

CarPricePrediction

January 8, 2024

Problem Statement

- Given the attributes of the customers, how much is the customer willing to pay ### Intuition
- Regression problem ### Implementation
- Using ANN(tensorflow)

```
[4]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import tensorflow as tf
import tensorflow.keras # keras is an API on top of tensorflow
from keras.models import Sequential # Building the model sequential..
from keras.layers import Dense # Since it is backpropagated..
```

```
[5]: # importing data set
df = pd.read_csv('Car_Purchasing_Data.csv',encoding= 'ISO-8859-1')
df.shape
```

```
[5]: (500, 9)
```

```
[6]: df.head(5)
```

```
[6]:      Customer Name      Customer e-mail \
0  Martina Avila  cubilia.Curae.Phasellus@quisaccumsanconvallis.edu
1   Harlan Barnes                        eu.dolor@diam.co.uk
2  Naomi Rodriquez  vulputate.mauris.sagittis@ametconsectetueradip...
3  Jade Cunningham                        malesuada@dignissim.com
4   Cedric Leach    felis.ullamcorper.viverra@egetmollislectus.net
```

```
      Country  Gender      Age  Annual Salary  Credit Card Debt \
0   Bulgaria      0  41.851720    62812.09301    11609.380910
1    Belize      0  40.870623    66646.89292     9572.957136
2   Algeria      1  43.152897    53798.55112    11160.355060
3 Cook Islands      1  58.271369    79370.03798    14426.164850
4    Brazil      1  57.313749    59729.15130     5358.712177
```

	Net Worth	Car Purchase Amount
0	238961.2505	35321.45877
1	530973.9078	45115.52566
2	638467.1773	42925.70921
3	548599.0524	67422.36313
4	560304.0671	55915.46248

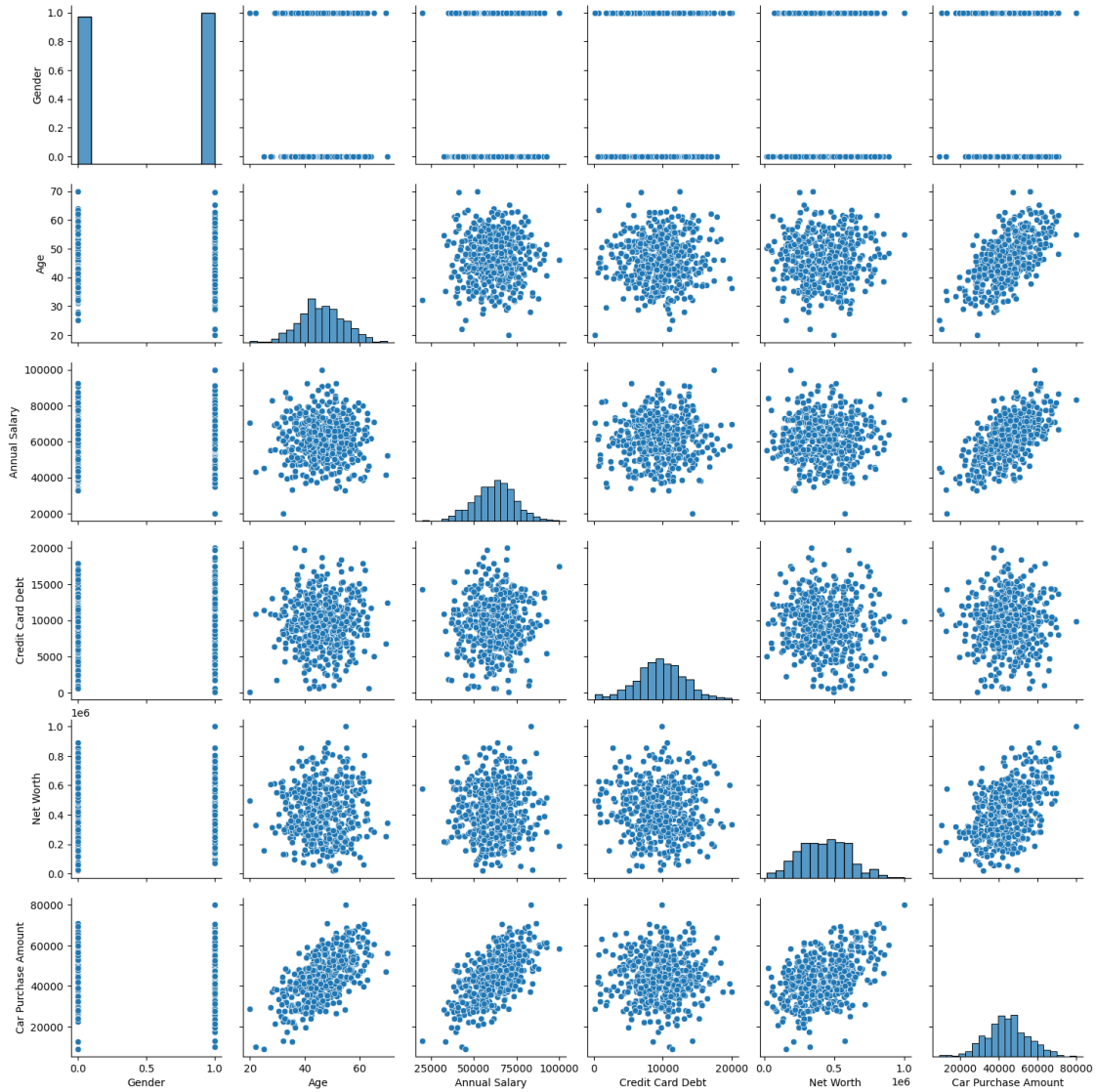
```
[7]: df.columns
```

```
[7]: Index(['Customer Name', 'Customer e-mail', 'Country', 'Gender', 'Age',
        'Annual Salary', 'Credit Card Debt', 'Net Worth',
        'Car Purchase Amount'],
        dtype='object')
```

