

Instructions:

In this Assignment, you will demonstrate the data regression skills you have learned by completing this course. You are expected to leverage a wide variety of tools, but also this report should focus on present findings, insights, and next steps. You may include some visuals from your code output, but this report is intended as a summary of your findings, not as a code review.

The grading will center around 5 main points:

1. Does the report include a section describing the data?
2. Does the report include a paragraph detailing the main objective(s) of this analysis?
3. Does the report include a section with variations of linear regression models and specifies which one is the model that best suits the main objective(s) of this analysis.
4. Does the report include a clear and well-presented section with key findings related to the main objective(s) of the analysis?
5. Does the report highlight possible flaws in the model and a plan of action to revisit this analysis with additional data or different predictive modeling techniques?

Import the required libraries

The following required modules are pre-installed in the Skills Network Labs environment. However if you run this notebook commands in a different Jupyter environment (e.g. Watson Studio or Ananconda) you will need to install these libraries by removing the # sign before `mamba` in the code cell below.

```
# All Libraries required for this lab are listed below. The libraries
pre-installed on Skills Network Labs are commented.
# !mamba install -qy pandas==1.3.4 numpy==1.21.4 seaborn==0.9.0
matplotlib==3.5.0 scikit-learn==0.20.1
# Note: If your environment doesn't support "!mamba install", use "!
pip install"

# Surpress warnings:
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn

import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.linear_model import
LinearRegression,Ridge,Lasso,ElasticNet
```

```

from sklearn.metrics import r2_score
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import scale
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.decomposition import PCA

```

Importing the Dataset

Before you begin, you will need to choose a data set that you feel passionate about. You can brainstorm with your peers about great public data sets using the discussion board in this module.

Read your chosen dataset into pandas dataframe:

Dataset taken from [Kaggle](#).

```

data = pd.read_csv('data/Energy_consumption.csv')
data.head(15)

```

	Occupancy \	Timestamp	Temperature	Humidity	SquareFootage
0	2022-01-01 00:00:00	25.139433	43.431581	1565.693999	
5					
1	2022-01-01 01:00:00	27.731651	54.225919	1411.064918	
1					
2	2022-01-01 02:00:00	28.704277	58.907658	1755.715009	
2					
3	2022-01-01 03:00:00	20.080469	50.371637	1452.316318	
1					
4	2022-01-01 04:00:00	23.097359	51.401421	1094.130359	
9					
5	2022-01-01 05:00:00	29.576037	36.824263	1871.709180	
6					
6	2022-01-01 06:00:00	25.131167	35.709622	1607.001228	
6					
7	2022-01-01 07:00:00	23.182844	31.679920	1633.955330	
8					
8	2022-01-01 08:00:00	25.391999	46.399364	1240.309224	
6					
9	2022-01-01 09:00:00	22.212549	32.418464	1705.420336	
1					
10	2022-01-01 10:00:00	28.064814	36.451472	1341.467129	
2					
11	2022-01-01 11:00:00	23.422546	30.527342	1604.418355	

6						
12	2022-01-01	12:00:00	25.388888	47.601018	1244.618914	
1						
13	2022-01-01	13:00:00	20.058738	41.861642	1806.052632	
2						
14	2022-01-01	14:00:00	26.731525	37.297870	1419.749014	
6						
	HVACUsage	LightingUsage	RenewableEnergy	DayOfWeek	Holiday	\
0	On	Off	2.774699	Monday	No	
1	On	On	21.831384	Saturday	No	
2	Off	Off	6.764672	Sunday	No	
3	Off	On	8.623447	Wednesday	No	
4	On	Off	3.071969	Friday	No	
5	Off	Off	17.626690	Sunday	Yes	
6	On	Off	24.264702	Friday	Yes	
7	Off	Off	27.517099	Thursday	Yes	
8	On	Off	2.307595	Sunday	No	
9	On	Off	29.140071	Tuesday	No	
10	Off	Off	0.352238	Monday	Yes	
11	On	On	19.529548	Thursday	Yes	
12	On	Off	21.797444	Tuesday	Yes	
13	Off	Off	6.384949	Friday	Yes	
14	Off	Off	12.074223	Friday	Yes	
	EnergyConsumption					
0	75.364373					
1	83.401855					
2	78.270888					
3	56.519850					
4	70.811732					
5	84.321885					
6	76.165791					
7	74.131906					
8	78.206236					
9	77.992214					
10	82.274434					
11	73.278670					
12	84.144776					
13	60.022519					
14	81.183188					

Once you have selected a data set, you will produce the deliverables listed below and submit them to one of your peers for review. Treat this exercise as an opportunity to produce analysis that are ready to highlight your analytical skills for a senior audience, for example, the Chief Data Officer, or the Head of Analytics at your company. Sections required in your report:

- Main objective of the analysis that specifies whether your model will be focused on prediction or interpretation.
- Brief description of the data set you chose and a summary of its attributes.

- Brief summary of data exploration and actions taken for data cleaning and feature engineering.
- Summary of training at least three linear regression models which should be variations that cover using a simple linear regression as a baseline, adding polynomial effects, and using a regularization regression. Preferably, all use the same training and test splits, or the same cross-validation method.
- A paragraph explaining which of your regressions you recommend as a final model that best fits your needs in terms of accuracy and explainability.
- Summary Key Findings and Insights, which walks your reader through the main drivers of your model and insights from your data derived from your linear regression model.
- Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model adding specific data features to achieve a better explanation or a better prediction.

1. About the Data

This dataset encapsulates a diverse array of features, including temperature, humidity, occupancy, HVAC and lighting usage, renewable energy contributions, and more. Each timestamp provides a snapshot of a hypothetical environment, allowing for in-depth analysis and modeling of energy consumption behaviors. Dive into the nuances of this synthetic dataset, designed to emulate real-world scenarios, and unravel the complexities that influence energy usage. Whether you are delving into predictive modeling or honing your data analysis skills, this dataset offers a dynamic playground for experimentation and discovery.

```
data.columns
```

```
Index(['Timestamp', 'Temperature', 'Humidity', 'SquareFootage',
      'Occupancy',
      'HVACUsage', 'LightingUsage', 'RenewableEnergy', 'DayOfWeek',
      'Holiday',
      'EnergyConsumption'],
      dtype='object')
```

```
sum(data.duplicated())
```

```
0
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 1000 entries, 0 to 999
```

```
Data columns (total 11 columns):
```

#	Column	Non-Null Count	Dtype
0	Timestamp	1000 non-null	object
1	Temperature	1000 non-null	float64
2	Humidity	1000 non-null	float64
3	SquareFootage	1000 non-null	float64

```

4   Occupancy          1000 non-null   int64
5   HVACUsage          1000 non-null   object
6   LightingUsage      1000 non-null   object
7   RenewableEnergy    1000 non-null   float64
8   DayOfWeek          1000 non-null   object
9   Holiday            1000 non-null   object
10  EnergyConsumption  1000 non-null   float64
dtypes: float64(5), int64(1), object(5)
memory usage: 86.1+ KB

```

```
pd.DataFrame(data.isnull().value_counts()).T
```

```

Timestamp      False
Temperature     False
Humidity        False
SquareFootage  False
Occupancy       False
HVACUsage       False
LightingUsage   False
RenewableEnergy False
DayOfWeek       False
Holiday         False
EnergyConsumption False
count          1000

```

```
data.describe().T
```

	count	mean	std	min
25% \				
Temperature	1000.0	24.982026	2.836850	20.007565
22.645070				
Humidity	1000.0	45.395412	8.518905	30.015975
38.297722				
SquareFootage	1000.0	1500.052488	288.418873	1000.512661
1247.108548				
Occupancy	1000.0	4.581000	2.865598	0.000000
2.000000				
RenewableEnergy	1000.0	15.132813	8.745917	0.006642
7.628385				
EnergyConsumption	1000.0	77.055873	8.144112	53.263278
71.544690				

	50%	75%	max
Temperature	24.751637	27.418174	29.998671
Humidity	45.972116	52.420066	59.969085
SquareFootage	1507.967426	1740.340165	1999.982252
Occupancy	5.000000	7.000000	9.000000
RenewableEnergy	15.072296	22.884064	29.965327
EnergyConsumption	76.943696	82.921742	99.201120

```
feature_cols = data.select_dtypes(include=object)
for col in feature_cols.columns:
    print(col, ': ', data[col].unique(), '\n')
```

```
Timestamp : ['2022-01-01 00:00:00' '2022-01-01 01:00:00' '2022-01-01 02:00:00'
```

```
'2022-01-01 03:00:00' '2022-01-01 04:00:00' '2022-01-01 05:00:00'
'2022-01-01 06:00:00' '2022-01-01 07:00:00' '2022-01-01 08:00:00'
'2022-01-01 09:00:00' '2022-01-01 10:00:00' '2022-01-01 11:00:00'
'2022-01-01 12:00:00' '2022-01-01 13:00:00' '2022-01-01 14:00:00'
'2022-01-01 15:00:00' '2022-01-01 16:00:00' '2022-01-01 17:00:00'
'2022-01-01 18:00:00' '2022-01-01 19:00:00' '2022-01-01 20:00:00'
'2022-01-01 21:00:00' '2022-01-01 22:00:00' '2022-01-01 23:00:00'
'2022-01-02 00:00:00' '2022-01-02 01:00:00' '2022-01-02 02:00:00'
'2022-01-02 03:00:00' '2022-01-02 04:00:00' '2022-01-02 05:00:00'
'2022-01-02 06:00:00' '2022-01-02 07:00:00' '2022-01-02 08:00:00'
'2022-01-02 09:00:00' '2022-01-02 10:00:00' '2022-01-02 11:00:00'
'2022-01-02 12:00:00' '2022-01-02 13:00:00' '2022-01-02 14:00:00'
'2022-01-02 15:00:00' '2022-01-02 16:00:00' '2022-01-02 17:00:00'
'2022-01-02 18:00:00' '2022-01-02 19:00:00' '2022-01-02 20:00:00'
'2022-01-02 21:00:00' '2022-01-02 22:00:00' '2022-01-02 23:00:00'
'2022-01-03 00:00:00' '2022-01-03 01:00:00' '2022-01-03 02:00:00'
'2022-01-03 03:00:00' '2022-01-03 04:00:00' '2022-01-03 05:00:00'
'2022-01-03 06:00:00' '2022-01-03 07:00:00' '2022-01-03 08:00:00'
'2022-01-03 09:00:00' '2022-01-03 10:00:00' '2022-01-03 11:00:00'
'2022-01-03 12:00:00' '2022-01-03 13:00:00' '2022-01-03 14:00:00'
'2022-01-03 15:00:00' '2022-01-03 16:00:00' '2022-01-03 17:00:00'
'2022-01-03 18:00:00' '2022-01-03 19:00:00' '2022-01-03 20:00:00'
'2022-01-03 21:00:00' '2022-01-03 22:00:00' '2022-01-03 23:00:00'
'2022-01-04 00:00:00' '2022-01-04 01:00:00' '2022-01-04 02:00:00'
'2022-01-04 03:00:00' '2022-01-04 04:00:00' '2022-01-04 05:00:00'
'2022-01-04 06:00:00' '2022-01-04 07:00:00' '2022-01-04 08:00:00'
'2022-01-04 09:00:00' '2022-01-04 10:00:00' '2022-01-04 11:00:00'
'2022-01-04 12:00:00' '2022-01-04 13:00:00' '2022-01-04 14:00:00'
'2022-01-04 15:00:00' '2022-01-04 16:00:00' '2022-01-04 17:00:00'
'2022-01-04 18:00:00' '2022-01-04 19:00:00' '2022-01-04 20:00:00'
'2022-01-04 21:00:00' '2022-01-04 22:00:00' '2022-01-04 23:00:00'
'2022-01-05 00:00:00' '2022-01-05 01:00:00' '2022-01-05 02:00:00'
'2022-01-05 03:00:00' '2022-01-05 04:00:00' '2022-01-05 05:00:00'
'2022-01-05 06:00:00' '2022-01-05 07:00:00' '2022-01-05 08:00:00'
'2022-01-05 09:00:00' '2022-01-05 10:00:00' '2022-01-05 11:00:00'
'2022-01-05 12:00:00' '2022-01-05 13:00:00' '2022-01-05 14:00:00'
'2022-01-05 15:00:00' '2022-01-05 16:00:00' '2022-01-05 17:00:00'
'2022-01-05 18:00:00' '2022-01-05 19:00:00' '2022-01-05 20:00:00'
'2022-01-05 21:00:00' '2022-01-05 22:00:00' '2022-01-05 23:00:00'
'2022-01-06 00:00:00' '2022-01-06 01:00:00' '2022-01-06 02:00:00'
'2022-01-06 03:00:00' '2022-01-06 04:00:00' '2022-01-06 05:00:00'
'2022-01-06 06:00:00' '2022-01-06 07:00:00' '2022-01-06 08:00:00'
'2022-01-06 09:00:00' '2022-01-06 10:00:00' '2022-01-06 11:00:00'
'2022-01-06 12:00:00' '2022-01-06 13:00:00' '2022-01-06 14:00:00'
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
'2022-02-06 06:00:00' '2022-02-06 07:00:00' '2022-02-06 08:00:00'
'2022-02-06 09:00:00' '2022-02-06 10:00:00' '2022-02-06 11:00:00'
'2022-02-06 12:00:00' '2022-02-06 13:00:00' '2022-02-06 14:00:00'
'2022-02-06 15:00:00' '2022-02-06 16:00:00' '2022-02-06 17:00:00'
'2022-02-06 18:00:00' '2022-02-06 19:00:00' '2022-02-06 20:00:00'
'2022-02-06 21:00:00' '2022-02-06 22:00:00' '2022-02-06 23:00:00'
'2022-02-07 00:00:00' '2022-02-07 01:00:00' '2022-02-07 02:00:00'
'2022-02-07 03:00:00' '2022-02-07 04:00:00' '2022-02-07 05:00:00'
'2022-02-07 06:00:00' '2022-02-07 07:00:00' '2022-02-07 08:00:00'
'2022-02-07 09:00:00' '2022-02-07 10:00:00' '2022-02-07 11:00:00'
'2022-02-07 12:00:00' '2022-02-07 13:00:00' '2022-02-07 14:00:00'
'2022-02-07 15:00:00' '2022-02-07 16:00:00' '2022-02-07 17:00:00'
'2022-02-07 18:00:00' '2022-02-07 19:00:00' '2022-02-07 20:00:00'
'2022-02-07 21:00:00' '2022-02-07 22:00:00' '2022-02-07 23:00:00'
'2022-02-08 00:00:00' '2022-02-08 01:00:00' '2022-02-08 02:00:00'
'2022-02-08 03:00:00' '2022-02-08 04:00:00' '2022-02-08 05:00:00'
'2022-02-08 06:00:00' '2022-02-08 07:00:00' '2022-02-08 08:00:00'
'2022-02-08 09:00:00' '2022-02-08 10:00:00' '2022-02-08 11:00:00'
'2022-02-08 12:00:00' '2022-02-08 13:00:00' '2022-02-08 14:00:00'
'2022-02-08 15:00:00' '2022-02-08 16:00:00' '2022-02-08 17:00:00'
'2022-02-08 18:00:00' '2022-02-08 19:00:00' '2022-02-08 20:00:00'
'2022-02-08 21:00:00' '2022-02-08 22:00:00' '2022-02-08 23:00:00'
'2022-02-09 00:00:00' '2022-02-09 01:00:00' '2022-02-09 02:00:00'
'2022-02-09 03:00:00' '2022-02-09 04:00:00' '2022-02-09 05:00:00'
'2022-02-09 06:00:00' '2022-02-09 07:00:00' '2022-02-09 08:00:00'
'2022-02-09 09:00:00' '2022-02-09 10:00:00' '2022-02-09 11:00:00'
'2022-02-09 12:00:00' '2022-02-09 13:00:00' '2022-02-09 14:00:00'
'2022-02-09 15:00:00' '2022-02-09 16:00:00' '2022-02-09 17:00:00'
'2022-02-09 18:00:00' '2022-02-09 19:00:00' '2022-02-09 20:00:00'
'2022-02-09 21:00:00' '2022-02-09 22:00:00' '2022-02-09 23:00:00'
'2022-02-10 00:00:00' '2022-02-10 01:00:00' '2022-02-10 02:00:00'
'2022-02-10 03:00:00' '2022-02-10 04:00:00' '2022-02-10 05:00:00'
'2022-02-10 06:00:00' '2022-02-10 07:00:00' '2022-02-10 08:00:00'
'2022-02-10 09:00:00' '2022-02-10 10:00:00' '2022-02-10 11:00:00'
'2022-02-10 12:00:00' '2022-02-10 13:00:00' '2022-02-10 14:00:00'
'2022-02-10 15:00:00' '2022-02-10 16:00:00' '2022-02-10 17:00:00'
'2022-02-10 18:00:00' '2022-02-10 19:00:00' '2022-02-10 20:00:00'
'2022-02-10 21:00:00' '2022-02-10 22:00:00' '2022-02-10 23:00:00'
'2022-02-11 00:00:00' '2022-02-11 01:00:00' '2022-02-11 02:00:00'
'2022-02-11 03:00:00' '2022-02-11 04:00:00' '2022-02-11 05:00:00'
'2022-02-11 06:00:00' '2022-02-11 07:00:00' '2022-02-11 08:00:00'
'2022-02-11 09:00:00' '2022-02-11 10:00:00' '2022-02-11 11:00:00'
'2022-02-11 12:00:00' '2022-02-11 13:00:00' '2022-02-11 14:00:00'
'2022-02-11 15:00:00']
```

HVACUsage : ['On' 'Off']

LightingUsage : ['Off' 'On']

DayOfWeek : ['Monday' 'Saturday' 'Sunday' 'Wednesday' 'Friday']

```
'Thursday' 'Tuesday']  
Holiday : ['No' 'Yes']
```

2. Objectives

```
df = data.copy()  
df
```

	Timestamp	Temperature	Humidity	SquareFootage
Occupancy \				
0	2022-01-01 00:00:00	25.139433	43.431581	1565.693999
5				
1	2022-01-01 01:00:00	27.731651	54.225919	1411.064918
1				
2	2022-01-01 02:00:00	28.704277	58.907658	1755.715009
2				
3	2022-01-01 03:00:00	20.080469	50.371637	1452.316318
1				
4	2022-01-01 04:00:00	23.097359	51.401421	1094.130359
9				
..
...				
995	2022-02-11 11:00:00	28.619382	48.850160	1080.087000
5				
996	2022-02-11 12:00:00	23.836647	47.256435	1705.235156
4				
997	2022-02-11 13:00:00	23.005340	48.720501	1320.285281
6				
998	2022-02-11 14:00:00	25.138365	31.306459	1309.079719
3				
999	2022-02-11 15:00:00	23.051165	42.615421	1018.140606
6				

	HVACUsage	LightingUsage	RenewableEnergy	DayOfWeek	Holiday	\
0	On	Off	2.774699	Monday	No	
1	On	On	21.831384	Saturday	No	
2	Off	Off	6.764672	Sunday	No	
3	Off	On	8.623447	Wednesday	No	
4	On	Off	3.071969	Friday	No	
..	
995	Off	Off	21.194696	Saturday	No	
996	Off	On	25.748176	Tuesday	Yes	
997	Off	On	0.297079	Friday	Yes	
998	On	Off	20.425163	Thursday	Yes	
999	Off	On	2.455657	Saturday	No	

EnergyConsumption

```

0      75.364373
1      83.401855
2      78.270888
3      56.519850
4      70.811732
..      ...
995    82.306692
996    66.577320
997    72.753471
998    76.950389
999    71.545311

```

```
[1000 rows x 11 columns]
```

We will now encode our categorical data.

```

df.replace({'On':1, 'Off':0, 'Yes':1, 'No':0,
            'Monday':1, 'Saturday':6, 'Sunday':7, 'Wednesday':3,
            'Friday':5, 'Thursday':4, 'Tuesday':2},inplace=True)
df

```

	Occupancy \	Timestamp	Temperature	Humidity	SquareFootage
0	2022-01-01	00:00:00	25.139433	43.431581	1565.693999
5					
1	2022-01-01	01:00:00	27.731651	54.225919	1411.064918
1					
2	2022-01-01	02:00:00	28.704277	58.907658	1755.715009
2					
3	2022-01-01	03:00:00	20.080469	50.371637	1452.316318
1					
4	2022-01-01	04:00:00	23.097359	51.401421	1094.130359
9					
..	
...					
995	2022-02-11	11:00:00	28.619382	48.850160	1080.087000
5					
996	2022-02-11	12:00:00	23.836647	47.256435	1705.235156
4					
997	2022-02-11	13:00:00	23.005340	48.720501	1320.285281
6					
998	2022-02-11	14:00:00	25.138365	31.306459	1309.079719
3					
999	2022-02-11	15:00:00	23.051165	42.615421	1018.140606
6					

	HVACUsage	LightingUsage	RenewableEnergy	DayOfWeek	Holiday \
0	1	0	2.774699	1	0
1	1	1	21.831384	6	0

2	0	0	6.764672	7	0
3	0	1	8.623447	3	0
4	1	0	3.071969	5	0
..
995	0	0	21.194696	6	0
996	0	1	25.748176	2	1
997	0	1	0.297079	5	1
998	1	0	20.425163	4	1
999	0	1	2.455657	6	0

EnergyConsumption	
0	75.364373
1	83.401855
2	78.270888
3	56.519850
4	70.811732
..	...
995	82.306692
996	66.577320
997	72.753471
998	76.950389
999	71.545311

[1000 rows x 11 columns]

```
df['Timestamp_unix'] =
pd.to_datetime(df['Timestamp']).astype('int64')/10**9
df
```

	Occupancy	Timestamp	Temperature	Humidity	SquareFootage
0	5	2022-01-01 00:00:00	25.139433	43.431581	1565.693999
1	1	2022-01-01 01:00:00	27.731651	54.225919	1411.064918
2	2	2022-01-01 02:00:00	28.704277	58.907658	1755.715009
3	1	2022-01-01 03:00:00	20.080469	50.371637	1452.316318
4	9	2022-01-01 04:00:00	23.097359	51.401421	1094.130359
..
995	5	2022-02-11 11:00:00	28.619382	48.850160	1080.087000
996	4	2022-02-11 12:00:00	23.836647	47.256435	1705.235156
997	6	2022-02-11 13:00:00	23.005340	48.720501	1320.285281
998		2022-02-11 14:00:00	25.138365	31.306459	1309.079719

```
3
999 2022-02-11 15:00:00      23.051165  42.615421      1018.140606
6
```

	HVACUsage	LightingUsage	RenewableEnergy	DayOfWeek	Holiday	\
0	1	0	2.774699	1	0	
1	1	1	21.831384	6	0	
2	0	0	6.764672	7	0	
3	0	1	8.623447	3	0	
4	1	0	3.071969	5	0	
..	
995	0	0	21.194696	6	0	
996	0	1	25.748176	2	1	
997	0	1	0.297079	5	1	
998	1	0	20.425163	4	1	
999	0	1	2.455657	6	0	

	EnergyConsumption	Timestamp_unix
0	75.364373	1.640995e+09
1	83.401855	1.640999e+09
2	78.270888	1.641002e+09
3	56.519850	1.641006e+09
4	70.811732	1.641010e+09
..
995	82.306692	1.644577e+09
996	66.577320	1.644581e+09
997	72.753471	1.644584e+09
998	76.950389	1.644588e+09
999	71.545311	1.644592e+09

```
[1000 rows x 12 columns]
```

```
df = df.drop(columns='Timestamp')
df
```

	Temperature	Humidity	SquareFootage	Occupancy	HVACUsage	\
0	25.139433	43.431581	1565.693999	5	1	
1	27.731651	54.225919	1411.064918	1	1	
2	28.704277	58.907658	1755.715009	2	0	
3	20.080469	50.371637	1452.316318	1	0	
4	23.097359	51.401421	1094.130359	9	1	
..	
995	28.619382	48.850160	1080.087000	5	0	
996	23.836647	47.256435	1705.235156	4	0	
997	23.005340	48.720501	1320.285281	6	0	
998	25.138365	31.306459	1309.079719	3	1	
999	23.051165	42.615421	1018.140606	6	0	

LightingUsage	RenewableEnergy	DayOfWeek	Holiday
EnergyConsumption	\		

0	0	2.774699	1	0
75.364373				
1	1	21.831384	6	0
83.401855				
2	0	6.764672	7	0
78.270888				
3	1	8.623447	3	0
56.519850				
4	0	3.071969	5	0
70.811732				
..
...				
995	0	21.194696	6	0
82.306692				
996	1	25.748176	2	1
66.577320				
997	1	0.297079	5	1
72.753471				
998	0	20.425163	4	1
76.950389				
999	1	2.455657	6	0
71.545311				

	Timestamp_unix
0	1.640995e+09
1	1.640999e+09
2	1.641002e+09
3	1.641006e+09
4	1.641010e+09
..	...
995	1.644577e+09
996	1.644581e+09
997	1.644584e+09
998	1.644588e+09
999	1.644592e+09

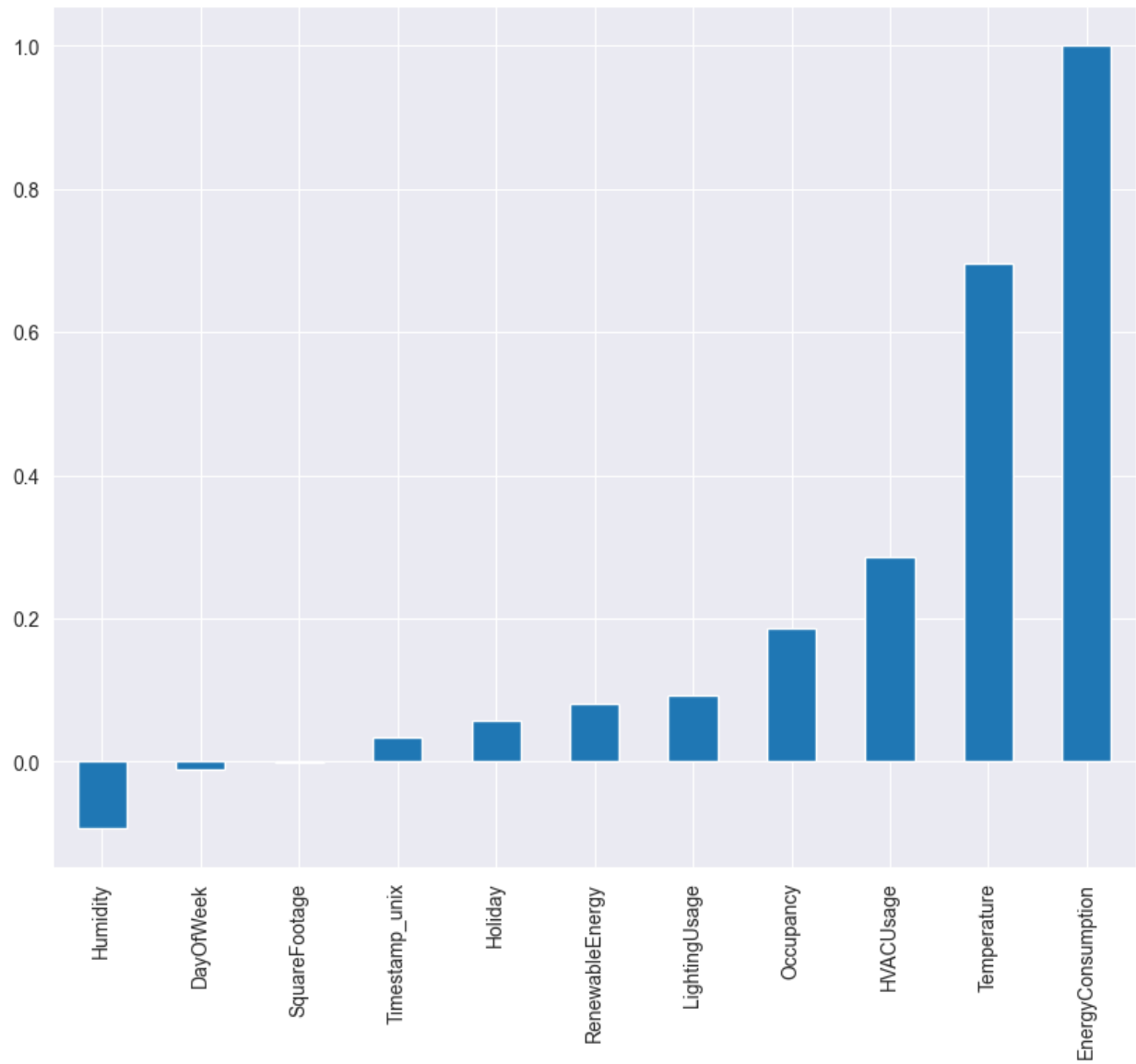
[1000 rows x 11 columns]

```
df.EnergyConsumption.skew()
```

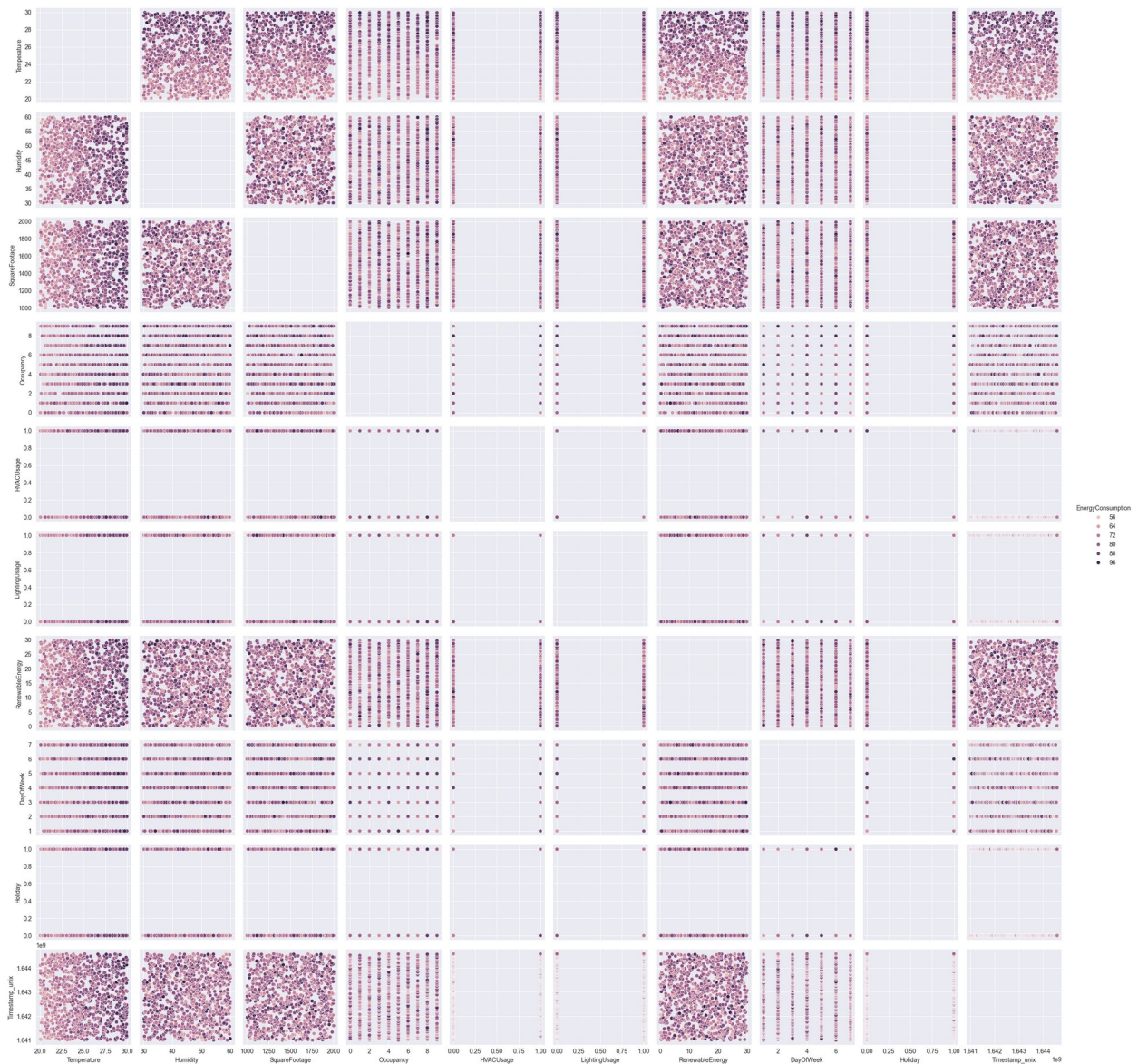
```
0.027398907453860765
```

```
correlations = df.corr()['EnergyConsumption'].sort_values()
correlations.plot(kind='bar', figsize=(10,8))
```

```
<Axes: >
```



```
sns.pairplot(df, hue='EnergyConsumption')  
<seaborn.axisgrid.PairGrid at 0x1dcf0a35c10>
```



Data visualisation and encoding is important for representation of data and preparation for our prediction models.

After cleaning and encoding our data we can start implementing couple regression models. After we do that we will check their efficiency in predicting values on our holdout set (we will set it to 10% of the whole dataframe).

3. Linear Regression Models

```
X = df.drop('EnergyConsumption',axis=1)
y = df['EnergyConsumption']

skb = SelectKBest(k=4,score_func=f_regression)
transX = skb.fit_transform(X,y)
```

```

srt_skb = skb.pvalues_.argsort()[::-1]
print(srt_skb)
skb.pvalues_

[2 7 9 8 6 5 1 3 4 0]

array([5.70222544e-146, 3.05498261e-003, 9.71553934e-001, 2.76301328e-
009,
       2.42306979e-020, 3.10566753e-003, 1.02428573e-002, 7.39582072e-
001,
       7.32207624e-002, 2.77040556e-001])

skb.feature_names_in_

array(['Temperature', 'Humidity', 'SquareFootage', 'Occupancy',
       'HVACUsage', 'LightingUsage', 'RenewableEnergy', 'DayOfWeek',
       'Holiday', 'Timestamp_unix'], dtype=object)

X_SKB = df[['Temperature', 'HVACUsage', 'Occupancy',
            'Humidity', 'LightingUsage']]
X_SKB

```

	Temperature	HVACUsage	Occupancy	Humidity	LightingUsage
0	25.139433	1	5	43.431581	0
1	27.731651	1	1	54.225919	1
2	28.704277	0	2	58.907658	0
3	20.080469	0	1	50.371637	1
4	23.097359	1	9	51.401421	0
...
995	28.619382	0	5	48.850160	0
996	23.836647	0	4	47.256435	1
997	23.005340	0	6	48.720501	1
998	25.138365	1	3	31.306459	0
999	23.051165	0	6	42.615421	1

```

[1000 rows x 5 columns]

```

SelectKBest p-values shows us that all of our features are significant, top five are selected in X_SKB above.

```

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.1, random_state=72018)

Input1=[('polynomial', PolynomialFeatures(include_bias=False)),
        ('ss', StandardScaler()), ('model', Lasso(tol = 0.2))]
pipe1 = Pipeline(Input1)

param_grid1 = {
    "polynomial__degree": [1, 2, 3, 4, 5],
    "model__alpha": [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
}

```

```

}
search1 = GridSearchCV(pipe1, param_grid1, n_jobs=2)
search1.fit(X_train, y_train)
best1=search1.best_estimator_
print(search1.best_params_)
best1

{'model__alpha': 0.1, 'polynomial__degree': 1}

Pipeline(steps=[('polynomial',
                  PolynomialFeatures(degree=1, include_bias=False)),
                ('ss', StandardScaler()),
                ('model', Lasso(alpha=0.1, tol=0.2))])

Input2=[('polynomial', PolynomialFeatures(include_bias=False)),
        ('ss',StandardScaler() ), ('model',Ridge())]
pipe2 = Pipeline(Input2)

param_grid2 = {
    "polynomial__degree": [ 1, 2,3,4,5],
    "model__alpha": [0.0001,0.001,0.01,0.1,1,10,100,1000]
}

search2 = GridSearchCV(pipe2, param_grid2, n_jobs=2)
search2.fit(X_train, y_train)
best2=search2.best_estimator_
print(search2.best_params_)
best2

{'model__alpha': 10, 'polynomial__degree': 1}

Pipeline(steps=[('polynomial',
                  PolynomialFeatures(degree=1, include_bias=False)),
                ('ss', StandardScaler()), ('model', Ridge(alpha=10))])

Input3 = [('polynomial', PolynomialFeatures(include_bias=False)),
          ('ss', StandardScaler()), ('model',ElasticNet(tol=0.2))]
pipe3 = Pipeline(Input3)

param_grid3 = {
    "polynomial__degree": [ 1, 2,3,4,5],
    "model__alpha": [0.0001,0.001,0.01,0.1,1,10,100,1000],
    "model__l1_ratio": [0.0001,0.001,0.01,0.1,1,10,100,1000]
}

search3 = GridSearchCV(pipe3, param_grid3, n_jobs=2)
search3.fit(X_train, y_train)
best3=search3.best_estimator_

```

```

print(search3.best_params_)
best3

{'model__alpha': 0.1, 'model__l1_ratio': 1, 'polynomial__degree': 1}
Pipeline(steps=[('polynomial',
                  PolynomialFeatures(degree=1, include_bias=False)),
                ('ss', StandardScaler()),
                ('model', ElasticNet(alpha=0.1, l1_ratio=1,
tol=0.2))])

print('for the training set R^2 of the best estimators for Lasso,
Ridge and ElasticNet (in that order) are:')
print(best1.score(X_train,y_train))
print(best2.score(X_train,y_train))
print(best3.score(X_train,y_train))

for the training set R^2 of the best estimators for Lasso, Ridge and
ElasticNet (in that order) are:
0.6111921987614747
0.6124810926429878
0.6111921987614747

print('for the test set R^2 of the best estimators for Lasso, Ridge
and ElasticNet (in that order) are:')
print(best1.score(X_test,y_test))
print(best2.score(X_test,y_test))
print(best3.score(X_test,y_test))

for the test set R^2 of the best estimators for Lasso, Ridge and
ElasticNet (in that order) are:
0.6645368081717871
0.6686871143154163
0.6645368081717871

Input4 = [('ss', StandardScaler()), ('model',LinearRegression())]
pipe4 = Pipeline(Input4)

pipe4.fit(X_train, y_train)

Pipeline(steps=[('ss', StandardScaler()), ('model',
LinearRegression())])

pipe4.score(X_train, y_train)

0.6125550867319011

pipe4.score(X_test, y_test)

0.6700805211563543

print(mean_squared_error(best1.predict(X_train), y_train))

```

```
25.245331859788127
print(mean_squared_error(best2.predict(X_train), y_train))
25.161643843068298
print(mean_squared_error(best3.predict(X_train), y_train))
25.245331859788127
print(mean_squared_error(pipe4.predict(X_train), y_train))
25.15683939901052
```

All above outputs present R^2 score as well as MSE score for Lasso, Ridge, ElasticNet and Linear regression models. Maximum prediction score from all of the models is 0.67 for the test set of data and 0.61 when predicting on train set.

Those scores are low but there should be a model that predicts more accurately for this specific dataset. That model is not amongst these above because even after performing grid search we could not find a good enough model.

In above outputs we can also see the best estimators with their respective best hyperparameters picked from `param_grid` for each model (except `LinearRegression()` model).

4. Insights and key findings

The chosen dataset proves that linear regression is sometimes not enough to make the most accurate predictions. Although that is true, we can still see that our linear models have scored above 60% in predicting the values of the holdout set.

We also need to keep in mind that all features of the set are to some degree statistically significant to the target value outcomes. From above histogram we see strong correlations between features.

Finally, this dataset is consisted of enough information and there is no missing or duplicated values that would hinder our possibilities to predict the target values.

Our MSE and R^2 scores are not that high but not so low, they are somewhere in the middle meaning that we didn't find the best model for this dataset, but we did not miss completely with our models as well.

5. Next Steps

Next step would be to find some other model or models that would suit better to this dataset. We would need to explore more models and tune them with their respective hyperparameters to find the best estimator using grid search.

Generally speaking this project shows only what can be called a great introduction to some linear models.

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