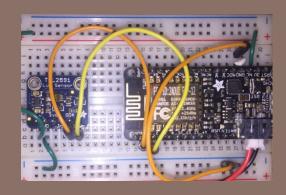
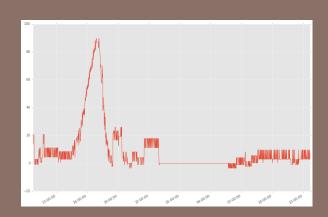


### PYTHON AND IOT:

From Chips and Bits to Data Science



Jeff Fischer
Data-Ken Research
jeff@data-ken.org
https://data-ken.org
Sunnyvale, California, USA



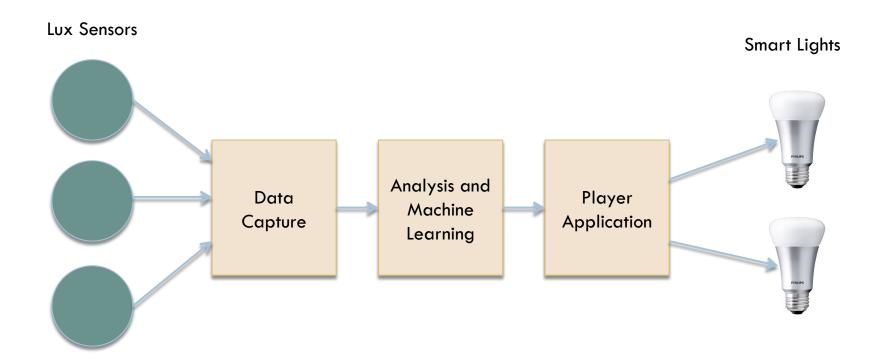
## Agenda

- □ Project overview
- Hardware
- Data capture
- Data analysis
- Player
- Parting thoughts

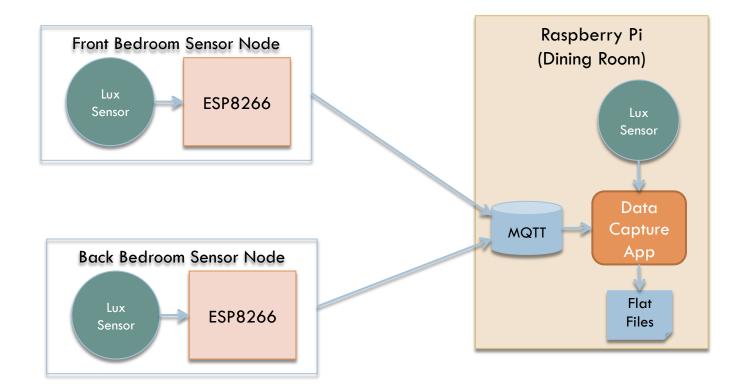
### **Project Motivation**

- If out of town for the weekend, don't want to leave the house dark
- Timers are flakey and predictable
- Would like a self-contained solution
  - Avoid security issues with cloud solutions
- "Wouldn't be cool to use machine learning?"

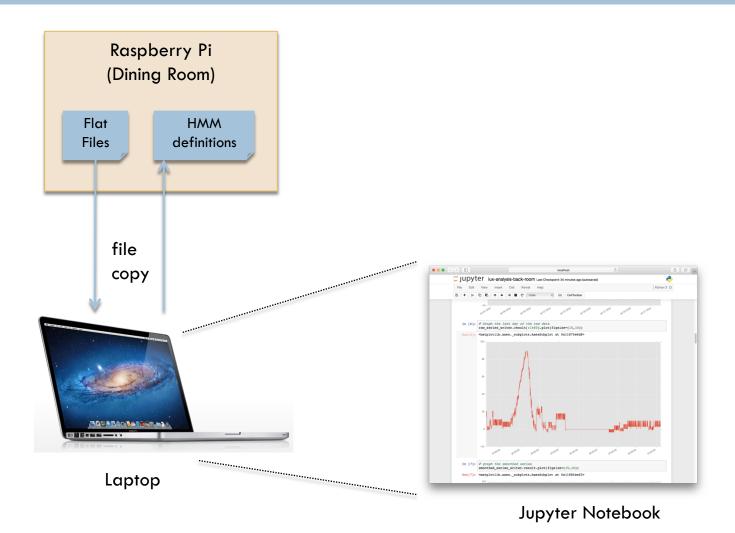
## Lighting Replay Application



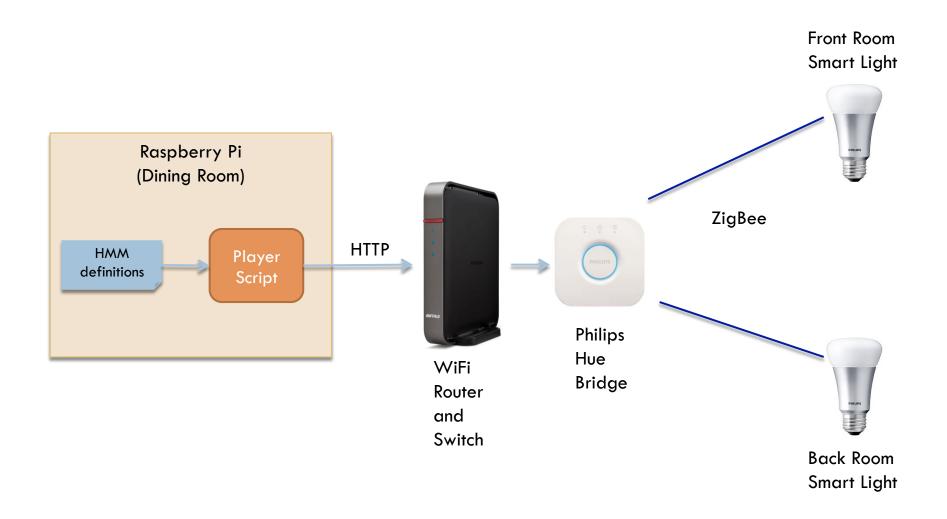
### Lighting Replay Application: Capture



### Lighting Replay Application: Analysis



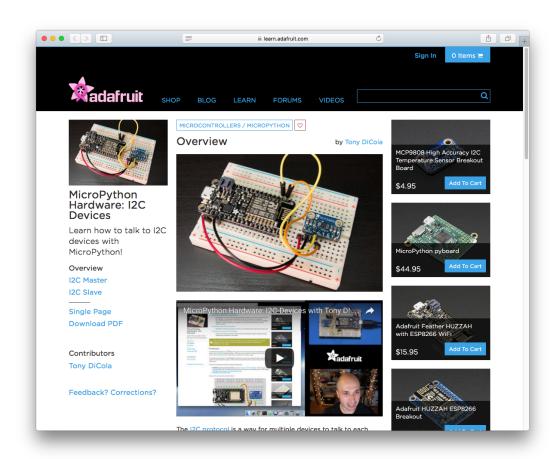
## Lighting Replay Application: Replay



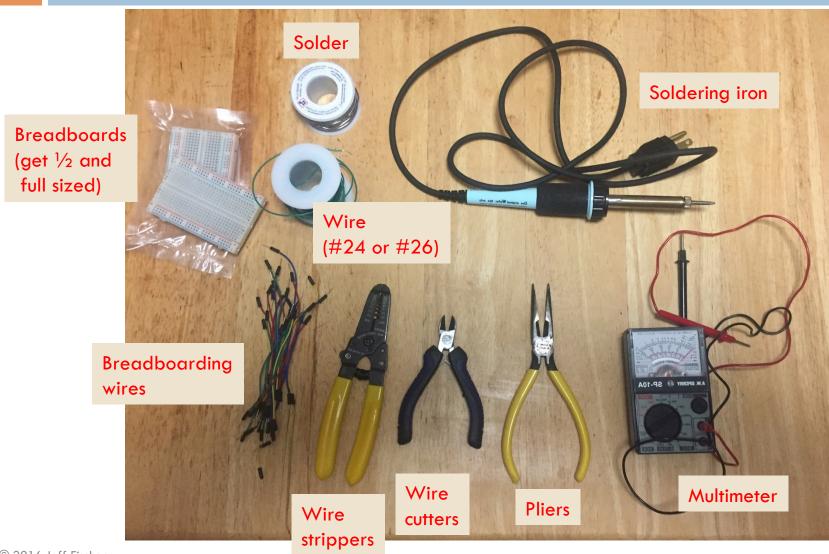
# Hardware

## Recommended Hardware Supplier: Adafruit

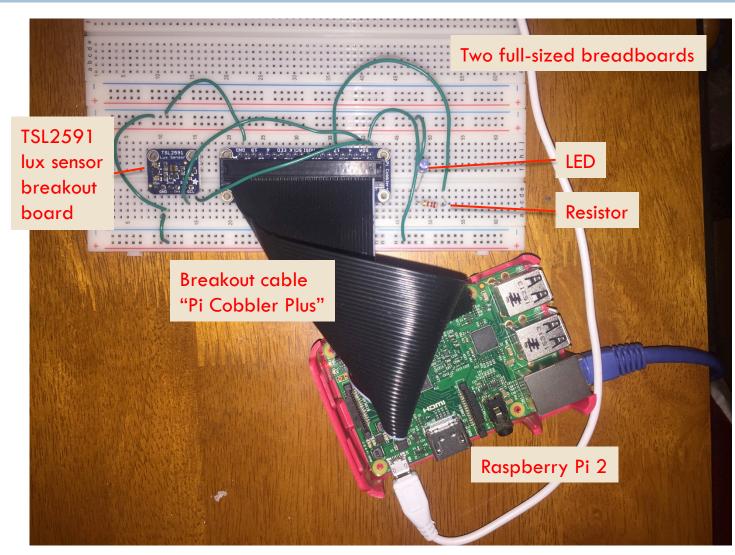
- Focused on the hobbyist
- Plenty of documentation and examples
- Breakout boards
   make it easy to
   work with
   peripheral ICs



