In [1]:
```
!pip install heuristicsearch
```

```
Collecting heuristicsearch
  Downloading heuristicsearch-0.1.1-py3-none-any.whl (5.5 kB)
Installing collected packages: heuristicsearch
Successfully installed heuristicsearch-0.1.1
```

In [3]:
```
from heuristicsearch.a_star_search import AStar
aj_list={'A': [('B', 6), ('F', 3)],
         'B': [('C', 3), ('D', 2)],
         'C': [('D', 1), ('E', 5)],
         'D': [('C', 1),('E', 8)],
         'E': [('I', 5), ('J', 5)],
         'F': [('G', 1),('H', 7)],
         'G': [('I', 3)],
         'H': [('I', 2)],
         'I': [('E', 5), ('J', 3)],
        }
heuristics={'A': 10,'B': 8,'C': 5,'D': 7,'E': 3,'F': 6,'G': 5,'H': 
3,'I': 1,'J': 0}
graph=AStar(aj_list,heuristics)
graph.apply_a_star(start='A',stop='J')
```

```
Path
A -> F -> G -> I -> J
Cost
0 -> 3 -> 4 -> 7 -> 10
```

In [4]:
```
from heuristicsearch.ao_star import AOStar
print("Graphs-1")
heuristic={'A':1,'B':6,'C':2,'D':12,'E':2,'F':1,'G':5,'H':7,'J':
1,'T':3}
aj_list={'A':[[('B',1),('C',1)],[('D',1)]],
         'B':[[('G',1)],[('H',1)]],
         'C':[[('J',1)]],
         'D':[[('E',1),('F',1)]],
         'G':[[('I',1)]]
        }
graph=AOStar(aj_list,heuristic,'A')
graph.applyAOStar()
```

```
Graphs-1
PROCESSING NODE : A
-------------------------------------------------------------------------------------------------
10 ['B', 'C']

PROCESSING NODE : B
-------------------------------------------------------------------------------------------------
6 ['G']

PROCESSING NODE : A
-------------------------------------------------------------------------------------------------
10 ['B', 'C']

PROCESSING NODE : G
-------------------------------------------------------------------------------------------------
1 ['I']

PROCESSING NODE : B
-------------------------------------------------------------------------------------------------
2 ['G']

PROCESSING NODE : A
-------------------------------------------------------------------------------------------------
6 ['B', 'C']

PROCESSING NODE : I
-------------------------------------------------------------------------------------------------
0 []

PROCESSING NODE : G
-------------------------------------------------------------------------------------------------
1 ['I']

PROCESSING NODE : B
-------------------------------------------------------------------------------------------------
2 ['G']

PROCESSING NODE : A
-------------------------------------------------------------------------------------------------
6 ['B', 'C']

PROCESSING NODE : C
-------------------------------------------------------------------------------------------------
2 ['J']

PROCESSING NODE : A
```

```
------------------------------------------------------------------------
------------------
6 ['B', 'C']

PROCESSING NODE : J
------------------------------------------------------------------------
------------------
0 []

PROCESSING NODE : C
------------------------------------------------------------------------
------------------
1 ['J']

PROCESSING NODE : A
------------------------------------------------------------------------
------------------
5 ['B', 'C']

FOR THE SOLUTION, TRAVERSE THE GRAPH FROM THE START NODE: A
------------------------------------------------------------
{'I': [], 'G': ['I'], 'B': ['G'], 'J': [], 'C': ['J'], 'A': ['B', 'C']}
------------------------------------------------------------
```

In [5]:
```
import numpy as np
import pandas as pd
data = pd.DataFrame(data=pd.read_csv('rashika.csv'))
```

In [6]:
```
data
```

Out[6]:

	Sky	Air Temp	Humidity	Wind	Water	Forecast	Enjoy Sport
0	Sunny	Warm	Normal	Strong	Warm	Same	Yes
1	Sunny	Warm	High	Strong	Warm	Same	Yes
2	Rainy	Cold	High	Strong	Warm	Change	No
3	Sunny	Warm	High	Strong	Cold	Change	Yes

