowners, they frequently change and user-provided schedules have been reported to be very inaccurate (Krumm). Research suggests that predictive scheduling could provide energy savings from 6% up to 17% (Gupta, Kleiminger).

Again a probabilistic graphical model is used to predict a future state of occupancy based on the current state of all fixtures. This model would also be re-trained daily from collected data. Multiple models could be maintained to predict states for different future time points.



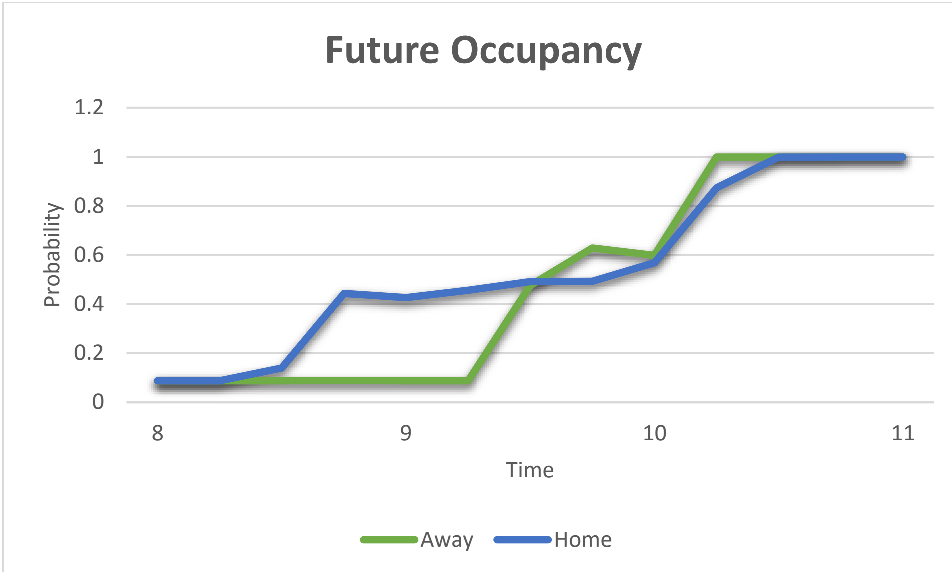
- Time is the time of day
- Occupied is true/false if anyone is present at fixture *i*
- Motion is the type of motion near fixture *i* (frequency and magnitude)
- Sound is the type of sound at fixture *i* (noise, music, TV)
- +1Hr Occ is true/false if anyone **will be** present at fixture *j* one hour from now
- +1Hr WiFi is true/false if the WiFi of person *m* **will be** present at fixture *j* one hour from now

The goal of this network is to predict where people will be one hour from current time based on the time of day and their currently know location.

Validation

The same sample generator used to validate the current state model was used to generate the simulated occupancy data of two individuals at two locations in the home: the living room and the bedroom. 28 days were simulated where each day, each person arrived home at various times in the evening, spent various amounts of time in the living room and then retired to the bedroom.

The following graph shows the predicted occupancy of the bedroom for person A one hour from the current time for two cases: Away – person A is not currently home and Home – person A is currently in the living room.



As one would expect, the probability of being in the bedroom is going to approach 1 as it gets later regardless of whether they are currently home or not. However, also as expected, the probability of being in the bedroom one hour from now is higher if they are currently in the living room because we know their typical pattern is to spend at least some time in the living room.

This example demonstrates the kind of information that would be useful in controlling heating/cooling in different areas of the home based on home usage patterns.

Personalized Lighting

The Rhythm Lighting Application leverages this platform just described to provide predictive lighting that automatically adjusts to the preferences of the occupants based on the platform's current state model and lights the way of home owners ahead of them as the move about the home based on the platform's next state model.

The Rhythm light fixtures provide dimmable dual CCT illumination. The light levels and CCT mixture can be manually set via a smartphone app. The data about actual light settings are collected over time and used to train the predictive models described above for each fixture. As the models learn personal preferences they begin to automatically adjust LED output (lighting levels/CCT mixture) based on the current-state model. For example, if you typically dim the lights when you watch TV, the model will learn that and automatically dim the lights when they fixture detects the TV is on (based on the sound characteristics).

