```python
#importing the libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
import warnings
warnings.filterwarnings('ignore')

#loading the datasets
df1 = pd.read_csv('datatest.csv')
df2 = pd.read_csv('datatraining.csv')

df = pd.concat([df1, df2])
df.head()
```

```
             date  Temperature  Humidity       Light         CO2  \
0  2/2/2015 14:19      23.7000    26.272  585.200000  749.200000
1  2/2/2015 14:19      23.7180    26.290  578.400000  760.400000
2  2/2/2015 14:21      23.7300    26.230  572.666667  769.666667
3  2/2/2015 14:22      23.7225    26.125  493.750000  774.750000
4  2/2/2015 14:23      23.7540    26.200  488.600000  779.000000

   HumidityRatio  Occupancy
0       0.004764          1
1       0.004773          1
2       0.004765          1
3       0.004744          1
4       0.004767          1
```

Some Numerical Information about the Data

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10808 entries, 0 to 8142
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           10808 non-null  object
 1   Temperature    10808 non-null  float64
 2   Humidity       10808 non-null  float64
 3   Light          10808 non-null  float64
 4   CO2            10808 non-null  float64
 5   HumidityRatio  10808 non-null  float64
 6   Occupancy      10808 non-null  int64
dtypes: float64(5), int64(1), object(1)
memory usage: 675.5+ KB
```

```python
df.nunique()
```

```
date               8645
Temperature         437
Humidity           1749
Light              1195
CO2                3516
HumidityRatio      5044
Occupancy             2
dtype: int64
```

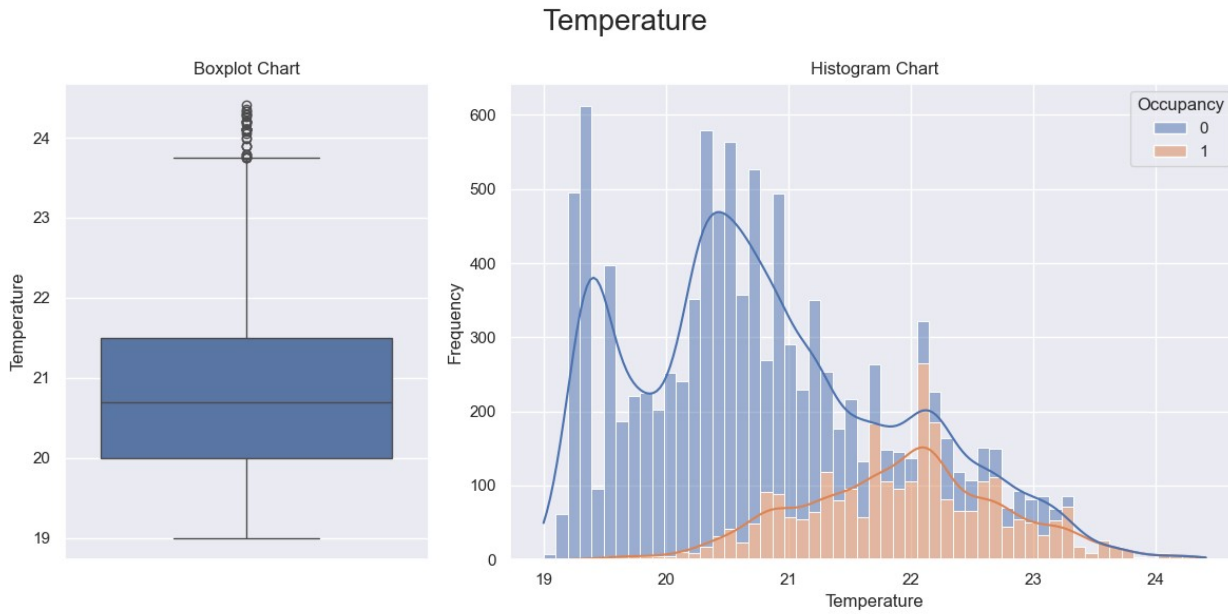
Data Cleaning

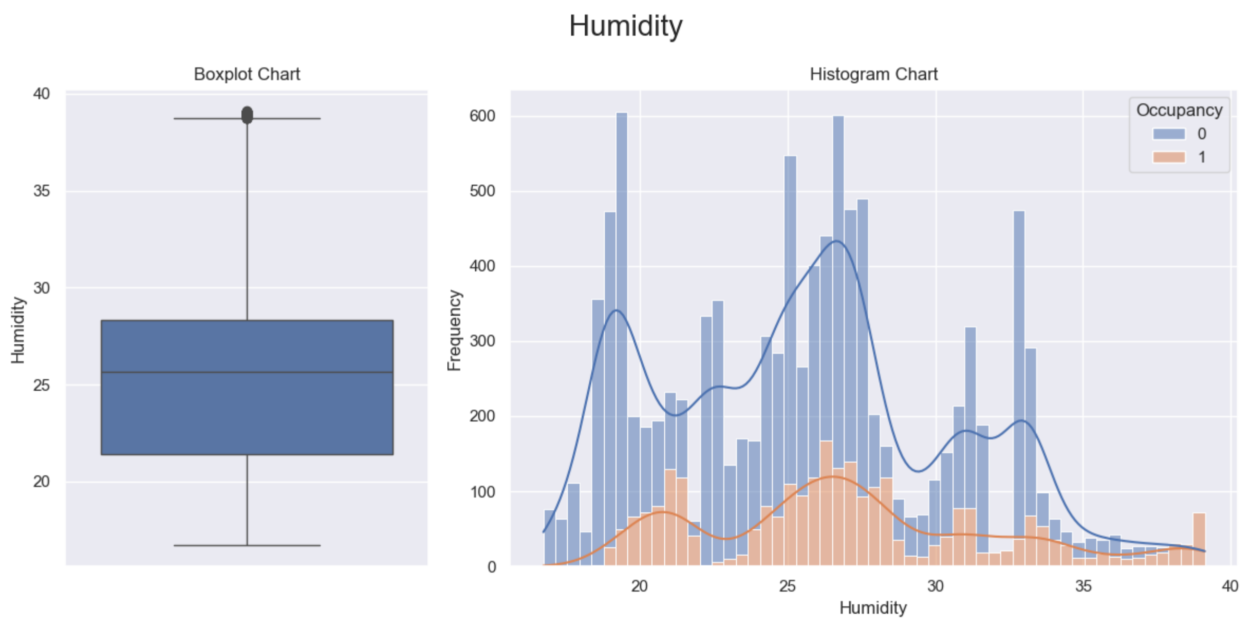
```
#removing the duplicate values
df.drop_duplicates(inplace=True)

# Split time column values into date and time
df['time'] = df['date'].apply(lambda x : x.split()[1])
df['date'] = df['date'].apply(lambda x : x.split()[0])

# Split time column and only save Hour values
df['time'] = df['time'].apply(lambda x : x.split(':')[0])
# Split date column and only save day values
df['date'] = df['date'].apply(lambda x : x.split('/')[1])
```

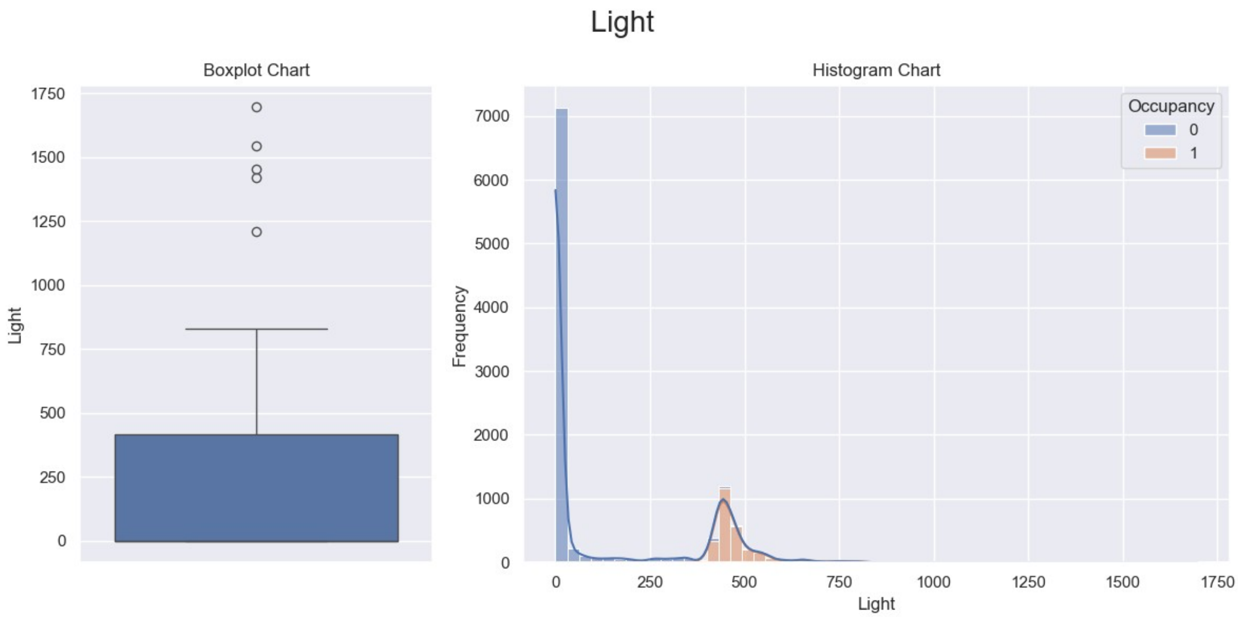
Data Visualization

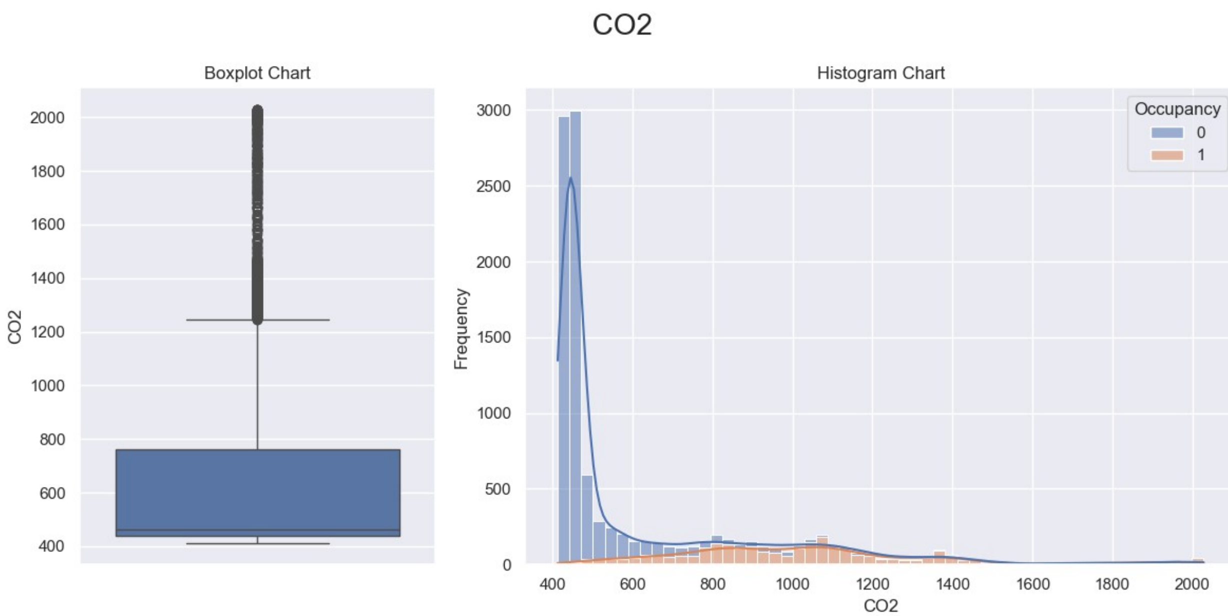
```
# Define list of Continuous columns Names
continuous = ['Temperature', 'Humidity', 'Light', 'CO2',
'HumidityRatio', 'date', 'time']

# Distribution of Categorical Features
def plot_continious_distribution(df, column, hue):

    width_ratios = [2, 4]
    gridspec_kw = {'width_ratios':width_ratios}
    fig, ax = plt.subplots(1, 2, figsize=(12, 6), gridspec_kw =
gridspec_kw)
    fig.suptitle(f' {column} ', fontsize=20)

    sns.boxplot(df[column], ax=ax[0])
    ax[0].set_title('Boxplot Chart')
    ax[0].set_ylabel(column)

    sns.histplot(x = df[column], kde=True, ax=ax[1], hue=df[hue],
multiple = 'stack', bins=55)
    ax[1].set_title('Histogram Chart')
    ax[1].set_ylabel('Frequency')
    ax[1].set_xlabel(column)

