Capstone Project

Appliances Energy Prediction

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Presented By

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Introduction

- In this time of global uncertainty, one thing is certain: the world requires energy in greater quantities to support economic and social progress and to improve people's quality of life, particularly in developing countries.
- These outages are primarily caused by excess load consumed by household appliances.
- In this project, we will analyse appliance usage in the home as collected by home sensors.
- For 4.5 months, all readings are taken at 10-minute intervals.
- The goal is to forecast appliance energy consumption.
- In the age of smart homes, the ability to predict energy consumption can not only save money for the end user but also help the user generate money by returning excess energy.

Problem Statement

- We should predict Appliance energy consumption for a house based on factors like temperature, humidity & pressure . In order to achieve this, we need to develop a supervised learning model using regression algorithms. Regression algorithms are used as data consist of continuous features and there are no identification of appliances in dataset

Dataset Information

- The data set is at 10 min for about 4.5 months.
- The house temperature and humidity conditions were monitored with a ZigBee wireless sensor network.
- Each wireless node transmitted the temperature and humidity conditions around 3.3 min. Then, the wireless data was averaged for 10 minutes’ periods.
- The energy data was logged every 10 minutes with m-bus energy meters. Weather from the nearest airport weather station (Chèvres Airport, Belgium) was downloaded from a public data set from Reliable Prognosis (rp5.ru), and merged together with the experimental data sets using the date and time column.
- Two random variables have been included in the data set for testing the regression models and to filter out non predictive attributes (parameters).
- The dataset has 19375 instances and 29 attributes including predictors and target variable.
- The training data provided by author contains 14803 instances and testing data contains 4932 instances.

Attribute Information

1. date time year-month-day hour:minute:second
2. Appliances, energy use in Wh
3. lights, energy use of light fixtures in the house in Wh
4. T1, Temperature in kitchen area, in Celsius
5. RH_1, Humidity in kitchen area, in %
6. T2, Temperature in living room area, in Celsius
7. RH_2, Humidity in living room area, in %
8. T3, Temperature in laundry room area
9. RH_3, Humidity in laundry room area, in %
10. T4, Temperature in office room, in Celsius
11. RH_4, Humidity in office room, in %
12. T5, Temperature in bathroom, in Celsius
13. RH_5, Humidity in bathroom, in %
14. T6, Temperature outside the building (north side), in Celsius
15. RH_6, Humidity outside the building (north side), in %
16. T7, Temperature in ironing room , in Celsius
17. RH_7, Humidity in ironing room, in %
18. T8, Temperature in teenager room 2, in Celsius
19. RH_8, Humidity in teenager room 2, in %
20. T9, Temperature in parents room, in Celsius
21. RH_9, Humidity in parents room, in %
22. To, Temperature outside (from Chievres weather station), in Celsius
23. Pressure (from Chievres weather station), in mm Hg
24. RH_out, Humidity outside (from Chievres weather station), in %
25. Wind speed (from Chievres weather station), in m/s
26. Visibility (from Chievres weather station), in km
27. Tdewpoint (from Chievres weather station), Â°C
28. rv1, Random variable 1, nondimensional
29. rv2, Random variable 2, nondimensional

Where indicated, hourly data (then interpolated) from the nearest airport weather station (Chievres Airport, Belgium) was downloaded from a public data set from Reliable Prognosis, rp5.ru. Permission was obtained from Reliable Prognosis for the distribution of the 4.5 months of weather data.

