Used Car Price Prediction

Project Description

We are using the pre-processed data from a previous case study on predicting old car prices. You can check the data cleansing and feature selection steps from this link: https://thinkingneuron.com/car-price-prediction-case-study-in-python/.

Importing the Libraries

```
import numpy as np
import pandas as pd
import tensorflow as tf
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

Data Preprocessing

Importing the Dataset

Note: The type of data is "pickle", which is very similar to csv; and after uploading it into the code; we treat the file same as csv files.

```
dataset = pd.read_pickle('/content/gdrive/MyDrive/Colab Notebooks/Tutorial 4/CarPricesData.pkl')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1435 entries, 0 to 1435
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Age       1435 non-null   float64
 1   KM        1435 non-null   int64
 2   Weight    1435 non-null   float64
 3   HP        1435 non-null   int64
 4   MetColor  1435 non-null   int64
 5   CC        1435 non-null   float64
 6   Doors     1435 non-null   int64
 7   Price     1435 non-null   int64
dtypes: float64(3), int64(5)
memory usage: 100.9 KB
```

```
import random
my_random_subset = random.sample(range(len(dataset)), 10)
dataset.iloc[my_random_subset]
```

	Age	KM	Weight	HP	MetColor	CC	Doors	Price
152	10.0	13747	1110.0	97	1	1400.0	5	18450
159	16.0	11754	1180.0	110	0	1600.0	5	19750
275	41.0	47350	1075.0	110	1	1600.0	5	11480
754	68.0	80426	1055.0	110	1	1600.0	3	9950
816	58.0	70560	1050.0	110	1	1600.0	3	8000
1381	77.0	54439	1015.0	86	1	1300.0	3	7750
233	41.0	61200	1045.0	110	1	1600.0	3	12900
988	68.0	44458	1015.0	86	0	1300.0	3	9995
236	44.0	60500	1075.0	110	0	1600.0	5	10950
1297	79.0	71263	1015.0	86	0	1300.0	3	5950

Feature Scaling

Recal from the past examples:StandardScaler only accept the data in Matrix format. So, we need to first reshape the vecctor y which is 1D array to a matrix of length (y)x1

```
y = y.reshape(len(y),1)
```

```
from sklearn.preprocessing import StandardScaler

sc_X = StandardScaler()
sc_y = StandardScaler()

X = sc_X.fit_transform(X)
y = sc_y.fit_transform(y)
```

Splitting the Dataset into the Training set and Test set

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0)
```

Building the ANN Regressor

Initializing the ANN

```
CarPrice_1 = tf.keras.models.Sequential()
CarPrice_2 = tf.keras.models.Sequential()
CarPrice_3 = tf.keras.models.Sequential()
```

Adding the Input Layer

```
CarPrice_1.add(tf.keras.layers.Dense(units=7, activation='relu')) #
One Large hidden layer: 7/140/1
CarPrice_2.add(tf.keras.layers.Dense(units=7, activation='relu')) # 1
hidden Layers: 7/14/1
CarPrice_3.add(tf.keras.layers.Dense(units=7, activation='relu')) # 4
hidden Layers: 7/28/14/7/3/1
```

Adding the First, Second, Third,... Hidden layers

1. CarPrice_1: 1 large hidden layer with 140 nodes

```
CarPrice_1.add(tf.keras.layers.Dense(units=140, activation='relu'))
```

1. CarPrice_2: 1 hidden layer as described in the lecture

```
CarPrice_2.add(tf.keras.layers.Dense(units=14, activation='relu'))
```

1. CarPrice_3: 4 hidden layers

```
CarPrice_3.add(tf.keras.layers.Dense(units=28, activation='relu'))
CarPrice_3.add(tf.keras.layers.Dense(units=14, activation='relu'))
CarPrice_3.add(tf.keras.layers.Dense(units=7, activation='relu'))
CarPrice_3.add(tf.keras.layers.Dense(units=3, activation='relu'))
```

Adding the Output Layer

Remember that in ANN Regression, our output is just one number, so, units=1.

```
CarPrice_1.add(tf.keras.layers.Dense(units=1))
CarPrice_2.add(tf.keras.layers.Dense(units=1))
CarPrice_3.add(tf.keras.layers.Dense(units=1))
```

Compiling the ANN

```
CarPrice_1.compile(loss='mean_squared_error', optimizer='adam')
CarPrice_2.compile(loss='mean_squared_error', optimizer='adam')
CarPrice_3.compile(loss='mean_squared_error', optimizer='adam')
```

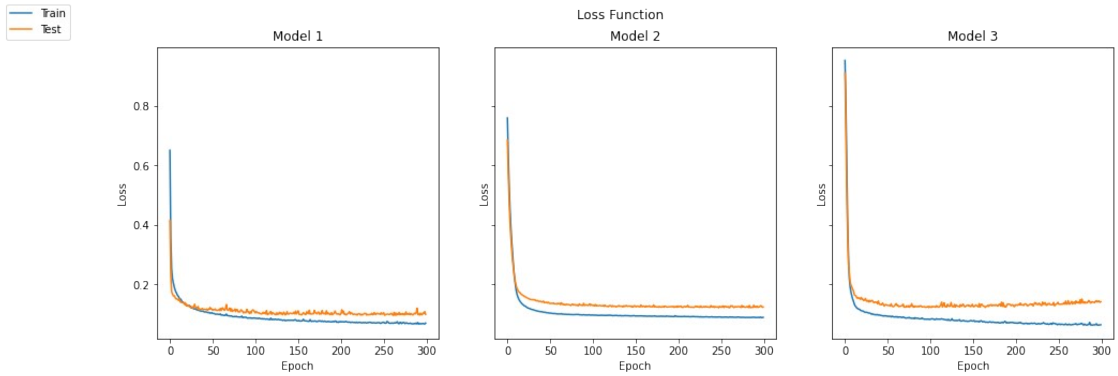
Training the ANN

```
h1 = CarPrice_1.fit(X_train, y_train, validation_split=0.2, batch_size
= 32, epochs = 300)
h2 = CarPrice_2.fit(X_train, y_train, validation_split=0.2, batch_size
= 32, epochs = 300)
h3 = CarPrice_3.fit(X_train, y_train, validation_split=0.2, batch_size
= 32, epochs = 300)
```

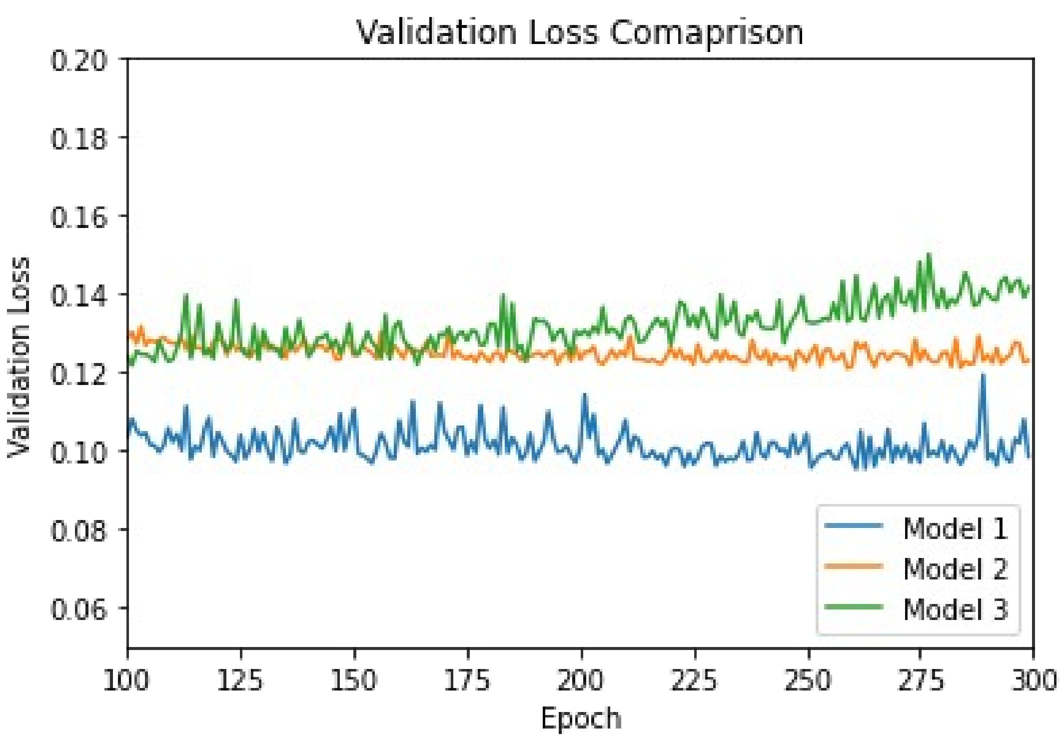
Plotting Learning Curves

```
from matplotlib import legend
h = [h1, h2, h3]
fig, axs = plt.subplots(1,3, sharex=True, sharey=True, figsize =
(16,5))
fig.suptitle('Loss Function')
for i in range(3):
  axs[i].plot(h[i].history['loss'])
  axs[i].plot(h[i].history['val_loss'])
  axs[i].set_title("Model {}".format(i + 1))

for ax in axs.flat:
    ax.set(xlabel='Epoch', ylabel='Loss')
```

```
fig.legend(labels=['Train','Test'], loc="upper left")
plt.show()
```




```
for i in range(3):
  plt.plot(h[i].history['val_loss'])

plt.title('Validation Loss Comaprison')
plt.ylabel('Validation Loss')
plt.xlabel('Epoch')
plt.xlim(100, 300)
plt.ylim(0.05, 0.2)
plt.legend(['Model 1', 'Model 2', 'Model 3'], loc='lower right')
plt.show()
```



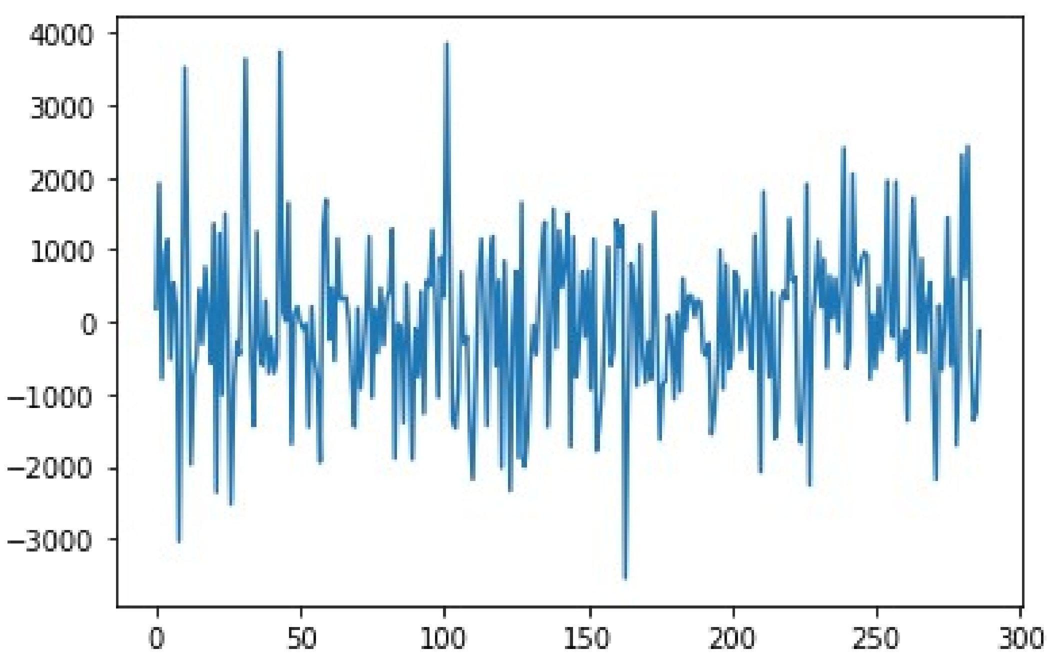
Evaluating the Model

Prediction on the Test Set

```
y_pred_1 = CarPrice_1.predict(X_test)
# remember that these are scaled numbers; you can inverse them back:
PredictedPrice_1=sc_y.inverse_transform(y_pred_1)
# The actual price:
ActualPrice=sc_y.inverse_transform(y_test)

# Let's call the differenc between Predicted and Actual price, Error:
Error_1 = PredictedPrice_1-ActualPrice

import matplotlib.pyplot as plt
plt.plot(range(len(Error_1)), Error_1)
```

```
9/9 [==============================] - 0s 2ms/step
```

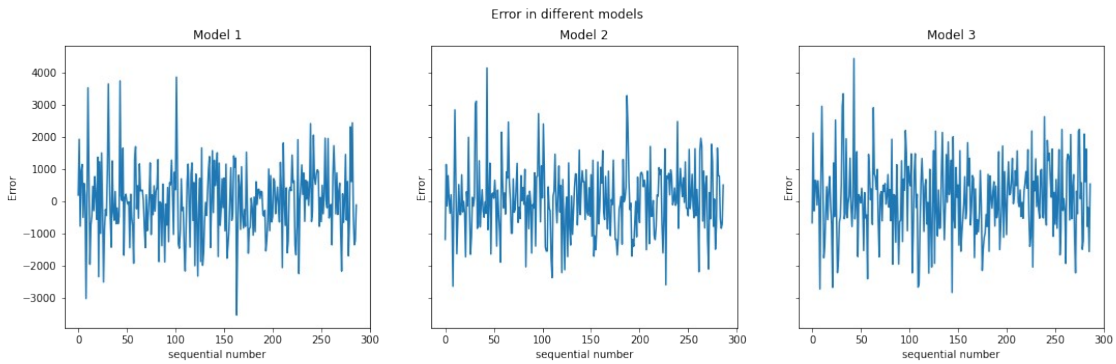
```
[<matplotlib.lines.Line2D at 0x7fec953143d0>]
```




```
# Model 2
y_pred_2 = CarPrice_2.predict(X_test)
PredictedPrice_2=sc_y.inverse_transform(y_pred_2)
Error_2 = PredictedPrice_2 - ActualPrice
# Model 3
y_pred_3 = CarPrice_3.predict(X_test)
PredictedPrice_3=sc_y.inverse_transform(y_pred_3)
Error_3 = PredictedPrice_3 - ActualPrice
```

```
9/9 [==============================] - 0s 2ms/step
9/9 [==============================] - 0s 2ms/step
```

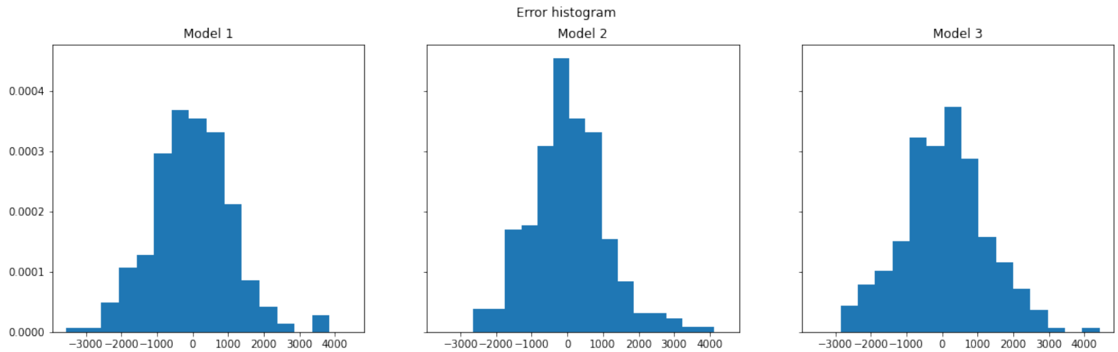
```
# Plot all 3
Error = [Error_1, Error_2, Error_3]
fig, axs = plt.subplots(1, 3, sharex=True, sharey=True, figsize =
(18,5))
fig.suptitle('Error in different models')
for i in range(3):
  axs[i].plot(range(len(Error[i])), Error[i])
  axs[i].set_title('Model {}'.format(i+1))

for ax in axs.flat:
    ax.set(xlabel='sequential number', ylabel='Error')
```



Checking the Model Accuracy

```
error_mean = np.zeros(3)
error_std = np.zeros(3)
for i in range(3):
  error_mean[i] = np.average(Error[i])
  error_std[i] = np.std(Error[i])


#AverageError= np.average(Error_6)
#print('The avergae error is $',AverageError)
print('The avergae error is $',error_mean)
print('The std in error is $',error_std)


fig, axs = plt.subplots(1, 3, sharex=True, sharey=True, figsize =
(18,5))
fig.suptitle('Error histogram')
for i in range(3):
  axs[i].hist(Error[i], 15, density=True)
  axs[i].set_title('Model {}'.format(i+1))

#n, bins, patches = plt.hist(Error_1, 15, density=True, facecolor='g',
alpha=0.75)
plt.show()
```

```
The avergae error is $ [-16.28994379  23.93266142  83.74552551]
The std in error is $ [1114.99180039 1071.0483664  1186.7422981 ]
```



Predicting a car price

```
# You must Scaled it
my_car = sc_X.transform(np.array([[23.0,46986,1165.0,90,1,2000.0,3]]))
pred_val = np.zeros(3)
models = [CarPrice_1, CarPrice_2, CarPrice_3]
for i in range(3):
  # You must Scaled it back
  pred_val[i] = sc_y.inverse_transform(models[i].predict(my_car))

#PredictPrice=CarPrice.predict(sc.transform(np.array([[23.0,46986,1165
.0,90,1,2000.0,3]])))
# Wait! You must Scaled it back
#PredictPrice=sc_y.inverse_transform(PredictPrice)
print('My car is worth $', pred_val, 'in Model 1, 2, and 3,
respectively')
```

```
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 25ms/step
My car is worth $ [14145.41113281 17111.84375    14434.07617188] in
Model 1, 2, and 3, respectively
```

```
# Change the Age of the car and see if the predicted price makes
sense..
PredictPrice=CarPrice_1.predict(sc_X.transform(np.array([[3.0,46986,11
65.0,90,1,2000.0,3]])))
# Wait! You must Scaled it back
PredictPrice=sc_y.inverse_transform(PredictPrice)
print('My friend your car is worth $',PredictPrice, 'in Model 1')
```

```
1/1 [==============================] - 0s 17ms/step
My friend your car is worth $ [[17448.066]] in Model 1
```

Regression Model

```
from sklearn.linear_model import LinearRegression
reg_model = LinearRegression()
reg_model.fit(X_train, y_train)
y_pred_reg = reg_model.predict(X_test)
from sklearn.metrics import r2_score
score = r2_score(y_test, y_pred_reg)
print('R2 Score = %.3f' %score)
```

```
R2 Score = 0.895
```

```
reg_pred = sc_y.inverse_transform(reg_model.predict(my_car))
print('Regression prediction of my car price is $', reg_pred)
```

```
Regression prediction of my car price is $ [[16381.39048715]]
```

Random Forest Regressor

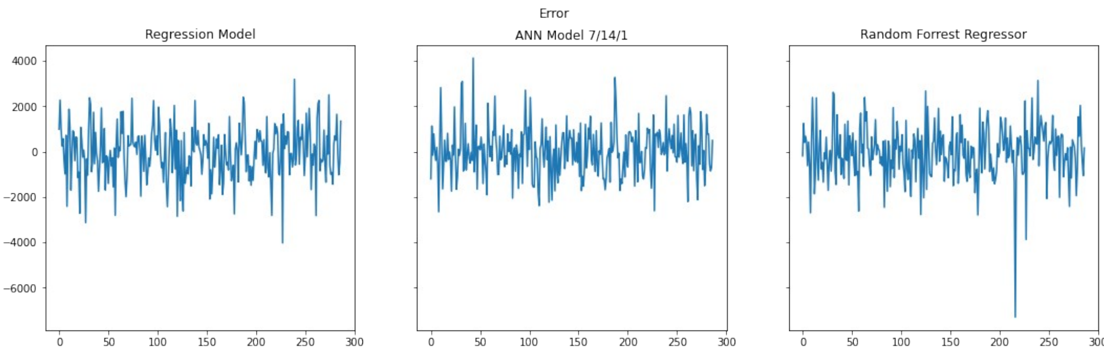
```
from sklearn.ensemble import RandomForestRegressor
rf=RandomForestRegressor(n_estimators=30)
rf.fit(X_train,y_train.ravel())
y_pred_rf = rf.predict(X_test)
rf_score = r2_score(y_test,y_pred_rf)
print('R2 Score = %.3f' %rf_score)
```

```
R2 Score = 0.891
```

```
rf_pred = sc_y.inverse_transform(rf.predict(my_car).reshape(-1, 1))
print('Regression prediction of my car price is $', rf_pred)
```

```
Regression prediction of my car price is $ [[14938.3]]
```

```
PredictedPrice_reg=sc_y.inverse_transform(y_pred_reg)
Error_reg = PredictedPrice_reg-ActualPrice
PredictedPrice_rf = sc_y.inverse_transform(y_pred_rf.reshape(-1, 1))
Error_rf = PredictedPrice_rf-ActualPrice

fig, axs = plt.subplots(1, 3, sharex=True, sharey=True, figsize =
(18,5))
fig.suptitle('Error')
axs[0].plot(range(len(Error_reg)), Error_reg)
axs[0].set_title('Regression Model')
axs[1].plot(range(len(Error_2)), Error_2)
axs[1].set_title('ANN Model 7/14/1')
axs[2].plot(range(len(Error_rf)), Error_rf)
axs[2].set_title('Random Forrest Regressor')

plt.show()
```


Error
Regression Model
ANN Model 7/14/1
Random Forrest Regressor
4000
2000
0
−2000
−4000
−6000
0
50
100
150
200
250
300