ml-group-assignment

November 24, 2024

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import LabelEncoder
import datetime
from sklearn.preprocessing import LabelEncoder
from tqdm import tqdm
import math
from scipy import stats
from scipy.stats import norm
from scipy.special import softmax
from sklearn.metrics import classification_report
import plotly.graph_objects as grp
from  dataclasses import dataclass
import keras
from sklearn.preprocessing import OneHotEncoder
from scipy import optimize
from sklearn.metrics import multilabel_confusion_matrix
import plotly.subplots as sp
import plotly.graph_objects as go
import missingno as msno
from pandas.core.common import random_state
from scipy import optimize
from sklearn import svm
from scipy.optimize import Bounds, minimize
from os import supports_effective_ids
```

[2]:
```
df = pd.read_csv('/content/Occupancy_Estimation.csv')
df = pd.DataFrame(df)
df
```

[2]:
```
          Date      Time  S1_Temp  S2_Temp  S3_Temp  S4_Temp  S1_Light  \
0   2017/12/22  10:49:41    24.94    24.75    24.56    25.38       121
1   2017/12/22  10:50:12    24.94    24.75    24.56    25.44       121
```

```
2      2017/12/22  10:50:42    25.00    24.75    24.50    25.44        121
3      2017/12/22  10:51:13    25.00    24.75    24.56    25.44        121
4      2017/12/22  10:51:44    25.00    24.75    24.56    25.44        121
…          …          …      …      …      …      …      …
10124  2018/01/11  08:58:07    25.06    25.13    24.69    25.31          6
10125  2018/01/11  08:58:37    25.06    25.06    24.69    25.25          6
10126  2018/01/11  08:59:08    25.13    25.06    24.69    25.25          6
10127  2018/01/11  08:59:39    25.13    25.06    24.69    25.25          6
10128  2018/01/11  09:00:09    25.13    25.06    24.69    25.25          6

       S2_Light  S3_Light  S4_Light  S1_Sound  S2_Sound  S3_Sound  S4_Sound  \
0            34        53        40      0.08      0.19      0.06      0.06
1            33        53        40      0.93      0.05      0.06      0.06
2            34        53        40      0.43      0.11      0.08      0.06
3            34        53        40      0.41      0.10      0.10      0.09
4            34        54        40      0.18      0.06      0.06      0.06
…         …         …         …         …         …         …         …
10124         7        33        22      0.09      0.04      0.06      0.08
10125         7        34        22      0.07      0.05      0.05      0.08
10126         7        34        22      0.11      0.05      0.06      0.08
10127         7        34        22      0.08      0.08      0.10      0.08
10128         7        34        22      0.08      0.05      0.06      0.08

       S5_CO2  S5_CO2_Slope  S6_PIR  S7_PIR  Room_Occupancy_Count
0         390      0.769231       0       0                     1
1         390      0.646154       0       0                     1
2         390      0.519231       0       0                     1
3         390      0.388462       0       0                     1
4         390      0.253846       0       0                     1
…        …             …       …      …                    …
10124     345      0.000000       0       0                     0
10125     345      0.000000       0       0                     0
10126     345      0.000000       0       0                     0
10127     345      0.000000       0       0                     0
10128     345      0.000000       0       0                     0

[10129 rows x 19 columns]
```

[3]:
```
num_cols =␣
 ↪['S1_Temp','S2_Temp','S3_Temp','S4_Temp','S1_Light','S2_Light','S3_Light','S4_Light','S1_So
cat_cols = ['S6_PIR','S7_PIR','Room_Occupancy_Count']
```

1 Exploratory Data Analysis

[4]:
```
df.shape
```

[4]:
```
(10129, 19)
```

2 Data types of columns

[5]:
```
df.dtypes
```

[5]:
```
Date                        object
Time                        object
S1_Temp                    float64
S2_Temp                    float64
S3_Temp                    float64
S4_Temp                    float64
S1_Light                     int64
S2_Light                     int64
S3_Light                     int64
S4_Light                     int64
S1_Sound                   float64
S2_Sound                   float64
S3_Sound                   float64
S4_Sound                   float64
S5_CO2                       int64
S5_CO2_Slope               float64
S6_PIR                       int64
S7_PIR                       int64
Room_Occupancy_Count         int64
dtype: object
```

3 Checking for Missing Values

[6]:
```
df.isna().sum()
```

[6]:
```
Date                        0
Time                        0
S1_Temp                     0
S2_Temp                     0
S3_Temp                     0
S4_Temp                     0
S1_Light                    0
S2_Light                    0
S3_Light                    0
S4_Light                    0
```

```
S1_Sound               0
S2_Sound               0
S3_Sound               0
S4_Sound               0
S5_CO2                 0
S5_CO2_Slope           0
S6_PIR                 0
S7_PIR                 0
Room_Occupancy_Count   0
dtype: int64
```

[7]:
```
df.describe()
```

[7]:

	S1_Temp	S2_Temp	S3_Temp	S4_Temp	S1_Light
count	10129.000000	10129.000000	10129.000000	10129.000000	10129.000000
mean	25.454012	25.546059	25.056621	25.754125	25.445059
std	0.351351	0.586325	0.427283	0.356434	51.011264
min	24.940000	24.750000	24.440000	24.940000	0.000000
25%	25.190000	25.190000	24.690000	25.440000	0.000000
50%	25.380000	25.380000	24.940000	25.750000	0.000000
75%	25.630000	25.630000	25.380000	26.000000	12.000000
max	26.380000	29.000000	26.190000	26.560000	165.000000

	S2_Light	S3_Light	S4_Light	S1_Sound	S2_Sound
count	10129.00000	10129.000000	10129.000000	10129.000000	10129.000000
mean	26.01629	34.248494	13.220259	0.168178	0.120066
std	67.30417	58.400744	19.602219	0.316709	0.266503
min	0.00000	0.000000	0.000000	0.060000	0.040000
25%	0.00000	0.000000	0.000000	0.070000	0.050000
50%	0.00000	0.000000	0.000000	0.080000	0.050000
75%	14.00000	50.000000	22.000000	0.080000	0.060000
max	258.00000	280.000000	74.000000	3.880000	3.440000

	S3_Sound	S4_Sound	S5_CO2	S5_CO2_Slope	S6_PIR
count	10129.000000	10129.000000	10129.000000	10129.000000	10129.000000
mean	0.158119	0.103840	460.860401	-0.004830	0.090137
std	0.413637	0.120683	199.964940	1.164990	0.286392
min	0.040000	0.050000	345.000000	-6.296154	0.000000
25%	0.060000	0.060000	355.000000	-0.046154	0.000000
50%	0.060000	0.080000	360.000000	0.000000	0.000000
75%	0.070000	0.100000	465.000000	0.000000	0.000000
max	3.670000	3.400000	1270.000000	8.980769	1.000000

	S7_PIR	Room_Occupancy_Count
count	10129.000000	10129.000000
mean	0.079574	0.398559
std	0.270645	0.893633

