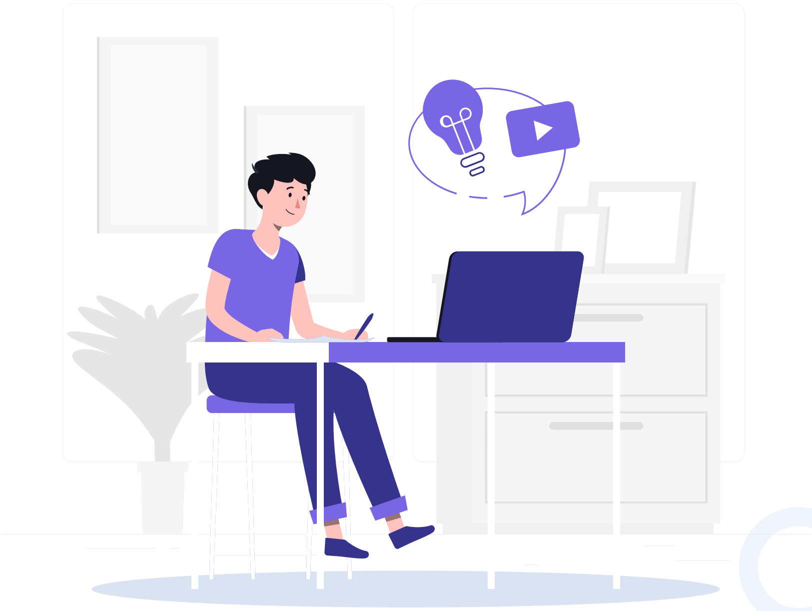
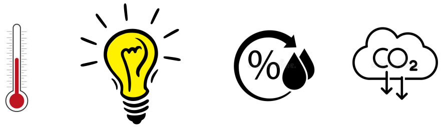
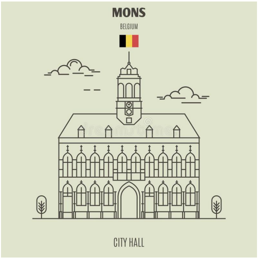
Occupancy Detection

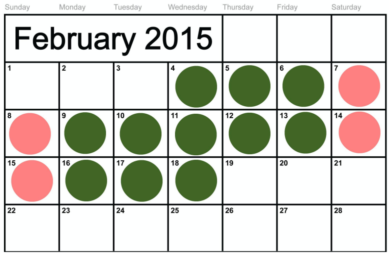
Created and Presented
By
Cristina Sahoo



Problem Statement







- Identify trends over time and correlation between environment variables and occupancy
- Identify algorithms/models with best accuracy score for predicting occupancy

Applications

- Recent studies and measurements *[12-15]* report energy savings of 30% to 42% with accurate occupancy determination

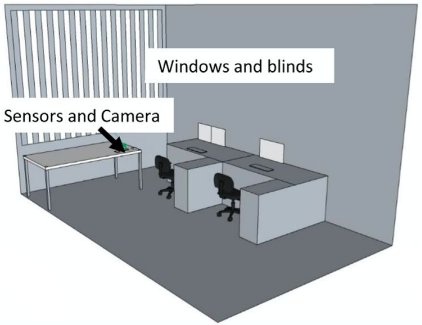
- When occupancy data was used as an input for HVAC control algorithms, energy savings were as high as 80% *[16]*

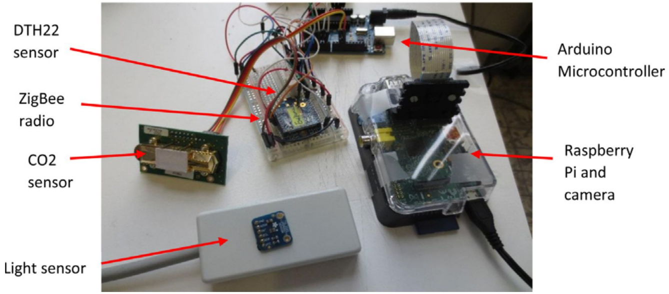
- A system that could accurately detect the presence of the occupants without using a camera is very interesting due to privacy concerns

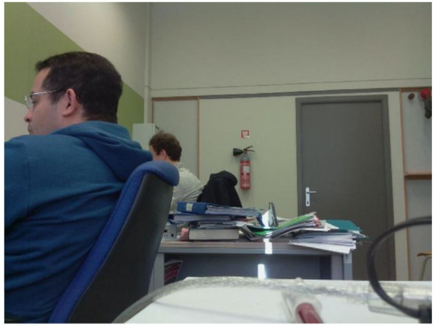
- Other applications for occupancy detection include security and determination of building occupant behaviors