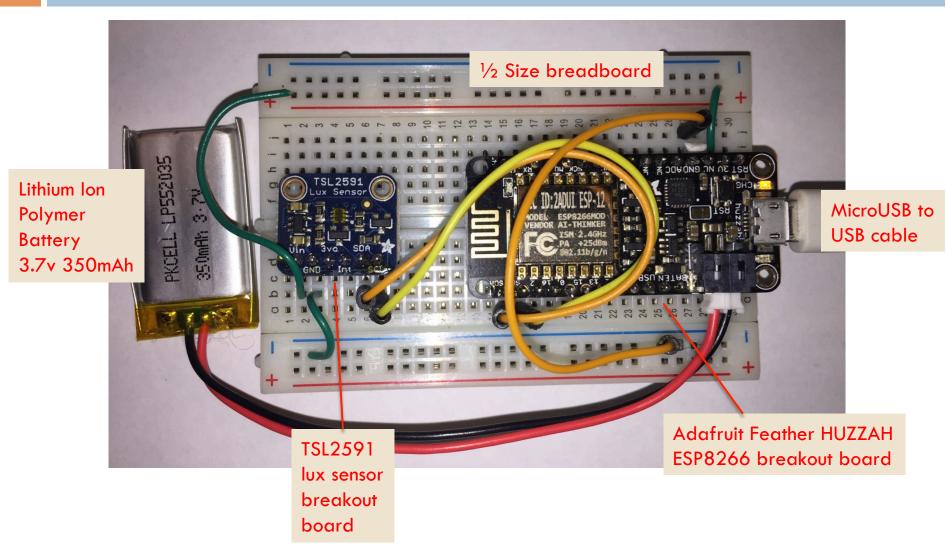
### Recommended Tools



# Raspberry Pi

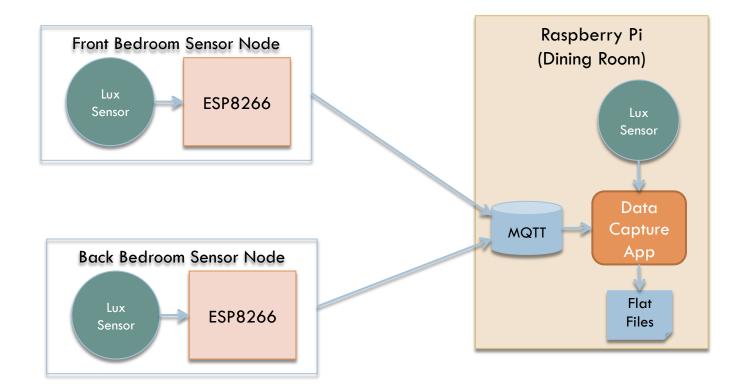


### ESP8266



# Data Capture

### Lighting Replay Application: Capture



#### **AntEvents**

- Python3 library for processing IoT event streams
  - Built on Python 3.4's asyncio module
  - Port to Micropython, which runs on the ESP8266
- □ Key library features:
  - Push-style streams of events
  - Assemble "elements" into a DAG
    - Fine-grained pub/sub model: an element is a publisher, a subscriber, or both
    - Special support for pipelines of stateful filters
    - Elements can be proxies for external systems
  - Event-driven scheduling, with separate threads for blocking elements
- https://github.com/mpi-sws-rse/antevents-python

### Simple AntEvents Example

Sample a light sensor every two seconds and turn on an LED if the average of the last 5 samples exceeds a threshold

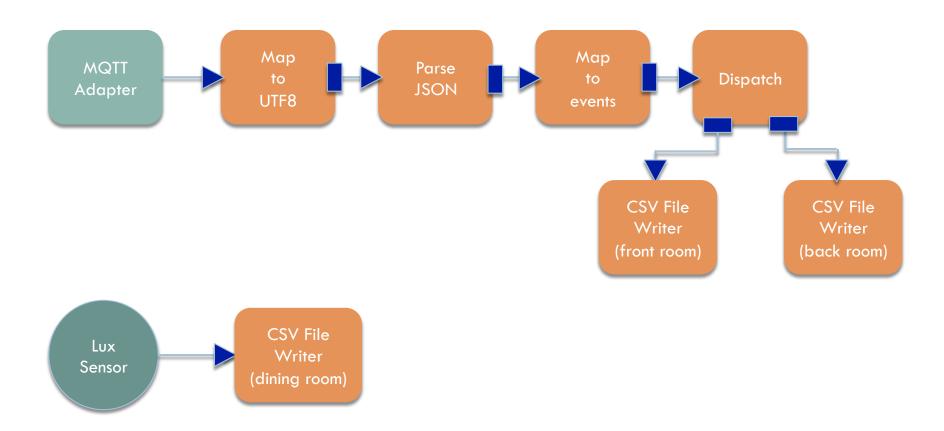
```
lux = LuxSensor()
Lux.map(lambda e: e.val).running_avg(5) \
    .map(lambda v: v > threshold).GpioPinOut()
scheduler.schedule_recurring(lux, 2.0)
```



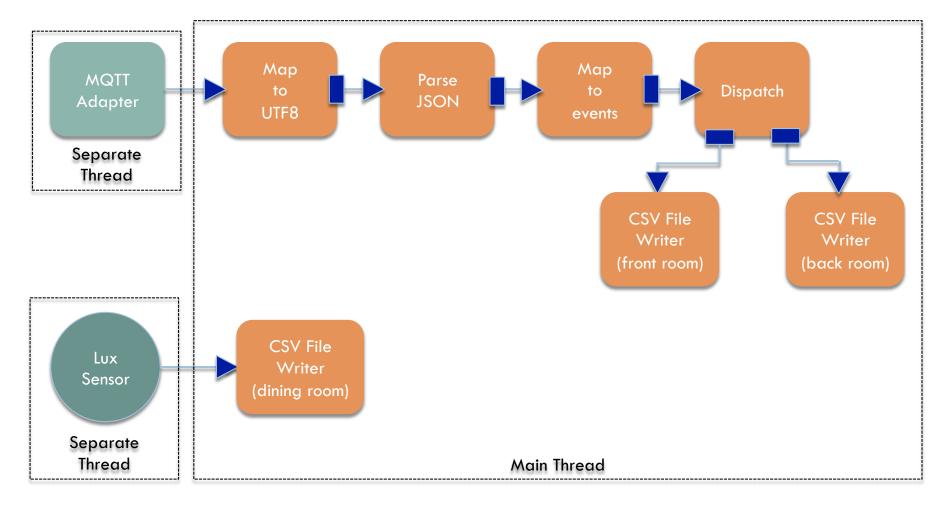
### ESP8266 Code

```
from antevents import Scheduler
                                                         https://github.com/jfischer/micropython-tsl2591
from tsl2591 import Tsl2591
from matt_writer import MQTTWriter
from wifi import wifi connect
import os
# Params to set
WIFI_SID= ...
WIFI_PW= ...
SENSOR ID="front-room"
BROKER='192.168.11.153'
wifi connect(WIFI SID, WIFI PW)
sensor = Tsl2591()
                                                              Sample at 60 second intervals
writer = MQTTWriter(SENSOR_ID, BROKER, 1883,
                    'remote-sensors')
sched = Scheduler()
sched.schedule sensor(sensor, SENSOR ID, 60, writer)
sched.run forever()
                                                               The MQTT writer subscribes to events from
                                                                The lux sensor.
```

## Raspberry Pi Code

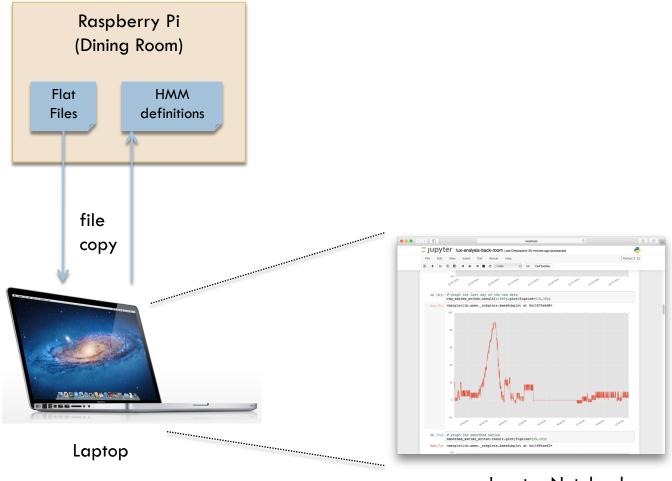


## Raspberry Pi Code: Threading Model



# Data Analysis

### Lighting Replay Application: Analysis

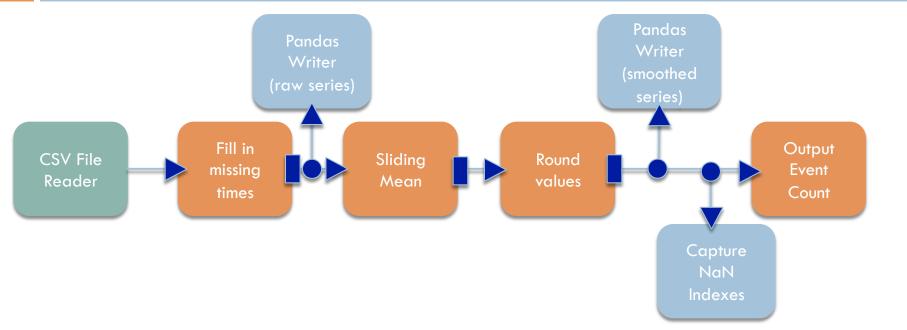


### Steps in Data Analysis

- Read and preprocess data files
- Convert to discrete levels using K-means clustering
- Map to on-off values
- 4. Train Hidden Markov Models (HMMs) on data
- 5. Validate predictions
- Export HMM definitions for player

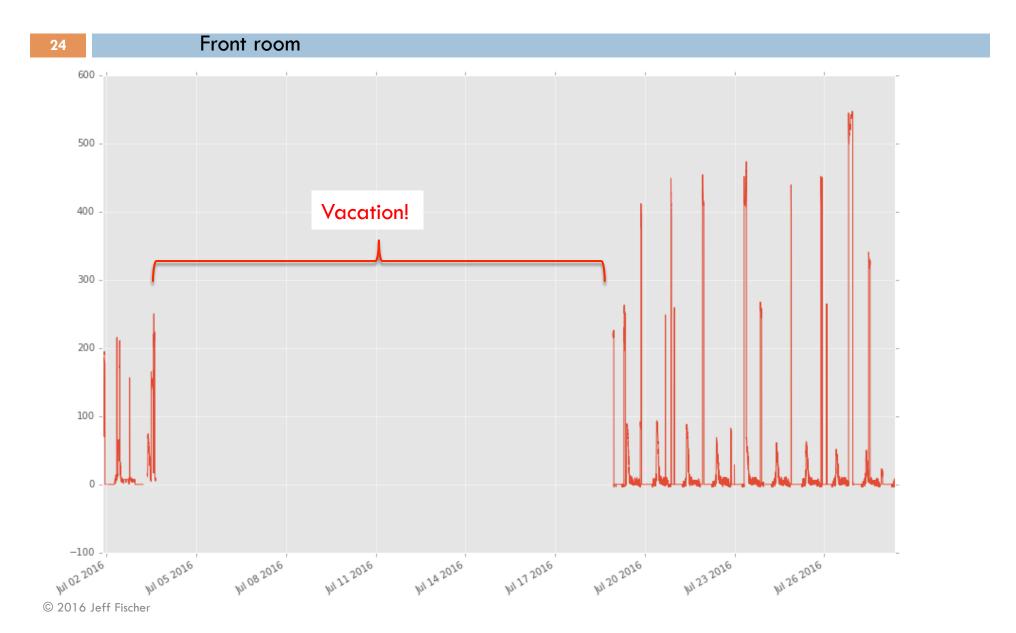
#### Read and Process CSV Files

(AntEvents running in a Jupyter Notebook)

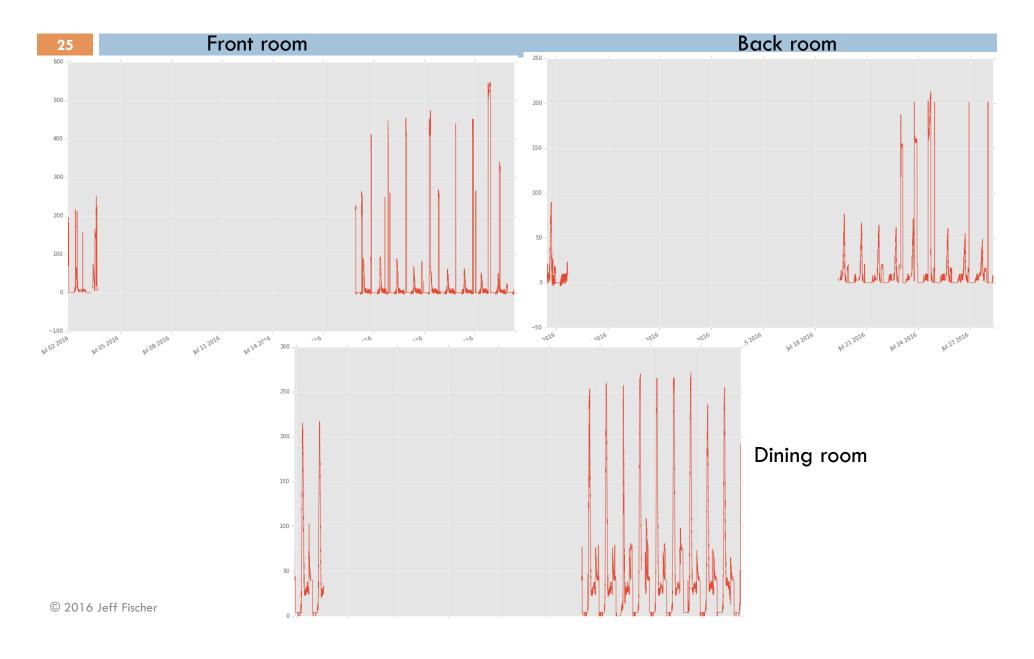


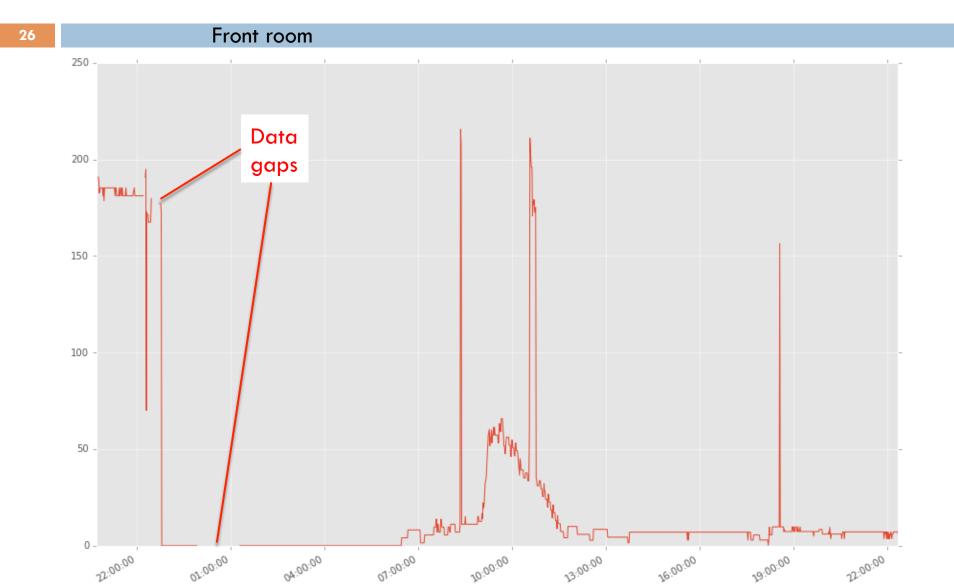
```
reader.fill_in_missing_times()\
    .passthrough(raw_series_writer)\
    .transduce(SensorSlidingMeanPassNaNs(5)).select(round_event_val).passthrough(smoothed_series_writer)\
    .passthrough(capture_nan_indexes).output_count()
```