```
min         0.000000            0.000000
25%         0.000000            0.000000
50%         0.000000            0.000000
75%         0.000000            0.000000
max         1.000000            3.000000
```

4 Unique values in each column

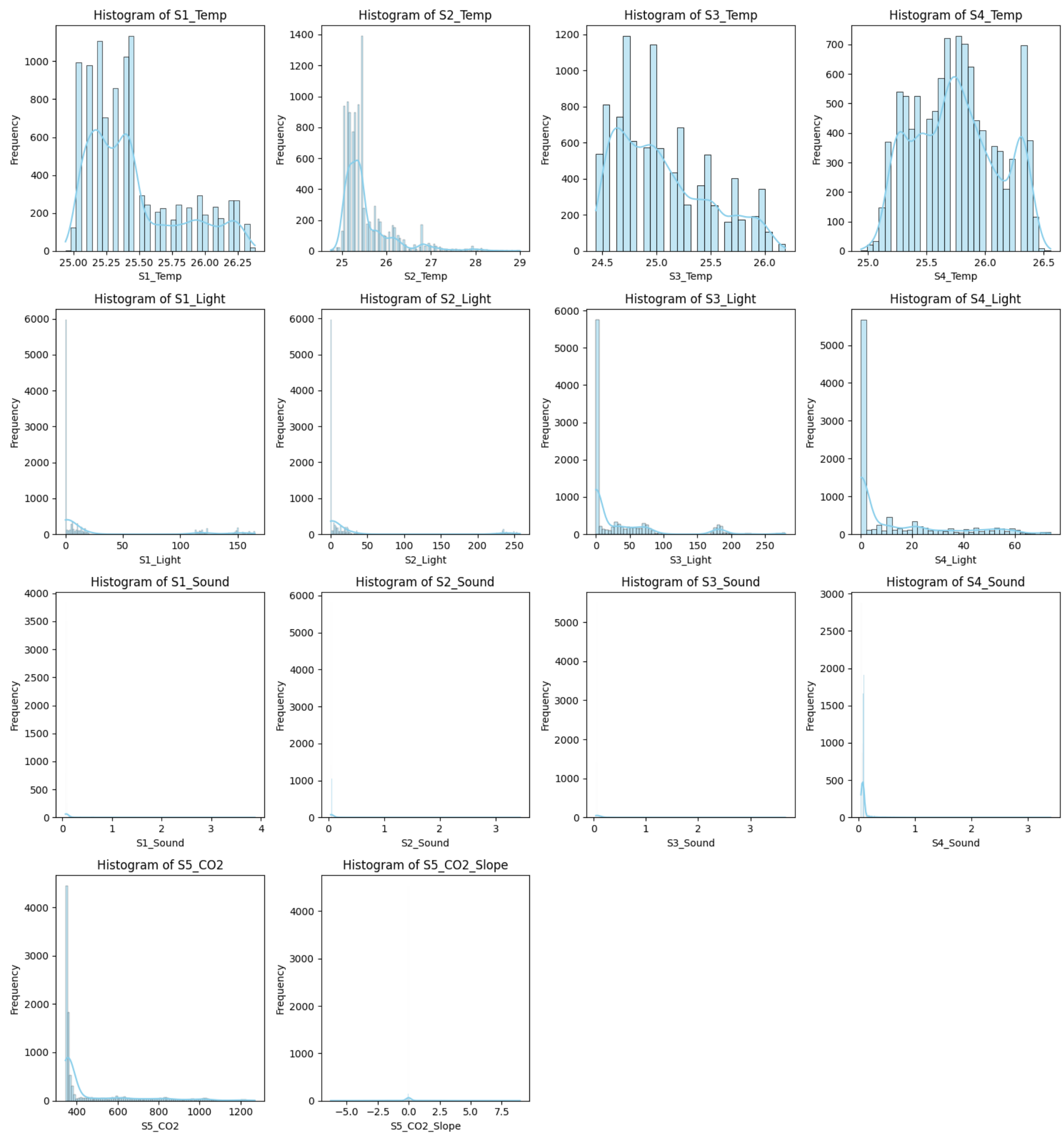
[8]:
```python
df.nunique()
```

[8]:
```
Date                        7
Time                    10129
S1_Temp                    24
S2_Temp                    69
S3_Temp                    29
S4_Temp                    27
S1_Light                   68
S2_Light                   82
S3_Light                  177
S4_Light                   75
S1_Sound                  231
S2_Sound                  185
S3_Sound                  258
S4_Sound                  106
S5_CO2                    186
S5_CO2_Slope             1579
S6_PIR                      2
S7_PIR                      2
Room_Occupancy_Count        4
dtype: int64
```

5 Histograms

[32]:
```python
# Set the number of rows and columns for the plot grid
num_plots = len(num_cols)
cols = 4  # Number of columns in the grid
rows = math.ceil(num_plots / cols)  # Number of rows

# Create a grid of subplots
fig, axes = plt.subplots(rows, cols, figsize=(15, rows * 4))
axes = axes.flatten()  # Flatten the grid to easily iterate over

# Plot each histogram
for i, col in enumerate(num_cols):
    sns.histplot(df[col], kde=True, ax=axes[i], color="skyblue")
```

```
    axes[i].set_title(f'Histogram of {col}')
    axes[i].set_xlabel(col)
    axes[i].set_ylabel('Frequency')

# Turn off unused subplots
for j in range(i + 1, len(axes)):
    axes[j].axis('off')

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



6 Checking for Duplicates

[10]:
```
duplicates = df[df.duplicated()]
print(f"Number of duplicate rows: {len(duplicates)}")
```

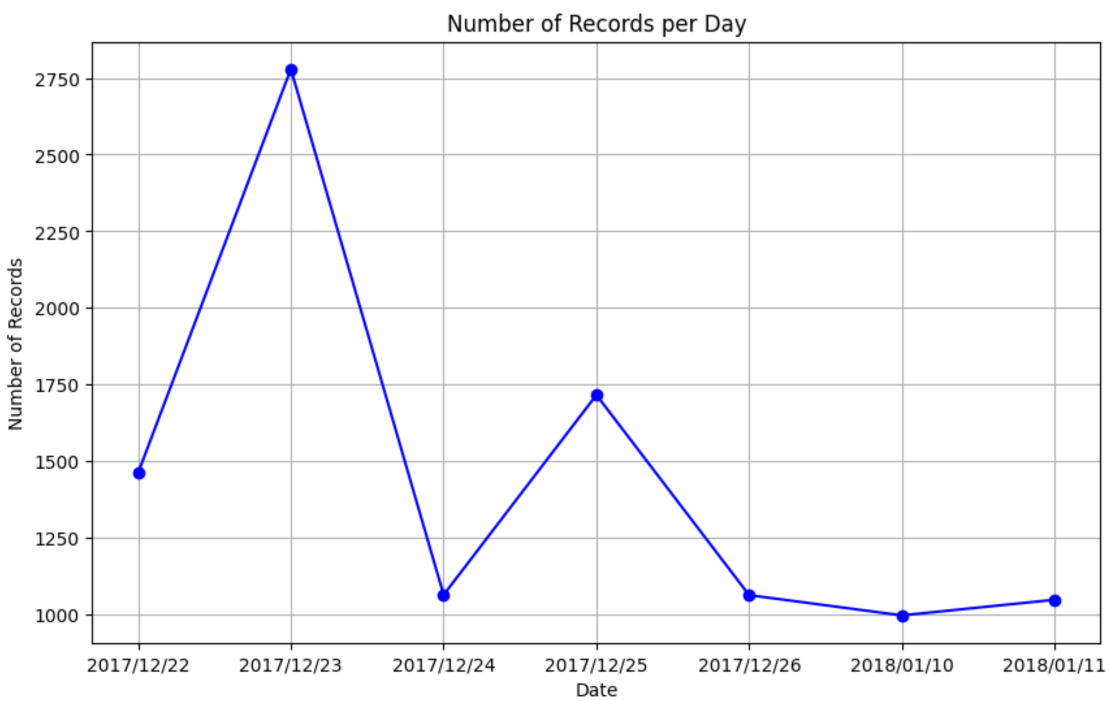
```
Number of duplicate rows: 0
```

7 Seasonality check

[11]:
```
df['Date'].unique()
```

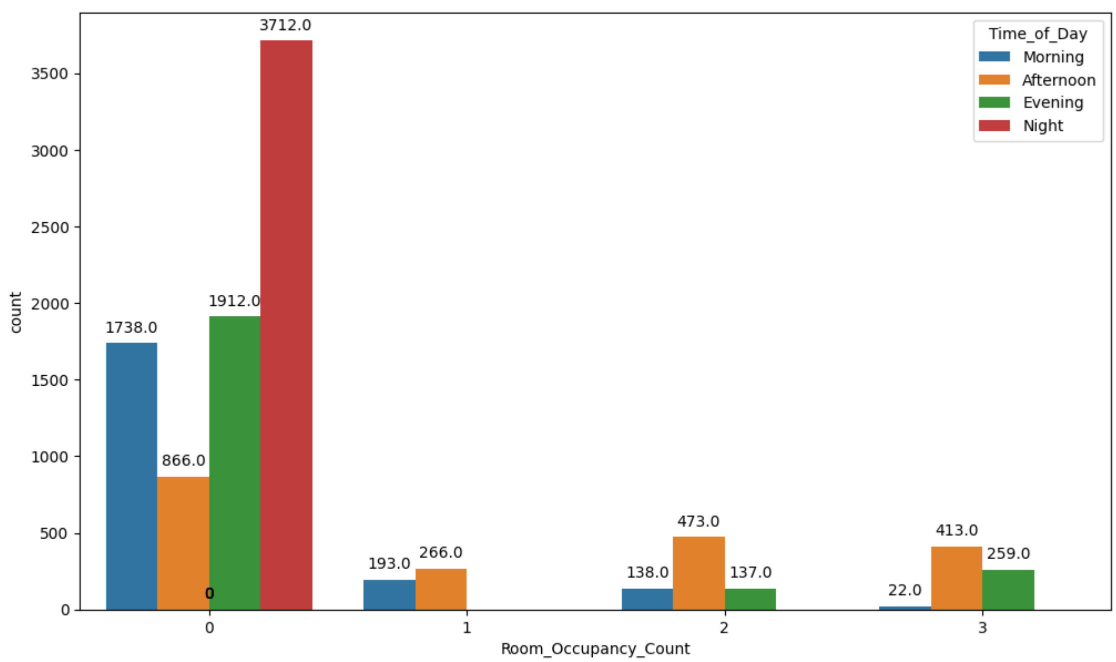
[11]:
```
array(['2017/12/22', '2017/12/23', '2017/12/24', '2017/12/25',
       '2017/12/26', '2018/01/10', '2018/01/11'], dtype=object)
```

[12]:
```
# Group by date and count the number of records for each day
daily_counts = df.groupby('Date').size().reset_index(name='count')
# Plotting
plt.figure(figsize=(10, 6))
plt.plot(daily_counts['Date'], daily_counts['count'], marker='o',␣
 ↪linestyle='-', color='b')
plt.title('Number of Records per Day')
plt.xlabel('Date')
plt.ylabel('Number of Records')
plt.grid(True)
plt.show()
```



[13]:
```
df['Date_time'] = pd.to_datetime(df['Date'] +' '+ df['Time'])
dt_time = df.pop('Date_time')
df.insert(2, 'Date_time', dt_time)

df['Hours'] = df['Date_time'].dt.hour
df['Time_of_Day'] = pd.cut(df['Hours'], bins = [0,6,12,17,22,24], labels =␣
↪['Night','Morning','Afternoon','Evening','Night'], include_lowest=True,␣
↪ordered = False)

df.pop('Hours')
day_time = df.pop('Time_of_Day')
df.insert(2, 'Time_of_Day', day_time)
```

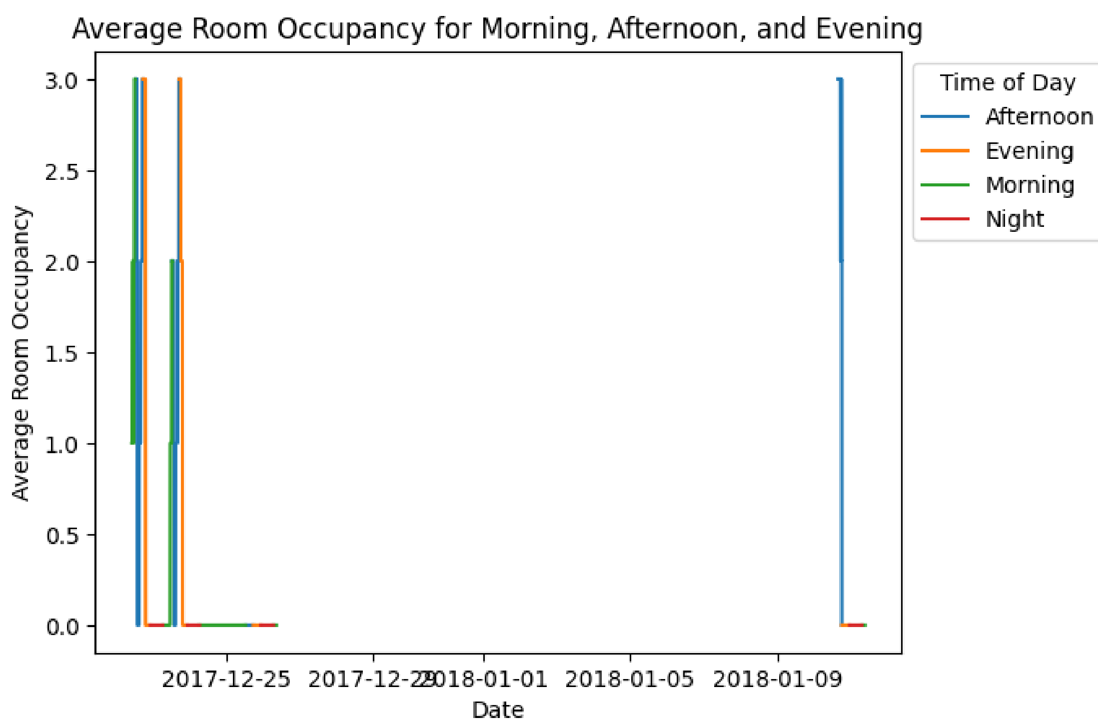
[14]:
```
plt.figure(figsize=(12,7))
ax = sns.countplot(data = df,x = 'Room_Occupancy_Count', hue = 'Time_of_Day',␣
↪hue_order = ['Morning','Afternoon','Evening','Night'])
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.
↪get_height()),
                ha='center', va='center', xytext=(0, 10), textcoords='offset␣
↪points')
plt.show()
```



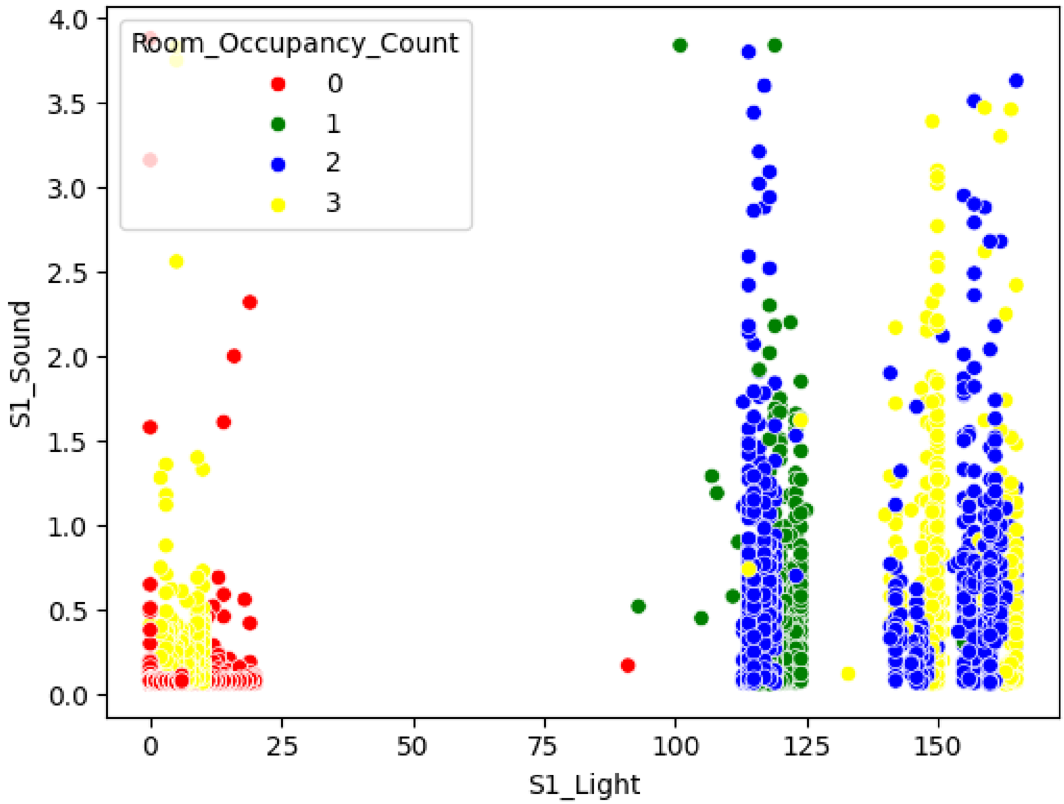
[15]:
```
# Group by date and time_of_day, calculate average room occupancy
avg_occupancy = df.groupby(['Date_time',␣
↪'Time_of_Day'])['Room_Occupancy_Count'].mean().reset_index()

# Pivot the DataFrame for easier plotting
pivot_df = avg_occupancy.pivot(index='Date_time', columns='Time_of_Day',␣
↪values='Room_Occupancy_Count')
```

```
<ipython-input-15-c8f6d6836c4d>:2: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  avg_occupancy = df.groupby(['Date_time',
'Time_of_Day'])['Room_Occupancy_Count'].mean().reset_index()
```

[16]:
```
# Plot lines for each time of day
for time_of_day in pivot_df.columns:
    plt.plot(pivot_df.index, pivot_df[time_of_day], label=time_of_day)

plt.title('Average Room Occupancy for Morning, Afternoon, and Evening')
plt.xlabel('Date')
plt.ylabel('Average Room Occupancy')
plt.legend(title='Time of Day', loc='upper left', bbox_to_anchor=(1, 1))
plt.show()
```

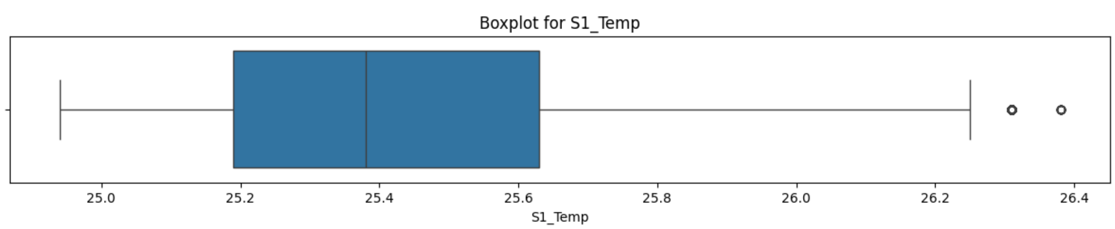


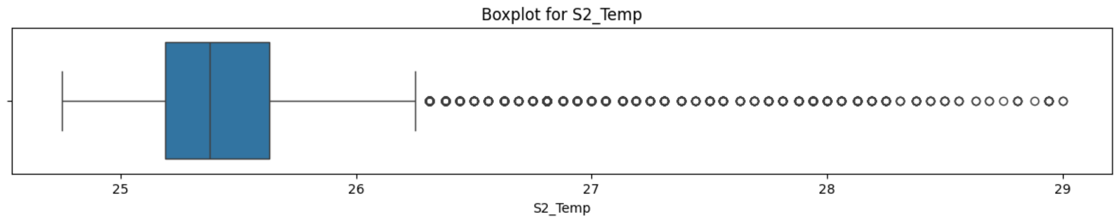
[17]:
```
sns.scatterplot(data = df, x = 'S1_Light', y = 'S1_Sound', hue =␣
 ↪'Room_Occupancy_Count', palette = ['Red','Green','Blue','Yellow'])
plt.show()
```

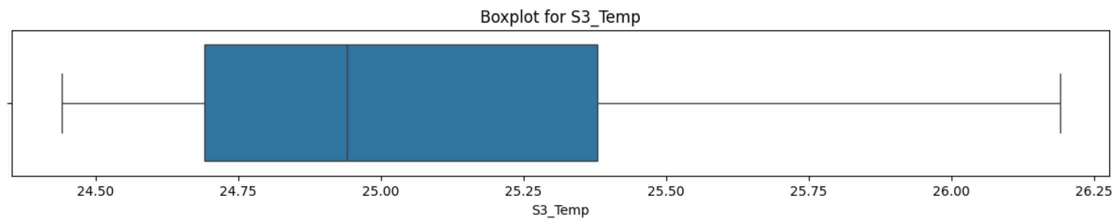


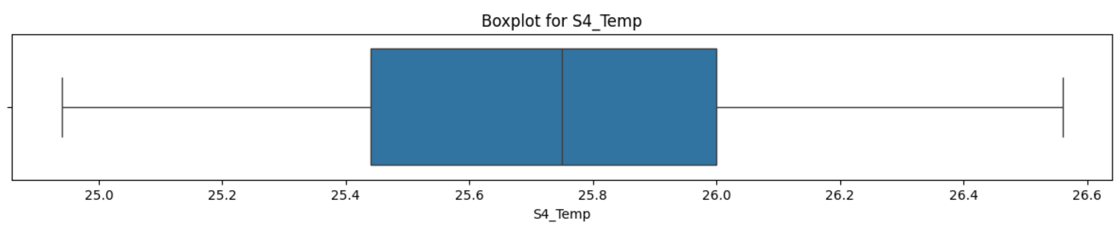
8 Boxplot showing range and outliers for each numerical column