    plt.tight_layout()
    plt.show()
```

```
for conti in continuous :
    plot_continious_distribution(df, conti, 'Occupancy')
```

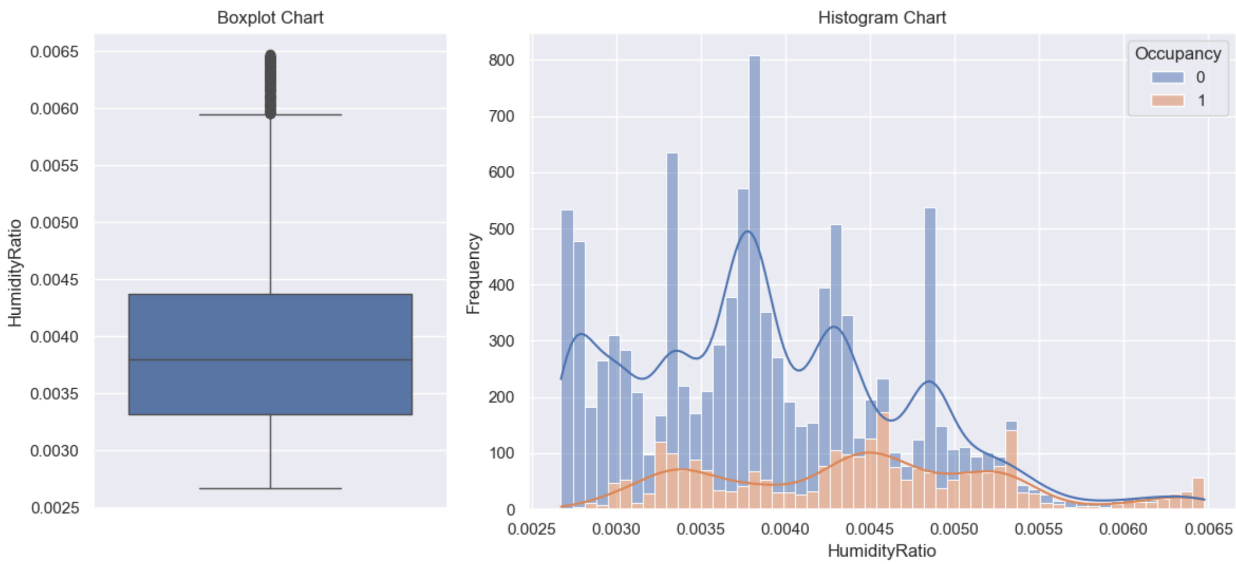