The next-state model learns the layout of the home by tracking the patterns of lights turning on in succession. This model is used to turn on lights for you automatically when you move around the home. Multiple lights may be selected by the system for illumination but they will only remain on a short period of time if no one moves into that area.

Implementation

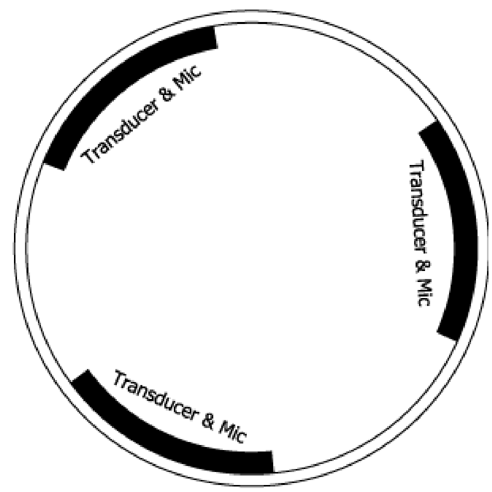
The rest of this document describes the Rhythm hardware and software design.

Hardware

The hardware of the system includes a collection of lighting fixtures and a base station.

Light fixtures

The Rhythm platform and lighting application would make use of at least two different bulbs: one for living areas, and another for transit areas (entry ways, halls, etc.). Living area lights would consist of an array of dimmable LEDs at two different color temperatures, three microphones, one or more transducers, a PCB and a standard base. The PCB hosts a microcontroller and WiFi radio.



Sensor Ring

The microphone/transducer ring provides movement and audio input from multiple directions. The MCU and WiFI radio is located below the ring.

Transit area lights would have non-dimmable LEDs of a single color temperature. They do not require detailed movement data or sound classification and could also make use of less expensive passive infrared motion detectors instead of the microphones/transducers.

Base station

The base station would perform coordination, machine learning and prediction calculations. Although machine learning can be computationally expensive, the system does not require low-latency operation and could be implemented on modest hardware. A simple fanless device with a 1+ GHz CPU (with FPU), RAM, flash memory, and a WiFi radio would be sufficient. This includes low cost ARM A8/A9 chips such as those used in the Raspberry Pi, Udoo and other single board computers.

Software

The four main components of the software are sensor processing, machine learning, prediction, and LED control.

Sensor processing

The microphones are sampled by an in-fixture microcontroller. The microcontroller preprocesses the audio samples to produce an array of frequency domain components via the standard Fast Fourier Transform. The frequency domain data is sent to the base station for activity and movement classification as well has Doppler Effect calculation.

Machine learning

Machine learning is performed on the base station nightly to update the coefficients of the models for the LED output, next state and future state prediction. Standard algorithms are available for training probabilistic graphical models. The excellent Bayes Net Toolbox for Matlab (https://github.com/bayesnet/bnt) was used for the validation experiments described above.

Prediction

The base station will continually apply the machine-learned models to the current frequency domain data received from the fixtures to compute the current lighting level/CCT mix settings and the predicted future state. Standard algorithms are available for performing inference on probabilistic graphical models.

LED control

The outputs from the current state, and next state PGMs are used to determine current LED level settings for each fixture. The predicted light levels for each color temperature are sent to each fixture based on the personalized lighting model. The predicted next state is also sent to the fixture to illuminate areas in advance where people are headed. The in-fixture microcontroller will use this data to set the current light level. If a user sets the levels manually via the app, that will override the predicted levels.

Configurable auto-shutoff is also available. When the system determines that there is no one present for some configurable amount of time the lights will first dim, and then if there is no audio response then shut off. If anyone is present, they only need to say something and the shutoff will be aborted.

Future Directions

Speech recognition is one possible extension. Control commands would make sense here, but not general Alexa type assistants with audio response. The cost would be adding wake-up word hardware.

Gesture recognition could also be used as a form of input. Gestures can be recognized based on the Doppler Effect, as demonstrated by WiSee (http://wisee.cs.washington.edu/).

DNS requests are another source of information available via the WiFi radio. This information can be used to further help distinguish who is present and activities such as game console usage, or movie streaming.

References

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