# Capstone project

# Machine learning report

# Title: Appliances energy prediction

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## Definition

### Project overview:

My project is about the aim to the prediction of the energy consumption in a home.in the present world scenario smart homes is rising the energy management because in the now a days reduction of the energy prediction is the play main role .if we predict the energy consumption it is very useful to the future generation. Actually the energy consumption from day to day life is increases and in the same scenario many companies provide some electronic equipments also to predict the energy consumption. and here I predict and reduce this problem of the energy consumption by using the supervised learning.it is the important to reduce the energy consumption so I decided to choose this project.

In my project I used the linear regression at first and after the training and accuracy and r_2 scores I fixed the extra tree regressor of the supervised learning is best to my problem .and I used appliances energy as the target variable and I take features as sensor data and the weather data.

Dataset link: Reference:https://www.sciencedirect.com/science/article/pii/S037877881630 0305

### Problem statement:

This is project about the energy consumption using the regression in the supervised learning model, here I predict the appliance energy by the based on the sensor data and weather data as the features.

### Metrics:

Here in this project I used the regression so the common metrics of the regression is r2_score I.e coefficient of determination and by this metric which will measure the variance of the target variable explained by the our given featues as the input.

And it is mathematically shown as : r2=1-(residual sum of the squares / total sum of the squares) link: http://scikit-learn.org/stable/modules/generated/sklearn.metrics.r2_score.html

link: https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html

i used the pearsonr for the finding the r2_score form the scify library.

Here the r2_score defines the measure of the how well the model fits the data. and the root mean squared error gives the absolute measure of better the model fits the data than the r2 and how close our predicted values to the actual values.

Link for the rmse: http://scikit-learn.org/stable/modules/generated/sklearn.metrics.mean_squared_error.html

I used

=>>**np.sqrt(mean_squared_error(y_t, benchmark_model.predict(X_t) for finding the rmse score and from the scilit library.

Finally my metrics are R2_socre and rmse and these two are helpful in our project because my problem is based on the regression and by the r2 score it will explain the statically robustness of the model and Rmse give the idea about the how accurate the predictions are which compared to the actual values .

## Analysis:

### i.Data exploration:

The dataset has 19,375 instances and 29 attributes including the predictors and the target variables. And I here take all the features to predict more accurately and make correct predictions. The 29 attributes are explained below

Give below are the my input features:

1. T1:temperature in kitchen area, in Celsius
2. RH_1: humidity in kitchen area in %
3. T2: Temperature in living room area, in Celsius
4. RH_2: Humidity in living room area, in %
5. T3: Temperature in laundry room area
6. RH_3: Humidity in laundry room area, in %
7. T4: Temperature in office room, in Celsius
8. RH_4: Humidity in office room, in %
9. T5: Temperature in bathroom, in Celsius
10. RH_5: Humidity in bathroom, in %
11. T6: Temperature outside the building, in Celsius
12. RH_6: Humidity outside the building, in %
13. T7: Temperature in ironing room, in Celsius
14. RH_7: Humidity in ironing room, in %
15. T8: Temperature in teenager room 2, in Celsius
16. RH_8: Humidity in teenager room 2, in %

17. T9: Temperature in parents' room, in Celsius
18. RH_9: Humidity in parents' room, in %
19. T_out: Temperature outside, in Celsius
20. Pressure:  in mm Hg
21. RH_out: Humidity outside, in %
22. Wind speed: in m/s
23. Visibility:  in km
24. T_dewpoint:  Â°C
25. rv1: Random variable 1, non-dimensional
26. rv2:  Random variable 2, non-dimensional
27. Lights: energy use of light fixtures in the house in Wh

and appliances  is the my target variable .

here there is total 28 features I used only 25  and remaining  are light, date because we predict the energy consumption not the category wise energy consumption. And in all of these 25 features 24 are input features and 1 target variable. Here I train the data on the 14,801 instances and testing on the 4,934 instances and therefore 19,735 are the total instances. And here are 0 null values as I got in the project.

All above indicated hourly data climate conditions are collected from the chievres weather station it is the airport whether station.

In my project I evaluate the descriptive statistics as given below:

**A.Range of the columns I get are pated below:**

| | T1 | T2 | T3 | T4 | T5 | T6 | T7 | T8 | T9 |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 |
| **mean** | 21.691343 | 20.344518 | 22.278802 | 20.860393 | 19.604773 | 7.923216 | 20.273236 | 22.028122 | 19.493479 |
| **std** | 1.615790 | 2.202481 | 2.012934 | 2.048076 | 1.849641 | 6.117495 | 2.118416 | 1.960985 | 2.022560 |
| **min** | 16.790000 | 16.100000 | 17.200000 | 15.100000 | 15.340000 | -6.065000 | 15.390000 | 16.306667 | 14.890000 |
| **25%** | 20.760000 | 18.790000 | 20.790000 | 19.533333 | 18.290000 | 3.626667 | 18.700000 | 20.790000 | 18.000000 |
| **50%** | 21.600000 | 20.000000 | 22.100000 | 20.666667 | 19.390000 | 7.300000 | 20.075000 | 22.111111 | 19.390000 |

|  | T1 | T2 | T3 | T4 | T5 | T6 | T7 | T8 | T9 |
|---|---|---|---|---|---|---|---|---|---|
| 75% | 22.633333 | 21.500000 | 23.340000 | 22.100000 | 20.653889 | 11.226667 | 21.600000 | 23.390000 | 20.600000 |
| max | 26.260000 | 29.856667 | 29.236000 | 26.200000 | 25.795000 | 28.290000 | 26.000000 | 27.230000 | 24.500000 |

Above code is about the temperature columns.