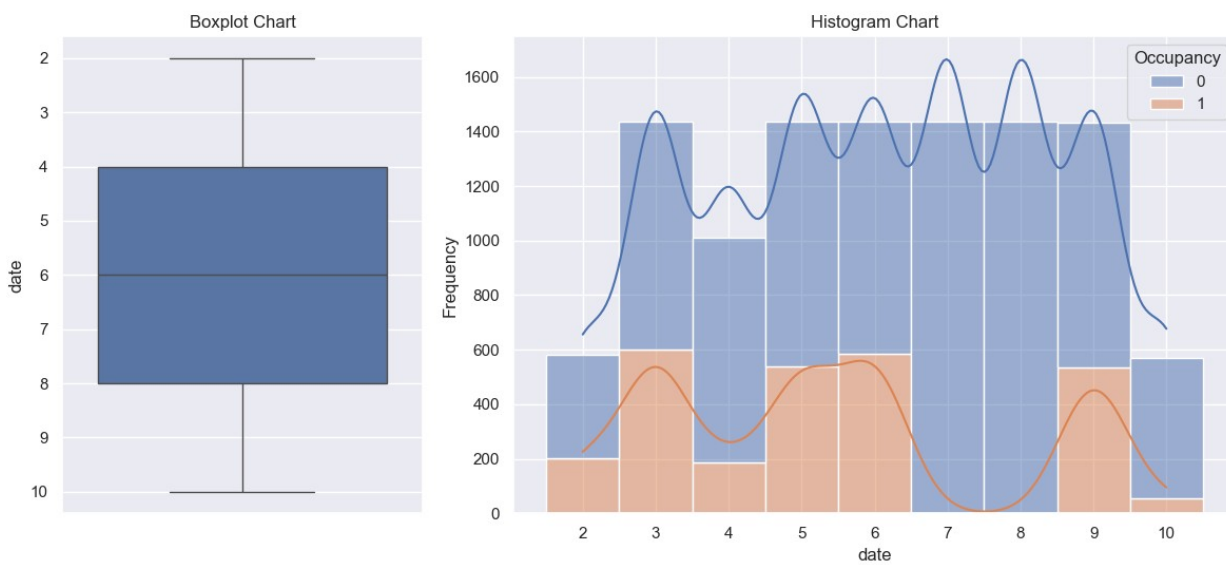

Light
Boxplot Chart
Light
1750
1500
1250
1000
750
500
250
0
Histogram Chart
Frequency
7000
6000
5000
4000
3000
2000
1000
0
0
250
500
750
1000
1250
1500
1750
Light
