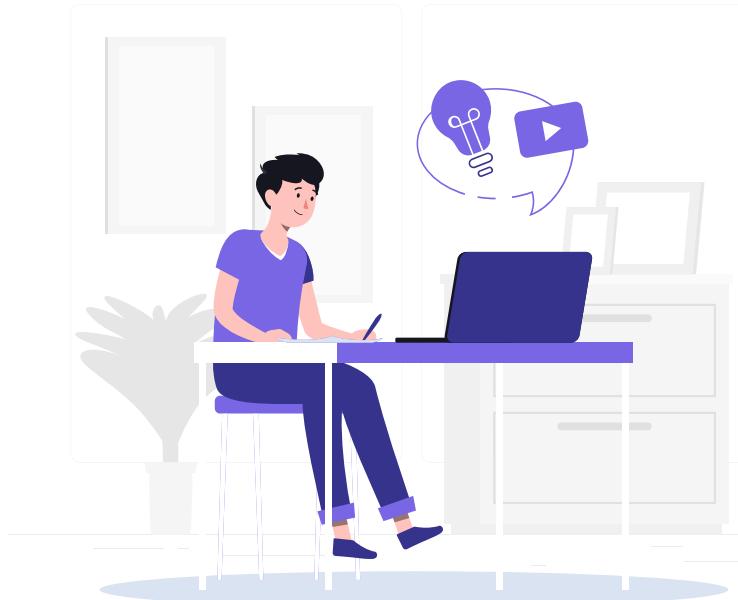


Occupancy Detection

Created and Presented
By
Cristina Sahoo



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]

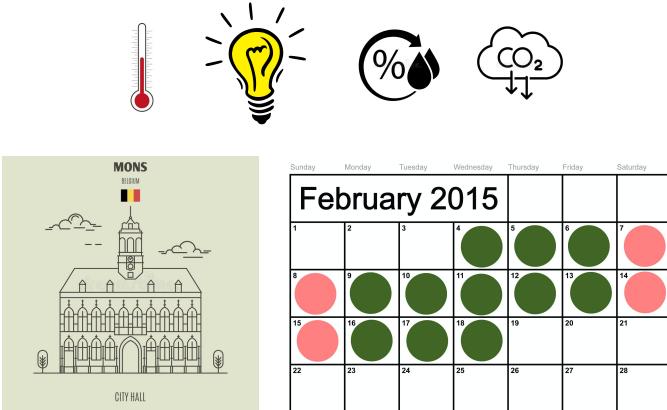


- A system that could accurately detect the presence of the occupants without using a camera is very interesting due to privacy concerns

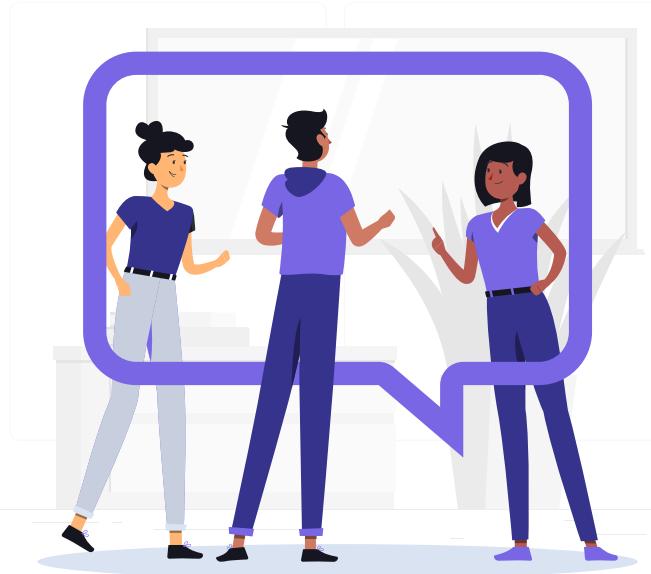


- Other applications for occupancy detection include security and determination of building occupant behaviors

Problem Statement

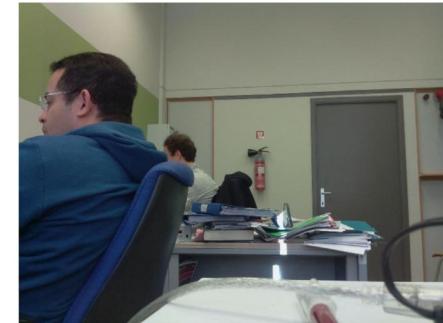
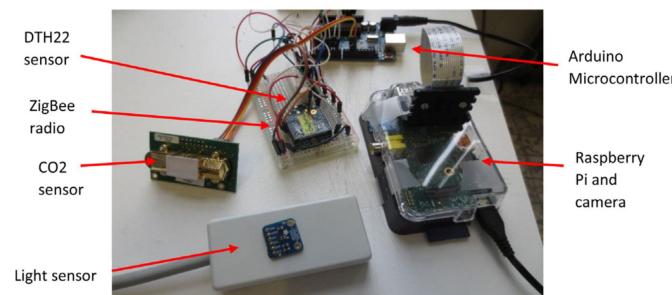
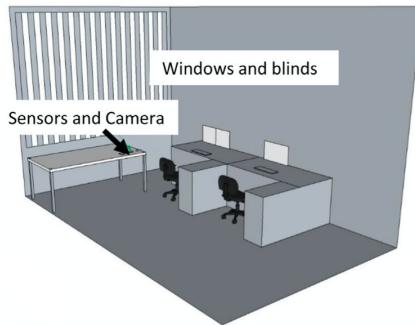


- Identify trends over time and correlation between environment variables and occupancy
- Identify algorithms/models with best accuracy score for predicting occupancy



Data Source and Collection

Occupancy Detection Dataset - UCI Machine Learning Repository



Data Cleaning and Preprocessing

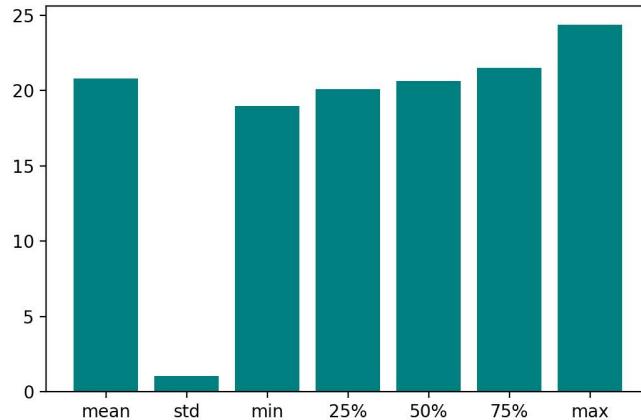
- Remove or impute null values
 - Remove/impute outliers
 - Remove duplicate observations
 - Rename columns
 - Round dates to nearest minute
 - Sort by date, chronologically
 - Index by date to allow time series type exploration of the data
 - Create the “weekday” feature

date	temperature	humidity	light	co2	humidity_ratio	occupancy
2015-02-04 17:51:00	23.18	27.272	426.0	721.25	0.00475699217650529	1
2015-02-04 17:52:00	23.15	27.2675	429.5	714.0	0.00478344094301635	1
2015-02-04 17:53:00	23.15	27.245	426.0	713.5	0.00477946352442199	1
2015-02-04 17:54:00	23.15	27.2	426.0	708.25	0.00477115088260175	1
2015-02-04 17:55:00	23.1	27.2	426.0	704.5	0.004756992933315180	1
2015-02-04 17:56:00	23.1	27.2	419.0	701.0	0.004756992933315180	1
2015-02-04 17:57:00	23.1	27.2	419.0	701.6666666666667	0.004756992933315180	1
2015-02-04 17:58:00	23.1	27.2	419.0	699.0	0.004756992933315180	1
2015-02-04 17:59:00	23.1	27.2	419.0	689.333333333333	0.004756992933315180	1
2015-02-04 18:00:00	23.075	27.175	419.0	688.0	0.004754535071966655	1
2015-02-04 18:01:00	23.075	27.15	419.0	690.25	0.00474095189694268	1
2015-02-04 18:02:00	23.1	27.1	419.0	691.0	0.00473937037050261	1
2015-02-04 18:03:00	23.1	27.16666666666667	419.0	683.5	0.0047511875560591	1
2015-02-04 18:04:00	23.05	27.15	419.0	687.5	0.004737317970825	1
2015-02-04 18:05:00	23.0	27.125	419.0	686.0	0.00471494214590473	1
2015-02-04 18:06:00	23.0	27.125	418.5	680.5	0.00471494214590473	1
2015-02-04 18:07:00	23.0	27.2	0.0	681.5	0.0047280779496687700	0
2015-02-04 18:08:00	22.945	27.29	0.0	685.0	0.00472795137178703	0
2015-02-04 18:09:00	22.945	27.39	0.0	685.0	0.0047454083970941	0
2015-02-04 18:10:00	22.89	27.39	0.0	689.0	0.0047295051591001	0
2015-02-04 18:11:00	22.89	27.39	0.0	689.5	0.0047295051591001	0
2015-02-04 18:12:00	22.89	27.39	0.0	689.0	0.0047295051591001	0
2015-02-04 18:13:00	22.89	27.445	0.0	691.0	0.00473907551474663	0
2015-02-04 18:14:00	22.89	27.5	0.0	688.0	0.00474864516581148	0
2015-02-04 18:15:00	22.89	27.5	0.0	689.5	0.00474864516581148	0
2015-02-04 18:16:00	22.79	27.445	0.0	689.0	0.004712040680625	0

