Artificial Neural Network

Objective:
You are working as a car salesman and you would like to develop a model to predict the total amount that customers are willing to pay given the following attributes:

Customer Name
Customer e-mail
Country
Gender
Age
Annual Salary
Credit Card Debt
Net Worth

The Model should predict:

Car Purchase Amount

Libraries Import

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Import Dataset

In [2]:

```
car_df =  pd.read_csv('G:/TCS Study/TCS Git Hub Projects/Artificial Neural Network Proj
car_df.head()
```

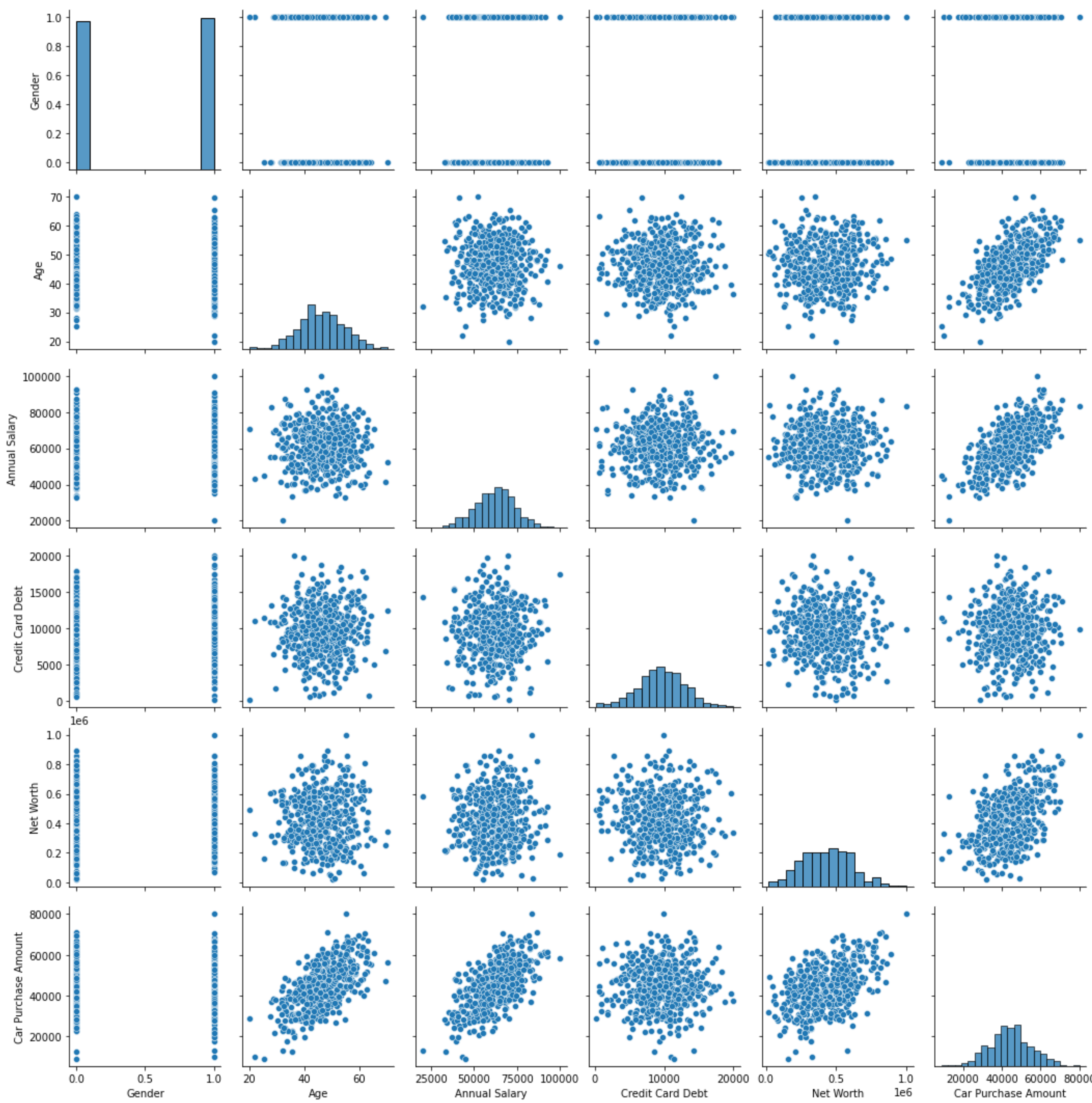
Out[2]:

	Customer Name	Customer e-mail	Country	Gender	Age	Annual Salary
0	Martina Avila	cubilia.Curae.Phasellus@quisaccumsanconvallis.edu	Bulgaria	0	41.851720	62812.09301
1	Harlan Barnes	eu.dolor@diam.co.uk	Belize	0	40.870623	66646.89292
2	Naomi Rodriquez	vulputate.mauris.sagittis@ametconsectetueradip...	Algeria	1	43.152897	53798.55112
3	Jade Cunningham	malesuada@dignissim.com	Cook Islands	1	58.271369	79370.03798
4	Cedric Leach	felis.ullamcorper.viverra@egetmollislectus.net	Brazil	1	57.313749	59729.15130

Visualize Dataset

In [3]:
```
sns.pairplot(car_df)
```

Out[3]:
```
<seaborn.axisgrid.PairGrid at 0x22b08430fc8>
```



Create Testing and Training Dataset/Data Cleaning

In [4]:
```
X = car_df.drop(['Customer Name', 'Customer e-mail', 'Country', 'Car Purchase Amount'],
X.head()
```

Out[4]:

	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

In [5]:

```
y = car_df['Car Purchase Amount']
y.head()
```

Out[5]:

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

In [6]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
X_scaled
```

Out[6]:

```
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.        , 0.67886994, 0.61110973, 0.52822145, 0.75972584],
       [1.        , 0.78321017, 0.37264988, 0.69914746, 0.3243129 ],
       [1.        , 0.53462305, 0.51713347, 0.46690159, 0.45198622]])
```

In [7]:

```
scaler.data_max_
```

Out[7]:

```
array([1.e+00, 7.e+01, 1.e+05, 2.e+04, 1.e+06])
```

In [8]:

```
scaler.data_min_
```

Out[8]:

```
array([    0.,    20., 20000.,   100., 20000.])
```

In [9]:

```
y_new = y.values.reshape(-1,1)
y_scaled = scaler.fit_transform(y_new)
y_scaled
```

Out[9]:

```
array([[0.37072477],
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```

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```
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```

Training the Model

In [10]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_size = 0.2
```

In [11]:

```
X_train.shape
```

Out[11]:

```
(375, 5)
```

In [25]:

```
import tensorflow.keras
from keras.models import Sequential
from keras.layers import Dense

model = Sequential()
model.add(Dense(5, input_dim = 5, activation = 'relu'))
model.add(Dense(5, activation = 'relu'))
model.add(Dense(1, activation = 'linear'))
```

In [26]:

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 5)                 30        
_________________________________________________________________
dense_5 (Dense)              (None, 5)                 30        
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 6         
=================================================================
Total params: 66
Trainable params: 66
Non-trainable params: 0
_________________________________________________________________
```

In [27]:

```
model.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

In [28]:

```
epochs_hist = model.fit(X_train,  y_train, epochs = 100, batch_size = 50, verbose = 1,
```

```
Train on 300 samples, validate on 75 samples
Epoch 1/100
300/300 [==============================] - 0s 959us/step - loss: 0.3144 - val_loss: 0.33
05
Epoch 2/100
300/300 [==============================] - 0s 113us/step - loss: 0.2968 - val_loss: 0.31
37
Epoch 3/100
```

```
300/300 [==============================] - 0s 100us/step - loss: 0.2812 - val_loss: 0.29
89
Epoch 4/100
300/300 [==============================] - 0s 80us/step - loss: 0.2673 - val_loss: 0.285
4
Epoch 5/100
300/300 [==============================] - 0s 77us/step - loss: 0.2550 - val_loss: 0.273
1
Epoch 6/100
300/300 [==============================] - 0s 73us/step - loss: 0.2439 - val_loss: 0.262
0
Epoch 7/100
300/300 [==============================] - 0s 80us/step - loss: 0.2340 - val_loss: 0.251
7
Epoch 8/100
300/300 [==============================] - 0s 73us/step - loss: 0.2247 - val_loss: 0.242
1
Epoch 9/100
300/300 [==============================] - 0s 80us/step - loss: 0.2160 - val_loss: 0.232
9
Epoch 10/100
300/300 [==============================] - 0s 83us/step - loss: 0.2076 - val_loss: 0.223
9
Epoch 11/100
300/300 [==============================] - 0s 70us/step - loss: 0.1994 - val_loss: 0.215
2
Epoch 12/100
300/300 [==============================] - 0s 80us/step - loss: 0.1914 - val_loss: 0.206
7
Epoch 13/100
300/300 [==============================] - 0s 80us/step - loss: 0.1833 - val_loss: 0.198
3
Epoch 14/100
300/300 [==============================] - 0s 73us/step - loss: 0.1754 - val_loss: 0.189
7
Epoch 15/100
300/300 [==============================] - 0s 87us/step - loss: 0.1676 - val_loss: 0.181
4
Epoch 16/100
300/300 [==============================] - 0s 100us/step - loss: 0.1599 - val_loss: 0.17
33
Epoch 17/100
300/300 [==============================] - 0s 73us/step - loss: 0.1525 - val_loss: 0.165
3
Epoch 18/100
300/300 [==============================] - 0s 87us/step - loss: 0.1452 - val_loss: 0.157
5
Epoch 19/100
300/300 [==============================] - 0s 83us/step - loss: 0.1381 - val_loss: 0.149
7
Epoch 20/100
300/300 [==============================] - 0s 90us/step - loss: 0.1310 - val_loss: 0.142
2
Epoch 21/100
300/300 [==============================] - 0s 77us/step - loss: 0.1238 - val_loss: 0.134
8
Epoch 22/100
300/300 [==============================] - 0s 87us/step - loss: 0.1166 - val_loss: 0.127
6
Epoch 23/100
300/300 [==============================] - 0s 90us/step - loss: 0.1098 - val_loss: 0.120
```

```
4
Epoch 24/100
300/300 [==============================] - 0s 97us/step - loss: 0.1029 - val_loss: 0.113
4
Epoch 25/100
300/300 [==============================] - 0s 93us/step - loss: 0.0960 - val_loss: 0.106
4
Epoch 26/100
300/300 [==============================] - 0s 100us/step - loss: 0.0893 - val_loss: 0.09
97
Epoch 27/100
300/300 [==============================] - 0s 103us/step - loss: 0.0827 - val_loss: 0.09
31
Epoch 28/100
300/300 [==============================] - 0s 90us/step - loss: 0.0766 - val_loss: 0.086
7
Epoch 29/100
300/300 [==============================] - 0s 80us/step - loss: 0.0707 - val_loss: 0.080
4
Epoch 30/100
300/300 [==============================] - 0s 83us/step - loss: 0.0652 - val_loss: 0.074
2
Epoch 31/100
300/300 [==============================] - 0s 67us/step - loss: 0.0599 - val_loss: 0.068
3
Epoch 32/100
300/300 [==============================] - 0s 100us/step - loss: 0.0549 - val_loss: 0.06
27
Epoch 33/100
300/300 [==============================] - 0s 100us/step - loss: 0.0501 - val_loss: 0.05
72
Epoch 34/100
300/300 [==============================] - 0s 110us/step - loss: 0.0453 - val_loss: 0.05
18
Epoch 35/100
300/300 [==============================] - 0s 80us/step - loss: 0.0411 - val_loss: 0.046
6
Epoch 36/100
300/300 [==============================] - 0s 103us/step - loss: 0.0377 - val_loss: 0.04
16
Epoch 37/100
300/300 [==============================] - 0s 87us/step - loss: 0.0347 - val_loss: 0.037
5
Epoch 38/100
300/300 [==============================] - 0s 110us/step - loss: 0.0321 - val_loss: 0.03
42
Epoch 39/100
300/300 [==============================] - 0s 90us/step - loss: 0.0300 - val_loss: 0.031
7
Epoch 40/100
300/300 [==============================] - 0s 87us/step - loss: 0.0284 - val_loss: 0.029
9
Epoch 41/100
300/300 [==============================] - 0s 97us/step - loss: 0.0271 - val_loss: 0.028
5
Epoch 42/100
300/300 [==============================] - 0s 110us/step - loss: 0.0261 - val_loss: 0.02
75
Epoch 43/100
300/300 [==============================] - 0s 103us/step - loss: 0.0250 - val_loss: 0.02
68
```

```
Epoch 44/100
300/300 [==============================] - 0s 107us/step - loss: 0.0239 - val_loss: 0.02
62
Epoch 45/100
300/300 [==============================] - 0s 87us/step - loss: 0.0226 - val_loss: 0.025
9
Epoch 46/100
300/300 [==============================] - 0s 70us/step - loss: 0.0214 - val_loss: 0.025
9
Epoch 47/100
300/300 [==============================] - 0s 83us/step - loss: 0.0205 - val_loss: 0.025
9
Epoch 48/100
300/300 [==============================] - 0s 70us/step - loss: 0.0198 - val_loss: 0.025
5
Epoch 49/100
300/300 [==============================] - 0s 67us/step - loss: 0.0192 - val_loss: 0.024
9
Epoch 50/100
300/300 [==============================] - 0s 77us/step - loss: 0.0187 - val_loss: 0.023
9
Epoch 51/100
300/300 [==============================] - 0s 73us/step - loss: 0.0183 - val_loss: 0.023
2
Epoch 52/100
300/300 [==============================] - 0s 97us/step - loss: 0.0179 - val_loss: 0.023
0
Epoch 53/100
300/300 [==============================] - 0s 97us/step - loss: 0.0176 - val_loss: 0.022
8
Epoch 54/100
300/300 [==============================] - 0s 97us/step - loss: 0.0174 - val_loss: 0.022
6
Epoch 55/100
300/300 [==============================] - 0s 77us/step - loss: 0.0170 - val_loss: 0.022
2
Epoch 56/100
300/300 [==============================] - 0s 63us/step - loss: 0.0168 - val_loss: 0.021
9
Epoch 57/100
300/300 [==============================] - 0s 90us/step - loss: 0.0166 - val_loss: 0.021
5
Epoch 58/100
300/300 [==============================] - 0s 73us/step - loss: 0.0164 - val_loss: 0.021
3
Epoch 59/100
300/300 [==============================] - 0s 97us/step - loss: 0.0161 - val_loss: 0.021
1
Epoch 60/100
300/300 [==============================] - 0s 77us/step - loss: 0.0160 - val_loss: 0.020
9
Epoch 61/100
300/300 [==============================] - 0s 97us/step - loss: 0.0158 - val_loss: 0.020
7
Epoch 62/100
300/300 [==============================] - 0s 63us/step - loss: 0.0156 - val_loss: 0.020
3
Epoch 63/100
300/300 [==============================] - 0s 90us/step - loss: 0.0154 - val_loss: 0.020
1
Epoch 64/100
```

```
300/300 [==============================] - 0s 87us/step - loss: 0.0153 - val_loss: 0.019
9
Epoch 65/100
300/300 [==============================] - 0s 97us/step - loss: 0.0151 - val_loss: 0.019
8
Epoch 66/100
300/300 [==============================] - 0s 77us/step - loss: 0.0149 - val_loss: 0.019
6
Epoch 67/100
300/300 [==============================] - 0s 90us/step - loss: 0.0148 - val_loss: 0.019
3
Epoch 68/100
300/300 [==============================] - 0s 77us/step - loss: 0.0146 - val_loss: 0.019
1
Epoch 69/100
300/300 [==============================] - 0s 63us/step - loss: 0.0145 - val_loss: 0.019
0
Epoch 70/100
300/300 [==============================] - 0s 63us/step - loss: 0.0143 - val_loss: 0.018
7
Epoch 71/100
300/300 [==============================] - 0s 67us/step - loss: 0.0141 - val_loss: 0.018
4
Epoch 72/100
300/300 [==============================] - 0s 60us/step - loss: 0.0140 - val_loss: 0.018
2
Epoch 73/100
300/300 [==============================] - 0s 67us/step - loss: 0.0138 - val_loss: 0.018
0
Epoch 74/100
300/300 [==============================] - 0s 63us/step - loss: 0.0136 - val_loss: 0.017
8
Epoch 75/100
300/300 [==============================] - 0s 73us/step - loss: 0.0135 - val_loss: 0.017
6
Epoch 76/100
300/300 [==============================] - 0s 60us/step - loss: 0.0133 - val_loss: 0.017
4
Epoch 77/100
300/300 [==============================] - 0s 57us/step - loss: 0.0131 - val_loss: 0.017
1
Epoch 78/100
300/300 [==============================] - 0s 60us/step - loss: 0.0129 - val_loss: 0.016
8
Epoch 79/100
300/300 [==============================] - 0s 60us/step - loss: 0.0127 - val_loss: 0.016
7
Epoch 80/100
300/300 [==============================] - 0s 63us/step - loss: 0.0126 - val_loss: 0.016
5
Epoch 81/100
300/300 [==============================] - 0s 73us/step - loss: 0.0124 - val_loss: 0.016
2
Epoch 82/100
300/300 [==============================] - 0s 73us/step - loss: 0.0122 - val_loss: 0.015
9
Epoch 83/100
300/300 [==============================] - 0s 60us/step - loss: 0.0121 - val_loss: 0.015
6
Epoch 84/100
300/300 [==============================] - 0s 67us/step - loss: 0.0119 - val_loss: 0.015
```

```
5
Epoch 85/100
300/300 [==============================] - 0s 67us/step - loss: 0.0118 - val_loss: 0.015
4
Epoch 86/100
300/300 [==============================] - 0s 63us/step - loss: 0.0116 - val_loss: 0.015
2
Epoch 87/100
300/300 [==============================] - 0s 83us/step - loss: 0.0114 - val_loss: 0.014
9
Epoch 88/100
300/300 [==============================] - 0s 70us/step - loss: 0.0113 - val_loss: 0.014
7
Epoch 89/100
300/300 [==============================] - 0s 80us/step - loss: 0.0111 - val_loss: 0.014
4
Epoch 90/100
300/300 [==============================] - 0s 63us/step - loss: 0.0109 - val_loss: 0.014
2
Epoch 91/100
300/300 [==============================] - 0s 63us/step - loss: 0.0107 - val_loss: 0.014
2
Epoch 92/100
300/300 [==============================] - 0s 73us/step - loss: 0.0105 - val_loss: 0.014
0
Epoch 93/100
300/300 [==============================] - 0s 63us/step - loss: 0.0103 - val_loss: 0.013
6
Epoch 94/100
300/300 [==============================] - 0s 67us/step - loss: 0.0101 - val_loss: 0.013
4
Epoch 95/100
300/300 [==============================] - 0s 77us/step - loss: 0.0099 - val_loss: 0.013
1
Epoch 96/100
300/300 [==============================] - 0s 67us/step - loss: 0.0097 - val_loss: 0.012
7
Epoch 97/100
300/300 [==============================] - 0s 60us/step - loss: 0.0095 - val_loss: 0.012
5
Epoch 98/100
300/300 [==============================] - 0s 63us/step - loss: 0.0093 - val_loss: 0.012
4
Epoch 99/100
300/300 [==============================] - 0s 103us/step - loss: 0.0091 - val_loss: 0.01
22
Epoch 100/100
300/300 [==============================] - 0s 77us/step - loss: 0.0089 - val_loss: 0.011
8
```

Model Evaluation

In [23]:

```
epochs_hist.history.keys()
```

Out[23]:

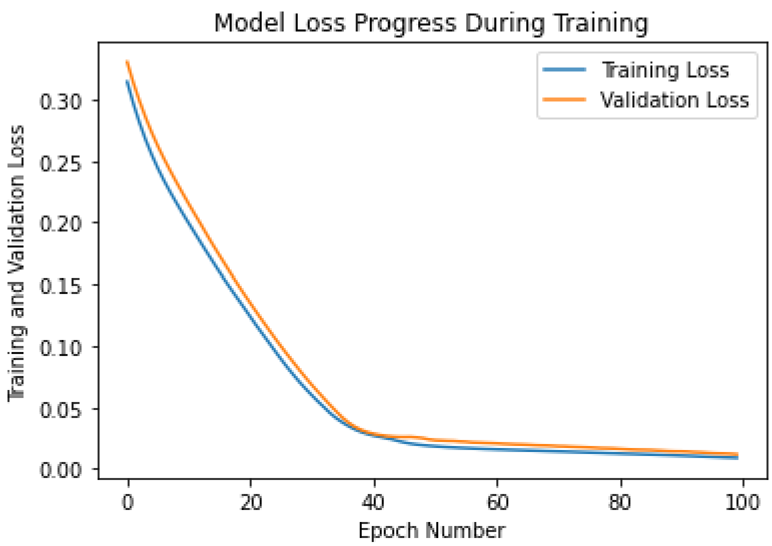
```
dict_keys(['val_loss', 'loss'])
```

In [29]:

```
plt.plot(epochs_hist.history['loss'])
```

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

Out[29]: <matplotlib.legend.Legend at 0x22b13a7d488>



In [30]:

```
# Gender, Age, Annual Salary, Credit Card Debt, Net Worth
X_testing = np.array([[1, 50, 50000, 10000, 600000]])
y_predict = model.predict(X_test)
```

In [31]:

```
print('Expected Purchase Amount', y_predict)
```

```
Expected Purchase Amount [[34385.254]]
```

In [ ]: