CYCLE - 4

1. Using the iris data set, implement the KNN algorithm. Take different values for the Test and training data set .Also use different values for k. Also find the accuracy level.

CODE:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset = pd.read_csv("iris.csv")

x = dataset.iloc[:,:-1].values

y = dataset.iloc[:,4].values

from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20)

from sklearn.neighbors import KNeighborsClassifier

classifier = KNeighborsClassifier(n_neighbors=5)

classifier.fit(x_train,y_train)

y_pred=classifier.predict(x_test)

from sklearn.metrics import classification_report,confusion_matrix

print(classification_report(y_test,y_pred))
```

OUTPUT:

K=5, TEST= 0.20, TRAIN= 0.80

K=3, TEST= 0.20, TRAIN= 0.80

	precision	recall	f1-score	support		precision	recall	f1-score	support
Setosa	1.00	1.00	1.00	16	Setosa	1.00	1.00	1.00	9
Versicolor	1.00	1.00	1.00	8	Versicolor	0.93	1.00	0.96	13
Virginica	1.00	1.00	1.00	6	Virginica	1.00	0.88	0.93	8
accuracy			1.00	30	accuracy			0.97	30
macro avg	1.00	1.00	1.00	30	macro avg	0.98	0.96	0.97	30
weighted avg	1.00	1.00	1.00	30	weighted avg	0.97	0.97	0.97	30

2. Download another data set suitable for the KNN and implement the KNN algorithm. Take different values for the Test and training data set .Also use different values for k.

CODE:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset = pd.read_csv("Blood Transfusion.csv")
x = dataset.iloc[:,:-1].values
y = dataset.iloc[:,4].values
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20)
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)
from sklearn.metrics import classification_report,confusion_matrix
print(classification_report(y_test,y_pred))
```

		precision	recall	f1-score	support
	Θ	0.83	0.93	0.87	120
	1	0.44	0.23	0.30	30
				0.70	450
accui	acy			0.79	150
macro	avg	0.63	0.58	0.59	150
weighted	avg	0.75	0.79	0.76	150

- 3. Using iris data set, implement naive bayes classification for different naive Bayes classification algorithms.((i) gaussian (ii) bernoulli etc)
 - Find out the accuracy level w.r.t to each algorithm
 - Display the no:of mislabeled classification from test data set
 - List out the class labels of the mismatching records
 - Gaussian