Occupancy
0
1

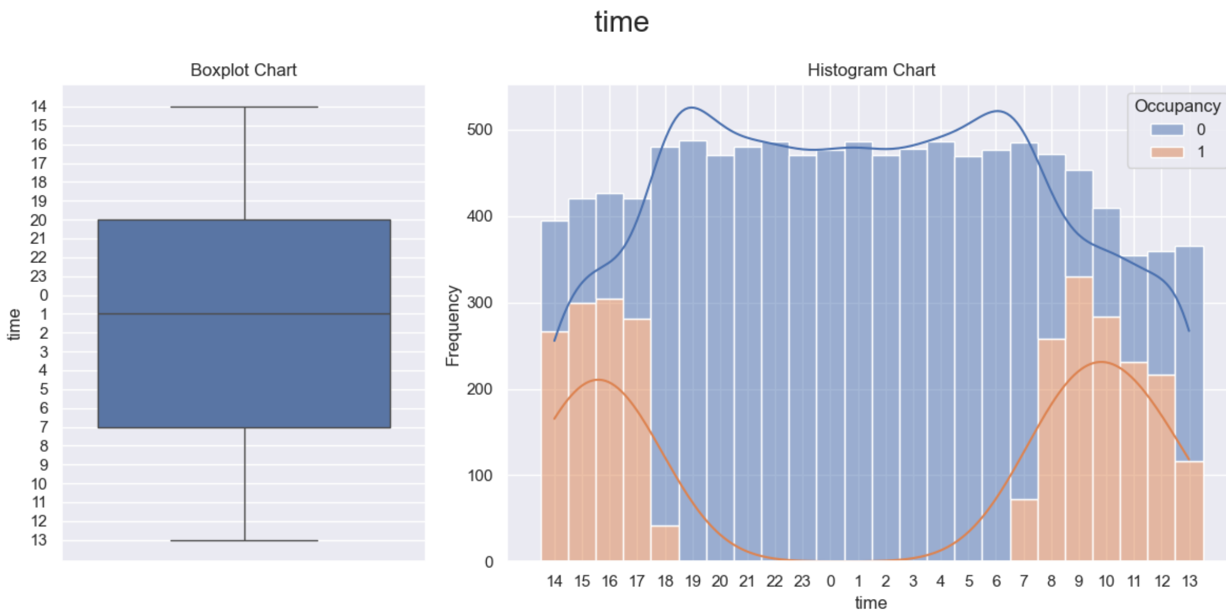

CO2
Boxplot Chart
CO2
2000
1800
1600
1400
1200
1000
800
600
400
Histogram Chart
Frequency
3000
2500
2000
1500
1000
500
0
400
600
800
1000