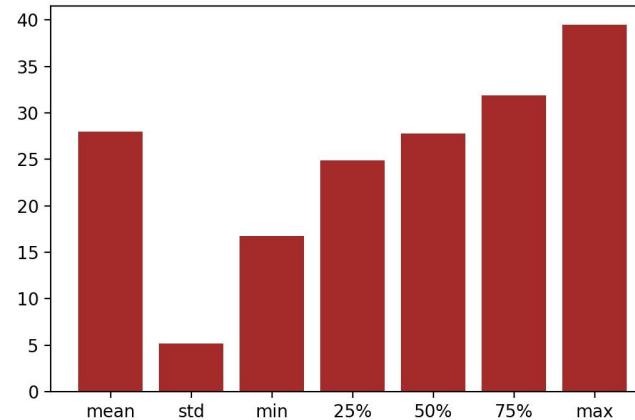
Data Dictionary

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

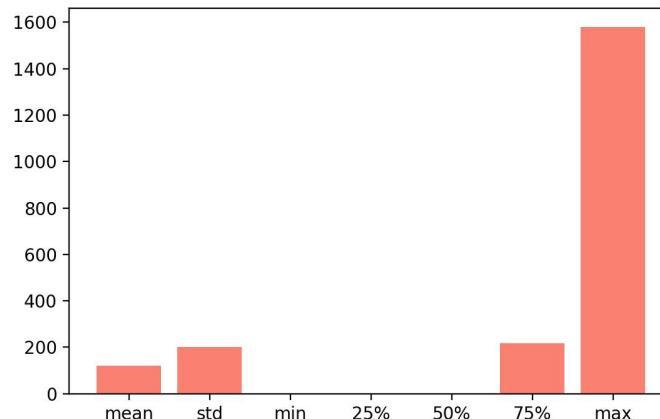
Descriptive Statistics: Temperature



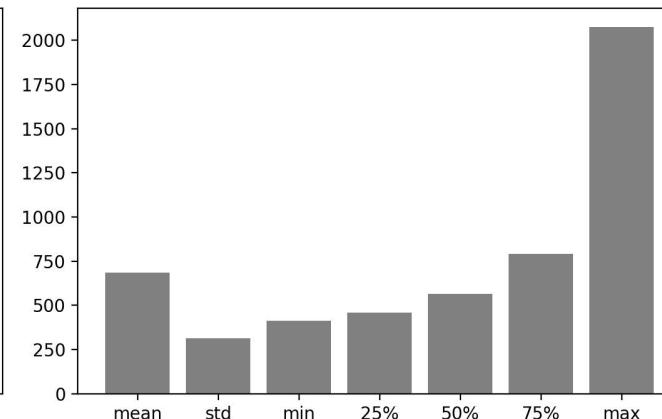
Descriptive Statistics: Humidity



Descriptive Statistics: Light

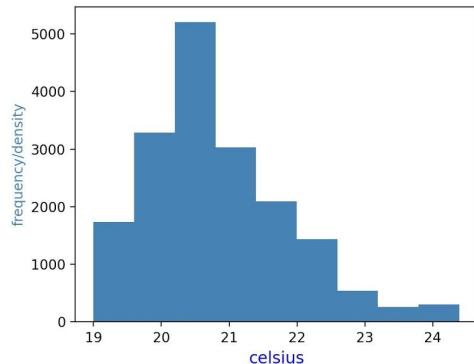


Descriptive Statistics: CO2

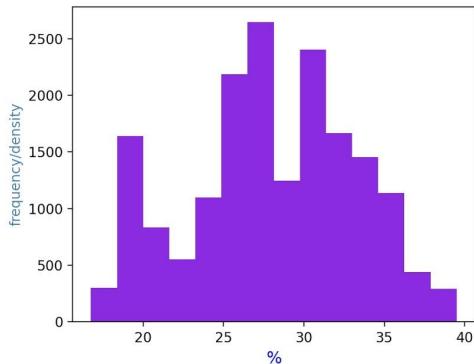


Data Distributions

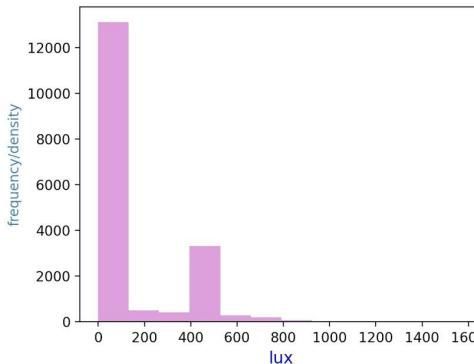
Temperature



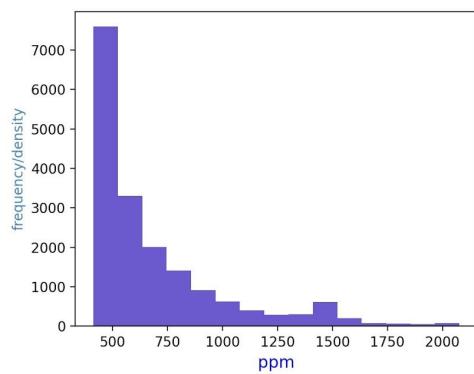
Humidity



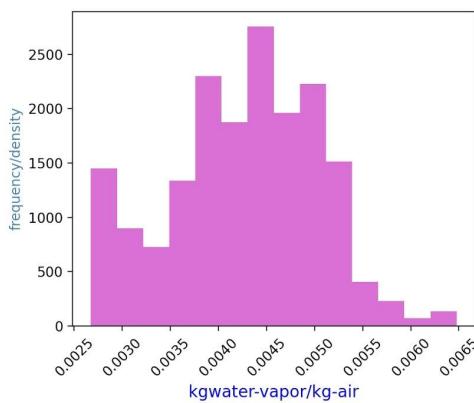
Light



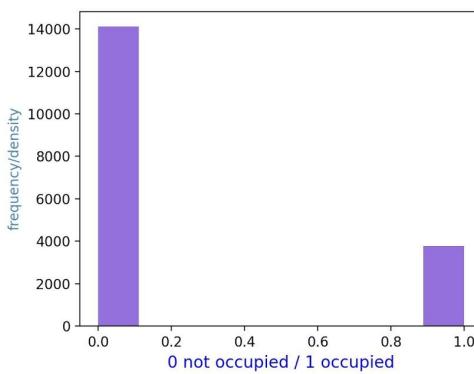
CO₂



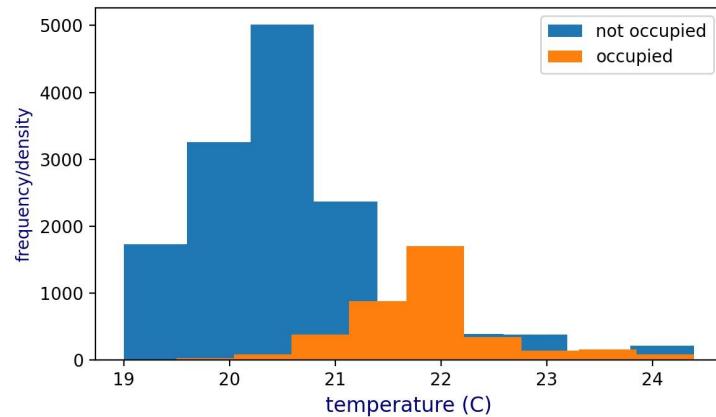
Humidity Ratio



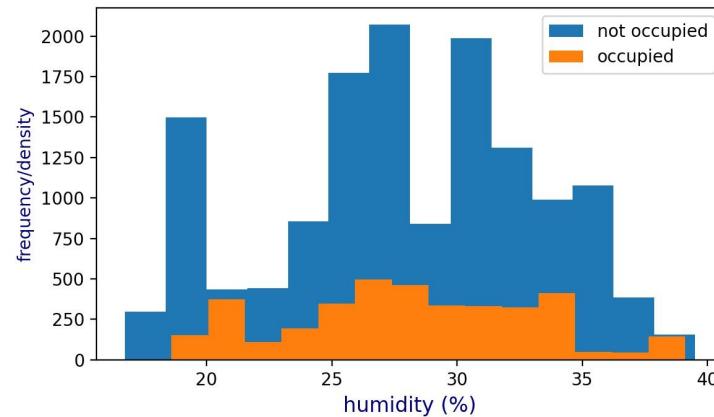
Occupancy



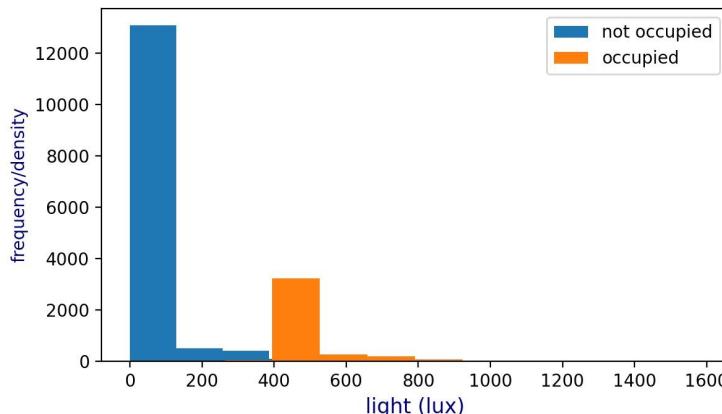
Temperature Distribution by Class



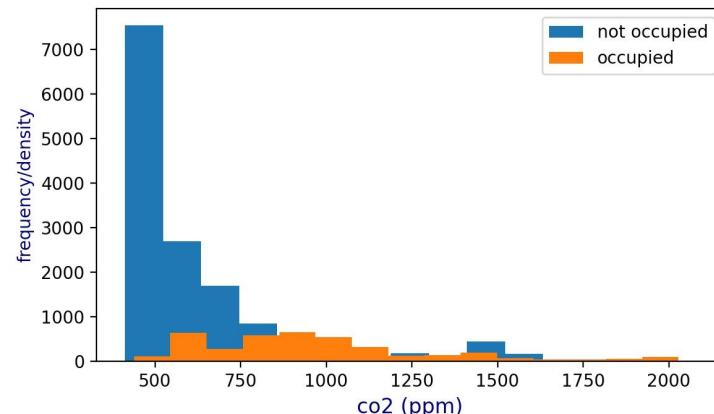
Humidity Distribution by Class



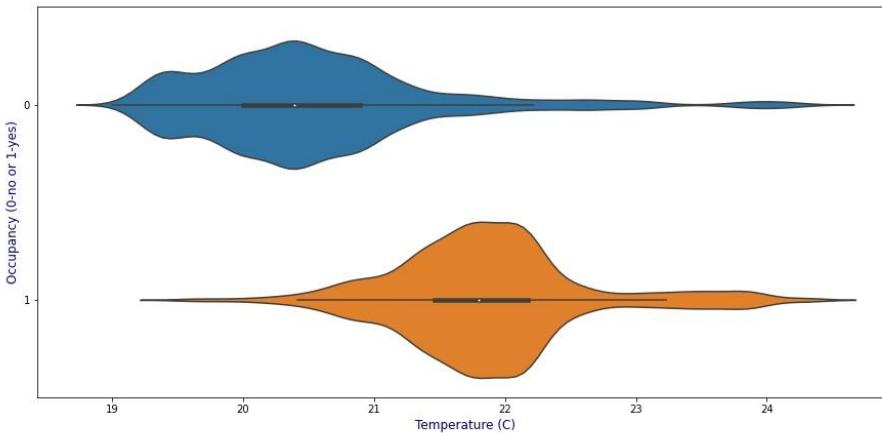
Light Distribution by Class



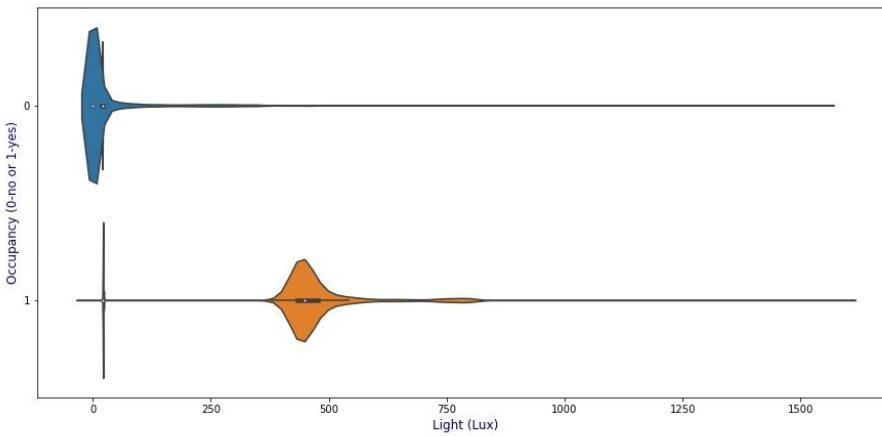
CO2 Distribution by Class

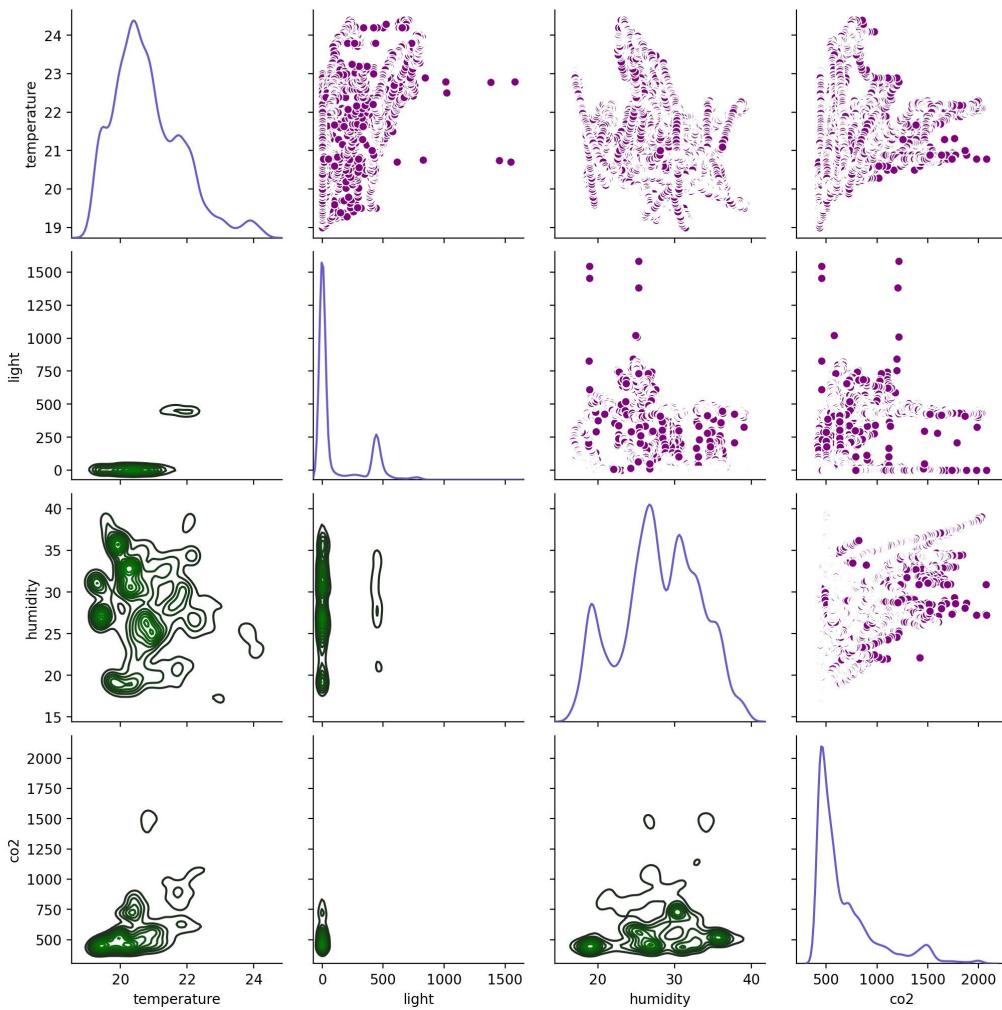


Temperature Distribution by Class

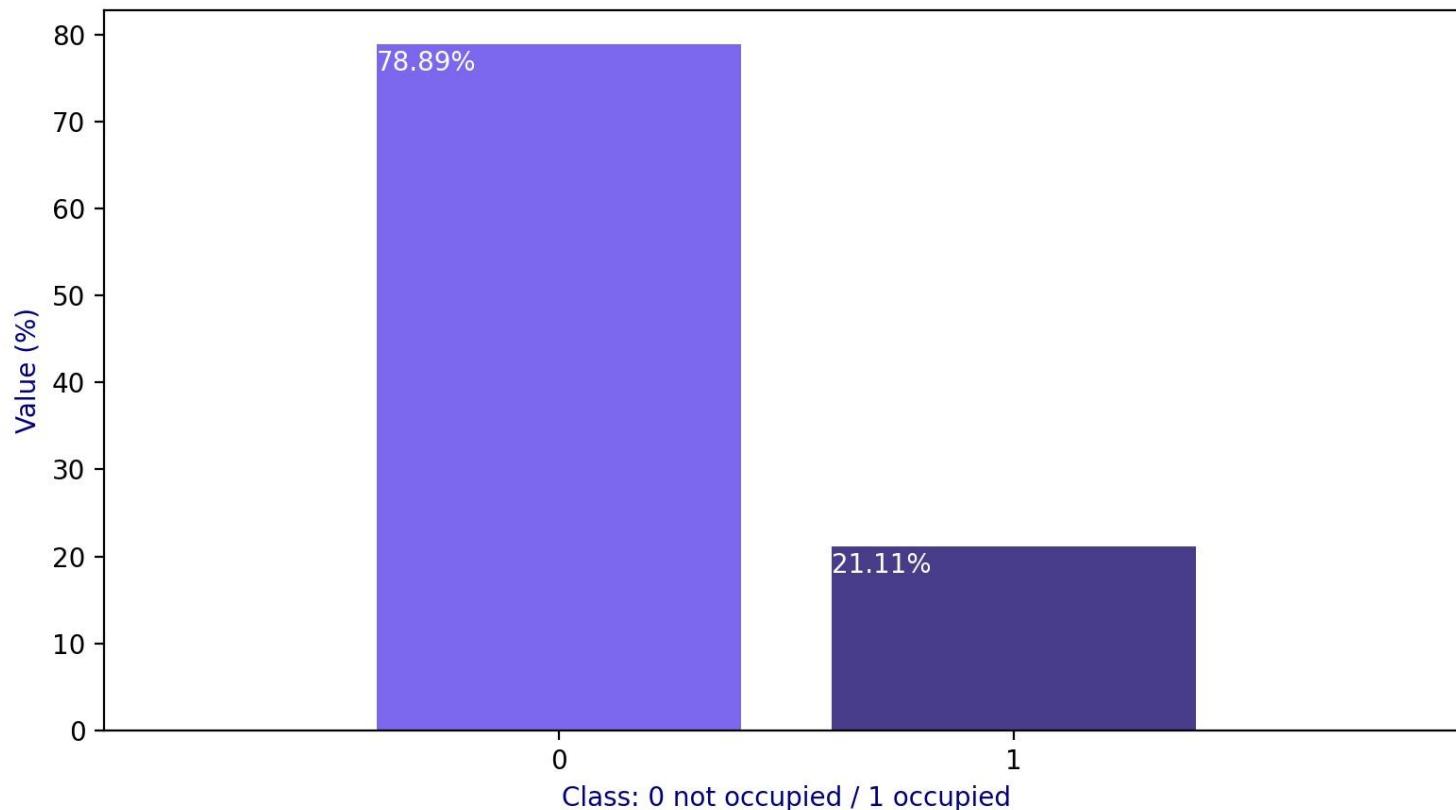


Light Distribution by Class

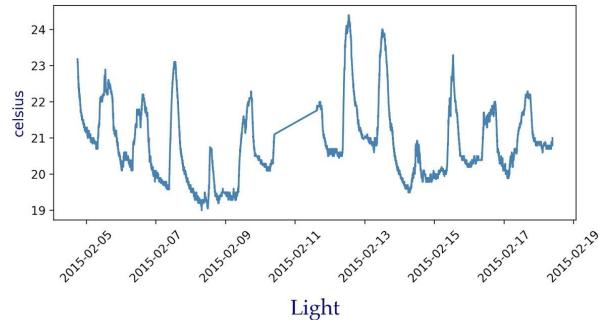




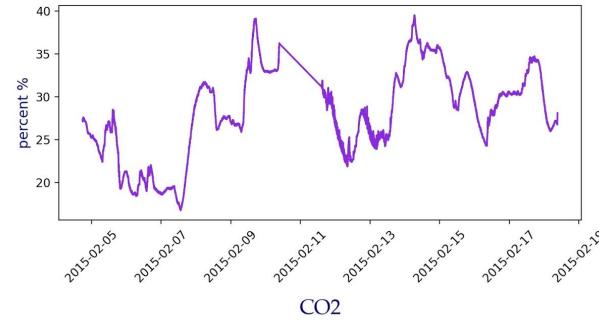
Data Distribution by Class



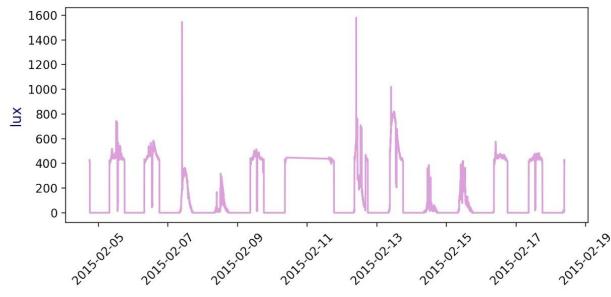
Temperature



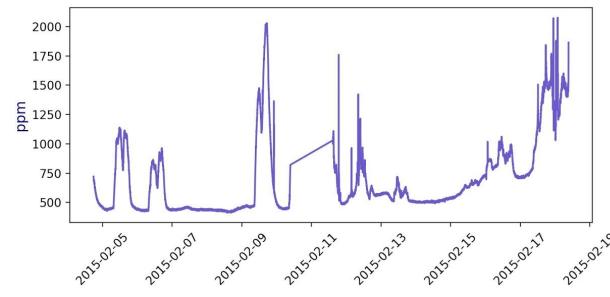
Humidity



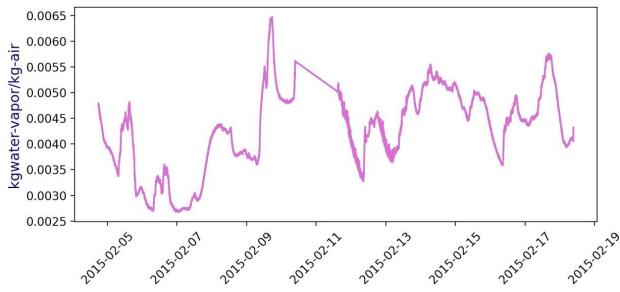
Light



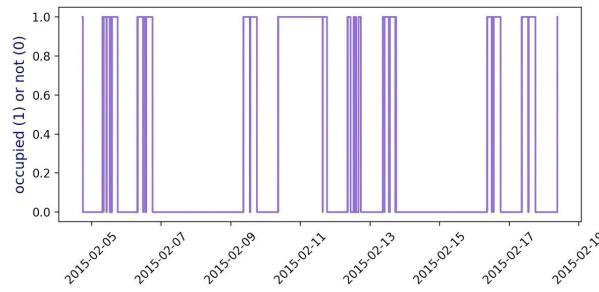
CO2



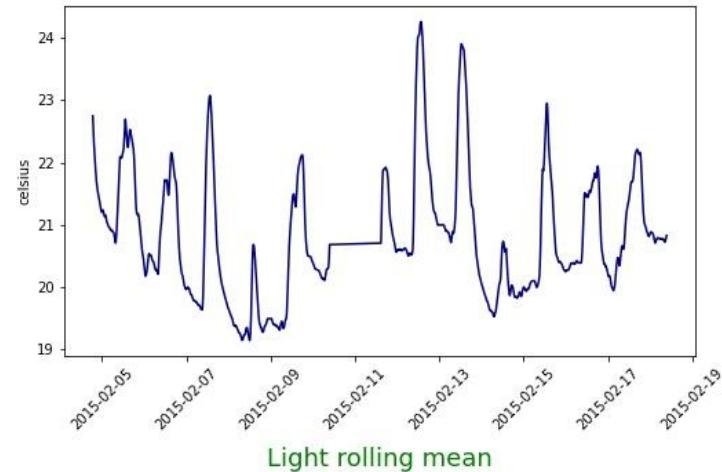
Humidity Ratio



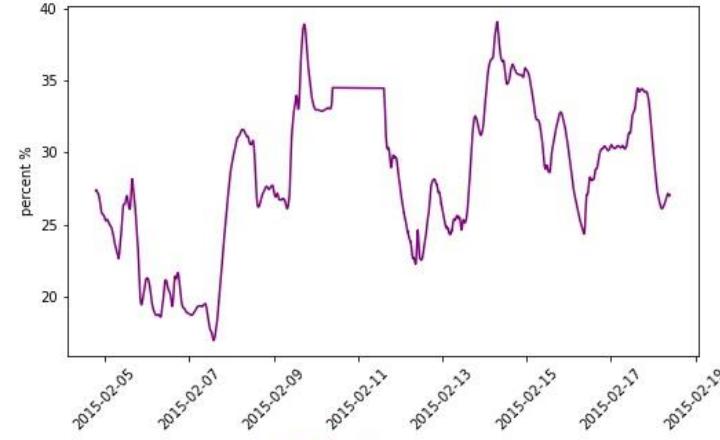
Occupancy



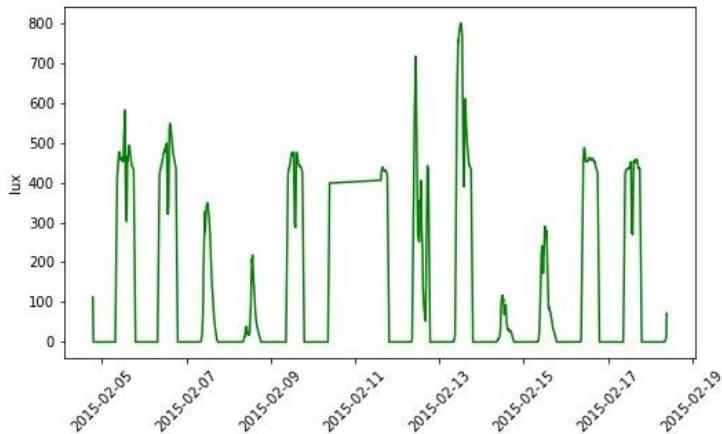
Temperature rolling mean



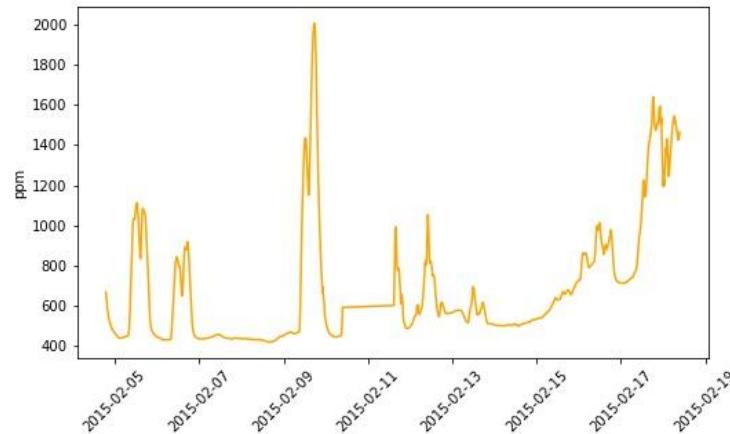
