Linear Regression

features- Input variables (independent variables)

label or target - output variable(Dependent variable)

features & labels & predecting/estimating continious variable data

exp and tech is features(independent variable

salary is label(dependent variable)

The problem statement

This data is about the amount spent on advertising through different channels like TV, Radio, and Newapaper . The goal is to predict how the expence on each channel affects the sales and is there a way to optimise that sale?

In [1]:

```
# necessary Imports
import pandas as pd
import matplotlib.pyplot as plt
import pickle
%matplotlib inline
```

In [2]:

```
data=pd.read_csv('https://raw.githubusercontent.com/training-ml/Files/main/Advertising.csv'
```

In [3]:

```
data.head() # checking the firstfive rows from the dataset
```

Out[3]:

	Unnamed: 0	TV	radio	newspaper	sales
0	1	230.1	37.8	69.2	22.1
1	2	44.5	39.3	45.1	10.4
2	3	17.2	45.9	69.3	9.3
3	4	151.5	41.3	58.5	18.5
4	5	180.8	10.8	58.4	12.9

In [4]:

```
data.shape
```

Out[4]:

```
(200, 5)
```

In [5]:

```
data.info()  # Print the summary of the dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  200 non-null    int64  
 1   TV          200 non-null    float64
 2   radio       200 non-null    float64
 3   newspaper   200 non-null    float64
 4   sales       200 non-null    float64
dtypes: float64(4), int64(1)
memory usage: 7.9 KB
```

In [6]:

```
data.isna().sum() # finding the count of missing values from different columns
```

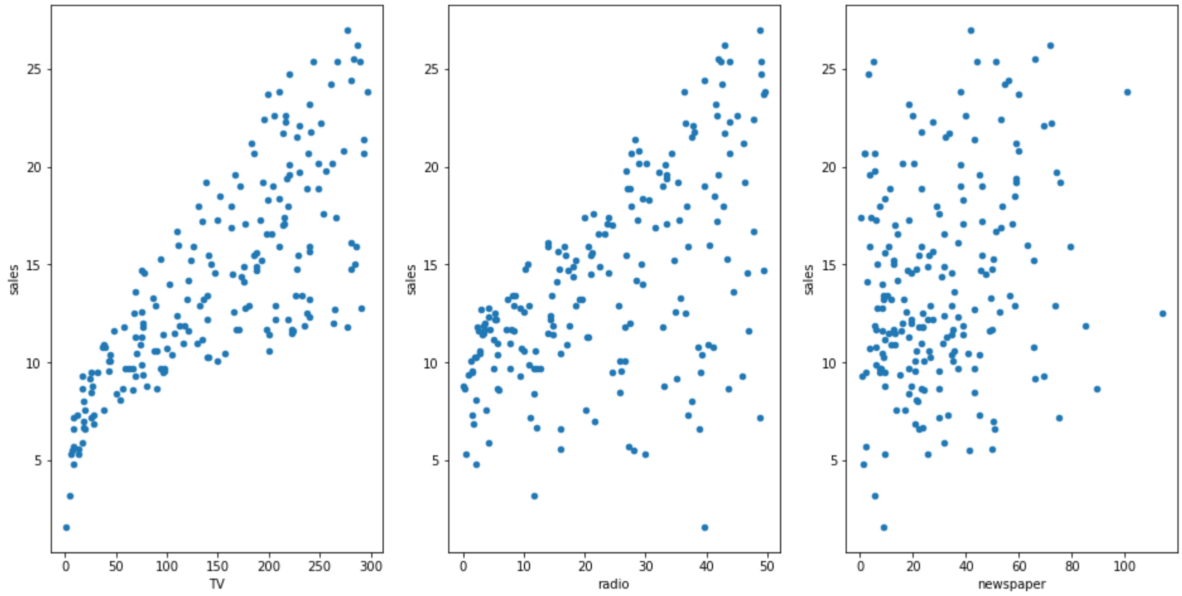
Out[6]:

```
Unnamed: 0    0
TV            0
radio         0
newspaper     0
sales         0
dtype: int64
```

Now, let's showcase the relationship between the feature and target column

In [7]:

```
# visualize the relationship between the features and the response using scatterplots
fig,axs=plt.subplots(1,3)
data.plot(kind='scatter',x='TV', y='sales',ax=axs[0],figsize=(16,8))
data.plot(kind='scatter',x='radio', y='sales',ax=axs[1])
data.plot(kind='scatter',x='newspaper', y='sales',ax=axs[2])
fig.savefig('testdata.jpg')
```



