Capstone Project 1: Appliances Energy Prediction

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1. Abstract - Business Problem Description –

Dataset contains the house temperature and humidity conditions were monitored with a ZigBee wireless sensor network. As per the description on UCI website, 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. Combining this data with the weather data based on the date time columns

2. Data Wrangling -

We have two data sets - **energydata_complete.csv** and **CrudeOilPrice.csv**. We have taken two different dataset to get better prediction with analyzing the engorge consumed and how was the fuel price during the particular date.

We do not have any missing values in energydata_complete.csv; it has 19735 observation with 29 attributes pertaining to temperature, humidity, light, wind speed, dew, and visibility from local weather channel.

We do not have any missing value in CrudeOilPrice.csv, which has the fuel price for respective months and dates. This dataset has 2519 observation and 2 attributes of date and fuel price.
Few Key observation are as below –

1. The dataset is from 2016-01-11 and 2016-05-27; have data starting JAN to MAY of 2016.

2. These are the temperature reading captured inside and outside the house. From the explored reading of each sensor is between 14.89 and 29.85 but '**T6'** is between -6 and 28.29. The possible reason can be its reading are for outside.

	T1	T2	T3	T4	T5	\
count	19735.000000	19735.000000	19735.000000	19735.000000	19735.000000	
mean	21.686571	20.341219	22.267611	20.855335	19.592106	
std	1.606066	2.192974	2.006111	2.042884	1.844623	
min	16.790000	16.100000	17.200000	15.100000	15.330000	
25%	20.760000	18.790000	20.790000	19.530000	18.277500	
50%	21.600000	20.000000	22.100000	20.666667	19.390000	
75%	22.600000	21.500000	23.290000	22.100000	20.619643	
max	26.260000	29.856667	29.236000	26.200000	25.795000	

	T6	T7	T8	T9
count	19735.000000	19735.000000	19735.000000	19735.000000
mean	7.910939	20.267106	22.029107	19.485828
std	6.090347	2.109993	1.956162	2.014712
min	-6.065000	15.390000	16.306667	14.890000
25%	3.626667	18.700000	20.790000	18.000000
50%	7.300000	20.033333	22.100000	19.390000
75%	11.256000	21.600000	23.390000	20.600000
max	28.290000	26.000000	27.230000	24.500000

3. There are Humidity related information as well in the dataset, from the explored reading of each sensor is between 20.46 to 58.79 but '**RH_5'** and '**RH_6'** has max of 96.32 and 99.9.

	RH_1	RH_2	RH_3	RH_4	RH_5
count	19735.000000	19735.000000	19735.000000	19735.000000	19735.000000
mean	40.259739	40.420420	39.242500	39.026904	50.949283
std	3.979299	4.069813	3.254576	4.341321	9.022034
min	27.023333	20.463333	28.766667	27.660000	29.815000
25%	37.333333	37.900000	36.900000	35.530000	45.400000
50%	39.656667	40.500000	38.530000	38.400000	49.090000
75%	43.066667	43.260000	41.760000	42.156667	53.663333
max	63.360000	56.026667	50.163333	51.090000	96.321667

	RH_6	RH_7	RH_8	RH_9
count	19735.000000	19735.000000	19735.000000	19735.000000
mean	54.609083	35.388200	42.936165	41.552401
std	31.149806	5.114208	5.224361	4.151497
min	1.000000	23.200000	29.600000	29.166667
25%	30.025000	31.500000	39.066667	38.500000
50%	55.290000	34.863333	42.375000	40.900000
75%	83.226667	39.000000	46.536000	44.338095
max	99.900000	51.400000	58.780000	53.326667

4. The max value is 1080wh, whereas 75% of usage is under 100wh. Some of the appliances has high consumption. These can be outliers but, currently keeping them as part of the dataset and not dropping them from the dataset.

5. If we see the statistics for Appliance Attributes, the minimum value is 10 and max value is 1080, and the mean is 97.69 and 75% of records are below 100 KWH. This column has outliers and we will keep them and check during our modeling.

	Appliances
count	19735.000000
mean	97.694958
std	102.524891
min	10.000000
25%	50.000000
50%	60.000000
75%	100.000000
max	1080.000000

When merging the two datasets, in energydata dataset, date is a timestamp and in crudeoilprice dataset, date is a date datatype, so we have to normalize the date, in order for us to merge the two datasets.

1. After the merge, we observe that " values" columns is merged on the dataset, but it doesn't have all the dates values and 5904 records has null values.

```
rv2             19735 non-null float64
 value          13831 non-null float64
dtypes: float64(27), int64(2), object(1)
memory usage: 4.7+ MB
None
```

To solve these null values, we used the "**forward fill" method** and value column was populated with previous day values for the records, which were null and renamed the column to "oilprice".

The total number of observation is 19735 and 30 Attributes.

From the Data Wrangling activity, we created the **input.csv** as the final dataset. This has 19735 observations and 30 attributes.

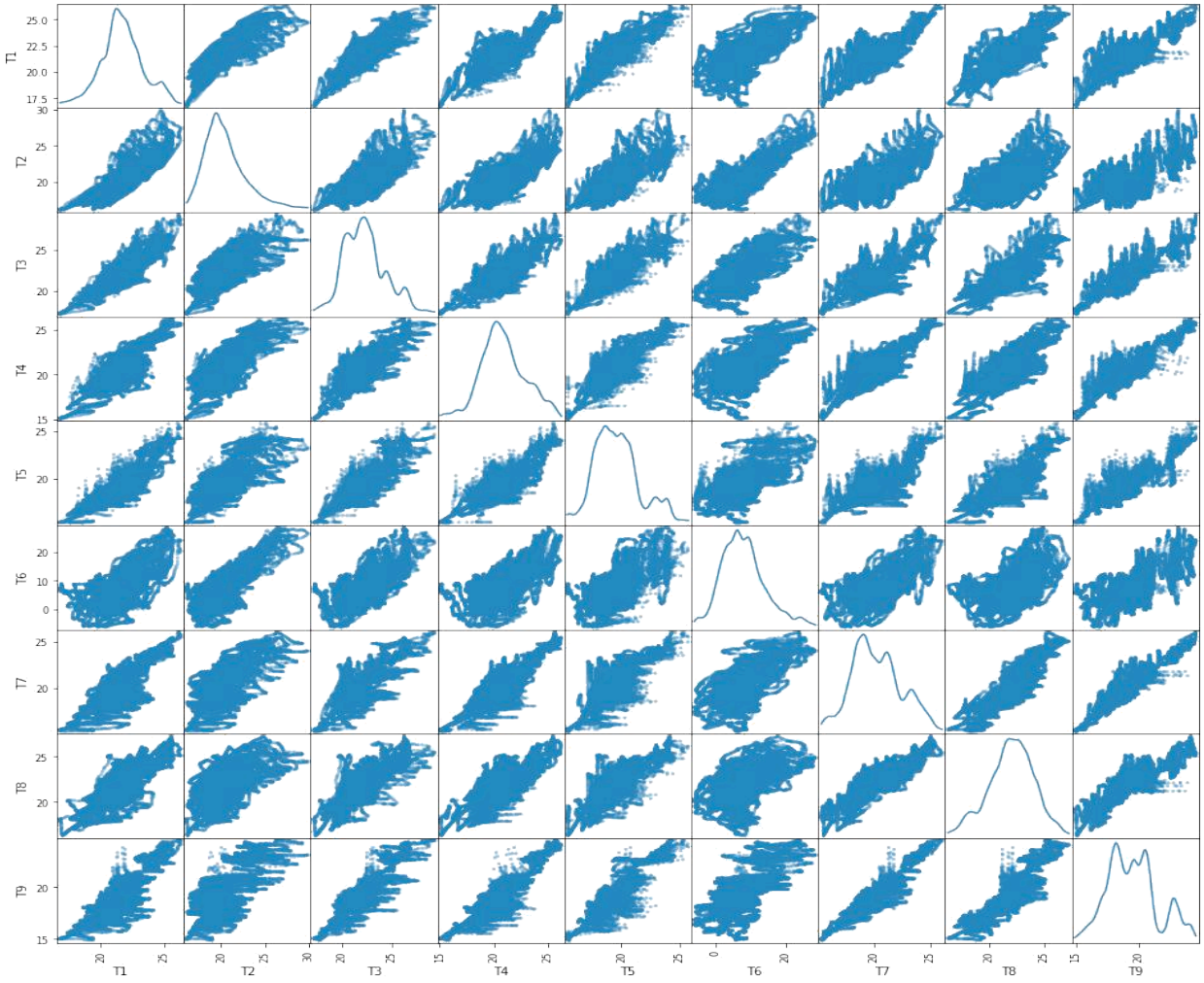
3. Data Visualization -

Divide the data in dimension wise to explore from the input dataset –

```
# Temperature sensors columns
temp_cols = ["T1", "T2", "T3", "T4", "T5", "T6", "T7", "T8", "T9"]

# Humidity sensors columns
hum_cols = ["RH_1", "RH_2", "RH_3", "RH_4", "RH_5", "RH_6", "RH_7", "RH_8"
, "RH_9"]

# Weather data columns
wth_cols = ["T_out", "Tdewpoint", "RH_out", "Press_mm_hg", "Windspeed", "V
isibility"]

# Target column
tgt = ["Appliances"]
```

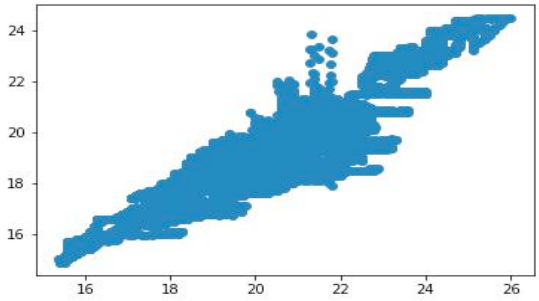
From the above dimensions, we will start to explore data for each – Plot the scatter matrix for Temperature attributes using method **" diagonal="kde"**

Plot the scatter matrix for Temperature attributes using method **" diagonal="kde"**

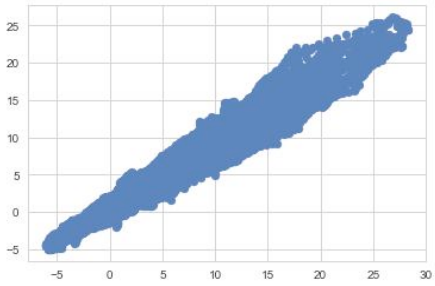


- From the above figure, we can see that there is some linear relation between T7 and T9. Others are having the shape but are not exactly linear.

