kNN

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

```
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))
```

```
              precision    recall  f1-score   support

      Setosa       1.00      1.00      1.00        10
  Versicolor       1.00      0.91      0.95        11
   Virginica       0.90      1.00      0.95         9

    accuracy                           0.97        30
   macro avg       0.97      0.97      0.97        30
weighted avg       0.97      0.97      0.97        30
```

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})

```
Accuracy :  0.9666666666666667
```

Reference: https://stackabuse.com/k-nearest-neighbors-algorithm-in-python-and-scikit-learn/

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

import numpy as np

import matplotlib.pyplot as plt

import pandas as pd

dataset = pd.read_csv("cancer.csv")

dataset.head()

dataset.info()

X = dataset.iloc[:, 2:35].values

print(X)

y = dataset.iloc[:, 1].values

print(y)

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 568 entries, 0 to 567
Data columns (total 32 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   842302    568 non-null    int64  
 1   M         568 non-null    object 
 2   17.99     568 non-null    float64
 3   10.38     568 non-null    float64
 4   122.8     568 non-null    float64
 5   1001      568 non-null    float64
 6   0.1184    568 non-null    float64
 7   0.2776    568 non-null    float64
 8   0.3001    568 non-null    float64
 9   0.1471    568 non-null    float64
 10  0.2419    568 non-null    float64
 11  0.07871   568 non-null    float64
 12  1.095     568 non-null    float64
 13  0.9053    568 non-null    float64
 14  8.589     568 non-null    float64
 15  153.4     568 non-null    float64
 16  0.006399  568 non-null    float64
 17  0.04904   568 non-null    float64
 18  0.05373   568 non-null    float64
 19  0.01587   568 non-null    float64
 20  0.03003   568 non-null    float64
 21  0.006193  568 non-null    float64
 22  25.38     568 non-null    float64
 23  17.33     568 non-null    float64
 24  184.6     568 non-null    float64
 25  2019      568 non-null    float64
 26  0.1622    568 non-null    float64
 27  0.6656    568 non-null    float64
 28  0.7119    568 non-null    float64
 29  0.2654    568 non-null    float64
 30  0.4601    568 non-null    float64
 31  0.1189    568 non-null    float64
dtypes: float64(30), int64(1), object(1)
memory usage: 142.1+ KB
```

```
memory usage: 142.1+ KB
[[2.057e+01 1.777e+01 1.329e+02 ... 1.860e-01 2.750e-01 8.902e-02]
 [1.969e+01 2.125e+01 1.300e+02 ... 2.430e-01 3.613e-01 8.758e-02]
 [1.142e+01 2.038e+01 7.758e+01 ... 2.575e-01 6.638e-01 1.730e-01]
 ...
 [1.660e+01 2.808e+01 1.083e+02 ... 1.418e-01 2.218e-01 7.820e-02]
 [2.060e+01 2.933e+01 1.401e+02 ... 2.650e-01 4.087e-01 1.240e-01]
 [7.760e+00 2.454e+01 4.792e+01 ... 0.000e+00 2.871e-01 7.039e-02]]
['M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M' 'M'
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 'M' 'B' 'M' 'B' 'M' 'M' 'B' 'M' 'M' 'B' 'B' 'M' 'B' 'B' 'M' 'B' 'B' 'B'
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 'B' 'B' 'B' 'B' 'M' 'M' 'B' 'M' 'M' 'M' 'B' 'M' 'M' 'B' 'B' 'B' 'B' 'B'
 'M' 'B' 'B' 'B' 'B' 'B' 'M' 'B' 'B' 'B' 'M' 'B' 'B' 'M' 'M' 'B' 'B' 'B'
 'B' 'B' 'B' 'M' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'M' 'B' 'B' 'B' 'B' 'B' 'M'
 'B' 'B' 'M' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'M' 'B' 'M'
 'M' 'B' 'M' 'B' 'B' 'B' 'B' 'B' 'M' 'B' 'B' 'M' 'B' 'M' 'B' 'B' 'M' 'B'
 'M' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'M' 'M' 'B' 'B' 'B' 'B' 'B' 'B' 'M'
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 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'M' 'B' 'M' 'M' 'B' 'B' 'B' 'B'
 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B' 'B'
 'B' 'B' 'B' 'M' 'M' 'M' 'M' 'M' 'M' 'B']
```

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

           B       0.97      0.96      0.97        75
           M       0.93      0.95      0.94        39

    accuracy                           0.96       114
   macro avg       0.95      0.95      0.95       114
weighted avg       0.96      0.96      0.96       114
```

```
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})
```

```
Accuracy :  0.956140350877193
```

Naive Bayes

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**

```
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)

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

---

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)

from sklearn.naive_bayes import GaussianNB

classifier = GaussianNB()

classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)

y_pred

```
array(['Versicolor', 'Setosa', 'Versicolor', 'Versicolor', 'Virginica',
       'Versicolor', 'Virginica', 'Versicolor', 'Versicolor', 'Virginica',
       'Virginica', 'Setosa', 'Setosa', 'Versicolor', 'Virginica',
       'Versicolor', 'Versicolor', 'Versicolor', 'Setosa', 'Setosa',
       'Versicolor', 'Setosa', 'Setosa', 'Versicolor', 'Setosa',
       'Virginica', 'Setosa', 'Virginica', 'Virginica', 'Versicolor'],
      dtype='<U10')
```

---

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred)

from sklearn.metrics import accuracy_score

print ("Accuracy : ", accuracy_score(y_test, y_pred)) cm

