In [1]:

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix
import seaborn as sns
```

In [2]:

```
# Read the datasets
weather_data = pd.read_csv('weather_data.csv')
energy_usage_data = pd.read_csv('energy_data.csv')
```

In [3]:

```
# weather_data
(weather_data)
```

Out[3]:

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	time
0	34.98	partly-cloudy-night	0.64	10.00	Partly Cloudy	1017.69	7.75	0.29	1388534400
1	16.49	clear-night	0.62	10.00	Clear	1022.76	2.71	0.06	1388538000
2	14.63	clear-night	0.68	10.00	Clear	1022.32	4.84	0.03	1388541600
3	13.31	clear-night	0.71	10.00	Clear	1021.64	4.00	0.14	1388545200
4	13.57	clear-night	0.71	9.93	Clear	1020.73	3.67	0.04	1388548800
...	...	...	...	...	...	...	...	...	...
8755	27.48	clear-day	0.35	10.00	Clear	1023.54	10.54	0.24	1420052400
8756	27.17	partly-cloudy-day	0.35	10.00	Partly Cloudy	1023.60	9.53	0.25	1420056000
8757	25.72	clear-day	0.37	10.00	Clear	1023.44	8.12	0.08	1420059600
8758	22.75	clear-night	0.42	10.00	Clear	1023.29	4.43	0.05	1420063200
8759	20.09	clear-night	0.51	10.00	Clear	1023.18	1.33	0.11	1420066800

8760 rows × 13 columns

In [4]:

```
# energy_usage_data
(energy_usage_data)
```

Out[4]:

	Date & Time	use [kW]	gen [kW]	Grid [kW]	AC [kW]	Furnace [kW]	Cellar Lights [kW]	Washer [kW]	First Floor lights [kW]	Utility Rm + Basement Bath [kW]
0	2014-01-01 00:00:00	0.304439	0.0	0.304439	0.000058	0.009531	0.005336	0.000126	0.011175	0.003836
1	2014-01-01 00:30:00	0.656771	0.0	0.656771	0.001534	0.364338	0.005522	0.000043	0.003514	0.003512
2	2014-01-01 01:00:00	0.612895	0.0	0.612895	0.001847	0.417989	0.005504	0.000044	0.003528	0.003484
3	2014-01-01 01:30:00	0.683979	0.0	0.683979	0.001744	0.410653	0.005556	0.000059	0.003499	0.003476
4	2014-01-01 02:00:00	0.197809	0.0	0.197809	0.000030	0.017152	0.005302	0.000119	0.003694	0.003865
...	...	...	...	...	...	...	...	...	...	...
17515	2014-12-31 21:30:00	1.560890	0.0	1.560890	0.003226	0.392996	0.006342	0.000872	0.030453	0.002248
17516	2014-12-31 22:00:00	0.958447	0.0	0.958447	0.000827	0.027369	0.006326	0.000811	0.030391	0.002543
17517	2014-12-31 22:30:00	0.834462	0.0	0.834462	0.001438	0.170561	0.020708	0.000636	0.012631	0.002372
17518	2014-12-31 23:00:00	0.543863	0.0	0.543863	0.001164	0.153533	0.008423	0.000553	0.003832	0.002353
17519	2014-12-31 23:30:00	0.414441	0.0	0.414441	0.000276	0.009223	0.006619	0.000526	0.003818	0.002424

17520 rows × 18 columns

In [5]:

```
# Q1.
# Parse time fields
weather_data['time'] = pd.to_datetime(weather_data['time'], unit='s')
energy_usage_data['Date & Time'] = pd.to_datetime(energy_usage_data['Date & Time'])

# Calculate daily energy usage
energy_usage_data['date'] = energy_usage_data['Date & Time'].dt.date
daily_energy_usage = energy_usage_data.groupby('date')['use [kW]'].sum().reset_index()

# Convert datetime column to same data type
daily_energy_usage['date'] = pd.to_datetime(daily_energy_usage['date'])

# Merge datasets
merged_data = pd.merge(weather_data, daily_energy_usage, left_on='time', right_on='date')
```

In [6]:

```
(merged_data)
```

Out[6]:

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	time	windBea
0	34.98	partly-cloudy-night	0.64	10.00	Partly Cloudy	1017.69	7.75	0.29	2014-01-01	
1	20.91	clear-night	0.57	10.00	Clear	1028.12	2.07	0.19	2014-01-02	
2	9.38	snow	0.81	1.37	Light Snow	1014.33	12.84	1.00	2014-01-03	
3	1.72	clear-night	0.57	10.00	Clear	1028.10	7.53	0.00	2014-01-04	
4	19.69	clear-night	0.50	10.00	Clear	1026.36	8.26	0.00	2014-01-05	
...	...	...	...	...	...	...	...	...	...	
360	35.08	clear-night	0.74	10.00	Clear	1021.86	3.64	0.00	2014-12-27	
361	36.15	clear-night	0.80	9.91	Clear	1020.43	3.33	0.06	2014-12-28	
362	40.13	clear-night	0.63	10.00	Clear	1014.32	9.34	0.16	2014-12-29	
363	30.73	clear-night	0.51	10.00	Clear	1022.70	7.19	0.04	2014-12-30	
364	21.03	clear-night	0.46	10.00	Clear	1028.35	7.75	0.00	2014-12-31	

365 rows × 15 columns

In [7]:

```
# Q2.
# Filter the merged_data to only include data before the month of December
train_data = merged_data.loc[(merged_data['date'].dt.month != 12)]

# Create a test set with only December data
test_data = merged_data.loc[(merged_data['date'].dt.month == 12)]
```

In [8]:

```
train_data
```

Out[8]:

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	time	windBea
0	34.98	partly-cloudy-night	0.64	10.00	Partly Cloudy	1017.69	7.75	0.29	2014-01-01	
1	20.91	clear-night	0.57	10.00	Clear	1028.12	2.07	0.19	2014-01-02	
2	9.38	snow	0.81	1.37	Light Snow	1014.33	12.84	1.00	2014-01-03	
3	1.72	clear-night	0.57	10.00	Clear	1028.10	7.53	0.00	2014-01-04	
4	19.69	clear-night	0.50	10.00	Clear	1026.36	8.26	0.00	2014-01-05	
...	...	...	...	...	...	...	...	...	...	

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	time	windBea
329	41.87	clear-night	0.58	10.00	Clear	1016.54	4.02	0.06	2014-11-26	
330	33.05	rain	0.91	1.95	Light Rain	1009.58	14.60	1.00	2014-11-27	
331	30.54	cloudy	0.85	7.64	Overcast	1016.39	1.90	1.00	2014-11-28	
332	25.40	clear-night	0.65	10.00	Clear	1022.73	6.71	0.07	2014-11-29	
333	25.82	clear-night	0.71	9.21	Clear	1026.28	3.53	0.23	2014-11-30	

334 rows × 15 columns

In [9]:

```
test_data
```

Out[9]:

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	time	windBea
334	44.86	cloudy	0.69	10.00	Overcast	1017.71	5.52	1.00	2014-12-01	
335	40.77	clear-night	0.64	10.00	Clear	1026.86	10.13	0.19	2014-12-02	
336	31.63	snow	0.81	7.27	Flurries	1035.05	5.34	1.00	2014-12-03	
337	43.58	cloudy	0.81	9.63	Overcast	1014.62	10.97	1.00	2014-12-04	
338	29.27	clear-night	0.67	10.00	Clear	1032.39	3.13	0.06	2014-12-05	
339	34.65	cloudy	0.66	9.05	Overcast	1033.58	4.19	1.00	2014-12-06	
340	36.14	rain	0.93	6.62	Rain	1022.18	4.88	1.00	2014-12-07	
341	24.73	clear-night	0.44	10.00	Clear	1038.44	11.39	0.01	2014-12-08	
342	24.22	cloudy	0.70	10.00	Overcast	1037.63	7.09	1.00	2014-12-09	
343	38.18	rain	0.90	3.07	Light Rain	1004.33	16.32	1.00	2014-12-10	
344	34.38	rain	0.90	3.30	Light Rain	998.86	5.54	1.00	2014-12-11	
345	30.83	partly-cloudy-night	0.79	9.17	Partly Cloudy	1007.89	7.28	0.50	2014-12-12	
346	30.91	partly-cloudy-night	0.73	9.30	Partly Cloudy	1013.79	5.72	0.39	2014-12-13	
347	31.48	clear-night	0.75	10.00	Clear	1011.20	6.19	0.05	2014-12-14	
348	36.50	partly-cloudy-night	0.74	10.00	Partly Cloudy	1012.97	5.36	0.31	2014-12-15	

	temperature	icon	humidity	visibility	summary	pressure	windSpeed	cloudCover	time	windBea
349	30.39	clear-night	0.83	10.00	Clear	1020.01	1.98	0.08	2014-12-16	
350	36.66	cloudy	0.86	8.34	Overcast	1015.81	3.48	1.00	2014-12-17	
351	40.85	cloudy	0.77	9.60	Overcast	1009.51	9.55	1.00	2014-12-18	
352	35.39	partly-cloudy-night	0.67	10.00	Partly Cloudy	1012.57	11.74	0.38	2014-12-19	
353	29.55	partly-cloudy-night	0.67	10.00	Partly Cloudy	1019.35	9.46	0.47	2014-12-20	
354	30.37	partly-cloudy-night	0.69	9.85	Mostly Cloudy	1026.13	2.29	0.66	2014-12-21	
355	31.89	cloudy	0.87	8.82	Overcast	1027.70	4.75	1.00	2014-12-22	
356	37.41	cloudy	0.84	8.80	Overcast	1026.05	3.85	1.00	2014-12-23	
357	40.51	cloudy	0.91	6.95	Overcast	1021.36	6.67	1.00	2014-12-24	
358	42.67	rain	0.94	4.53	Light Rain	1006.11	3.60	1.00	2014-12-25	
359	45.11	clear-night	0.51	10.00	Clear	1012.01	13.02	0.10	2014-12-26	
360	35.08	clear-night	0.74	10.00	Clear	1021.86	3.64	0.00	2014-12-27	
361	36.15	clear-night	0.80	9.91	Clear	1020.43	3.33	0.06	2014-12-28	
362	40.13	clear-night	0.63	10.00	Clear	1014.32	9.34	0.16	2014-12-29	
363	30.73	clear-night	0.51	10.00	Clear	1022.70	7.19	0.04	2014-12-30	
364	21.03	clear-night	0.46	10.00	Clear	1028.35	7.75	0.00	2014-12-31	

In [10]:

```
# Separate features (X) and target (y) for both training and testing sets
X_train = train_data.drop(['date', 'use [kW]', 'time'], axis=1)
y_train = train_data['use [kW]']
X_test = test_data.drop(['date', 'use [kW]', 'time'], axis=1)
y_test = test_data['use [kW]']
```

In [11]:

```
print(X_train.dtypes)
print(X_test.dtypes)
```

```
temperature           float64
icon                   object
humidity              float64
visibility            float64
summary                object
pressure              float64
```

```
windSpeed            float64
cloudCover           float64
windBearing            int64
precipIntensity      float64
dewPoint             float64
precipProbability    float64
dtype: object
temperature          float64
icon                  object
humidity             float64
visibility           float64
summary               object
pressure             float64
windSpeed            float64
cloudCover           float64
windBearing            int64
precipIntensity      float64
dewPoint             float64
precipProbability    float64
dtype: object
```

In [12]:

```
# One-hot encode the categorical columns in both train and test sets
X_train_encoded = pd.get_dummies(X_train)
X_test_encoded = pd.get_dummies(X_test)

# Ensure both train and test sets have the same columns after one-hot encoding
X_train_encoded, X_test_encoded = X_train_encoded.align(X_test_encoded, axis=1, fill_value
```

In [13]:

```
# Q3.
# Instantiate the LinearRegression model
lr_model = LinearRegression()
```

In [14]:

```
# Fit the model to the training data
lr_model.fit(X_train_encoded, y_train)
```

Out[14]:

```
LinearRegression()
```

In [15]:

```
# Make predictions on the test set
y_pred = lr_model.predict(X_test_encoded)

# Calculate the root mean squared error
rmse = mean_squared_error(y_test, y_pred, squared=False)
print(f"Root Mean Squared Error: {rmse}")
```

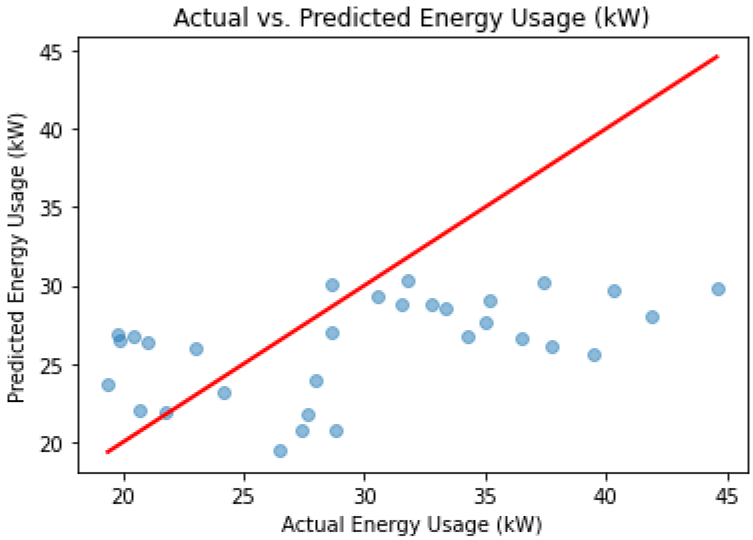
```
Root Mean Squared Error: 7.180460941817107
```

In [16]:

```
# Create a scatter plot of the actual vs. predicted energy usage values
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel('Actual Energy Usage (kW)')
plt.ylabel('Predicted Energy Usage (kW)')
plt.title('Actual vs. Predicted Energy Usage (kW)')

# Add a reference line representing a perfect prediction
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linewidth=2)

# Display the plot
plt.show()
```



In [17]:

```
# Create a new DataFrame with the date and predicted values
pred_df = pd.DataFrame({'date': test_data['date'], 'predicted_value': y_pred})

# Save the DataFrame as a CSV file
pred_df.to_csv('cse351_hw2_Lee_Michael_112424954_linear_regression.csv', index=False)
```

In [18]:

```
# Q4.
# Create copies of train_data and test_data to avoid SettingWithCopyWarning
train_data = train_data.copy()
test_data = test_data.copy()

# Create a binary column 'is_high' in the train_data and test_data DataFrames
# Assign 1 if the temperature is greater than or equal to 35, and 0 otherwise
train_data['is_high'] = np.where(train_data['temperature'] >= 35, 1, 0)
test_data['is_high'] = np.where(test_data['temperature'] >= 35, 1, 0)
```

In [19]:

```
# Prepare features (X) and target (y) for both training and testing sets
X_train = train_data.drop(['date', 'is_high', 'temperature'], axis=1)
y_train = train_data['is_high']
X_test = test_data.drop(['date', 'is_high', 'temperature'], axis=1)
y_test = test_data['is_high']
```

In [20]:

```
# Preprocess your features (e.g., One-Hot Encoding for categorical variables)
encoder = OneHotEncoder(handle_unknown='ignore')
X_train_encoded = encoder.fit_transform(X_train)
X_test_encoded = encoder.transform(X_test)
```

In [21]:

```
# Instantiate a LogisticRegression model
logistic_model = LogisticRegression()
```

In [22]:

```
# Fit the model to the training data
logistic_model.fit(X_train_encoded, y_train)
```

Out[22]:

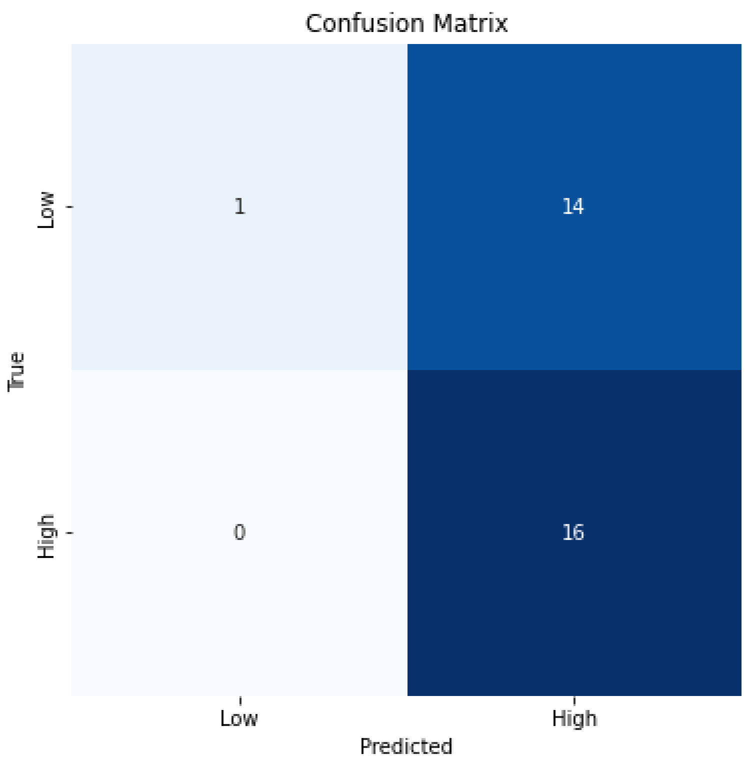
```
LogisticRegression()
```

In [23]:

```
# Make predictions on the test data
y_pred = logistic_model.predict(X_test_encoded)
```

In [24]:
```
# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(6, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=['Low', 'High']
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



In [25]:
```
# Caclculate F1 Score
f1 = f1_score(y_test, y_pred)
print("F1 Score:", f1)
```

```
F1 Score: 0.6956521739130436
```

In [26]:
```
# Create a new DataFrame with date and predicted classification
classification_output = pd.DataFrame({'date': test_data['date'], 'classification': y_pred}

# Save the DataFrame to a CSV file
classification_output.to_csv('cse351_hw2_Lee_Michael_112424954_logistic_regression.csv', i
```

In [27]:
```
# Q5.
# Filter energy usage data for day and night periods
day_data = energy_usage_data.loc[(energy_usage_data['Date & Time'].dt.hour >= 6) & (energy
night_data = energy_usage_data.loc[(energy_usage_data['Date & Time'].dt.hour < 6) | (energ
```

In [28]:
```
# Calculate average usage for each device during day and night periods
avg_washer_day = day_data['Washer [kW]'].mean()
avg_washer_night = night_data['Washer [kW]'].mean()
```

In [29]:
```
avg_ac_day = day_data['AC [kW]'].mean()
avg_ac_night = night_data['AC [kW]'].mean()
```

In [30]:

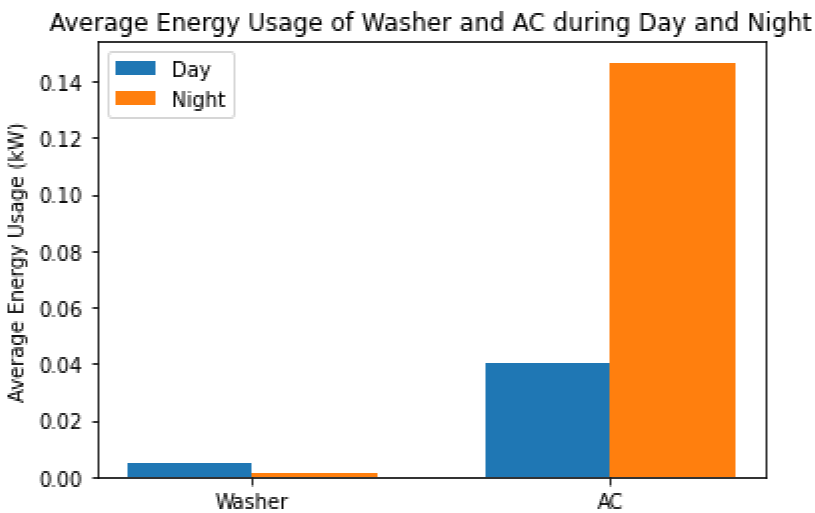
```
# Plot the results
fig, ax = plt.subplots()
devices = ['Washer', 'AC']
day_usage = [avg_washer_day, avg_ac_day]
night_usage = [avg_washer_night, avg_ac_night]

x = np.arange(len(devices))
width = 0.35

ax.bar(x - width/2, day_usage, width, label='Day')
ax.bar(x + width/2, night_usage, width, label='Night')

ax.set_ylabel('Average Energy Usage (kW)')
ax.set_title('Average Energy Usage of Washer and AC during Day and Night')
ax.set_xticks(x)
ax.set_xticklabels(devices)
ax.legend()

plt.show()
```



In [31]:

```
# Analysis:
# It seems plausible that the washer is used more during the day than at night, but with a
# because washer can be used during any time without preference. It seems it is used more
# because that is when people are most active.
# It is however, unexpected that AC energy usage is higher during the night time than day
# this may be.
# 1: It's possible that the location where the data was collected experiences hotter nigh
# during the night, which could lead to increased AC usage to maintain comfortable condit
# 2: People may have preferences for cooler sleeping environments, which could lead to hi
# night.
```

In [ ]: