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TEAM ID: 1 - SC

AIRLINE TICKET PRICE PREDICTION (REGRESSION)

كيرلس نبيل منير فهمي	20191700460	SC
خالد احمد عبد الظاهر	20191700221	SC
ندي مجدي عبد الكريم	20191700685	SC
يوسف نادر ميشيل صبحي	20191700793	SC
ابانوب جمال فكري فوزي	20191700001	SC

Introduction

The project aims to predict the price of the flight ticket with the least error. This approach will be achieved by using two regression techniques

- Multiple Regression
- Polynomial Regression

Pre-Processing

Pre-Processing is essential step in any ML process for success of the model.

Our processing is divided into several steps:

- X_preprocessData ()
- Y_preprocessData ()
- Feature encoding
- Feature scaling

X_preprocessData ()

This function processes the feature to apply the regression techniques on it. The number of features in the " airline-price-prediction.csv" is "10" features

{"date", "airline", "ch_code", "num_code", "dep_time", "time_taken", "stop", "arr_time", "type", "route"}

Date Column

- The data format "x/x/2022" and "x-x-2022"
- We iterate in all data and check if data has "-" and "/" then split using "strptime ()" function that return datetime object (day, month, year)
- Append day in day list and month in month list and ignore year because all rows have the same value in dataset "2022" to avoid data redundant
- Drop column date and make columns for day and month and assign its values from day list and month list.
- Convert 2 Columns from string to numeric.

Dep_Time Column

The values of Dep_Time is in form xx: xx, so the technique is

- Replace ":" to "." To act as float number.
- Convert Column from string to numeric using "to_numeric(X[dep_time])".
- Finally covert data from “xx: xx” to xx.xx numeric.

Time Taken Column

By reviewing our data, we found that all rows in format "08h 05m" but there with one mis-format "1.01h m" in row 91882 founded by "X['time_taken'].value_counts ()" function to found unique values and solved by:

- Remove “h m” -> Special Case founded in one only row.
- Replace "h "to "." To act as float number.
- Remove “m” to make sure the data become in format “xx.xx” only.
- Convert Column from string to numeric using "to_numeric(X[time_taken]) ".

Stop Column

- The value of Stop Column is one of three (1-stop or 2+-stop or non-stop), so the technique is:
- Split values by "– " and select index 0 in spilt.
- Replace "non" by "0" and “2+” by “2”.
- Convert Column from string to numeric using "to_numeric(X['stop']) ".
- Finally covert data from “xx: xx” to xx.xx numeric.

Arr_Time Column

The values of Dep_Time is in form xx: xx, so technique is:

- Replace “:” to “.” To act as float number
- Convert Column from string to numeric using “to_numeric(X[arr_time])”
- Finally covert data from “xx: xx” to xx.xx numeric

Route Column:

values such as {'source': 'Delhi', 'destination': 'Hyderabad'}, technique is

- Split each row in two half by “,” into new Variable, index [0] = {'source': 'Delhi' , index[1] = 'destination': 'Hyderabad'}
- Foreach row in new, Split index [0] by “: “and append second part in source list, ex: ‘Delhi’ and Split index [1] by “: “, get 'Hyderabad'} to remove ‘}’ made another split by ‘}’ and append first part of second split to destination list
- Drop column route and make columns for source and destination and assign its values from source list and destination list.

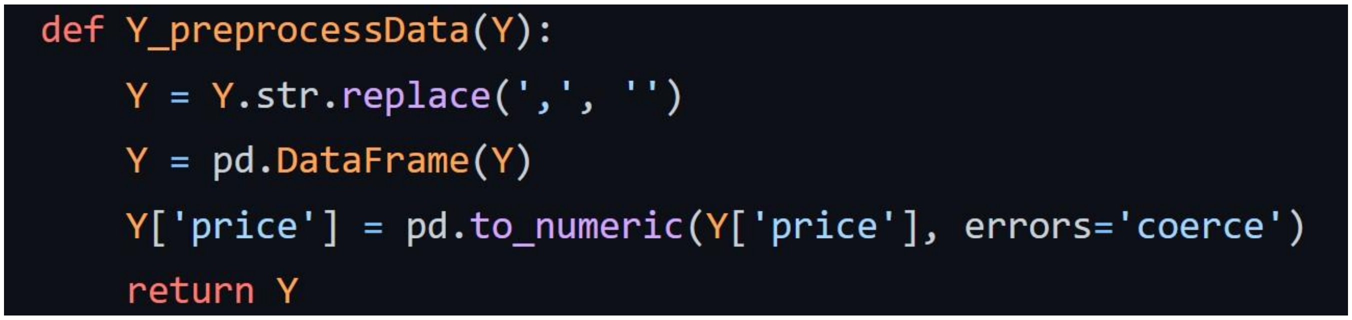
('airline', 'ch_code', 'type', 'source', 'destination') Columns

All Columns has strings values, so we use encoding Label to convert it from strings to numeric values

Y_preprocessData ()

This function is responsible for processing the "price" column (Y-label) the format of the column is string consists of sum digits with a comma ','

The processing aims to change the format of this string to make it a number so it can be used in the model and fitting.

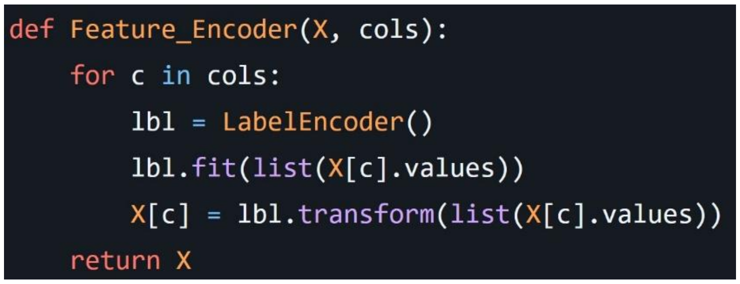


```
def Y_preprocessData(Y):
    Y = Y.str.replace(',', '')
    Y = pd.DataFrame(Y)
    Y['price'] = pd.to_numeric(Y['price'], errors='coerce')
    return Y
```

Figure 1:Y_preprocessData () function

Feature encoding

The idea of feature encoding is the inability of applying the mathematical operations on the categorical columns such as (airline, ch_code, type, source, and destination) which are include string values, so we encode these columns using “LabelEncoder” technique to convert it into numerical columns.



```python
def Feature_Encoder(X, cols):
    for c in cols:
        lbl = LabelEncoder()
        lbl.fit(list(X[c].values))
        X[c] = lbl.transform(list(X[c].values))
    return X
```

Figure 2:Feature encoding function

Feature scaling

The idea of feature scaling is to make the features on a similar scale.

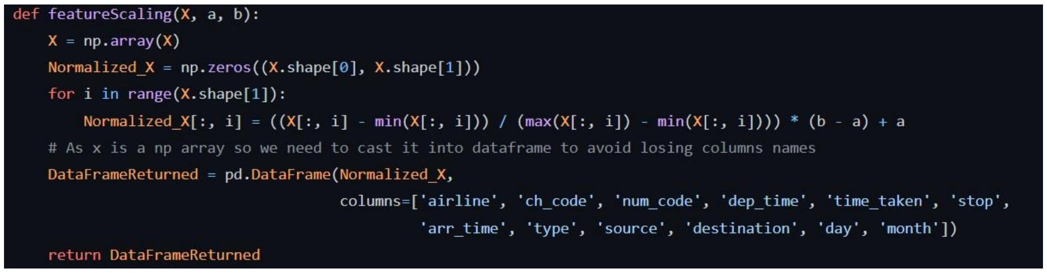
Our approach is to use "Min-Max Normalization"

$$X_{new} = \frac{X_i - \min(X)}{\max(X) - \min(X)} * \left((b - a) + a\right)$$

Min(X): the smallest value in the column.

Max(X): the largest value in the column.

a and b: are the range of numbers that the desired output wanted to be in.



```python
def featureScaling(X, a, b):
    X = np.array(X)
    Normalized_X = np.zeros((X.shape[0], X.shape[1]))
    for i in range(X.shape[1]):
        Normalized_X[:, i] = ((X[:, i] - min(X[:, i])) / (max(X[:, i]) - min(X[:, i]))) * (b - a) + a
    # As x is a np array so we need to cast it into dataframe to avoid losing columns names
    DataFrameReturned = pd.DataFrame(Normalized_X,
                                     columns=['airline', 'ch_code', 'num_code', 'dep_time', 'time_taken', 'stop',
                                              'arr_time', 'type', 'source', 'destination', 'day', 'month'])
    return DataFrameReturned
```

Figure 3:Featur scaling function

Feature analysis and selection

Feature analysis and selection is based on correlation in "Correlation.py" file as it calculates the correlation between all data after it processed producing a matrix with correlations with correlation greater than "0.1"

Feature discarded

Our assumption is to remove any unrelated features with the price and remove any highly correlated features as it will be redundant and cause error increment

- Any Feature has a correlation less than 0.1 with price will be discarded
- Features "airline" and "ch_code" are highly correlated as shown "0.88" so we choose only one of them "ch_code" as it has higher correlation with "price" feature.

Feature "price" is doped from the "top_feature" object to avoid redundant in data.

Our final features that will be used for model training are {'ch_code', num_code', 'time taken', 'stop', 'type'}

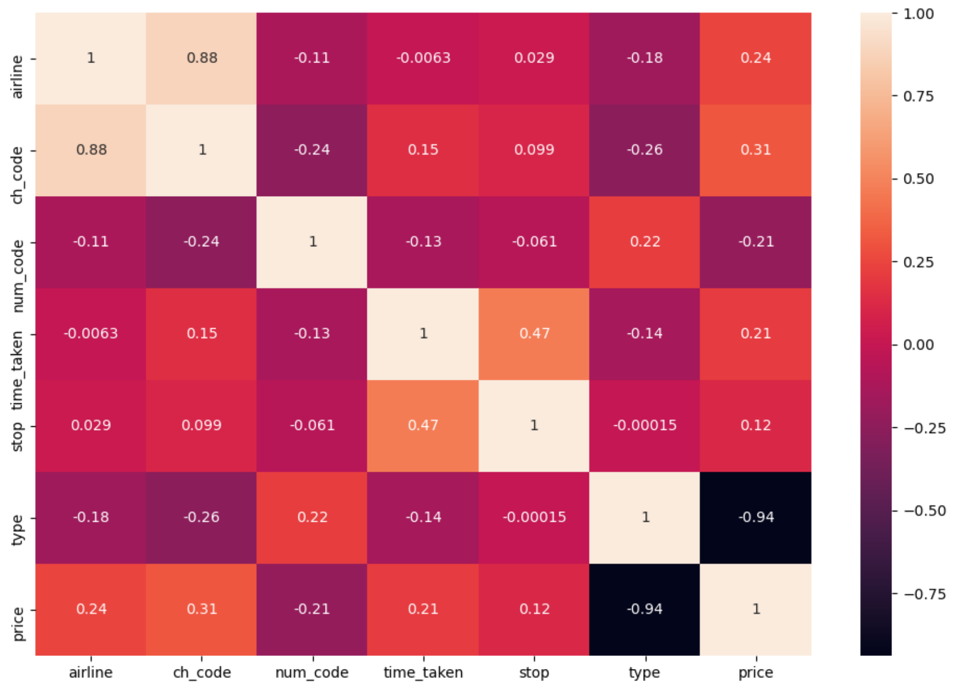


Figure 4:Correlation heatmap

Regression techniques:

Two regression techniques:

Multi-variable regression

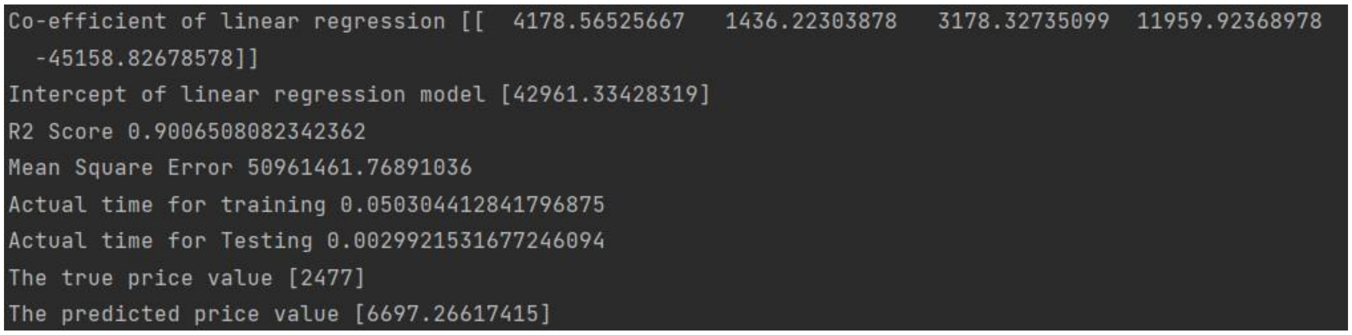
Hypothesis: $h_\theta(x) = \theta_1 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$

Our parameters are chosen as shown as in "Feature analysis and selection" section.

Using "sklearn" library to help us creating the model, our model consist of three main built-in functions

- LinearRegression ()
- fit ()
- predict ()

First create linear model using the " LinearRegression ()" function which returns a model that can be trained using "fit ()" function which is responsible for estimating the attributes out of the input data "x_train, y _train " and stores the model attributes and finally return the fitted estimator. "predict ()" will perform a prediction for each test "x_test" instance



```
Co-efficient of linear regression [[  4178.56525667   1436.22303878   3178.32735099  11959.92368978
  -45158.82678578]]
Intercept of linear regression model [42961.33428319]
R2 Score 0.9006508082342362
Mean Square Error 50961461.76891036
Actual time for training 0.050304412841796875
Actual time for Testing 0.0029921531677246094
The true price value [2477]
The predicted price value [6697.26617415]
```

Figure 5:multi-variable model output

Polynomial regression

Hypothesis: $y_i = w_0 h_0(x_i) + w_1 h_1(x_i) + \cdots + w_D h_D(x_D) = \sum_{j=0}^{D} w_j h_j(x_i)$

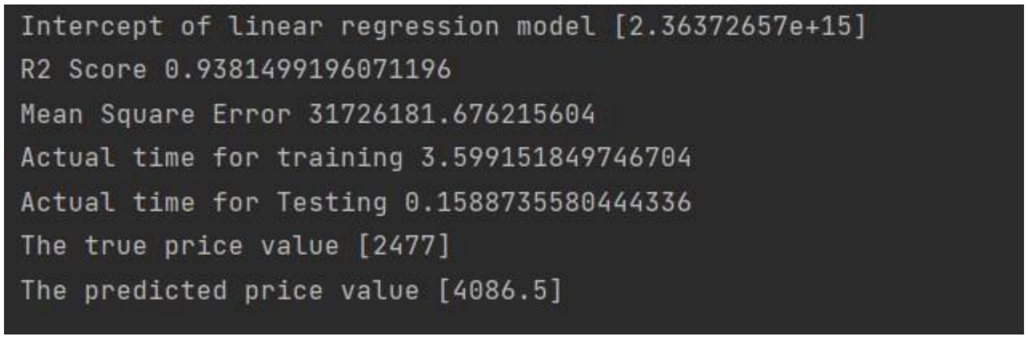
Hyperparameters: degree of the polynomial (5)

This value achieves a reasonable and stable error.

Using "sklearn" library to help us creating the model, our model consist of three main built-in functions

- fit_transform ()
- LinearRegression ()
- fit ()
- predict ()

Transform the existing features to higher degree features using fit transform function this is the different and additional step from the multivariable regression.



```
Intercept of linear regression model [2.36372657e+15]
R2 Score 0.9381499196071196
Mean Square Error 31726181.676215604
Actual time for training 3.599151849746704
Actual time for Testing 0.1588735580444336
The true price value [2477]
The predicted price value [4086.5]
```

Figure 6:Polynomial model output

Time analysis

Time analysis is divided into two sections

- Training time
- Prediction time

Both are done using "Time ()" function calling this function before and after training and prediction and subtract the (start – end) time to get the actual time for both.

It is obvious that the time for training a multi-variable model is much less using a polynomial model due to the difference in complexity of polynomial techniques.

And as the degree of the polynomial increase the complexity increase so the time.

Improvements

- Feature scaling
    - We tried different ranges of scaling it produces different accuracies but range from 0 --> 1 gives us fine accuracy
- Feature encoding

- We tried different types of encoding like
    - One-hot encoding: this type makes every unique value in the column as a column itself and gives it value '1' if it exists in the row and '0' if not this method is rejected because it increases the data size, and the accuracy was in the same range.
    - Mean encoding: this type is rejected as the accuracy was in the same range of label Encoding but its implementation was harder, so it is not worth.
    - Label encoding: this is the used type in the project it gives us good accuracy and do not change the scale of the data.

- Drop nulls
  - Dropping nulls is only from training data to not affect the testing data number
  - To solve nulls in testing data we tried to approach
    - Replace nulls with zeros.
    - Replace nulls with the mean of the column.
- Degree of the polynomial
  - We tried to change the degree of the polynomial till the accuracy become stable degree = 5

Data size

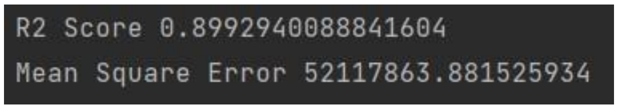
Our data are divided into two parts

- Training data
- Testing data

We divided the data into 80% for training and 20% for testing.

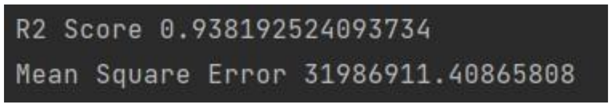
Improvements

We tried different data sizes like 60% for training and 40% for testing.



```
R2 Score 0.8992940088841604
Mean Square Error 52117863.881525934
```

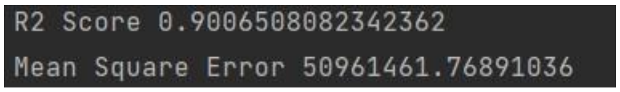
Figure 7:Multi-variable model 40% testing



```
R2 Score 0.938192524093734
Mean Square Error 31986911.40865808
```

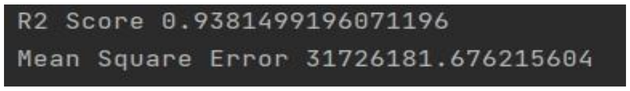
Figure 8:.Polynomial model 40% testing

Higher accuracy when using 80% for training and 20% for testing.



```
R2 Score 0.9006508082342362
Mean Square Error 50961461.76891036
```

Figure 10:Multi-variable model 20% testing



```
R2 Score 0.9381499196071196
Mean Square Error 31726181.676215604
```

Figure 9:Polynomial model 20% testing

Conclusion

	Multi-variable model	Polynomial model
MSE	50961461.76891036	31726181.676215604
R2_Score	0.9006508082342362	0.9381499196071196
Training time	0.03171110153198242	3.9175803661346436
Testing time	0.0014984607696533203	0.17902851104736328

Model accuracy

Polynomial model has "MSE" and "R2 Score" less than multi-variable model so that polynomial model is better than multi-variable model.

Using highly correlated features in model training dec the accuracy of the model.

Model time

Polynomial model has "Training time" greater than multi-variable model.