```
## do all imports here
import numpy as np
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from google.colab import files
## downloaded csv file from url and importing it into notebook
weather data = files.upload()
energy_data = files.upload()
weather_data = pd.read_csv('weather_data.csv') ## opening weather data
energy_data = pd.read_csv('energy_data.csv') ## opening energy_data
    Choose Files weather data.csv

    weather_data.csv(text/csv) - 670684 bytes, last modified: 3/31/2022 - 100% done

     Saving weather_data.csv to weather_data.csv
     Choose Files energy data.csv
    energy_data.csv(text/csv) - 3530451 bytes, last modified: 3/31/2022 - 100% done
     Saving energy data.csv to energy data.csv
## Task 1
copy energy = energy data
## adding a column just for the date in copy energy
just time = []
for i in range(365):
  for j in range(48):
    index = i * 48 + j
    time = energy_data.at[index, 'Date & Time']
    time = time[0:10]
    just time.append(time)
copy energy["Date"] = just time
## grouping copy energy by the date
columns = copy energy.columns[1:18:1]
daily energy = copy energy.groupby(["Date"])[columns].sum() ## adding per day usage
## copying time value in weather data into energy data
energy every two = energy data
energy_every_two = energy_every_two.iloc[::2, :] ## only retreiving every two rows
```

```
https://colab.research.google.com/drive/1YQTFGFrGzTPK7edRL7IPLP2g9Vo3qRUf? authuser=2\#scrollTo=TwYzOPUqMSLM\&printMode=trueformula for the control of the c
```

del merged\_data\_copy[columns[i]] ## removing each column

for i in range(len(columns)):

del daily merged data copy[columns[i]]

training\_data = daily\_merged\_data\_copy.head(334)
testing\_data = daily\_merged\_data\_copy.tail(31)

testing\_data\_without\_label = testing\_data.copy()
y\_actual = testing\_data["use [kW]"]
del testing\_data\_without\_label["use [kW]"]