1200
1400
1600
1800
2000
CO2
Occupancy
0
1

HumidityRatio



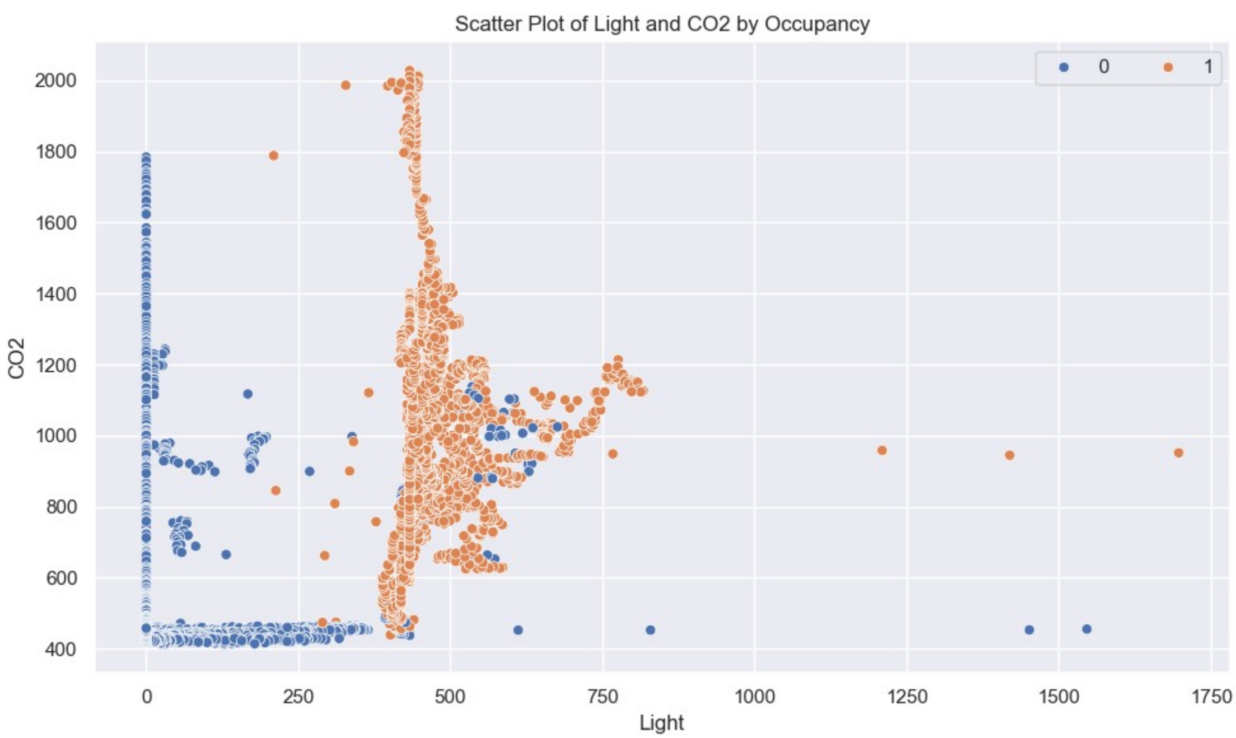
date

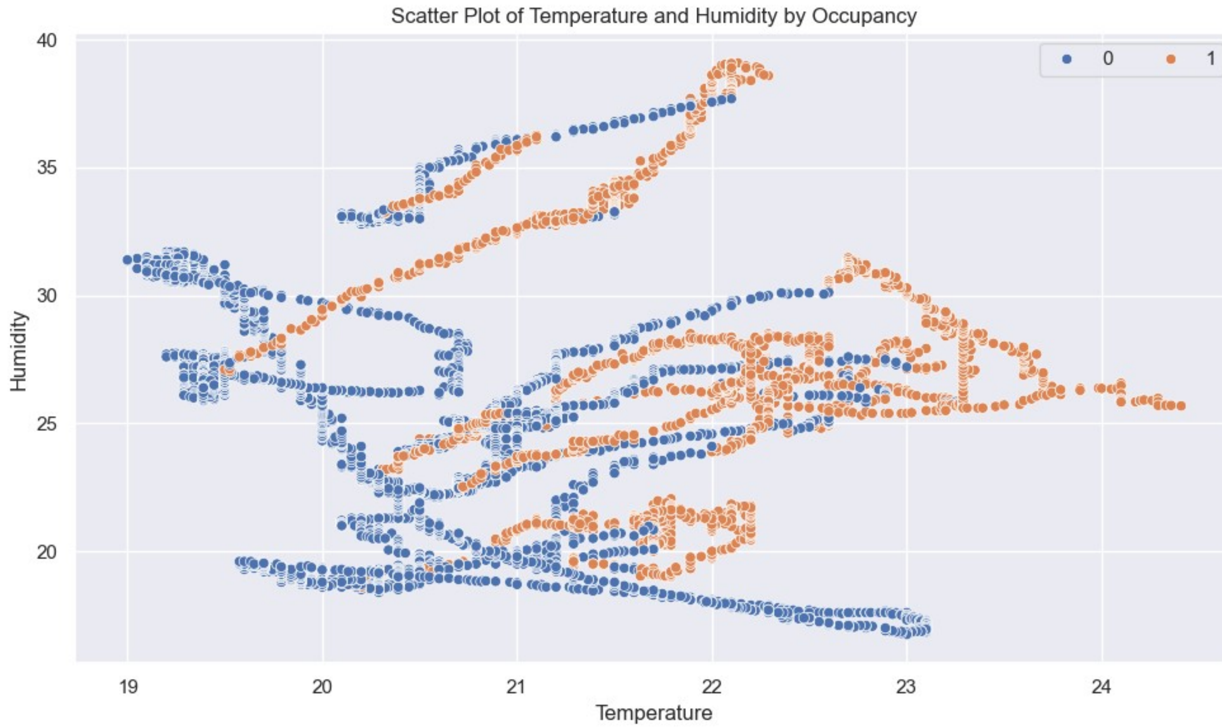


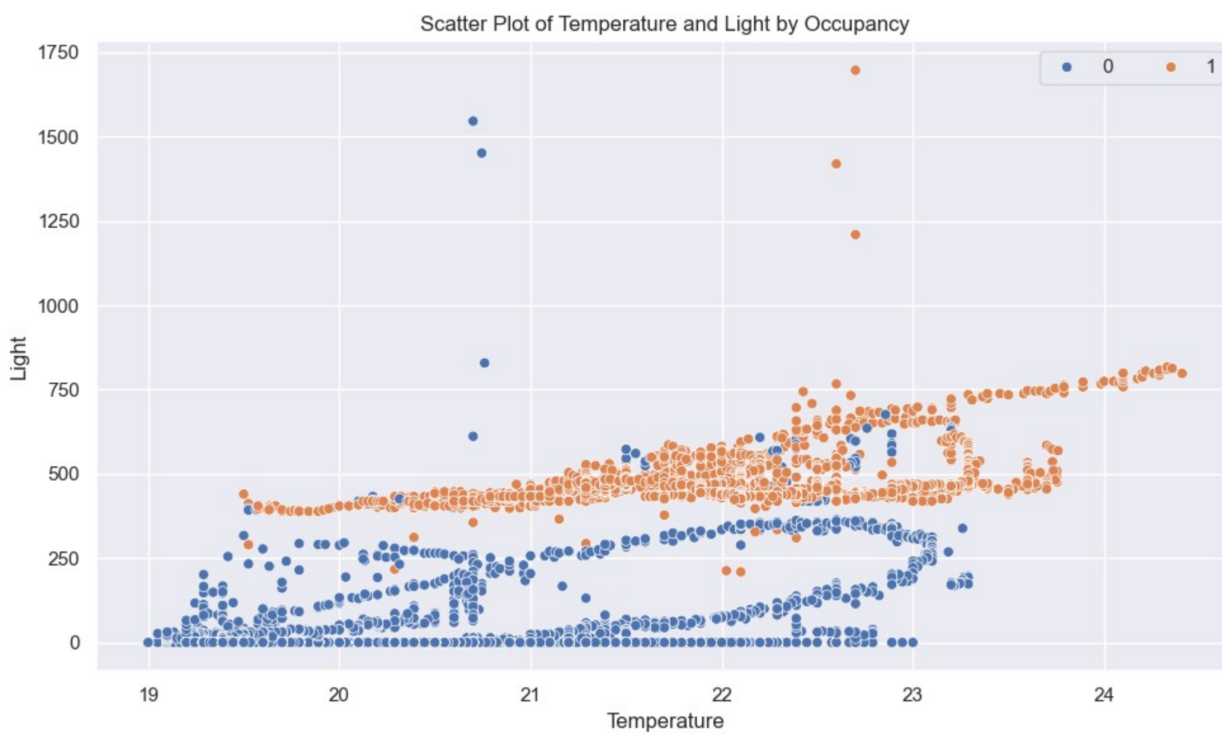



```python
# Define a Function for Scatter Plot
def scatter_plot(data, x, y, hue):
    plt.figure(figsize=(10,6))
    sns.scatterplot(data=data, x=x, y=y, hue=hue)
    plt.title(f'Scatter Plot of {x} and {y} by {hue}')
    plt.xlabel(x)
    plt.ylabel(y)
    plt.legend(title=None, ncol=2, loc='upper right')

    plt.tight_layout()
    plt.show()

scatter_plot(data=df, x="date", y="time", hue="Occupancy")
scatter_plot(data=df, x="Light", y="CO2", hue="Occupancy")
scatter_plot(data=df, x="Temperature", y="Humidity", hue="Occupancy")
scatter_plot(data=df, x="Temperature", y="Light", hue="Occupancy")
```


Scatter Plot of date and time by Occupancy
0
1
time
date
14
15
16
17
18
19
20
21
22
23
0
1
2
3
4
5
6
7
8
9
10
11
12
13
2
3
4
5
6
7
8
9
10


Scatter Plot of Light and CO2 by Occupancy
0
1
CO2
Light
2000
1800
1600
1400
1200
1000
800
600
400
0
250
500
750
1000
1250
1500
1750





Data Preprocessing

```
from sklearn.preprocessing import StandardScaler

# Initialize StandardScaler
```

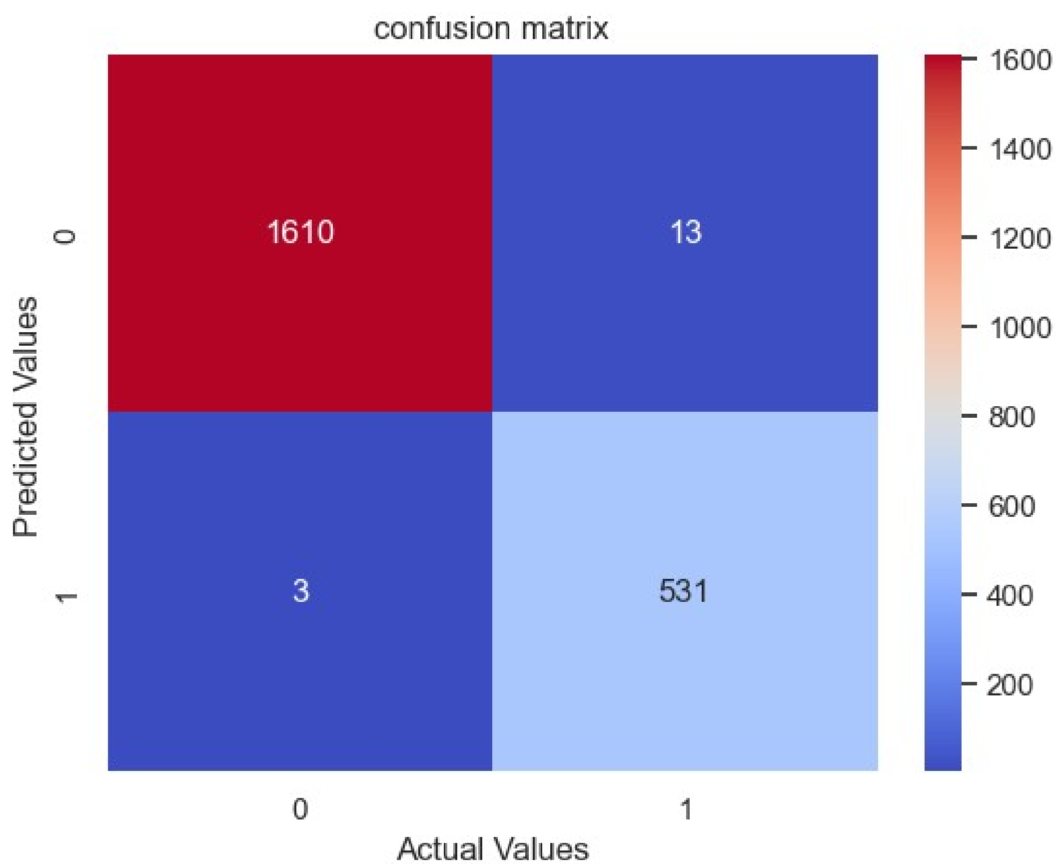
```python
stc = StandardScaler()

stc_cols = ['Temperature', 'Humidity', 'Light', 'CO2',
'HumidityRatio']

# Apply Standard Scaler to the selected columns
df[stc_cols] = stc.fit_transform(df[stc_cols])
```

Training and Evaluating Different Models

```python
from sklearn.model_selection import train_test_split

x = df.drop(['Occupancy'], axis=1)
y = df['Occupancy']  # Target Variable

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)

#Importing the Libraries
from sklearn.ensemble import  GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier

# List of Models to Try
models = [
    ('Decision Tree', DecisionTreeClassifier()),
    ('Random Forest', RandomForestClassifier()),
    ('Gradient Boosting', GradientBoostingClassifier()),
    ('K-Nearest Neighbors', KNeighborsClassifier()),
]

# Train and evaluate each model
for name, model in models:
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    print(f'Training accuracy: {name}', model.score(x_train, y_train))
    print(f'Test accuracy: {name}', accuracy_score(y_test, y_pred))
    print()
```

```
Training accuracy: Decision Tree 1.0
Test accuracy: Decision Tree 0.9911914696337506

Training accuracy: Random Forest 1.0
Test accuracy: Random Forest 0.9925822902178952

Training accuracy: Gradient Boosting 0.9939703153988868
Test accuracy: Gradient Boosting 0.9888734353268428
```

```
Training accuracy: K-Nearest Neighbors 0.9943181818181818
Test accuracy: K-Nearest Neighbors 0.990727862772369


rf = RandomForestClassifier()
rf.fit(x_train, y_train)
rf_pred = rf.predict(x_test)
print(f'Training accuracy: Random Forest', rf.score(x_train, y_train))
print(f'Test accuracy: Random Forest', accuracy_score(y_test,
rf_pred))

Training accuracy: K-Nearest Neighbors 1.0
Test accuracy: K-Nearest Neighbors 0.9925822902178952

# Visualize confusion matrix for Random Forest Classifier
from sklearn.metrics import confusion_matrix, classification_report
sns.heatmap(confusion_matrix(y_test,rf_pred),annot= True, cmap =
'coolwarm', fmt='.0f')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.title('confusion matrix')
plt.show()
```



```
# Visualize Classification report for Random Forest Classifier
from sklearn.metrics import classification_report
print(classification_report(y_test,rf_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1623
           1       0.98      0.99      0.99       534

    accuracy                           0.99      2157
   macro avg       0.99      0.99      0.99      2157
weighted avg       0.99      0.99      0.99      2157
```

Summary and Conclusion

In this project, I focused on predicting room occupancy using various data preprocessing techniques and a machine learning model. The steps and methodologies employed are as follows:

1. Data Cleaning and Feature Engineering:
   - Timestamp Splitting: The original column containing year, month, day, hour, and minute was split into two separate columns: one for day and another for hour.
   - Data Simplification: The day column was adjusted to store only the day value, and the hour column to store only the hour value.
2. Data Visualization:
   - Appropriate visualizations were created to explore and understand the data patterns and relationships. These visualizations provided significant insights into the data.
3. Data Standardization:
   - Data standardization was performed to normalize the features, ensuring consistency and enhancing model performance.
4. Model Training and Evaluation:
   - A Random Forest model was trained on the processed dataset, achieving a remarkably high accuracy of 99%.

These steps ensured a comprehensive analysis and model training process, leading to a highly accurate prediction model for room occupancy detection.

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