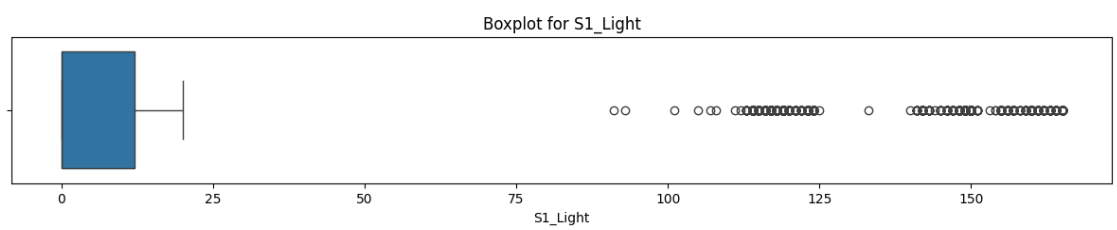
[18]:
```
for i in num_cols:
  plt.figure(figsize=(15,2))
  sns.boxplot(data = df, x = i)
  plt.title('Boxplot for {}'.format(i))
```

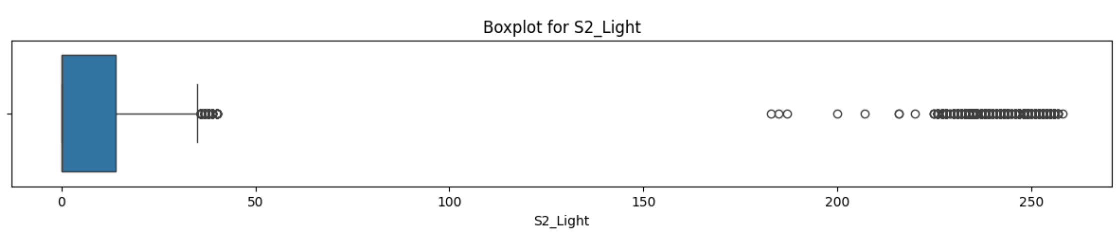


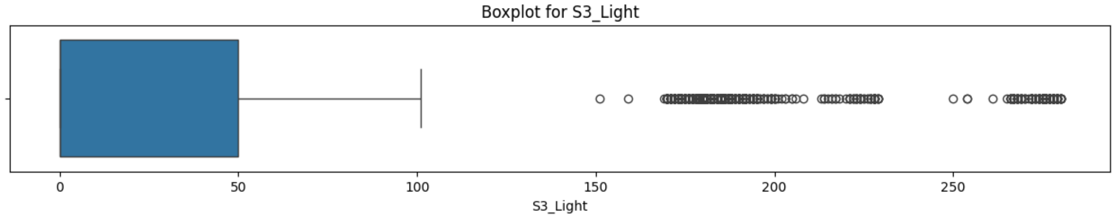

Boxplot for S2_Temp
25
26
27
28
29
S2_Temp

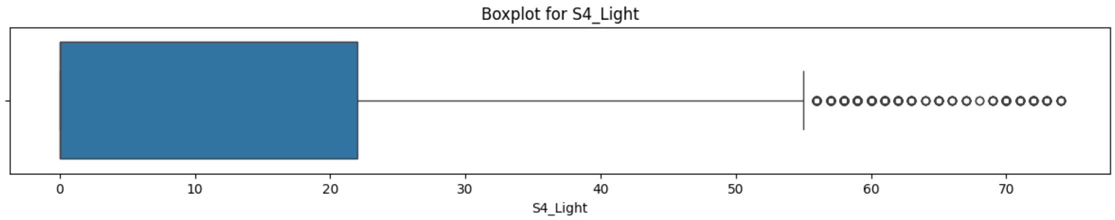

Boxplot for S3_Temp
24.50
24.75
25.00
25.25
25.50
25.75
26.00
26.25
S3_Temp

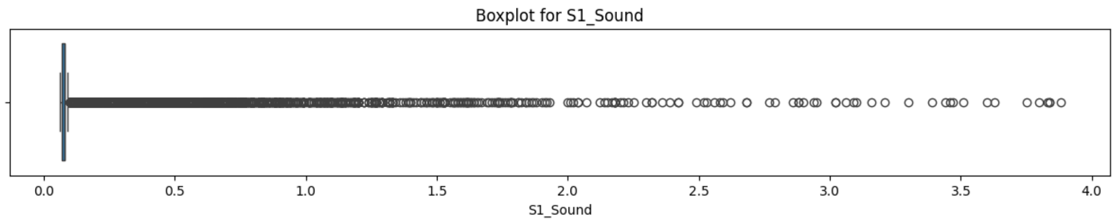

Boxplot for S4_Temp
25.0
25.2
25.4
25.6
25.8
26.0
26.2
26.4
26.6
S4_Temp

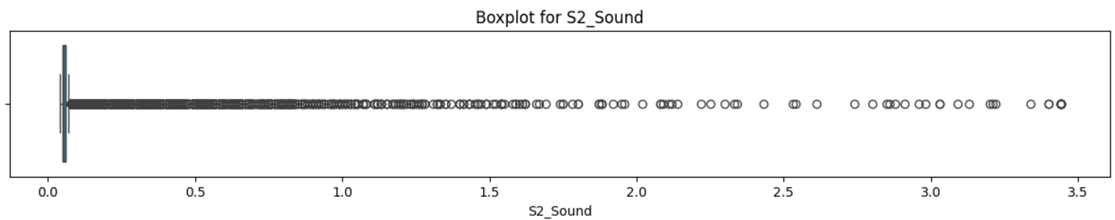

Boxplot for S1_Light
0
25
50
75
100
125
150
S1_Light

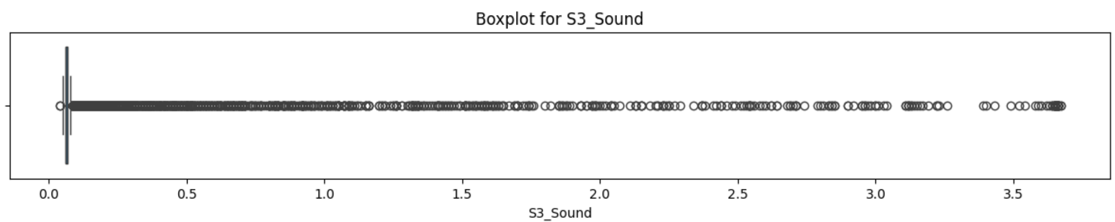

Boxplot for S2_Light
0
50
100
150
200
250
S2_Light

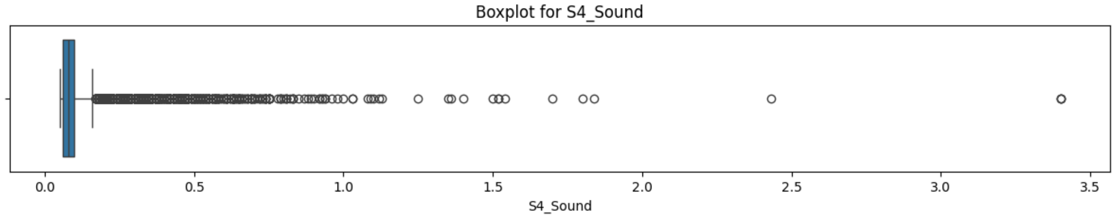

Boxplot for S3_Light
0
50
100
150
200
250
S3_Light

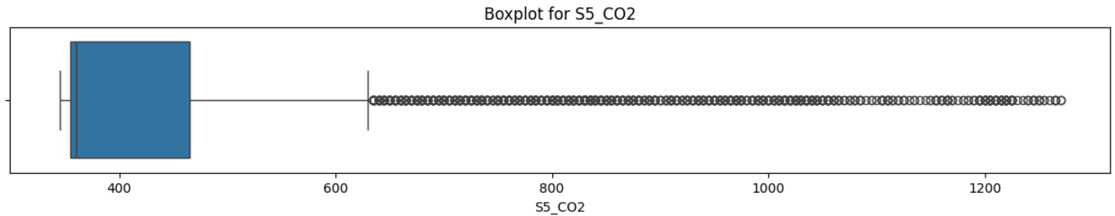

Boxplot for S4_Light
0
10
20
30
40
50
60
70
S4_Light

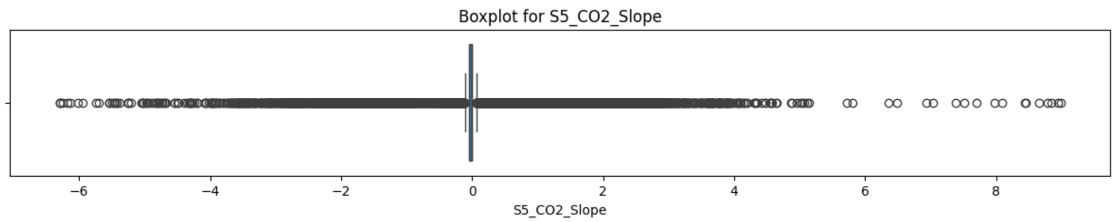

Boxplot for S1_Sound
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
S1_Sound


Boxplot for S2_Sound
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
S2_Sound


Boxplot for S3_Sound
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
S3_Sound

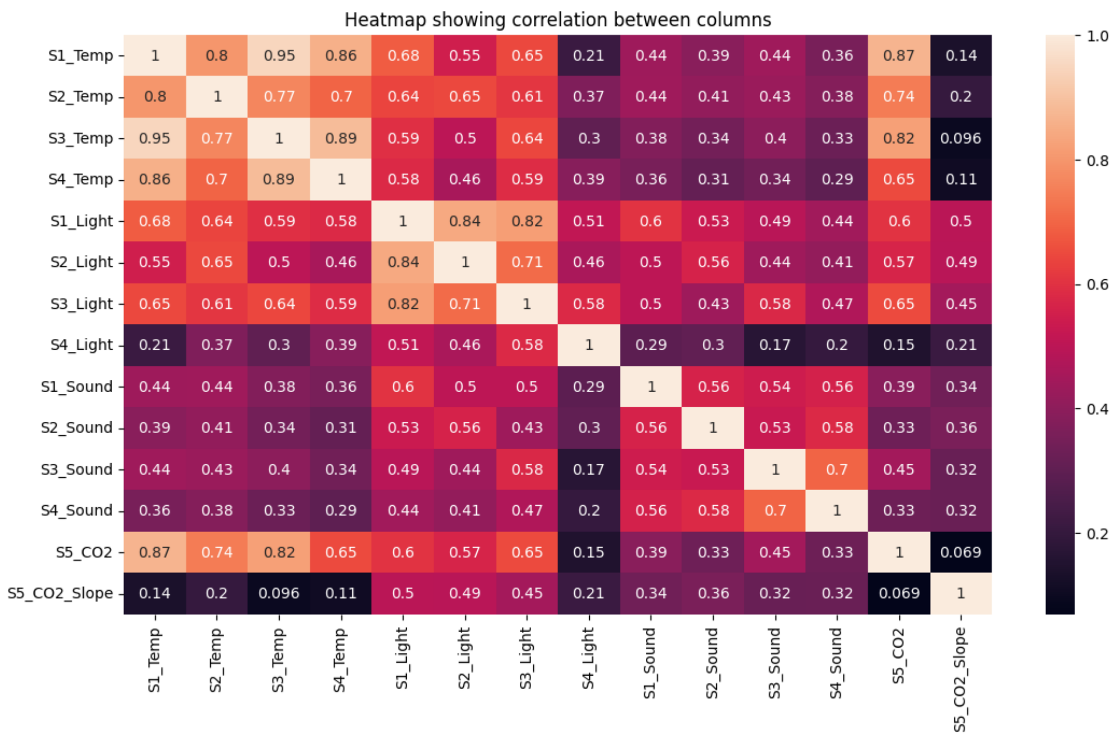






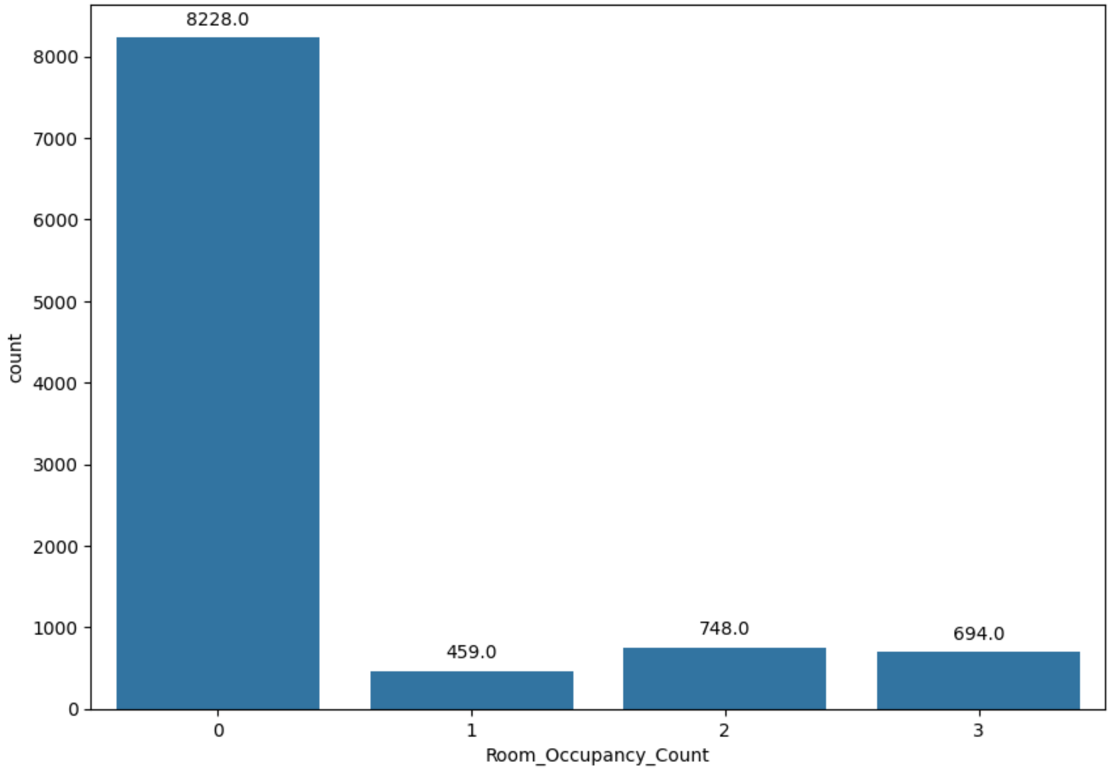
9 Correlation between numerical features

[19]:
```
plt.figure(figsize=(13,7))
sns.heatmap(df[num_cols].corr(),annot = True)
plt.title('Heatmap showing correlation between columns')
plt.show()
```

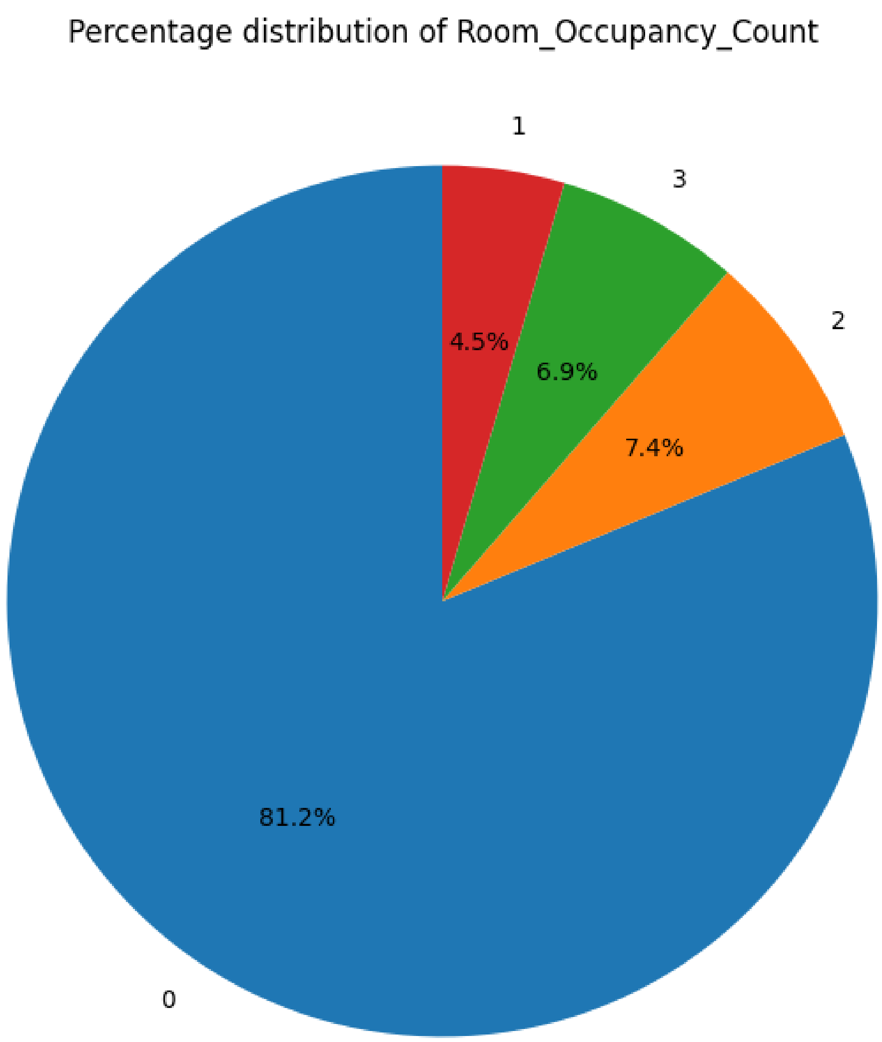


10 Count of Room Occupancy

[20]:
```
plt.figure(figsize=(10,7))
ax = sns.countplot(data = df,x = 'Room_Occupancy_Count')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.
 ↪get_height()),
                ha='center', va='center', xytext=(0, 10), textcoords='offset␣
 ↪points')
plt.show()
```



[21]:
```
value_counts = df['Room_Occupancy_Count'].value_counts()

percentages = (value_counts / value_counts.sum()) * 100

plt.figure(figsize=(8, 8))
plt.pie(percentages, labels=percentages.index, autopct='%1.1f%%', startangle=90)
plt.title('Percentage distribution of Room_Occupancy_Count')
plt.show()
```



11 Data Pre-processing

[22]:
```
label_encoder = LabelEncoder()
df['Time_of_Day'] = label_encoder.fit_transform(df['Time_of_Day'])
```

12 Removing columns with high correlation (> 0.9) and also removing redundant columns

[23]:
```
df1 = df.copy()
```

[24]:
```
df1.
↪drop(columns=['Date','Time','Date_time','S1_Temp','S3_Temp'],axis=1,inplace=True)
```

[25]:
```
df1.head()
```

[25]:
```
   Time_of_Day  S2_Temp  S4_Temp  S1_Light  S2_Light  S3_Light  S4_Light  \
0            2    24.75    25.38       121        34        53        40
1            2    24.75    25.44       121        33        53        40
2            2    24.75    25.44       121        34        53        40
3            2    24.75    25.44       121        34        53        40
4            2    24.75    25.44       121        34        54        40

   S1_Sound  S2_Sound  S3_Sound  S4_Sound  S5_CO2  S5_CO2_Slope  S6_PIR  \
0      0.08      0.19      0.06      0.06     390      0.769231       0
1      0.93      0.05      0.06      0.06     390      0.646154       0
2      0.43      0.11      0.08      0.06     390      0.519231       0
3      0.41      0.10      0.10      0.09     390      0.388462       0
4      0.18      0.06      0.06      0.06     390      0.253846       0

   S7_PIR  Room_Occupancy_Count
0       0                     1
1       0                     1
2       0                     1
3       0                     1
4       0                     1
```

13 Functions for splitting data and standardization

[26]:
```
def split_data(data):

  X = data.loc[:, data.columns!='Room_Occupancy_Count']
  y = data['Room_Occupancy_Count']
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=13, stratify = y)

  X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,␣
↪test_size=0.2, random_state=13, stratify = y_train)

  return X_train, X_val, X_test, y_train, y_val, y_test
```

[27]:
```
def standardize_data(X_train, X_val, X_test):
  mean = np.mean(X_train,axis=0)
  std = np.std(X_train,axis=0)

  X_train = (X_train - mean) / std
  X_val = (X_val - mean) / std
  X_test = (X_test - mean) / std

  return X_train, X_val, X_test
```

14 Handling Class Imbalance

[28]:
```
from imblearn.over_sampling import SMOTE
from collections import Counter

# Split the data first
X_train, X_val, X_test, y_train, y_val, y_test = split_data(df1)

# Apply SMOTE to the training data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

# Check new class distribution
print("Original Class Distribution:", Counter(y_train))
print("Resampled Class Distribution:", Counter(y_train_resampled))

# Standardize the data (optional, after resampling)
X_train_resampled, X_val, X_test = standardize_data(X_train_resampled, X_val,␣
 ↪X_test)
```

```
Original Class Distribution: Counter({0: 5265, 2: 479, 3: 444, 1: 294})
Resampled Class Distribution: Counter({0: 5265, 3: 5265, 2: 5265, 1: 5265})
```

15 Model Selection and Training

[29]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score

# Random Forest
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train_resampled, y_train_resampled)

# Logistic Regression
```

```python
lr_model = LogisticRegression(random_state=42, max_iter=1000)
lr_model.fit(X_train_resampled, y_train_resampled)

# Evaluate on Validation Set
rf_val_preds = rf_model.predict(X_val)
lr_val_preds = lr_model.predict(X_val)

print("Random Forest Validation Performance:")
print(classification_report(y_val, rf_val_preds, digits=6))  # High precision
print("Confusion Matrix:\n", confusion_matrix(y_val, rf_val_preds))

print("Logistic Regression Validation Performance:")
print(classification_report(y_val, lr_val_preds, digits=6))  # High precision
print("Confusion Matrix:\n", confusion_matrix(y_val, lr_val_preds))
```

```
Random Forest Validation Performance:
              precision    recall  f1-score   support

           0   0.999241  1.000000  0.999620      1317
           1   1.000000  1.000000  1.000000        73
           2   0.983471  0.991667  0.987552       120
           3   0.990826  0.972973  0.981818       111

    accuracy                       0.997532      1621
   macro avg   0.993385  0.991160  0.992248      1621
weighted avg   0.997532  0.997532  0.997525      1621

Confusion Matrix:
 [[1317    0    0    0]
 [   0   73    0    0]
 [   0    0  119    1]
 [   1    0    2  108]]
Logistic Regression Validation Performance:
              precision    recall  f1-score   support

           0   1.000000  0.997722  0.998860      1317
           1   1.000000  1.000000  1.000000        73
           2   0.966942  0.975000  0.970954       120
           3   0.946903  0.963964  0.955357       111

    accuracy                       0.993831      1621
   macro avg   0.978461  0.984172  0.981293      1621
weighted avg   0.993917  0.993831  0.993866      1621

Confusion Matrix:
 [[1314    0    0    3]
 [   0   73    0    0]
```

```
[   0    0  117    3]
[   0    0    4  107]]
```

16 Hyperparameter Tuning

[30]:
```python
from sklearn.model_selection import GridSearchCV

# Hyperparameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Grid Search
grid_search = GridSearchCV(estimator=RandomForestClassifier(random_state=42),
                           param_grid=param_grid,
                           cv=3,
                           scoring='accuracy',
                           verbose=2,
                           n_jobs=-1)

grid_search.fit(X_train_resampled, y_train_resampled)

# Best Parameters
print("Best Parameters:", grid_search.best_params_)

# Evaluate on Validation Set
best_rf_model = grid_search.best_estimator_
rf_val_preds_tuned = best_rf_model.predict(X_val)

print("Tuned Random Forest Validation Performance:")
print(classification_report(y_val, rf_val_preds_tuned,digits=6))
```

```
Fitting 3 folds for each of 108 candidates, totalling 324 fits
Best Parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split':
2, 'n_estimators': 200}
Tuned Random Forest Validation Performance:
              precision    recall  f1-score   support

           0   0.999241  1.000000  0.999620      1317
           1   1.000000  1.000000  1.000000        73
           2   0.983471  0.991667  0.987552       120
           3   0.990826  0.972973  0.981818       111

    accuracy                       0.997532      1621
```

```
   macro avg   0.993385  0.991160  0.992248      1621
weighted avg   0.997532  0.997532  0.997525      1621
```

17 Final Evaluation on Test Set

[33]:
```python
# Random Forest Test Performance
rf_test_preds = best_rf_model.predict(X_test)
print("Tuned Random Forest Test Performance:")
print(classification_report(y_test, rf_test_preds,digits=6))
print("Confusion Matrix:\n", confusion_matrix(y_test, rf_test_preds))

# Logistic Regression Test Performance
lr_test_preds = lr_model.predict(X_test)
print("Logistic Regression Test Performance:")
print(classification_report(y_test, lr_test_preds,digits=6))
print("Confusion Matrix:\n", confusion_matrix(y_test, lr_test_preds))
```

```
Tuned Random Forest Test Performance:
              precision    recall  f1-score   support

           0   1.000000  1.000000  1.000000      1646
           1   1.000000  1.000000  1.000000        92
           2   0.993289  0.993289  0.993289       149
           3   0.992806  0.992806  0.992806       139

    accuracy                       0.999013      2026
   macro avg   0.996524  0.996524  0.996524      2026
weighted avg   0.999013  0.999013  0.999013      2026

Confusion Matrix:
 [[1646    0    0    0]
 [   0   92    0    0]
 [   0    0  148    1]
 [   0    0    1  138]]
Logistic Regression Test Performance:
              precision    recall  f1-score   support

           0   1.000000  0.998177  0.999088      1646
           1   1.000000  1.000000  1.000000        92
           2   0.986395  0.973154  0.979730       149
           3   0.951389  0.985612  0.968198       139

    accuracy                       0.995558      2026
   macro avg   0.984446  0.989236  0.986754      2026
weighted avg   0.995664  0.995558  0.995586      2026
```

```
Confusion Matrix:
 [[1643    0    0    3]
 [   0   92    0    0]
 [   0    0  145    4]
 [   0    0    2  137]]
```

18 Comparison

[34]:
```python
import pandas as pd

# Collect Metrics
metrics = {
    'Model': ['Random Forest (Tuned)', 'Logistic Regression'],
    'Accuracy': [
        accuracy_score(y_test, rf_test_preds),
        accuracy_score(y_test, lr_test_preds)
    ],
    'Precision': [
        classification_report(y_test, rf_test_preds,␣
 ↪output_dict=True)['weighted avg']['precision'],
        classification_report(y_test, lr_test_preds,␣
 ↪output_dict=True)['weighted avg']['precision']
    ],
    'Recall': [
        classification_report(y_test, rf_test_preds,␣
 ↪output_dict=True)['weighted avg']['recall'],
        classification_report(y_test, lr_test_preds,␣
 ↪output_dict=True)['weighted avg']['recall']
    ],
    'F1-Score': [
        classification_report(y_test, rf_test_preds,␣
 ↪output_dict=True)['weighted avg']['f1-score'],
        classification_report(y_test, lr_test_preds,␣
 ↪output_dict=True)['weighted avg']['f1-score']
    ]
}

# Display as DataFrame
comparison_df = pd.DataFrame(metrics)
print(comparison_df)
```

```
                   Model  Accuracy  Precision    Recall  F1-Score
0  Random Forest (Tuned)  0.999013   0.999013  0.999013  0.999013
1    Logistic Regression  0.995558   0.995664  0.995558  0.995586
```