University Admission Prediction

- Featuring various machine learning models that predict Masters university admission acceptance probability

In this notebook, I have used various Machine Learning models to predict the chance of admission into a particular university based on the student's profile

Following are the four models I have built and compared their efficiency using regression key performance indicators(KPIs) :
1) Linear Regression Model
2) Artificial Neural Network Model
3) Decision Tree Model
4) Random Forest Model

Importing Libraries and Dataset

In this block, we will import all the relevant libraries and dataset.
Data Source : https://www.kaggle.com/mohansacharya/graduate-admissions (https://www.kaggle.com/mohansacharya/graduate-admissions)

The dataset contains several parameters which are considered important during the application for Masters Programs. The parameters included are :

1) GRE Scores (out of 340)
2) TOEFL Scores (out of 120)
3) University Rating (out of 5)
4) Statement of Purpose and Letter of Recommendation Strength (out of 5)
5) Undergraduate GPA (out of 10)
6) Research Experience (either 0 or 1)
7) Chance of Admit (ranging from 0 to 1)

In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from jupyterthemes import jtplot
jtplot.style(theme='monokai', context='notebook', ticks=True, grid=False)
```

In [4]:
```
# read the csv file
admission_df = pd.read_csv('Admission_Predict.csv')
```

In [5]:
```
admission_df.head()
```

Out[5]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65

In [6]:
```
# Let's drop the serial no.
# output is continuous, so regression based problem
admission_df.drop('Serial No.', axis = 1, inplace = True)
admission_df.head()
```

Out[6]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337	118	4	4.5	4.5	9.65	1	0.92
1	324	107	4	4.0	4.5	8.87	1	0.76
2	316	104	3	3.0	3.5	8.00	1	0.72
3	322	110	3	3.5	2.5	8.67	1	0.80
4	314	103	2	2.0	3.0	8.21	0	0.65

Exploratory Data Analysis

In the following block of code, we:
1) check for null values
2) study the data frame using .info() and .describe()
3) Extract meaningful insights from these statistics

In [7]:
```
# checking the null values
admission_df.isnull().sum()
```

Out[7]:
```
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

In [8]:
```
# Check the dataframe information
admission_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   GRE Score          500 non-null    int64
 1   TOEFL Score        500 non-null    int64
 2   University Rating  500 non-null    int64
 3   SOP                500 non-null    float64
 4   LOR                500 non-null    float64
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    int64
 7   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(4)
memory usage: 31.4 KB
```

In [9]:
```
# Statistical summary of the dataframe
admission_df.describe()
```

Out[9]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.00000
mean	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.72174
std	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0.14114
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.34000
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.63000
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.72000
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.82000
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.97000

In [10]:
```
# Grouping by University ranking

df_university = admission_df.groupby(by = 'University Rating').mean()
df_university
```

Out[10]:

University Rating	GRE Score	TOEFL Score	SOP	LOR	CGPA	Research	Chance of Admit
1	304.911765	100.205882	1.941176	2.426471	7.798529	0.294118	0.562059
2	309.134921	103.444444	2.682540	2.956349	8.177778	0.293651	0.626111
3	315.030864	106.314815	3.308642	3.401235	8.500123	0.537037	0.702901
4	323.304762	110.961905	4.000000	3.947619	8.936667	0.780952	0.801619
5	327.890411	113.438356	4.479452	4.404110	9.278082	0.876712	0.888082

From the above statistics, we can clearly see :
1) The mean for GRE score is 316
2) The mean for TOEFL score is 107

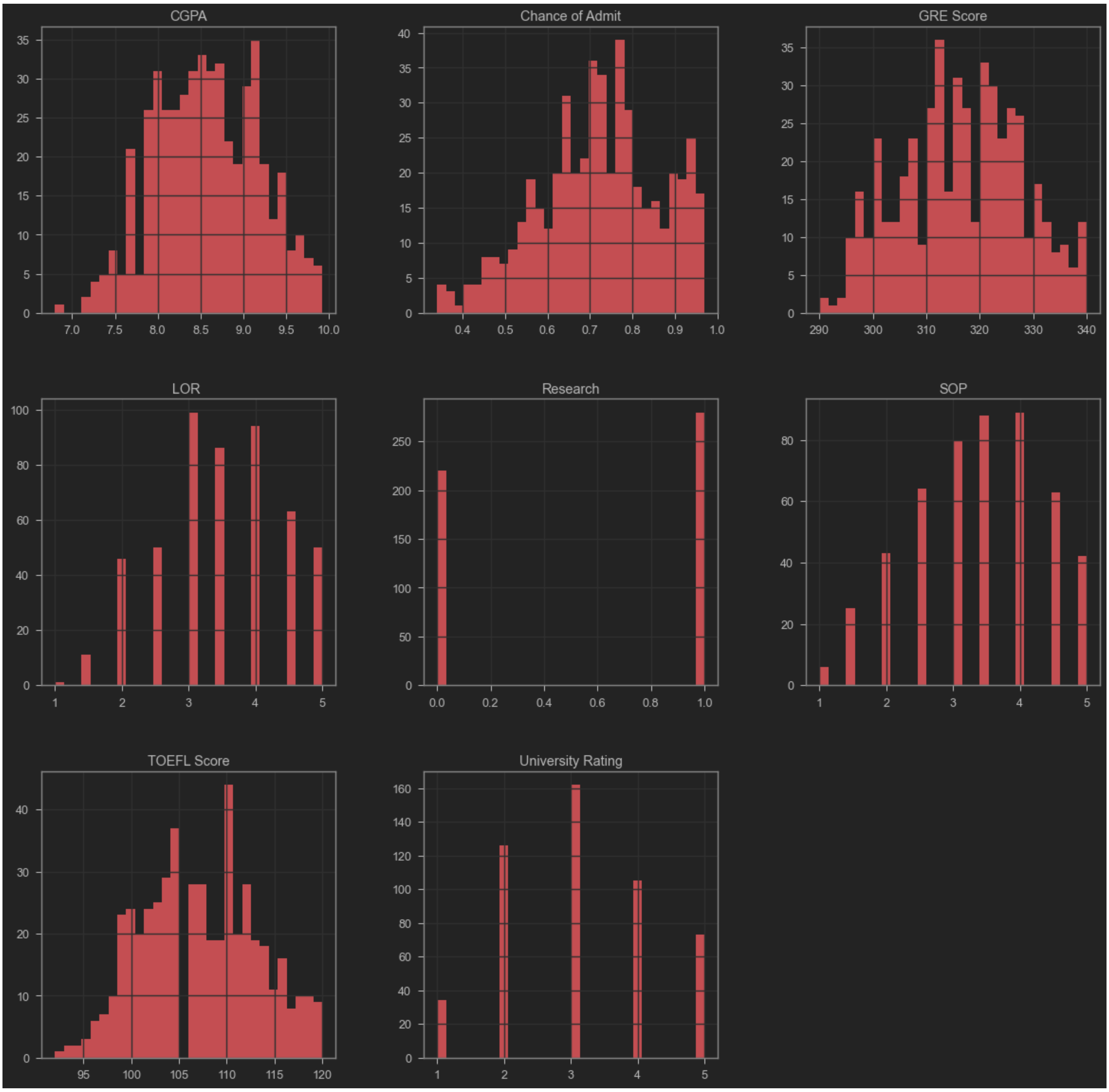
3) Standard deviation for the GRE score is 11, which suggests that about 68% of the students score between 305 and 327

4) We also see that the average University Ranking is 3

Data Visualization

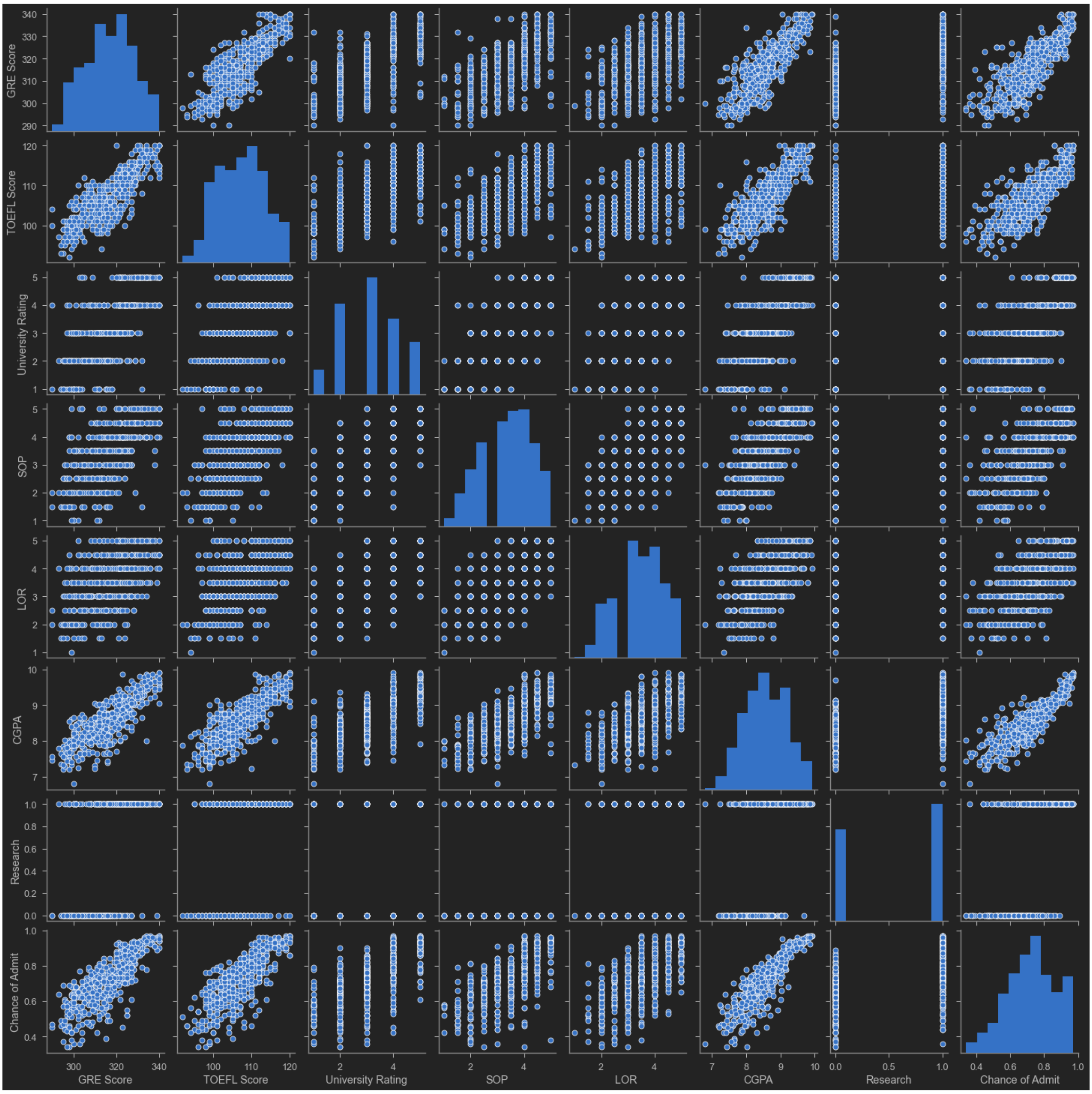
In [11]:
```
admission_df.hist(bins = 30, figsize = (20,20),color = 'r')
```

Out[11]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000001CC45C90FC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001CC463E61C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001CC46414D88>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001CC46452988>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001CC4648D808>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001CC464C56C8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001CC464FD588>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001CC46536288>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001CC46536488>]],
      dtype=object)
```

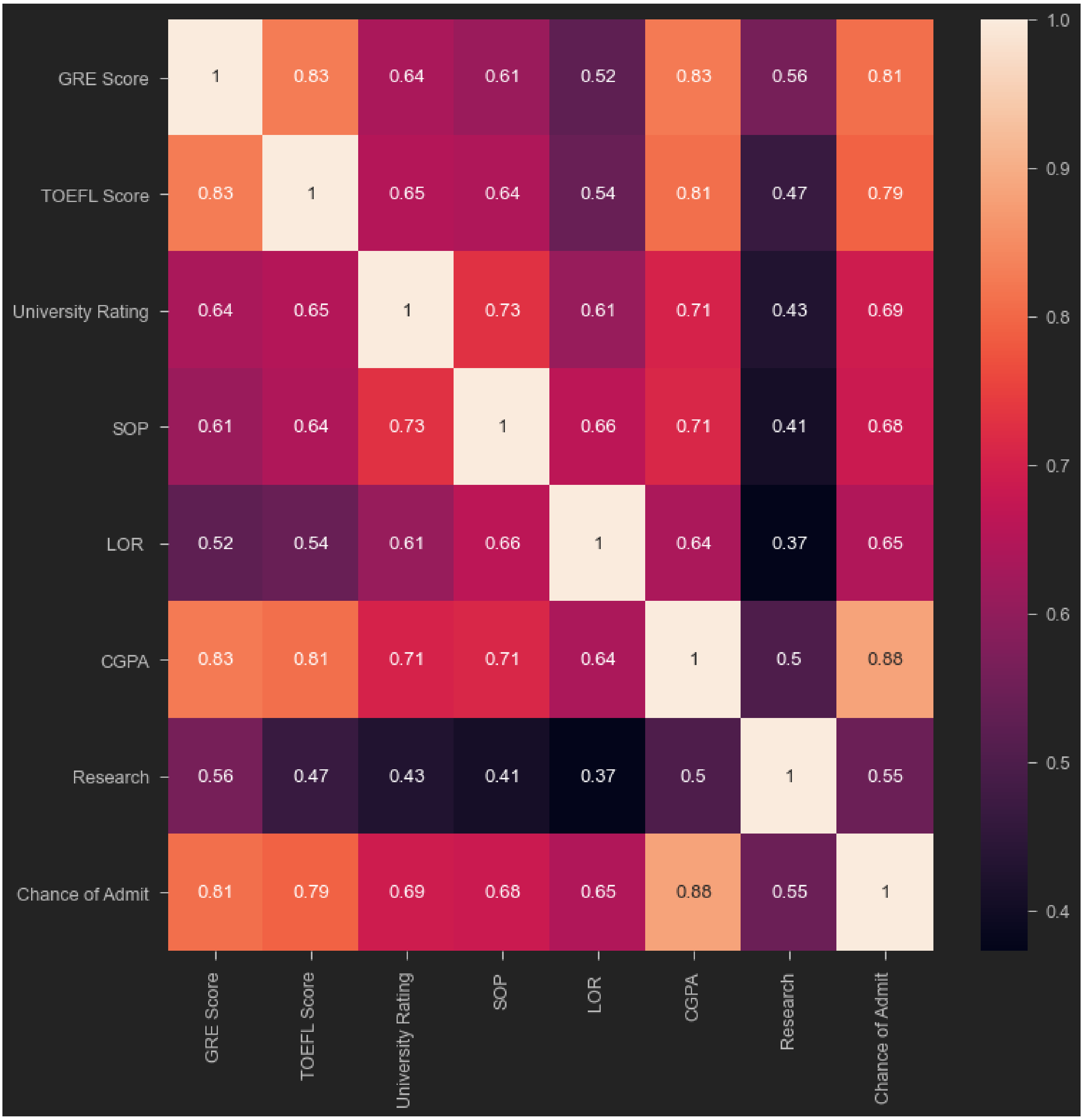


In [12]:
```
sns.pairplot(admission_df)
```

Out[12]: <seaborn.axisgrid.PairGrid at 0x1cc47232fc8>



In [13]:
```
corr_matrix = admission_df.corr()
plt.figure(figsize = (12,12))
sns.heatmap(corr_matrix,annot = True)
plt.show()
```



From the above graphs, we can observe that :

1) There is a very high correlation between GRE and TOEFL scores. A student who scores a high GRE score tends to score a similar high TOEFL score
2) The chances of admission acceptance increase as GPA, SOP and University Ranking improve/increase
3) Students who have research experience in the past, tend to have a higher change of acceptance to a university
4) We can see that approximately 160 out of 500 students have a high chance of getting into a University with a ranking of 3

In [ ]:

```

```

Creation of training and testing dataset

In the following block of code, we divide the original dataset into training and testing datasets respectively

In [14]:

```
admission_df.columns
```

Out[14]:

```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA',
       'Research', 'Chance of Admit'],
      dtype='object')
```

In [15]:

```
X = admission_df.drop(columns = ['Chance of Admit'])
```

In [16]:

```
y = admission_df['Chance of Admit']
```

In [17]:

```
X.shape
```

Out[17]:

```
(500, 7)
```

In [18]:

```
y.shape
```

Out[18]:

```
(500,)
```

In [19]:

```
y
```

Out[19]:

```
0      0.92
1      0.76
2      0.72
3      0.80
4      0.65
       ...
495    0.87
496    0.96
497    0.93
498    0.73
499    0.84
Name: Chance of Admit, Length: 500, dtype: float64
```

In [20]:

```
X = np.array(X)
y = np.array(y)
```

In [21]:
```
#Instead of (500,) we want (500,1), further on we can successfully use sklearn for our t
y = y.reshape(-1,1)
y.shape
```

Out[21]: (500, 1)

In [22]:
```
# scaling the data before training the model
#df consists of diff features and their ranges are variable for these features, hence, w
#This is done to avoid biasing while predicting the y variable
from sklearn.preprocessing import StandardScaler,MinMaxScaler
scaler_x = StandardScaler()
X = scaler_x.fit_transform(X)
```

In [23]:
```
scaler_y = StandardScaler()
y = scaler_y.fit_transform(y)
```

In [24]:
```
# splitting the data in to test and train sets
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.15)
```

Linear Regression Model

In the following block of code, I have implemented a multiple linear regression model using least sum of squares to find the best fit line

In [25]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, accuracy_score
```

In [26]:
```
LinearRegression_model = LinearRegression()
LinearRegression_model.fit(X_train,y_train)
```

Out[26]: LinearRegression()

In [27]:
```
accuracy_LinearRegression = LinearRegression_model.score(X_test,y_test)
accuracy_LinearRegression
```

Out[27]: 0.8228312589182746

Artificial Neural Networks

In the following block of code, I have implemented a neural network model with 4 deep layers and 1 output layer. Additionally, I have also implemented Dropout regularization in order to minimize the dependence between the different neurons in each layer.

I have implemented this model using Keras library on top of Tensorflow

In [28]:
```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Dense, Activation, Dropout
from tensorflow.keras.optimizers import Adam
```

```
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:5
16: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in
a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:5
17: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in
a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:5
18: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in
a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:5
19: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in
a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:5
20: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in
a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:5
25: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in
a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub\dtyp
es.py:541: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depreca
ted; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub\dtyp
es.py:542: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depreca
ted; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub\dtyp
es.py:543: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depreca
ted; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub\dtyp
es.py:544: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depreca
ted; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub\dtyp
es.py:545: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depreca
ted; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorboard\compat\tensorflow_stub\dtyp
es.py:550: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is depreca
ted; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

In [29]:
```
ANN_model = keras.Sequential()
ANN_model.add(Dense(50, input_dim = 7))
ANN_model.add(Activation('relu'))
ANN_model.add(Dense(150))
ANN_model.add(Activation('relu'))
ANN_model.add(Dropout(0.5))
ANN_model.add(Dense(150))
ANN_model.add(Activation('relu'))
ANN_model.add(Dropout(0.5))
ANN_model.add(Dense(50))
ANN_model.add(Activation('linear'))
ANN_model.add(Dense(1))
ANN_model.compile(loss = 'mse', optimizer = 'adam')
ANN_model.summary()
```

```
WARNING:tensorflow:From C:\Users\Aishwarya\anaconda3\lib\site-packages\tensorflow\pyth
on\ops\init_ops.py:1251: calling VarianceScaling.__init__ (from tensorflow.python.ops.
init_ops) with dtype is deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constru
ctor
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 50)                400
_________________________________________________________________
activation (Activation)      (None, 50)                0
_________________________________________________________________
dense_1 (Dense)              (None, 150)               7650
_________________________________________________________________
activation_1 (Activation)    (None, 150)               0
_________________________________________________________________
dropout (Dropout)            (None, 150)               0
_________________________________________________________________
dense_2 (Dense)              (None, 150)               22650
_________________________________________________________________
activation_2 (Activation)    (None, 150)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 150)               0
_________________________________________________________________
dense_3 (Dense)              (None, 50)                7550
_________________________________________________________________
activation_3 (Activation)    (None, 50)                0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 51
=================================================================
Total params: 38,301
Trainable params: 38,301
Non-trainable params: 0
_________________________________________________________________
```

In [30]:
```
ANN_model.compile(optimizer='Adam', loss='mean_squared_error')
```

In [31]:
```
epochs_hist = ANN_model.fit(X_train, y_train, epochs = 100, batch_size = 20, validation_
```

```
Train on 340 samples, validate on 85 samples
Epoch 1/100
340/340 [==============================] - 1s 3ms/sample - loss: 0.5585 - val_loss:
0.2503
Epoch 2/100
340/340 [==============================] - 0s 147us/sample - loss: 0.3727 - val_los
s: 0.2251
Epoch 3/100
340/340 [==============================] - 0s 148us/sample - loss: 0.3154 - val_los
s: 0.1859
Epoch 4/100
340/340 [==============================] - 0s 171us/sample - loss: 0.2813 - val_los
s: 0.1827
Epoch 5/100
340/340 [==============================] - 0s 240us/sample - loss: 0.2726 - val_los
s: 0.1817
Epoch 6/100
340/340 [==============================] - 0s 239us/sample - loss: 0.2577 - val_los
s: 0.1910
```

In [32]:
```
result = ANN_model.evaluate(X_test, y_test)
accuracy_ANN = 1 - result
print("Accuracy : {}".format(accuracy_ANN))
```

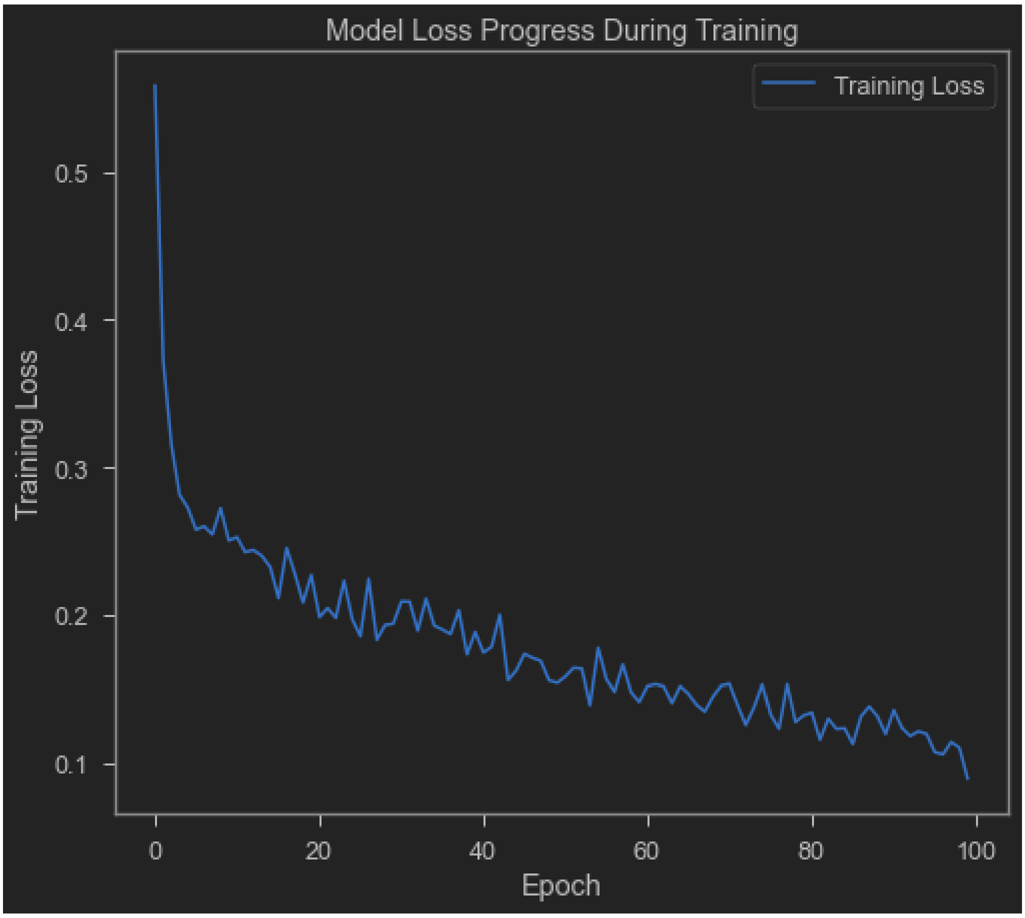
```
75/75 [==============================] - 0s 133us/sample - loss: 0.1944
Accuracy : 0.8055628619591395
```

In [33]:
```
epochs_hist.history.keys()
```

Out[33]:
```
dict_keys(['loss', 'val_loss'])
```

In [34]:
```
plt.plot(epochs_hist.history['loss'])
plt.title('Model Loss Progress During Training')
plt.xlabel('Epoch')
plt.ylabel('Training Loss')
plt.legend(['Training Loss'])
```

Out[34]: <matplotlib.legend.Legend at 0x1cc5291abc8>



From the above graph, we can see that as the number of epochs increase, the training loss decreases.

Decision Tree and Random Forest Models

In the following block of code, I have implemented regression decision tree and random forest models using sklearn library functions

In [35]:
```
# Decision tree builds regression or classification models in the form of a tree structu
# Decision tree breaks down a dataset into smaller subsets while at the same time an ass
# The final result is a tree with decision nodes and leaf nodes.
# Great resource: https://www.saedsayad.com/decision_tree_reg.htm

from sklearn.tree import DecisionTreeRegressor
DecisionTree_model = DecisionTreeRegressor()
DecisionTree_model.fit(X_train, y_train)
```

Out[35]: DecisionTreeRegressor()

In [36]:
```
accuracy_DecisionTree = DecisionTree_model.score(X_test,y_test)
accuracy_DecisionTree
```

Out[36]: 0.46002013484242976

Many decision trees make up a random forest model which is an ensemble model. Predictions made by each decision tree are averaged to get the prediction of random forest model.
A random forest regressor fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

In [37]:
```
from sklearn.ensemble import RandomForestRegressor
RandomForest_model = RandomForestRegressor(n_estimators = 100, max_depth = 10)
RandomForest_model.fit(X_train,y_train)
```

```
C:\Users\Aishwarya\anaconda3\lib\site-packages\ipykernel_launcher.py:3: DataConversion
Warning: A column-vector y was passed when a 1d array was expected. Please change the
shape of y to (n_samples,), for example using ravel().
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[37]: RandomForestRegressor(max_depth=10)

In [38]:
```
accuracy_RandomForest = RandomForest_model.score(X_test,y_test)
accuracy_RandomForest
```

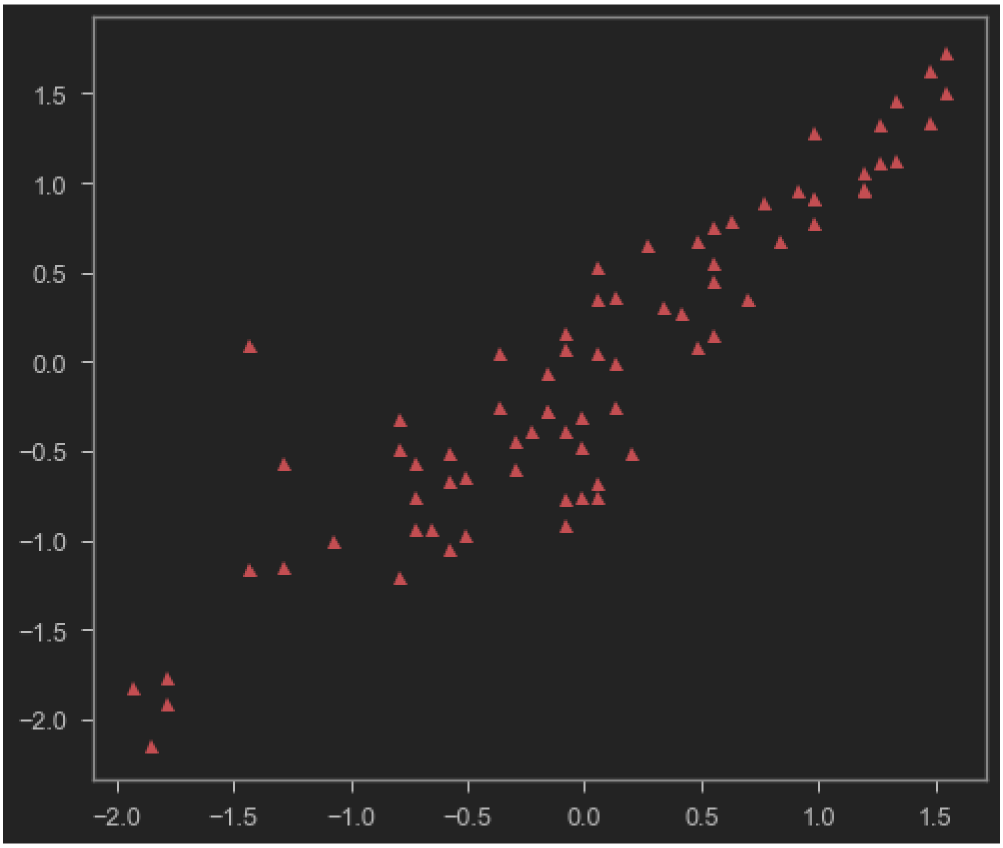
Out[38]: 0.7972999061987249

Regression KPIs

Upon model fitting, I have assessed the performance of each model by comparing their predictions to the true labels.

In [39]:
```
y_predict = LinearRegression_model.predict(X_test)
plt.plot(y_test, y_predict, '^', color = 'r')
```

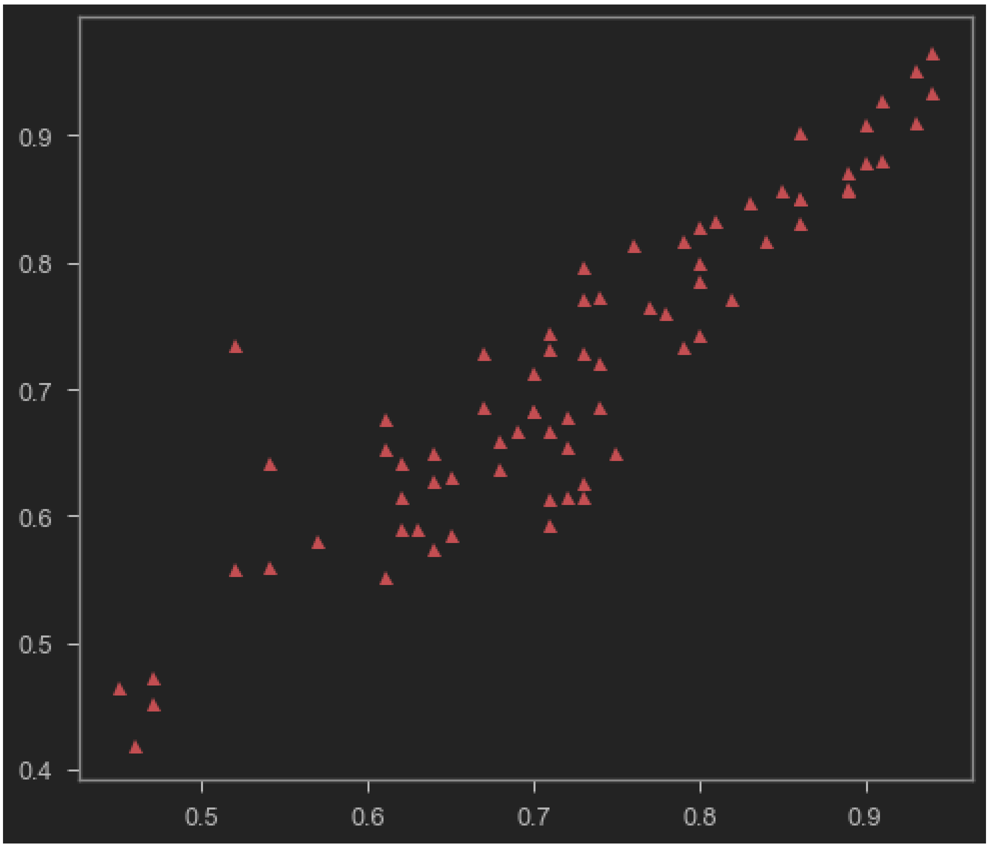
Out[39]: [<matplotlib.lines.Line2D at 0x1cc52b93f48>]



In [40]:
```
#After Inverse Transformation(change in scale values)
y_predict_orig = scaler_y.inverse_transform(y_predict)
y_test_orig = scaler_y.inverse_transform(y_test)
```

In [43]:
```
plt.plot(y_test_orig,y_predict_orig,"^", color='r')
```

Out[43]: [<matplotlib.lines.Line2D at 0x1cc52dcaf88>]



In [42]:
```
k = X_test.shape[1]
n = len(X_test)
n
```

Out[42]: 75

In [44]:
```
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from math import sqrt

RMSE = float(format(np.sqrt(mean_squared_error(y_test_orig, y_predict_orig)),'.3f'))
MSE = mean_squared_error(y_test_orig, y_predict_orig)
MAE = mean_absolute_error(y_test_orig, y_predict_orig)
r2 = r2_score(y_test_orig, y_predict_orig)
adj_r2 = 1-(1-r2)*(n-1)/(n-k-1)

print('RMSE =',RMSE, '\nMSE =',MSE, '\nMAE =',MAE, '\nR2 =', r2, '\nAdjusted R2 =', adj_
```

```
RMSE = 0.052
MSE = 0.002684315880210931
MAE = 0.038308312064558404
R2 = 0.8228312589182746
Adjusted R2 = 0.8043210919395869
```

Thus we can see, that our Adjusted R-squared value is very high and our MSE and MAE are very low values. These values are indication that our model is a good predictive model.

In [ ]:
```
```