In [1]:
```
import pandas as pd
import numpy as np
import re
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from math import sqrt
from urllib.request import urlopen
import json
```

Combined Cycle Power Plant Dataset

Dataset Information:

(Extracted from UCI's Machine learning repository)

"The dataset contains 9568 data points collected from a Combined Cycle Power Plant over 6 years (2006-2011), when the power plant was set to work with full load. Features consist of hourly average ambient variables Temperature (T) **[°C]** , Ambient Pressure (AP) **[milibar]** , Relative Humidity (RH) **[%]** and Exhaust Vacuum (V) to predict the net hourly electrical energy output (EP) **[MW]** of the plant."

We will train a model to predict power output given three variables:

- Temperature (T) ...... **[°C]**
- Ambient Pressure (AP) ...... **[milibar]**
- Relative Humidity (RH) ...... **[%]**

Then we will take average data for these three variables from diferent locations in the US and feed them to the model, so we can predict in which locations a power plant would have the highest energy output.

In [2]:
```
data = pd.read_excel('CCPP/Folds5x2_pp.xlsx')
data.head(10)
```

Out[2]:

	AT	V	AP	RH	PE
0	14.96	41.76	1024.07	73.17	463.26
1	25.18	62.96	1020.04	59.08	444.37
2	5.11	39.40	1012.16	92.14	488.56
3	20.86	57.32	1010.24	76.64	446.48
4	10.82	37.50	1009.23	96.62	473.90
5	26.27	59.44	1012.23	58.77	443.67
6	15.89	43.96	1014.02	75.24	467.35
7	9.48	44.71	1019.12	66.43	478.42
8	14.64	45.00	1021.78	41.25	475.98
9	11.74	43.56	1015.14	70.72	477.50

In [3]:
```
data = data.drop(['V'], axis = 1)

data.columns = ['Temperature', 'Pressure', 'Humidity', 'Power Out']

data.head()
```

Out[3]:

	Temperature	Pressure	Humidity	Power Out
0	14.96	1024.07	73.17	463.26
1	25.18	1020.04	59.08	444.37
2	5.11	1012.16	92.14	488.56
3	20.86	1010.24	76.64	446.48
4	10.82	1009.23	96.62	473.90

In [4]:
```
data.describe()
```

Out[4]:

	Temperature	Pressure	Humidity	Power Out
count	9568.000000	9568.000000	9568.000000	9568.000000
mean	19.651231	1013.259078	73.308978	454.365009
std	7.452473	5.938784	14.600269	17.066995
min	1.810000	992.890000	25.560000	420.260000
25%	13.510000	1009.100000	63.327500	439.750000
50%	20.345000	1012.940000	74.975000	451.550000
75%	25.720000	1017.260000	84.830000	468.430000
max	37.110000	1033.300000	100.160000	495.760000

In [5]:
```
data.corr()
```

Out[5]:

	Temperature	Pressure	Humidity	Power Out
Temperature	1.000000	-0.507549	-0.542535	-0.948128
Pressure	-0.507549	1.000000	0.099574	0.518429
Humidity	-0.542535	0.099574	1.000000	0.389794
Power Out	-0.948128	0.518429	0.389794	1.000000

Weather Datasets

We are going to extract information about the average Temperature, Relative Humidity and Ambient Pressure in US from three different datasets with yearly data taken from different stations around US:

- US Weather Stations Temperatures Dataset.
- US Weather Stations Relative Humidity Dataset.
- Station metadata Dataset.

The last one contains infomation about stations all over the world. This include elevation over sea level. With this we can stimate the Ambient Pressure. We'll extract only the data for the stations in the US.

Temperature Data

In [6]:
```python
tempdata = pd.read_excel('Weather/temp.xlsx')
tempdata.head()
```

Out[6]:

	wban	city	st	YRS	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OC
0	13876	BIRMINGHAM	AL	30	43.8	47.7	55.2	62.5	70.6	77.7	81.1	80.7	74.7	64.
1	3856	HUNTSVILLE	AL	30	41.5	45.7	53.5	61.8	70.3	77.7	80.6	80.1	73.7	62.
2	13894	MOBILE	AL	30	50.4	53.8	60.2	66.4	74.1	79.8	81.8	81.6	77.5	68.
3	13895	MONTGOMERY	AL	30	46.6	50.5	57.5	64.1	72.4	79.0	81.8	81.5	76.3	65.
4	26451	ANCHORAGE	AK	30	17.1	20.2	26.6	36.8	47.8	55.2	58.8	56.7	48.6	34.