=>

|  | RH_1 | RH_2 | RH_3 | RH_4 | RH_5 | RH_6 | RH_7 | RH_8 | RH_9 |
|---|---|---|---|---|---|---|---|---|---|
| count | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 |
| mean | 40.267556 | 40.434363 | 39.243995 | 39.043799 | 51.014065 | 54.615000 | 35.410874 | 42.948244 | 41.556594 |
| std | 3.974692 | 4.052420 | 3.245701 | 4.333479 | 9.107390 | 31.160835 | 5.097243 | 5.210450 | 4.161295 |
| min | 27.023333 | 20.596667 | 28.766667 | 27.660000 | 29.815000 | 1.000000 | 23.260000 | 29.600000 | 29.166667 |
| 25% | 37.363333 | 37.900000 | 36.900000 | 35.560000 | 45.433333 | 29.996667 | 31.500000 | 39.096667 | 38.530000 |
| 50% | 39.693333 | 40.500000 | 38.560000 | 38.433333 | 49.096000 | 55.267500 | 34.900000 | 42.390000 | 40.900000 |
| 75% | 43.066667 | 43.273453 | 41.730000 | 42.200000 | 53.773333 | 83.226667 | 39.000000 | 46.500000 | 44.326667 |
| max | 63.360000 | 54.766667 | 50.163333 | 51.090000 | 96.321667 | 99.900000 | 51.327778 | 58.780000 | 53.326667 |

It is about the pressure

=>

|  | T_out | Tdewpoint | RH_out | Press_mm_hg | Windspeed | Visibility |
|---|---|---|---|---|---|---|
| count | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 | 14801.000000 |
| mean | 7.421836 | 3.782509 | 79.824197 | 755.480135 | 4.029001 | 38.290284 |

| | T_out | Tdewpoint | RH_out | Press_mm_hg | Windspeed | Visibility |
|---|---|---|---|---|---|---|
| **std** | 5.343737 | 4.194994 | 14.901776 | 7.389218 | 2.448171 | 11.789650 |
| **min** | -5.000000 | -6.600000 | 24.000000 | 729.300000 | 0.000000 | 1.000000 |
| **25%** | 3.666667 | 0.933333 | 70.500000 | 750.900000 | 2.000000 | 29.000000 |
| **50%** | 6.933333 | 3.483333 | 83.833333 | 756.000000 | 3.666667 | 40.000000 |
| **75%** | 10.433333 | 6.600000 | 91.666667 | 760.833333 | 5.500000 | 40.000000 |
| **max** | 26.100000 | 15.316667 | 100.000000 | 772.300000 | 14.000000 | 66.000000 |

It is about the humidity.

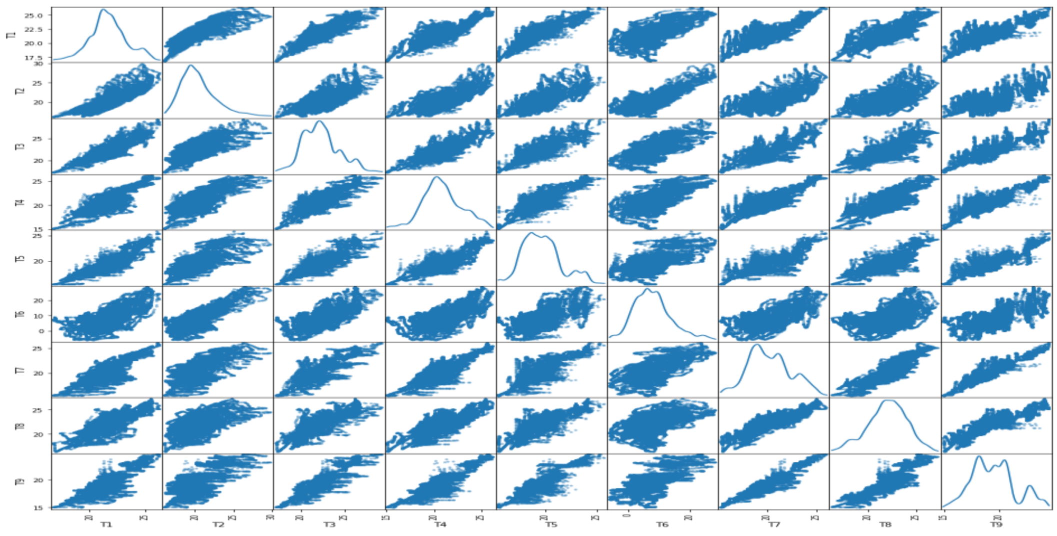
=>

| | Appliances |
|---|---|
| **count** | 14801.000000 |
| **mean** | 97.875144 |
| **std** | 102.314986 |
| **min** | 10.000000 |
| **25%** | 50.000000 |
| **50%** | 60.000000 |
| **75%** | 100.000000 |
| **max** | 1080.000000 |

