ECE 9063 Data Analytics Foundations

Assignment 1: Forecasting

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Problem Statement

The used car market is a perfect place for finding cars in decent conditions and with fair prices. It is also the reason that the market has been growing in recent years. However, it is difficult to choose the opportune moment to buy or sell as the price fluctuates constantly. And there are many factors contributing to the price fluctuations. For instance, cars have diverse conditions and the market trend is not stationary all the time. It will be beneficial for both buyers and sellers if we could make a model to predict the value of cars such that they can make a more confident decision. With the help of a suitable model, buyers will be able to make sure the car is worthy of its price, and sellers can get a more accurate price estimation in accordance with other cars having similar conditions. In this report, the forecasting problem is defined as follow: predict the price of a used car in the current year given a set of relevant information.

Dataset Description

Link to the data: https://www.kaggle.com/adityadesai13/used-car-dataset-ford-and-mercedes

These datasets list scraped data of used cars in the British market and are separated into files specific for each car manufacturer. In this report, the dataset selected is "Audi.csv". It contains 9 attributes and 10668 samples. The dataset is suitable for this assignment as it has adequate attributes and samples. With over 10,000 samples, it is easier to strike a balance between computational time and reliability of the model . The attributes are listed below:

- Model: The model code of the car
- Year: registration year of the car
- Price: price on the market
- Transmission: type of gearbox, either manual, automatic, or semi-auto
- Mileage: distance used so far
- fuelType: type of fuel the engine uses, either diesel, petrol, hybrid, or other
- tax: road tax
- mpg: miles per gallon
- engineSize: size of engine in litres

Noticeably, model, transmission, and fuelType have nominal data that needs to be transformed into numerical values. All the attributes in the dataset are considered in the model as they are all important factors while estimating the price of cars in the real-world.

Algorithms Overview

The first algorithm is support vector regression (SVR). Support vector regression adheres to the basic principle of support vector machine, which is the maximum margin characteristic, but it is used for regression instead. Linear kernel is used in this assignment.

The second algorithm is decision tree regression. The algorithm proceeds incrementally as breaking down the data into smaller subsets and build the associated sub-trees from them. At the end, a tree structure with decision nodes and leaf nodes is constructed. However, one major issue with decision tree regression is that it is very prone to overfitting if leave unconstrained. At the result comparison section, we will inspect whether this problem arises.

The third algorithm is random forest regression. Random forest regression is built on top of decision tree regression by training many decision trees on random subsets of features. It also utilizes the idea of ensemble learning which can take advantages of multiple machine learning algorithms such that more accurate predictions can be obtained.

Before applying the algorithms, it is beneficial to normalize our dataset as it is a common requirement of many machine learning algorithms and it is also considered good practice. The normalization technique used is standardization, which will make the data have zero mean and unit variance.

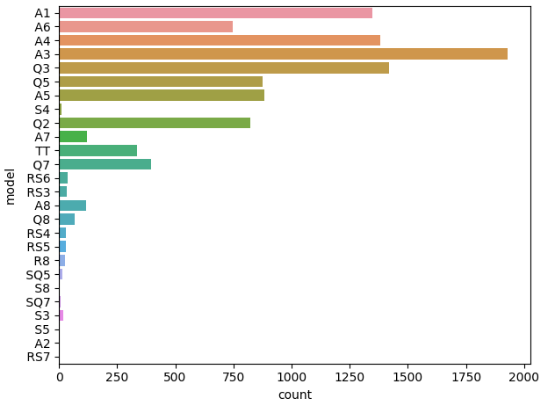
Detailed Procedures

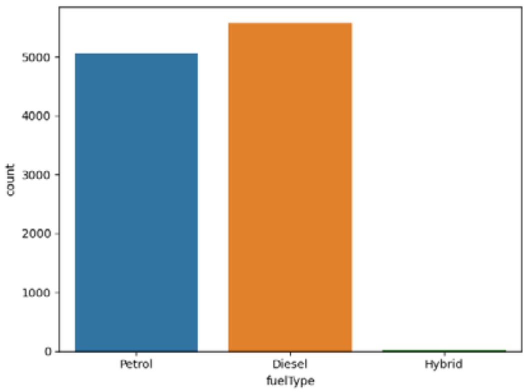
1. <u>Exploratory Data Analysis</u>

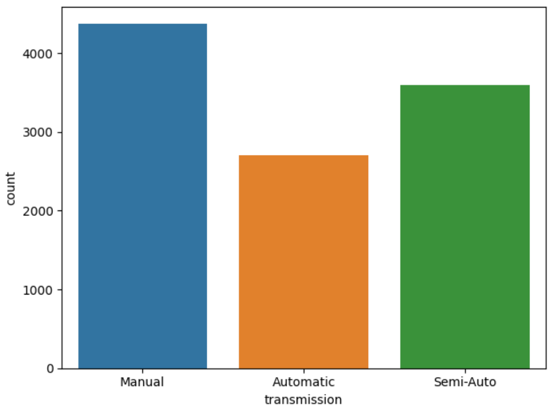
	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	A1	2017	12500	Manual	15735	Petrol	150	55.4	1.4
1	A6	2016	16500	Automatic	36203	Diesel	20	64.2	2.0
2	A1	2016	11000	Manual	29946	Petrol	30	55.4	1.4
3	A4	2017	16800	Automatic	25952	Diesel	145	67.3	2.0
4	A3	2019	17300	Manual	1998	Petrol	145	49.6	1.0
...	...	...	...	...	...	...	...	...	...
10663	A3	2020	16999	Manual	4018	Petrol	145	49.6	1.0
10664	A3	2020	16999	Manual	1978	Petrol	150	49.6	1.0
10665	A3	2020	17199	Manual	609	Petrol	150	49.6	1.0
10666	Q3	2017	19499	Automatic	8646	Petrol	150	47.9	1.4
10667	Q3	2016	15999	Manual	11855	Petrol	150	47.9	1.4

After importing the csv file, I printed the data to have an overview of its structure.

Clearly, model, transmission, and fuelType has nominal values. I plotted the counts of each type of observation versus that attribute.

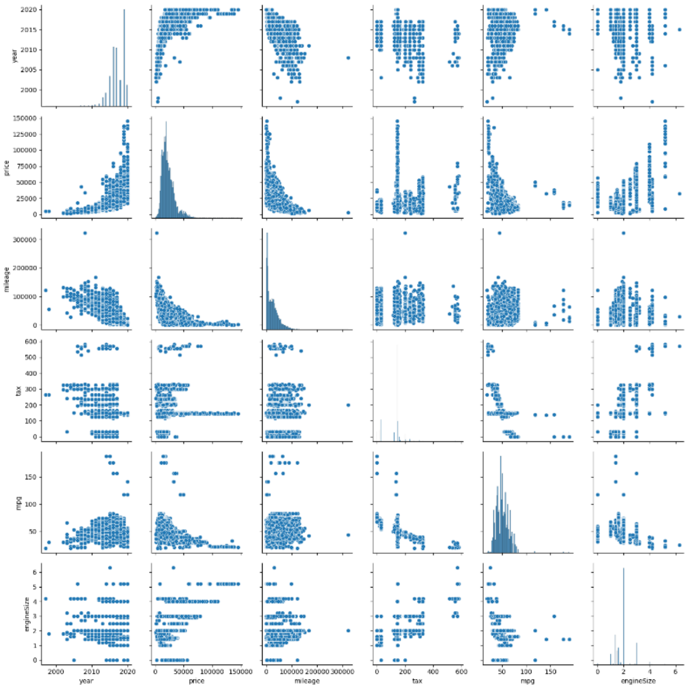







```
model           0
year            0
price           0
transmission    0
mileage         0
fuelType        0
tax             0
mpg             0
engineSize      0
```

It is observed that there are finite number of possibilities in each attribute, so one-hot encoding is selected as encoding scheme. And there is no null data in each attribute, which is very clean.



From the pair plot graph, we can see the data is dense (No zeros). Therefore, standardization will be used to normalize the data.

2. Preprocessing

	model	price	transmission	mileage	...	tax	mpg	engineSize	age_of_car
0	A1	12500	Manual	15735	...	150	55.4	1.4	3
1	A6	16500	Automatic	36203	...	20	64.2	2.0	4
2	A1	11000	Manual	29946	...	30	55.4	1.4	4
3	A4	16800	Automatic	25952	...	145	67.3	2.0	3
4	A3	17300	Manual	1998	...	145	49.6	1.0	1
...	...	...	...	...	...	...	...	...	...
10663	A3	16999	Manual	4018	...	145	49.6	1.0	0
10664	A3	16999	Manual	1978	...	150	49.6	1.0	0
10665	A3	17199	Manual	609	...	150	49.6	1.0	0
10666	Q3	19499	Automatic	8646	...	150	47.9	1.4	3
10667	Q3	15999	Manual	11855	...	150	47.9	1.4	4

Firstly, compute a new attribute called “age_of_car” by subtracting 2020 from the ‘year’ attribute. The result is number of years that car has been used since its registration. I believe the ‘age of car’ will be more informative and intuitive than its original. Secondly, use one-hot encoding to encode categorical values. Now, we can separate the dataset into X (features) and Y (target) set. X set contains all the attributes except ‘price’. Y set is the price attribute. At this stage, we can split X and Y into X_train, Y_train, X_test, and Y_test. Finally, fit the standard scaler to X_train, then use the fitted scaler to transform both the training data and testing data (and new data in the future). This is to prevent data snooping.

3. Modeling

By using sklearn, we can easily create regression model to fit the training data. When creating the regression model instance, all the optional arguments are set to default to keep simplicity. All three algorithms will expect two arguments to pass into the function, one is X_train and the other is Y_train. This corresponds to the idea of train the model on the training set. After fitting the model, we can compute the fitted value of X_train by applying the learned parameters, then compare the fitted results with the target values, Y_train.

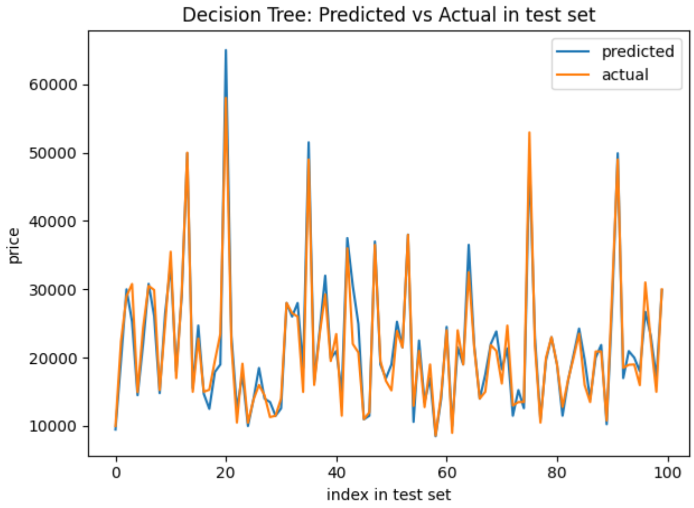
4. Accuracy & Evaluation

Different metrics are applied to reveal how well the models fit the data. Firstly, I will compute the mean absolute error (MAE). The rational is that MAE gives an intuitive measurement of the distance between predicted and actual values. To change the perspective, I also used the mean absolute percentage error (MAPE) to show the error as percentage values. However, these two metrics do not penalize errors that are bigger than others. Therefore, root mean squared error (RMSE) will be our primary error metric. In RMSE, bigger errors are penalized much heavier than the smaller errors as the error is squared.

The error metrics will be calculated on training set first. Then, 5-fold cross validation is used to validate the model before we launch the test set. The training data is split into 5 subsets and in each cross-validation iteration, one non-repeatable subset is selected as validation and the other 4 subsets is used for training. The validation error (measured in RMSE) in each iteration is stored to allow computation of overall error for the 5 folds by simply taking average value. After the cross validation, we can compute the generalization error on the test set.

Generally, it is anticipated that the test set error will be larger than the training error. We will use test error as an indication of how well the model performs on unseen data.

Comparison of Results

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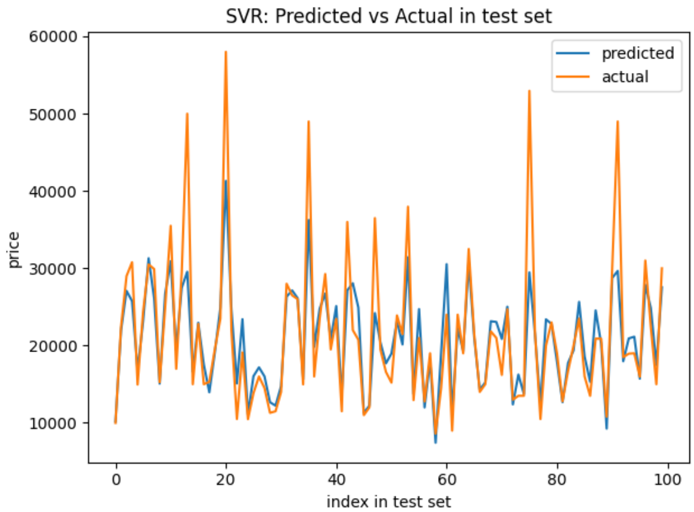
Train Set MAE: 47.79
Train Set RMSE: 319.57
Train Set MAPE: 0.16%

Cross Validation RMSE: [3115.67 3610.83 3175.47 2894.75 3000.57]
Cross Validation Overall RMSE: 3159.46

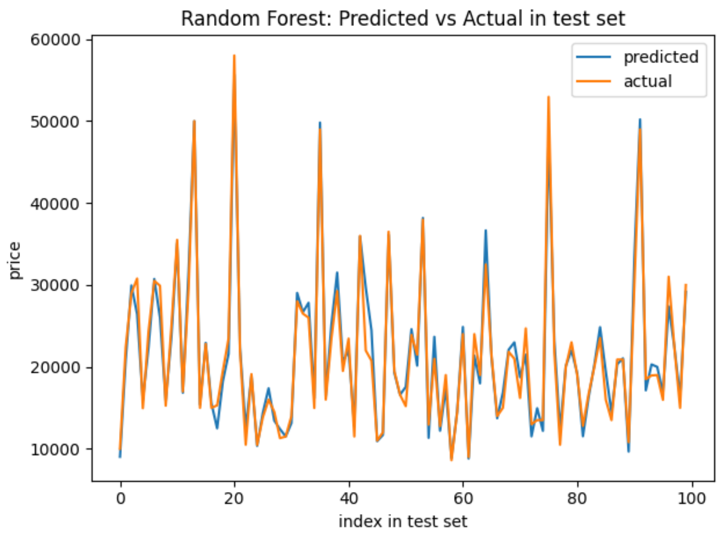
Test Set MAE: 1940.34
Test Set RMSE: 3056.46
Test Set MAPE: 8.95%
```




```
Train Set MAE: 3166.68
Train Set RMSE: 6084.54
Train Set MAPE: 12.72%

Cross Validation RMSE: [5393.95 7398.04 7044.6  6050.16 6473.6 ]
Cross Validation Overall RMSE: 6472.07

Test Set MAE: 3420.31
Test Set RMSE: 6690.45
Test Set MAPE: 12.94%
```

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Train Set MAE: 582.12
Train Set RMSE: 918.08
Train Set MAPE: 2.73%

Cross Validation RMSE: [2324.27 2613.88 2352.31 2305.15 2281.27]
Cross Validation Overall RMSE: 2375.38

Test Set MAE: 1527.45
Test Set RMSE: 2305.57
Test Set MAPE: 7.07%
```

We can see that random forest regression has the lowest RMSE, MAE and MAPE in the test set. It also has the lowest overall RMSE in cross validation. The lowest RMSE indicates that large errors are fewer in random forest regression. In contrast, support vector regression has very high RMSE which means large errors are more prevalent.

Decision tree regression has stunningly low RMSE, MAE and MAPE (0.16%) in the training data. In comparison, RMSE in cross validation rises drastically to 10 times of that in training set. It is very likely that the model has overfitted the data. In the test set, the error becomes much larger and closer to results obtained from other two models.

As anticipated, all error metrics in test set are larger than those of the training set in all three algorithms. Since the model is not fitted to the test data, then it may not perform as good as it was in the training stage.

To sum up, random forest regression has the overall best performance. What’s better still, its cross-validation error is stable, which makes it a suitable model on this dataset and our forecasting problem. Support vector regression has very high RMSE as it is penalized more by making larger errors. And decision tree regression potentially suffers from overfitting, thus it needs more constraints on the model to make it useful on our problem.