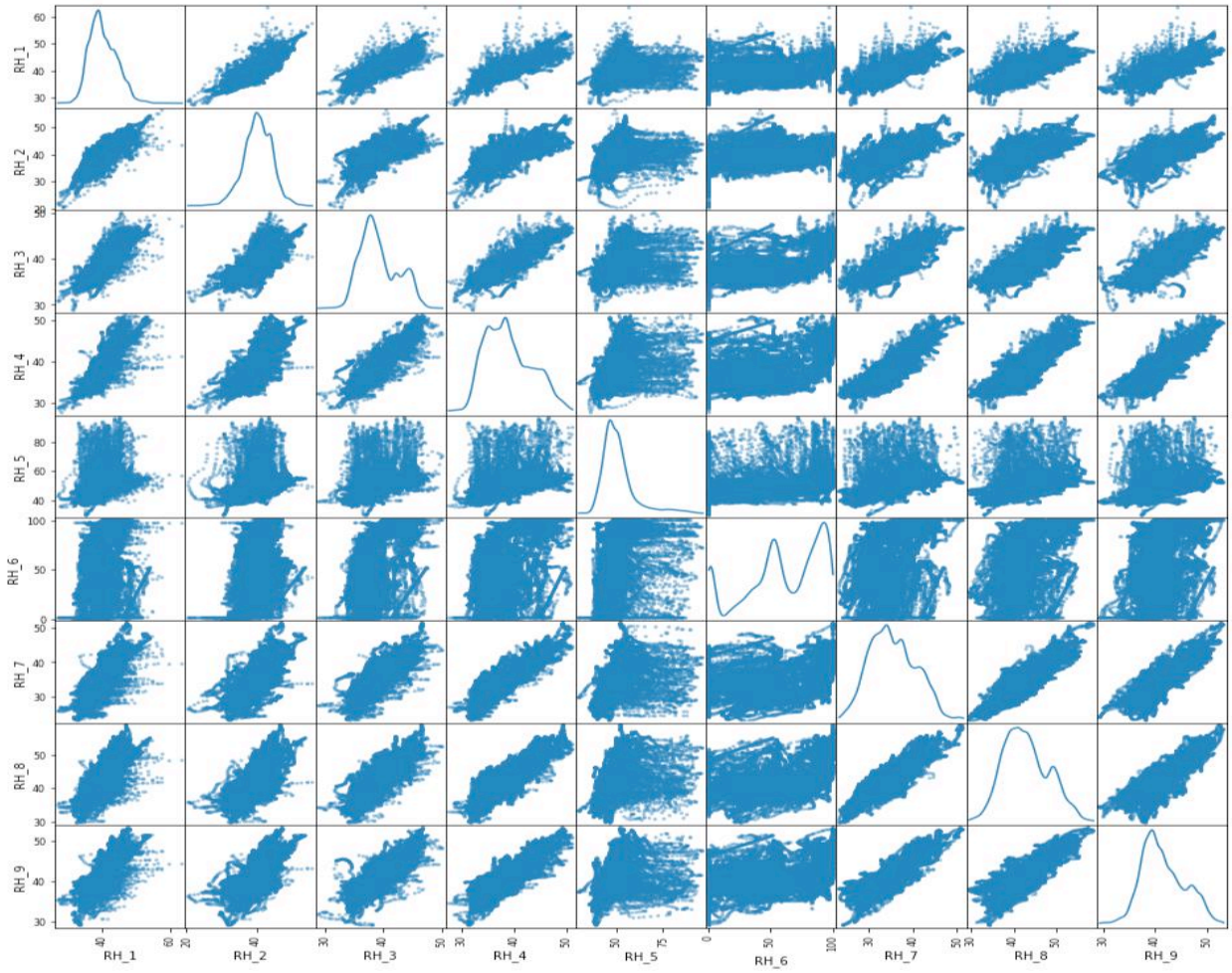
- There is a relation between these two attributes but also have some outliers



T6 and T_out is highly correlated, T6 is from the outside the house reading and T_out is the data collected from weather's site

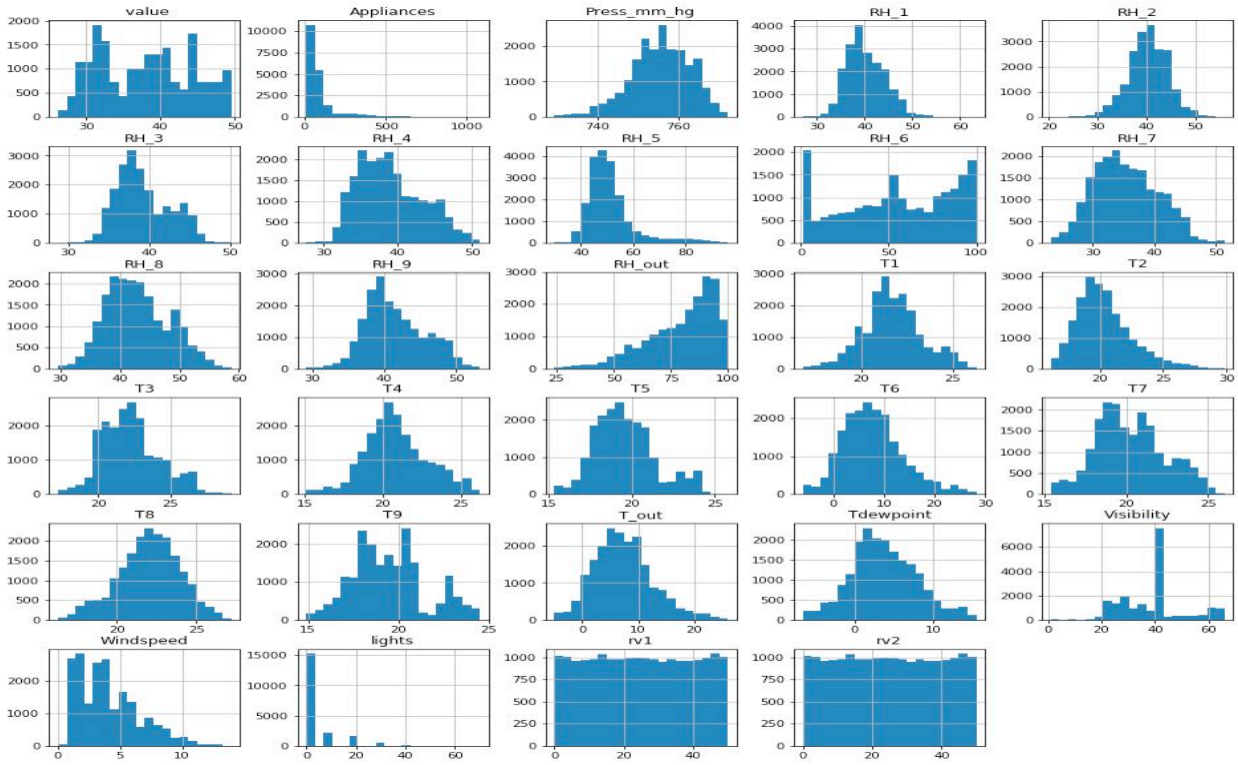


Explore the data using the Weather Dimension -



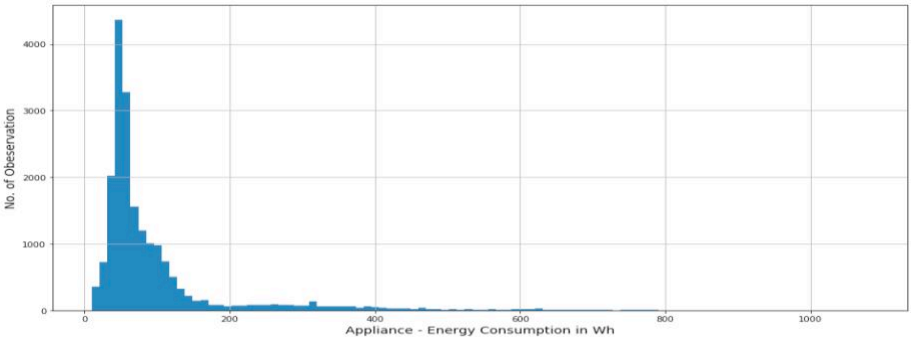
- There doesn't seems to be having any linearity between any of the attributes.

Lets explore the distribution using the histogram –

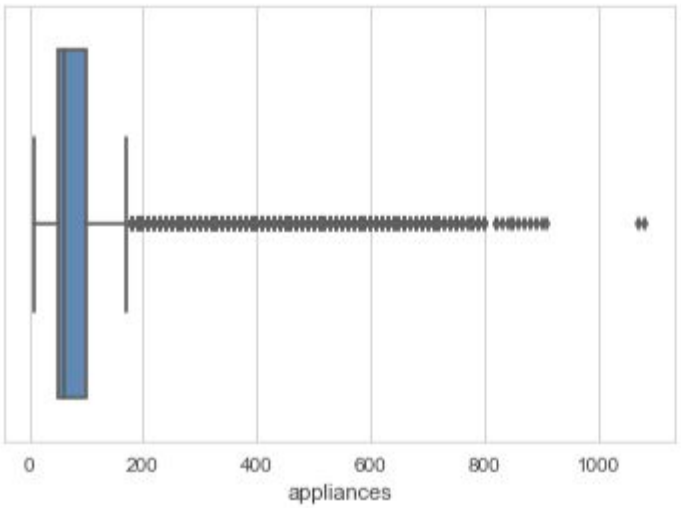


- All humidity values are almost having normal distribution except RH_6 and RH_out. In other words the reading from inside the home is having normal distribution.
- All temperature readings follow a Normal distribution except for T9.
- Visibility, Windspeed and Appliances are having skewed data.
- Rv1 and Rv2 are random variables and doesn't seems to be contributing

On the Target Attribute – Appliance, the below histograms is rightly skewed and most of the data is with 200 KWh.



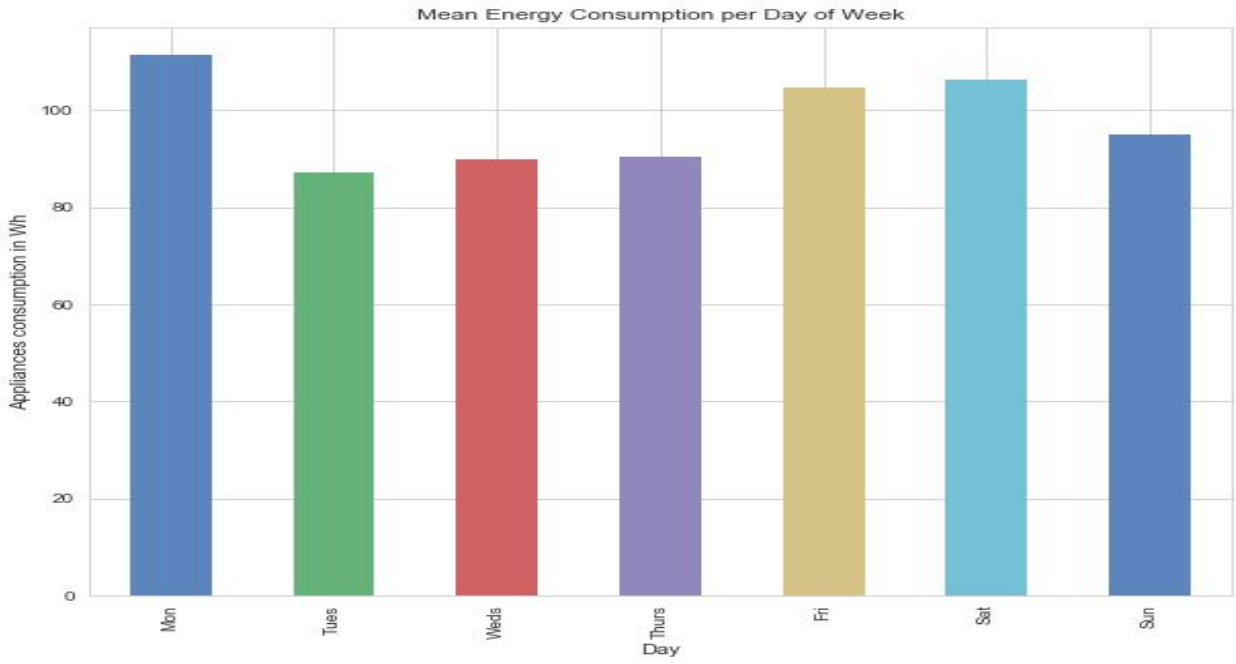
Target variable, Appliances is highly right skewed.
Alternatively exploring using Boxplot – on Appliance Attribute



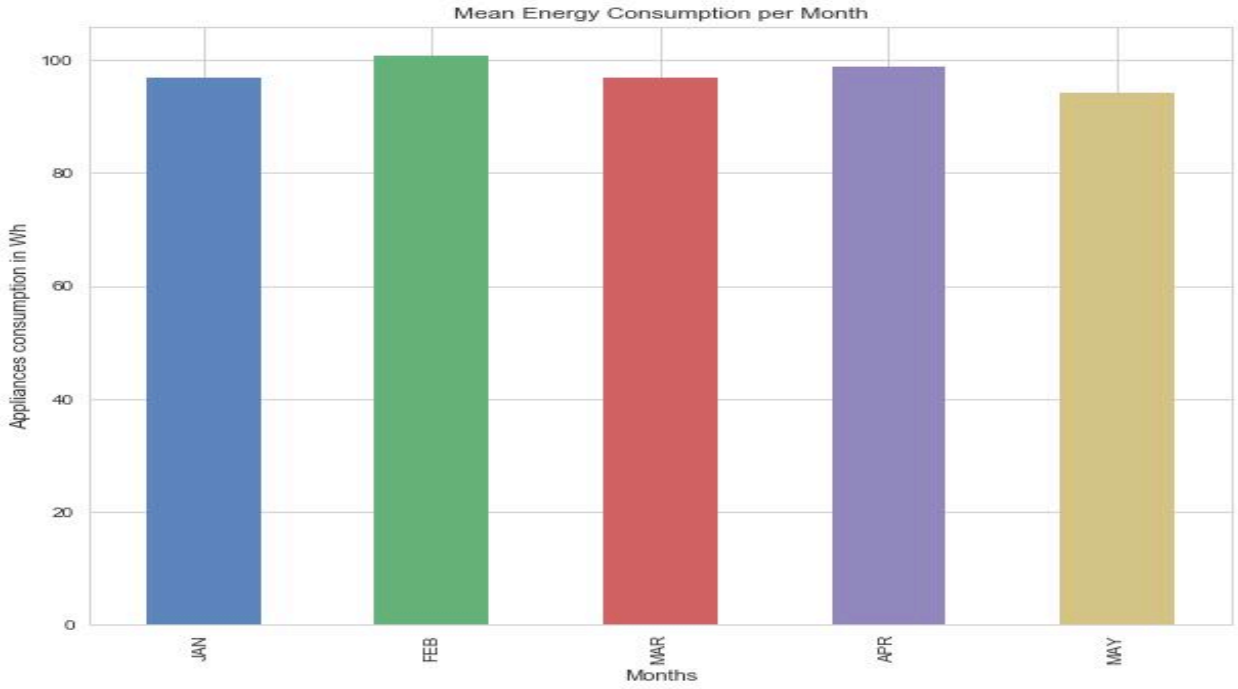
- Percentage of dataset in range of 0-200 KWh is 90.291%

Using the date attributes, created new columns for Month and Weeks using the **datetimestamp** method

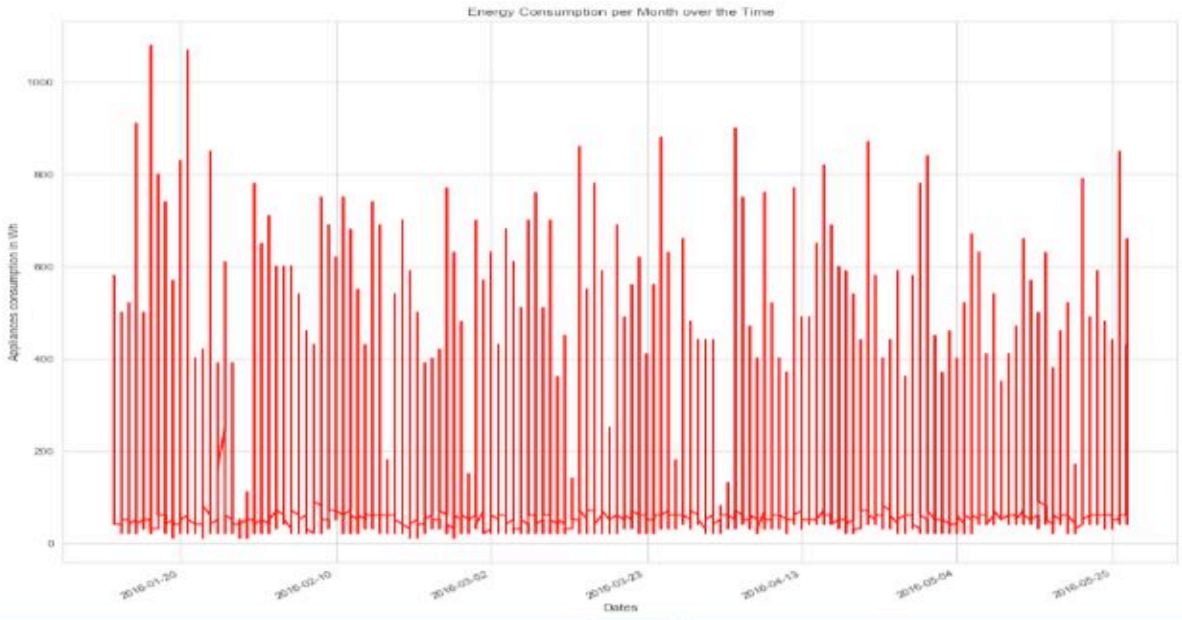
With taking the average on week – Monday the usage has been higher, followed by Saturday and Friday.



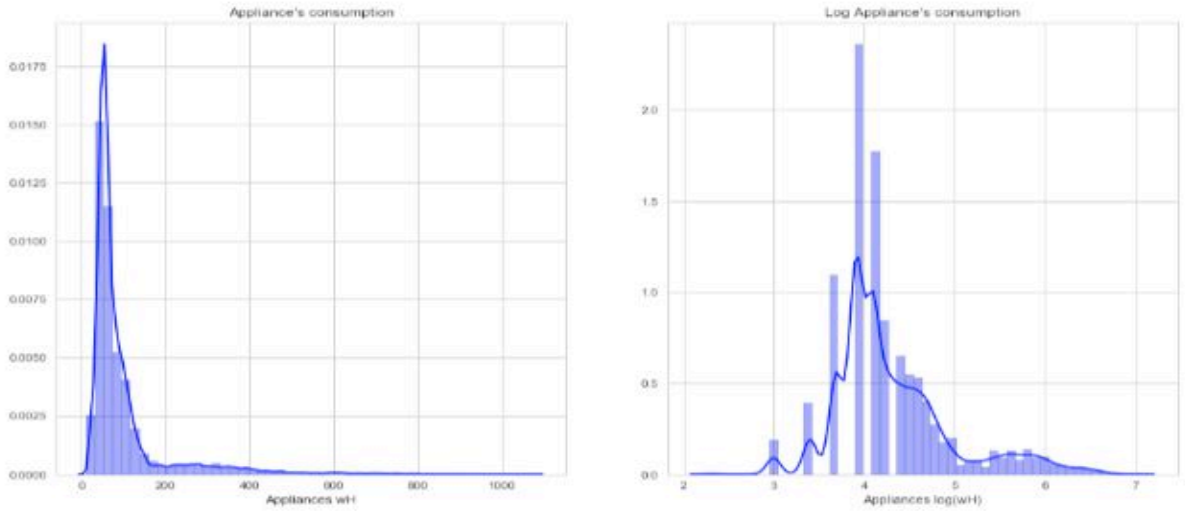
For Monthly Average – On a average, February and April the consumption has been more than other months.



For Day wise consumption – plotting this date wise, energy consumption, In January month there were 2 days when the consumption was more than 1000 KWh.

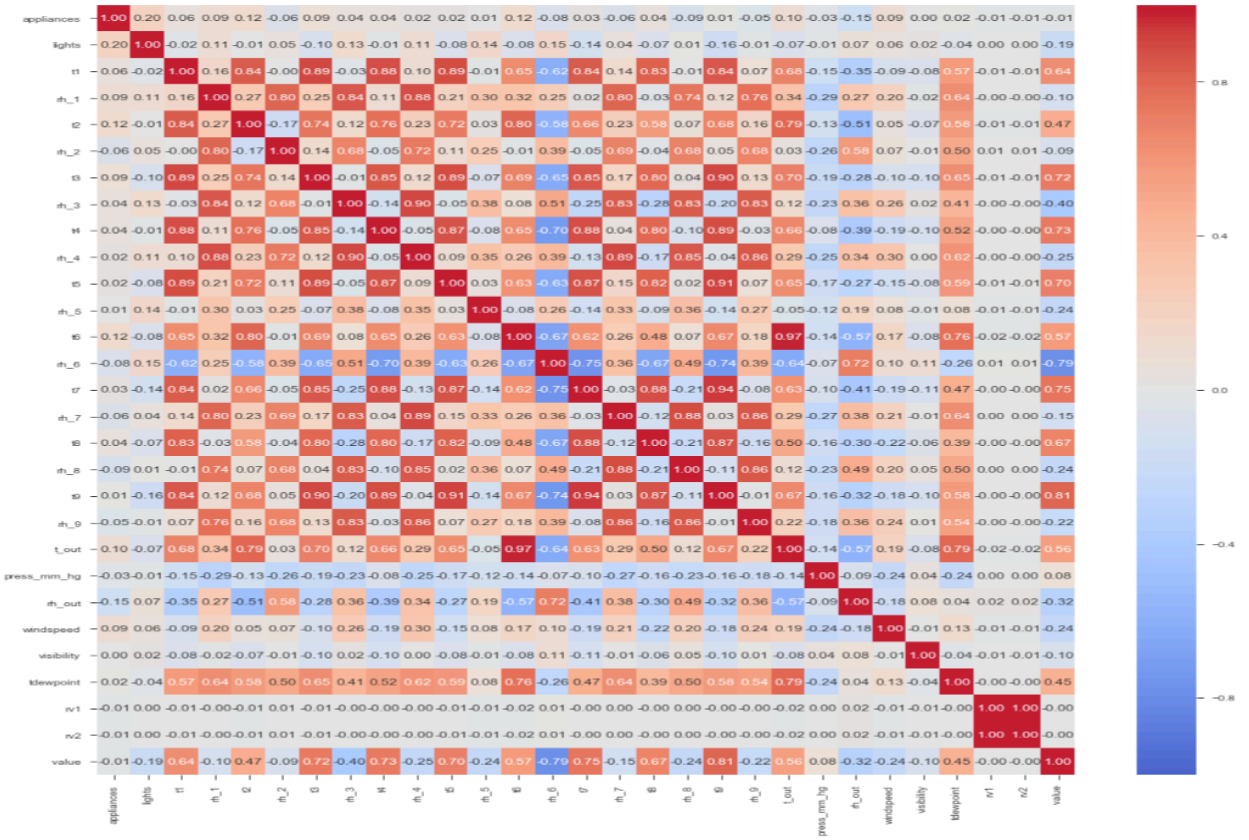


Since the Appliance data captured were rightly skewed, converting the column to Log values to see if it has the normal distribution.

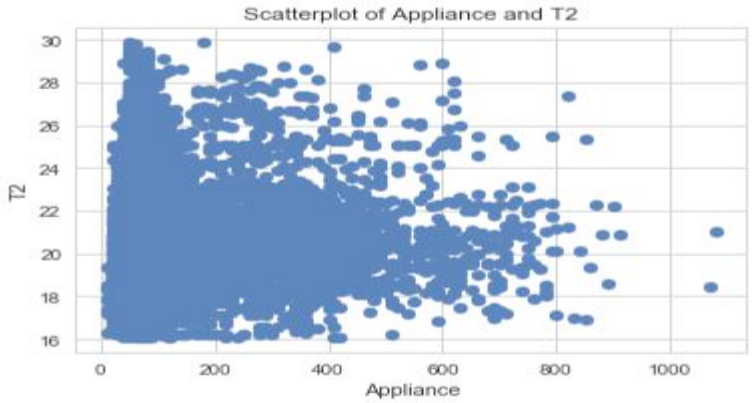


Let's explore the Correlation plot –

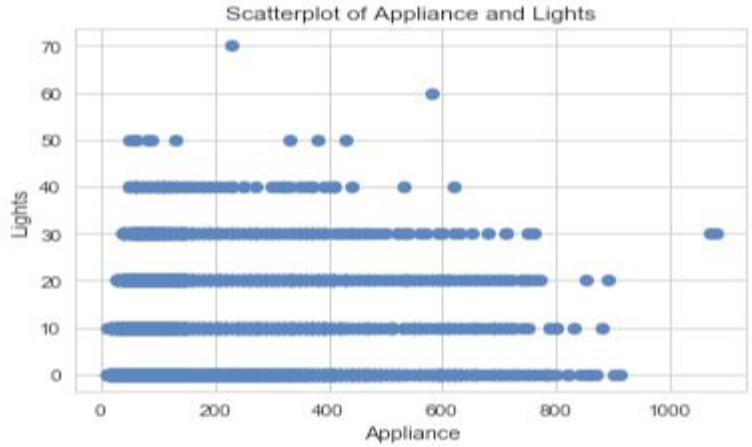
With Appliance attribute –



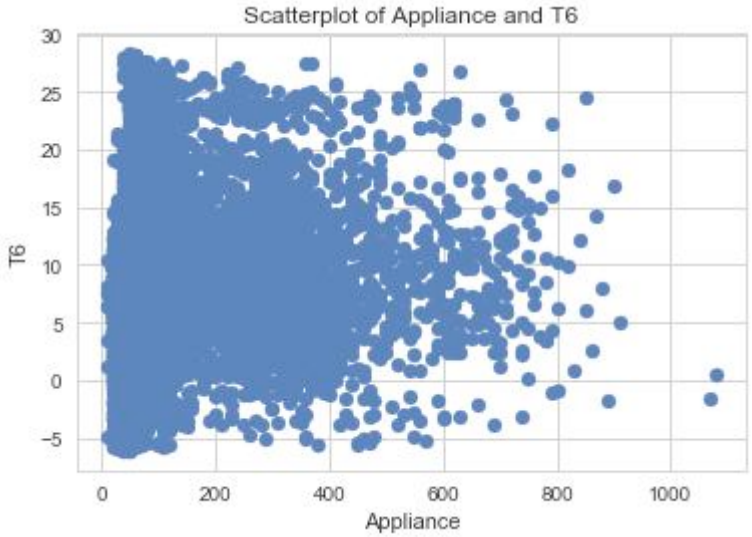
Scatterplot between appliances and t2



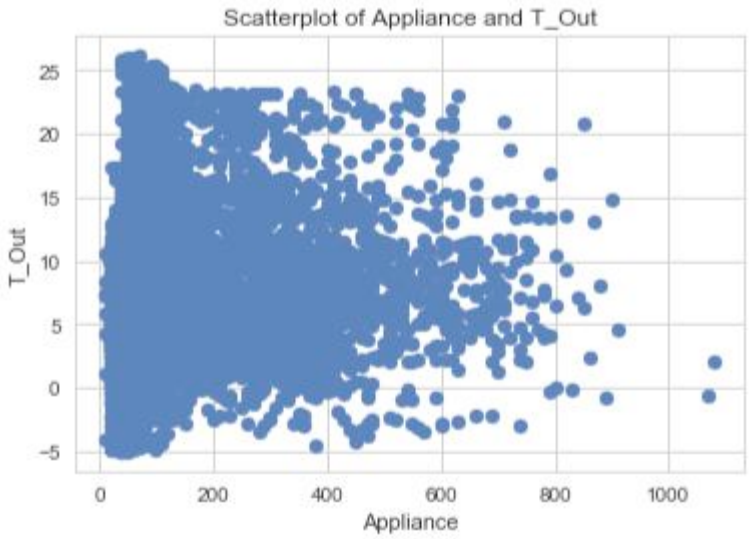
Scatter plot between Appliance and Lights