It is about the appiances

**B.and my scatter plots are:**

**=>**This below plot is about the  temperature

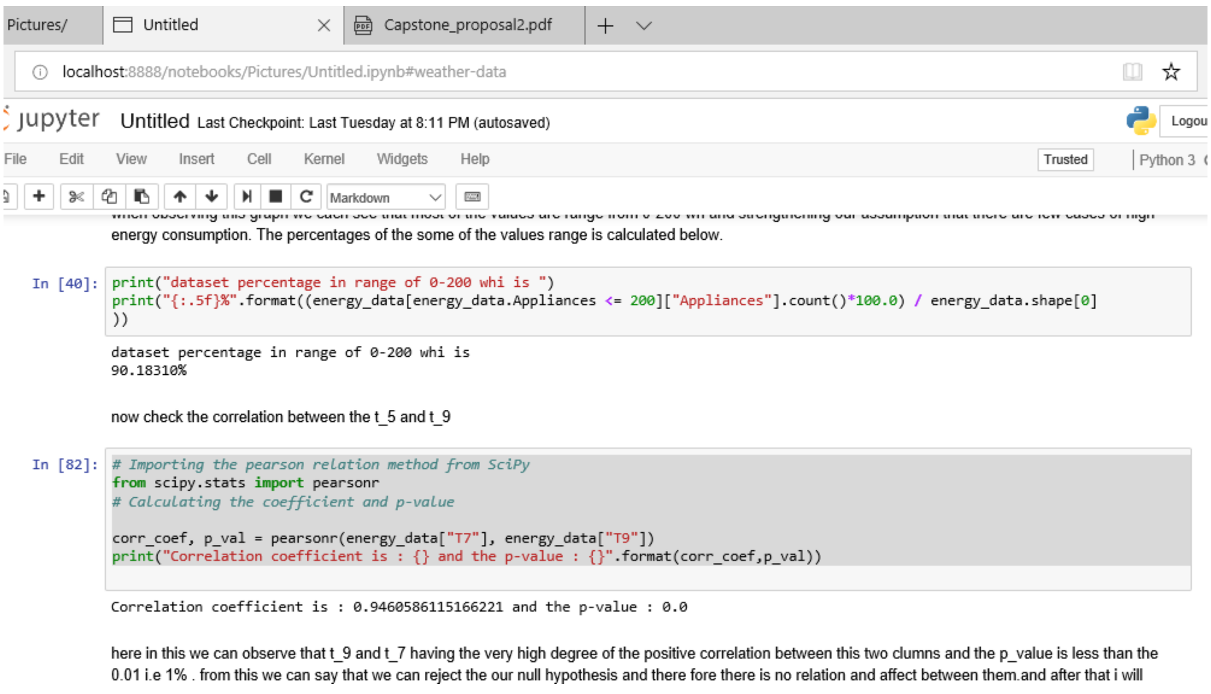


Here by this I evaluated the correlation between the t7 and t9.

by this plots above obtained, We can see that there is a significant correlation between the columns T7 and T9 and this is confirmed the my computing values of there pearson coefficient and it gives the ouput as

```
Correlation coefficient is : 0.9460586115166221 and the p-value : 0.0
```

And my code for this is


Pictures/
Untitled
Capstone_proposal2.pdf
localhost:8888/notebooks/Pictures/Untitled.ipynb#weather-data
jupyter
Untitled Last Checkpoint: Last Tuesday at 8:11 PM (autosaved)
Logou
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Trusted
Python 3
Markdown

when observing this graph we can see that most of the values are range from 0-200 wh and strengthening our assumption that there are few cases of high energy consumption. The percentages of the some of the values range is calculated below.

```
In [40]: print("dataset percentage in range of 0-200 whi is ")
         print("{:.5f}%".format((energy_data[energy_data.Appliances <= 200]["Appliances"].count()*100.0) / energy_data.shape[0]
         ))
```

```
dataset percentage in range of 0-200 whi is
90.18310%
```

now check the correlation between the t_5 and t_9

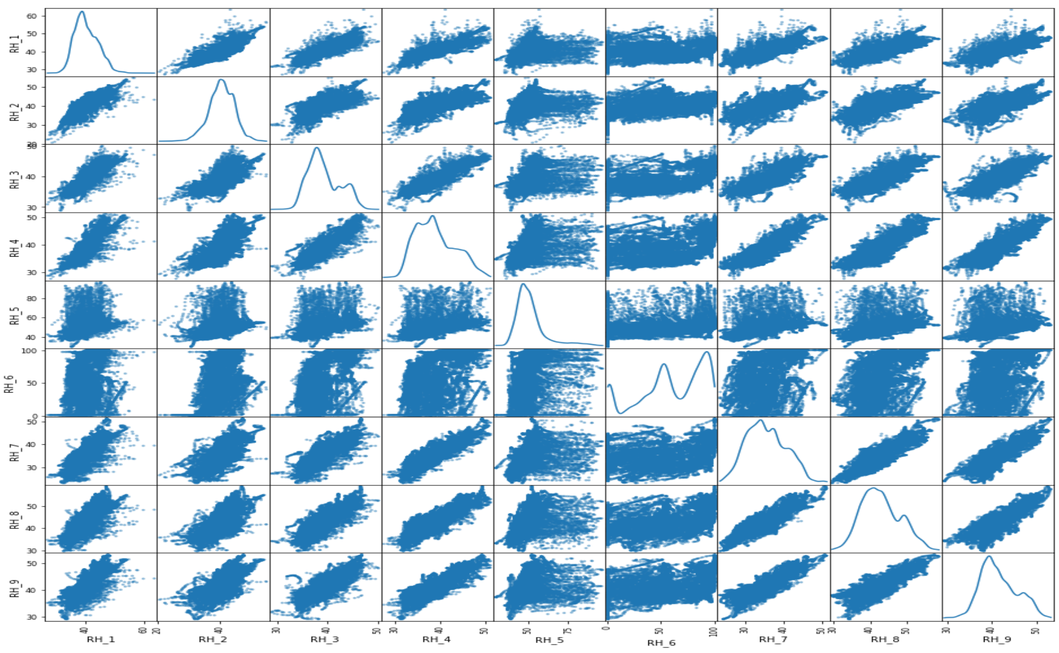
```
In [82]: # Importing the pearson relation method from SciPy
         from scipy.stats import pearsonr
         # Calculating the coefficient and p-value

         corr_coef, p_val = pearsonr(energy_data["T7"], energy_data["T9"])
         print("Correlation coefficient is : {} and the p-value : {}".format(corr_coef,p_val))
```

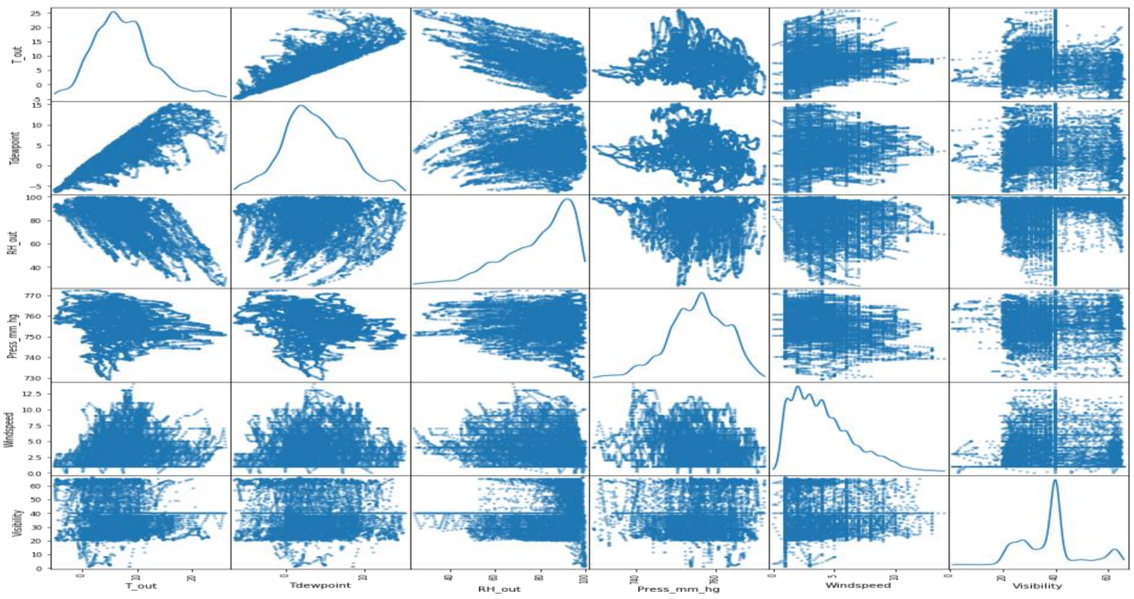
```
Correlation coefficient is : 0.9460586115166221 and the p-value : 0.0
```

here in this we can observe that t_9 and t_7 having the very high degree of the positive correlation between this two clumns and the p_value is less than the 0.01 i.e 1% . from this we can say that we can reject the our null hypothesis and there fore there is no relation and affect between them.and after that i will

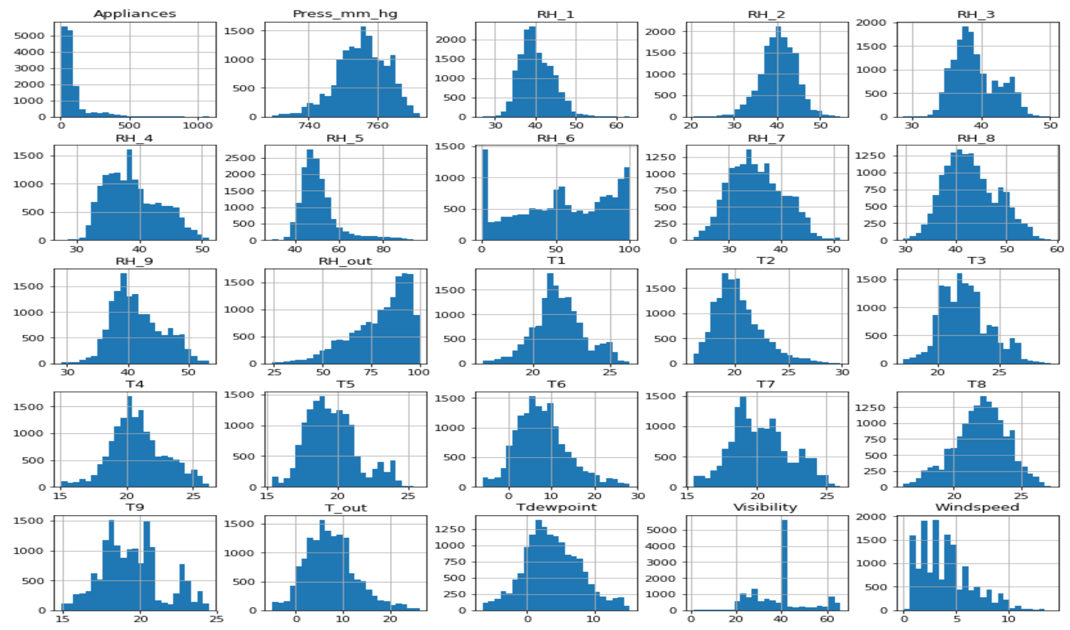
=>This below plot is about the  humidit



=> This below plot is about the  weather data



**c.Districution of all the columns:**



by the histograms we observe that:-

=>here in this all the humidity values except rh_out and rh_6 shows the normal distribution.by that all that readings from the sensors are inside the home are form a normal distribution.and remaining are skew ones for the humidity columns. =>in the same way except th t_9 all the temperature readings follow the normal distribution.

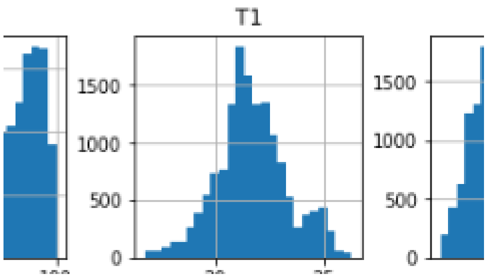
=>and for the remaining columns like visibility,appliances and windspeed are follows the skewed distribution.

=>Also, there is no similarity between our target variable, Appliances and the remaining 24 columns.windspeed looks similar but the number of observations are different as seen from the y-axes of both plots.

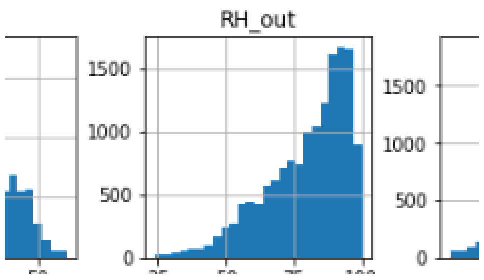
Let's confirm this by plotting Appliances against the Windspeed. Also, let's plot Appliances histogram separately to get better idea about it's distribution.
** Here the histogram theory is copied from my code markdown theory cell.

## 2.Exploratory visualization:

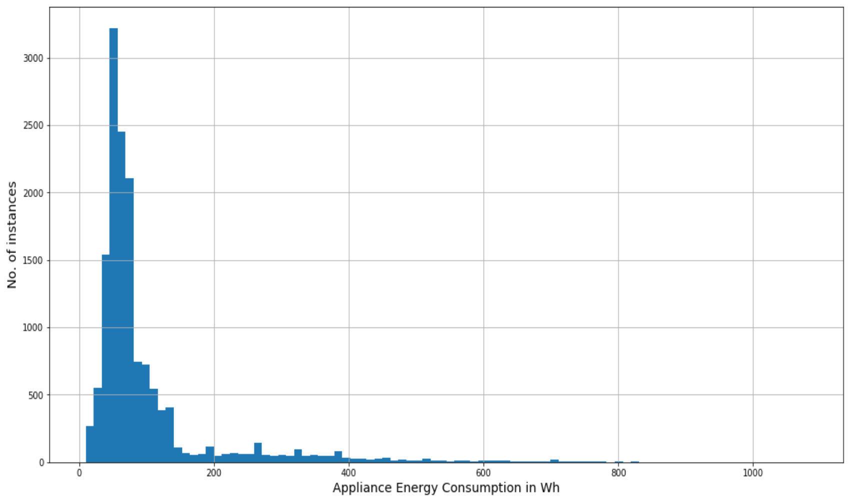
In this data maximum of the features having the normal distribution



And  some features having the right or left skew distribution shown as shown below:



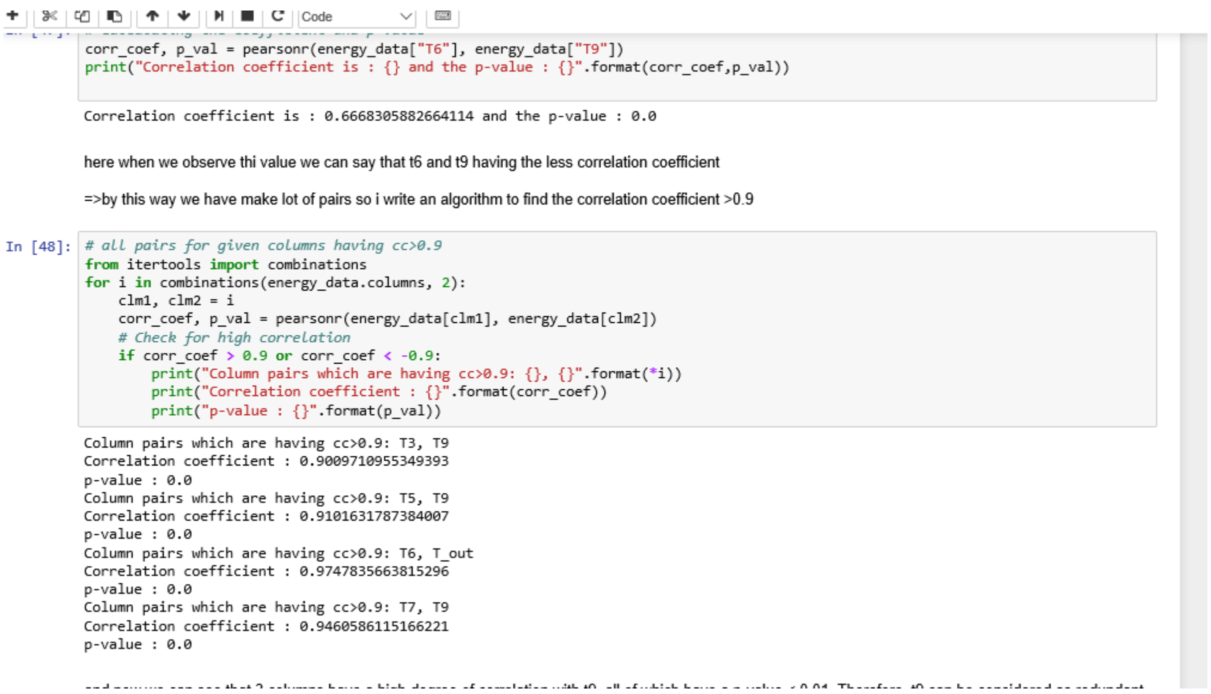
=>And the  target variable distribution :



when observing this graph we can see that most of the values are range from 0-200 wh and strengthening our assumption that there are few cases of high energy consumption