In [9]:
```
concepts = np.array(data.iloc[:,0:-1])
target = np.array(data.iloc[:,-1])
def learn(concepts, target):
    specific_h = concepts[0].copy()
    print("initialization of specific_h and general_h")
    print(specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range
(len(specific_h))]
    print(general_h)
    for i, h in enumerate(concepts):
        if target[i] == "Yes":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    specific_h[x] = '?'
                    general_h[x][x] = '?'
        if target[i] == "No":
                for x in range(len(specific_h)):
                    if h[x] != specific_h[x]:
                             general_h[x][x] = specific_h[x]
                    else:
                          general_h[x][x] = '?'
    print(" steps of Candidate Elimination Algorithm",i+1)
    print("Specific_h ",i+1,"\n ")
    print(specific_h)
    print("general_h ", i+1, "\n ")
    print(general_h)
    indices = [i for i, val in enumerate(general_h) if val == ['?',
'?', '?', '?', '?', '?']]
    for i in indices:
            general_h.remove(['?', '?', '?', '?', '?', '?'])
    return specific_h, general_h
s_final, g_final = learn(concepts, target)
print("Final Specific_h:", s_final, sep="\n")
print("Final General_h:", g_final, sep="\n")
```

```
initialization of specific_h and general_h
['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?',
'?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
 steps of Candidate Elimination Algorithm 4
Specific_h  4

['Sunny' 'Warm' '?' 'Strong' '?' '?']
general_h  4

[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Final Specific_h:
['Sunny' 'Warm' '?' 'Strong' '?' '?']
Final General_h:
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?']]
```

In [15]:

```
import pandas as pd
from pprint import pprint
from sklearn.feature_selection import mutual_info_classif
from collections import Counter

def id3(df, target_attribute, attribute_names, default_class=None):
    cnt=Counter(x for x in df[target_attribute])
    if len(cnt)==1:
        return next(iter(cnt))

    elif df.empty or (not attribute_names):
         return default_class

    else:
        gainz = mutual_info_classif(df[attribute_names],df[target_attr
ibute],discrete_features=True)
        index_of_max=gainz.tolist().index(max(gainz))
        best_attr=attribute_names[index_of_max]
        tree={best_attr:{}}
        remaining_attribute_names=[i for i in attribute_names if i!=be
st_attr]

        for attr_val, data_subset in df.groupby(best_attr):
            subtree=id3(data_subset, target_attribute, remaining_attri
bute_names,default_class)
            tree[best_attr][attr_val]=subtree

        return tree


df=pd.read_csv("kirana.csv")

attribute_names=df.columns.tolist()
print("List of attribut name")

attribute_names.remove("PlayTennis")

for colname in df.select_dtypes("object"):
    df[colname], _ = df[colname].factorize()

print(df)

tree= id3(df,"PlayTennis", attribute_names)
print("The tree structure")
pprint(tree)
```

```
List of attribut name
    Outlook  Temperature  Humidity  Wind  PlayTennis
0         0            0         0     0           0
1         0            0         0     1           0
2         1            0         0     0           1
3         2            1         0     0           1
4         2            2         1     0           1
5         2            2         1     1           0
6         1            2         1     1           1
7         0            1         0     0           0
8         0            2         1     0           1
9         2            1         1     0           1
10        0            1         1     1           1
11        1            1         0     1           1
12        1            0         1     0           1
13        2            1         0     1           0
The tree structure
{'Outlook': {0: {'Humidity': {0: 0, 1: 1}}, 1: 1, 2: {'Wind': {0: 1, 1: 0}}}}
```

In [16]:

In [19]:

```
import numpy as np
X=np.array(([2,9],[1,5],[3,6]),dtype=float)
y=np.array(([92],[86],[89]),dtype=float)
X=X/np.amax(X,axis=0)
y=y/100
def sigmoid(x):
       return 1/(1+np.exp(-x))
def derivatives_sigmoid(x):
      return x*(1-x)
epoch=7000
lr=0.25
inputlayer_neurons=2
hiddenlayer_neurons=3
output_neurons=1
wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons))
bh=np.random.uniform(size=(1,hiddenlayer_neurons))
wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))
bout=np.random.uniform(size=(1,output_neurons))
for i in range(epoch):
    hinp1=np.dot(X,wh)
    hinp=hinp1+bh
    hlayer_act=sigmoid(hinp)
    outinp1=np.dot(hlayer_act,wout)
    outinp=outinp1+bout
    output=sigmoid(outinp)
    EO=y-output
    outgrad=derivatives_sigmoid(output)
    d_output=EO*outgrad
    EH=d_output.dot(wout.T)
    hiddengrad=derivatives_sigmoid(hlayer_act)
    d_hiddenlayer=EH*hiddengrad
    wout+=hlayer_act.T.dot(d_output)*lr
    wh+=X.T.dot(d_hiddenlayer)*lr
print("Input=\n"+str(X))
print("Actual output:\n"+str(y))
print("predicated output:",output)
```

```
Input=
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual output:
[[0.92]
 [0.86]
 [0.89]]
predicated output: [[0.89574228]
 [0.87965404]
 [0.89400144]]
```

In [20]:

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

data = pd.read_csv('kirana.csv')
```

In [21]:
```
data
```

Out[21]:

	Outlook	Temperature	Humidity	Wind	PlayTennis
0	Sunny	Hot	High	Weak	No
1	Sunny	Hot	High	Strong	No
2	Overcast	Hot	High	Weak	Yes
3	Rain	Mild	High	Weak	Yes
4	Rain	Cool	Normal	Weak	Yes
5	Rain	Cool	Normal	Strong	No
6	Overcast	Cool	Normal	Strong	Yes
7	Sunny	Mild	High	Weak	No
8	Sunny	Cool	Normal	Weak	Yes
9	Rain	Mild	Normal	Weak	Yes
10	Sunny	Mild	Normal	Strong	Yes
11	Overcast	Mild	High	Strong	Yes
12	Overcast	Hot	Normal	Weak	Yes
13	Rain	Mild	High	Strong	No

In [24]:

```
print("The first 5 Values of data is :\n", data.head())
X = data.iloc[:, :-1]
print("\nThe First 5 values of the train attributes is\n", X.head())

Y = data.iloc[:, -1]
print("\nThe First 5 values of target values is\n", Y.head())

obj1= LabelEncoder()
X.Outlook = obj1.fit_transform(X.Outlook)
print("\n The Encoded and Transformed Data in Outlook\n",X.Outlook)

obj2 = LabelEncoder()
X.Temperature = obj2.fit_transform(X.Temperature)

obj3 = LabelEncoder()
X.Humidity = obj3.fit_transform(X.Humidity)

obj4 = LabelEncoder()
X.Wind = obj4.fit_transform(X.Wind)
print("\n The Encoded and Transformed Training Examples \n", X.head())

obj5 = LabelEncoder()
Y = obj5.fit_transform(Y)
print("The class Label encoded in numerical form is",Y)

X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size =
0.20)

from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, Y_train)
from sklearn.metrics import accuracy_score
print("Accuracy is:", accuracy_score(classifier.predict(X_test), Y_tes
t))
```

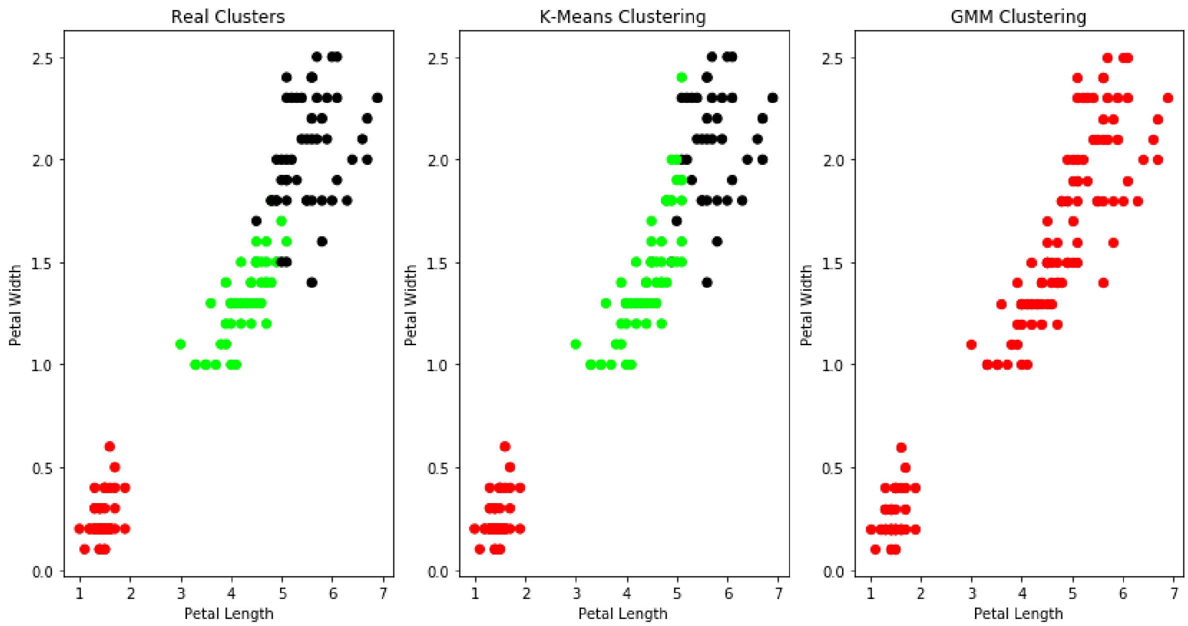
```
The first 5 Values of data is :
     Outlook Temperature Humidity    Wind PlayTennis
0     Sunny         Hot     High    Weak         No
1     Sunny         Hot     High  Strong         No
2  Overcast         Hot     High    Weak        Yes
3      Rain        Mild     High    Weak        Yes
4      Rain        Cool   Normal    Weak        Yes

The First 5 values of the train attributes is
     Outlook Temperature Humidity    Wind
0     Sunny         Hot     High    Weak
1     Sunny         Hot     High  Strong
2  Overcast         Hot     High    Weak
3      Rain        Mild     High    Weak
4      Rain        Cool   Normal    Weak

The First 5 values of target values is
 0     No
1     No
2    Yes
3    Yes
4    Yes
Name: PlayTennis, dtype: object

 The Encoded and Transformed Data in Outlook
 0     2
1     2
2     0
3     1
4     1
5     1
6     0
7     2
8     2
9     1
10    2
11    0
12    0
13    1
Name: Outlook, dtype: int32

 The Encoded and Transformed Training Examples
    Outlook  Temperature  Humidity  Wind
0        2            1         0     1
1        2            1         0     0
2        0            1         0     1
3        1            2         0     1
4        1            0         1     1
The class Label encoded in numerical form is [0 0 1 1 1 0 1 0 1 1 1 1 1
0]
Accuracy is: 0.6666666666666666
```

```
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\generic.py:5303:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[name] = value
```

In [29]:

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import pandas as pd
import numpy as np
iris = datasets.load_iris()
X = pd.DataFrame(iris.data)
X.columns =['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']
y = pd.DataFrame(iris.target)
y.columns = ['Targets']

model = KMeans(n_clusters=3)
model.fit(X) # model.labels_ : Gives cluster no for which samples belo
ngs to
plt.figure(figsize=(14,7))
colormap = np.array(['red', 'lime', 'black'])
plt.subplot(1, 3, 1)
plt.scatter(X.Petal_Length, X.Petal_Width,
c=colormap[y.Targets], s=40)
plt.title('Real Clusters')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.subplot(1, 3, 2)
plt.scatter(X.Petal_Length, X.Petal_Width,
c=colormap[model.labels_], s=40)
plt.title('K-Means Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

from sklearn import preprocessing
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
from sklearn.mixture import GaussianMixture

gmm = GaussianMixture(n_components=40)
gmm.fit(xs)
plt.subplot(1, 3, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[0], s=40)
plt.title('GMM Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

print('Observation: The GMM using EM algorithm based clustering matche
d the true labels more closely than the Kmeans.')
```

Observation: The GMM using EM algorithm based clustering matched the tr
ue labels more closely than the Kmeans.



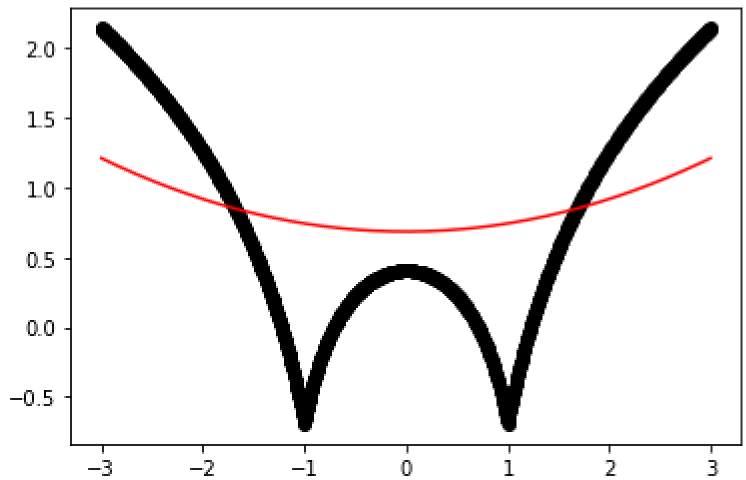
In [31]:

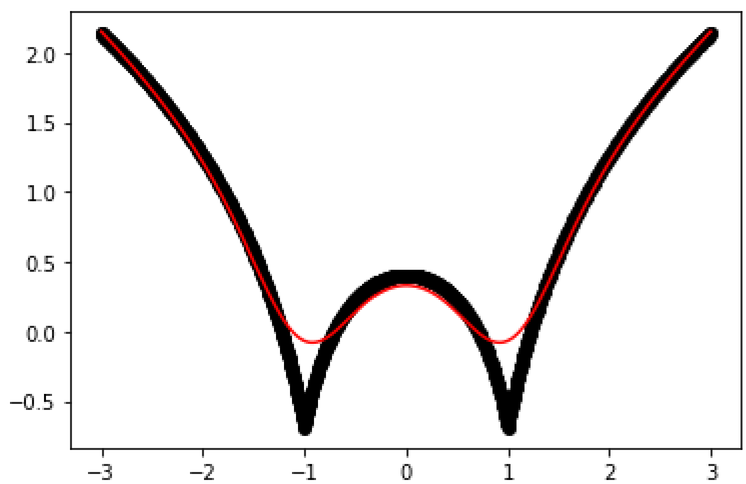
```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import datasets
iris=datasets.load_iris()
print("Iris Data set loaded...")
x_train, x_test, y_train, y_test =train_test_split(iris.data,iris.targ
et,test_size=0.1)
#random_state=0
for i in range(len(iris.target_names)):
    print("Label", i , "-",str(iris.target_names[i]))
classifier = KNeighborsClassifier(n_neighbors=2)
classifier.fit(x_train, y_train)
y_pred=classifier.predict(x_test)
print("Results of Classification using K-nn with K=1 ")
for r in range(0,len(x_test)):
    print(" Sample:", str(x_test[r]), " Actual-label:",
str(y_test[r])," Predicted-label:", str(y_pred[r]))
    print("Classification Accuracy :" ,
classifier.score(x_test,y_test));
```

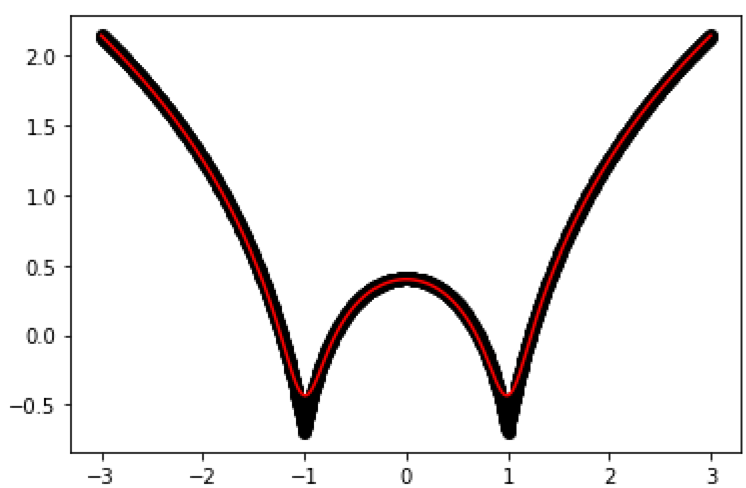
```
Iris Data set loaded...
Label 0 - setosa
Label 1 - versicolor
Label 2 - virginica
Results of Classification using K-nn with K=1
 Sample: [6.6 2.9 4.6 1.3]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 1.0
 Sample: [6.9 3.1 4.9 1.5]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 1.0
 Sample: [6.7 3.3 5.7 2.5]  Actual-label: 2  Predicted-label: 2
Classification Accuracy : 1.0
 Sample: [5.7 2.5 5.  2. ]  Actual-label: 2  Predicted-label: 2
Classification Accuracy : 1.0
 Sample: [4.8 3.  1.4 0.3]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 1.0
 Sample: [5.  2.  3.5 1. ]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 1.0
 Sample: [5.1 3.8 1.5 0.3]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 1.0
 Sample: [6.4 3.1 5.5 1.8]  Actual-label: 2  Predicted-label: 2
Classification Accuracy : 1.0
 Sample: [6.3 3.3 4.7 1.6]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 1.0
 Sample: [5.2 4.1 1.5 0.1]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 1.0
 Sample: [4.9 2.4 3.3 1. ]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 1.0
 Sample: [5.  3.5 1.6 0.6]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 1.0
 Sample: [5.5 2.5 4.  1.3]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 1.0
 Sample: [6.  2.9 4.5 1.5]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 1.0
 Sample: [4.9 3.6 1.4 0.1]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 1.0
```

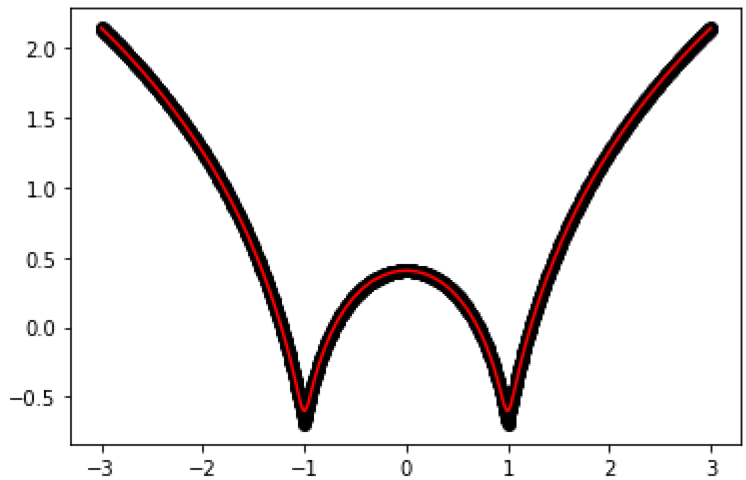
In [37]:

```
import numpy as np
import matplotlib.pyplot as plt
def local_regression(x0, X, Y, tau):
    x0 = [1, x0]
    X = [[1, i] for i in X]
    X = np.asarray(X)
    xw = (X.T) * np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 *tau))
    beta = np.linalg.pinv(xw @ X) @ xw @ Y @ x0
    return beta

def draw(tau):
    prediction = [local_regression(x0, X, Y, tau) for x0 in domain]
    plt.plot(X, Y, 'o', color='black')
    plt.plot(domain, prediction, color='red')
    plt.show()
X = np.linspace(-3, 3, num=1000)
domain = X
Y = np.log(np.abs(X ** 2 - 1) + .5)

draw(10)
draw(0.1)
draw(0.01)
draw(0.001)
```


2.0
1.5
1.0
0.5
0.0
−0.5
−3
−2
−1
0
1
2
3


2.0
1.5
1.0
0.5
0.0
−0.5
−3
−2
−1
0
1
2
3


2.0
1.5
1.0
0.5
0.0
−0.5
−3
−2
−1
0
1
2
3



In [ ]: