Capstone Project

Machine Learning Engineer Nanodegree

Title**: Air Quality**

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I. Definition

Project Overview:

In early 2011, officials reported that pollution in Italy was reaching crisis levels. What's particularly troublesome is particle pollution that pervades Italy, and accounts for breathing and heart problems, causing a whopping 9% of deaths of Italians over the age of 30. New report finds that air pollution is the single biggest environmental health risk in Europe, causing hundreds of thousands of premature deaths. Particulate matter, ozone, nitrogen dioxide. Europe's air quality is significantly threatened by these pollutants, mostly in urban centres

Air quality is a significant concern for both healthy population and people suffering for different pathologies. Long or even short term exposure to significant pollution levels have been associated with the development or worsening of multiple pathologies ranging from Asthma to Lung Cancer .
Air quality patterns may significantly vary in space and time due to complex fluid dynamic effects occurring in the city landscape or to the hourly, daily and seasonal variation of human activities. However, most of the national states rely on the operation of networks of certified air quality monitoring stations in order to detect and monitor air quality in cities. Unfortunately, the average low spatial density of such networks do not permit to achieve the required resolution.

Reference link:
https://www.researchgate.net/publication/319338229_Cooperative_Air_Quality_Sensing_with_Crowdfunded_Mobile_Chemical_Multisensor_Devices

Problem Statement:

To check the quality of air using 'Air Quality Chemical Multisensor Device' by finding the R^2 score and coefficient of regression using different regression models and the best model is selected to evaluate the Air Quality.

Metrics:

R^2 Score:

R-squared is a statistical measure that's used to assess the goodness of fit of our regression model. In R-squared we have a baseline model which is the worst model. This baseline model doesn't make use of any independent variables to predict the value of dependent variable Y. Instead it uses the mean of the observed responses of dependent variable Y and always predicts this mean as the value of Y.

R-squared is given by

$$R^2 = 1 - \frac{SSE}{SST}$$

Where SSE is the sum of squared errors of our regression model

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

And SST is the sum of squared errors of our baseline model.

$$SST = \sum_{i=1}^{n} (y_i - \bar{y}_i)^2.$$

II. Analysis:

Data Exploration:

Dataset Link: https://archive.ics.uci.edu/ml/datasets/Air+Quality

In this project I have used 15 attributes and around 9300 trained and test data to evaluate the R-squared score. And this coefficient is found out by using different Regression Methods. The dataset used are shown in the below.

	Date	Time	CO (GT)	PT08.S1 (CO)	NMHC (GT)	C6H6(GT)	PT08.S2 (NMHC)	NOx (GT)	PT08.S3 (NOx)	NO2 (GT)	PT08.S4 (NO2)	PT08.S5 (O3)	T	RH	AH
0	2004-03-10	18:00:00	2.6	1360.000000	150	11.881723	1045.500000	166.0	1056.250000	113.0	1692.000000	1267.500000	13.600000	48.875001	0.757754
1	2004-03-10	19:00:00	2.0	1292.250000	112	9.397165	954.750000	103.0	1173.750000	92.0	1558.750000	972.250000	13.300000	47.700000	0.725487
2	2004-03-10	20:00:00	2.2	1402.000000	88	8.997817	939.250000	131.0	1140.000000	114.0	1554.500000	1074.000000	11.900000	53.975000	0.750239
3	2004-03-10	21:00:00	2.2	1375.500000	80	9.228796	948.250000	172.0	1092.000000	122.0	1583.750000	1203.250000	11.000000	60.000000	0.786713
4	2004-03-10	22:00:00	1.6	1272.250000	51	6.518224	835.500000	131.0	1205.000000	116.0	1490.000000	1110.000000	11.150000	59.575001	0.788794
5	2004-03-10	23:00:00	1.2	1197.000000	38	4.741012	750.250000	89.0	1336.500000	96.0	1393.000000	949.250000	11.175000	59.175000	0.784772
6	2004-03-11	00:00:00	1.2	1185.000000	31	3.624399	689.500000	62.0	1461.750000	77.0	1332.750000	732.500000	11.325000	56.775000	0.760312
7	2004-03-11	01:00:00	1.0	1136.250000	31	3.326677	672.000000	62.0	1453.250000	76.0	1332.750000	729.500000	10.675000	60.000000	0.770238
8	2004-03-11	02:00:00	0.9	1094.000000	24	2.339416	608.500000	45.0	1579.000000	60.0	1276.000000	619.500000	10.650000	59.674999	0.764819
9	2004-03-11	03:00:00	0.6	1009.750000	19	1.696658	560.750000	-200.0	1705.000000	-200.0	1234.750000	501.250000	10.250000	60.200001	0.751657
10	2004-03-11	04:00:00	-200.0	1011.000000	14	1.293620	526.750000	21.0	1817.500000	34.0	1196.750000	445.250000	10.075000	60.474999	0.746495
11	2004-03-11	05:00:00	0.7	1066.000000	8	1.133431	512.000000	16.0	1918.000000	28.0	1182.000000	421.750000	11.000000	56.175000	0.736560
12	2004-03-11	06:00:00	0.7	1051.750000	16	1.603768	553.250000	34.0	1738.250000	48.0	1221.250000	471.500000	10.450000	58.125000	0.735295
13	2004-03-11	07:00:00	1.1	1144.000000	29	3.243618	667.000000	98.0	1489.750000	82.0	1339.000000	729.750000	10.200000	59.599999	0.741736

The 15 attributes that I have used in dataset are explained below.

Attributes:

1.Date	- DD/MM/YY
2.Time	- HH.MM.SS
3.CO(GT)	- True hourly averaged concentration CO in mg/m^3
4.PT08.S1(CO)	- PT08.S1 (tin oxide) hourly averaged sensor response (nominally CO targeted)
5. NMHC(GT)	- True hourly averaged overall Non Metanic HydroCarbons concentration in microg/m^3
6. C6H6(GT)	- True hourly averaged Benzene concentration in microg/m^3
7. PT08.S2(NMHC)	- PT08.S2 (titania) hourly averaged sensor response (nominally NMHC targeted)
8. NOx(GT)	- True hourly averaged NOx concentration in ppb
9. PT08.S3(NOx)	- PT08.S3 (tungsten oxide) hourly averaged sensor response
10. NO2(GT)	- True hourly averaged NO2 concentration in microg/m^3
11. PT08.S4(NO2)	- PT08.S4 (tungsten oxide) hourly averaged sensor response
12. PT08.S5(O3)	- PT08.S5 (indium oxide) hourly averaged sensor response (nominally O3 targeted)
13.T	- Temperature in A°C
14.RH	- Relative Humidity (%)
15.AH	- Absolute Humidity

Data Set Information:

The dataset contains 9358 instances of hourly averaged responses from an array of 5 metal oxide chemical sensors embedded in an Air Quality Chemical Multisensor Device. The device was located on the field in a significantly polluted area, at road level, within an Italian city. Data were recorded from March 2004 to February 2005 (one year)representing the longest freely available recordings of on field deployed air quality chemical sensor devices responses. Ground Truth hourly averaged concentrations for CO, Non Metanic Hydrocarbons, Benzene, Total Nitrogen Oxides (NOx) and Nitrogen Dioxide (NO2) and were provided by a co-located reference certified analyser. Evidences of cross-sensitivities as well as both concept and sensor drifts are present as described in De Vito et al., Sens. And Act. B, Vol. 129,2,2008 (citation required) eventually affecting sensors concentration estimation capabilities. Missing values are tagged with -200 value.
This dataset can be used exclusively for research purposes. Commercial purposes are fully excluded.

Information of Data set:

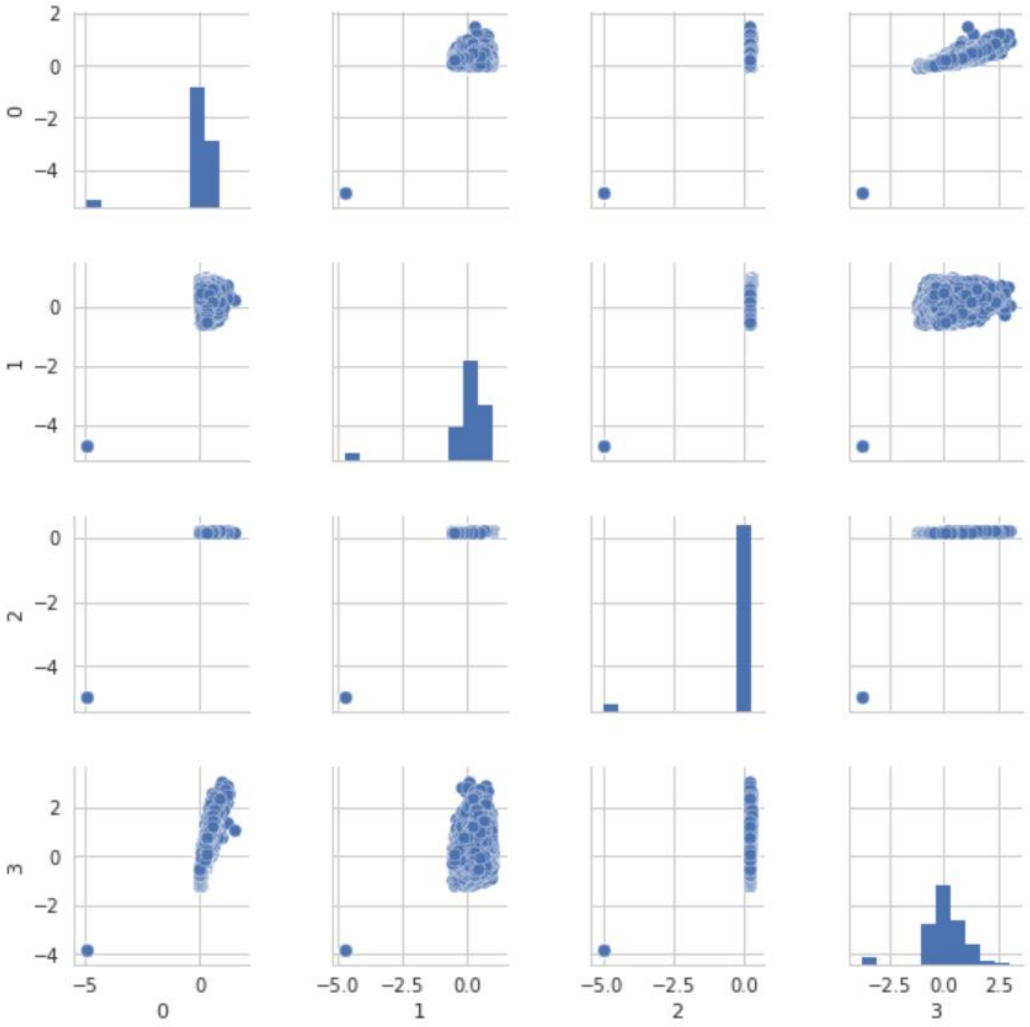
```
In [5]: air_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9357 entries, 0 to 9356
Data columns (total 15 columns):
Date             9357 non-null datetime64[ns]
Time             9357 non-null object
CO(GT)           9357 non-null float64
PT08.S1(CO)      9357 non-null float64
NMHC(GT)         9357 non-null int64
C6H6(GT)         9357 non-null float64
PT08.S2(NMHC)    9357 non-null float64
NOx(GT)          9357 non-null float64
PT08.S3(NOx)     9357 non-null float64
NO2(GT)          9357 non-null float64
PT08.S4(NO2)     9357 non-null float64
PT08.S5(O3)      9357 non-null float64
T                9357 non-null float64
RH               9357 non-null float64
AH               9357 non-null float64
dtypes: datetime64[ns](1), float64(12), int64(1), object(1)
memory usage: 1.1+ MB
```

There are no missing values existing in the data set, so we don’t need to modify any data.

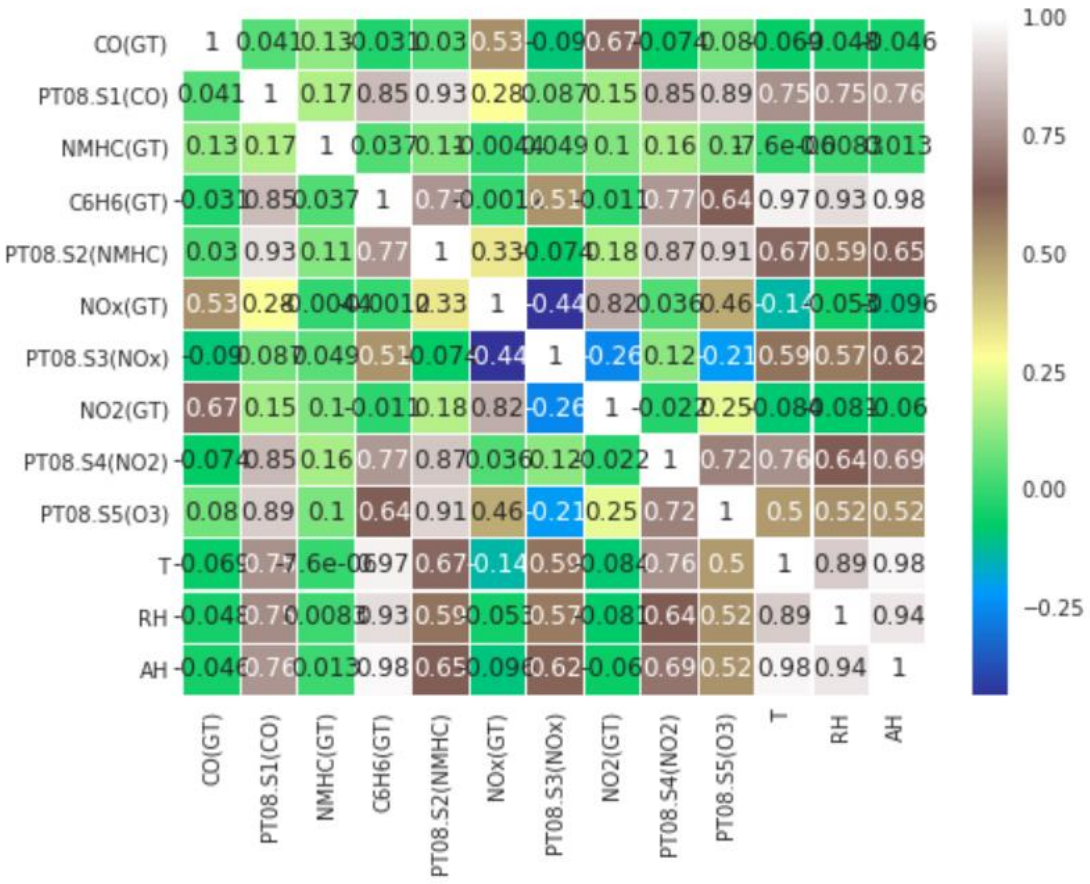
Data Visualization:

Let us visualize the absolute correlation coefficient of target variable with all the other variables. Higher absolute correlation coefficient means the variable can provide more information about how the target variable moves as shown in below figure.



Heat Map:

The heat map is a 2-D representation of data in which values are represented by colours. A simple heat map provides the immediate visual summary of information. More elaborate heat maps allow the user to understand complex data.



Seeing above heatmap, I infer that none of displayed value pairs is having an explicitly high correlation, so there is no necessity to ditch any feature at this stage. I also notice a negative correlation between ‘PT08.S3(NOx)' and ‘NOx(GT)’, PT08.S3(NOx)’ and ‘NO2(GT)’, ‘PT08.S3(NOx)' and ‘PT08.S5(O3)’ . And there also exists some of negative correlation values relatively less than the mentioned above.

Algorithms and Techniques:

1. Linear Regression
2. Support Vector Regression
3. Decision Tree Regression
4. Lasso Regression

Regression analysis is a form of predictive modelling technique which investigates the relationship between a **dependent** (target) and **independent variable (s)** (predictor). This

technique is used for forecasting, time series modelling and finding the causal effect relationship between the variables.

Regression analysis is an important tool for modelling and analyzing data. Here, we fit a curve / line to the data points, in such a manner that the differences between the distances of data points from the curve or line is minimized.

1. Linear Regression

It is one of the most widely known modeling technique. Linear regression is usually among the first few topics which people pick while learning predictive modeling. In this technique, the dependent variable is continuous, independent variable(s) can be continuous or discrete, and nature of regression line is linear.

Linear Regression establishes a relationship between **dependent variable (Y)** and one or more **independent variables (X)** using a **best fit straight line** (also known as regression line).

It is represented by an equation **Y=a+b*X + e**, where a is intercept, b is slope of the line and e is error term. This equation can be used to predict the value of target variable based on given predictor variable(s).

- There must be **linear relationship** between independent and dependent variables
- Multiple regression suffers from **multicollinearity, autocorrelation, heteroskedasticity**.
- Linear Regression is very sensitive to **Outliers**. It can terribly affect the regression line and eventually the forecasted values.

2. Support Vector Regression

Support vector regression can solve both linear and non-linear models. SVM uses non-linear kernel functions (such as polynomial) to find the optimal solution for non-linear models.

Maintaining all the main features that characterize the algorithm (maximal margin). The Support Vector Regression (SVR) uses the same principles as the SVM for classification, with only a few minor differences. First of all, because output is a real number it becomes very difficult to predict the information at hand, which has infinite possibilities. In the case of regression, a margin of tolerance (epsilon) is set in approximation to the SVM which would have already requested from the problem. But besides this fact, there is also a more complicated reason, the algorithm is more complicated therefore to be taken in consideration.

However, the main idea is always the same: to minimize error, individualizing the hyperplane which maximizes the margin, keeping in mind that part of the error is tolerated.

3.Decision Tree Regression

A decision tree is a flow-chart-like structure, where each internal (non-leaf) node denotes a test on an attribute, each branch represents the outcome of a test, and each leaf (or terminal) node holds a class label. The topmost node in a tree is the root node.

Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with **decision nodes** and **leaf nodes**. A decision node (e.g., Outlook) has two or more branches (e.g., Sunny, Overcast and Rainy), each representing values for the attribute tested. Leaf node (e.g., Hours Played) represents a decision on the numerical target. The topmost decision node in a tree which corresponds to the best predictor called **root node**. Decision trees can handle both categorical and numerical data.

Types of decision tree is based on the type of target variable we have. It can be of two types:

1. **Categorical Variable Decision Tree:** Decision Tree which has categorical target variable then it called as categorical variable decision tree. Example:- In above scenario of student problem, where the target variable was "Student will play cricket or not" i.e. YES or NO.
2. **Continuous Variable Decision Tree:** Decision Tree has continuous target variable then it is called as Continuous Variable Decision Tree.

4. Lasso Regression

Lasso (Least Absolute Shrinkage and Selection Operator) also penalizes the absolute size of the regression coefficients. In addition, it is capable of reducing the variability and improving the accuracy of linear regression models. Look at the equation below:

$$= \underset{\beta \in \mathbb{R}^p}{\operatorname{argmin}} \underbrace{\|y - X\beta\|_2^2}_{\text{Loss}} + \lambda \underbrace{\|\beta\|_1}_{\text{Penalty}}$$

Lasso regression differs from ridge regression in a way that it uses absolute values in the penalty function, instead of squares. This leads to penalizing (or equivalently constraining the sum of the absolute values of the estimates) values which causes some of the parameter estimates

to turn out exactly zero. Larger the penalty applied, further the estimates get shrunk towards absolute zero. This results to variable selection out of given n variables.

- The assumptions of this regression is same as least squared regression except normality is not to be assumed
- It shrinks coefficients to zero (exactly zero), which certainly helps in feature selection
- This is a regularization method and uses l1 regularization
- If group of predictors are highly correlated, lasso picks only one of them and shrinks the others to zero

Benchmark Model:

Here we compare the final model with the remaining models to see if it got better or same or worse. The R^2 score is compared among the models and the best model is selected. I think Linear Regression model can be set as the benchmark model and I'm sure that the final solution would outperform the Benchmark model.

III. Methodology

Pre-processing:

In this step we will pre-process the data. Data pre-processing is considered to be the first and foremost step that is to be done before starting any process. We will read the data by using read_excel. Then we will know the shape of the data. And by using the info() we will know the information of the attributes. Then we will check whether there are any null values by using isnull(). After that we will divide the whole data into training and testing data. We will assign 70% of the data to the training data and the remaining 30% of the data into testing data. We will do this by using train_test_split from sklearn.model_selection.

Implementation:

Out of the chosen algorithms we will start with Linear Regression model. We will take a classifier and fit the training data. After that we will predict that by using predict (X_test). Now we will predict the regression score of the testing data by using regressor.score(X_test, y_test). By doing so for, the Linear Regression will give us the R-squared score of 0.999384. We will continue the same procedure on Support Vector Regression, Decision tree Regression, Lasso

Regression . By following the same procedure above that is fitting, predicting and finding the R-Squared score as bellow.

	R-Squared Score
Linear Regression	0.9993846
Support Vector Regression	0.2699190
Decision Tree Regression	0.9999983
Lasso Regression	0.9993083

From the above reports Decision tree Regression seems to be performing well.

Refinement:

I found out 'Decision Tree Regression' as the best regression model out of the chosen techniques. Decision Tree Regression's R-Squared score is almost 100% so it indicates that the model explains all the variability of the response data around its mean. Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line.

An extra-trees regressor has been used .This class implements a meta estimator that fits a number of randomized decision trees (a.k.a. extra-trees) on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

```
In [33]: from sklearn.ensemble import ExtraTreesRegressor

In [34]: etr = ExtraTreesRegressor(n_estimators=300)
         etr.fit(X_train, y_train)

Out[34]: 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=300, n_jobs=1,
                   oob_score=False, random_state=None, verbose=0, warm_start=False)

In [35]: print(etr.feature_importances_)
         indecis = np.argsort(etr.feature_importances_)[::-1]

         [  6.43662201e-05   1.05664014e-01   4.99600719e-06   8.26801841e-02
            4.20774616e-04   4.99618819e-02   1.10631182e-04   3.08662234e-02
            2.22975866e-01   2.45561338e-01   2.61689724e-01]

In [37]: print("Coefficient of determination R^2 <-- on test set: {}".format(etr.score(X_test, y_test)))

         Coefficient of determination R^2 <-- on test set: 0.999996916529
```

Complications:

High air pollution levels can cause immediate health problems including:

- Aggravated cardiovascular and respiratory illness
- Added stress to heart and lungs, which must work harder to supply the body with oxygen
- Damaged cells in the respiratory system

Long-term exposure to polluted air can have permanent health effects such as:

- Accelerated aging of the lungs
- Loss of lung capacity and decreased lung function
- Development of diseases such as asthma, bronchitis, emphysema, and possibly cancer
- Shortened life span

Other long-term complications

Skin is the body's first line of defense against a foreign pathogen or infectious agent and it is the first organ that may be contaminated by a pollutant. The skin is a target organ for pollution in which the absorption of environmental pollutants from this organ is equivalent to the respiratory uptake. Research on the skin has provided evidence that traffic-related air pollutants, especially PAHs, VOCs, oxides, and PM affect skin aging and cause pigmented spots on the face.

IV. Result

Model evaluation and validation

The final model we have chosen is Decision Tree Regression which gave us more R-Squared score that is 0.9999983. Here we can say that the solution is reasonable because we are getting much less R-Squared value while using other models but relatively small change in Linear Regression and Lasso Regression. This model is also robust enough for the given problem. So the results found from this model can be trusted.

Justification:

My final model's solution is better than the benchmark model.

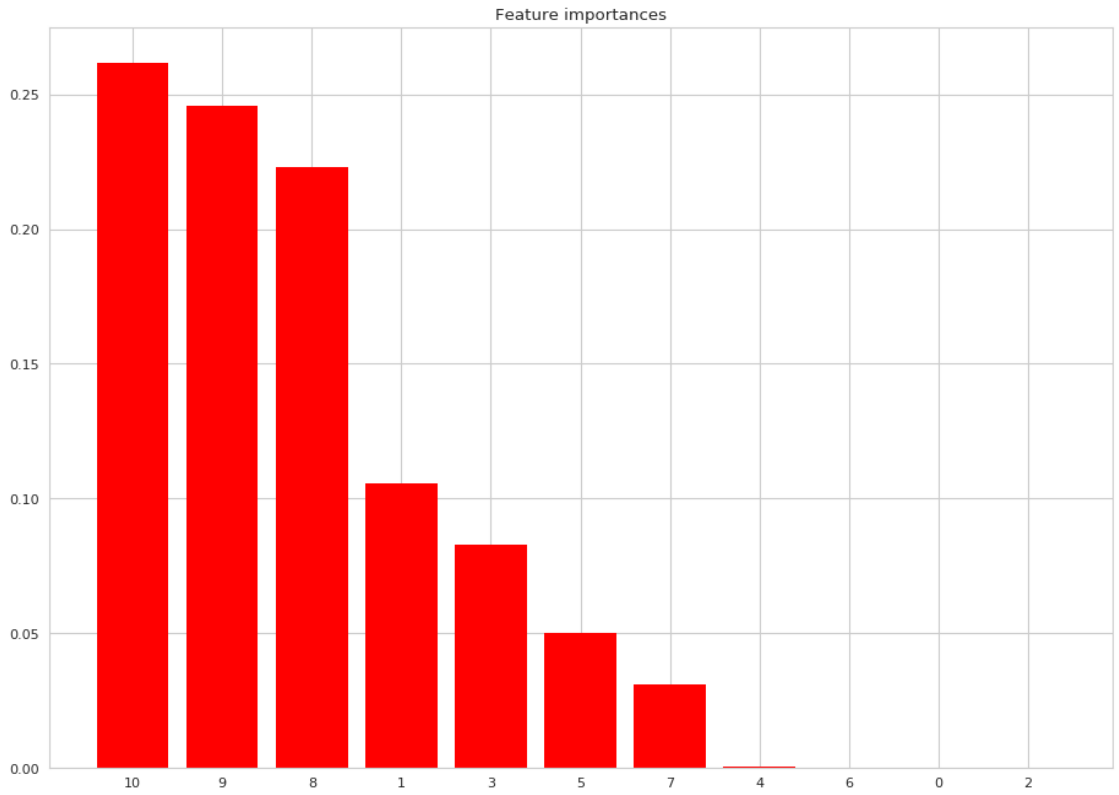
	Decision Tree Regression	Benchmark Model
R-Squared Value	0.9999983	0.9993846

From the above we can conclude that the results for the final model are stronger than the benchmark model. Hence we can say that the decision tree provides the significant to solve the problem of predicting Air Quality.

V. Conclusion:

The goal of the project was to compare different machine learning algorithms and predict whether the gases present in air is responsible for human health issues and if any harmful gases exists and what measures should be taken. Here are the final results.

```
In [36]: plt.figure(num=None, figsize=(14, 10), dpi=80, facecolor='w')
         plt.title("Feature importances")
         plt.bar(range(X_train.shape[1]), etr.feature_importances_[indecis],
                color="r", align="center")
         plt.xticks(range(X_train.shape[1]), indecis)
         plt.show()
```



Reflection:

1. I have learnt how to visualize and understand the data.
2. I have learnt that the data cleaning place a very vital role in data analytics.
3. Removing the data features which are not necessary in evaluating model is very important.
4. I got to know how to use the best technique for the data using appropriate ways
5. I got to know how to tune the parameters in order to achieve the best score.
6. On a whole I learnt how to graph a dataset and applying cleaning techniques on it and to fit the best techniques to get best score.

Improvement:

The process which I have followed can be improved to describe a cooperative air quality sensor architecture based on crowdfunded, mobile, electrochemical sensor based, monitoring systems. The platform aims to produce enhanced information on personal pollutant exposure and enable cooperative reconstruction of high resolution pictures of air pollution in the urban landscape. The calibrated devices are connected to smartphones that provide georeferenced visualization of personal exposure and session based log capabilities. A cloud based interface provides a sensor fusion based mapping capability exploiting google maps APIs. An in-lab calibration by linear regression with temperature correction has been computed and preliminary results have been reported. A small set of calibrated devices will be shipped to crowdfunders for extended field tests in different italian cities.