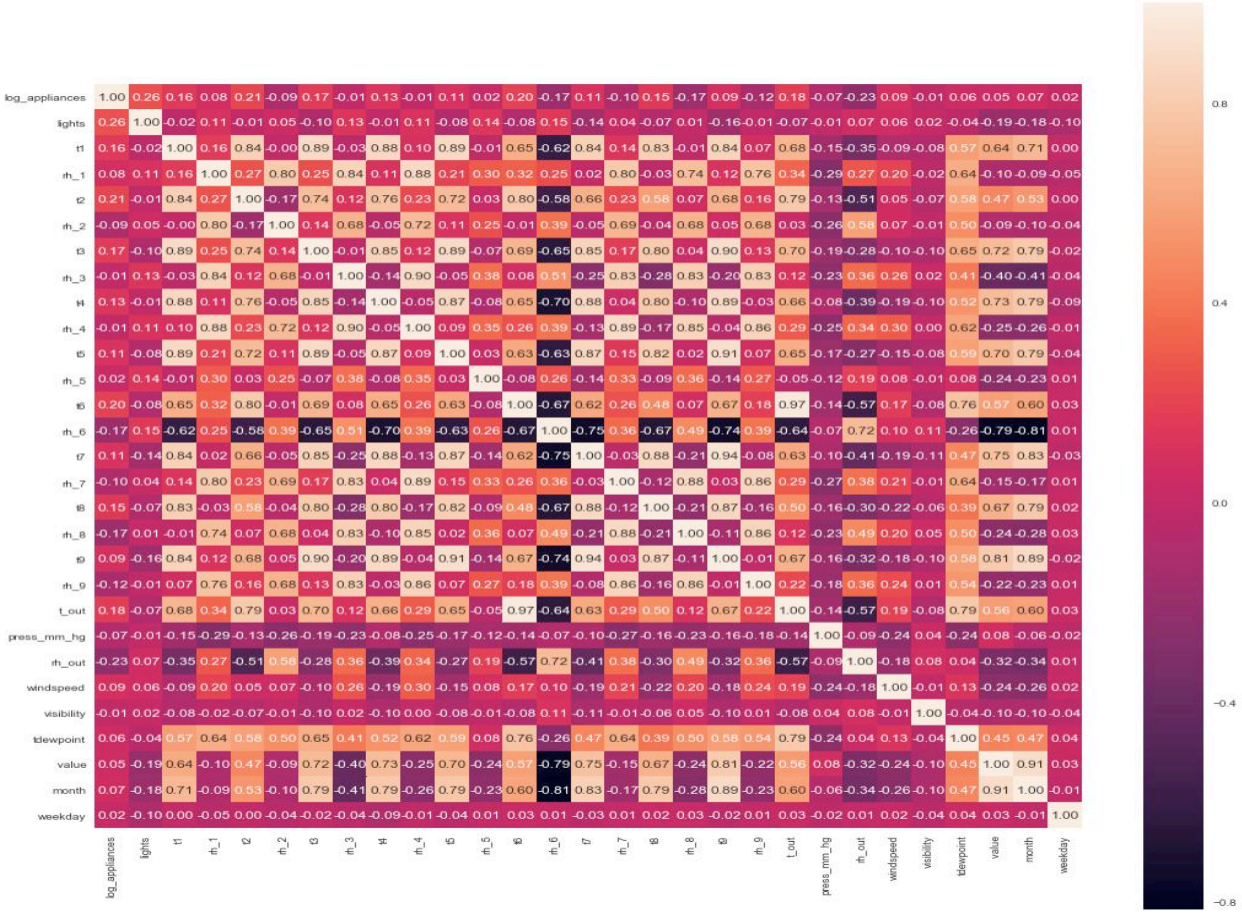
Scatterplot between Appliance and T6



Scatterplot between Appliance and T_out



Correlation plot of using Log value of Appliance -

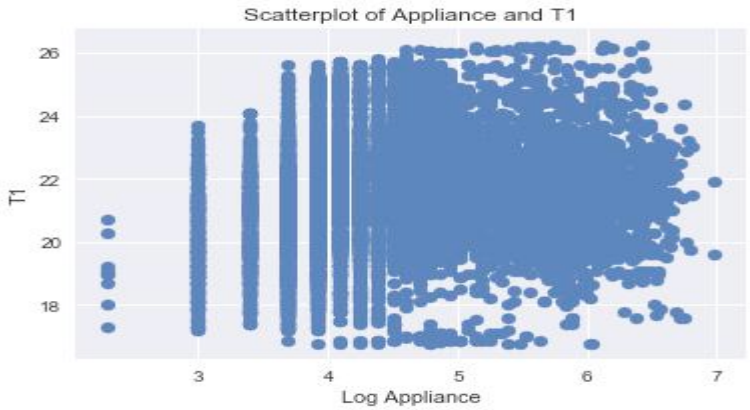


With Log Appliance

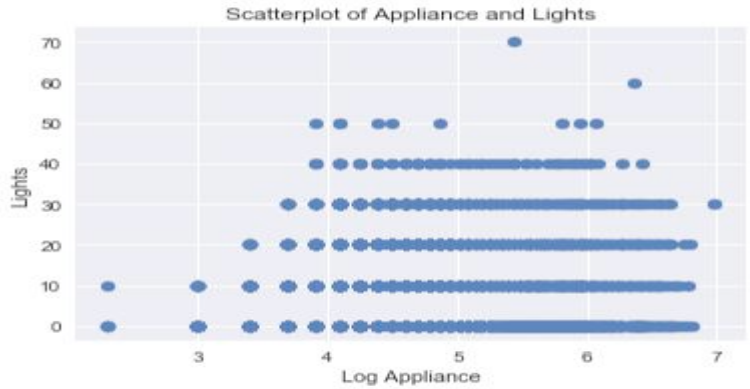
- The most correlated features with energy consumption(log_appliances) are: lights=0.26, t6=0.20, t2=0.22, t3 = 0.17,t_out = 0.18, rh_out = -0.23, rh_8 = -0.17, rh_6 = -0.17, windspeed = 0.09.

- In a linear regression problem only linear independent variables can be be used as features to explain energy consumption otherwise we will have multicollinearity issues.

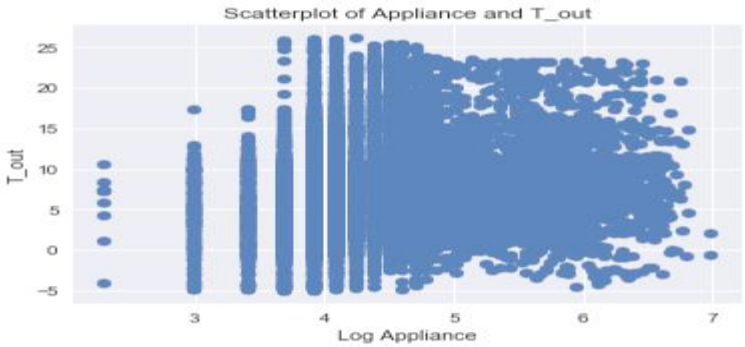
Scatter plot of log_appliance and t1



Scatterplot between log_appliance and lights

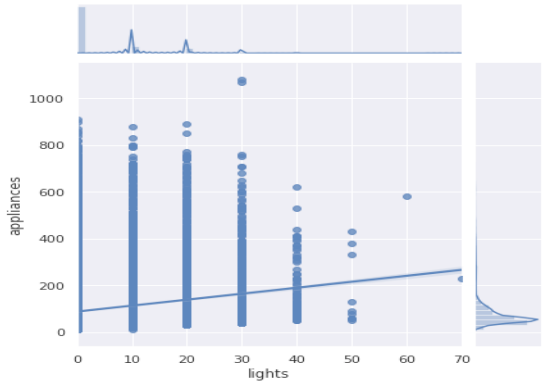


Scatter plot between log appliance and t_out

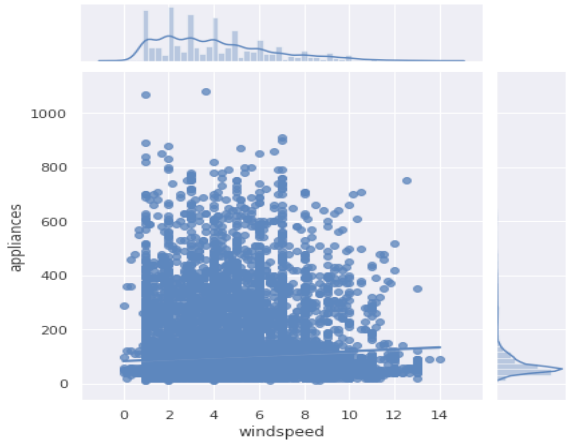


Variables that are particularly significant in terms of predicting Appliance Energy Consumption based on the correlation matrix –

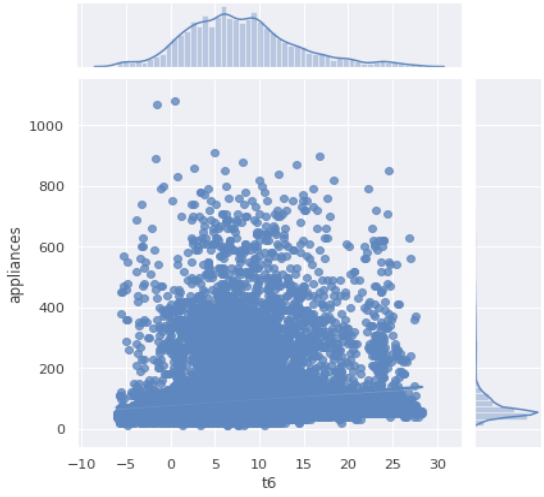
- Between Appliance and Lights



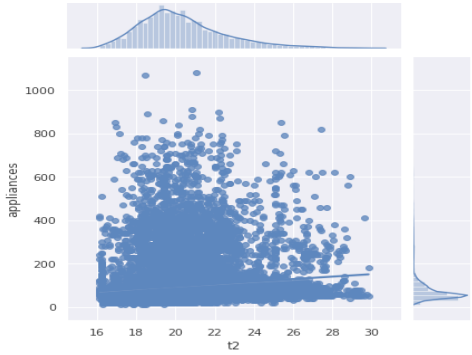
- Between Appliance and Windspeed



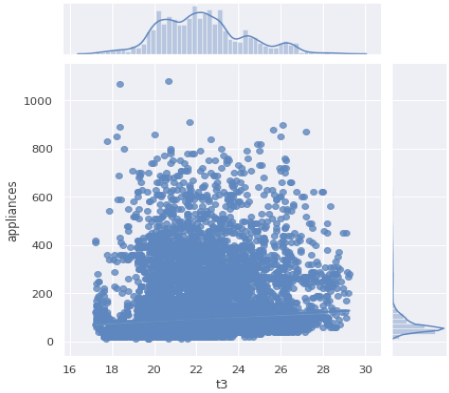
- Between Appliance and T6



- Between Appliance and T2



- Between Appliance and T3



4. Inference Statistics Analysis -

Below are the correlation stats between the temperature dimensions, this will help us to see if any two attributes are redundant or are very similar to each other.

Calculate the Correlation between Temperature features -

- Correlation between T9 and T1 pearson 0.84 0.00 None
- Correlation between T9 and T2 pearson 0.68 0.00 None
- Correlation between T9 and T3 pearson 0.90 0.00 None
- Correlation between T9 and T4 pearson 0.89 0.00 None
- Correlation between T9 and T5 pearson 0.91 0.00 None
- Correlation between T9 and T6 pearson 0.67 0.00 None
- Correlation between T9 and T7 pearson 0.94 0.00 None
- Correlation between T9 and T8 pearson 0.87 0.00 None

Check, if the Temperature, Humidity and Weather features influences Appliance –

1. Coefficient table (middle table). We can interpret the t3 coefficient (4.3471) by first noticing that the p-value (under P>|t|) is so small, basically zero. This means that the t3 is a statistical significant predictor of appliance energy consumption.

The regression coefficient for t3 of 4.3471 means that on average, each additional t3 temperature is associated with an increase the appliance energy consumption

The confidence interval gives us a range of plausible values for this average change, about (3.637 and 5.058)

R^2 is only 0.007, hence t3 doesn't contribute much on the variance. F-Statistic The F-Statistic is 143.8 and the probability for this statistic is 5.09e-33, which is close to 0. We can safely reject the null hypothesis, indicating that at least one coefficient is nonzero.

OLS Regression Results

Dep. Variable:	appliances	R-squared:	0.007
Model:	OLS	Adj. R-squared:	0.007
Method:	Least Squares	F-statistic:	143.8
Date:	Mon, 18 May 2020	Prob (F-statistic):	5.09e-33
Time:	21:12:10	Log-Likelihood:	-1.1931e+05
No. Observations:	19735	AIC:	2.386e+05
Df Residuals:	19733	BIC:	2.386e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.8955	8.105	0.110	0.912	-14.990	16.781
t3	4.3471	0.362	11.992	0.000	3.637	5.058

Omnibus:	14099.091	Durbin-Watson:	0.498
Prob(Omnibus):	0.000	Jarque-Bera (JB):	196052.616
Skew:	3.410	Prob(JB):	0.00
Kurtosis:	16.854	Cond. No.	250.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

2. Coefficient table (middle table). We can interpret the t3+t6 coefficient (0.4119, 1.8871) by first noticing that the p-value (under P>|t|) is so small, basically zero. This means that the t6 is a statisticall significant predictor of appliance energy consumption.

The regression coefficient for t6 of 1.8871, means that on average, each additional t6 temperature is associated with an increase the appliance energy consumption

The confidence interval gives us a range of plausible values for this average change, about (1.566 and 2.208)

R^2 is only 0.014, hence t3 and t6 doesn't contribute much on the variance. F-Statistic The F-Statistic is 138.8 and the probability for this statistic is 1.39e-60, which is close to 0. We can safely reject the null hypothesis, indicating that at least one coefficient is nonzero.

OLS Regression Results

Dep. Variable:	appliances	R-squared:	0.014
Model:	OLS	Adj. R-squared:	0.014
Method:	Least Squares	F-statistic:	138.8
Date:	Mon, 18 May 2020	Prob (F-statistic):	1.39e-60
Time:	21:12:21	Log-Likelihood:	-1.1924e+05
No. Observations:	19735	AIC:	2.385e+05
Df Residuals:	19732	BIC:	2.385e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	73.5949	10.249	7.181	0.000	53.506	93.684
t3	0.4119	0.497	0.828	0.407	-0.563	1.386
t6	1.8871	0.164	11.525	0.000	1.566	2.208

Omnibus:	14117.484	Durbin-Watson:	0.500
Prob(Omnibus):	0.000	Jarque-Bera (JB):	197909.447
Skew:	3.412	Prob(JB):	0.00
Kurtosis:	16.932	Cond. No.	339.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

3. Coefficient table (middle table). We can interpret the t3+t6+rh_out coefficient (1.8057, 0.3079, -0.9076) by first noticing that the p-value (under P>|t|) is so small, basically zero. This means that the t6 is a statistical significant predictor of appliance energy consumption.

The regression coefficient for rh_out of -0.9076, means that on average, each additional t6 temperature is associated with an decrease the appliance energy consumption

The confidence interval gives us a range of plausible values for this average change, about (-1.025 and -0.790)

R^2 is only 0.025 better than previous, hence t3, t6 and rh_out doesn't contribute much on the variance. F-Statistic The F-Statistic is 170.3 and the probability for this statistic is 4.96e-109, which is close to 0. We can safely reject the null hypothesis, indicating that at least one coefficient is nonzero.

OLS Regression Results

Dep. Variable:	appliances	R-squared:	0.025
Model:	OLS	Adj. R-squared:	0.025
Method:	Least Squares	F-statistic:	170.3
Date:	Mon, 18 May 2020	Prob (F-statistic):	4.96e-109
Time:	21:12:55	Log-Likelihood:	-1.1913e+05
No. Observations:	19735	AIC:	2.383e+05
Df Residuals:	19731	BIC:	2.383e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	127.4360	10.790	11.810	0.000	106.286	148.586
t3	1.8057	0.503	3.592	0.000	0.820	2.791
t6	0.3079	0.193	1.593	0.111	-0.071	0.687
rh_out	-0.9076	0.060	-15.173	0.000	-1.025	-0.790

Omnibus:	14135.525	Durbin-Watson:	0.507
Prob(Omnibus):	0.000	Jarque-Bera (JB):	199836.330
Skew:	3.415	Prob(JB):	0.00
Kurtosis:	17.014	Cond. No.	1.26e+03

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.26e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

4. Coefficient table (middle table). We can interpret the t1+t2+t3+t4+t5+t6+t7+t8+rh_1+rh_2+windspeed, coefficient (9.0446, -25.6614, 17.7293,-1.4768,-7.3830,-7.5650,1.0356,-6.2685,9.4475,20.0347,-20.3286,1.6784) by first noticing that the p-value (under P>|t|) is so small, basically zero. This means that the t6 is a statisticall significant predictor of appliance energy consumption.

The confidence interval of t3 gives us a range of plausible values for this average change, about (15.814 and 19.644)

R^2 is only 0.098 better than previous, F-Statistic The F-Statistic is 194.5 and the probability for this statistic is 0. We can safely reject the null hypothesis, indicating that at least one β coefficient is nonzero.

OLS Regression Results

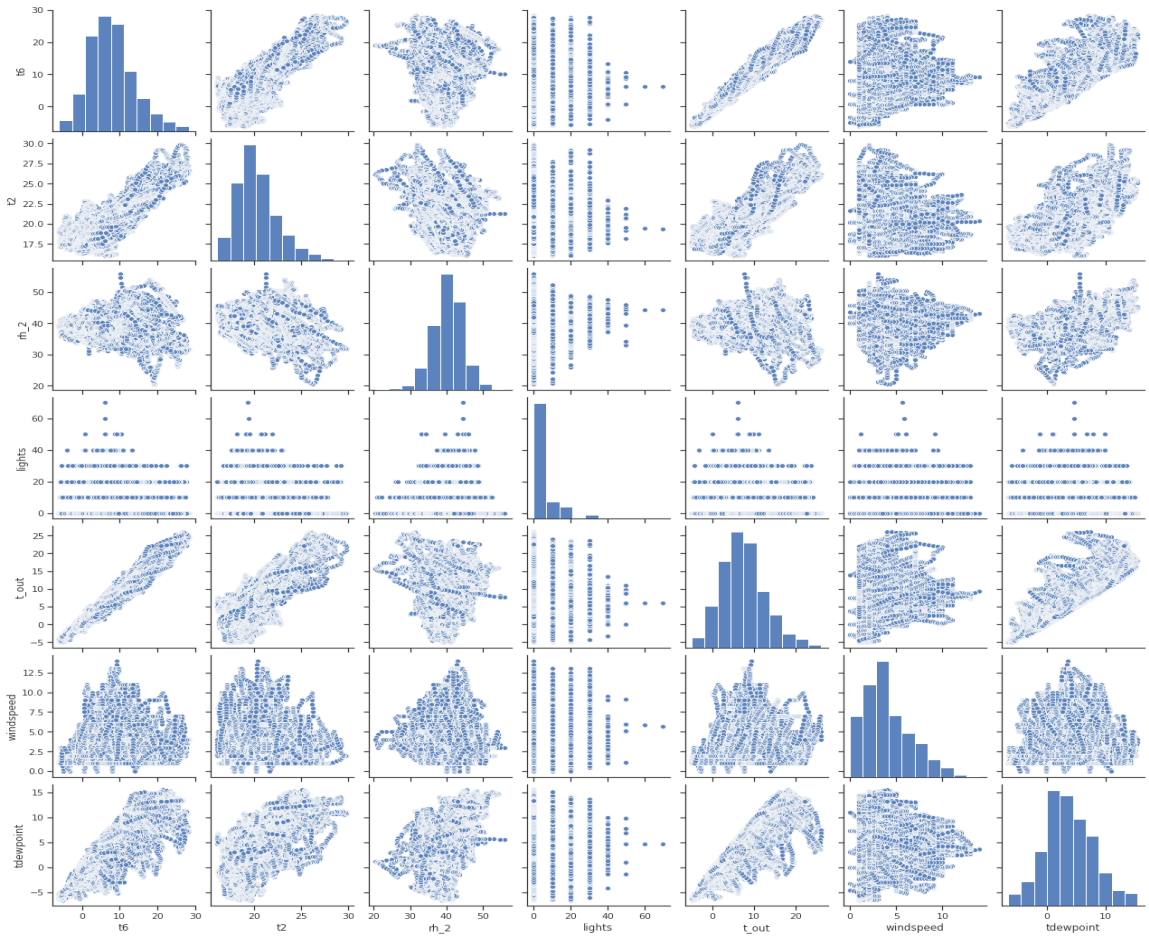
Dep. Variable:	appliances	R-squared:	0.098
Model:	OLS	Adj. R-squared:	0.097
Method:	Least Squares	F-statistic:	194.5
Date:	Mon, 18 May 2020	Prob (F-statistic):	0.00
Time:	21:35:34	Log-Likelihood:	-1.1836e+05
No. Observations:	19735	AIC:	2.367e+05
Df Residuals:	19723	BIC:	2.368e+05
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	123.2455	15.477	7.963	0.000	92.909	153.582
t1	9.0446	1.764	5.127	0.000	5.587	12.502
t2	-25.6614	1.450	-17.697	0.000	-28.504	-22.819
t3	17.7293	0.977	18.148	0.000	15.814	19.644
t4	-1.4768	0.907	-1.628	0.103	-3.255	0.301
t5	-7.3830	1.065	-6.930	0.000	-9.471	-5.295
t6	1.0356	0.227	4.552	0.000	0.590	1.482
t7	-6.2685	0.971	-6.457	0.000	-8.171	-4.366
t8	9.4475	0.881	10.730	0.000	7.722	11.173
rh_1	20.0347	0.630	31.792	0.000	18.799	21.270
rh_2	-20.3286	0.630	-32.261	0.000	-21.564	-19.094
windspeed	1.6784	0.320	5.239	0.000	1.050	2.306

Omnibus:	13836.970	Durbin-Watson:	0.578
Prob(Omnibus):	0.000	Jarque-Bera (JB):	196316.384
Skew:	3.306	Prob(JB):	0.00
Kurtosis:	16.965	Cond. No.	1.80e+03

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.8e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

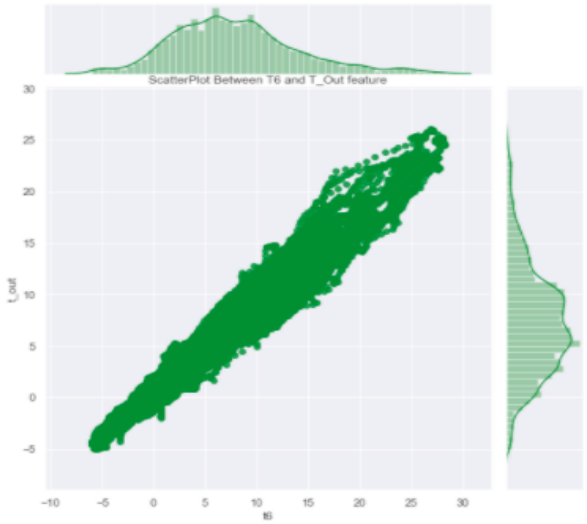
Pairplot for 't6','t2', 'rh_2','lights','t_out','windspeed','tdewpoint' features for their distribution –



Is there a significant difference between T6 and T_out and impact my future Prediction Models

	t6	t_out
count	19735.000000	19735.000000
mean	7.910939	7.411665
std	6.090347	5.317409
min	-6.065000	-5.000000
25%	3.626667	3.666667
50%	7.300000	6.916667
75%	11.256000	10.408333
max	28.290000	26.100000

With Description and plotting the **jointplot** of the two features -



It seems like there is linear relation between 'T6' and T_out'

To find the Correlation between all the Features and Target – Appliances -

	Correlation coefficients	p-value
appliances	1.000000	0.000000e+00
lights	0.197278	2.305108e-172
t2	0.120073	2.784947e-64
t6	0.117638	9.333867e-62
t_out	0.099155	2.624854e-44
windspeed	0.087122	1.456471e-34
rh_1	0.086031	9.639431e-34
weekday_avg	0.085900	1.208067e-33
t3	0.085060	5.086416e-33
t1	0.055447	6.449169e-15
house_temp	0.054740	1.411780e-14
t4	0.040281	1.507881e-08
t8	0.039572	2.683103e-08
rh_3	0.036292	3.402540e-07
t7	0.025801	2.890302e-04
t5	0.019760	5.503451e-03

	Correlation coefficients	p-value
rh_4	0.016965	1.715603e-02
tdewpoint	0.015353	3.102113e-02
t9	0.010010	1.596635e-01
rh_5	0.006955	3.286027e-01
weekday	0.003060	6.672580e-01
visibility	0.000230	9.741858e-01
week	-0.011356	1.106606e-01
month	-0.011606	1.030264e-01
value	-0.013535	5.725207e-02
house_hum	-0.020075	4.799007e-03
press_mm_hg	-0.034885	9.493922e-07
rh_9	-0.051462	4.697109e-13
rh_7	-0.055642	5.187296e-15
rh_2	-0.060465	1.873022e-17
rh_6	-0.083178	1.209481e-31
rh_8	-0.094039	5.211566e-40
rh_out	-0.152282	1.077516e-102

Create a New DataFrame to conducting T-Statistics and Changing it to Categorical column –

- Create the dataframe with “lights” and “appliances”.
- Update the feature where the number of lights are 40 or more as 1
- Update the feature where the number of lights are 39 or less as 0

dateupdate	lights	appliances
2016-01-11	0	60
2016-01-11	0	60
2016-01-11	0	50
2016-01-11	1	50
2016-01-11	1	60

- When conducted the T-test , T-Statistics is 133.85 and pvalue is 0, hence we can reject the null hypothesis and conclude that there is a statically significant difference.

Major Statistical Inference –

- Temperature feature from T1-T9 and T_out have positive correlation with the target Appliances. For the indoor temperatures, the correlations are high as expected. Four columns have a high degree of correlation with T9 & T3,T5,T7,T8 also T6 & T_Out has high correlation (both temperatures from outside) . Hence we can remove the T9 and T_out from the model in next section.

- Weather attributes - Visibility, Tdewpoint, Press_mm_hg have low correlation values

- Humidity - There are no significantly high correlation cases for humidity sensors.

- Random variables have no role to play; hence we will remove these features from the model in next section.

5. Model Building and Implementation -

1. Continuing from previous section, from the dataset, we are dropping the below field and running the dummy repressor as benchmark algorithm.

    a. 'date_x', 'appliances','rv1', 'rv2','t6','t9' from the dataset.

    b. Created the X will all the features and Y with the target feature.

    c. Using train_test_split method, we have done the split of the dataset in 70% Training data and 30% test data.

    d. Upon running the DummyRegressor regression model- we get the below score for R^2 and RMSE(Root Mean Square Error)

```
Classifier fitted in 0.001 seconds
R^2: -0.000
Root Mean Squared Error: 101.502
```

2. Also, with Cross validation, we didn't see the improvement in the performance of the benchmark algorithms –

```
[-0.00101888 -0.00057843 -0.00062295 -0.00286296 -0.00019133]
Average 5-Fold CV Score: -0.0010549098420414627

[-4.07557636e-03 -1.17519136e-04 -9.02785691e-05 -1.28999781e-03
 -2.71734096e-03 -6.22692398e-05 -9.52786017e-04 -4.21755698e-03
 -9.02788776e-04 -5.71588542e-05]
Average 10-Fold CV Score: -0.0014483272712929375
```

3. Now, we will try to scale the data and find best performing model –

    a. Dropped the x_date feature from the dataset, and using the StandardScaler method, scaled the dfactual dataframe.

    b. From the scaled dataset, dropped the 'appliances','rv1', 'rv2','t6','t9'.

    c. Created the Training and Test Dataset with 70-30% ratio.

4. Create the following models with key important features –

    - Regularized linear models as an improvement over Linear Regression.

        - Linear Regression

- Ridge Regression
- Lasso Regression

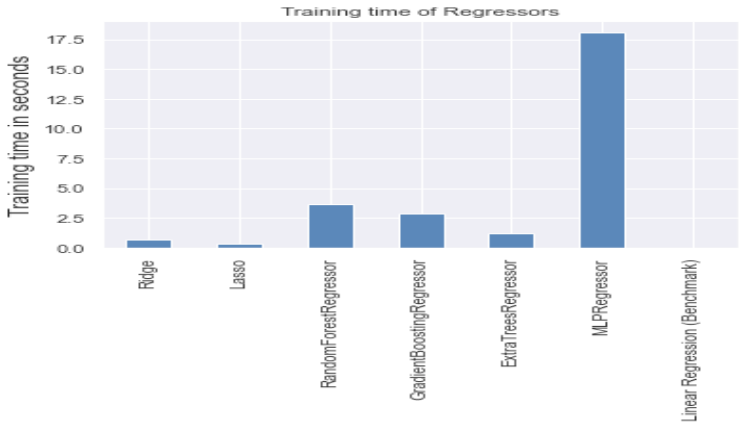
- Ensemble based Tree Regression models, which deal with number of features and outlier data.
  - Random Forests
  - Gradient Boosting
  - Extra Trees

- Neural networks for non-linear relationships target feature and predictors.
  - Multi-Layer Perceptron

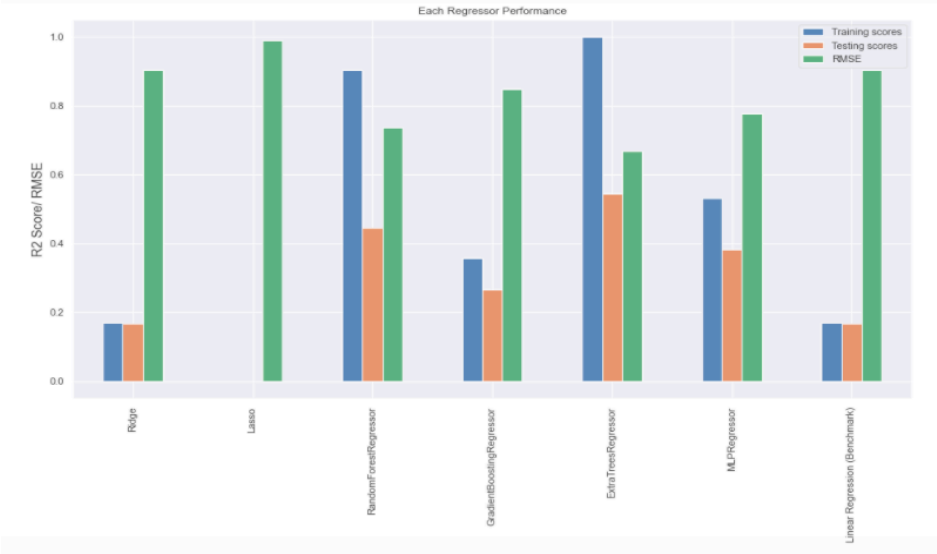
a. Implemented them in a iterative manner with creating different functions
   i. Created function to capture the fit and predict the models and capture the score and accuracy for the models
   ii. Created the pipeline and passed all the algorithms to be executed in the above function.
   iii. Created a function to display and store the results / outcome.
   iv. Below is the results displaying the R^2 and RMSE and time it took to predict.

	Training times	Training scores	Testing scores	RMSE
ExtraTreesRegressor	1.20606	1	0.543191	0.669149
RandomForestRegressor	3.62582	0.904629	0.44562	0.737156
MLPRegressor	18.0836	0.531666	0.383224	0.777534
GradientBoostingRegressor	2.84227	0.357163	0.265424	0.848543
Ridge	0.717286	0.170043	0.166668	0.903784
Linear Regression (Benchmark)	0.0219181	0.169898	0.166489	0.903881
Lasso	0.381927	0	-1.15367e-06	0.990047

b. Comparing the Training time –



c. Plot to compare the performance of the algorithms on datasets



Interpretation –

Least performing Repressor - Lasso Repressor and best performing Repressor - Extra Trees Repressor. Even though Extra Trees Repressor has a R2 score of 1.0 on training set, which might suggest over-fitting but, it has the highest score on test set and also, it's RMSE value is also the lowest. Clearly, ExtraTreesRegressor is the best model out of given models.

d. Hyper-parameter tuning the best Model – "ExtraTreesRegressor" observed from above step – Using the RandomizedSearchCV, we will find the best estimators and using those estimators we will perform the prediction.

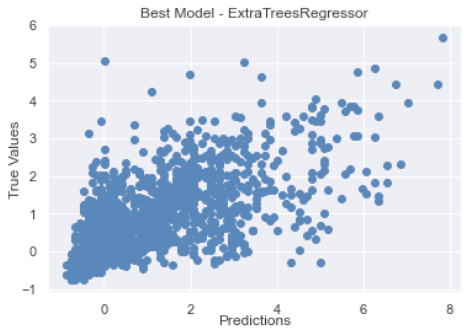
```
RandomizedSearchCV(cv=5, error_score='raise-deprecating',
          estimator=ExtraTreesRegressor(bootstrap=False, criterion='mse', max_depth=None,
          max_features='auto', max_leaf_nodes=None,
          min_impurity_decrease=0.0, min_impurity_split=None,
          min_samples_leaf=1, min_samples_split=2,
          min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
          oob_score=False, random_state=79, verbose=0, warm_start=False),
          fit_params=None, iid='warn', n_iter=20, n_jobs=-1,
          param_distributions={'n_estimators': [10, 50, 100, 200, 250], 'max_features': ['auto', 'sqrt', 'log2'], 'ma
x_depth': [None, 10, 50, 100, 200, 500]},
          pre_dispatch='2*n_jobs', random_state=79, refit=True,
          return_train_score='warn', scoring='r2', verbose=2)
```

```
Parameters of best Regressor : {'n_estimators': 250, 'max_features': 'log2', 'max_depth': None}
```

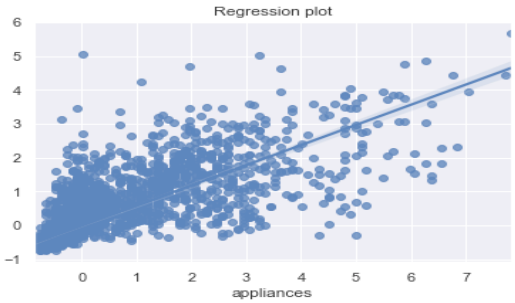
e. Using the best parameter we will fit and predict the training data and predict on test data.

```
R2 score on Training set = 1.000
RMSE on Training set = 0.000
R2 score on Testing set = 0.627
RMSE on Testing set = 0.605
```

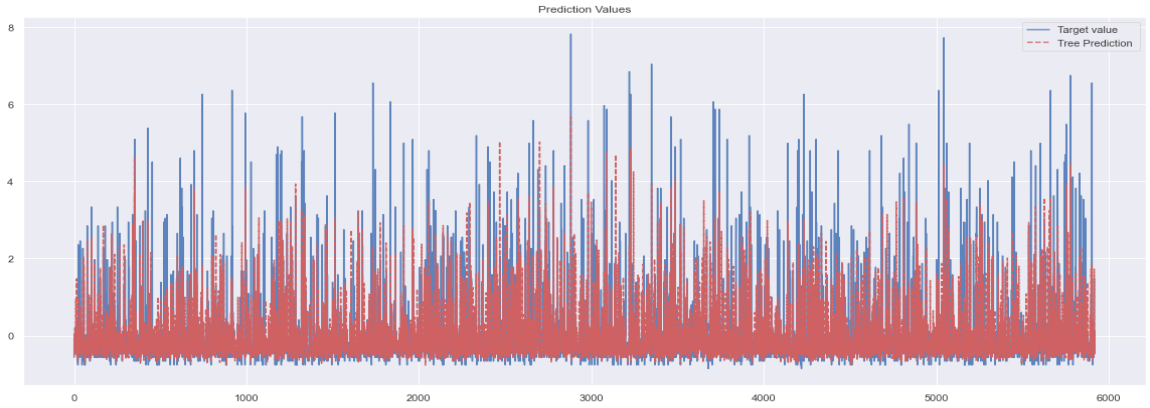
f. Plotting the data for y_test_s and predicted data – scatterplot as below



Using the seaborn plot using regplot function, we find the regression line on the scaled test data and predicted data from ExtraTree Regression algorithm



Overlaying the test data and predicted data, we can see that the prediction on not so accurate.

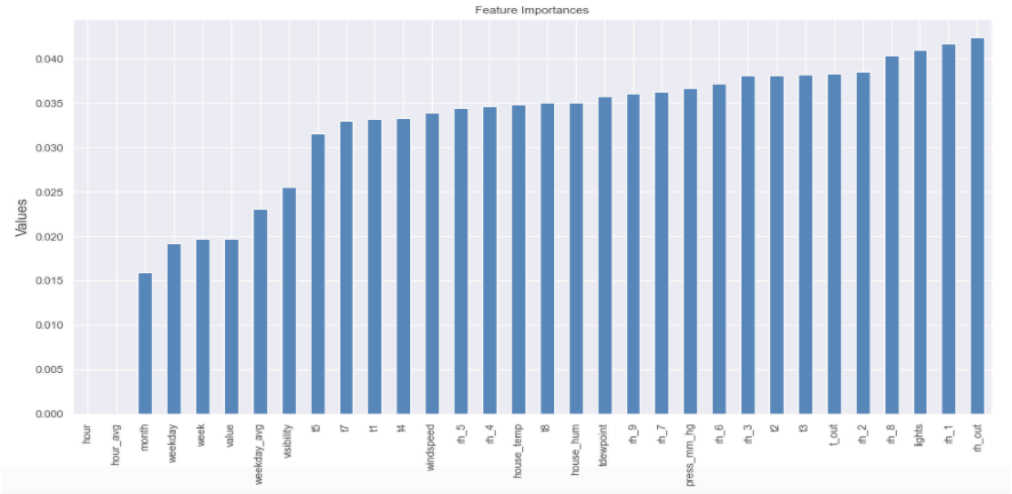


<u>Interpretation from Implementation -</u>

- R2 score improvement compared to Benchmark model = 0.463.
- RMSE improvement compared to Benchmark model = 0.301.
- R2 score improvement compared to without tuned model = 0.086.
- RMSE improvement compared to without tuned model = 0.066.

g. Important features contributing from the data set are as below –

```
Most important feature = rh_out
Least important feature = hour

Top 5 most important features:-
rh_out
rh_1
lights
rh_8
rh_2

Top 5 least important features:-
hour
hour_avg
month
weekday
week
```



5. Feature and Model Evaluation-

    1. Clone the above best model clone with the 'rh_out', 'rh_1', 'lights', 'rh_8', 'rh_2', 't_out', 't3', 't2' and do a prediction only with the most important feature, to verify if there is any improvement in the model accuracy.

        ```
        R2 Score on testing dataset = 0.519
        RMSE Score on testing dataset = 0.686
        ```

    2. Comparing these results with above best performing algorithms – Extratreeregressor

        - R2 Score on testing dataset = 0.52
        - RMSE Score on testing dataset = 0.69
        - Difference in R2 score = 0.109 or 11% loss of explained variance.
        - Increase in RMSE = 0.083

        The model has not performed better with reduced number of features.

    6. **Conclusion** -

        1. Best Algorithm is ExtraTreesRegressor.
        2. Top 5 most important features:- rh_out, rh_1, lights, rh_8, rh_2
        3. Variance explained on test set = 0.627
        4. RMSE error = 0.603
        5. R2 score improvement compared to Benchmark model = 0.463.
        6. RMSE improvement compared to Benchmark model = 0.301.
        7. R2 score improvement compared to without tuned model = 0.086.
        8. RMSE improvement compared to without tuned model = 0.066.

6. Reference of data source

- https://archive.ics.uci.edu/ml/datasets/Appliances+energy+prediction
- https://www.macrotrends.net/2516/wti-crude-oil-prices-10-year-daily-chart

7. Link for Code

- https://github.com/arijitsinha80/Springboard/blob/master/Project/Capstoneproject_Phase2_Final.ipynb

8. Link for PPT

- https://github.com/arijitsinha80/Springboard_CapstoneProject1/blob/master/Capstone%20Project%201_Final.pptx