### Raw Sensor Data: Entire Set

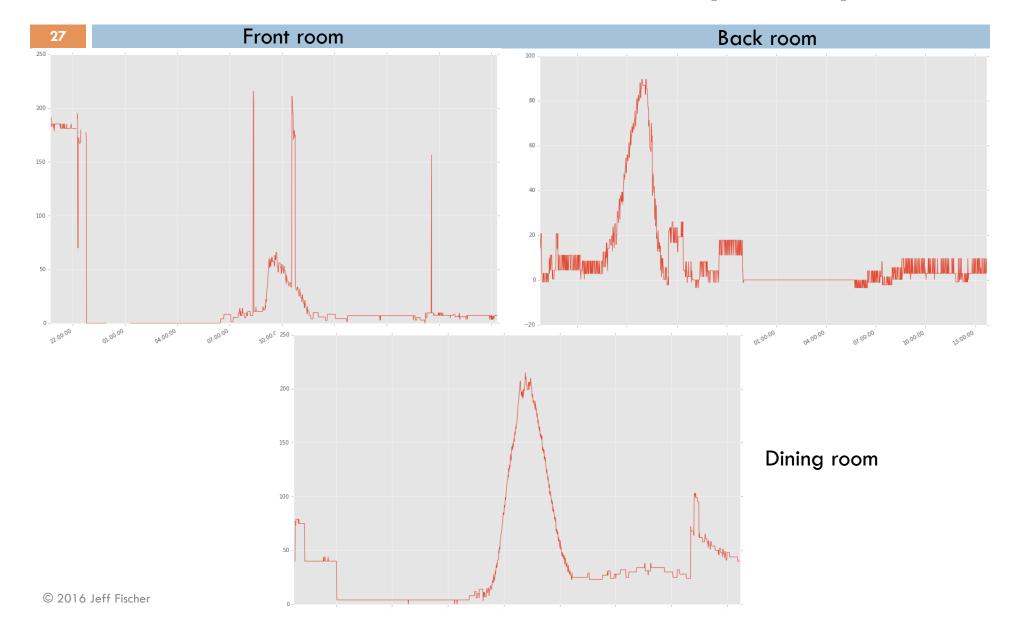


### Raw Sensor Data: Entire Set

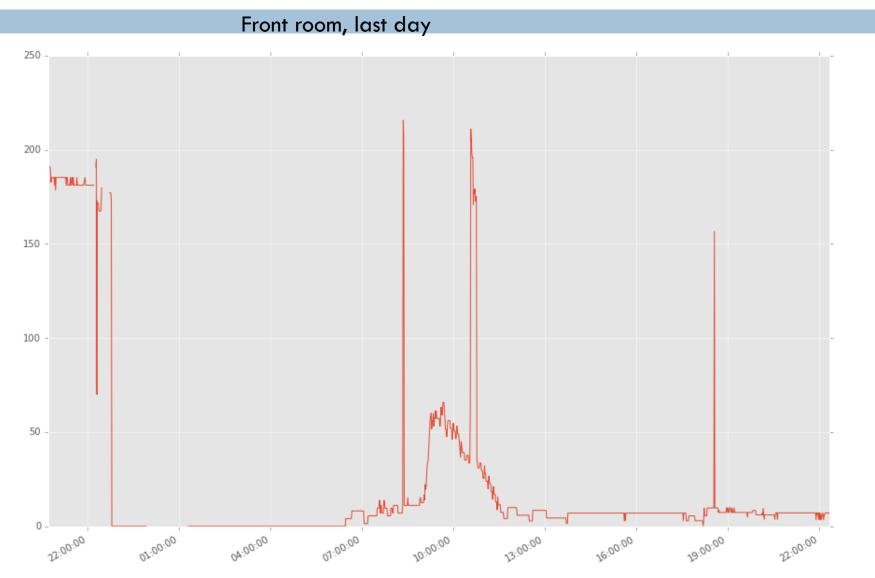




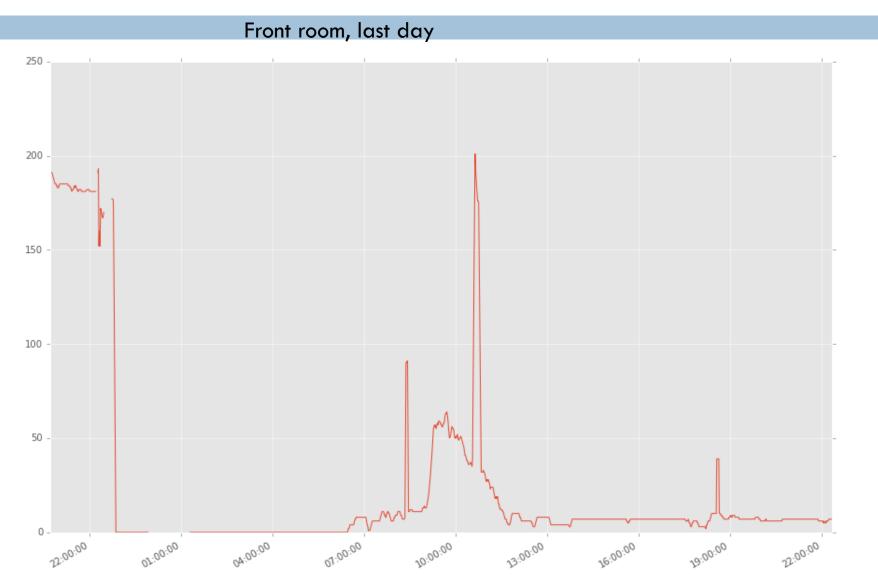
# Raw Sensor Data: Last Day Only



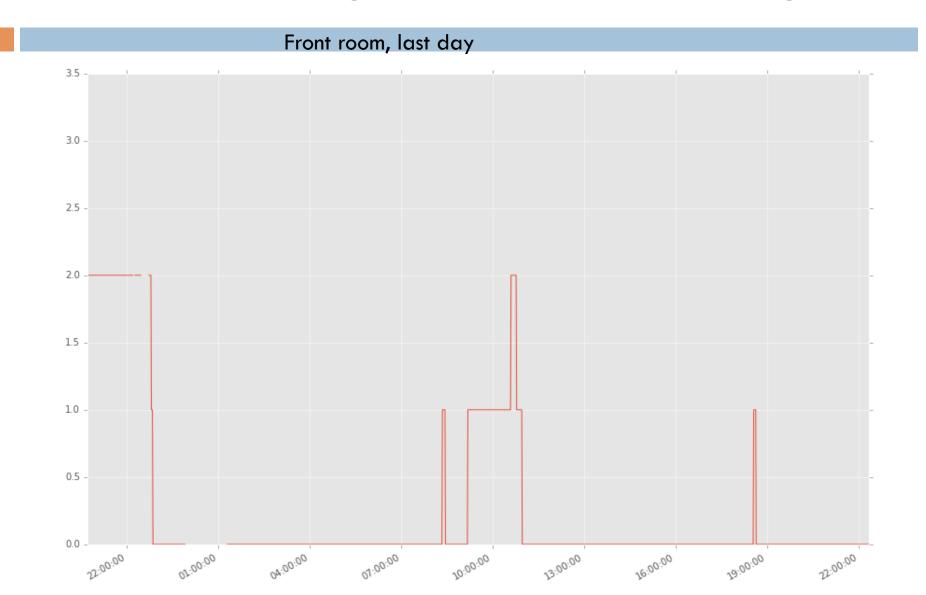
### Data Processing: Raw Data



### Data Processing: Smoothed Data



### Data Processing: K-Means Clustering

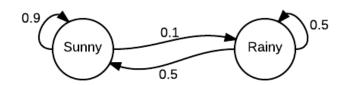


### Data Processing: Mapping to on-off values



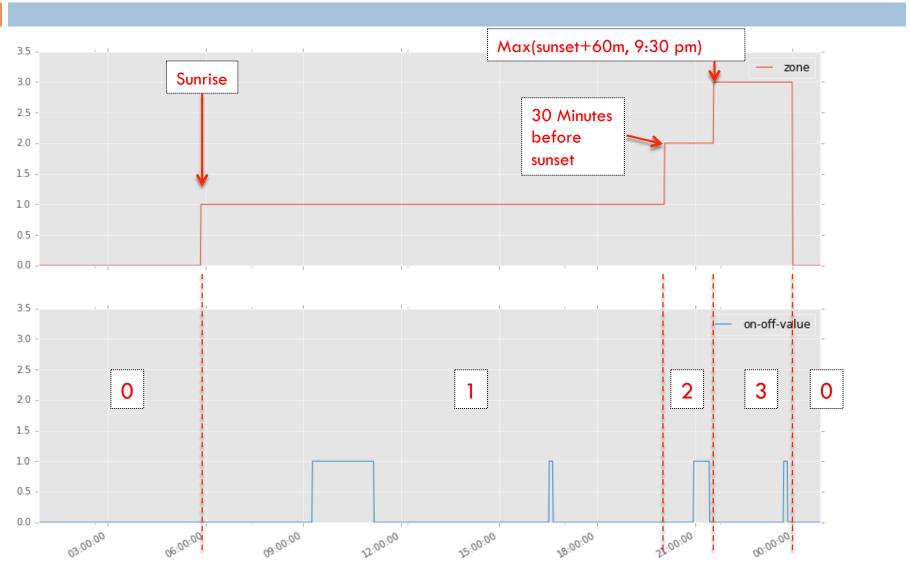
## Hidden Markov Models (HMMs)

