Capstone Project 1: Data Wrangling

Appliances Energy Prediction –

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

Link for Jupyter notebook uploaded on Github - https://github.com/arijitsinha80/Springboard/blob/master/Project/Capstoneproject Phase1.ipynb

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	

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	
	DII 6	DII 7	DII O	BU O		
	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 19/35 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.

We have saved the dataset as input for other phase of this capstone project.