Visualization

```
[8]: sns.pairplot(df)
```

```
[8]: <seaborn.axisgrid.PairGrid at 0x16ff6c032d0>
```



0.0.1 Data Cleaning

- Dropping customer name, email and country that doesn't have any effect on the data
- X-> denotes the input features, so drop Car purchase amount as well

Separating Features and Target

```
[9]: X = df.drop(['Customer Name', 'Customer e-mail', 'Country', 'Car Purchase_
↳ Amount'], axis=1)
X.head(5)
```

```
[9]:   Gender      Age  Annual Salary  Credit Card Debt  Net Worth
0       0  41.851720    62812.09301    11609.380910  238961.2505
1       0  40.870623    66646.89292     9572.957136  530973.9078
```

2	1	43.152897	53798.55112	11160.355060	638467.1773
3	1	58.271369	79370.03798	14426.164850	548599.0524
4	1	57.313749	59729.15130	5358.712177	560304.0671

```
[10]: Y = df['Car Purchase Amount']
      Y.head(5)
```

```
[10]: 0    35321.45877
      1    45115.52566
      2    42925.70921
      3    67422.36313
      4    55915.46248
      Name: Car Purchase Amount, dtype: float64
```

```
[11]: # Shape of feature and target....
      X.shape,Y.shape
```

```
[11]: ((500, 5), (500,))
```

Perform Normalization

- Since ANN works better after on normalized data
- Converts values from 0 to 1
- Scaling features

```
[12]: scaler = MinMaxScaler()
      X_scaled = scaler.fit_transform(X)
```

```
[13]: X_scaled[:5]
```

```
[13]: array([[0.          , 0.4370344 , 0.53515116, 0.57836085, 0.22342985],
             [0.          , 0.41741247, 0.58308616, 0.476028   , 0.52140195],
             [1.          , 0.46305795, 0.42248189, 0.55579674, 0.63108896],
             [1.          , 0.76542739, 0.74212547, 0.71990778, 0.53938679],
             [1.          , 0.74627499, 0.49661439, 0.26425689, 0.55133068]])
```

```
[14]: # Returns the maximum and minimum value of each feature
      scaler.data_max_,scaler.data_min_
```

```
[14]: (array([1.e+00, 7.e+01, 1.e+05, 2.e+04, 1.e+06]),
      array([ 0., 20., 20000., 100., 20000.]))
```

- Reshaping target since it is an 1D array

```
[15]: Y = Y.values.reshape(-1,1)
```

```
[16]: # If the feature is an 1d array it should be reshaped such that it has n rows
      ↪and 1 columns..
```

```
# to train tensorflow model  
Y.shape
```

```
[16]: (500, 1)
```

- Scaling Target

```
[17]: # Scaling the target  
Y_scaled = scaler.fit_transform(Y)  
Y_scaled[:5]
```

```
[17]: array([[0.37072477],  
          [0.50866938],  
          [0.47782689],  
          [0.82285018],  
          [0.66078116]])
```

Training Model

- Splitting data

```
[18]: X_train, X_test, Y_train, Y_test = train_test_split(X_scaled,Y_scaled)
```

```
[19]: X_train.shape,X_test.shape
```

```
[19]: ((375, 5), (125, 5))
```

- Building Model

```
[20]: # 25 -> neurons in the hidden layer...  
# input_dim -> No. of features..  
# activation -> activation function...  
model = Sequential([  
    #Hidden layer - 1  
    #input_dim is optional..  
    Dense(25, input_dim = 5,activation = 'relu'),  
    # Another hidden layer..  
    Dense(25, activation = 'relu'),  
    # Output layer...  
    # 'linear' - for regression  
    Dense(1, activation = 'linear')  
)
```

WARNING:tensorflow:From C:\Users\samli\AppData\Roaming\Python\Python311\site-packages\keras\src\backend.py:873: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

```
[21]: model.summary()
      #150 = 5 x 25 + 25
      #650 = 25 x 25 + 25
      #26 = 25 x 1 + 1
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 25)	150
dense_1 (Dense)	(None, 25)	650
dense_2 (Dense)	(None, 1)	26

=====
 Total params: 826 (3.23 KB)
 Trainable params: 826 (3.23 KB)
 Non-trainable params: 0 (0.00 Byte)
 =====

```
[22]: model.compile(optimizer= 'adam', loss= 'mean_squared_error')
```

WARNING:tensorflow:From C:\Users\samli\AppData\Roaming\Python\Python311\site-packages\keras\src\optimizers__init__.py:309: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

```
[24]: epochs_hist = model.fit(X_train,Y_train, epochs = 20, batch_size = 25, verbose=
      ↪= 1, validation_split = 0.2)
      # validation_split -> To avoid overfitting
```

```
Epoch 1/20
12/12 [=====] - 0s 17ms/step - loss: 0.0016 - val_loss:
0.0016
Epoch 2/20
12/12 [=====] - 0s 9ms/step - loss: 0.0014 - val_loss:
0.0014
Epoch 3/20
12/12 [=====] - 0s 9ms/step - loss: 0.0013 - val_loss:
0.0013
Epoch 4/20
12/12 [=====] - 0s 10ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 5/20
12/12 [=====] - 0s 7ms/step - loss: 9.6032e-04 -
val_loss: 0.0010
Epoch 6/20
12/12 [=====] - 0s 9ms/step - loss: 8.4678e-04 -
```

```

val_loss: 9.1730e-04
Epoch 7/20
12/12 [=====] - 0s 9ms/step - loss: 7.7136e-04 -
val_loss: 8.4126e-04
Epoch 8/20
12/12 [=====] - 0s 8ms/step - loss: 6.4754e-04 -
val_loss: 7.3718e-04
Epoch 9/20
12/12 [=====] - 0s 8ms/step - loss: 5.7045e-04 -
val_loss: 6.7446e-04
Epoch 10/20
12/12 [=====] - 0s 8ms/step - loss: 5.0783e-04 -
val_loss: 6.1279e-04
Epoch 11/20
12/12 [=====] - 0s 9ms/step - loss: 4.4649e-04 -
val_loss: 5.5932e-04
Epoch 12/20
12/12 [=====] - 0s 10ms/step - loss: 4.0033e-04 -
val_loss: 5.0437e-04
Epoch 13/20
12/12 [=====] - 0s 11ms/step - loss: 3.6614e-04 -
val_loss: 4.6812e-04
Epoch 14/20
12/12 [=====] - 0s 9ms/step - loss: 3.3139e-04 -
val_loss: 4.2996e-04
Epoch 15/20
12/12 [=====] - 0s 9ms/step - loss: 3.1255e-04 -
val_loss: 4.0578e-04
Epoch 16/20
12/12 [=====] - 0s 8ms/step - loss: 2.8246e-04 -
val_loss: 3.7452e-04
Epoch 17/20
12/12 [=====] - 0s 8ms/step - loss: 2.5609e-04 -
val_loss: 3.4812e-04
Epoch 18/20
12/12 [=====] - 0s 8ms/step - loss: 2.3939e-04 -
val_loss: 3.3054e-04
Epoch 19/20
12/12 [=====] - 0s 7ms/step - loss: 2.2756e-04 -
val_loss: 3.1276e-04
Epoch 20/20
12/12 [=====] - 0s 7ms/step - loss: 2.1449e-04 -
val_loss: 2.9999e-04

```

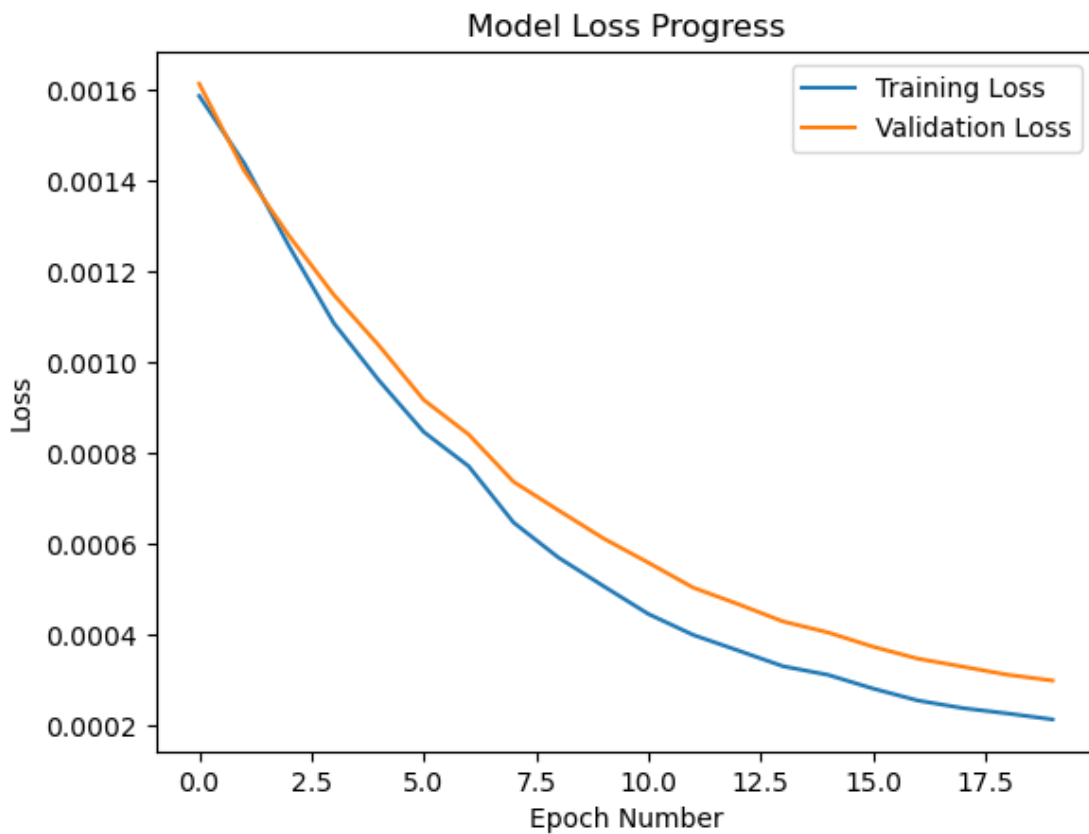
Model Evaluation

[25]: `epochs_hist.history.keys()`

```
[25]: dict_keys(['loss', 'val_loss'])
```

```
[27]: plt.plot(epochs_hist.history['loss'])
plt.plot(epochs_hist.history['val_loss'])
plt.title('Model Loss Progress')
plt.ylabel('Loss')
plt.xlabel('Epoch Number')
plt.legend(['Training Loss', 'Validation Loss'])
```

```
[27]: <matplotlib.legend.Legend at 0x16ff992a950>
```



Prediction

- Considering Random data point

```
[28]: #Gender, Age, Annual Salary, Credit Card Debt, Net worth
X_test = np.array([[1, 50, 5000, 10000, 600000]])
y_prediction = model.predict(X_test)
print(f'Expected purchase amount: {y_prediction}')
```

```
1/1 [=====] - 0s 221ms/step
```


Expected purchase amount: [[179020.28]]