# SHIVAM KHARE 201505547 ASSIGNMENT-1

## 1. Iris Data Set

#### **Data Set Information:**

This is perhaps the best known database to be found in the pattern recognition literature. Fisher's paper is a classic in the field and is referenced frequently to this day. (See Duda & Hart, for example.) The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant. One class is linearly separable from the other 2; the latter are NOT linearly separable from each other.

Predicted attribute: class of iris plant.

This is an exceedingly simple domain.

This data differs from the data presented in Fishers article (identified by Steve Chadwick, <a href="mailto:spchadwick">spchadwick</a> '@' espeedaz.net ). The 35th sample should be: 4.9,3.1,1.5,0.2,"Iris-setosa" where the error is in the fourth feature. The 38th sample: 4.9,3.6,1.4,0.1,"Iris-setosa" where the errors are in the second and third features.

# **Attribute Information:**

- 1. sepal length in cm
- 2. sepal width in cm
- 3. petal length in cm
- 4. petal width in cm
- 5. class:
- -- Iris Setosa
- -- Iris Versicolour
- -- Iris Virginica

Data Set Characteristics:	Multivariate	Number of Instances:	150	Area:	Life
Attribute Characteristics:	Real	Number of Attributes:	4	Date Donated	1988-07- 01
Associated Tasks:	Classification	Missing Values?	No	Number of Web Hits:	862043

# **DISTANCE FUNCTION:**-(euclidean distance)

for i in range(trainigsetlength):

distance=0

for j in range(length):

distance=distance+pow((testset[x][j]-trainigset[i][j]),2)

distance=math.sqrt(distance)

# **2.Balance Scale Data Set**

#### **Data Set Information:**

This data set was generated to model psychological experimental results. Each example is classified as having the balance scale tip to the right, tip to the left, or be balanced. The attributes are the left weight, the left distance, the right weight, and the right distance. The correct way to find the class is the greater of (left-distance \* left-weight) and (right-distance \* right-weight). If they are equal, it is balanced.

#### **Attribute Information:**

Class Name: 3 (L, B, R)
 Left-Weight: 5 (1, 2, 3, 4, 5)
 Left-Distance: 5 (1, 2, 3, 4, 5)
 Right-Weight: 5 (1, 2, 3, 4, 5)
 Right-Distance: 5 (1, 2, 3, 4, 5)

Data Set Characteristics:	Multivariate	Number of Instances:	625	Area:	Social
Attribute Characteristics:	Categorical	Number of Attributes:	4	<b>Date Donated</b>	1994-04- 22
Associated Tasks:	Classification	Missing Values?	No	Number of Web Hits:	103064

# **DISTANCE FUNCTION:**-(euclidean distance)

for i in range(trainigsetlength):

distance=0

for j in range(length):

# $\label{linear} distance=distance+pow((testset[x][j]-trainigset[i][j]),2) \\ distance=math.sqrt(distance)$

#### 3. Haberman's Survival Data Set

#### **Data Set Information:**

The dataset contains cases from a study that was conducted between 1958 and 1970 at the University of Chicago's Billings Hospital on the survival of patients who had undergone surgery for breast cancer.

## **Attribute Information:**

- 1. Age of patient at time of operation (numerical)
- 2. Patient's year of operation (year 1900, numerical)
- 3. Number of positive axillary nodes detected (numerical)
- 4. Survival status (class attribute)
- -- 1 = the patient survived 5 years or longer
- -- 2 = the patient died within 5 year

Data Set Characteristics:	Multivariate	Number of Instances:	306	Area:	Life
Attribute Characteristics:	Integer	Number of Attributes:	3	<b>Date Donated</b>	1999-03- 04
Associated Tasks:	Classification	Missing Values?	No	Number of Web Hits:	84419

# **DISTANCE FUNCTION:**-(euclidean distance)

distance=math.sqrt(distance)

for i in range(trainigsetlength):
 distance=0

for j in range(length):
 distance=distance+pow((testset[x][j]-trainigset[i][j]),2)

# 1. Iris Data Set

# Random subsampling approach

## confusion matrix for k=1

	class1	class2	class3
class1	29	0	0
class2	0	21	2
class3	0	0	19

Accuracy for k=1: 97.183099 %

# confusion matrix for k=3

	class1	class2	class3
class1	29	0	0
class2	0	21	2
class3	0	0	19

Accuracy for k=3: 97.183099 %

# 5-fold cross validation

# confusion matrix for k=1

	class1	class2	class3
class1	42	0	0
class2	0	38	0
class3	0	7	33

# confusion matrix for k=3

	class1	class2	class3
class1	42	0	0
class2	0	37	1
class3	0	11	29

# iteration 1:

mean Accuracy for k=1: 95.0

mean Accuracy for k=3: 95.1666666667 Standard deviation for k=1: 1.05409255339 Standard deviation for k=3: 1.91485421551

# iteration 2:

mean Accuracy for k=1: 95.0

#### iteration 3:

mean Accuracy for k=1: 93.5

mean Accuracy for k=3: 95.1666666667 Standard deviation for k=1: 2.84800124844 Standard deviation for k=3: 1.14260910007

#### iteration 4:

mean Accuracy for k=1: 92.833333333

mean Accuracy for k=3: 95.0

Standard deviation for k=1: 1.77169096879 Standard deviation for k=3: 1.78730088246

#### iteration 5:

## iteration 6:

mean Accuracy for k=1: 95.5

#### iteration 7:

mean Accuracy for k=1: 94.666666667 mean Accuracy for k=3: 93.8333333333 Standard deviation for k=1: 1.42400062422 Standard deviation for k=3: 2.0275875101

#### iteration 8:

# iteration 9:

mean Accuracy for k=1: 94.1666666667 mean Accuracy for k=3: 94.3333333333 Standard deviation for k=1: 1.97202659437 Standard deviation for k=3: 2.18581284143

## iteration 10:

mean Accuracy for k=1: 95.833333333

mean Accuracy for k=3: 95.0

Standard deviation for k=1: 1.23603308118 Standard deviation for k=3: 1.53659074288

Grand Mean for k=1: 94.7166666667 Grand Mean for k=3: 94.6833333333

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# 2. Balance Scale Data Set

# Random subsampling approach

#### confusion matrix for k=1

	class1	class2
class1	85	23
class2	33	10

Accuracy for k=1: **62.913907** 

#### confusion matrix for k=3

	class1	class2
class1	99	9
class2	30	13

Accuracy for k=3: **74.172185** 

#### 5-fold cross validation

#### confusion matrix for k=1

146	37
45	17

# confusion matrix for k=3

	class1	class
class1	157	26
class2	46	16

## **Iteration: 1**

mean Accuracy for k=1: 65.6871863499 mean Accuracy for k=3: 70.0180662429 Standard deviation for k=1: 1.15515510447 Standard deviation for k=3: 1.00189157016

# **Iteration: 2**

mean Accuracy for k=1: 66.5005018401 mean Accuracy for k=3: 69.3629976581 Standard deviation for k=1: 3.55830938769 Standard deviation for k=3: 2.91905807437

# **Iteration: 3**

mean Accuracy for k=1: 66.0946804951 mean Accuracy for k=3: 68.2154566745 Standard deviation for k=1: 2.4696156724 Standard deviation for k=3: 2.23657617157

#### **Iteration: 4**

mean Accuracy for k=1: 65.6885245902 mean Accuracy for k=3: 71.8116426899 Standard deviation for k=1: 2.04758728473 Standard deviation for k=3: 1.68173225934

#### **Iteration: 5**

mean Accuracy for k=1: 64.6239544998 mean Accuracy for k=3: 68.5453328873 Standard deviation for k=1: 1.8416575861 Standard deviation for k=3: 0.691726515565

## **Iteration: 6**

mean Accuracy for k=1: 66.8287052526 mean Accuracy for k=3: 72.218802275 Standard deviation for k=1: 1.01257915071 Standard deviation for k=3: 1.85467517075

# **Iteration: 7**

mean Accuracy for k=1: 66.0103713617 mean Accuracy for k=3: 71.7296754767 Standard deviation for k=1: 1.62615700847 Standard deviation for k=3: 1.67850749394

#### **Iteration: 8**

mean Accuracy for k=1: 67.237537638 mean Accuracy for k=3: 72.3007694881 Standard deviation for k=1: 2.69757781501 Standard deviation for k=3: 3.01236166695

#### **Iteration: 9**

mean Accuracy for k=1: 67.4827701572 mean Accuracy for k=3: 72.469053195 Standard deviation for k=1: 1.43092207079 Standard deviation for k=3: 0.880227437256

# **Iteration: 10**

mean Accuracy for k=1: 66.8323854132 mean Accuracy for k=3: 71.2415523586 Standard deviation for k=1: 1.51903852433 Standard deviation for k=3: 1.38785664392

Grand Mean for k=1: 66.2986617598 Grand Mean for k=3: 70.7913348946

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# 3. Haberman's Survival Data Set

# Random subsampling approach

#### confusion matrix for k=1

	class1	class2	class3
class1	107	27	16
class2	3	2	16

class3 6 6 128

Accuracy for k=1: **76.205788** %

# confusion matrix for k=3

	class1	class2	class3
class1	115	16	19
class2	4	2	15
class3	4	7	129

Accuracy for k=3: **79.099678** %

# **5-fold cross validation**

# confusion matrix for k=1

	class1	class2	class3
class1	193	18	28
class2	14	2	19
class3	8	23	195

#### confusion matrix for k=3

	class1	class2	class3
class1	195	17	27
class2	6	5	24
class3	2	18	206

# **Iteration: 1**

mean Accuracy for k=1: 79.2 mean Accuracy for k=3: 82.24

Standard deviation for k=1: 0.779743547585 Standard deviation for k=3: 0.960832971957

# Iteration: 2

mean Accuracy for k=1: 76.84 mean Accuracy for k=3: 81.64

Standard deviation for k=1: 0.712179752591 Standard deviation for k=3: 1.36937942149

## **Iteration: 3**

mean Accuracy for k=1: 77.88 mean Accuracy for k=3: 81.44

Standard deviation for k=1: 1.32544332206 Standard deviation for k=3: 0.739729680356

#### **Iteration: 4**

mean Accuracy for k=1: 78.64 mean Accuracy for k=3: 81.56

Standard deviation for k=1: 1.14332847424 Standard deviation for k=3: 0.99357938787

# **Iteration: 5**

mean Accuracy for k=1: 79.16 mean Accuracy for k=3: 81.04

Standard deviation for k=1: 0.393954312072 Standard deviation for k=3: 1.20797350964

#### **Iteration: 6**

mean Accuracy for k=1: 76.2 mean Accuracy for k=3: 80.16

Standard deviation for k=1: 1.54660919433 Standard deviation for k=3: 1.03305372561

## Iteration: 7

mean Accuracy for k=1: 79.16 mean Accuracy for k=3: 82.44

Standard deviation for k=1: 0.712179752591 Standard deviation for k=3: 0.913892772704

# **Iteration: 8**

mean Accuracy for k=1: 77.68 mean Accuracy for k=3: 81.96

Standard deviation for k=1: 0.678822509939 Standard deviation for k=3: 1.15723809132

# **Iteration: 9**

mean Accuracy for k=1: 77.92 mean Accuracy for k=3: 83.0

Standard deviation for k=1: 0.932094415818

Standard deviation for k=3: 0.6

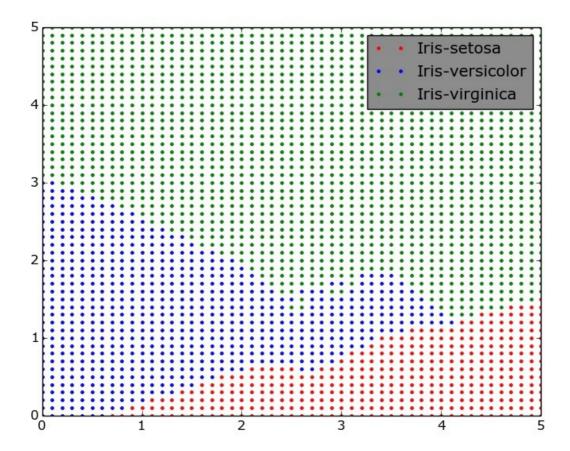
# **Iteration: 10**

mean Accuracy for k=1: 77.72 mean Accuracy for k=3: 82.48

Standard deviation for k=1: 1.39025177576 Standard deviation for k=3: 0.822678552048

Grand Mean for k=1: 78.04 Grand Mean for k=3: 81.796

# Answer: 3



# Answer4

yes

The decision boundary of 3-NN will be piece-wise linear. Reason: In 3-NN the decision boundary is formed by considering the perpendicular bisectors of the imaginary line formed by connecting the transition-points. Eah of these perpendicular bisectors are linear. Hene we can conlude that the deision boundary of 3-NN is piece-wise linear

```
Graph plot code:
#!/usr/bin/python
import csv
import matplotlib.pyplot as plt
import math
import operator
from numpy import arange
l1=[]
i=0
while(i<4):
       j=0
       while(j<4):
              l1.append((i,j))
              j+=.1
       i=i+0.1
print len(l1)
f= open('iris.data','rb')
xcord=[]
ycord=[]
lines=csv.reader(f)
data=list(lines)
for i in range(len(data)):
       for j in range(4):
              data[i][j]=float(data[i][j])
              if(j==1):
                     xcord.append(data[i][j])
              if(j==3):
                     ycord.append(data[i][j])
neighbour=[]
for i in range(len(l1)):
       distancelist=[]
       dist1=0
       dist2=0
       for j in range(len(data)):
              dist1=pow((xcord[j]-l1[i][0]),2)
              dist2=pow((ycord[j]-l1[i][1]),2)
              dist3=math.sqrt(dist1+dist2)
              distancelist.append((data[j][-1],dist3))
       distancelist.sort(key=operator.itemgetter(1))
       #print distancelist
       neighbour.append(distancelist[0][0])
12=[]
13=[]
14=[]
15=[]
16=[]
17=[]
```

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for i in range(len(l1)):
       if(neighbour[i]=='Iris-setosa'):
              l2.append(l1[i][0])
              l3.append(l1[i][1])
       elif(neighbour[i]=='Iris-versicolor'):
              l4.append(l1[i][0])
              l5.append(l1[i][1])
       else:
              l6.append(l1[i][0])
              17.append(l1[i][1])
count=0
lx=[]
ly=[]
for i in arange(0,4,.1):
       for j in arange(0,4,.1):
              count+=1
              if(neighbour[count-1]!=neighbour[count]):
                     lx.append(i)
                     ly.append(j)
              break
lx1=[]
ly1=[]
count1=0
for i in arange(0,4,.1):
       count1+=400
       for j in arange(4,0,.1):
              count-=1;
              if(neighbour[count1+1]!=neighbour[count1]):
                     lx1.append(i)
                      ly1.append(j)
              break
plt.plot(l2,l3,'.r',label='Iris-setosa')
plt.plot(l4,l5,'.b',label='Iris-versicolor')
plt.plot(l6,l7,'.g',label='Iris-virginica')
legend=plt.legend(loc='upper right')
frame=legend.get_frame()
frame.set_facecolor('.55')
plt.show()
18=[]
19=[]
110=[]
111=[]
l12=[]
113=[]
for i in range(len(data)):
       if(data[i][-1]=='Iris-setosa'):
              l8.append(data[i][1])
              19.append(data[i][3])
       elif(data[i][-1]=='Iris-versicolor'):
              l10.append(data[i][1])
```

```
l11.append(data[i][3])
else:
l12.append(data[i][1])
l13.append(data[i][3])

plt.plot(l8,l9,'.r',label='Iris-setosa')
plt.plot(l10,l11,'.b',label='Iris-versicolor')
plt.plot(l12,l13,'.g',label='Iris-virginica')
plt.plot(lx,ly,'.k')
plt.plot(lx1,ly1,'.k')
plt.show()
```