Sample Data

	date	Appliances	lights	T1	RH_1	T2	RH_2	T3	RH_3	T4	RH_4	T5	RH_5	T6	RH_6	T7	RH_7	T8	RH_8
0	2016-01-11 17:00:00	60	30	19.890000	47.596667	19.200000	44.790000	19.790000	44.730000	19.000000	45.566667	17.166667	55.200000	7.026667	84.256667	17.200000	41.626667	18.2000	48.900000
1	2016-01-11 17:10:00	60	30	19.890000	46.693333	19.200000	44.722500	19.790000	44.790000	19.000000	45.992500	17.166667	55.200000	6.833333	84.063333	17.200000	41.560000	18.2000	48.863333
2	2016-01-11 17:20:00	50	30	19.890000	46.300000	19.200000	44.626667	19.790000	44.933333	18.926667	45.890000	17.166667	55.090000	6.560000	83.156667	17.200000	41.433333	18.2000	48.730000
3	2016-01-11 17:30:00	50	40	19.890000	46.066667	19.200000	44.590000	19.790000	45.000000	18.890000	45.723333	17.166667	55.090000	6.433333	83.423333	17.133333	41.290000	18.1000	48.590000
4	2016-01-11 17:40:00	60	40	19.890000	46.333333	19.200000	44.530000	19.790000	45.000000	18.890000	45.530000	17.200000	55.090000	6.366667	84.893333	17.200000	41.230000	18.1000	48.590000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
19730	2016-05-27 17:20:00	100	0	25.566667	46.560000	25.890000	42.025714	27.200000	41.163333	24.700000	45.590000	23.200000	52.400000	24.796667	1.000000	24.500000	44.500000	24.7000	50.074000
19731	2016-05-27 17:30:00	90	0	25.500000	46.500000	25.754000	42.080000	27.133333	41.223333	24.700000	45.590000	23.230000	52.326667	24.196667	1.000000	24.557143	44.414286	24.7000	49.790000
19732	2016-05-27 17:40:00	270	10	25.500000	46.596667	25.628571	42.768571	27.050000	41.690000	24.700000	45.730000	23.230000	52.266667	23.626667	1.000000	24.540000	44.400000	24.7000	49.660000
19733	2016-05-27 17:50:00	420	10	25.500000	46.990000	25.414000	43.036000	26.890000	41.290000	24.700000	45.790000	23.200000	52.200000	22.433333	1.000000	24.500000	44.295714	24.6625	49.518750
19734	2016-05-27 18:00:00	430	10	25.500000	46.600000	25.264286	42.971429	26.823333	41.156667	24.700000	45.963333	23.200000	52.200000	21.026667	1.000000	24.500000	44.054000	24.7360	49.736000

19735 rows × 29 columns

Data Preprocessing & Implementation

Data processing-1: In first part we have to remove unnecessary features. Since there were many column with all null values.

Data processing-2: we have manually go through each features select from part 1, and encoded the numerical features.

EDA: In this part we do some exploratory data analysis (EDA) on the features selected in part-1 and part-2 to see the trend.

Split the data: we have to split the data into two parts train and test.

Create the model: Finally, in the last part but not the last part we creates models and function, and import some libraries it’s not the easy task. Its also an iterative process. We show how to start with simple models and then add complexity for better performance.

Key observation

- 1. Date column is only used for understanding the consumption vs date time behavior and given this is not a time series problem it was removed.
- 2. Light column was also removed as the are the reading of submeter and we are not focusing on appliance specific reading\
- 3. Number of Independent variables at this stage – 26
- 4. Number of Dependent variable at this stage – 1
- 5. Total number of rows – 19735
- 6. The data set will be split 80-20 % between train & test.
- 7. Total # of rows in training set – 15788
- 8. Total # of rows in test set – 3947
- 9. All the features have numerical values. There are no categorical or ordinal features.
- 10. Number of missing values & null values = 0

Solution Statement :

Regression is used for problems like this . Regression analysis is a form of predictive modelling technique which investigates the relationship between a dependent (target) and independent variable (s) (predictor). The regression methods used are:

1. **Linear Regression** : In linear regression we wish to fit a function in the following equation form $\hat{Y} = \beta 0+\beta 1X1+\beta 2X2+\beta 3X3$ where X is the vector of features and $\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$ are the coefficients we wish to learn. It updates β at every step by reducing the loss function as much as possible. Once we reach the minimum point of the loss function we can say that we completed the iterative process and learned the parameters.

2. **Ridge regression** : Regularized machine learning model, in which model's loss function contains another element that should be minimized as well.

$$L = \sum(\hat{Y}_i - Y_i)^2 + \lambda \sum \beta^2 .$$

The second element sums over squared β values and multiplies it by another parameter λ. The reason for doing that is to "punish" the loss function for high values of the coefficients β

3. **Lasso regression** : Lasso is another extension built on regularized linear regression. The loss function of Lasso is in the form:

$$L = \sum(\hat{Y}_i - Y_i)^2 + \lambda \sum |\beta|.$$

The only difference from Ridge regression is that the regularization term is in absolute value.

Evaluation Metrics :

- The regression metrics used as standards to measure regression models are
- 1. Mean Absolute Error
- $MSE = \frac{1}{n}\Sigma(y - \hat{y})^2$ where, y = actual value
- $\hat{y}$ = predicted value

2. Root Mean Squared Error (RMSE)

$$RMsE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}}$$

3. MAE (Mean Absolute Error):

$$MAE = \frac{1}{n}\Sigma|y - \hat{y}|$$

MAPE (Mean Absolute Percentage Error):

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_\mathrm{i} - \hat{y}_i}{y_i}\right|$$

4. R2 (R – Squared):

$$R^2 = 1 - \frac{MSE(model)}{MSE(baseline)}$$

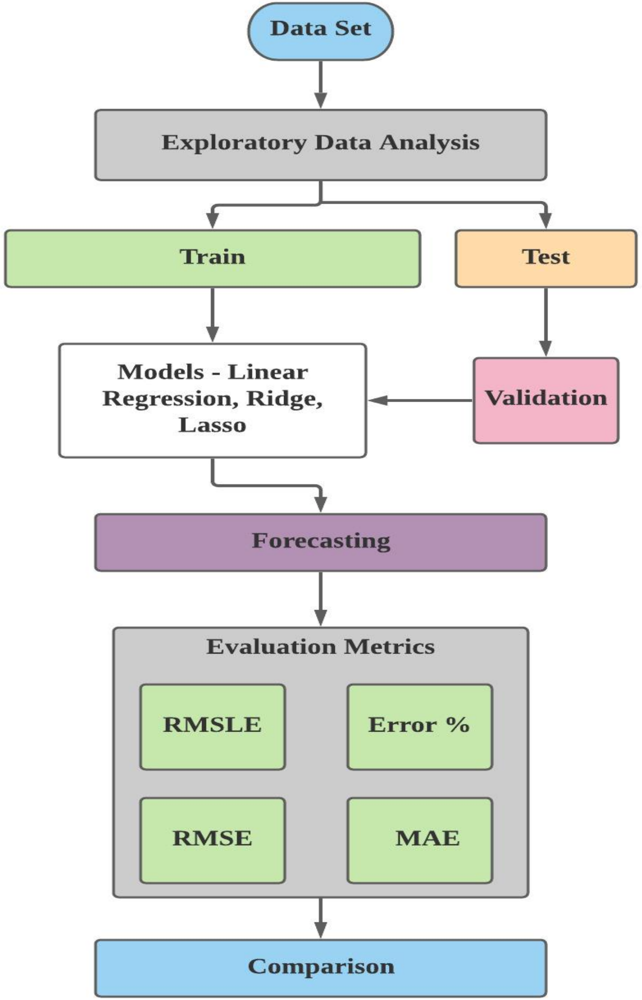
5. Adjusted R2:

$$R_a^2 = 1 - \left[\left(\frac{n-1}{n-k-1}\right) \times (1 - R^2)\right]$$

Project design:

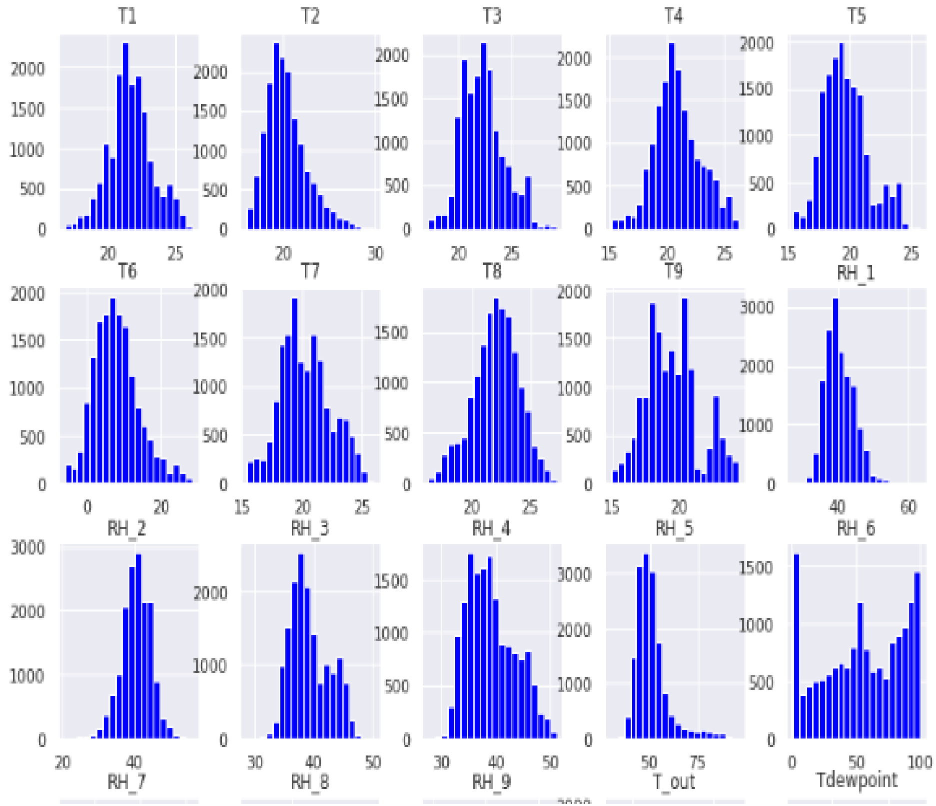
The steps to be followed are mentioned below:

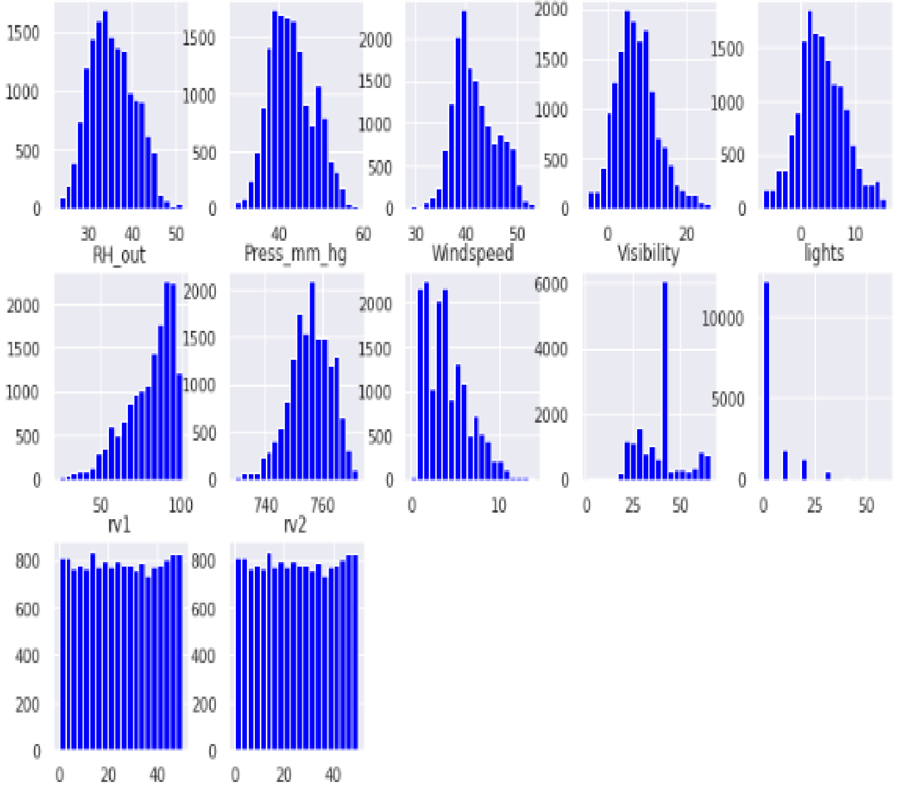
1. Data Visualization : Visual plots to detect the correlation between different independent variables and between independent and dependent variables . Ranges and other statistical data can also be verified
2. Pre Processing : In this process we will be organizing and tidying up the data, removing what is no longer needed, replacing what is missing and standardizing the format across all the data collected.
3. Feature Engineering : Find all the features which impacts the models and reduce the number of features if possible using PCA
4. Choosing a Model : Check all the applicable models and select the one which provides best metrics.
5. Hyperparameter Tuning : Find best possible combination of selected algorithm in order to maximize the performance using Grid Search
6. Prediction : Using Test set predict the dependent variable and check accuracy



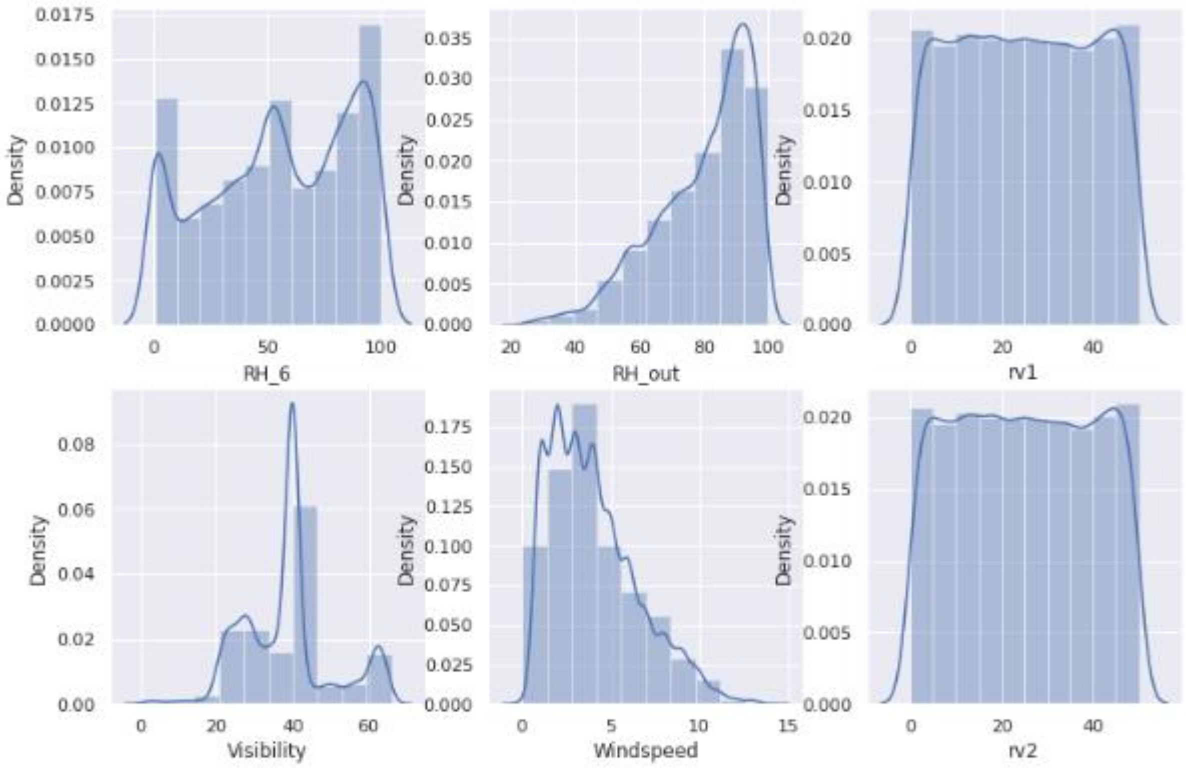
Flow chart for the ML- Regression

Independent variable



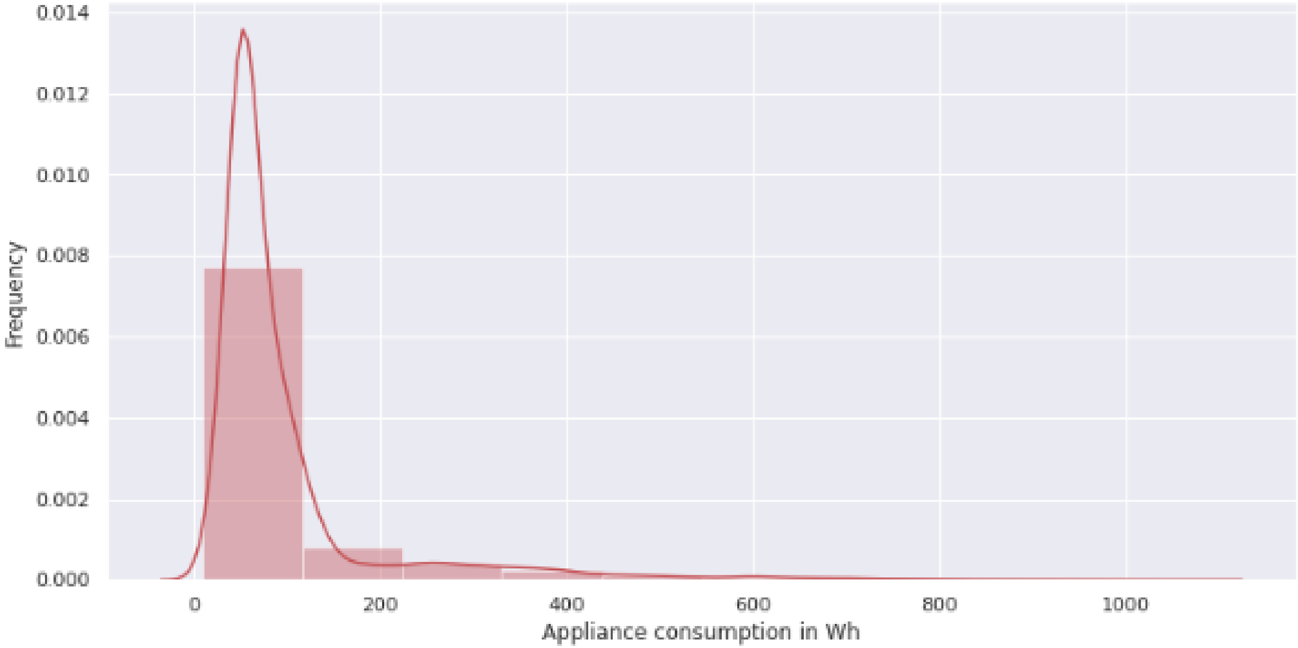


Independent variable

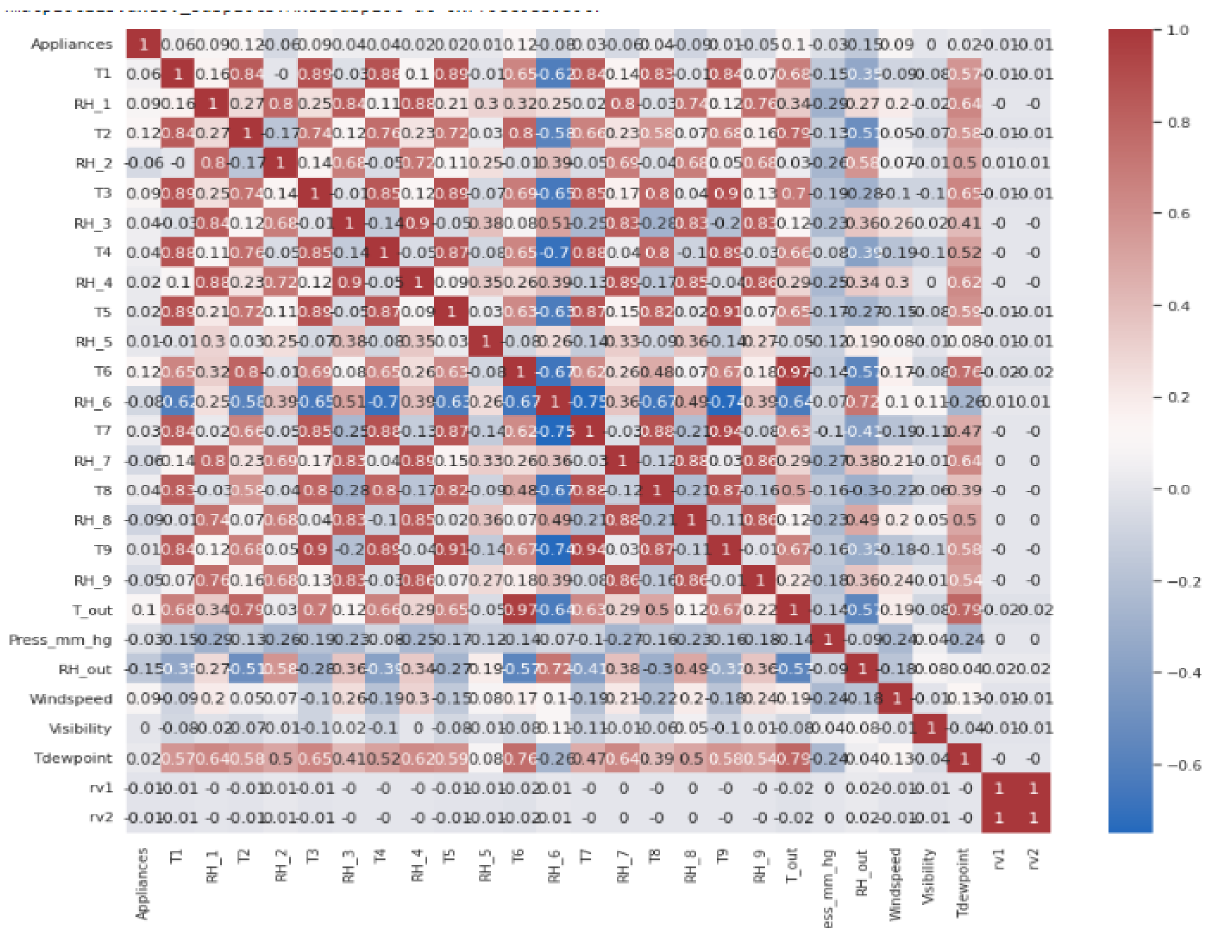


This graph which is not showing normal distribution so we have removed this variable from the train data sets,

Dependent variable consumption graph:



Correlation by heatmap



Result:

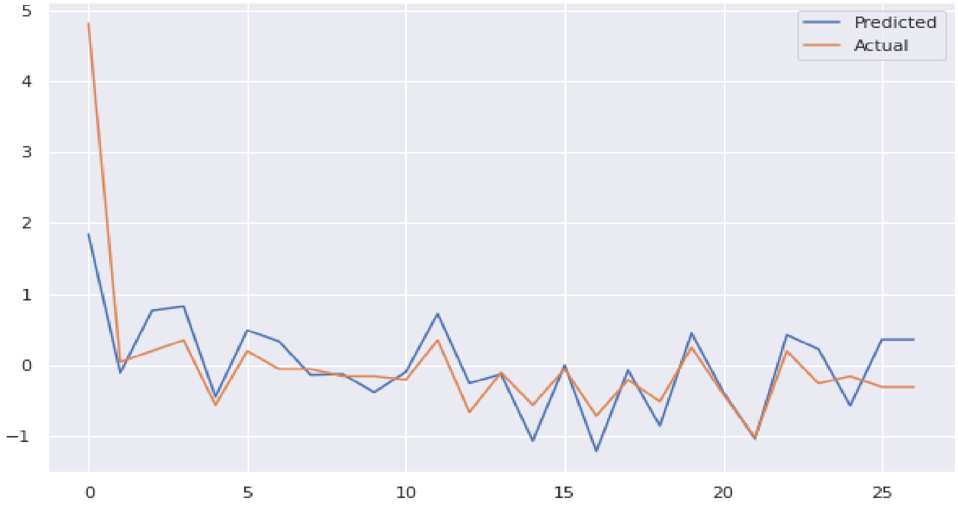
Linear regression:

```
# Training dataset metrics
print_metrics(train_y, y_train_pred)
```

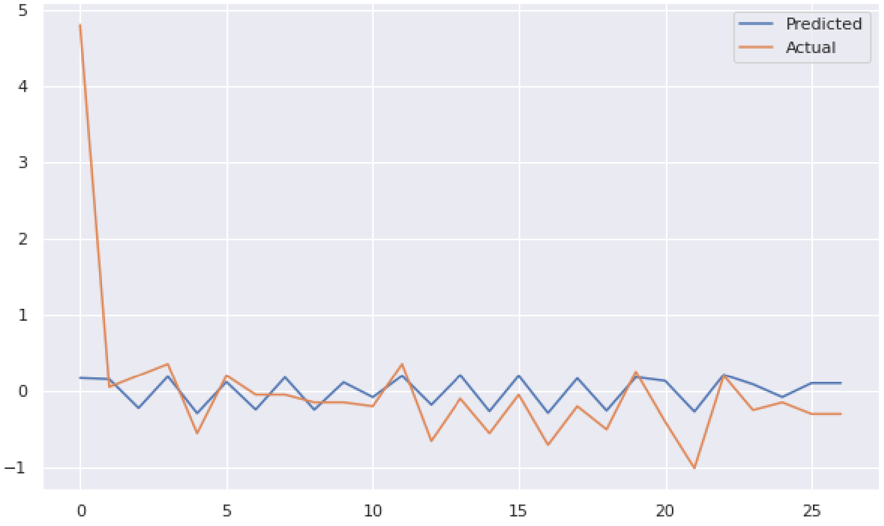
```
MSE is 0.10088764399263299
RMSE is 0.3176281536524006
RMSE is 0.899112356007367
MAE is 0.23709647133422 89
r2_score is 0.899112356007367
```

```
# Test dataset metrics
print_metrics(test_y, y_pred)
```

```
MSE is 0.10088764399263299
RMSE is 0.3176281536524006
RMSE is 0.899112356007367
MAE is 0.2370964713342289
r2_score is 0.899112356007367
```



Ridge algorithm result between predicted and actual.



Lasso algorithm result between predicted and actual.

	Name	Train_Time	Train_R2_Score	Test_R2_Score	Test_RMSE_Score
0	Lasso:	0.003463	0.000000	0.000000	1.000000
1	Ridge:	0.022982	0.410477	0.410477	0.767804

Conclusion:

- - The top 3 important features are humidity attributes, which leads to the conclusion that humidity affects power consumption more than temperature. Windspeed is least important as the speed of wind doesn’t affect power consumption inside the house. So controlling humidity inside the house may lead to energy savings.
- - When predicting electricity consumption, it is necessary to determine an appropriate prediction method according to the expected Fore-casting results and characteristics of the prediction model.
- - Here in this study we have predicted the result on the test data set with the supervised machine learning algorithm based on regression (Lasso and Ridge). We performed exploratory data analysis, pre-processing, and train-test split before training the model.
- - We used various metrics to test the advantages of the proposed model: mean absolute error, mean absolute percent error, mean squared error and r2_score.

Challenges & Learning gained during project

1. Feature scaling is very important for regressions models , I initially tried without it and the results were not good . On Kaggle this is suggested by all users.
2. Using seed value helped in reproducing results for algortithms . Without this value the results were different each time.
3. It is very important to check the intercorrelation between all the variables in order to remove the redundant features with high correlation values.
4. While scaling data , it is useful to maintain separate copies of dataframe which can be created using index and column names of original dataframe
5. The pipeline of adding algorithms should be easy to manage
6. Seaborn and pyplot are good libraries to plot various properties of dataframe
7. For performing Exhaustive search or Random search in the hyperparameter space for tuning the model, always parallelize the process since there are a lot of models with different configurations to be fitted. (Set n_jobs parameter with the value -1 to utilize all CPUs)
8. One effective way to check the robustness of the model is to fit it on a reduced feature space in case of high dimensional data. Select the first ‘k’ (usually >= 3) key features for this task.

Reference:

1) https://www.almabetter.com/
2) https://www.wikipedia.org
3) https://www.kaggle.com/
4) https://github.com/