In [7]:
```python
tempdata = tempdata[['wban','city','st', 'ANN']]
tempdata.columns = ['Wban','City','State', 'Temp(°F)']
tempdata.head()
```

Out[7]:

	Wban	City	State	Temp(°F)
0	13876	BIRMINGHAM	AL	63.3
1	3856	HUNTSVILLE	AL	62.1
2	13894	MOBILE	AL	67.2
3	13895	MONTGOMERY	AL	65.1
4	26451	ANCHORAGE	AK	37.1

Fahrenheit to Celsius conversion

```
T(°C) = (T(°F) - 32) / 1.8
```

In [8]:
```
tempF = np.array(tempdata['Temp(°F)'])
temperature = (tempF - 32)/ 1.8
tempdata['Temperature'] = temperature
tempdata = tempdata.drop('Temp(°F)', axis = 1)
tempdata.head()
```

Out[8]:

	Wban	City	State	Temperature
0	13876	BIRMINGHAM	AL	17.388889
1	3856	HUNTSVILLE	AL	16.722222
2	13894	MOBILE	AL	19.555556
3	13895	MONTGOMERY	AL	18.388889
4	26451	ANCHORAGE	AK	2.833333

In [9]:
```
tempdata.isnull().any()
```

Out[9]:
```
Wban           False
City           False
State          False
Temperature    False
dtype: bool
```

In [10]:
```
tempdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 263 entries, 0 to 262
Data columns (total 4 columns):
Wban           263 non-null int64
City           263 non-null object
State          263 non-null object
Temperature    263 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 8.3+ KB
```

Humidity Data

In [11]:
```python
humdata = pd.read_excel('Weather/relhum.xlsx')
humdata.head()
```

Out[11]:

	Unnamed: 0	POR	JAN	Unnamed: 3	FEB	Unnamed: 5	MAR	Unnamed: 7	APR
0	NaN	NaN	M	A	M	A	M	A	M
1	13876BIRMINGHAM,AL	194801-201812	81	60	80	56	80	52	83
2	03856HUNTSVILLE,AL	195809-201812	81	64	81	60	80	55	82
3	13894MOBILE,AL	194801-201812	83	60	84	58	85	54	88
4	13895MONTGOMERY,AL	194801-201812	83	59	82	56	83	52	87

5 rows × 28 columns

In [12]:
```python
humdata.columns = ['0', 'POR', 'JAN', 'JAN', 'FEB', 'FEB', 'MAR',
          'MAR', 'APR', 'APR', 'MAY', 'MAY', 'JUN',
          'JUN', 'JUL', 'JUL', 'AUG', 'AUG', 'SEP',
          'SEP', 'OCT', 'OCT', 'NOV', 'NOV', 'DEC',
          'DEC', 'ANN1', 'ANN2']
```

In [13]:
```python
humdata.head()
```

Out[13]:

	0	POR	JAN	JAN	FEB	FEB	MAR	MAR	APR	APR	...	SEP
0	NaN	NaN	M	A	M	A	M	A	M	A	...	M
1	13876BIRMINGHAM,AL	194801-201812	81	60	80	56	80	52	83	50	...	87
2	03856HUNTSVILLE,AL	195809-201812	81	64	81	60	80	55	82	51	...	89
3	13894MOBILE,AL	194801-201812	83	60	84	58	85	54	88	53	...	90
4	13895MONTGOMERY,AL	194801-201812	83	59	82	56	83	52	87	51	...	90

5 rows × 28 columns

In [14]:
```python
humdata = humdata[['0' ,'ANN1', 'ANN2']].drop([0])
humdata.head()
```

Out[14]:

	0	ANN1	ANN2
1	13876BIRMINGHAM,AL	84	55
2	03856HUNTSVILLE,AL	85	57
3	13894MOBILE,AL	87	57
4	13895MONTGOMERY,AL	87	55
5	26451ANCHORAGE,AK	74	64

In [15]:
```python
wban = humdata['0']
wban = [re.findall(r'[0-9]+', i)[0] for i in wban]
```

In [16]:
```python
humdata['Wban'] = wban
humdata = humdata.drop(['0'], axis = 1)

humdata['Humidity'] = humdata[['ANN1', 'ANN2']].mean(axis=1)
humdata = humdata.drop(['ANN1', 'ANN2'], axis = 1)
humdata.head()
```

Out[16]:

	Wban	Humidity
1	13876	69.5
2	03856	71.0
3	13894	72.0
4	13895	71.0
5	26451	69.0

In [17]:
```python
humdata['Wban'] = humdata['Wban'].astype('int64')
```

In [18]:
```python
humdata.isnull().any()
```

Out[18]:
```
Wban        False
Humidity    False
dtype: bool
```

In [19]:
```
humdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 266 entries, 1 to 266
Data columns (total 2 columns):
Wban         266 non-null int64
Humidity     266 non-null float64
dtypes: float64(1), int64(1)
memory usage: 6.2 KB
```

In [20]:
```
print (humdata['Wban'].dtype)
print (tempdata['Wban'].dtype)
```

```
int64
int64
```

Pressure Data

In [21]:
```
presdata = pd.read_excel('Weather/stations.xltx')
presdata.head()
```

Out[21]:

	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7
0	USAF	WBAN	STATION NAME	CTRY	ST CALL	LAT	LON	ELEV(M)
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	7018	99999	WXPOD 7018	NaN	NaN	0	0	7018
3	7026	99999	WXPOD 7026	AF	NaN	0	0	7026
4	7070	99999	WXPOD 7070	AF	NaN	0	0	7070

In [22]:
```
columns = presdata.iloc[0]
presdata.columns = columns

presdata = presdata.drop([0])
presdata.head()
```

Out[22]:

	USAF	WBAN	STATION NAME	CTRY	ST CALL	LAT	LON	ELEV(M)	BEGIN	END
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	7018	99999	WXPOD 7018	NaN	NaN	0	0	7018	20110309	20130730
3	7026	99999	WXPOD 7026	AF	NaN	0	0	7026	20120713	20170822
4	7070	99999	WXPOD 7070	AF	NaN	0	0	7070	20140923	20150926
5	8260	99999	WXPOD8270	NaN	NaN	0	0	0	20050101	20100920

In [23]:
```
presdata = presdata[presdata['CTRY']==('US')]
presdata.head()
```

Out[23]:

	USAF	WBAN	STATION NAME	CTRY	ST CALL	LAT	LON	ELEV(M)	BEGIN	END
13135	621010	99999	MOORED BUOY	US	NaN	50.6	-2.933	-999	20080721	20080721
13137	621110	99999	MOORED BUOY	US	NaN	58.9	-0.2	-999	20041118	20041118
13138	621130	99999	MOORED BUOY	US	NaN	58.4	0.3	-999	20040726	20040726
13139	621160	99999	MOORED BUOY	US	NaN	58.1	1.8	-999	20040829	20040829
13140	621170	99999	MOORED BUOY	US	NaN	57.9	0.1	-999	20040726	20040726

In [24]:
```
presdata = presdata[['WBAN','ELEV(M)']]


presdata['ELEV(M)'] = pd.to_numeric(presdata['ELEV(M)'], errors='coerc
e')

presdata['WBAN'] = presdata['WBAN'].astype('int64')

presdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7326 entries, 13135 to 29745
Data columns (total 2 columns):
WBAN       7326 non-null int64
ELEV(M)    7209 non-null float64
dtypes: float64(1), int64(1)
memory usage: 171.7 KB
```

In [25]:
```
presdata.dropna(inplace=True)

presdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7209 entries, 13135 to 29745
Data columns (total 2 columns):
WBAN       7209 non-null int64
ELEV(M)    7209 non-null float64
dtypes: float64(1), int64(1)
memory usage: 169.0 KB
```

In [26]:
```
presdata.columns = ['Wban', 'Elevation']
presdata.head()
```

Out[26]:

	Wban	Elevation
13135	99999	-999.0
13137	99999	-999.0
13138	99999	-999.0
13139	99999	-999.0
13140	99999	-999.0

In [27]:
```
presdata = presdata[presdata['Elevation']>=0]
presdata.head()
```

Out[27]:

	Wban	Elevation
13149	99999	0.0
14465	99999	1224.0
14466	93218	317.0
14467	99999	317.0
14468	93217	43.0

Average ambient pressure calculation

For this calculation we will use the following expresion:

```
p ~ 101325 (1 - 2.25577^10-5 * h)^5
```

Where:

```
101325 = normal temperature and pressure at sea level (Pa)

p = air pressure (Pa)

h = altitude above sea level (m)
```

Pascal to milibar convertion:

```
1 Pa = 0.01 milibar
```

In [28]:
```
elev = np.array(presdata['Elevation'])


Pasc = 101325*(1 - 2.25577*10**(-5) * elev)**5


milibar = Pasc * 0.01
```

In [29]:
```
presdata['Pressure'] = milibar
presdata = presdata.drop('Elevation', axis = 1)

presdata.head()
```

Out[29]:

	Wban	Pressure
13149	99999	1013.250000
14465	99999	880.881800
14466	93218	977.536727
14467	99999	977.536727
14468	93217	1008.345357

In [30]:
```
presdata['Wban'].value_counts().head()
```

Out[30]:
```
99999    3548
23176       6
3849        5
14897       4
24255       4
Name: Wban, dtype: int64
```

In [31]:
```
presdata[presdata['Wban']==23176]
```

Out[31]:

	Wban	Pressure
19714	23176	849.441660
19722	23176	849.650098
19743	23176	849.650098
21748	23176	849.650098
21749	23176	849.650098
29011	23176	849.650098

In [32]:
```
presdata['Wban'] = presdata[presdata['Wban']!=99999]
presdata = presdata.drop_duplicates(subset = 'Wban')
presdata['Wban'].value_counts().head()
```

Out[32]:
```
54791.0    1
24164.0    1
24048.0    1
4898.0     1
3930.0     1
Name: Wban, dtype: int64
```

Merging weather datasets into US Locations

In [33]:
```
USloc = tempdata.merge(humdata, how='inner')
print (len(USloc))
USloc.head(10)
```

```
260
```

Out[33]:

	Wban	City	State	Temperature	Humidity
0	13876	BIRMINGHAM	AL	17.388889	69.5
1	3856	HUNTSVILLE	AL	16.722222	71.0
2	13894	MOBILE	AL	19.555556	72.0
3	13895	MONTGOMERY	AL	18.388889	71.0
4	26451	ANCHORAGE	AK	2.833333	69.0
5	25308	ANNETTE	AK	8.111111	77.5
6	27502	BARROW	AK	-11.222222	81.0
7	26615	BETHEL	AK	-0.722222	78.5
8	26533	BETTLES	AK	-4.722222	67.0
9	26415	BIG DELTA	AK	-1.666667	62.5

In [34]:
```
usloc = USloc.merge(presdata, how='left')

print (len(usloc))
usloc.head(10)
```

260

Out[34]:

	Wban	City	State	Temperature	Humidity	Pressure
0	13876	BIRMINGHAM	AL	17.388889	69.5	992.002445
1	3856	HUNTSVILLE	AL	16.722222	71.0	991.699106
2	13894	MOBILE	AL	19.555556	72.0	1005.786554
3	13895	MONTGOMERY	AL	18.388889	71.0	1006.229708
4	26451	ANCHORAGE	AK	2.833333	69.0	1009.074145
5	25308	ANNETTE	AK	8.111111	77.5	1009.461485
6	27502	BARROW	AK	-11.222222	81.0	1012.164777
7	26615	BETHEL	AK	-0.722222	78.5	1009.700784
8	26533	BETTLES	AK	-4.722222	67.0	991.362149
9	26415	BIG DELTA	AK	-1.666667	62.5	969.545252

In [35]:
```
usloc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 260 entries, 0 to 259
Data columns (total 6 columns):
Wban           260 non-null int64
City           260 non-null object
State          260 non-null object
Temperature    260 non-null float64
Humidity       260 non-null float64
Pressure       251 non-null float64
dtypes: float64(3), int64(1), object(2)
memory usage: 14.2+ KB
```

In [36]:
```
usloc = usloc.dropna()

usloc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 251 entries, 0 to 250
Data columns (total 6 columns):
Wban           251 non-null int64
City           251 non-null object
State          251 non-null object
Temperature    251 non-null float64
Humidity       251 non-null float64
Pressure       251 non-null float64
dtypes: float64(3), int64(1), object(2)
memory usage: 13.7+ KB
```

Multiple Linear Regression Model

We are going to create a model to preddict energy output (EP) [MW], taking Temperature (T) [°C] , Ambient Pressure (AP) [milibar] , Relative Humidity (RH) [%] as parameters.

We will use the dataset called 'data', which contains the values for the CCPP.

We will use scikit-learn, and train the model as a multiple linear regrssion

In [37]:
```
X = data[['Temperature', 'Pressure', 'Humidity']]
Y = data[['Power Out']]
```

In [38]:
```
Xtrain, Xtest, Ytrain, Ytest =  train_test_split(X,Y, test_size=0.25,
random_state=10)
```

In [39]:
```
regression = LinearRegression()
model = regression.fit(Xtrain, Ytrain)
```

In [40]:
```
Ypred = model.predict(Xtest)
Ypred
```

Out[40]:
```
array([[455.39353049],
       [447.47658286],
       [437.21191769],
       ...,
       [487.93736352],
       [440.41536484],
       [453.40714577]])
```

In [41]:
```
RMSE = sqrt(mean_squared_error(y_true = Ytest, y_pred = Ypred))
RMSE
```

Out[41]:
```
4.657571391074255
```

In [42]:
```
r2 = r2_score(Ytest, Ypred)
r2
```

Out[42]:
```
0.9266765701220129
```

Performance prediction at US locations

In this step we will use the model previously trained with the CCPP data, to predict the expected power output of a CCPP situated in differents US locations based on their climate average conditions.

In [43]:
```
usweather = usloc[['Temperature', 'Pressure', 'Humidity']]

usweather.head()
```

Out[43]:

	Temperature	Pressure	Humidity
0	17.388889	992.002445	69.5
1	16.722222	991.699106	71.0
2	19.555556	1005.786554	72.0
3	18.388889	1006.229708	71.0
4	2.833333	1009.074145	69.0

In [44]:
```
X.head()
```

Out[44]:

	Temperature	Pressure	Humidity
0	14.96	1024.07	73.17
1	25.18	1020.04	59.08
2	5.11	1012.16	92.14
3	20.86	1010.24	76.64
4	10.82	1009.23	96.62

In [45]:
```
USpred = model.predict(usweather)
USpred[:5]
```

Out[45]:
```
array([[459.91897085],
       [461.1913595 ],
       [454.64134399],
       [457.62249043],
       [495.01181029]])
```

In [46]:
```
usloc['Power_out'] = USpred

usloc.head()
```

Out[46]:

	Wban	City	State	Temperature	Humidity	Pressure	Power_out
0	13876	BIRMINGHAM	AL	17.388889	69.5	992.002445	459.918971
1	3856	HUNTSVILLE	AL	16.722222	71.0	991.699106	461.191360
2	13894	MOBILE	AL	19.555556	72.0	1005.786554	454.641344
3	13895	MONTGOMERY	AL	18.388889	71.0	1006.229708	457.622490
4	26451	ANCHORAGE	AK	2.833333	69.0	1009.074145	495.011810

Findings

In [47]:
```
usloc.Power_out.describe()
```

Out[47]:
```
count    251.000000
mean     472.345828
std       14.272938
min      440.563445
25%      462.034303
50%      473.768200
75%      480.319051
max      526.034436
Name: Power_out, dtype: float64
```

In [48]:
```
usloc.drop('Wban',axis=1).corr()
```

Out[48]:

	Temperature	Humidity	Pressure	Power_out
Temperature	1.000000	-0.057025	0.236537	-0.991844
Humidity	-0.057025	1.000000	0.586223	-0.048887
Pressure	0.236537	0.586223	1.000000	-0.243565
Power_out	-0.991844	-0.048887	-0.243565	1.000000

In [49]:
```
usloc.sort_values('Power_out', ascending=False).head(10)
```

Out[49]:

	Wban	City	State	Temperature	Humidity	Pressure	Power_out
6	27502	BARROW	AK	-11.222222	81.0	1012.164777	526.034436
147	14755	MT. WASHINGTON	NH	-2.555556	0.0	812.822902	516.454667
8	26533	BETTLES	AK	-4.722222	67.0	991.362149	512.871904
17	26616	KOTZEBUE	AK	-5.055556	78.0	1012.210452	512.005739
11	26411	FAIRBANKS	AK	-2.388889	65.0	998.288099	507.921088
18	26510	MCGRATH	AK	-2.555556	68.5	1001.703277	507.703816
19	26617	NOME	AK	-2.555556	76.0	1012.792951	506.490944
12	26425	GULKANA	AK	-2.111111	66.0	959.996103	506.043838
9	26415	BIG DELTA	AK	-1.666667	62.5	969.545252	505.946333
7	26615	BETHEL	AK	-0.722222	78.5	1009.700784	501.556013

In [50]:
```
usloc.sort_values('Power_out', ascending=False).tail(10)
```

Out[50]:

	Wban	City	State	Temperature	Humidity	Pressure	Power_out
61	12842	TAMPA	FL	23.000000	72.0	1012.587332	446.648664
70	21504	HILO	HI	23.277778	74.0	1011.925011	445.569949
211	12919	BROWNSVILLE	TX	23.611111	75.0	1012.416009	444.591033
53	12835	FORT MYERS	FL	23.944444	71.5	1012.724408	444.511729
72	22516	KAHULUI	HI	24.388889	67.5	1011.479853	444.228015
63	12844	WEST PALM BEACH	FL	24.111111	71.5	1012.587332	444.112604
73	22536	LIHUE	HI	24.333333	72.0	1009.769163	443.409941
71	22521	HONOLULU	HI	25.388889	65.0	1013.010029	442.398239
57	12839	MIAMI	FL	25.111111	71.5	1012.244709	441.730603
56	12836	KEY WEST	FL	25.444444	73.5	1013.215716	440.563445

In [51]:
```
statemean = usloc.groupby('State', as_index=False).mean()
statemean = statemean.sort_values('Power_out', ascending=False)
statemean.head()
```

Out[51]:

	State	Wban	Temperature	Humidity	Pressure	Power_out
30	NH	14750.00	2.722222	33.250	907.087592	499.751931
0	AK	26143.45	0.519444	74.325	1003.855505	499.293539
28	ND	36963.75	5.416667	70.875	968.073548	487.415893
21	ME	14685.50	6.222222	69.250	1001.692198	486.723986
23	MN	14920.80	5.755556	71.900	973.431288	486.548040

Plotting color US map

In [52]:
```
city = pd.read_excel('uscities.xlsx')
city.head(10)
```

Out[52]:

	city	city_ascii	state_id	state_name	county_fips	county_name	county_fips_all	co
0	South Creek	South Creek	WA	Washington	53053	Pierce	53053	
1	Roslyn	Roslyn	WA	Washington	53037	Kittitas	53037	
2	Sprague	Sprague	WA	Washington	53043	Lincoln	53043	
3	Gig Harbor	Gig Harbor	WA	Washington	53053	Pierce	53053	
4	Lake Cassidy	Lake Cassidy	WA	Washington	53061	Snohomish	53061	
5	Tenino	Tenino	WA	Washington	53067	Thurston	53067	
6	Jamestown	Jamestown	WA	Washington	53009	Clallam	53009	
7	Three Lakes	Three Lakes	WA	Washington	53061	Snohomish	53061	
8	Curlew Lake	Curlew Lake	WA	Washington	53019	Ferry	53019	
9	Chain Lake	Chain Lake	WA	Washington	53061	Snohomish	53061	

In [53]:
```
city = city[['city','state_id', 'county_fips']]
city.head()
```

Out[53]:

	city	state_id	county_fips
0	South Creek	WA	53053
1	Roslyn	WA	53037
2	Sprague	WA	53043
3	Gig Harbor	WA	53053
4	Lake Cassidy	WA	53061

In [54]:
```
city.city = city.city.str.upper()
city.head()
```

Out[54]:

	city	state_id	county_fips
0	SOUTH CREEK	WA	53053
1	ROSLYN	WA	53037
2	SPRAGUE	WA	53043
3	GIG HARBOR	WA	53053
4	LAKE CASSIDY	WA	53061

In [55]:
```
DF = usloc[['City','State','Power_out']]
DF.columns = ['city','state_id','Power_out']
DF.city = DF.city.str.rstrip()
DF.head()
```

```
/Users/sandra/anaconda3/lib/python3.7/site-packages/pandas/core/gene
ric.py:5096: SettingWithCopyWarning:
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: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  self[name] = value
```

Out[55]:

	city	state_id	Power_out
0	BIRMINGHAM	AL	459.918971
1	HUNTSVILLE	AL	461.191360
2	MOBILE	AL	454.641344
3	MONTGOMERY	AL	457.622490
4	ANCHORAGE	AK	495.011810

In [56]:
```
city.head()
```

Out[56]:

	city	state_id	county_fips
0	SOUTH CREEK	WA	53053
1	ROSLYN	WA	53037
2	SPRAGUE	WA	53043
3	GIG HARBOR	WA	53053
4	LAKE CASSIDY	WA	53061

In [57]:
```
city.city[0]
```

Out[57]:
```
'SOUTH CREEK'
```

n=0 for i in city.city: if 'Huntsville' in i: print (city.iloc[n]) n =n+1

In [58]:
```
x = pd.merge(DF, city, on=['city','state_id'])
x.head()
```

Out[58]:

	city	state_id	Power_out	county_fips
0	BIRMINGHAM	AL	459.918971	1073
1	HUNTSVILLE	AL	461.191360	1089
2	MOBILE	AL	454.641344	1097
3	MONTGOMERY	AL	457.622490	1101
4	ANCHORAGE	AK	495.011810	2020

In [59]:
```
x.county_fips[x.county_fips<10000]= ('0'+ x.county_fips.astype(str))
```

```
/Users/sandra/anaconda3/lib/python3.7/site-packages/ipykernel_launch
er.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  """Entry point for launching an IPython kernel.
```

In [60]:
```
len (x)
```

Out[60]: 232

In [61]:
```
x.head()
```

Out[61]:

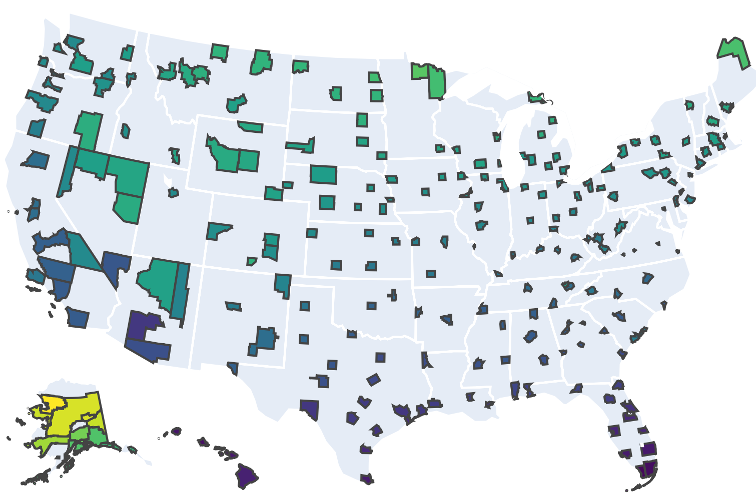
	city	state_id	Power_out	county_fips
0	BIRMINGHAM	AL	459.918971	01073
1	HUNTSVILLE	AL	461.191360	01089
2	MOBILE	AL	454.641344	01097
3	MONTGOMERY	AL	457.622490	01101
4	ANCHORAGE	AK	495.011810	02020

In [62]:
```
with urlopen('https://raw.githubusercontent.com/plotly/datasets/master
/geojson-counties-fips.json') as response:
    counties = json.load(response)



import plotly.express as px

fig = px.choropleth(x, geojson=counties, locations='county_fips', colo
r='Power_out',
                           color_continuous_scale="Viridis",
                           range_color=(439, 512),
                           scope="usa", labels={'Power_out':'Power Out
put [MW]'},
                          )
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()
```



Combined Cycle Power Plant Performance

Sandra Poza

Abstract

This project studies the relationship between weather conditions and performance of a combined cycle power plant (CCPP). We used a dataset containing CCPP performance to train a regression model that predict the power output of the plant.

Then with data from US weather datasets we predicted the performance it would have in different US locations.

It was found that it would perform better in coldest weather in northern areas.

Motivation

Energy efficiency has become an essential matter in todays society. For climate, economic and sustainability reasons, every one gets benefit from a more effective use of energy.

In this project we try to find out where would a Combined Cycle Power Plant (CCPP) have the highest power output (which would mean a highest efficiency), based on the weather conditions.

Dataset(s)

Combined Cycle Power Plant Data Set: The dataset contains 9568 data points collected from a Combined Cycle Power Plant over 6 years (2006-2011). Obtained from UCI's Machine learning repository.

US Weather datasets: Obtained from NOAA National Centers for Environmental Information

- **Temperatures dataset:** Contains monthly and yearly average temperatures for different US weather stations.
- **Relative Humidity dataset:** Contains monthly and yearly average relative humidity for different US weather stations.
- **Weather station locations dataset:** Contains weather stations information with elevation, used for ambient pressure calculation.

US cities dataset: Contains US cities information, including the fips codes. Obtained from https://simplemaps.com

Methods

The Combined Cycle Power Plant Dataset contains data of a CCPP working at full load over 6 years. This include the following features:

Temperature (T) [°C]
Ambient Pressure (AP) [milibar]
Relative Humidity (RH) [%]
Energy output (EP) [MW] of the plant

With this data we will train a model that predict **Energy output** based on the 3 first. We will use scikit-learn, and train the model as a multiple linear regression.

Then, from the weather datasets we are going to extract information about the average Temperature, Relative Humidity and Ambient Pressure in different US locations.

Then we will use the model previously trained with the CCPP data, and feed the weather average data from different locations to predict the expected power output of a CCPP in this locations.

We will use Matplotlib and Plotly for plotting results.

Findings

Multiple Linear Regression Model Accuracy

The mean squared error for the model with test data is 4.65. Taking into consideration that the output of the model is in the order of 400-500 it is a good number.

```
RMSE = sqrt(mean_squared_error(y_true = Ytest, y_pred = Ypred))
RMSE
```

```
4.657571391074255
```

A better stimator is the R2 score. This is a statistical measure of how well the regression predictions approximate the real data points. It ranges from 0-1 being 1 the best possible result.
Our R2 score is 0.92, what means that **the model is highly accurate** on test data.

```
from sklearn.metrics import r2_score

r2 = r2_score(Ytest, Ypred)
r2
```

```
0.9266765701220129
```

Findings

Performance prediction at US locations

We can appreciate how the energy output is higher in the coldest areas like Alaska, and lower in the warmer ones like Florida.

	Wban	City	State	Temperature	Humidity	Pressure	Power_out
6	27502	BARROW	AK	-11.222222	81.0	1012.164777	526.034436
147	14755	MT. WASHINGTON	NH	-2.555556	0.0	812.822902	516.454667
8	26533	BETTLES	AK	-4.722222	67.0	991.362149	512.871904
17	26616	KOTZEBUE	AK	-5.055556	78.0	1012.210452	512.005739
11	26411	FAIRBANKS	AK	-2.388889	65.0	998.288099	507.921088
18	26510	MCGRATH	AK	-2.555556	68.5	1001.703277	507.703816
19	26617	NOME	AK	-2.555556	76.0	1012.792951	506.490944
12	26425	GULKANA	AK	-2.111111	66.0	959.996103	506.043838
9	26415	BIG DELTA	AK	-1.666667	62.5	969.545252	505.946333
7	26615	BETHEL	AK	-0.722222	78.5	1009.700784	501.556013

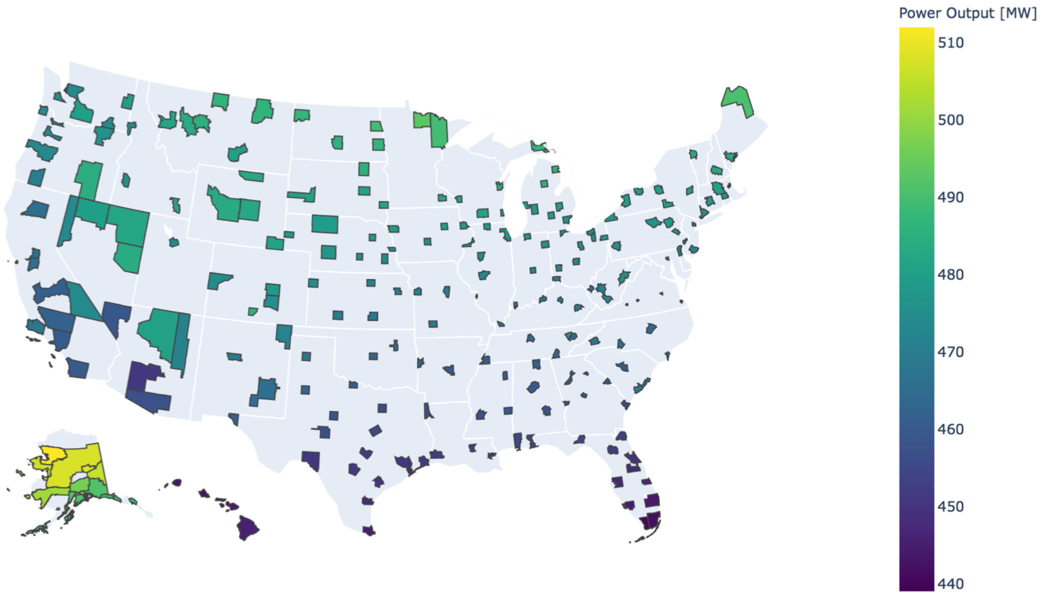
10 Highest Energy Output

	Wban	City	State	Temperature	Humidity	Pressure	Power_out
61	12842	TAMPA	FL	23.000000	72.0	1012.587332	446.648664
70	21504	HILO	HI	23.277778	74.0	1011.925011	445.569949
211	12919	BROWNSVILLE	TX	23.611111	75.0	1012.416009	444.591033
53	12835	FORT MYERS	FL	23.944444	71.5	1012.724408	444.511729
72	22516	KAHULUI	HI	24.388889	67.5	1011.479853	444.228015
63	12844	WEST PALM BEACH	FL	24.111111	71.5	1012.587332	444.112604
73	22536	LIHUE	HI	24.333333	72.0	1009.769163	443.409941
71	22521	HONOLULU	HI	25.388889	65.0	1013.010029	442.398239
57	12839	MIAMI	FL	25.111111	71.5	1012.244709	441.730603
56	12836	KEY WEST	FL	25.444444	73.5	1013.215716	440.563445

10 Lowest Energy Output

Findings

Performance prediction at US locations



This map shows the power output that it would be obtained by a CCPP situated in different US counties.

We can observe the relationship between southern, warmer, and more humid areas with lower power output

Also the northern, colder and drier areas whit highest power output.

It should be mentioned that Alaska is represented on the bottom left, but is in fact the northernmost state, with the lowest temperatures, so we can appreciate how that region is the most yellowish.

Limitations

We did not have enough weather data to study the whole US map.

The weather data is average, so it doesn’t reflect seasonal changes.

The CCPP dataset measures was taken in a fixed location, so the pressure changes were not well represented.

Conclusions

We can conclude, that the performance of a Combined Cycle Power Plant would be the best in the coldest and driest possible weathers.

A CCPP situated in Alaska would have the highest efficiency, and one located in Florida the lowest. That means that the same power plant would consume less gas in Alaska to produce the same power output.