Data Source and Collection

Occupancy Detection Dataset - UCI Machine Learning Repository





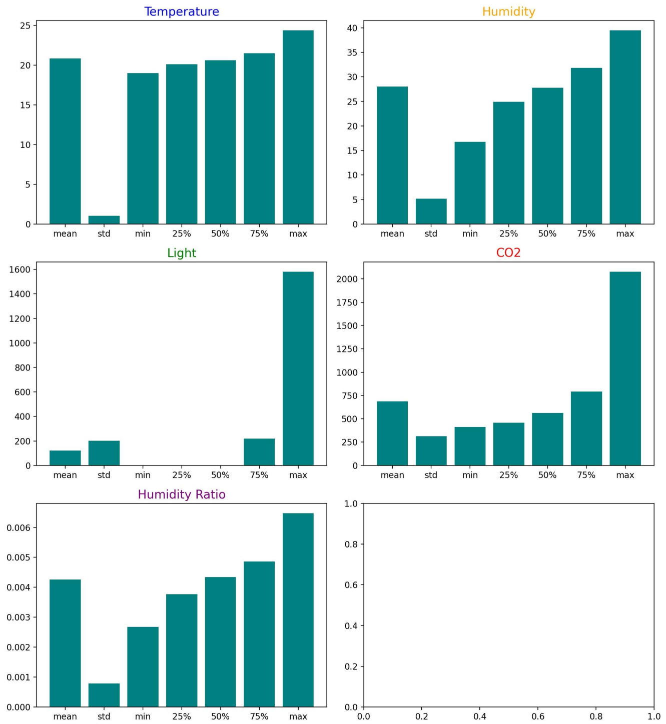


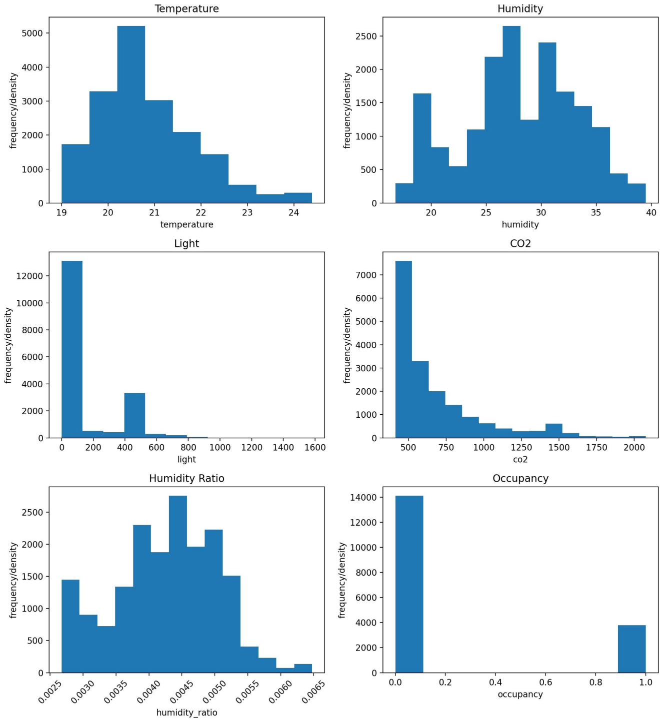
Data Cleaning

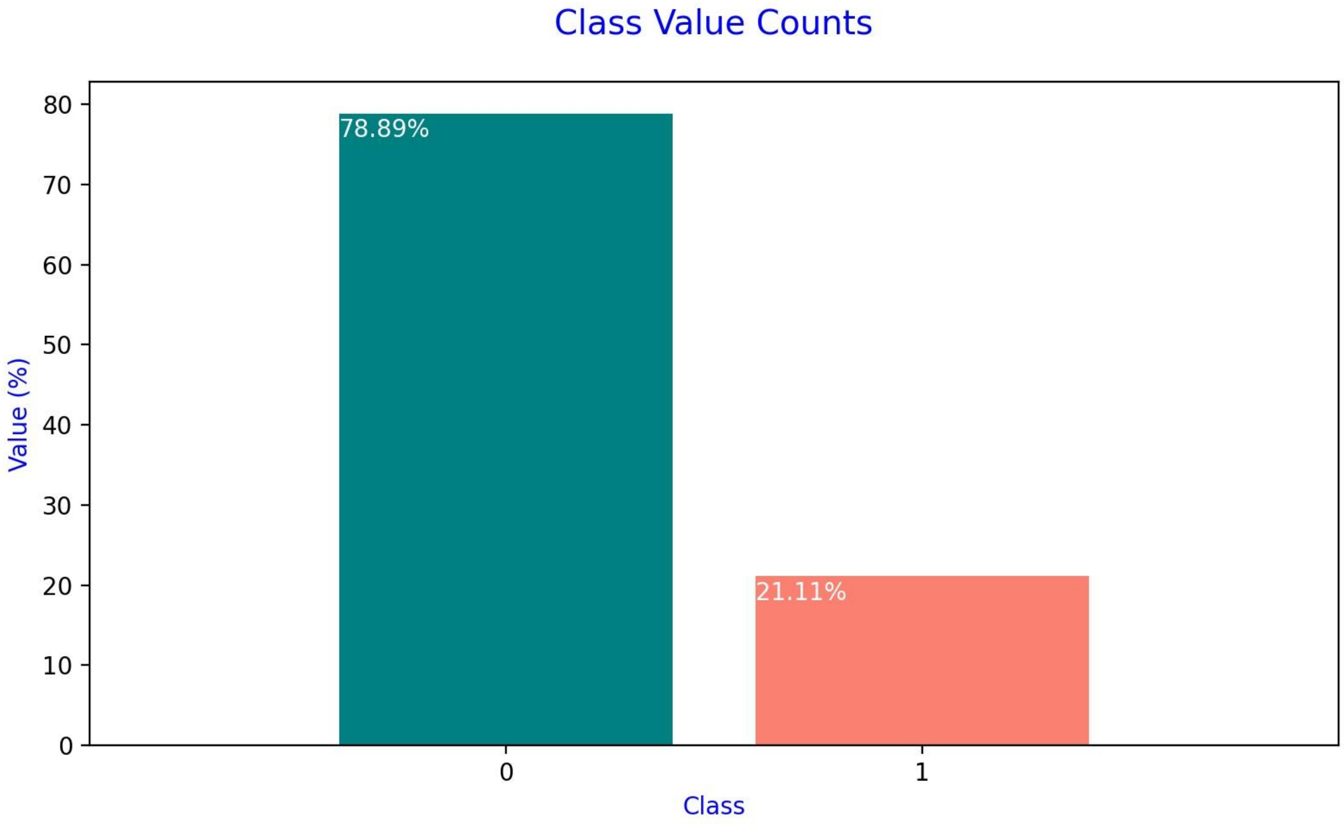
Data Dictionary

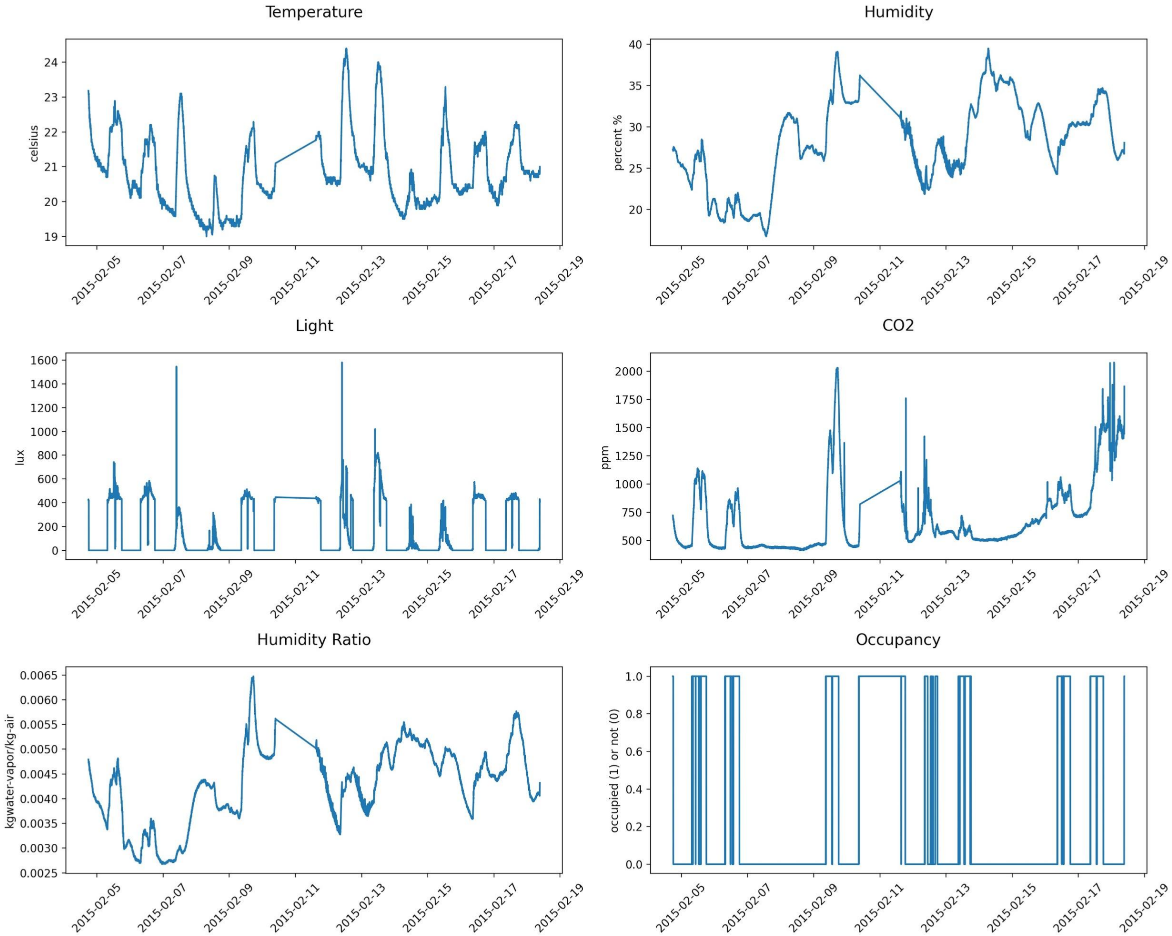
Feature Name	Feature Description	Units of Measurement or Format
date	time the observation was recorded	year-month-day hour:minute:second
temperature	temperature recorded	Celsius
humidity	relative humidity recorded	%
light	light recorded at time of observation	Lux
co2	CO2 measured at the time of observation	ppm, parts per million
humidity_ratio	derived quantity from temperature and relative humidity	kgwater-vapor/kg-air
occupancy	status of room occupancy	0 for not occupied, 1 for occupied status
weekday	indicates if the timestamp is weekday or weekend	1 for weekday, 0 for weekend