```
Accuracy :  0.9666666666666667

array([[ 9,  0,  0],
       [ 0, 13,  1],
       [ 0,  0,  7]], dtype=int64)
```

df = pd.DataFrame({'Real Values':y_test, 'Predicted Values':y_pred})

df

	Real Values	Predicted Values
0	Versicolor	Versicolor
1	Setosa	Setosa
2	Versicolor	Versicolor
3	Versicolor	Versicolor
4	Virginica	Virginica
5	Versicolor	Versicolor
6	Virginica	Virginica
7	Versicolor	Versicolor
8	Versicolor	Versicolor
9	Versicolor	Virginica
10	Virginica	Virginica
11	Setosa	Setosa
12	Setosa	Setosa
13	Versicolor	Versicolor
14	Virginica	Virginica
15	Versicolor	Versicolor
16	Versicolor	Versicolor
17	Versicolor	Versicolor
18	Setosa	Setosa
19	Setosa	Setosa
20	Versicolor	Versicolor
21	Setosa	Setosa
22	Setosa	Setosa
23	Versicolor	Versicolor
24	Setosa	Setosa
25	Virginica	Virginica
26	Setosa	Setosa
27	Virginica	Virginica
28	Virginica	Virginica
29	Versicolor	Versicolor

References:

- https://towardsdatascience.com/machine-learning-basics-naive-bayes-classification-964af6f2a965
- https://scikit-learn.org/stable/modules/classes.html#module-sklearn.naive_bayes

Decision Tree

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 os
import numpy as np
import pandas as pd
import numpy as np, pandas as pd
import matplotlib.pyplot as plt
from sklearn import tree, metrics, model_selection

data = pd.read_csv('car.csv',names=['buying','maint','doors','persons','lug_boot','safety','class'])
data.head()
```

	buying	maint	doors	persons	lug_boot	safety	class
0	vhigh	vhigh	2	2	small	low	unacc
1	vhigh	vhigh	2	2	small	med	unacc
2	vhigh	vhigh	2	2	small	high	unacc
3	vhigh	vhigh	2	2	med	low	unacc
4	vhigh	vhigh	2	2	med	med	unacc

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1728 entries, 0 to 1727
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   buying    1728 non-null   object
 1   maint     1728 non-null   object
 2   doors     1728 non-null   object
 3   persons   1728 non-null   object
 4   lug_boot  1728 non-null   object
 5   safety    1728 non-null   object
 6   class     1728 non-null   object
dtypes: object(7)
memory usage: 94.6+ KB
```

```
data['class'],class_names = pd.factorize(data['class'])
```

```
print(class_names)
print(data['class'].unique())
```

```
Index(['unacc', 'acc', 'vgood', 'good'], dtype='object')
[0 1 2 3]
```

```
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'])
data.head()
```

	buying	maint	doors	persons	lug_boot	safety	class
0	0	0	0	0	0	0	0
1	0	0	0	0	0	1	0
2	0	0	0	0	0	2	0
3	0	0	0	0	1	0	0
4	0	0	0	0	1	1	0

data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1728 entries, 0 to 1727
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   buying    1728 non-null   int64
 1   maint     1728 non-null   int64
 2   doors     1728 non-null   int64
 3   persons   1728 non-null   int64
 4   lug_boot  1728 non-null   int64
 5   safety    1728 non-null   int64
 6   class     1728 non-null   int64
dtypes: int64(7)
memory usage: 94.6 KB
```

X = data.iloc[:,:-1]

y = data.iloc[:,-1]

split data randomly into 70% training and 30% test

X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0.3, random_state=0)

train the decision tree

```
dtree = tree.DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=0)
dtree.fit(X_train, y_train)
```

```
DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=0)
```

```
# use the model to make predictions with the test data
y_pred = dtree.predict(X_test)
# how did our model perform?
accuracy = metrics.accuracy_score(y_test, y_pred)
print('Accuracy: {:.2f}'.format(accuracy))
```

```
Accuracy: 0.82
```

```
count_misclassified = (y_test != y_pred).sum()
print('Misclassified samples: {}'.format(count_misclassified))
```

```
Misclassified samples: 96
```

Single Linear Regression

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
#data set contains details of no.of hours spend by students for studt and their marks
student = pd.read_csv('student_scores.csv')
student.head()
```

	Hours	Scores
0	2.5	21
1	5.1	47
2	3.2	27
3	8.5	75
4	3.5	30

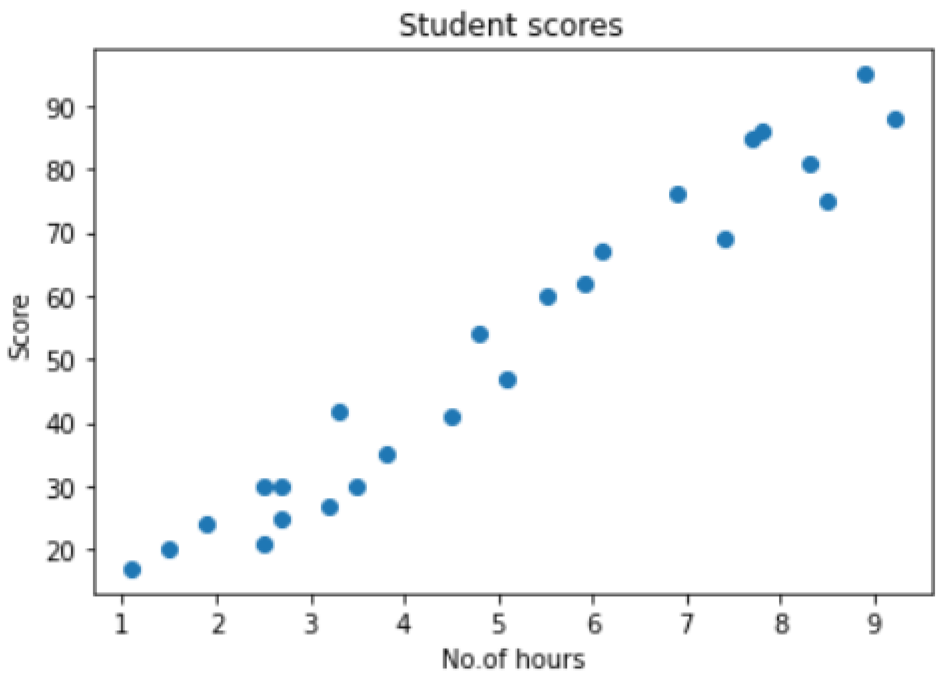
student.describe()

	Hours	Scores
count	25.000000	25.000000
mean	5.012000	51.480000
std	2.525094	25.286887
min	1.100000	17.000000
25%	2.700000	30.000000
50%	4.800000	47.000000
75%	7.400000	75.000000
max	9.200000	95.000000

student.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25 entries, 0 to 24
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Hours   25 non-null     float64
 1   Scores  25 non-null     int64
dtypes: float64(1), int64(1)
memory usage: 528.0 bytes
```

```
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()
```



#Perform the simple linear regression model

#Equation: Y=w0+w1.x

#Here Y(marks)=w0+w1.x

#Create x as hours and Y as marks

X = student.iloc[:, :-1]

y = student.iloc[:, 1]

print(X)

```
    Hours
0     2.5
1     5.1
2     3.2
3     8.5
4     3.5
5     1.5
6     9.2
7     5.5
8     8.3
9     2.7
10    7.7
11    5.9
12    4.5
13    3.3
14    1.1
15    8.9
16    2.5
17    1.9
18    6.1
19    7.4
20    2.7
21    4.8
22    3.8
23    6.9
24    7.8
```

print(y)

```
0     21
1     47
2     27
3     75
4     30
5     20
6     88
7     60
8     81
9     25
10    85
11    62
12    41
13    42
14    17
15    95
16    30
17    24
18    67
19    69
20    30
21    54
22    35
23    76
24    86
Name: Scores, dtype: int64
```

```
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)
```

```
    Hours
0   2.5
18  6.1
11  5.9
5   1.5
15  8.9
16  2.5
12  4.5
21  4.8
1   5.1
14  1.1
7   5.5
19  7.4
24  7.8
4   3.5
23  6.9
17  1.9
13  3.3
20  2.7
3   8.5
6   9.2
```

```
from sklearn.linear_model import LinearRegression

regressor = LinearRegression()

regressor.fit(X_train, y_train)
```

```
LinearRegression()
```

```
print(regressor.intercept_)
```

```
4.505813953488371
```

```
print(regressor.coef_)
```

```
[9.47674419]
```

```
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())
```

```
Actual value : 27 Predicted value : 34.831395348837205
Actual value : 35 Predicted value : 40.51744186046511
Actual value : 81 Predicted value : 83.16279069767442
Actual value : 85 Predicted value : 77.47674418604652
Actual value : 25 Predicted value : 30.093023255813954
Number of mislabeled points from test data set : 5
```

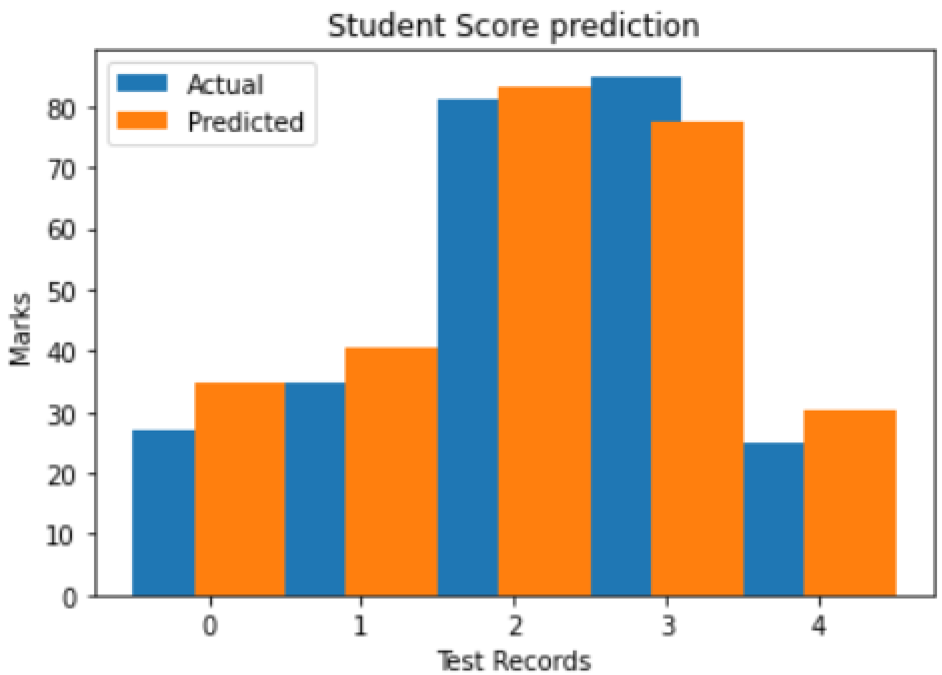
```
from sklearn import metrics
print("Mean Absolute error :", metrics.mean_absolute_error(y_test,y_pred))
print("Mean Squared error :", metrics.mean_squared_error(y_test,y_pred))
print("Root Mean Squared error :", np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

```
Mean Absolute error : 5.625581395348836
Mean Squared error : 35.79776906435908
Root Mean Squared error : 5.983123687870666
```

```
import matplotlib.pyplot as plt
c=X_test['Hours'].count()
xax=np.arange(c)
```

```
print(xax)

X_axis = np.arange(len(xax))

plt.bar(X_axis-0.2, y_test, 0.6, label='Actual')

plt.bar(X_axis+0.2, y_pred, 0.6, label='Predicted')

plt.xlabel("Test Records")

plt.ylabel("Marks")

plt.title("Student Score prediction")

plt.legend()

plt.show()
```

```
[0 1 2 3 4]
```



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()

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9

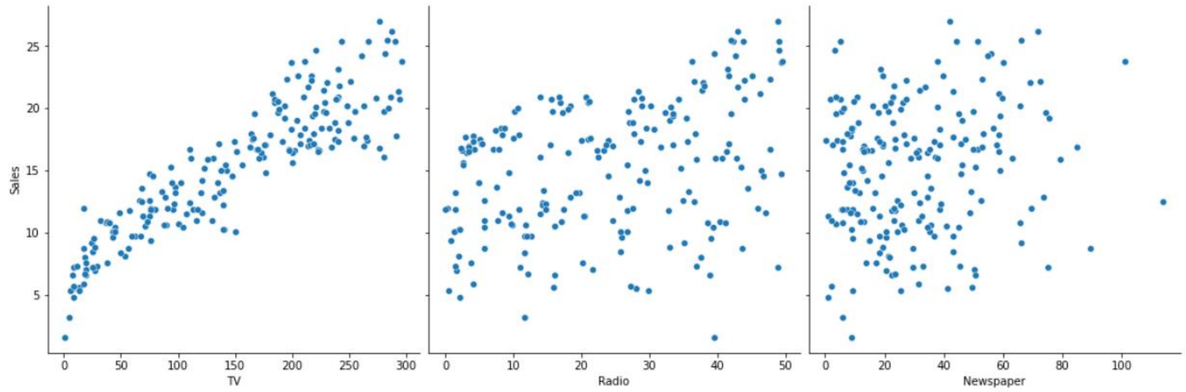
advertising.describe()

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

advertising.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   TV         200 non-null    float64
 1   Radio      200 non-null    float64
 2   Newspaper  200 non-null    float64
 3   Sales      200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB
```

```
import matplotlib.pyplot as plt

import seaborn as sns

sns.pairplot(advertising, x_vars=['TV', 'Radio', 'Newspaper'],

        y_vars='Sales', height=5, aspect=1, kind='scatter')

plt.show()
```




```
#perform the multiple linear regression model

#Equation : Y=w0+w1.x1 + w2.x2 + w3.x3

#Here Y(sales)=w0+w1.x1(TV)+w2.x2(Radio)+w3.x3(Newspaper)

#create x and Y as sales

X = advertising.iloc[:, :-1]
```

```
print(X)
```

```
        TV  Radio  Newspaper
0    230.1   37.8       69.2
1     44.5   39.3       45.1
2     17.2   45.9       69.3
3    151.5   41.3       58.5
4    180.8   10.8       58.4
..     ...    ...        ...
195   38.2    3.7       13.8
196   94.2    4.9        8.1
197  177.0    9.3        6.4
198  283.6   42.0       66.2
199  232.1    8.6        8.7

[200 rows x 3 columns]
```

```
y = advertising.iloc[:, -1]
print(y)
```

```
0      22.1
1      10.4
2      12.0
3      16.5
4      17.9
       ...
195     7.6
196    14.0
197    14.8
198    25.5
199    18.4
Name: Sales, Length: 200, dtype: float64
```

```
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)
```

print(X_train)

```
      TV  Radio  Newspaper
110  225.8    8.2       56.5
35   290.7    4.1        8.5
93   250.9   36.5       72.3
34    95.7    1.4        7.4
33   265.6   20.0        0.3
..     ...    ...        ...
46    89.7    9.9       35.7
41   177.0   33.4       38.7
154  187.8   21.1        9.5
155    4.1   11.6        5.7
145  140.3    1.9        9.0

[140 rows x 3 columns]
```

from sklearn.linear_model import LinearRegression

regressor = LinearRegression()

regressor.fit(X_train, y_train)

```
LinearRegression()
```

print(regressor.intercept_)

```
4.780074764277845
```

print(regressor.coef_)

```
[ 0.05279519  0.11509193 -0.00387093]
```

```
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())
```

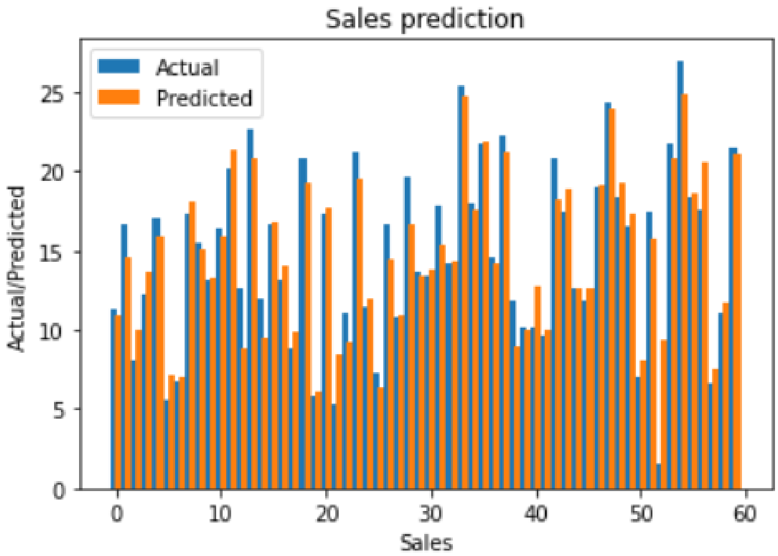
```
Actual value : 11.3 Predicted value : 10.966113994467026
Actual value : 16.7 Predicted value : 14.527277208391718
Actual value : 8.0 Predicted value : 9.968953413183009
Actual value : 12.2 Predicted value : 13.675884658838232
Actual value : 17.1 Predicted value : 15.819315834150443
Actual value : 5.6 Predicted value : 7.114935130854711
Actual value : 6.7 Predicted value : 7.069377609028534
Actual value : 17.3 Predicted value : 18.101923896386566
Actual value : 15.5 Predicted value : 15.1456626548412
Actual value : 13.2 Predicted value : 13.336956187345159
Actual value : 16.4 Predicted value : 15.851572230620034
Actual value : 20.2 Predicted value : 21.291597447352572
Actual value : 12.6 Predicted value : 8.84369386890375
Actual value : 22.6 Predicted value : 20.850999610728728
Actual value : 12.0 Predicted value : 9.497482368655788
Actual value : 16.7 Predicted value : 16.82384903279395
Actual value : 13.2 Predicted value : 14.116287882918703
Actual value : 8.8 Predicted value : 9.918310874223506
Actual value : 20.9 Predicted value : 19.28959183675782
Actual value : 5.9 Predicted value : 6.0377077618576465
Actual value : 17.3 Predicted value : 17.76940195974936
Actual value : 5.3 Predicted value : 8.470030904269402
Actual value : 11.0 Predicted value : 9.265868879789966
Actual value : 21.2 Predicted value : 19.510501079467186
Actual value : 11.5 Predicted value : 12.01937253182573
Actual value : 7.3 Predicted value : 6.334914647239472
Actual value : 16.7 Predicted value : 14.438390246944877
Actual value : 10.8 Predicted value : 10.916833285704087
Actual value : 19.7 Predicted value : 16.610583324570968
Actual value : 13.6 Predicted value : 13.375052067517128
Actual value : 13.4 Predicted value : 13.763794823723991
Actual value : 17.9 Predicted value : 15.34237657916908
Actual value : 14.2 Predicted value : 14.367048542118573
Actual value : 25.4 Predicted value : 24.745039724184014
Actual value : 18.0 Predicted value : 17.61882720916648
Actual value : 21.8 Predicted value : 21.824361042505423
Actual value : 14.6 Predicted value : 14.161414429708417
Actual value : 22.3 Predicted value : 21.173319422071206
Actual value : 11.9 Predicted value : 8.978636776223743
Actual value : 10.1 Predicted value : 9.992632723214165
Actual value : 10.1 Predicted value : 12.744350785659439
Actual value : 9.6 Predicted value : 9.951795175611297
Actual value : 20.9 Predicted value : 18.175422265479305
Actual value : 17.4 Predicted value : 18.86192552894356
Actual value : 12.6 Predicted value : 12.569213668131322
Actual value : 11.9 Predicted value : 12.638619875133234
Actual value : 19.0 Predicted value : 19.164035792398092
Actual value : 24.4 Predicted value : 23.97828513858184
Actual value : 18.4 Predicted value : 19.26323447878202
Actual value : 16.5 Predicted value : 17.305394270434576
Actual value : 7.0 Predicted value : 8.07502468615355
Actual value : 17.5 Predicted value : 15.686823631382202
Actual value : 1.6 Predicted value : 9.340994892733395
Actual value : 21.7 Predicted value : 20.869964432349207
Actual value : 27.0 Predicted value : 24.865254707076446
Actual value : 18.3 Predicted value : 18.663606137287985
Actual value : 17.6 Predicted value : 20.514825307737535
Actual value : 6.6 Predicted value : 7.559450801917562
Actual value : 11.0 Predicted value : 11.701106723009303
Actual value : 21.5 Predicted value : 21.032475161719105
Number of mislabeled points from test data set : 60
```

```
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)))
```

```
Mean Absolute error : 1.269238095316301
Mean Squared error : 3.223690527274012
Root Mean Squared error : 1.7954638752350358
```

```
import matplotlib.pyplot as plt

c=X_test['TV'].count()

xax=np.arange(c)

print(xax)

X_axis = np.arange(len(xax))

plt.bar(X_axis-0.2, y_test, 0.6, label='Actual')

plt.bar(X_axis+0.2, y_pred, 0.6, label='Predicted')


plt.xlabel("Sales")

plt.ylabel("Actual/Predicted")

plt.title("Sales prediction")

plt.legend()

plt.show()
```

```
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58 59]
```



Neural Networks

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

import pandas as pd

df = pd.read_csv('housepricedata.csv')

df

	LotArea	OverallQual	OverallCond	TotalBsmtSF	FullBath	HalfBath	BedroomAbvGr	TotRmsAbvGrd	Fireplaces	GarageArea	AboveMedianPrice
0	8450	7	5	856	2	1	3	8	0	548	1
1	9600	6	8	1262	2	0	3	6	1	460	1
2	11250	7	5	920	2	1	3	6	1	608	1
3	9550	7	5	756	1	0	3	7	1	642	0
4	14260	8	5	1145	2	1	4	9	1	836	1
...	...	...	...	...	...	...	...	...	...	...	...
1455	7917	6	5	953	2	1	3	7	1	460	1
1456	13175	6	6	1542	2	0	3	7	2	500	1
1457	9042	7	9	1152	2	0	4	9	2	252	1
1458	9717	5	6	1078	1	0	2	5	0	240	0
1459	9937	5	6	1256	1	1	3	6	0	276	0

1460 rows × 11 columns

dataset = df.values

dataset

```
array([[ 8450,     7,     5, ...,     0,   548,     1],
       [ 9600,     6,     8, ...,     1,   460,     1],
       [11250,     7,     5, ...,     1,   608,     1],
       ...,
       [ 9042,     7,     9, ...,     2,   252,     1],
       [ 9717,     5,     6, ...,     0,   240,     0],
       [ 9937,     5,     6, ...,     0,   276,     0]], dtype=int64)
```

X = dataset[:,0:10]

Y = dataset[:,10]

from sklearn import preprocessing

min_max_scaler = preprocessing.MinMaxScaler()

X_scale = min_max_scaler.fit_transform(X)

X_scale

```
array([[0.0334198 , 0.66666667, 0.5       , ..., 0.5       , 0.        ,
        0.3864598 ],
       [0.03879502, 0.55555556, 0.875     , ..., 0.33333333, 0.33333333,
        0.32440056],
       [0.04650728, 0.66666667, 0.5       , ..., 0.33333333, 0.33333333,
        0.42877292],
       ...,
       [0.03618687, 0.66666667, 1.        , ..., 0.58333333, 0.66666667,
        0.17771509],
       [0.03934189, 0.44444444, 0.625     , ..., 0.25      , 0.        ,
        0.16925247],
       [0.04037019, 0.44444444, 0.625     , ..., 0.33333333, 0.        ,
        0.19464034]])
```

```
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)
```

```
(1022, 10) (219, 10) (219, 10) (1022,) (219,) (219,)
```

```
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))

```
767
Epoch 95/100
32/32 [==============================] - 0s 4ms/step - loss: 0.2773 - accuracy: 0.8914 - val_loss: 0.3128 - val_accuracy: 0.8
767
Epoch 96/100
32/32 [==============================] - 0s 4ms/step - loss: 0.2773 - accuracy: 0.8894 - val_loss: 0.3155 - val_accuracy: 0.8
767
Epoch 97/100
32/32 [==============================] - 0s 4ms/step - loss: 0.2760 - accuracy: 0.8894 - val_loss: 0.3114 - val_accuracy: 0.8
813
Epoch 98/100
32/32 [==============================] - 0s 4ms/step - loss: 0.2755 - accuracy: 0.8914 - val_loss: 0.3099 - val_accuracy: 0.8
813
Epoch 99/100
32/32 [==============================] - 0s 4ms/step - loss: 0.2749 - accuracy: 0.8904 - val_loss: 0.3078 - val_accuracy: 0.8
904
Epoch 100/100
32/32 [==============================] - 0s 4ms/step - loss: 0.2743 - accuracy: 0.8914 - val_loss: 0.3140 - val_accuracy: 0.8
767
```

model.evaluate(X_test, Y_test)[1]

```
7/7 [==============================] - 0s 3ms/step - loss: 0.2653 - accuracy: 0.8584

0.8584474921226501
```

import matplotlib.pyplot as plt

plt.plot(hist.history['loss'])

plt.plot(hist.history['val_loss'])

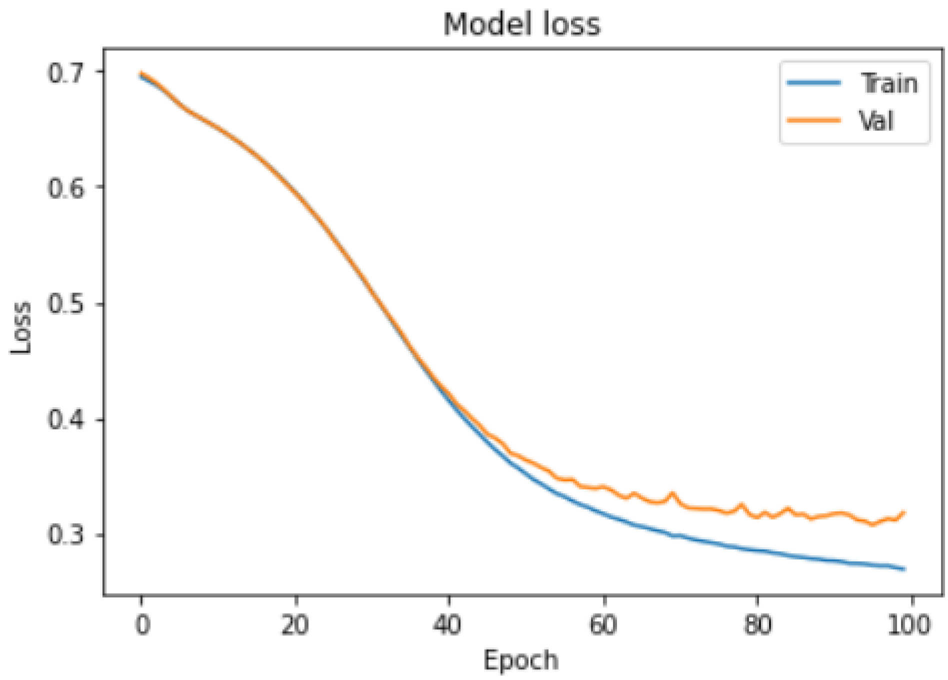
plt.title('Model loss')

plt.ylabel('Loss')

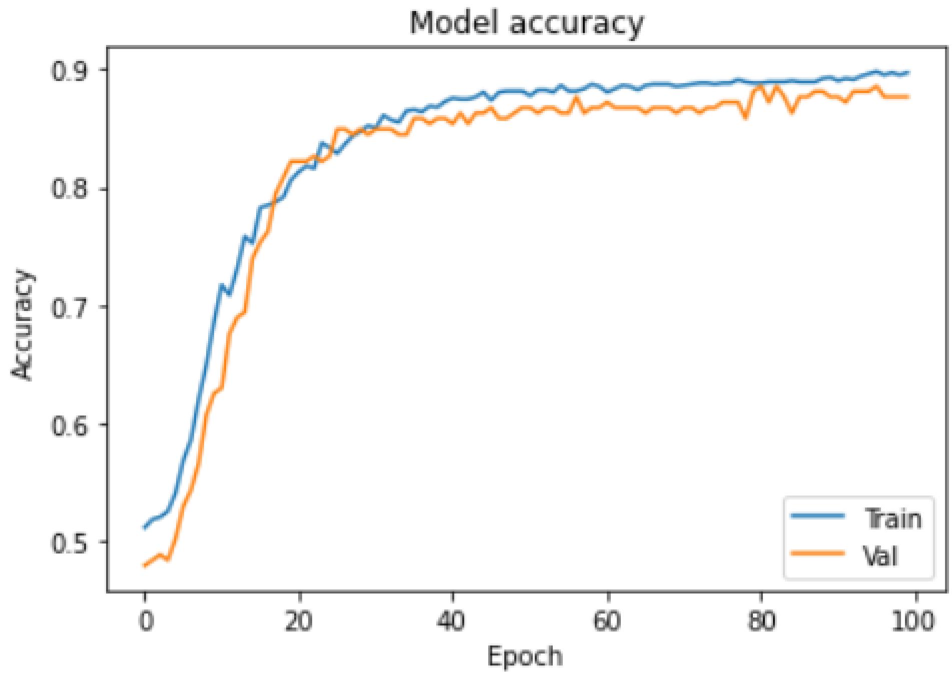
plt.xlabel('Epoch')

plt.legend(['Train', 'Val'], loc='upper right')

plt.show()



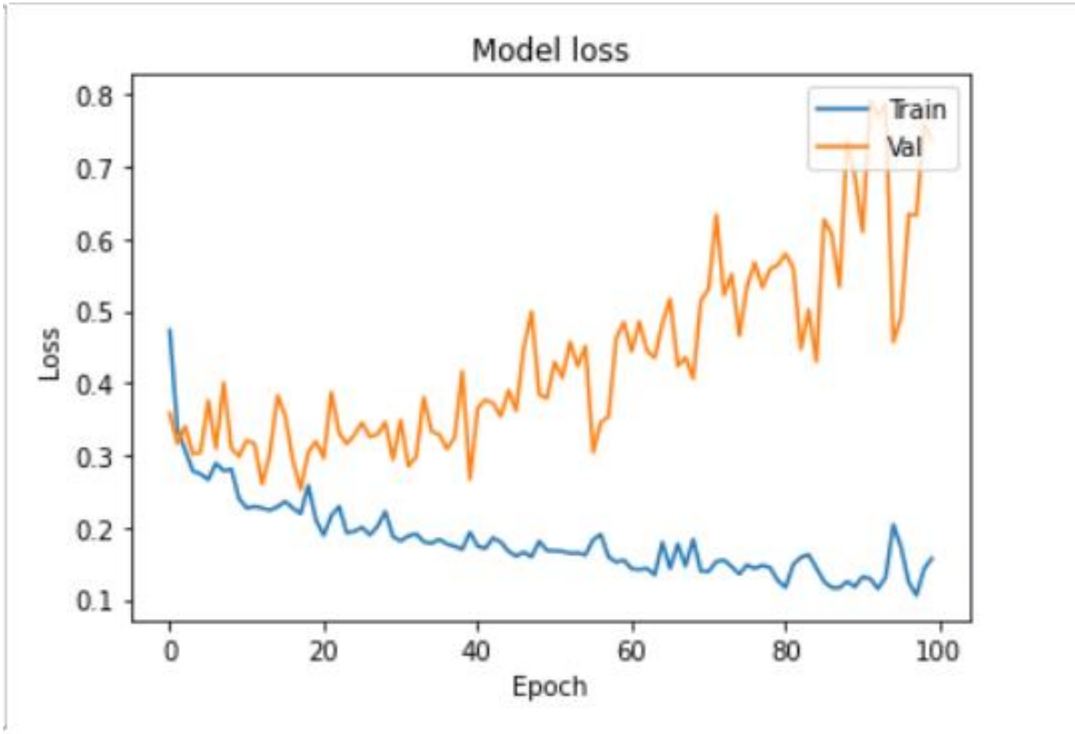

```
plt.plot(hist.history['accuracy'])

plt.plot(hist.history['val_accuracy'])

plt.title('Model accuracy')

plt.ylabel('Accuracy')

plt.xlabel('Epoch')

plt.legend(['Train', 'Val'], loc='lower right')

plt.show()
```



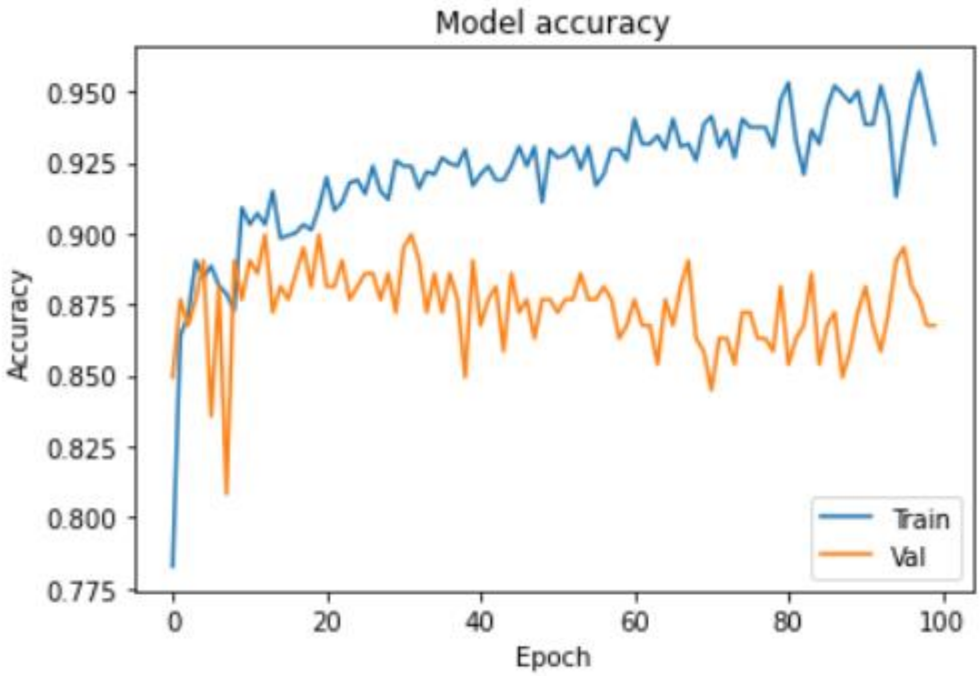

```
model_2 = Sequential([
    Dense(1000, activation='relu', input_shape=(10,)),
    Dense(1000, activation='relu'),
    Dense(1000, activation='relu'),
    Dense(1000, activation='relu'),
    Dense(1, activation='sigmoid'),
])
model_2.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
hist_2 = model_2.fit(X_train, Y_train,
          batch_size=32, epochs=100,
          validation_data=(X_val, Y_val))
```

```
8721
Epoch 95/100
32/32 [==============================] - 1s 38ms/step - loss: 0.2040 - accuracy: 0.9129 - val_loss: 0.4571 - val_accuracy: 0.
8904
Epoch 96/100
32/32 [==============================] - 1s 42ms/step - loss: 0.1727 - accuracy: 0.9315 - val_loss: 0.4910 - val_accuracy: 0.
8950
Epoch 97/100
32/32 [==============================] - 1s 45ms/step - loss: 0.1240 - accuracy: 0.9472 - val_loss: 0.6341 - val_accuracy: 0.
8813
Epoch 98/100
32/32 [==============================] - 1s 37ms/step - loss: 0.1060 - accuracy: 0.9569 - val_loss: 0.6325 - val_accuracy: 0.
8767
Epoch 99/100
32/32 [==============================] - 1s 39ms/step - loss: 0.1429 - accuracy: 0.9442 - val_loss: 0.7589 - val_accuracy: 0.
8676
Epoch 100/100
32/32 [==============================] - 1s 39ms/step - loss: 0.1572 - accuracy: 0.9315 - val_loss: 0.7380 - val_accuracy: 0.
8676
```

```
plt.plot(hist_2.history['loss'])
plt.plot(hist_2.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```



```
plt.plot(hist_2.history['accuracy'])
plt.plot(hist_2.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='lower right')
plt.show()
```

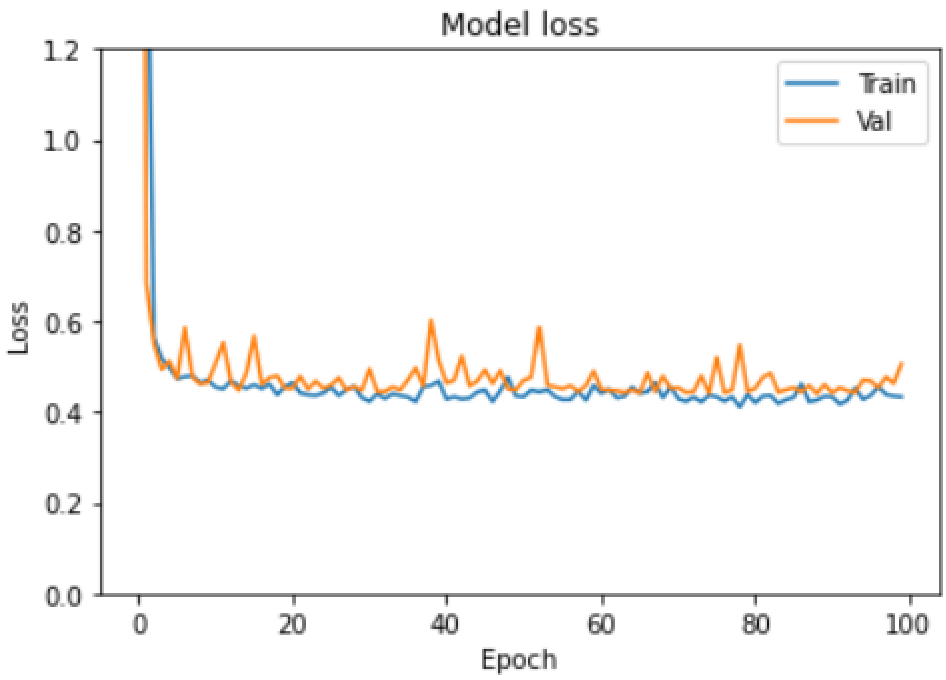


```
from keras.layers import Dropout
from keras import regularizers

model_3 = Sequential([
    Dense(1000, activation='relu', kernel_regularizer=regularizers.l2(0.01), input_shape=(10,)),
    Dropout(0.3),
    Dense(1000, activation='relu', kernel_regularizer=regularizers.l2(0.01)),
    Dropout(0.3),
    Dense(1000, activation='relu', kernel_regularizer=regularizers.l2(0.01)),
```

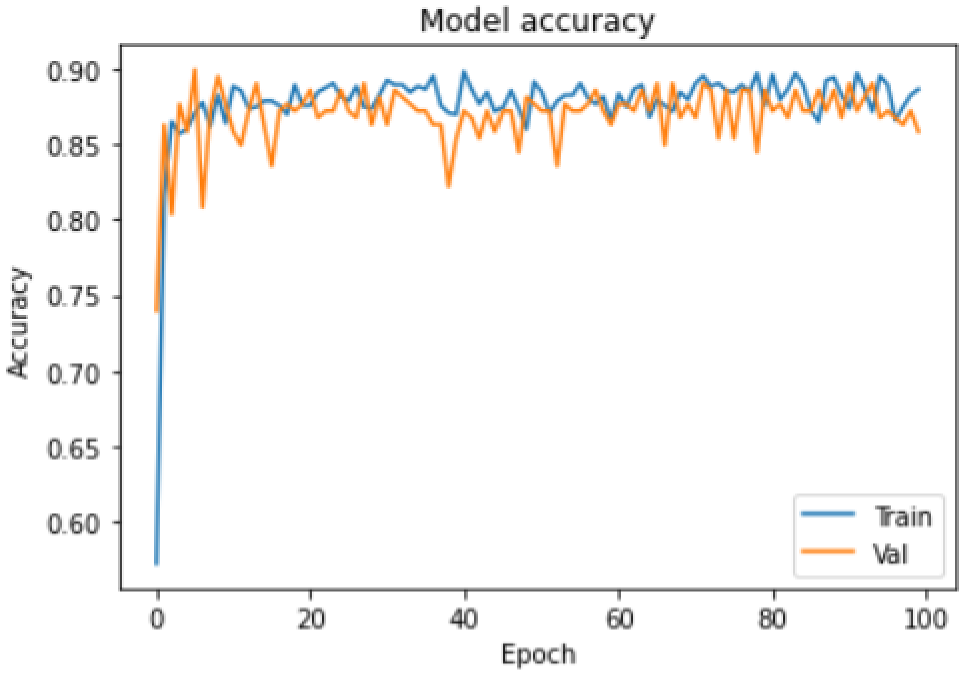
```
    Dropout(0.3),

    Dense(1000, activation='relu', kernel_regularizer=regularizers.l2(0.01)),

    Dropout(0.3),

    Dense(1, activation='sigmoid', kernel_regularizer=regularizers.l2(0.01)),

])


model_3.compile(optimizer='adam',

            loss='binary_crossentropy',

            metrics=['accuracy'])


hist_3 = model_3.fit(X_train, Y_train,

          batch_size=32, epochs=100,

          validation_data=(X_val, Y_val))
```

```
8904
Epoch 95/100
32/32 [==============================] - 2s 64ms/step - loss: 0.4279 - accuracy: 0.8953 - val_loss: 0.4703 - val_accuracy: 0.
8676
Epoch 96/100
32/32 [==============================] - 2s 60ms/step - loss: 0.4363 - accuracy: 0.8894 - val_loss: 0.4686 - val_accuracy: 0.
8721
Epoch 97/100
32/32 [==============================] - 2s 54ms/step - loss: 0.4557 - accuracy: 0.8659 - val_loss: 0.4532 - val_accuracy: 0.
8676
Epoch 98/100
32/32 [==============================] - 2s 56ms/step - loss: 0.4385 - accuracy: 0.8748 - val_loss: 0.4772 - val_accuracy: 0.
8630
Epoch 99/100
32/32 [==============================] - 2s 60ms/step - loss: 0.4351 - accuracy: 0.8826 - val_loss: 0.4628 - val_accuracy: 0.
8721
Epoch 100/100
32/32 [==============================] - 2s 59ms/step - loss: 0.4332 - accuracy: 0.8865 - val_loss: 0.5059 - val_accuracy: 0.
8584
```

```
plt.plot(hist_3.history['loss'])

plt.plot(hist_3.history['val_loss'])

plt.title('Model loss')

plt.ylabel('Loss')

plt.xlabel('Epoch')

plt.legend(['Train', 'Val'], loc='upper right')

plt.ylim(top=1.2, bottom=0)

plt.show()
```




```
plt.plot(hist_3.history['accuracy'])
plt.plot(hist_3.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='lower right')
plt.show()
```



Model accuracy
0.90
0.85
0.80
0.75
0.70
0.65
0.60
Accuracy
0
20
40
60
80
100
Epoch
Train
Val