**observations:**

here in this most of this features are normally distributed and to the target variable has the high skewed distribution and it is not maintain a linear relation with the any of the other features. And here the t9 is highly correlated with the t3,t5, and t7 and the t6 with t_out.



```python
corr_coef, p_val = pearsonr(energy_data["T6"], energy_data["T9"])
print("Correlation coefficient is : {} and the p-value : {}".format(corr_coef,p_val))
```

```
Correlation coefficient is : 0.6668305882664114 and the p-value : 0.0
```

here when we observe thi value we can say that t6 and t9 having the less correlation coefficient

=>by this way we have make lot of pairs so i write an algorithm to find the correlation coefficient >0.9

```python
In [48]: # all pairs for given columns having cc>0.9
         from itertools import combinations
         for i in combinations(energy_data.columns, 2):
             clm1, clm2 = i
             corr_coef, p_val = pearsonr(energy_data[clm1], energy_data[clm2])
             # Check for high correlation
             if corr_coef > 0.9 or corr_coef < -0.9:
                 print("Column pairs which are having cc>0.9: {}, {}".format(*i))
                 print("Correlation coefficient : {}".format(corr_coef))
                 print("p-value : {}".format(p_val))
```

```
Column pairs which are having cc>0.9: T3, T9
Correlation coefficient : 0.9009710955349393
p-value : 0.0
Column pairs which are having cc>0.9: T5, T9
Correlation coefficient : 0.9101631787384007
p-value : 0.0
Column pairs which are having cc>0.9: T6, T_out
Correlation coefficient : 0.9747835663815296
p-value : 0.0
Column pairs which are having cc>0.9: T7, T9
Correlation coefficient : 0.9460586115166221
p-value : 0.0
```

and now we can see that 3 columns have a high degree of correlation with t9, all of which have a p-value < 0.01. Therefore, t9 can be considered as redundant

## 3.Algorithms and techniques:

For this problem I used the regression algorithm and I take the most basic algorithm in the regression that is the linear regression algorithm of the supervised learning model. If the basic algorithm explains data set well then no need to apply other algorithms. As modifications to original least squares regression ,we can apply the regularization technique on the data to evaluate the coefficient values of the features because higher values generally towards the overfitting and there may be a loss in the generalization. We used the regularization technique because it improves the performance of the linear regression. There are some chances to fit the data by the linear model without the regularization.There some of the linear models are linear,lasso,ridge which are used in the problem .

some of the tree based models are random forest, gradient boosting, extreme randomized trees. After the linear regression I took the tree base regression models and in this model the main advantage is these are more robust to outliers.in the linear regression we can not see the linear relation between the features and the target variable but by the tree based algorithm it provides the better relation between them. After this model i skip the decision trees because when there is substantial number of the features it is evident that the decision tree will leads to overfit the data, so I took the ensemble models, which include building multiple regressors on copies of same training data and combining their output either through mean, median, mode (Bagging) or growing trees sequentially. And in this ensemble, random forest is one of the method and it makes the better performance on the high dimensional data like mine. And we also go with extreme trees regression because It will leads to further by making the split random gradient boosting machine(boosting mrthod)

And finally the one more algorithm in the supervised algorithm is neural networks and it is the non linear hypothesis and make best work when there is no relation between the inputs and the outputs. We cant prefer for the small sized data sets because it takes more time to train the data I used the mlpregression (multi layer regressor) for the choice of the neural networks. Here the error function  is squared.

## 4.Bench mark:

As I declared in the proposal I choose my bench mark model as the linear regression and on the all features without scaling the data. And in this model I make some obseravations are: r2_score on the training data, testing data sets is 14.68%,14.25 respectively and rmse on the test data is 0.92 and time taken to the fitting is 0.032 sec.

## Methodologies :

### 1.Data preprocessing:

Here are the features ranges

Temperature ->-6 to 30

Humidity->1 to 100

Windspeed ->0 to 14

Visibility=> 1 to 66

Pressure=>729 to 772

Appliances energy usage->10 to 1080

As we observe there are different ranges of the features it is leads to thr domination in the regession and to avoid the situation all the features to be scaled as in the bench mark model we train the data with out the scaling. The scaling is based on the 0 mean and unit variance.

Link to the scale: http://scikit-learn.org/stable/modules/preprocessing.html

And after the scaling I removed the some of the clumns t6 and t9 and these are having the significant correlation along with the t_out and t3,t5,t7 respectively. And finally there are 22 features are in the training set.

### 2.Implementation:

Here the model implementation has done in the three stages they are:

a. Record the each metrics and execute the each regressor by using the pipline() function .

Link: http://scikit-learn.org/stable/tutorial/text_analytics/working_with_text_data.html#building-a-pipeline

b. And anfter that I pass the each regressor to above pipeline() from the execute_pipeline().
c. And finally take the data into the dataframes using the get_prorperties and plot the metrics .
For the choosing the best model I tested below algorithms when compared to the linear regressor they are
Ridge regressor, lasso, random forest, gradient boosting, extra tree regressor,mlpregrssor.
And here are the links to them
http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Ridge.html
http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.ExtraTreesRegressor.html
http://scikit-learn.org/stable/modules/neural_networks_supervised.html

and on all these methods I used the r2 score and rmse as I described above.
Results :

| | RMSE | Testing scores | Training scores | Training times |
|---|---|---|---|---|
| **Ridge** | 0.936121 | 0.123677 | 0.137409 | 0.015626 |
| **Lasso** | 1 | 0 | 0 | 0.0156186 |
| **RandomForestRegressor** | 0.72144 | 0.479525 | 0.916954 | 4.30872 |
| **GradientBoostingRegressor** | 0.86829 | 0.246073 | 0.331539 | 2.43047 |
| **ExtraTreesRegressor** | 0.661027 | 0.563044 | 1 | 1.20285 |
| **MLPRegressor** | 0.870117 | 0.242897 | 0.290518 | 2.76574 |
| **Linear Regression (Benchmark)** | 0.926026 | 0.142476 | 0.146873 | 0.0156221 |

By observing the above data I decided that extra tree regressor is better than others and we can consider this as better method only without considering the training times. when comparing to the times of training in the linear training time is less but it doesn’t perform well than the extra tree regressor.

## 3.Refinement:

For this model I.e extra tree regressor

I use some of the functions which consisted by the extra tree regressor for my convinience

Link: http://scikit-learn.org/stable/modules/generated/sklearn.tree.ExtraTreeRegressor.html#sklearn.tree.ExtraTreeRegressor

They are ,

max_features :it will say about the number of features to be considered

max_depth: to find the depth of the tree

n_estimators: the number of the trees used

and after that tune the model with our data on the test set r2 score is 0.610 and before tuning it is 0.56

=>R2 score improvement from Benchmark model = 0.467.

=>RMSE improvement from Benchmark model = 0.302.

=>R2 score improvement from Untuned model = 0.058.

=>RMSE improvement from Untuned model = 0.041

## **Result**:

### 1.Model evalution and validation :

Features of the untuned model

n_estimators=1

max_features=22

max_depth=none

features of the best model after the hyper parameters

n_estimators=200

max_features : log2(n_features)

max_depth=200

### Robustness of the checking:

Here from all of the  22 features we have to predict the best features and give the ranking to to them among their importance by this model by the rmse and r2 scores.

And after that I checked for the best features among the 22

R2 score on test data = 0.499.

R2 score of untuned model = 0.558.

Difference = 0.059 or 5.9%.

RMSE on test data = 0.708

RMSE of untuned model = 0.665

Difference = 0.343

## <u>2.Justification</u>:

Benchmarks values

Classifier fitted with in the 1.65641 seconds

Score on training data : 0.146873

Score on testing data :0.1425787

Rmse on test data:0.92

And for the best model:

Score on training data : 1.0

Score on testing data : 0.613

Rmse on test data:0.62

Difference in Score on training data :0.85

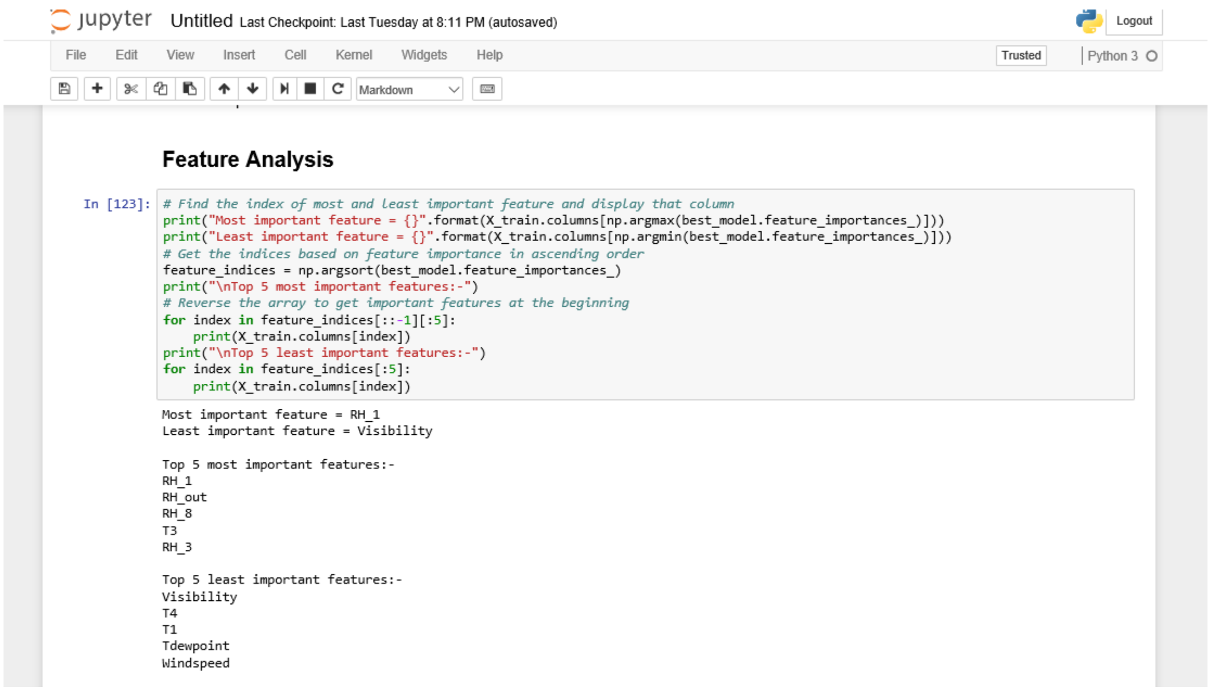
Difference in Score on testing data :0.46

Difference in Score on training data :0.3

## <u>**Conclusions**</u>:

### <u>1.Free from visualization:</u>

As I declared the best ranked important features are



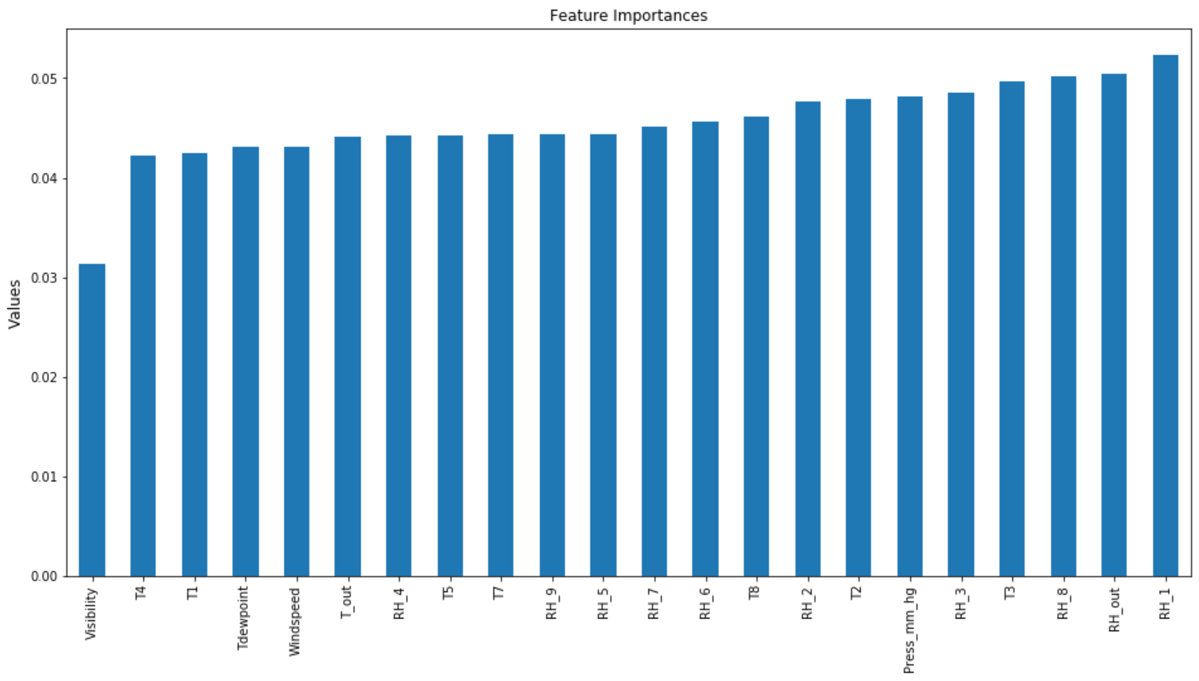
### Feature Analysis

```
In [123]: # Find the index of most and least important feature and display that column
          print("Most important feature = {}".format(X_train.columns[np.argmax(best_model.feature_importances_)]))
          print("Least important feature = {}".format(X_train.columns[np.argmin(best_model.feature_importances_)]))
          # Get the indices based on feature importance in ascending order
          feature_indices = np.argsort(best_model.feature_importances_)
          print("\nTop 5 most important features:-")
          # Reverse the array to get important features at the beginning
          for index in feature_indices[::-1][:5]:
              print(X_train.columns[index])
          print("\nTop 5 least important features:-")
          for index in feature_indices[:5]:
              print(X_train.columns[index])
```

```
Most important feature = RH_1
Least important feature = Visibility

Top 5 most important features:-
RH_1
RH_out
RH_8
T3
RH_3

Top 5 least important features:-
Visibility
T4
T1
Tdewpoint
Windspeed
```



By this we can say the best features and I came to an intuition that in this data humidity effects energy power conjumption  more than the temperature and I make this observation because more of the features of humid is towards the higher end than the temperature and out of the weather parameters humid and pressure are affect power consumption more than other.

## 2.Reflections:

My project is summarized as the following steps;

1. At 1st I search for the data set for my project in the Kaggle and in the UCI machine learning repositories
2. And then I decide that is my problem is belongs to the classification or the regression.
3. I visualized the different aspects of the dataset.
4. After done with the data preprocessing and the selection of the features
5. We have choose the algorithms to be used for the project
6. Choosing the benchmark model to solve the problem
7. Noe apply the selected algorithm and then visualize the result
8. Tuning of the hyper parameters to train the model in the getting of better score
9. And finally decide the best features to this problem and then check the robustness of the model.

Among the above steps 1,3,6 are the little bit interesting steps because they can decide the problem is under the regressor or the classification , and In this I decide the regressor model. After that we have to visualize the data and in the preprocessing if there are any null values or outliers we will drop those ones. Here we train the data based on the some certain inputs and give the output by the testing it will evaluated and find the scores for the models which is the best method in that model. In this project, I had initially decided to create two benchmark models, one that would always return the mean of the target variable and one which would return the median. But, after visualizing the data and concluding that there are no Linear relationships of any feature with the target variable, and after that I realized that linear regression is better to choose as the benchmark model.

## 3.mprovements:

By all the above things I think that there some improvements are

- ⇨ In this we have to drop the in wanted and irrelevant data features like windspeed and visibility
- ⇨ By using the grid search instead of the randomized one to determine the best solution to search the parameters.
- ⇨ And performing the more aggressive feature engineering.