In [8]:

```
# create X=feature and y = label
```

In [9]:

```
x=data[['TV']]
y= data.sales

# follow the usual sklearn pattern: import,instantiate,fit

from sklearn.linear_model import LinearRegression
lm=LinearRegression()
lm.fit(x,y)
```

Out[9]:

```
LinearRegression()
```

In [10]:

```
# print intercept and coefficient
print(lm.intercept_)
print(lm.coef_)
```

```
7.032593549127693
[0.04753664]
```

In [11]:

```
# Prediction using the model
#calculate the prediction

7.03259354 + 0.047537*50
```

Out[11]:

```
9.40944354
```

In [12]:

```
# Thus, we would predict sales of 9.40944354 widgets in That market.
# Lets do the same thing using code
```

In [13]:

```
# let's create a DataFrame since model

X_new=pd.DataFrame({'TV':[50]})
X_new.head()
```

Out[13]:

	TV
0	50

In [14]:

```
# use the model to make predictions on a new value
lm.predict(X_new)
```

Out[14]:

```
array([9.40942557])
```

In [15]:

```
#  lm.fit(features,label)
# lm.predict(feature)
```

In [16]:

```
# print the p-values for the model coefficients
import statsmodels.formula.api as smf
lm= smf.ols(formula='sales ~ TV', data=data).fit()
lm.pvalues
```

Out[16]:

```
Intercept    1.406300e-35
TV           1.467390e-42
dtype: float64
```

In [17]:

```
# print thr R- squared value for the model
lm.rsquared
```

Out[17]:

```
0.611875050850071
```

In [18]:

```
# Multiple Linear Regression
```

In [19]:

```
# Create X and Y
x=data[['TV','radio','newspaper']]
y=data.sales

lm=LinearRegression()
lm.fit(x,y)

#print intercept and coefficients

print('Intercept  :  ->',lm.intercept_)
print('TV  :  ->',lm.coef_[0])
print('Radio :  ->',lm.coef_[1])
print('Newspaper  :  ->',lm.coef_[2])
```

```
Intercept  :  -> 2.9388893694594067
TV  :  -> 0.04576464545539761
Radio :  -> 0.18853001691820462
Newspaper  :  -> -0.0010374930424762972
```

In [20]:

```
lm=smf.ols(formula='sales~ TV+radio++newspaper',data=data).fit()
lm.summary()
```

Out[20]:

OLS Regression Results

Dep. Variable:	sales	**R-squared:**	0.897
Model:	OLS	**Adj. R-squared:**	0.896
Method:	Least Squares	**F-statistic:**	570.3
Date:	Tue, 17 May 2022	**Prob (F-statistic):**	1.58e-96
Time:	13:00:52	**Log-Likelihood:**	-386.18
No. Observations:	200	**AIC:**	780.4
Df Residuals:	196	**BIC:**	793.6
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.9389	0.312	9.422	0.000	2.324	3.554
TV	0.0458	0.001	32.809	0.000	0.043	0.049
radio	0.1885	0.009	21.893	0.000	0.172	0.206
newspaper	-0.0010	0.006	-0.177	0.860	-0.013	0.011

Omnibus:	60.414	**Durbin-Watson:**	2.084
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	151.241
Skew:	-1.327	**Prob(JB):**	1.44e-33
Kurtosis:	6.332	**Cond. No.**	454.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [21]:

```
# learnt from summary

#TV and radio ahs positive p value and newspaper has negative p value
```

In [22]:

```
# only include TV and radio in the model

lm=smf.ols(formula='sales ~ TV + radio',data=data).fit()
lm.rsquared
```

Out[22]:

0.8971942610828957

In [23]:

```
#add newspaper to the model (which we believe has no association with sales)
lm=smf.ols(formula='sales~ TV+radio++newspaper',data=data).fit()
lm.rsquared
```

Out[23]:

```
0.8972106381789522
```

project _1 with Linear Regression

problem statement

we need to predict the chance of admission based on the students various scores

Features or Independent variables

.GRE Score

. TOEFL Score

. University Rating

.SOP

.LOR

.CGPA

.Research

Label/Target

.Chance of Admit

In [24]:

```
# Let's start with importing necessary Libraries

import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# import statsmodels.api as sm

import matplotlib.pyplot as plt
import seaborn as sns
import pickle


import warnings
warnings.filterwarnings('ignore')
```

In [25]:

```
#Read csv file and convert into dataframe
data=pd.read_csv('https://raw.githubusercontent.com/training-ml/Files/main/Admission_Predic
data.head()
```

Out[25]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337.0	118.0	4.0	4.5	4.5	9.65	1	0.92
1	2	324.0	107.0	4.0	4.0	4.5	8.87	1	0.76
2	3	NaN	104.0	3.0	3.0	3.5	8.00	1	0.72
3	4	322.0	110.0	3.0	3.5	2.5	8.67	1	0.80
4	5	314.0	103.0	2.0	2.0	3.0	8.21	0	0.65

In [26]:

```
data.shape
```

Out[26]:

```
(500, 9)
```

In [27]:

```
# understand data at high level. check the statistics of data set

data.describe()
```

Out[27]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Re
count	500.000000	485.000000	490.000000	485.000000	500.000000	500.00000	500.000000	500
mean	250.500000	316.558763	107.187755	3.121649	3.374000	3.48400	8.576440	0
std	144.481833	11.274704	6.112899	1.146160	0.991004	0.92545	0.604813	0
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1
max	500.000000	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1

In [28]:

```
data.isna().sum()
```

Out[28]:

```
Serial No.            0
GRE Score            15
TOEFL Score          10
University Rating    15
SOP                   0
LOR                   0
CGPA                  0
Research              0
Chance of Admit       0
dtype: int64
```

In [29]:

```
# fill the null values
data['University Rating']=data['University Rating'].fillna(data['University Rating'].mode()
data['TOEFL Score']=data['TOEFL Score'].fillna(data['TOEFL Score'].mean())
data['GRE Score']=data['GRE Score'].fillna(data['GRE Score'].mean())
```

In [30]:

```
# verify if Nan's are filled

data.isna().sum()
```

Out[30]:

```
Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

Now the data looks good and there are no missing values. Also , the first cloumn is just serial numbers,so we don't need that column.Let's drop it from data and make it more clean.

In [31]:

```
# Dropping unwanted columns

data=data.drop(columns=['Serial No.'])
data.head()
```

Out[31]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337.000000	118.0	4.0	4.5	4.5	9.65	1	0.92
1	324.000000	107.0	4.0	4.0	4.5	8.87	1	0.76
2	316.558763	104.0	3.0	3.0	3.5	8.00	1	0.72
3	322.000000	110.0	3.0	3.5	2.5	8.67	1	0.80
4	314.000000	103.0	2.0	2.0	3.0	8.21	0	0.65

In [32]:

```
# Let's visualize the data and analyze the relationship between independent and dependent v
```

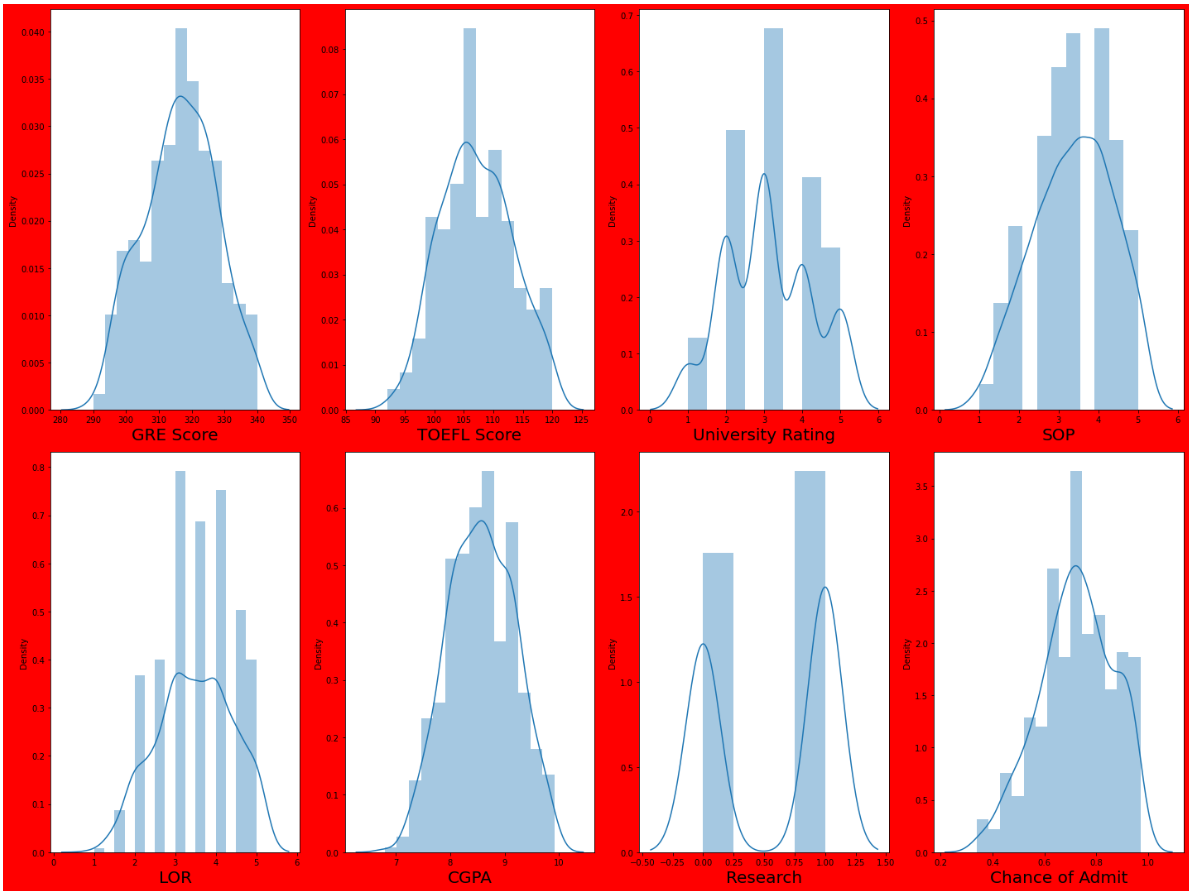
In [33]:

```
# let's see how data is distributed for every columns


plt.figure(figsize=(20,15), facecolor='red')
plotnumber=1

for column in data:
    if plotnumber<=8:
        ax=plt.subplot(2,4,plotnumber)
        sns.distplot(data[column])
        plt.xlabel(column,fontsize=20)

    plotnumber+=1
plt.tight_layout()
```



In [34]:

```
#Lets observe the relation between independent variables and dependent variable.
```

In [35]:

```
# Divide data set into features and label

y= data['Chance of Admit']
x= data.drop(columns=['Chance of Admit'])
```

In [36]:

```
y
```

Out[36]:

```
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 [37]:

```
x
```

Out[37]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
0	337.000000	118.0	4.0	4.5	4.5	9.65	1
1	324.000000	107.0	4.0	4.0	4.5	8.87	1
2	316.558763	104.0	3.0	3.0	3.5	8.00	1
3	322.000000	110.0	3.0	3.5	2.5	8.67	1
4	314.000000	103.0	2.0	2.0	3.0	8.21	0
...	...	...	...	...	...	...	...
495	332.000000	108.0	5.0	4.5	4.0	9.02	1
496	337.000000	117.0	5.0	5.0	5.0	9.87	1
497	330.000000	120.0	5.0	4.5	5.0	9.56	1
498	312.000000	103.0	4.0	4.0	5.0	8.43	0
499	327.000000	113.0	4.0	4.5	4.5	9.04	0

500 rows × 7 columns

In [38]:

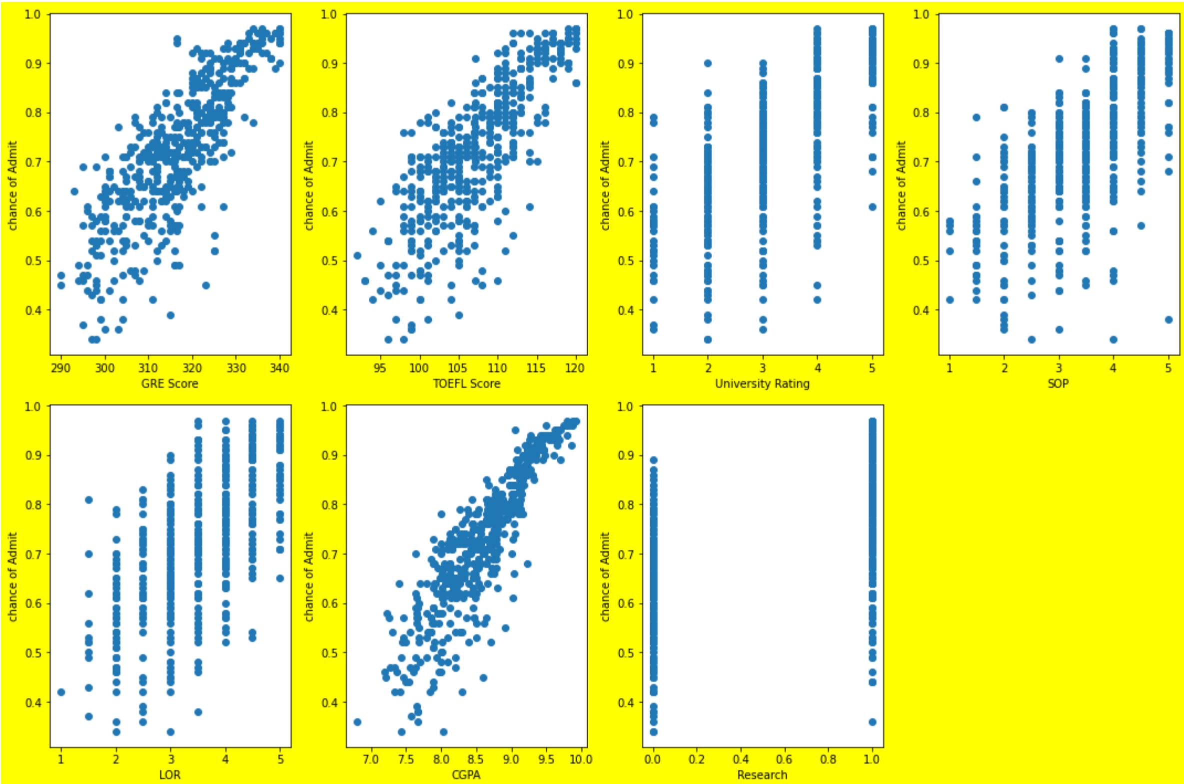
```
# visualizing relationship

plt.figure(figsize=(15,10), facecolor='yellow')
plotnumber=1

for column in x:
    if plotnumber<=8:
        ax=plt.subplot(2,4,plotnumber)
        plt.scatter(x[column],y)


        plt.xlabel(column,fontsize=10)
        plt.ylabel('chance of Admit',fontsize=10)

    plotnumber+=1
plt.tight_layout()
```



In [39]:

```
# Data scaling.Formula Z=(X-mean)/std

scaler= StandardScaler()
X_scaled=scaler.fit_transform(x)
```

In [40]:

```
X_scaled
```

Out[40]:

```
array([[ 1.84274116e+00,  1.78854223e+00,  7.82009548e-01, ...,
         1.09894429e+00,  1.77680627e+00,  8.86405260e-01],
       [ 6.70814288e-01, -3.10581135e-02,  7.82009548e-01, ...,
         1.09894429e+00,  4.85859428e-01,  8.86405260e-01],
       [ 5.12433309e-15, -5.27312752e-01, -1.04622593e-01, ...,
         1.73062093e-02, -9.54042814e-01,  8.86405260e-01],
       ...,
       [ 1.21170361e+00,  2.11937866e+00,  1.66864169e+00, ...,
         1.63976333e+00,  1.62785086e+00,  8.86405260e-01],
       [-4.10964364e-01, -6.92730965e-01,  7.82009548e-01, ...,
         1.63976333e+00, -2.42366993e-01, -1.12815215e+00],
       [ 9.41258951e-01,  9.61451165e-01,  7.82009548e-01, ...,
         1.09894429e+00,  7.67219636e-01, -1.12815215e+00]])
```

Train Test Split

In [41]:

```
#split data into train and test.Model will be built on training data and tested on test dat

x_train,x_test,y_train,y_test=train_test_split(X_scaled,y,test_size=0.25,random_state=49)
y_train.head()
```

Out[41]:

```
401    0.66
221    0.75
110    0.61
76     0.74
195    0.78
Name: Chance of Admit, dtype: float64
```

model instantiating and training

In [42]:

```
regression=LinearRegression()
regression.fit(x_train,y_train)
```

Out[42]:

```
LinearRegression()
```

predict the chance of admission given features

In [43]:

```
data.tail(2)
```

Out[43]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
498	312.0	103.0	4.0	4.0	5.0	8.43	0	0.73
499	327.0	113.0	4.0	4.5	4.5	9.04	0	0.84

In [44]:

```
# since we have already fit the scaler,you can transform the data

print('Chance of Admission is: ', regression.predict(scaler.transform([[312.0,103.0,4.0,4.0
```

```
Chance of Admission is:  [0.70551753]
```

In [45]:

```
print('Chance of Admission is: ', regression.predict(scaler.transform([[327.0,113.0,4.0,4.5
```

```
Chance of Admission is:  [0.82582913]
```

In [46]:

```
# you can save the model and later you can use it for prediction
```

In [47]:

```
# saving the model to the local file system
filename='finalized_model.pickle'
pickle.dump(regression,open(filename,'wb'))
# prediction using the saved model
loaded_model=pickle.load(open(filename,'rb'))
a=loaded_model.predict(scaler.transform([[314,103,2,2,3,8.21,0]]))

a
```

Out[47]:

```
array([0.62816808])
```

In [48]:

```
#Adjusted R2 score
regression.score(x_train,y_train)
```

Out[48]:

```
0.8145910304382725
```

Let's check how well model fits the test data

In [49]:

```
regression.score(x_test,y_test)
```

Out[49]:

```
0.8377796652353541
```

Let's plot and visualize

In [50]:

```
y_pred=regression.predict(x_test)
```

In [51]:

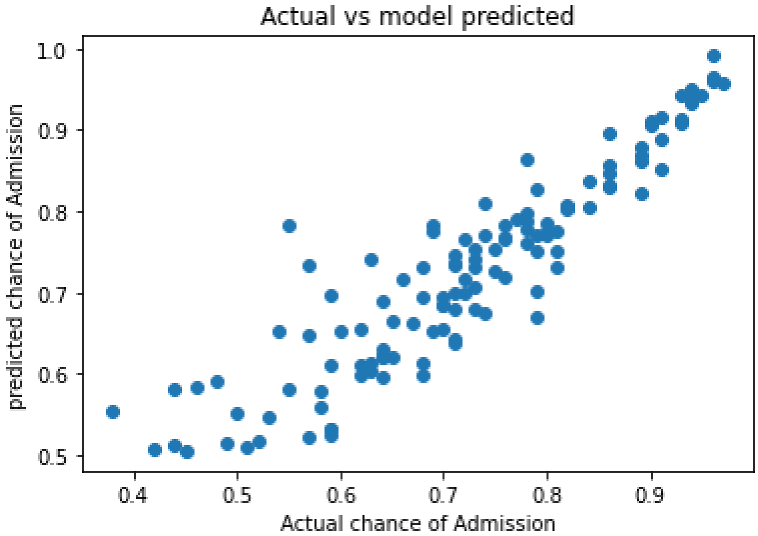
```
y_pred
```

Out[51]:

```
array([0.77592728, 0.82189355, 0.53237459, 0.53158915, 0.71913576,
       0.78296644, 0.67493981, 0.71765858, 0.95026714, 0.51343088,
       0.82749034, 0.65490214, 0.65336809, 0.69515263, 0.67870849,
       0.68422187, 0.77066709, 0.69587358, 0.61306985, 0.91270759,
       0.83613353, 0.5101666 , 0.62095565, 0.90970737, 0.67081486,
       0.91154893, 0.52166984, 0.61229555, 0.85070914, 0.83034104,
       0.50493884, 0.73415525, 0.76966228, 0.61102598, 0.79870804,
       0.58112644, 0.75399139, 0.84620015, 0.86249992, 0.75216791,
       0.65235971, 0.96012442, 0.66118549, 0.6427768 , 0.6556939 ,
       0.50748275, 0.68440277, 0.61035881, 0.51200968, 0.73397561,
       0.76162862, 0.89663454, 0.58197652, 0.9320727 , 0.59682293,
       0.71741367, 0.94389341, 0.76641482, 0.59803781, 0.78678587,
       0.76864083, 0.69049847, 0.74159936, 0.85564167, 0.77807617,
       0.74212136, 0.69536291, 0.73242447, 0.99167787, 0.96534931,
       0.66420324, 0.65200556, 0.75069108, 0.73163753, 0.67942462,
       0.80875614, 0.80406733, 0.87948903, 0.7894791 , 0.51691218,
       0.60365812, 0.88808084, 0.70551753, 0.77577971, 0.74618247,
       0.62000587, 0.55450618, 0.86895409, 0.93914717, 0.78582073,
       0.9151853 , 0.75370722, 0.76510885, 0.95759472, 0.59104282,
       0.59812655, 0.78368959, 0.73221101, 0.64712177, 0.62138309,
       0.90581763, 0.80541578, 0.83129909, 0.6228944 , 0.94569246,
       0.546378  , 0.77562982, 0.77165753, 0.578246  , 0.63875151,
       0.80283399, 0.630066  , 0.5248563 , 0.70095093, 0.55074863,
       0.55954685, 0.72612893, 0.73706486, 0.81126228, 0.69918993,
       0.8634861 , 0.58322612, 0.70006657, 0.78383877, 0.94194593])
```

In [52]:

```
plt.scatter(y_test,y_pred)
plt.xlabel('Actual chance of Admission')
plt.ylabel('predicted chance of Admission')
plt.title('Actual vs model predicted')
plt.show()
```



Model Evaluation

.Mean absolute error(MAE): Represents average error

.Mean squared error(MSE): similar to MAE but noise is exaggerated and larger errors are "punished". It is harder to interpret than MAE as it's not in base units.however ,it is generally more popular

.Root mean squared error(RMSE): Most popular metric,similar to to MSE.however the result is square rooted to make it more interpretable as it's in base units.It is recommended that RSME be used as the primary metric to interpret your model

In [53]:

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

In [54]:

```
y_pred=regression.predict(x_test)
```

In [55]:

```
mean_absolute_error(y_test,y_pred)
```

Out[55]:

```
0.039094962124450475
```

In [56]:

```
mean_squared_error(y_test,y_pred)
```

Out[56]:

```
0.0030559237967637495
```

In [57]:

```
np.sqrt(mean_squared_error(y_test,y_pred))
```

Out[57]:

```
0.05528041060596194
```

you have succesfully completed building linear regression model

In [58]:

```
# now let's check if our model is overfitting our data using regularization.
# Let's see if our model is overfitting our training data
```

Regularization

LASSO

RIDGE

ELASTICNET (Less popular)

In [ ]:

```
# LASSO(Least Absolute Shrinkage and Selection Operator) Regression (L1 Form)
# Ridge Regression (L2 form)
```

In [59]:

```
from sklearn.linear_model import Ridge,Lasso,RidgeCV,LassoCV
```

Lasso Regularization

In [60]:

```
# LassoCV will return best alpha after max iteration
# Normalize is subtrating the mean and dividing by the l2-norm

lasscv= LassoCV(alphas=None,max_iter=100,normalize=True)
lasscv.fit(x_train,y_train)
```

Out[60]:

```
LassoCV(max_iter=100, normalize=True)
```

In [61]:

```
#best alpha parameter
alpha= lasscv.alpha_
alpha
```

Out[61]:

```
2.4249979092466713e-05
```

In [62]:

```
#now that we have best parameter,Let's use lasso regression and see how well our data has f

lasso_reg=Lasso(alpha)
lasso_reg.fit(x_train,y_train)
```

Out[62]:

```
Lasso(alpha=2.4249979092466713e-05)
```

In [63]:

```
lasso_reg.score(x_test,y_test)
```

Out[63]:

```
0.8377701661591364
```

Using Ridge regression model

In [65]:

```
ridgecv = RidgeCV(alphas=np.arange(0.001,0.1,0.01),normalize=True)
ridgecv.fit(x_train,y_train)
```

Out[65]:

```
RidgeCV(alphas=array([0.001, 0.011, 0.021, 0.031, 0.041, 0.051, 0.061, 0.07
1, 0.081,
       0.091]),
        normalize=True)
```

In [66]:

```
ridgecv.alpha_
```

Out[66]:

```
0.020999999999999998
```

In [67]:

```
ridge_model=Ridge(alpha=ridgecv.alpha_)
ridge_model.fit(x_train,y_train)
```

Out[67]:

```
Ridge(alpha=0.020999999999999998)
```

In [68]:

```
ridge_model.score(x_test,y_test)
```

Out[68]:

```
0.8377744626802441
```

Type *Markdown* and LaTeX: α^2

In [ ]:

```

```