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset=pd.read csv('iris.csv')
x=dataset.iloc[:,:4].values
y=dataset['variety'].values
dataset.head(5)
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
from sklearn.naive bayes import GaussianNB
classifier=GaussianNB()
classifier.fit(x train,y train)
y pred=classifier.predict(x test)
print(y_pred)
from sklearn.metrics import confusion matrix
cm=confusion matrix(y test,y pred)
print(cm)
from sklearn.metrics import accuracy score
print("Accuracy : ",accuracy_score(y_test,y_pred))
df=pd.DataFrame({'Real values':y_test,'Predicted values':y_pred})
print(df)
```

				-	-
			16	Setosa	Setosa
			17	Versicolor	Versicolor
[ICotoool ICoto	ool Winginiaal	 Versicolor' 'Setosa' 'Virginica'	18	Setosa	Setosa
	-	color' 'Setosa' 'Virginica' 'Versicolor'	19	Versicolor	Versicolor
•	-	'Virginica' 'Setosa' 'Versicolor' 'Setosa'	20	Setosa	Setosa
		or' 'Versicolor' 'Setosa' 'Virginica'	21	Versicolor	Versicolor
'Versicolor' '	Versicolor' 'Vers	sicolor' 'Setosa' 'Virginica' 'Versicolor'	22	Versicolor	Versicolor
'Virginica' 'S	Setosa' 'Setosa'	Setosa' 'Virginica' 'Setosa' 'Setosa'	23	Setosa	Setosa
'Virginica' 'S	Setosa' 'Versicolo	or' 'Virginica' 'Setosa' 'Setosa'	24	Virginica	Virginica
'Virginica']			25	Versicolor	Versicolor
[[19 0 0]			26	Versicolor	Versicolor
[0 13 1]			27	Versicolor	Versicolor
[0 0 12]]			28	Setosa	Setosa
	7777777777777777777777 Predicted values		29	Virginica	Virginica
0 Setosa	Setosa		30	Versicolor	Versicolor
1 Setosa	Setosa		31	Virginica	Versicotor
2 Virginica	Virginica			_	-
3 Versicolor	Versicolor		32	Setosa	Setosa
4 Setosa	Setosa		33	Setosa	Setosa
5 Virginica	Virginica		34	Setosa	Setosa
6 Virginica	Virginica		35	Virginica	Virginica
7 Virginica	Virginica		36	Setosa	Setosa
8 Versicolor	Versicolor		37	Setosa	Setosa
9 Setosa	Setosa		38	Virginica	Virginica
10 Virginica	Virginica		39	Setosa	Setosa
11 Versicolor	Versicolor		40	Versicolor	Versicolor
12 Setosa13 Versicolor	Setosa Versicolor		41	Versicolor	Virginica
14 Setosa	Setosa		42	Setosa	Setosa
15 Virginica	Virginica		43	Setosa	Setosa
16 Setosa	Setosa		44	Virginica	Virginica

II. Bernoulli

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset=pd.read_csv('iris.csv')
x=dataset.iloc[:,:4].values
y=dataset['variety'].values
dataset.head(5)
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
from sklearn.naive_bayes import BernoulliNB
classifier=BernoulliNB()
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)
print(y_pred)
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,y_pred)
print(cm)
from sklearn.metrics import accuracy_score
print("Accuracy : ",accuracy_score(y_test,y_pred))
df=pd.DataFrame({'Real values':y_test,'Predicted values':y_pred})
print(df)
```

```
['Versicolor' 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor'
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor'
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor' 15 Versicolor
                                                                                 Versicolor
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor' <sup>16</sup> Setosa
                                                                                 Versicolor
                                                              17 Versicolor
                                                                                 Versicolor
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor'
                                                              18 Versicolor
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor'
                                                               19 Virginica
                                                                                 Versicolor
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor'
                                                               20 Versicolor
                                                                                 Versicolor
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor'
                                                               21 Versicolor
                                                                                 Versicolor
 'Versicolor' 'Versicolor' 'Versicolor' 'Versicolor']
                                                               22 Versicolor
                                                                                 Versicolor
[[ 0 15 0]
                                                               23
                                                                      Setosa
                                                                                 Versicolor
[ 0 13 0]
                                                               24 Virginica
                                                                                 Versicolor
[ 0 17 0]]
                                                               25 Versicolor
                                                                                 Versicolor
Accuracy: 0.2888888888888888
                                                                  Virginica
                                                                                 Versicolor
                                                                   Virginica
                                                                                 Versicolor
  Real values Predicted values
                                                                                 Versicolor
                                                               28 Virginica
Θ
      Setosa Versicolor
                                                               29 Virginica
                                                                                 Versicolor
1 Virginica
                 Versicolor
                                                               30 Versicolor
                                                                                 Versicolor
2
   Virginica
                 Versicolor
                                                               31 Virginica
                                                                                 Versicolor
3
       Setosa
                   Versicolor
                                                               32
                                                                      Setosa
                                                                                 Versicolor
4 Versicolor
                  Versicolor
                                                               33 Virginica
                                                                                 Versicolor
5 Versicolor
                  Versicolor
                                                                     Setosa
                                                                                 Versicolor
                  Versicolor
   Virginica
6
                                                               35
                                                                     Setosa
                                                                                 Versicolor
7
   Virginica
                  Versicolor
                                                               36
                                                                     Setosa
                                                                                 Versicolor
8
      Setosa
                   Versicolor
                                                               37
                                                                      Setosa
                                                                                 Versicolor
   Virginica
9
                  Versicolor
                                                               38 Virginica
                                                                                 Versicolor
10 Versicolor
                  Versicolor
                                                               39 Virginica
                                                                                 Versicolor
11
       Setosa
                  Versicolor
                                                               40 Versicolor
                                                                                 Versicolor
12
       Setosa
                   Versicolor
                                                               41
                                                                                 Versicolor
13
                  Versicolor
                                                                   Virginica
                                                                                 Versicolor
       Setosa
                                                               43
                                                                      Setosa
                                                                                 Versicolor
14 Virginica
                  Versicolor
                                                               44 Versicolor
                                                                                 Versicolor
15 Versicolor
                 Versicolor
```

- 4. Use car details CSV file and implement decision tree algorithm
 - Find out the accuracy level.
 - Display the no: of mislabelled classification from test data set
 - · List out the class labels of the mismatching records

```
import pandas as pd
data = pd.read csv('car.csv')
print(data.head())
col_names = ['buying','maint','doors','persons','lug_boot','safety','class']
data.columns = col names
print(col names)
#The decision trees implemented in scikit-learn uses only numerical
# features and these features are interpreted
# always as continuous numeric variables.
# pandas.factorize() method helps to get the numeric representation
# of an array by identifying distinct values
data['class'],class_names = pd.factorize(data['class'])
data['buying'],_ = pd.factorize(data['buying'])
data['maint'],_ = pd.factorize(data['maint'])
data['doors'],_ = pd.factorize(data['doors'])
data['persons'], = pd.factorize(data['persons'])
data['lug_boot'],_ = pd.factorize(data['lug_boot'])
data['safety'],_ = pd.factorize(data['safety'])
print(data.head())
x = data.iloc[:, :-1]
#print(x)
y = data.iloc[:, -1]
#print(y)
from sklearn.model_selection import train_test_split
x train, x test, y train, y test = train test split(x,y,test size=0.3)
from sklearn.tree import DecisionTreeClassifier
tree1 = DecisionTreeClassifier()
tree1.fit(x train,y train)
y_pred = tree1.predict(x_test)
#how did our model perform?
```

```
count_missclassified = (y_test != y_pred).sum()
print('Misclassified samples count : ',count_missclassified)
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test,y_pred)
print("Accuracy",accuracy)
```

```
vhigh vhigh.1 2 2.1 small
                             low unacc
0 vhigh vhigh 2
                   2 small
                             med unacc
1 vhigh vhigh 2
                   2 small high unacc
2 vhigh vhigh 2
                   2
                        med
                             low unacc
3 vhigh vhigh 2
                   2
                        med
                             med unacc
4 vhigh vhigh 2
                   2
                        med high unacc
['buying', 'maint', 'doors', 'persons', 'lug_boot', 'safety', 'class']
  buying maint doors persons lug_boot safety class
Θ
       Θ
             Θ
                   Θ
                            Θ
                                     Θ
                                            Θ
                                                  Θ
1
       Θ
             Θ
                   Θ
                                     Θ
                                            1
                                                  Θ
                            Θ
                                                  Θ
3
       Θ
             Θ
                   Θ
                            Θ
                                     1
                                            0
                                                  Θ
                    Θ
                                     1
                                            1
                                                  Θ
       Θ
             0
                            Θ
Misclassified samples count: 16
```

Accuracy 0.9691714836223507

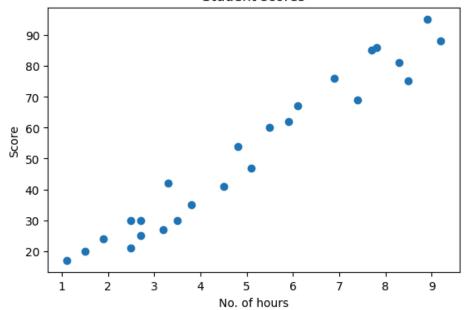
5. Implement Simple and multiple linear regression for the data sets 'student_score.csv' and 'company_data .csv' respectively

CODE (Single linear Regression):

```
import numpy as np
import pandas as pd
student = pd.read csv('student scores.csv')
print(student.head())
student.describe()
student.info()
import matplotlib.pyplot as plt
Xax = student.iloc[:,0]
Yax = student.iloc[:,1]
plt.scatter(Xax,Yax)
plt.xlabel("No. of hours")
plt.ylabel("Score")
plt.title("Student scores")
plt.show()
x = student.iloc[:,:-1]
y = student.iloc[:,1]
print('x values : ')
print(x)
print('y values : ')
print(y)
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)
print(x_train)
from sklearn.linear model import LinearRegression
regressor = LinearRegression()
regressor.fit(x_train,y_train)
print('INTERCEPT = ',regressor.intercept )
print('CO-EFFICIENT = ',regressor.coef_)
y pred = regressor.predict(x test)
for(i,j) in zip(y_test,y_pred):
   if(i!=j):
       print("Actual value : ",i,"Predicted value : ",j)
print("Number of mislabeled points from test data set : ", (y test !=
y pred).sum())
```

```
12
                                          4.5
                                                        7.4
   Hours Scores
                                         3.3
                                                        9.2
    2.5
           21
                                                        7.7
    5.1
             47
                                     15
                                           8.9
    3.2
                                     16
                                          2.5
                                                        3.2
    8.5
                                     17
                                          1.9
                                                   20
                                                        2.7
             30
    3.5
<class 'pandas.core.frame.DataFrame'> 18
                                          6.1
                                                   22
                                                        3.8
                                          7.4
                                     19
                                                   1
                                                        5.1
RangeIndex: 25 entries, 0 to 24
                                     20
                                          2.7
                                                        3.5
Data columns (total 2 columns):
                                     21
                                           4.8
                                                   14
                                                        1.1
# Column Non-Null Count Dtype
                                     22
                                           3.8
                                                   8
                                                        8.3
    ----- ------ -----
                                     23
                                           6.9
                                                   23
                                                        6.9
                           float64
0
    Hours 25 non-null
                                     24
                                           7.8
                                                   24
                                                        7.8
1
    Scores 25 non-null
                         int64
                                     y values :
                                                        1.5
dtypes: float64(1), int64(1)
                                           21
                                                   18
                                                        6.1
memory usage: 528.0 bytes
                                     1
                                           47
                                                   16
                                                        2.5
x values :
                                     2
                                           27
                                                   15
                                                        8.9
   Hours
                                     3
                                           75
                                                   21
                                                        4.8
     2.5
Θ
                                     4
                                           30
                                                   17
                                                        1.9
1
     5.1
                                     5
                                           20
                                                        5.5
2
     3.2
                                           88
                                                   INTERCEPT = 2.612204693008323
3
     8.5
                                           60
                                                   CO-EFFICIENT = [9.93021104]
     3.5
                                     8
                                           81
                                                   Actual value : 75 Predicted value : 87.01899854838967
     1.5
                                           25
                                                   Actual value : 25 Predicted value : 29.423774505894166
     9.2
                                          85
                                     10
                                                   Actual value : 42 Predicted value : 35.381901130979905
7
     5.5
                                          62
                                     11
                                                   Actual value : 41 Predicted value : 47.29815438115139
     8.3
                                     12
                                          41
                                                   Actual value : 21 Predicted value : 27.43773229753225
     2.7
                                     13
                                          42
                                                   Number of mislabeled points from test data set : 5
     7.7
                                          17
                                                   Mean Absolute error : 7.159351720397515
                                     14
     5.9
                                     15
                                          95
                                                   Mean Squared error : 57.78729707376474
     4.5
                                           30
                                                   Root Mean Squared error : 7.6017956479877
                                     16
```

Student scores



CODE (Multiple linear regression):

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
advertising = pd.read csv('Company data.csv')
advertising.head()
advertising.describe()
advertising.info()
print("Feature values : ")
x = advertising.iloc[:, :-1]
print(x)
print("Target variable values : ")
y = advertising.iloc[:, -1]
print(y)
from sklearn.model selection import train test split
x train,x test,y train,y test = train test split(x,y,test size=0.3)
from sklearn.linear model import LinearRegression
regressor = LinearRegression()
regressor.fit(x train,y train)
print("intercept is : ")
print(regressor.intercept )
print("Co-efficients are : ")
print(regressor.coef )
y pred = regressor.predict(x test)
for(i,j) in zip(y_test,y_pred):
   if i!=j:
       print("Actual values : ",i," Predicted values : ",j)
print("Number of mislabeled points from test data set : ",(y test !=
y pred).sum())
#MSE, MAE, RMSE and R-Squared are mainly used metrics to evaluate
#the prediction error rates and model performance in regression
analysis.
from sklearn import metrics
print("Mean Absolute error :",
metrics.mean_absolute_error(y_test,y_pred))
print("Mean Squared error :", metrics.mean_squared_error(y_test,y_pred))
```

```
print("Root Mean Squared error :",
np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

```
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
                                              [200 rows x 3 columns]
 # Column Non-Null Count Dtype
                                              Target variable values :
--- -----
                 -----
                                                        22.1
     TV
                 200 non-null float64
                200 non-null float64 f 1
                                                        10.4
     Radio
 2 Newspaper 200 non-null float64 2
                                                        12.0
                 200 non-null float64 3
                                                      16.5
dtypes: float64(4)
                                                      17.9
memory usage: 6.4 KB
                                                        . . .
Feature values :
         TV Radio Newspaper
                                              195
                                                        7.6
     230.1 37.8 69.2
                                              196
                                                        14.0
    44.5 39.3
1
                         45.1
                                              197
                                                        14.8
      17.2 45.9
                          69.3
                                              198
                                                        25.5
3
   151.5 41.3
                        58.5
   180.8 10.8
                                              199
                                                        18.4
                         58.4
      . . . .
               . . .
                          . . . .
                                              Name: Sales, Length: 200, dtype: float64
195 38.2 3.7
                         13.8
                                              intercept is :
196 94.2 4.9
                         8.1
                                              4.528450435723583
             9.3
197 177.0
                          6.4
198 283.6 42.0
                                              Co-efficients are :
                           66.2
199 232.1 8.6
                           8.7
                                               [ 0.05466747  0.1117412  -0.0002813 ]
Actual values : 14.0 Predicted values : 13.447976708088397
Actual values : 16.0 Predicted values : 18.318509452905268
Actual values : 17.0 Predicted values : 18.939637902572528
Actual values : 17.2 Predicted values : 16.409281011965177
Actual values : 16.0 Predicted values : 15.0990544646798
Actual values : 22.3 Predicted values : 21.278146220965652
Actual values : 6.9 Predicted values : 6.204768961696529
Actual values: 1.6 Predicted values: 8.989222053373664
Actual values : 17.4 Predicted values : 18.94622073271653
Actual values : 6.6 Predicted values : 9.287355769826737
Actual values : 10.6 Predicted values : 10.60671466067842
Actual values : 12.0 Predicted values : 11.767960988436206
Actual values : 10.9 Predicted values : 11.105637500633627
Actual values: 13 2 Predicted values: 10 00130165618592
Actual values : 11.0 Predicted values : 8.998690627131847
Actual values : 20.8 Predicted values : 22.703465125752615
Actual values : 8.7 Predicted values : 8.229332686829284
Actual values : 19.9 Predicted values : 16.843116971804193
Actual values : 21.5 Predicted values : 21.196276213226028
Actual values : 20.2 Predicted values : 21.476724859954288
Actual values : 25.5 Predicted values : 24.70665444012566
Actual values : 16.6 Predicted values : 18.08155360471116
Actual values : 23.2 Predicted values : 22.275233287701035
Actual values : 21.8 Predicted values : 21.98121841035531
Actual values : 11.8 Predicted values : 11.682262577123913
Actual values : 17.6 Predicted values : 14.693845221839664
Actual values : 15.9 Predicted values : 15.50112329945018
Actual values : 5.6 Predicted values : 7.01279372196412
Actual values : 22.6 Predicted values : 21.00696045154617
Actual values : 9.7 Predicted values : 9.115402255705765
Actual values : 13.2 Predicted values : 13.286345287949693
```

```
Actual values : 14.6 Predicted values : 15.24621124737743
Actual values: 10.3 Predicted values: 12.408073568263916
Actual values : 10.9 Predicted values : 10.43701469882918
Actual values: 13.4 Predicted values: 13.761007711902913
Actual values : 26.2 Predicted values : 25.035490254857223
Actual values : 10.4 Predicted values : 11.339895688395877
Actual values : 25.4 Predicted values : 25.07786790253533
Actual values : 18.0 Predicted values : 17.576577079105668
Actual values : 16.7 Predicted values : 15.857709761004456
Actual values: 17.6 Predicted values: 20.774703878787804
Actual values: 14.0 Predicted values: 12.415207950084081
Actual values : 23.8 Predicted values : 24.7597120988801
Actual values: 12.9 Predicted values: 13.77446187102004
Actual values : 12.4 Predicted values : 12.119921031778599
Actual values : 16.7 Predicted values : 14.524214898408742
Actual values: 19.6 Predicted values: 18.339102949129643
Actual values : 20.7 Predicted values : 21.381475079685885
Actual values : 22.1 Predicted values : 21.311787638919434
Actual values: 19.8 Predicted values: 20.96884287777423
Actual values : 13.6 Predicted values : 13.230174929788635
Actual values : 25.4 Predicted values : 24.01205740712085
Actual values: 13.3 Predicted values: 13.199919922631574
Actual values : 14.8 Predicted values : 15.2419861468864
Actual values : 21.4 Predicted values : 23.69067735979671
Actual values: 12.0 Predicted values: 10.578158129553994
Actual values : 19.6 Predicted values : 20.27500482966528
Actual values: 11.3 Predicted values: 9.339446148742997
Number of mislabeled points from test data set : 60
```

Mean Absolute error : 1.2607485335180788

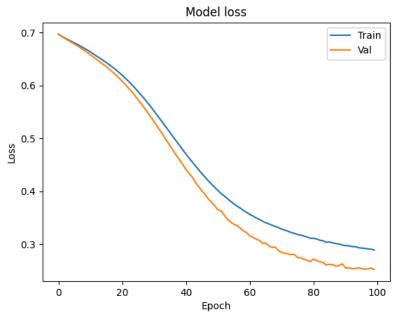
Mean Squared error : 2.932494017740453

Root Mean Squared error : 1.712452632261825

6. Create a neural network for the given 'houseprice.csv' to predict the weather price of the house is above or below median value or not

```
import tensorflow as tf
import keras
import pandas
import sklearn
import matplotlib
import pandas as pd
df = pd.read csv('housepricedata.csv')
print(df.head())
dataset = df.values
X = dataset[:, 0:10]
Y = dataset[:,10]
from sklearn import preprocessing
min max scaler = preprocessing.MinMaxScaler()
X scale = min max_scaler.fit_transform(X)
print(X scale)
from sklearn.model selection import train test split
X train, X val and test, Y train, Y val and test = train test split(X scale,
Y, test size=0.3)
X_val, X_test, Y_val, Y_test = train_test_split(X_val_and_test,
Y val and test, test size=0.5)
print(X_train.shape, X_val.shape, X_test.shape, Y_train.shape, Y_val.shape,
Y test.shape)
from keras.models import Sequential
from keras.layers import Dense
model = Sequential([Dense(32, activation='relu', input shape=(10,)), Dense(32,
activation='relu'),Dense(1, activation='sigmoid'),])
model.compile(optimizer='sgd', loss='binary crossentropy',
metrics=['accuracy'])
hist = model.fit(X_train, Y_train, batch_size=32, epochs=100,
validation_data=(X_val, Y_val))
model.evaluate(X_test, Y_test)[1]
import matplotlib.pyplot as plt
plt.plot(hist.history['loss'])
```

```
plt.plot(hist.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```



```
Eile <u>E</u>dit <u>V</u>iew <u>N</u>avigate <u>C</u>ode <u>R</u>efactor R<u>u</u>n <u>T</u>ools VC<u>S W</u>indow <u>H</u>elp
Cycle - 5) 🐇 neural_network.py
       neural_network.py ×
            LotArea OverallQual OverallCond ... Fireplaces GarageArea AboveMedianPrice 8450 7 5 ... 0 548 1
                                            5 ...
8 ...
                                                                       548
460
                                            5 ...
5 ...
              11250
                                                                       608
               9558
         [5 rows x 11 columns]
         ... 0.5 0. 0.3864598 ]
... 0.33333333 0.33333333 0.32440056]
          [0.04650728 0.66666667 0.5
                                            ... 0.33333333 0.33333333 0.42877292]
          [8.83618687 8.66666667 1.
[8.83934189 8.4444444 8.625
                                            ... 0.58333333 0.66666667 0.17771509]
                                            ... 0.25
                                              .. 0.33333333 0.
          [8.84837819 8.4444444 8.625
                                                                      0.1946403411
         (1822, 18) (219, 18) (219, 18) (1822,) (219,) (219,)
Epoch 1/188
         32/32 [=======
                                   :=======] - 1s 6ms/step - loss: 0.6969 - accuracy: 0.4276 - val_loss: 0.6971 - val_accuracy: 0.4429
         Epoch 2/100
32/32 [=====
Epoch 3/100
                                      :======] - 0s 1ms/step - loss: 0.6933 - accuracy: 0.4843 - val_loss: 0.6930 - val_accuracy: 0.4977
         32/32 [================================ ] - 0s 1ms/step - loss: 0.6898 - accuracy: 0.5783 - val_loss: 0.6890 - val_accuracy: 0.6119
         Epoch 4/100
32/32 [====
                                             ==] - 0s 1ms/step - loss: 0.6866 - accuracy: 0.6693 - val_loss: 0.6854 - val_accuracy: 0.7078
         Epoch 5/100
          32/32 [=======
                                       ======] - 0s 1ms/step - loss: 0.6835 - accuracy: 0.7436 - val_loss: 0.6819 - val_accuracy: 0.8174
         Epoch 7/100
          32/32 [=========
                                  =======] - 0s 2ms/step - loss: 0.6774 - accuracy: 0.7828 - val_loss: 0.6748 - val_accuracy: 0.8311
         Epoch 8/188
                                                                                                                                             14:42 LF UTF-8 4 spaces Python 3.8 (Cycle - 5) 🚡
```