Humidity rolling mean



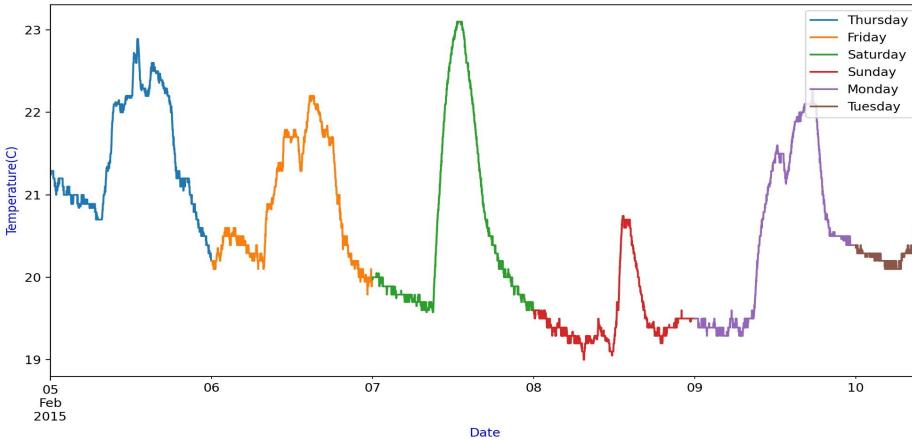
Light rolling mean



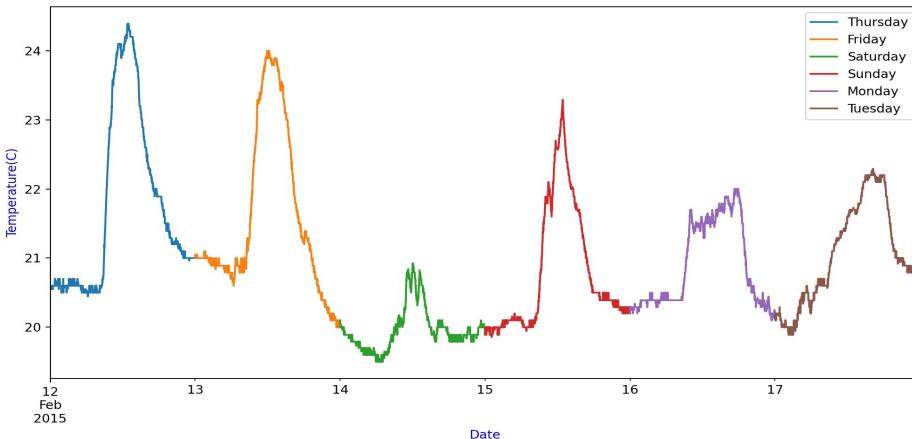
CO2 rolling mean



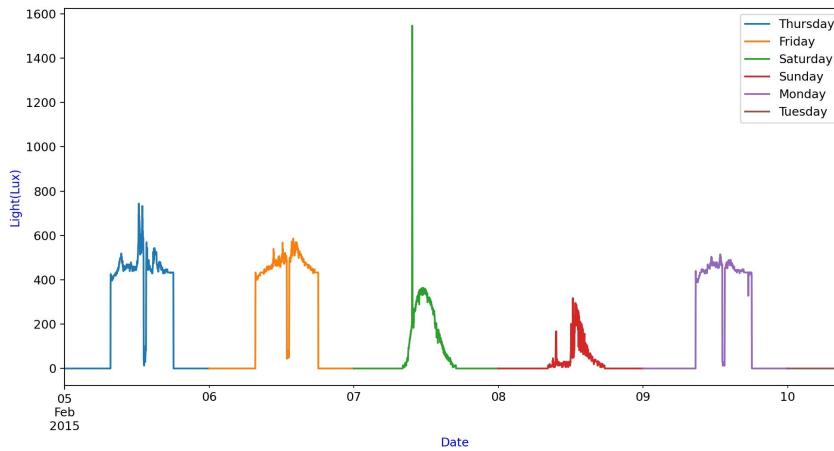
Temperature measurements Thur 02/05 to Tue 02/10



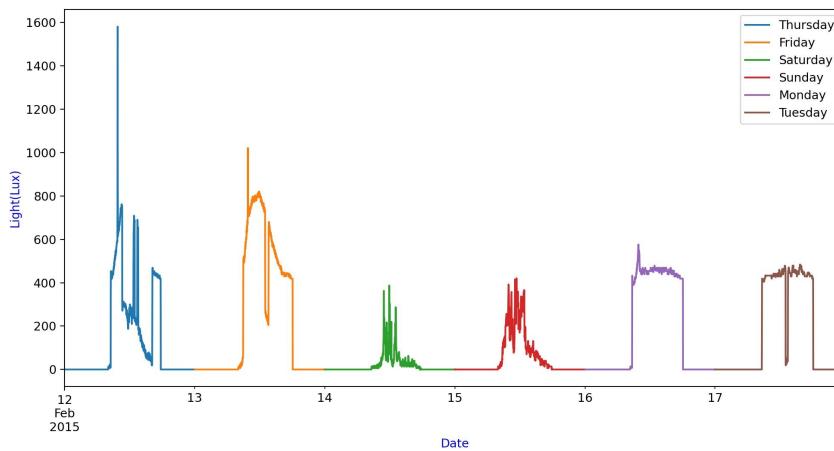
Temperature measurements Thur 02/12 to Tue 02/17



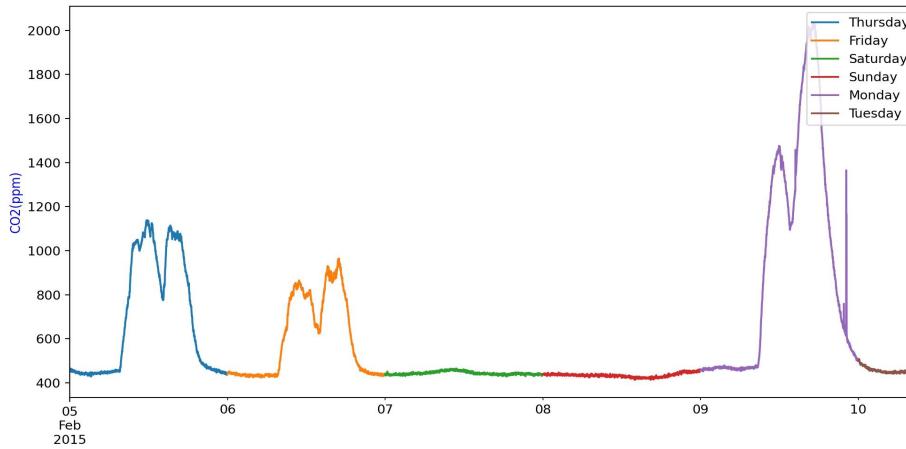
Light measurements Thur 02/05 to Tue 02/10



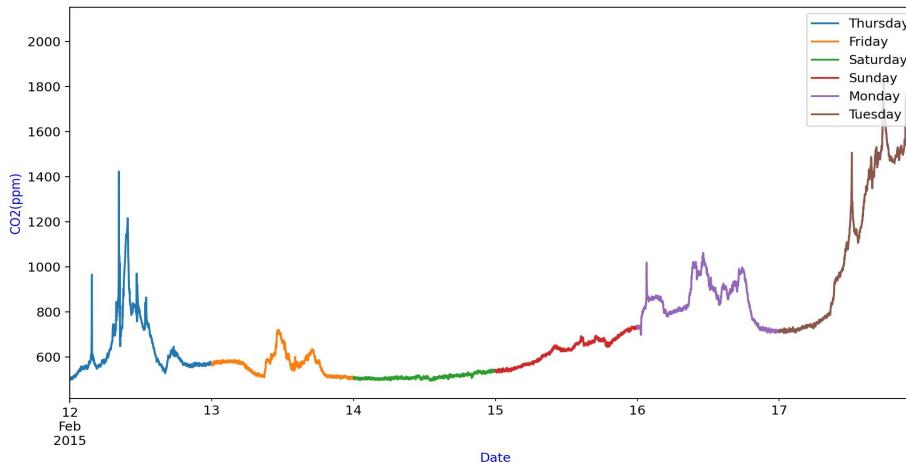
Light measurements Thur 02/12 to Tue 02/17



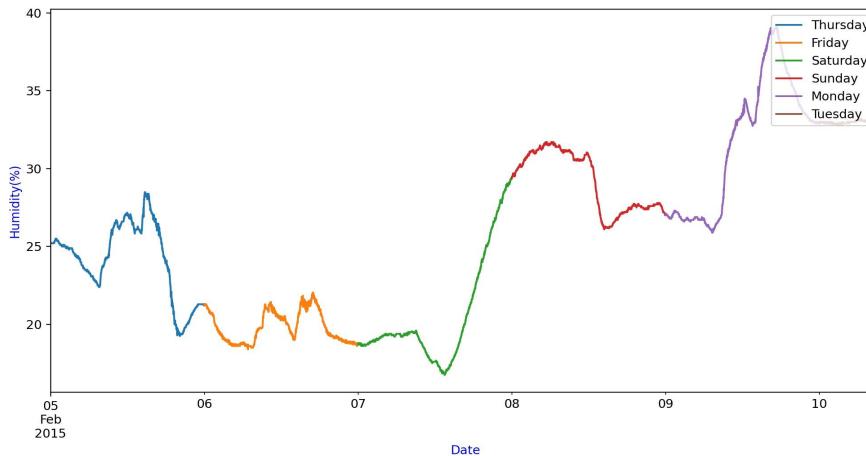
CO₂ measurements Thur 02/05 to Tue 02/10



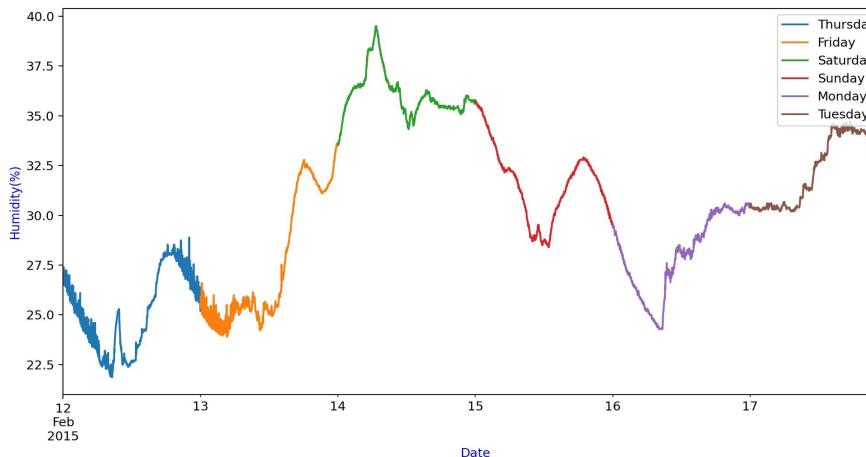
CO₂ measurements Thur 02/12 to Tue 02/17



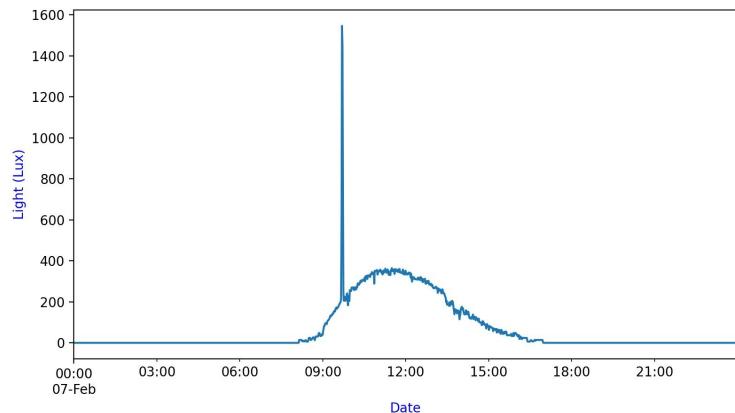
Humidity measurements Thur 02/05 to Tue 02/10



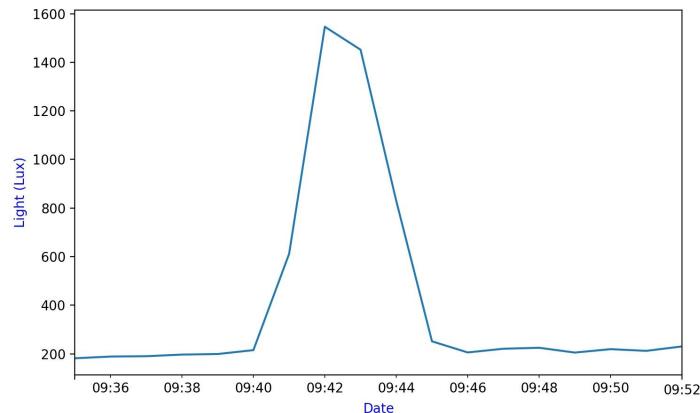
Humidity measurements Thur 02/12 to Tue 02/17



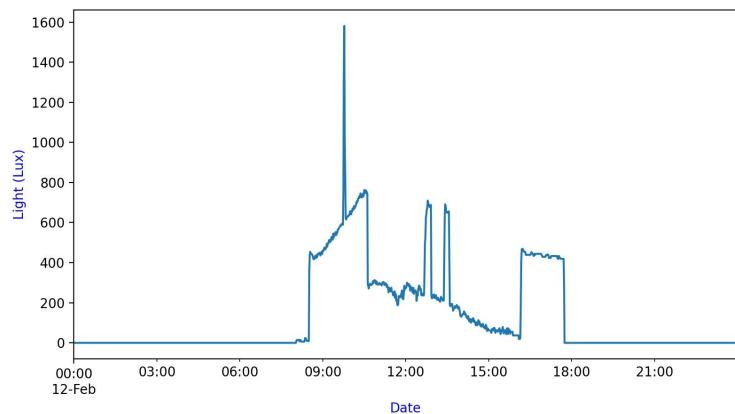
Light measurements on Saturday 2015-02-07



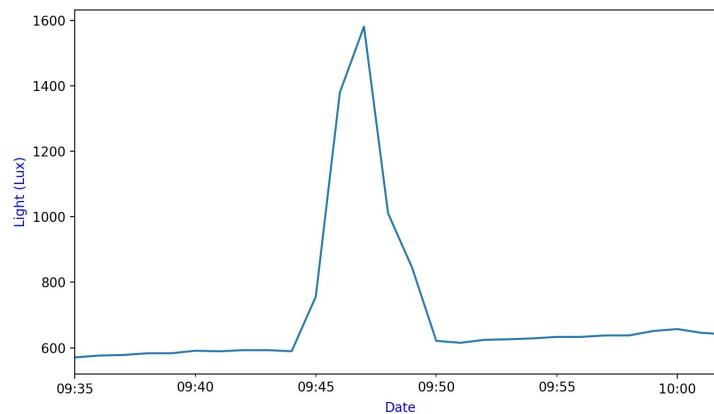
Light measurements on Saturday 2015-02-07 between 9:35am and 9:52am



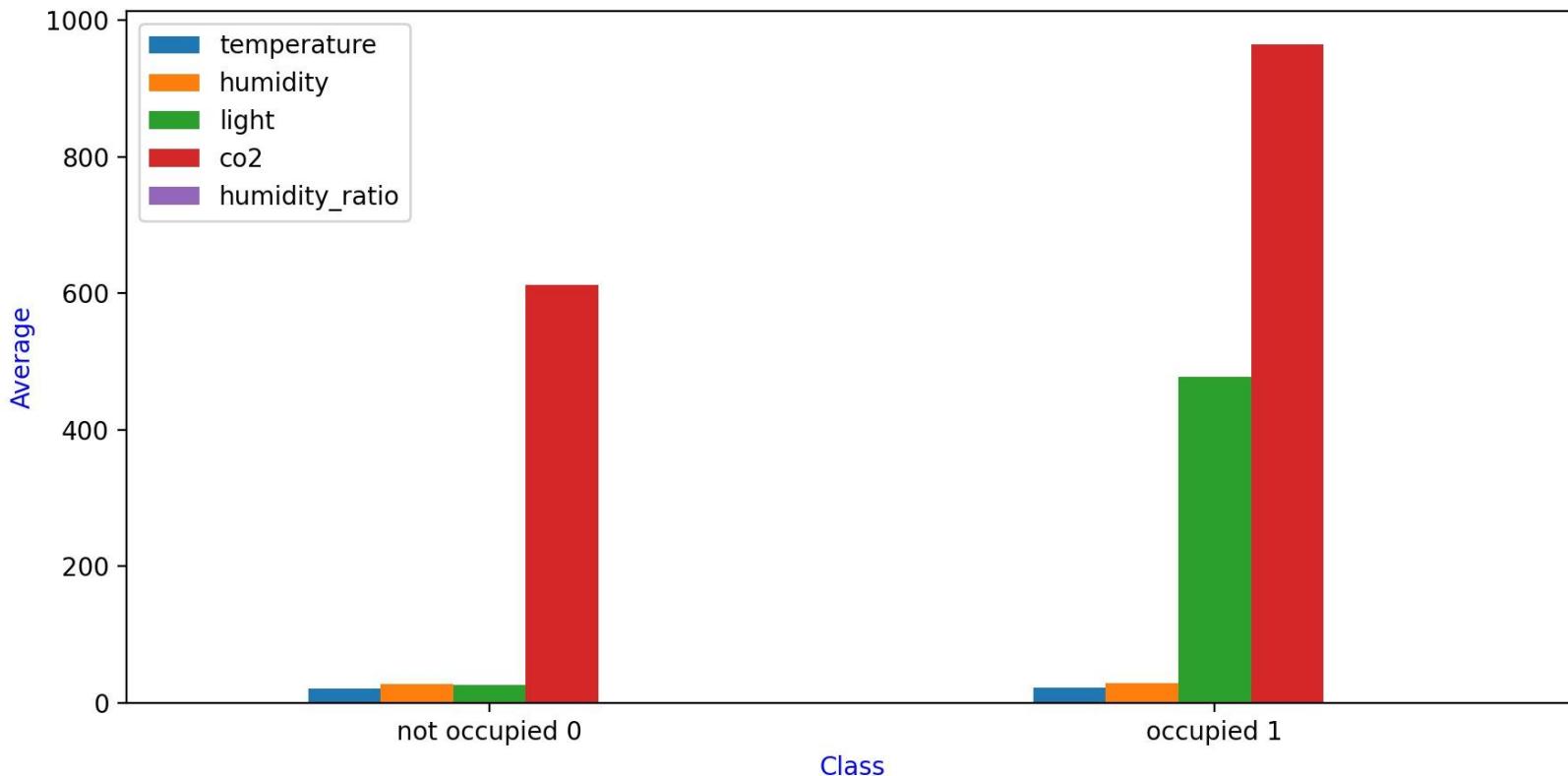
Light measurements on Thursday 2015-02-12

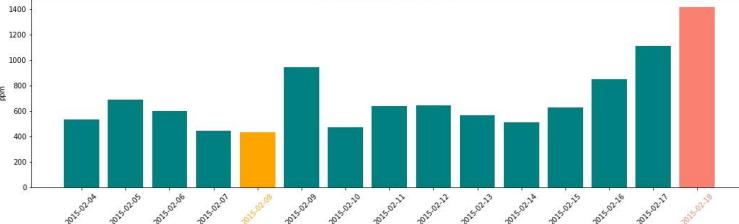
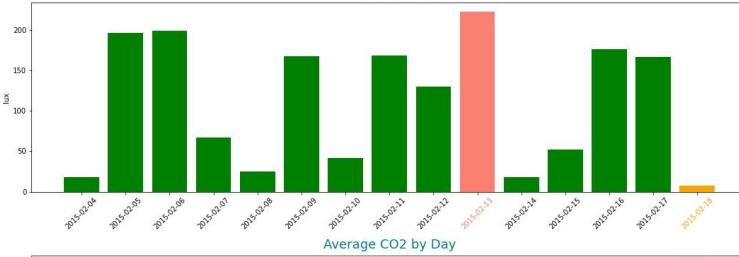
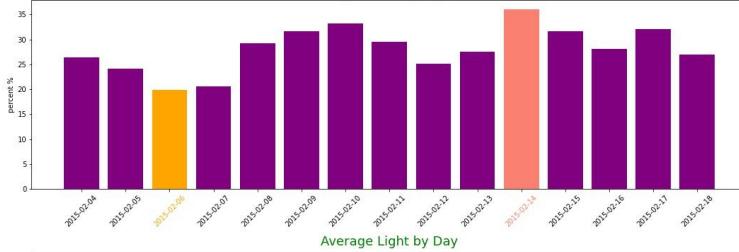
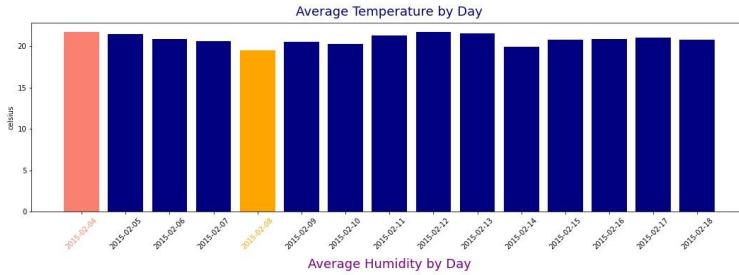


Light measurements on Thursday 2015-02-12 9:35am to 10:02am

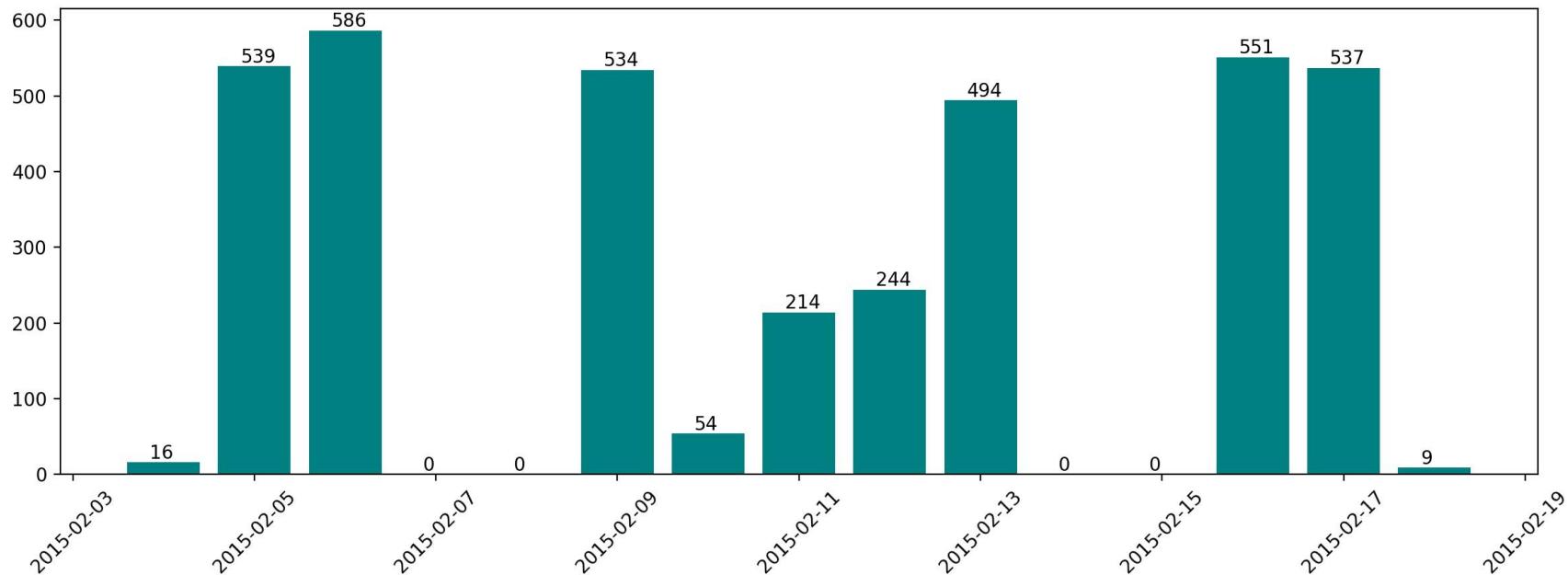


Average measurement values by Class

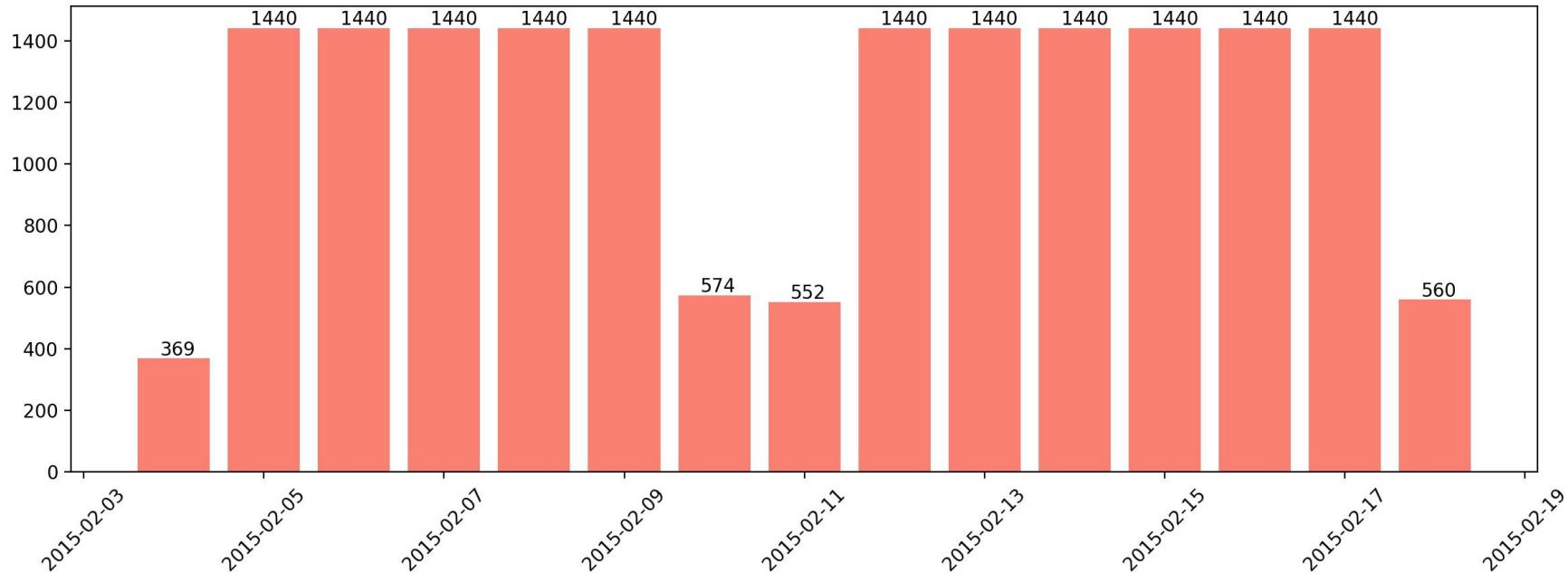




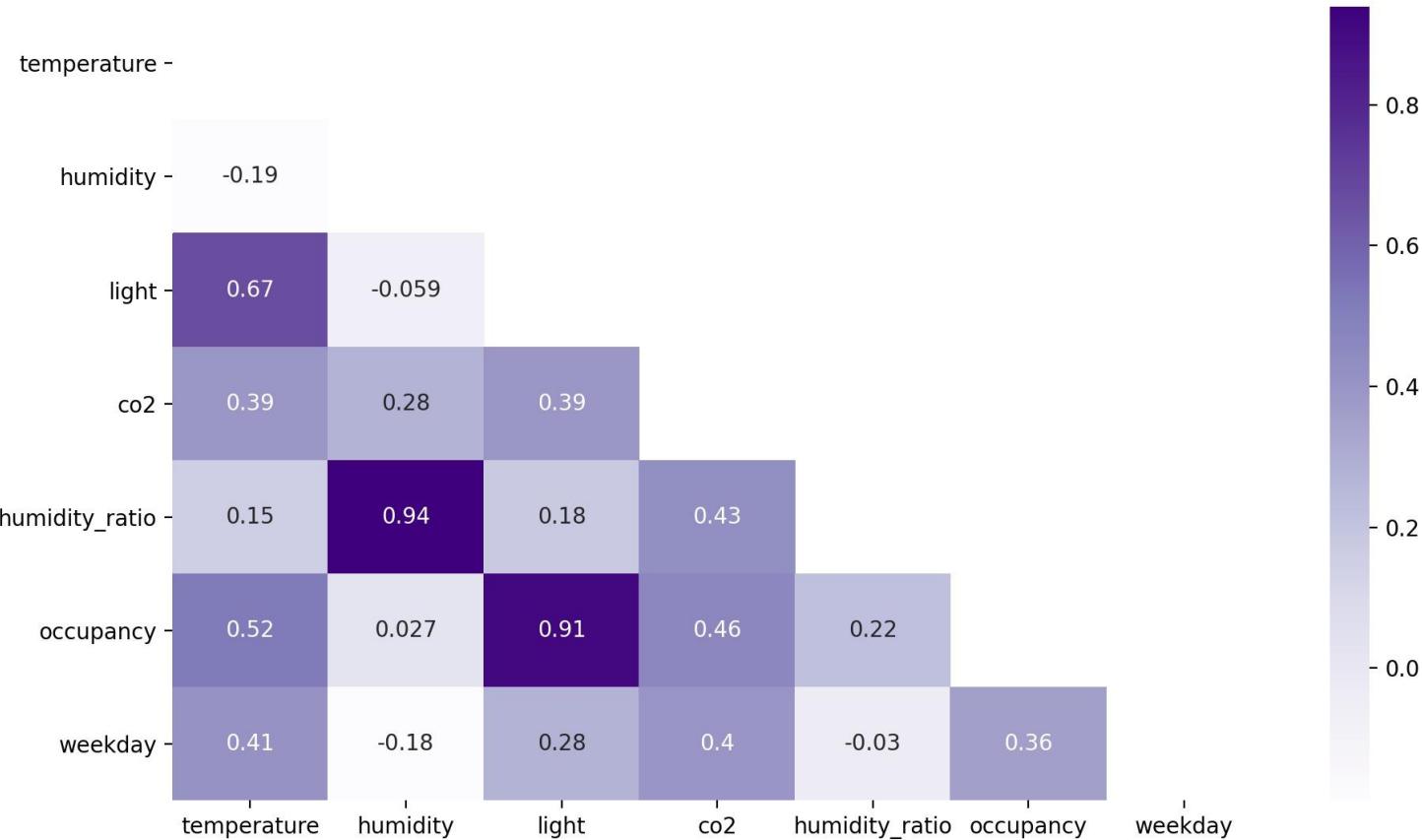
Number of "Occupied" type Observations, by Day



Number of Total Observations, by Day



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.

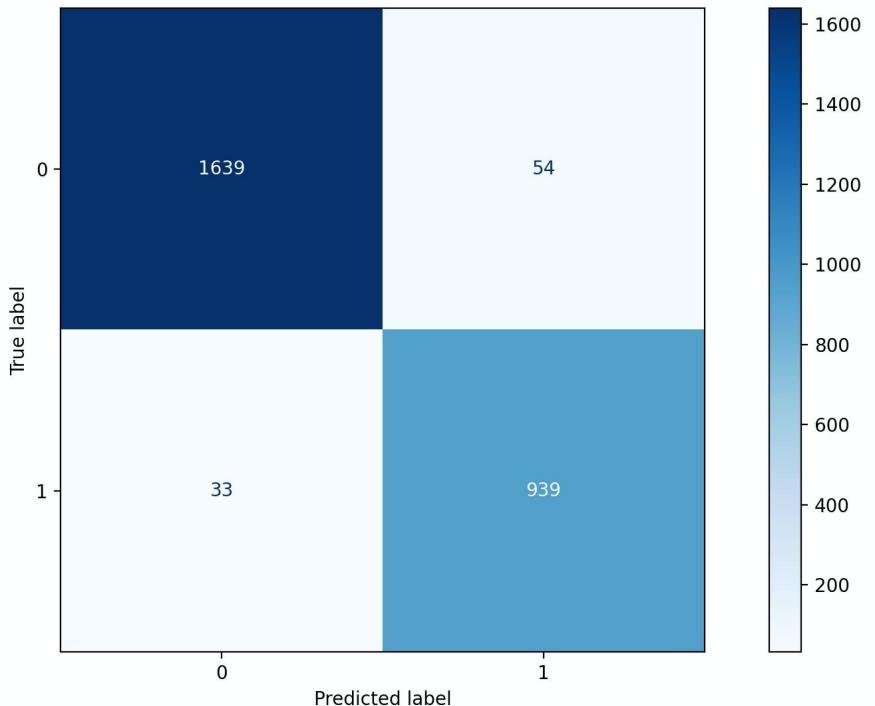
Abbreviation	Meaning
RF	Random Forest
LDA	Linear Discriminant Analysis
GBM	Gradient Boosting Machine
AdaBoost	Adaptive Boosting
KNN	K-Nearest Neighbor
SVC	Support Vector Classification

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

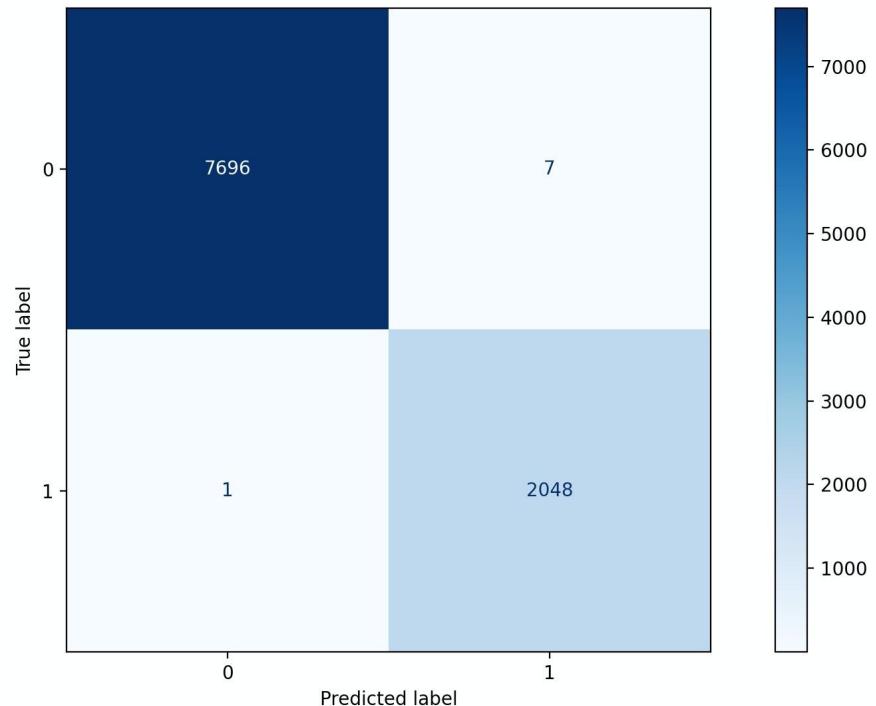
Random Forest

temperature, humidity, light, humidity_ratio, weekday

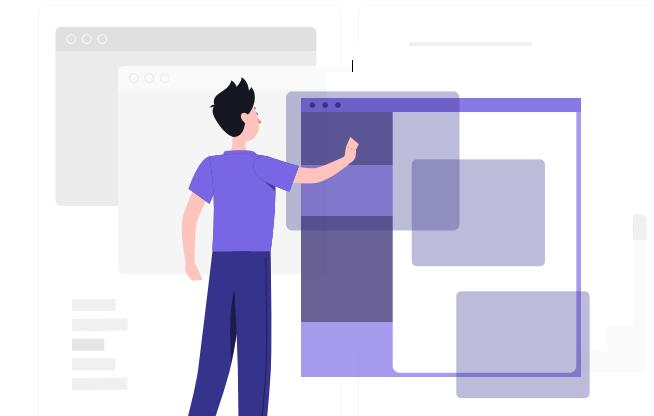
Model rf14, test data test.csv, accuracy 96.74%



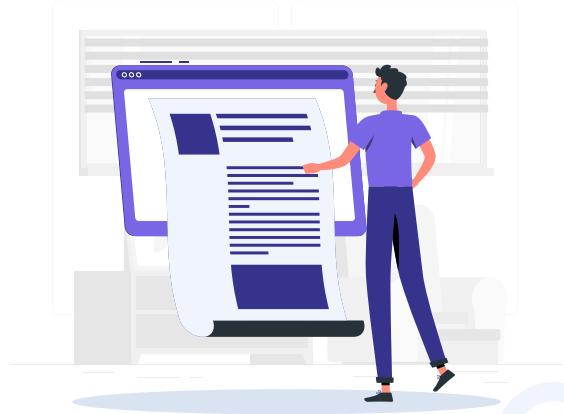
Model rf14, test data test2.csv, accuracy 99.92%



Conclusions



Recommendations



Next Steps



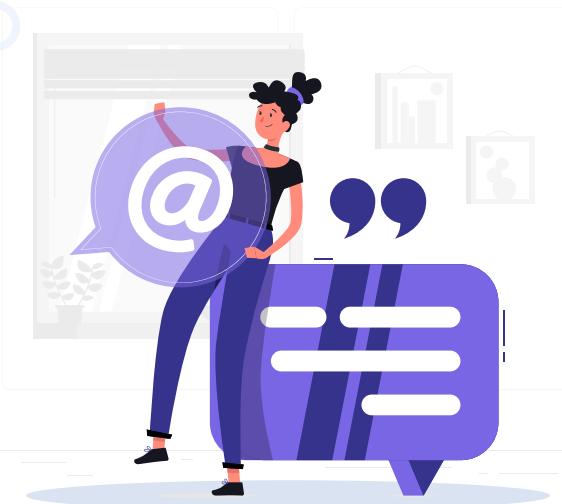
Resources

- (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, Véronique 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-Perpiñán, A.E.Carpa, 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.
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