- In a Markov process, the probability distribution of future states is determined only by the current state, not on the sequence of events that preceded it.
- In a HMM, the states are not visible to the observer, only the outputs ("emissions").
- In a machine learning context, we are given a sequence of emissions and a number of states. We want to infer the state machine.
- The hmmlearn library will do this for us.
  - https://github.com/hmmlearn/hmmlearn



Example Markov process (from Wikipedia)

### Slicing Data into Time-based "Zones"

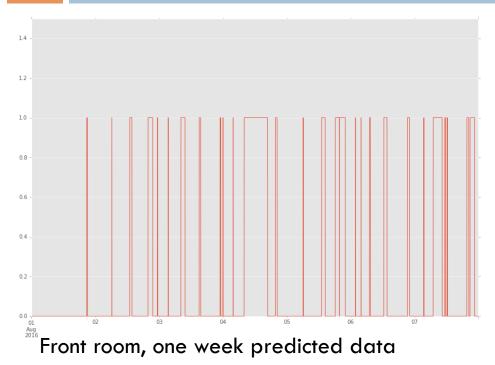


### HMM Training and Prediction Process

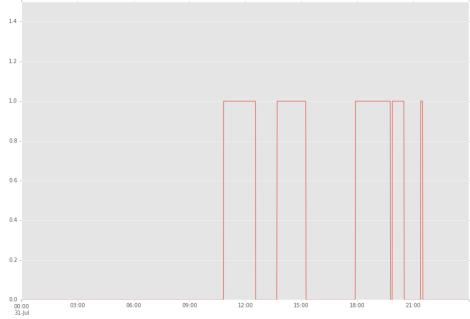
- Build a list of sample subsequences for each zone
  - Drop the timestamps
  - Beak into separate sequences at zone boundaries and NaNs
- 2. Guess a number of states (e.g. 5)
- 3. For each zone, create an HMM and call fit() with the subsequences
- 4. For each zone of a given day:
  - Run the associated HMM to generate N samples for an N minute zone duration
  - Associated a computed timestamp with each sample

### **HMM Predicted Data**

3

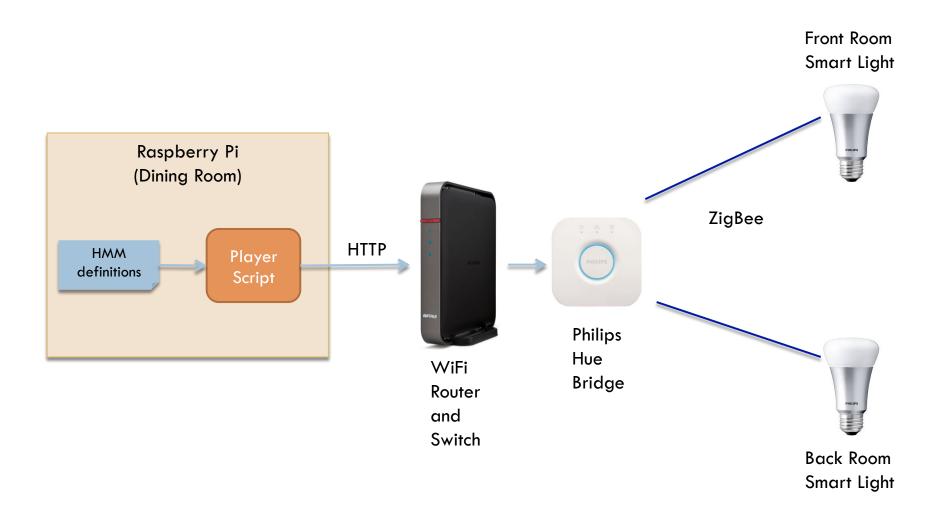


#### Front room, one day predicted data



# Replaying the Lights

### Lighting Replay Application: Replay



### Logic of the Replay Script

- Use phue library to control lights
- Reuse time zone logic and HMMs from analysis
- □ Pseudo-code:

Initial testing of lights

while True:

compute predicted values for rest of day organize predictions into a time-sorted list of on/off events for each event:

sleep until event time
send control message for event
wait until next day

## Parting Thoughts

### Acknowledgements

- Rupak Majumdar, Max Planck Institute for Software Systems
  - Co-designer of AntEvents
- Sze Ning Chng, Cambridge University
  - First user of AntEvents while interning at MPI
- Dmitrill Lourovitski, BayPiggies
  - Gave me advice regarding machine learning techniques

#### Lessons Learned

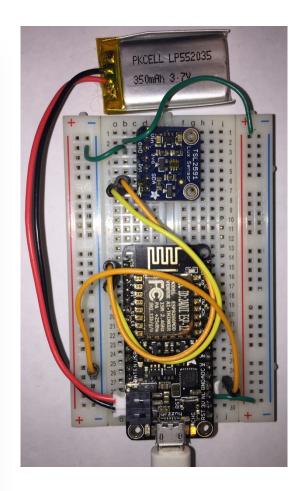
- An end-to-end project like this is a great way to learn a new area
- Applying machine learning to a problem can be very much a trial-and-error process
- Visualization is key to understanding/debugging these systems
- The Python ecosystem is great for both runtime IoT and offline analytics

#### **Future Work**

- Gather more data and re-try other machine learning algorithms
- Integrate AntEvents with visualization (looking at Bokeh)
- What are the right abstractions for IoT analytics?