2014-01-04 2014-01-05	0.18005 0.17855	
2014-12-27	0.11266	
2014-12-28	0.11567	3 0.257369
2014-12-29	0.11220	
2014-12-30	0.11593	
2014-12-31	0.11491	
	MBed + KBed outlets [kW] Drye	r + egauge [kW] \
Date		
2014-01-01	0.254839	31.938131
2014-01-02	0.798316	5.423866
2014-01-03	0.746972	0.005554
2014-01-04	0.640721	19.994908
2014-01-05	0.584570	9.493912
• • •		• • •
2014-12-27	5.422751	0.005953
2014-12-28	11.602281	0.008270
2014-12-29	5.951963	0.005461
2014-12-30	11.100021	0.008893
2014-12-31	7.741381	0.005618
	Panel GFI (central vac) [kW]	Home Office (R) [kW]
Date	runer off (central vac) [kw]	nome office (K) [KW] (
Date		
2014-01-01	0.350291	3.272944
	0.350291 0.346679	3.272944 3.475469
2014-01-01		
2014-01-01 2014-01-02	0.346679	3.475469
2014-01-01 2014-01-02 2014-01-03	0.346679 0.344061	3.475469 3.615520
2014-01-01 2014-01-02 2014-01-03 2014-01-04	0.346679 0.344061 0.346872	3.475469 3.615520 3.700408
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05	0.346679 0.344061 0.346872 0.346070	3.475469 3.615520 3.700408 3.699178
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05	0.346679 0.344061 0.346872 0.346070	3.475469 3.615520 3.700408 3.699178
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27	0.346679 0.344061 0.346872 0.346070 	3.475469 3.615520 3.700408 3.699178 0.473471
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30	0.346679 0.344061 0.346872 0.346070  0.015400 0.018872 0.015199 0.020299	3.475469 3.615520 3.700408 3.699178 0.473471 0.473571 0.493595 0.512197
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29	0.346679 0.344061 0.346872 0.346070  0.015400 0.018872 0.015199	3.475469 3.615520 3.700408 3.699178 0.473471 0.473571 0.493595
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158	3.475469 3.615520 3.700408 3.699178 0.473471 0.473571 0.493595 0.512197 0.514595
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31	0.346679 0.344061 0.346872 0.346070  0.015400 0.018872 0.015199 0.020299	3.475469 3.615520 3.700408 3.699178 0.473471 0.473571 0.493595 0.512197 0.514595
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31	0.346679 0.344061 0.346872 0.346070  0.015400 0.018872 0.015199 0.020299 0.017158 Dining room (R) [kW] Microwave	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW]
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31 Date 2014-01-01	0.346679 0.344061 0.346872 0.346070  0.015400 0.018872 0.015199 0.020299 0.017158 Dining room (R) [kW] Microwave	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 4.639598
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave 0.200970 0.207041	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 3.881399
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02 2014-01-03	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave 0.200970 0.207041 0.201975	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 1.667553 3.671391
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02 2014-01-03 2014-01-04	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave 0.200970 0.207041 0.201975 0.203913	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 3.881399 1.667553 3.671391 1.029198 3.357907
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave 0.200970 0.207041 0.201975 0.203913 0.197897	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 1.667553 1.029198 1.029198 1.619991 3.357907 4.373730
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05 	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave 0.200970 0.207041 0.201975 0.203913 0.197897	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 1.667553 1.029198 1.029198 1.619991 4.373730
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2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave  0.200970 0.207041 0.201975 0.203913 0.197897 0.668127 0.657405	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 1.667553 1.029198 1.029198 1.619991 4.373730  0.642506 0.311556 3.8839653 3.510436
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-29	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave 0.200970 0.207041 0.201975 0.203913 0.197897 0.668127 0.657405 0.670818	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 1.667553 1.029198 1.029198 1.029198 1.029198 1.029198 1.029198 3.357907 1.619991 4.373730  0.642506 0.311556 0.279923 3.702587
2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28 2014-12-30 2014-12-31 Date 2014-01-01 2014-01-02 2014-01-03 2014-01-04 2014-01-05  2014-12-27 2014-12-28	0.346679 0.344061 0.346872 0.346070 0.015400 0.018872 0.015199 0.020299 0.017158  Dining room (R) [kW] Microwave  0.200970 0.207041 0.201975 0.203913 0.197897 0.668127 0.657405	3.475469 3.615520 3.700408 3.699178  0.473471 0.473571 0.493595 0.512197 0.514595 e (R) [kW] Fridge (R) [kW] 4.997037 1.534426 1.667553 1.029198 1.029198 1.619991 4.373730  0.642506 0.311556 3.8839653 3.510436

[365 rows x 27 columns]

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:37: SettingWithCopyN
    A value is trying to be set on a copy of a slice from a DataFrame.
    Try using .loc[row_indexer,col_indexer] = value instead
    See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
     /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:48: FutureWarning: :
## Task 3
from sklearn.linear model import LinearRegression
import math
from sklearn.metrics import mean squared error
from math import sqrt
import csv
columns = testing data without label.columns ## retrieving columns to group
x_train = training_data[columns] ## only getting the necesary columns
y train = training data['use [kW]'] ## dependent variables
## print(x_train)
x_train = np.reshape(x_train, (334, 10)) ## shaping the data
testing data without label = np.reshape(testing data without label, (31, 10)) ## shapi
LR = LinearRegression() ## setting up linear regression model
LR = LR.fit(x train,y train) ## training the model
prediction = LR.predict(testing data without label) ## testing the model
## print(prediction)
## print(y actual)
rms = sqrt(mean_squared_error(y_actual, prediction)) ## rms calculation
print("Root mean square error value : " + str(rms))
## rms value is apx 8.629 || max-value: 44.563400 || min-value: 19.387136
adjusted rms = rms / (44.563400 - 19.387136)
print("Adjusted rmse value: " + str(adjusted rms))
## rms value is 0.3423 is which around an average fitting model. Closer to 0 is perfec
## creating csv file
dates = testing data.index
with open('cse351_hw2_raja_rahul_sbuid_linear_regression.csv', 'w', newline='') as fil
   writer = csv.writer(file)
   writer.writerow(["Date", "Predicted Value"])
    for i in range(len(prediction)):
        writer.writerow([dates[i], prediction[i]]) ## writing the data into the file
```

```
predictor = pd.read_csv('cse351_hw2_raja_rahul_sbuid_linear_regression.csv')
print(predictor)
```

Root mean square error value : 8.629044152737501 Adjusted rmse value: 0.3427452203685782

```
Date Predicted Value
0
    2014-12-01
                      30.640995
1
    2014-12-02
                      31.771946
2
    2014-12-03
                      18.535163
3
   2014-12-04
                      31.506958
    2014-12-05
4
                      23.720011
5
   2014-12-06
                      21.470628
    2014-12-07
                      22.177421
6
7
    2014-12-08
                      24.715977
8
    2014-12-09
                      20.536352
9
   2014-12-10
                      18.808375
   2014-12-11
                      20.117905
10
11
   2014-12-12
                      22.047780
   2014-12-13
                      25.695860
13
   2014-12-14
                      24.481432
14
   2014-12-15
                      28.048542
15
   2014-12-16
                      16.850926
   2014-12-17
                      23.628356
17
   2014-12-18
                      26.174668
18
   2014-12-19
                      25.953018
   2014-12-20
19
                      25.473606
20 2014-12-21
                      15.427852
21
   2014-12-22
                      13.876996
22 2014-12-23
                      14.176729
23 2014-12-24
                      17.301925
                      30.294769
24 2014-12-25
25 2014-12-26
                      34.086540
26 2014-12-27
                      26.694369
27 2014-12-28
                      27.611849
28 2014-12-29
                      30.600297
29 2014-12-30
                      29.890010
  2014-12-31
                      25.919144
```

```
## Task 4
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score

weather_copy = grouped_merged_data.copy()
temperatures = weather_copy["temperature"]
binary_temp = []

## classfying high and low data
for i in range(len(temperatures)):
   if temperatures[i] < 35:
        binary_temp.append(0)</pre>
```

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6

2014-12-06

2014-12-07

2014-12-08

```
CTPC:
    binary_temp.append(1)
weather copy["temperature"] = binary temp ## adding column to the table
weather_copy.head(10)
training data = weather copy.head(334)
testing_data = weather_copy.tail(31)
y_actual = testing_data["temperature"]
testing data with label = testing data.copy()
del testing data["temperature"]
columns = testing data.columns
x_train = training_data[columns] ## independent variables
y_train = training_data['temperature'] ## dependent variables
logreg = LogisticRegression() ## setting up logistic reg. model
logreg.fit(x_train,y_train) ## training log model
prediction = logreg.predict(testing_data) ## testing the model
flscore = fl_score(y_actual, prediction) ## calculating fl score
print("Fl score: " + str(flscore))
dates = testing data.index
## received a f1 score of around 0.7027, which is also above average. Closer to 1 is a
## creating csv file
with open('cse351 hw2 rahul raja sbuid logistic regression.csv', 'w', newline='') as 1
   writer = csv.writer(file)
   writer.writerow(["Date", "Temperature Classification"])
    for i in range(len(prediction)):
        writer.writerow([dates[i], prediction[i]]) ## writing data
predictor = pd.read csv('cse351 hw2 rahul raja sbuid logistic regression.csv')
print(predictor)
    Fl score: 0.7027027027027
              Date Temperature Classification
        2014-12-01
    1 2014-12-02
                                              1
    2
        2014-12-03
                                              1
    3
        2014-12-04
                                              1
        2014-12-05
                                              0
    4
```

0

1

```
8
   2014-12-09
                                          1
9
   2014-12-10
                                          1
10 2014-12-11
                                          0
11
   2014-12-12
                                          1
12 2014-12-13
                                          1
13 2014-12-14
                                          1
14 2014-12-15
                                          1
15 2014-12-16
                                          1
16 2014-12-17
                                          1
17 2014-12-18
                                          1
18 2014-12-19
                                          1
19 2014-12-20
                                          0
20 2014-12-21
                                          1
21 2014-12-22
                                          1
22 2014-12-23
                                          1
23 2014-12-24
                                          1
24 2014-12-25
                                          1
25 2014-12-26
                                          1
26 2014-12-27
                                          1
27 2014-12-28
                                          1
28 2014-12-29
                                          1
29 2014-12-30
                                          0
30 2014-12-31
```

/usr/local/lib/python3.7/dist-packages/sklearn/linear\_model/\_logistic.py:818: Col STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:

https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
extra\_warning\_msg=\_LOGISTIC\_SOLVER\_CONVERGENCE\_MSG,

```
## Task 5
import matplotlib.pyplot as plt

energy_data2 = energy_data.copy()
date_and_time = energy_data2["Date & Time"]

just_time = []

## 6AM - 7PM is considered daytime, rest is night time

for i in range(len(date_and_time)):
    digit = int(date_and_time[i][11:13])
    if digit >= 6 and digit < 19:
        just_time.append(1) ## 1 is daytime
    else:
        just_time.append(0) ## 0 is nighttime

energy_data2["daytime"] = just_time

grouped_data_with_washer = energy_data2.groupby(["Date","daytime"])["Washer [kW]"].meagrouped_data_with_ac = energy_data2.groupby(["Date","daytime"])["AC [kW]"].mean()</pre>
```

```
y1_data = []
y2_data = []
x_data = []

for i in range(len(grouped_data_with_washer)):
    if i % 2 == 0:
        y1_data.append(grouped_data_with_washer[i]) ## y1 data contains nighttime data
        x_data.append(i / 2)
    else:
        y2_data.append(grouped_data_with_washer[i]) ##y2 data contains daytime data

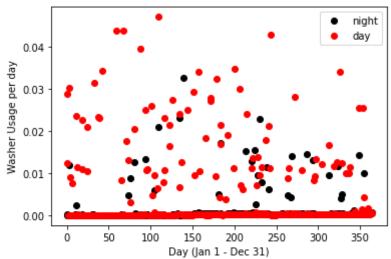
## First graph is washer
plt.plot(x_data, y1_data, 'o', color='black', label="night"); ## black is nighttime
plt.plot(x_data, y2_data, 'o', color='red', label="day"); ## red is daytime

plt.xlabel("Day (Jan 1 - Dec 31)")
plt.ylabel("Washer Usage per day")

plt.gca().legend(('night','day'))
```

## people generally use the washer more during the daytime rather than the night time





```
## Task 5 Continued

y1_data = []
y2_data = []
x_data = []

for i in range(len(grouped_data_with_ac)):
   if i % 2 == 0:
     y1_data.append(grouped_data_with_ac[i])
     x data.append(i / 2)
```

```
else:
```

```
## First graph is washer
plt.plot(x_data, .y1_data, .'o', color='black')
plt.plot(x_data, y2_data, 'o', color='red')

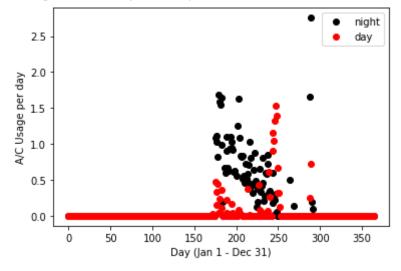
plt.xlabel("Day (Jan 1 - Dec 31)")
plt.ylabel("A/C Usage per day")

plt.gca().legend(('night', 'day'))
```

y2 data.append(grouped data with ac[i])

## results show people use the ac more during the night time compared to the daytime ¿

<matplotlib.legend.Legend at 0x7f41d8722910>



✓ 0s completed at 11:28 PM

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