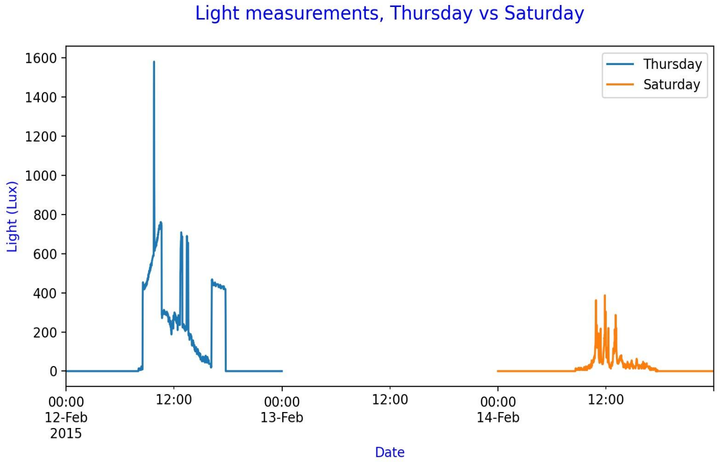
Statistics and Distributions

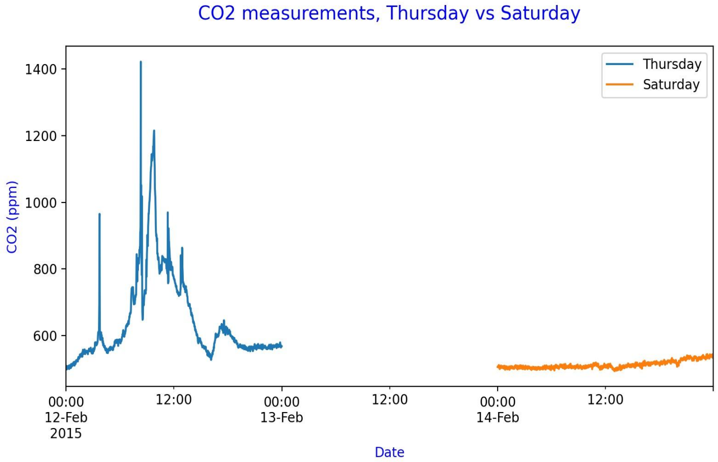


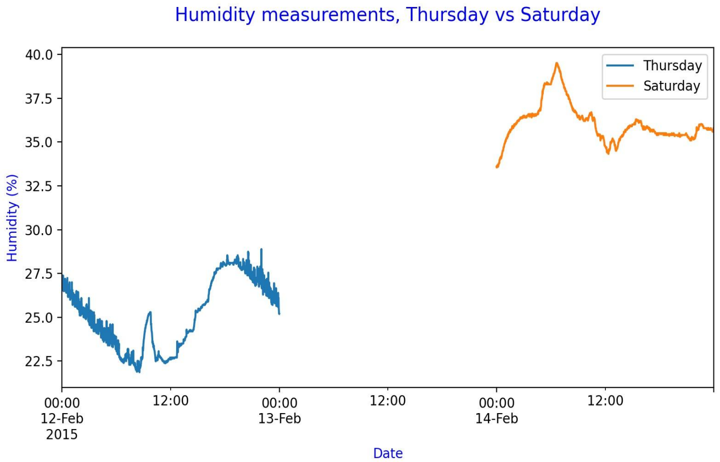


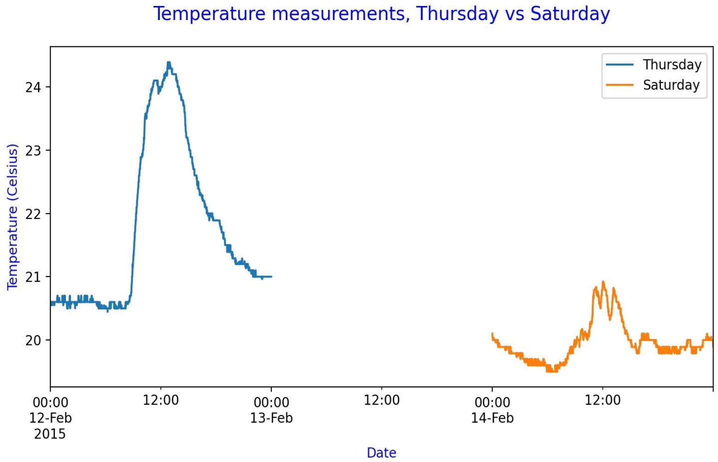

Class Value Counts
78.89%
21.11%
Value (%)
80
70
60
50
40
30
20
10
0
0
1
Class

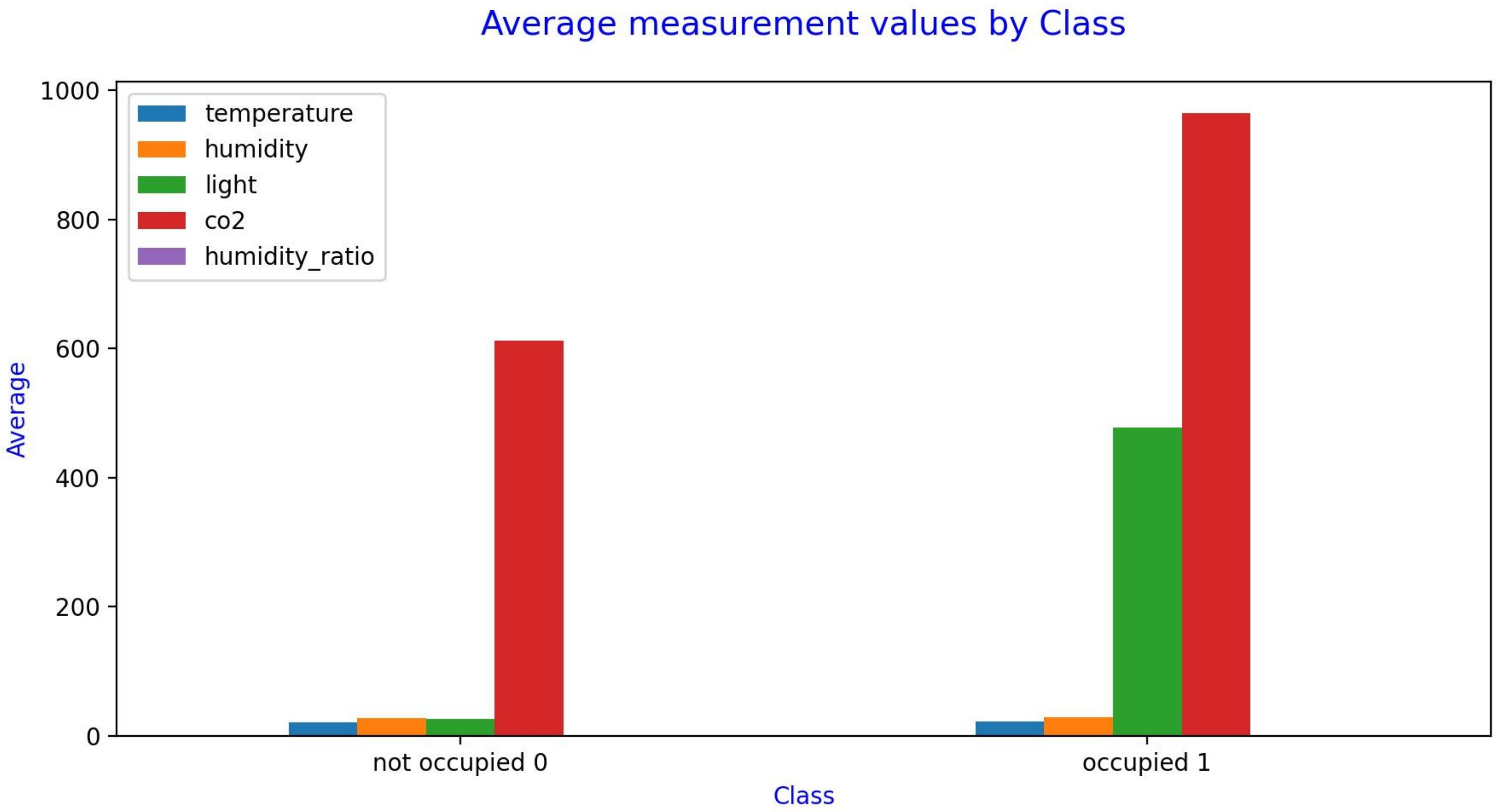

Temperature
celsius
19
20
21
22
23
24
Humidity
percent %
20
25
30
35
40
Light
lux
0
200
400
600
800
1000
1200
1400
1600
CO2
ppm
500
750
1000
1250
1500
1750
2000
Humidity Ratio
kgwater-vapor/kg-air
0.0025
0.0030
0.0035
0.0040
0.0045
0.0050
0.0055
0.0060
0.0065
Occupancy
occupied (1) or not (0)
0.0
0.2
0.4
0.6
0.8
1.0
2015-02-05
2015-02-07
2015-02-09
2015-02-11
2015-02-13
2015-02-15
2015-02-17
2015-02-19

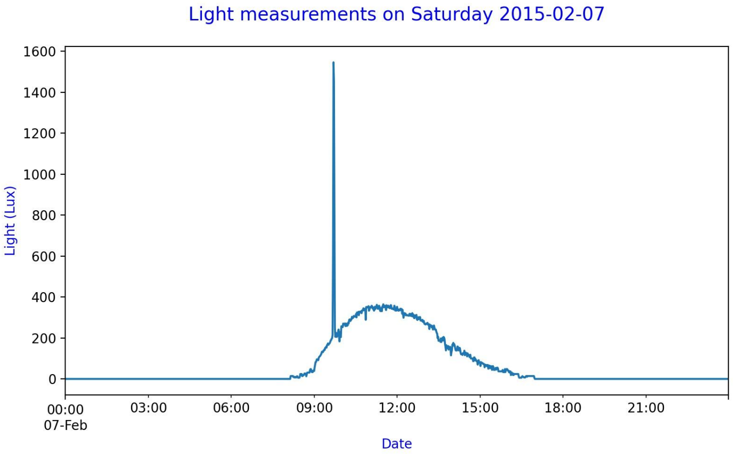

Light measurements, Thursday vs Saturday
Thursday
Saturday
Light (Lux)
1600
1400
1200
1000
800
600
400
200
0
00:00
12-Feb
2015
12:00
00:00
13-Feb
12:00
00:00
14-Feb
12:00
Date

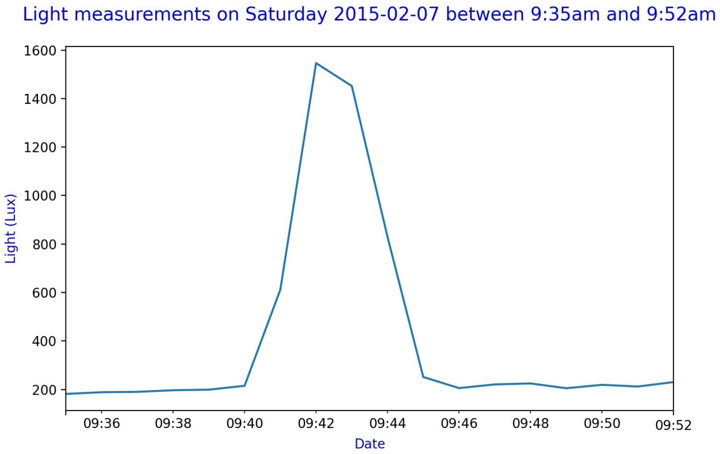

CO2 measurements, Thursday vs Saturday
Thursday
Saturday
CO2 (ppm)
1400
1200
1000
800
600
00:00
12-Feb
2015
12:00
00:00
13-Feb
12:00
00:00
14-Feb
12:00
Date

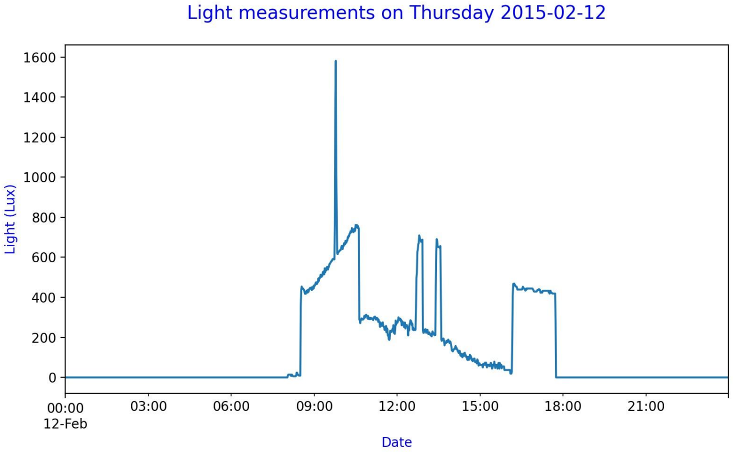

Humidity measurements, Thursday vs Saturday
Thursday
Saturday
Humidity (%)
40.0
37.5
35.0
32.5
30.0
27.5
25.0
22.5
00:00
12-Feb
2015
12:00
00:00
13-Feb
12:00
00:00
14-Feb
12:00
Date

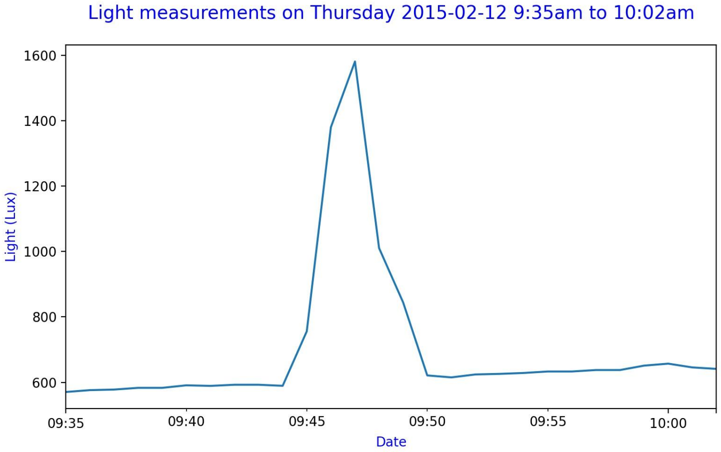

Temperature measurements, Thursday vs Saturday
Thursday
Saturday
Temperature (Celsius)
24
23
22
21
20
00:00
12-Feb
2015
12:00
00:00
13-Feb
12:00
00:00
14-Feb
12:00
Date

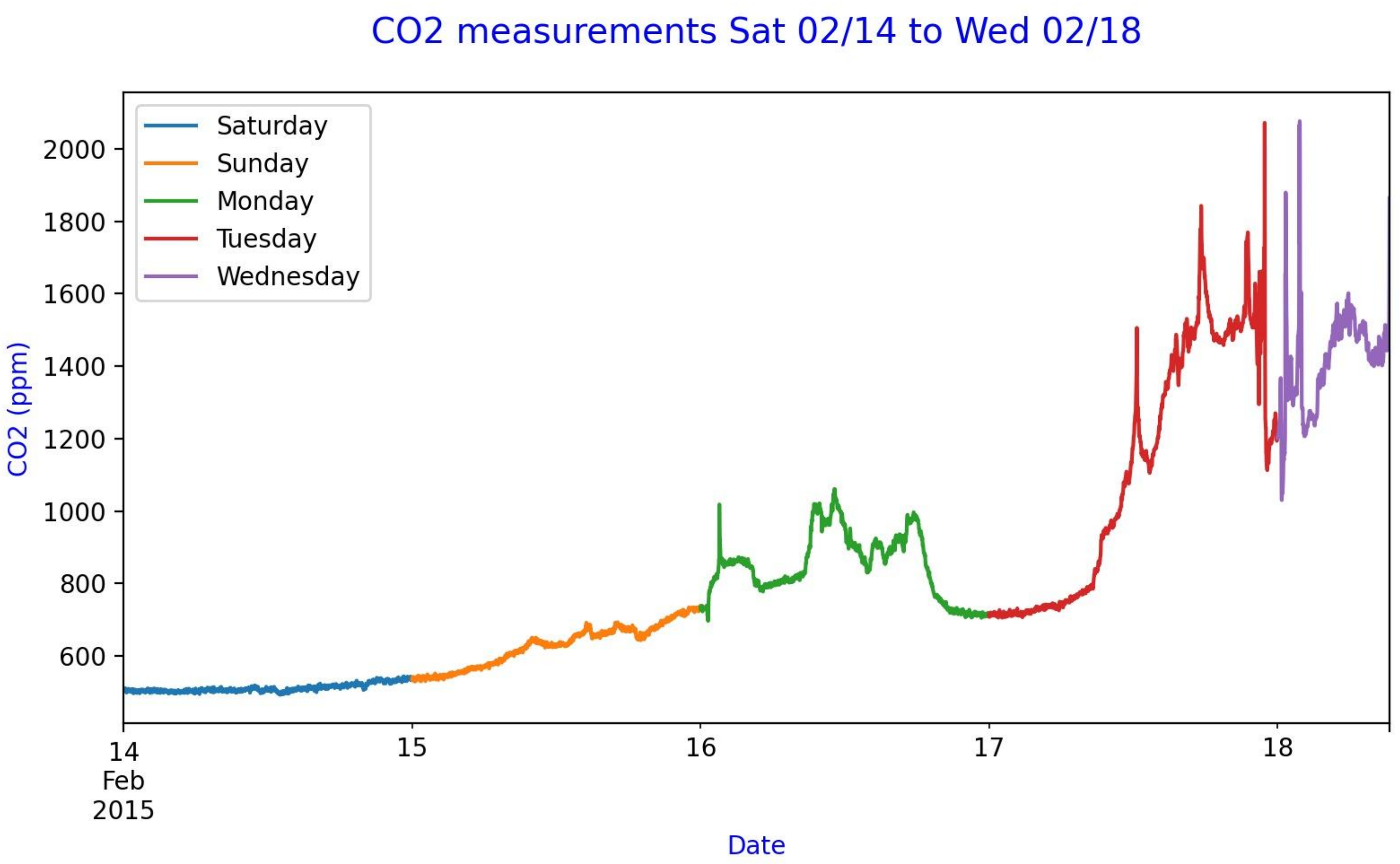

Average measurement values by Class
temperature
humidity
light
co2
humidity_ratio
1000
800
600
400
200
0
Average
not occupied 0
occupied 1
Class

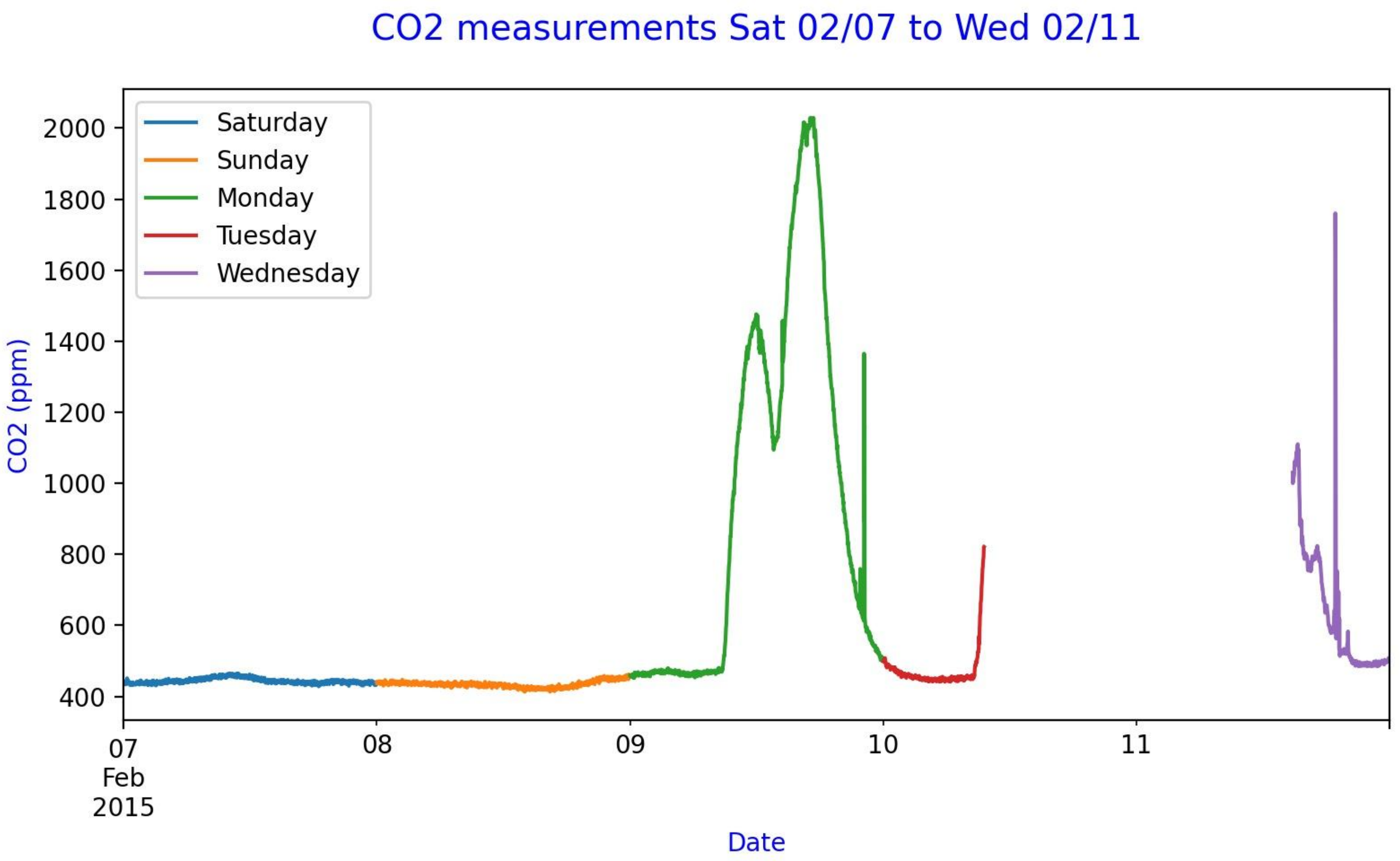

Light measurements on Saturday 2015-02-07
Light (Lux)
0
200
400
600
800
1000
1200
1400
1600
00:00
07-Feb
03:00
06:00
09:00
12:00
15:00
18:00
21:00
Date

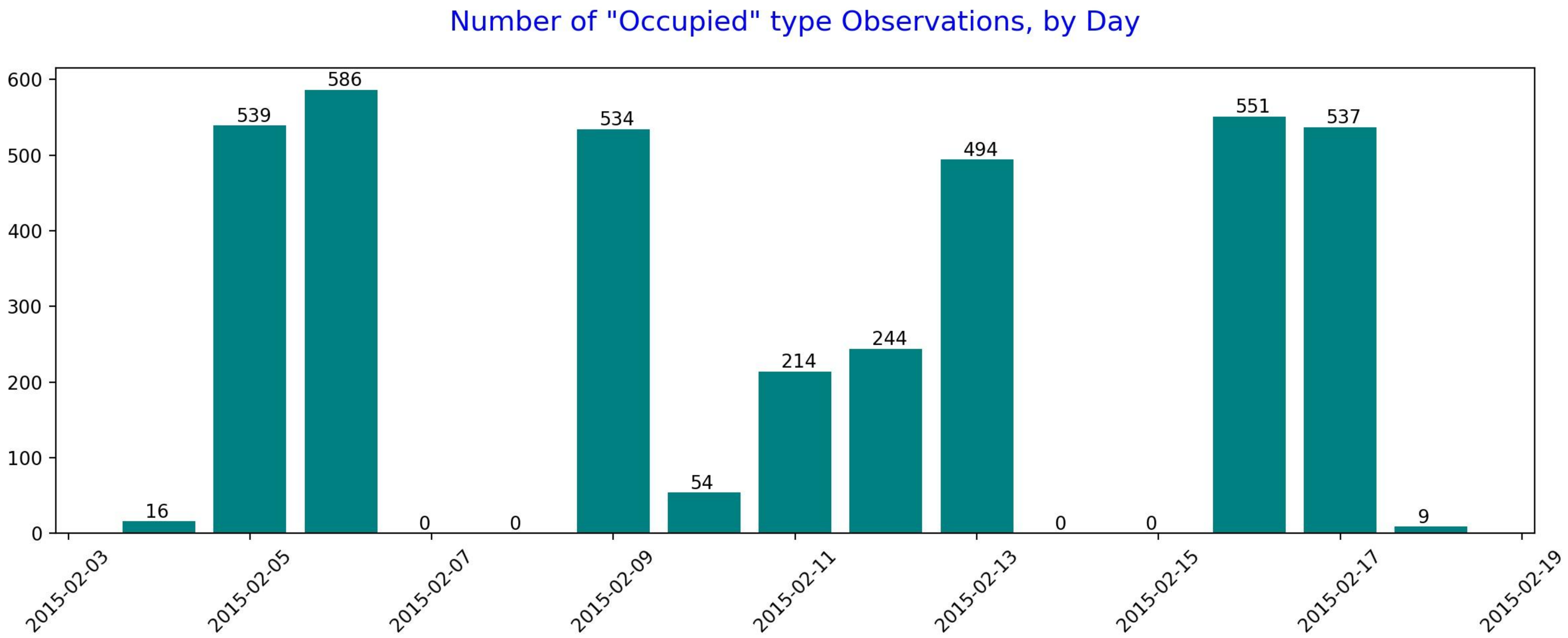

Light measurements on Saturday 2015-02-07 between 9:35am and 9:52am
Light (Lux)
200
400
600
800
1000
1200
1400
1600
09:36
09:38
09:40
09:42
09:44
09:46
09:48
09:50
09:52
Date

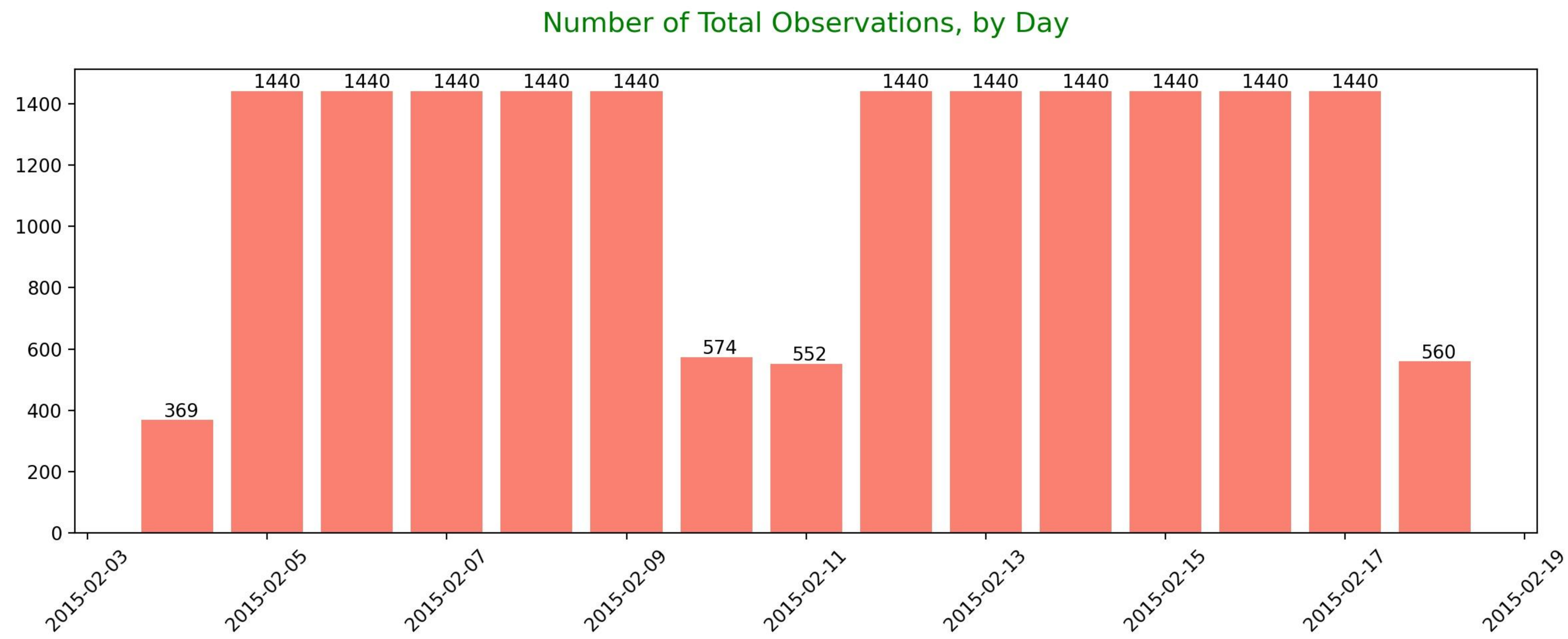

Light measurements on Thursday 2015-02-12
Light (Lux)
0
200
400
600
800
1000
1200
1400
1600
00:00
12-Feb
03:00
06:00
09:00
12:00
15:00
18:00
21:00
Date


Light measurements on Thursday 2015-02-12 9:35am to 10:02am
Light (Lux)
600
800
1000
1200
1400
1600
09:35
09:40
09:45
09:50
09:55
10:00
Date


CO2 measurements Sat 02/14 to Wed 02/18
Saturday
Sunday
Monday
Tuesday
Wednesday
CO2 (ppm)
2000
1800
1600
1400
1200
1000
800
600
14
Feb
2015
15
16
17
18
Date


CO2 measurements Sat 02/07 to Wed 02/11
Saturday
Sunday
Monday
Tuesday
Wednesday
CO2 (ppm)
2000
1800
1600
1400
1200
1000
800
600
400
07
Feb
2015
08
09
10
11
Date


Number of "Occupied" type Observations, by Day
600
500
400
300
200
100
0
16
539
586
0
0
534
54
214
244
494
0
0
551
537
9
2015-02-03
2015-02-05
2015-02-07
2015-02-09
2015-02-11
2015-02-13
2015-02-15
2015-02-17
2015-02-19



Number of Total Observations, by Day
369
1440
1440
1440
1440
1440
574
552
1440
1440
1440
1440
1440
1440
560
0
200
400
600
800
1000
1200
1400
2015-02-03
2015-02-05
2015-02-07
2015-02-09
2015-02-11
2015-02-13
2015-02-15
2015-02-17
2015-02-19

Correlation Observed between Occupancy and Measurements

Modeling

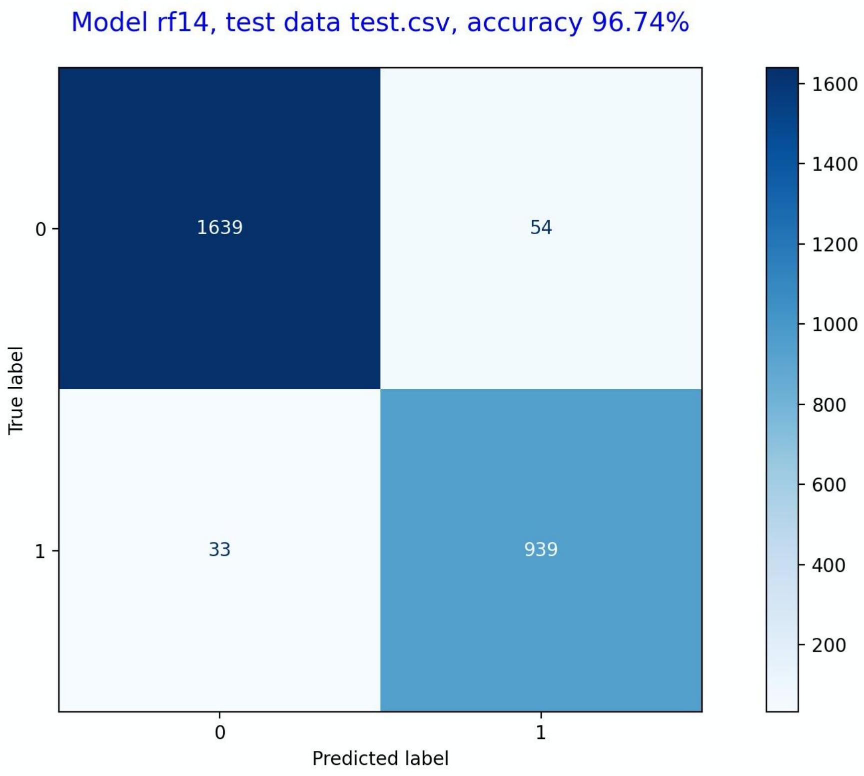
- Models were trained on 75% of the combined data, with 25% left for testing.
- 63 models were run on the [temperature, light, co2, humidity, humidity_ratio] features..
- 154 models were run on the [temperature, light, co2, humidity, humidity_ratio, weekday] features.
- A total of 217 models were run.
- The best model was Random Forest. At training time, the model reported 99.60% accuracy on a 75/25 train/test split of combined data, 96.74% accuracy on test data with the door open, and 99.72% accuracy on test data with the door closed.

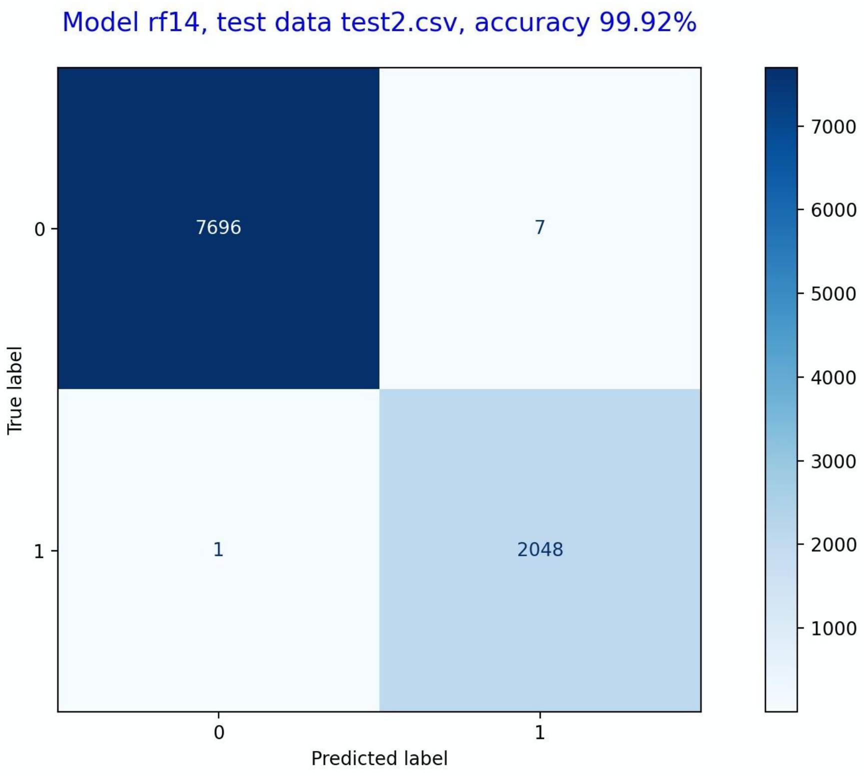
Abbreviation	Meaning
RF	Random Forest
LDA	Linear Discriminant Analysis
GBM	Gradient Boosting Machine
AdaBoost	Adaptive Boosting
KNN	K-Nearest Neighbor
SVC	Support Vector Classification

Model Id	Model name	Features	Best score	Train score	Test score	Sensitivity	Specificity	Precision	Accuracy	F1-score
14	rf14	temperature, humidity, light, humidity_ratio, weekday	0.994	0.9996	0.996	0.9905	0.9974	0.9905	0.996	0.9905
12	rf12	temperature, humidity, light, co2, weekday	0.9945	1	0.9958	0.9894	0.9974	0.9905	0.9958	0.9899
11	rf11	temperature, humidity, light, co2, humidity_ratio, weekday	0.9946	1	0.9955	0.9905	0.9969	0.9884	0.9955	0.9894
1	rf1	temperature, humidity, light, co2	0.994	1	0.9955	0.9884	0.9974	0.9905	0.9955	0.9894
0	rf0	temperature, humidity, light, co2, humidity_ratio	0.9938	1	0.9953	0.9873	0.9974	0.9904	0.9953	0.9889
77	gbm11	temperature, humidity, light, co2, humidity_ratio, weekday	0.994	1	0.9951	0.9884	0.9969	0.9884	0.9951	0.9884
67	gbm1	temperature, humidity, light, co2	0.9932	0.9989	0.9949	0.9873	0.9969	0.9883	0.9949	0.9878
18	rf18	humidity, light, weekday	0.992	0.9994	0.9949	0.9884	0.9966	0.9873	0.9949	0.9878
3	rf3	temperature, humidity, light, humidity_ratio	0.9931	0.9996	0.9944	0.9831	0.9974	0.9904	0.9944	0.9867
66	gbm0	temperature, humidity, light, co2, humidity_ratio	0.993	1	0.9944	0.9862	0.9966	0.9873	0.9944	0.9868

Random Forest

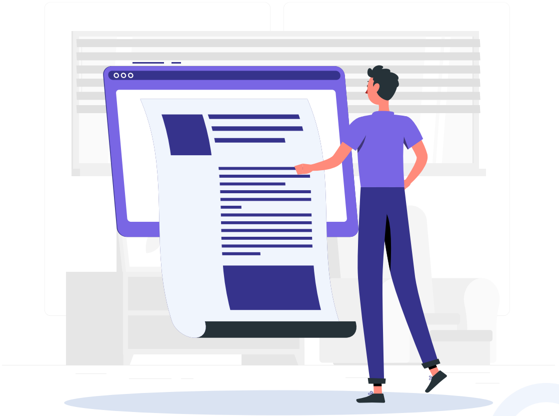
temperature, humidity, light, humidity_ratio, weekday





Conclusions

Recommendations



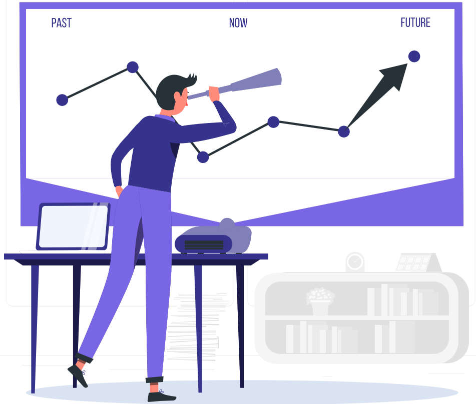
Next Steps

Resources

(1) Sensitivity and Specificity
(2) Accuracy
(3) Precision
(4) Executive Summary
(5) How to Predict Room Occupancy Based on Environmental Factors
(6) Technical Report and Project
(7) Improving Prediction of Office Room Occupancy Through Random Sampling
(8) Occupancy
(9) Room Occupancy Detection
(10) Classroom Occupancy Project
(11) Accurate occupancy detection of an office room from light, temperature, humidity and CO2 measurements using statistical learning models. Luis M. Candanedo, VÃ©ronique Feldheim. Energy and Buildings. Volume 112, 15 January 2016, Pages 28-39.
(12) Calculate day in the past
(13) V.L.Erickson, M.Á.Carreira-Perpinán, A.E.Cerpa, OBSERVE:Occupancy-based system for efficient reduction of HVAC energy, in: Proceedings of the 10th International Conference on, IEEE, Information Processing in Sensor Networks (IPSN), Chicago, IL, 2011, pp. 258–269.
(14) V.L.Erickson, M.Á.Carreira-Perpinán, A.E.Cerpa,Occupancy modeling and prediction for building energy management, ACM Trans. Sensor Netw. (TOSN) 10 (3) (2014) 42.
(14) Dong B., Andrews B., (2009). Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings. Proceedings of Building Simulation.
(15) J. Brooks, S. Goyal, R. Subramany, Y. Lin, T. Middelkoop, L. Arpan, L. Carloni, P. Barooah, An experimental investigation of occupancy-based energy-efficient control of commercial building indoor climate, in: Proceeding of the IEEE 53rd Annual Conference on, IEEE, Decision and Control (CDC), Los Angeles, CA, 2014, pp. 5680–5685.
(16) J. Brooks, S. Kumar, S. Goyal, R. Subramany, P. Barooah, Energy-efficient control of under-actuated HVAC zones in commercial buildings, Energy Build. 93 (2015) 160–168.

Title

ALTERNATIVE RESOURCES



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