### ESP8266 Demo

```
1. python3.5
MicroPython v1.8.5-10-g0e69e6b on 2016-10-17; ESP module with ESP8266
Type "help()" for more information.
>>> from antevents import *
>>> from tsl2591 import Tsl2591
>>> tsl = Tsl2591('lux-1')
>>> tsl.sample()
170.0544
>>> sched = Scheduler()
>>> class Output:
        def on_next(self, x):
            print(x)
       def on_completed(self):
        def on_error(self, e):
            pass
>>> sched.schedule_sensor(tsl, 2.0, Output())
<closure>
>>> sched.run_forever()
('lux-1', 89, 170.0544)
('lux-1', 91, 170.0544)
('lux-1', 93, 170.0544)
('lux-1', 95, 170.0544)
```



### 44 Thank You

#### Questions?

More information

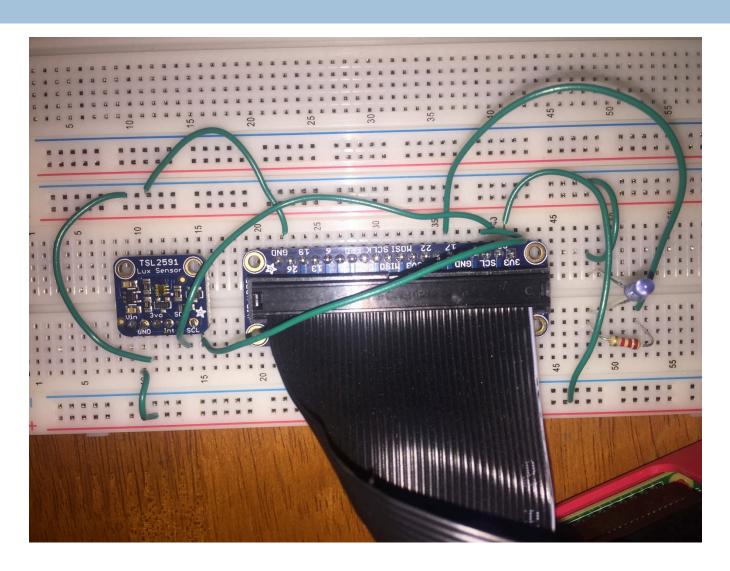
Website and blog: https://data-ken.org

**AntEvents:** https://github.com/mpi-sws-rse/antevents-python

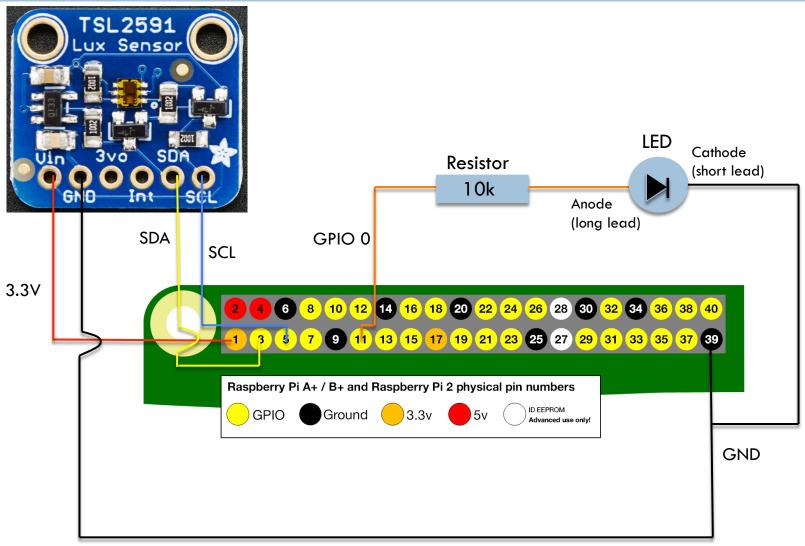
**Examples (including lighting replay app):** https://github.com/mpi-sws-rse/antevents-examples

# 45 Additional Details

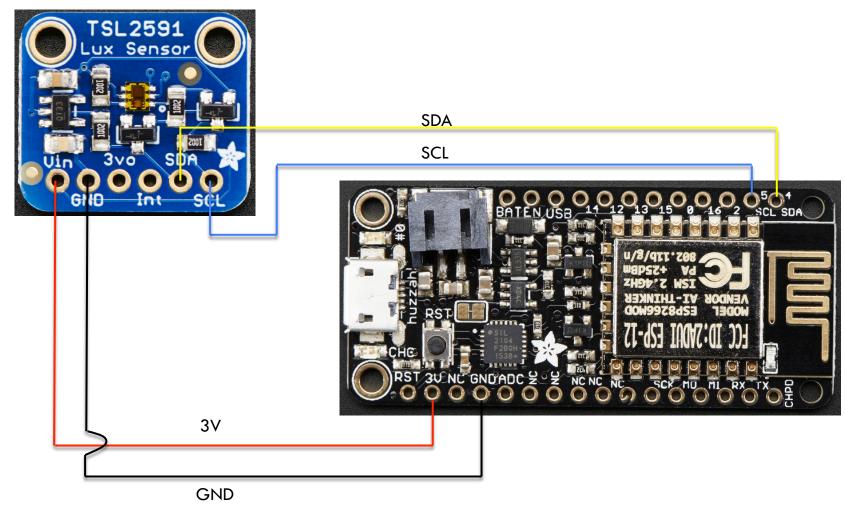
### Raspberry Pi 2: Wiring Detail



### Raspberry Pi 2: Wiring Diagram



### ESP8266: Wiring Diagram



### Third-party Resources

- Adafruit TSL2591 Lux Sensor tutorial
  - https://learn.adafruit.com/adafruit-tsl2591
- Adafruit ESP8266 tutorial

https://learn.adafruit.com/adafruit-feather-huzzah-esp8266

- LED tutorials
  - https://learn.adafruit.com/all-about-leds/overview
  - https://thepihut.com/blogs/raspberry-pi-tutorials/27968772turning-on-an-led-with-your-raspberry-pis-gpio-pins
  - https://projects.drogon.net/raspberry-pi/gpio-examples/tuxcrossing/gpio-examples-1-a-single-led/
- Micropython Getting Started on ESP8266

https://docs.micropython.org/en/latest/esp8266/esp8266/tutorial/intro.html

# Machine Learning: Other Approaches Tried

- Feature data
  - □ Time of day, zone, on-off value N-samples back
  - Also tried the number of samples since the last value change
    - made results worse
- Algorithms tried
  - K-nearest neighbors
  - Logistic Regression
  - Decision Tree (classifier, probabilistic classifier, regressor)
- Pure probability approach
  - Build a probability distribution based on length of time at current value – worked fairly well
- Conclusion: need more sample data