HOMEWORK 1

DATA EXPLORATION

Solution to question (a.i), (a.ii)

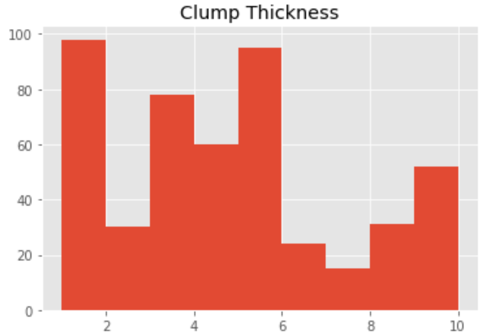
In this section, I have just parsed the dataset into lists to plot the histograms as required by question 2.(a) and 2.(b). It is visible that the data is not equally distributed. There are more data samples in the Benign case than in the Malignant case. Most features are more or less following a noraml distribution.

```
import csv
import matplotlib.pyplot as plt
import numpy as np

malign = 0
benign = 0
Clump_Thick =  []
Cell_Size = []
Cell_Shape =  []
Marg_Adh =  []
E_Cell_Size = []
B_Nuclei =  []
Bland_Chromatin =  []
Norm_Nucleoli =  []
Mitoses =  []
type_cancer =  []


with open('hw1_question1_train.csv') as csvfile:
  readCSV = csv.reader(csvfile)
  for row in readCSV:
    '''read each value from the row and place it in an appropriate list.
    these lists contain each individual column of our data.
    '''
    Clump_Thick.append(int(row[0]))
    Cell_Size.append(int(row [1]))
    Cell_Shape.append(int(row [2]))
    Marg_Adh.append(int(row [3]))
    E_Cell_Size.append(int(row [4]))
    B_Nuclei.append(int(row [5]))
    Bland_Chromatin.append(int(row [6]))
    Norm_Nucleoli.append(int(row [7]))
    Mitoses.append(int(row [8]))
    type_cancer.append(row [9])
    '''
    maintain two variables that hold the number of malignant cases and
    the number of benign cases
    '''
    if (row [9]== '2'):
      benign = benign + 1
    else:
      malign = malign + 1

#PLOTTING THE FEATURES
print ("Number of Benign cases are:", benign, "\nNumber of malignant cases are:",malign,"\nNo, the two classes are not equally distributed.\n")
plt.style.use('ggplot')
'''
Plotting the histogram of the various features.
'''
plt.title('Clump Thickness')
plt.hist(np.sort(Clump_Thick),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Cell Size')
plt.hist(np.sort(Cell_Size),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Cell Shape')
plt.hist(np.sort(Cell_Shape),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Marginal Adhesion')
plt.hist(np.sort(Marg_Adh),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Ephithelial Cell Size')
plt.hist(np.sort(E_Cell_Size),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Bare Nuclei')
plt.hist(np.sort(B_Nuclei),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Bland Chromatin')
plt.hist(np.sort(Bland_Chromatin),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Normal Nucleoli')
```

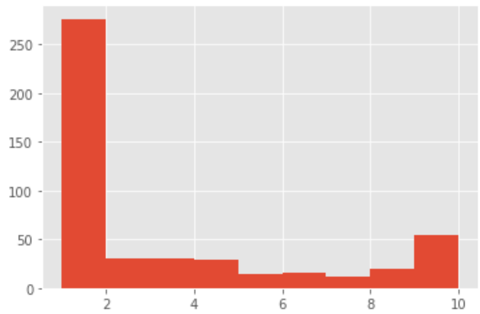
```
plt.title('Normal Nucleoli')
plt.hist(np.sort(Norm_Nucleoli),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
plt.title('Mitoses')
plt.hist(np.sort(Mitoses),bins=[1,2,3,4,5,6,7,8,9,10])
plt.show()
```

```
Number of Benign cases are: 330
Number of malignant cases are: 153
No, the two classes are not equally distributed.
```

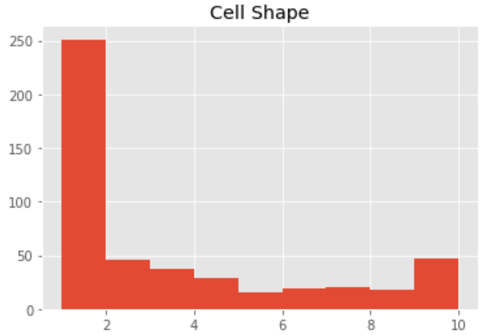
Clump Thickness



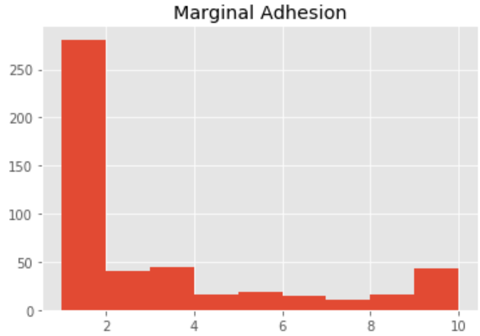
Cell Size



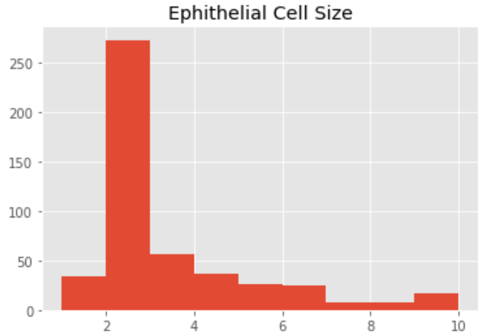
Cell Shape



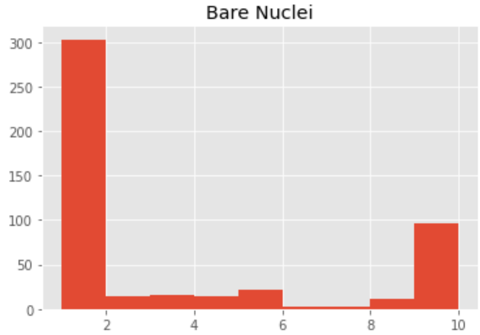
Marginal Adhesion

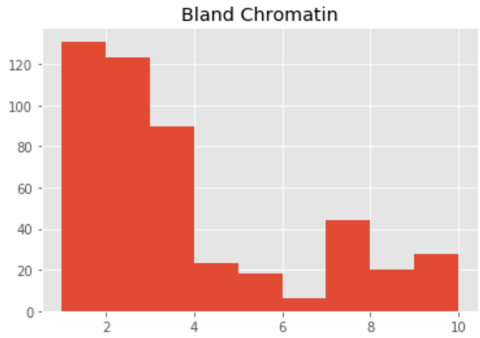


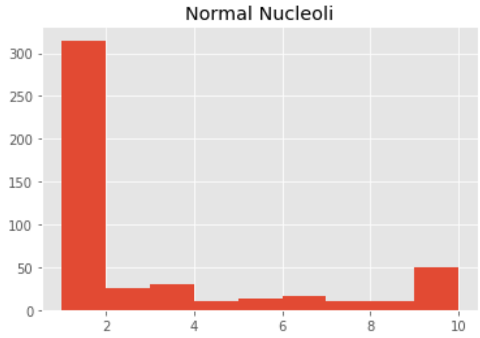
Ephithelial Cell Size

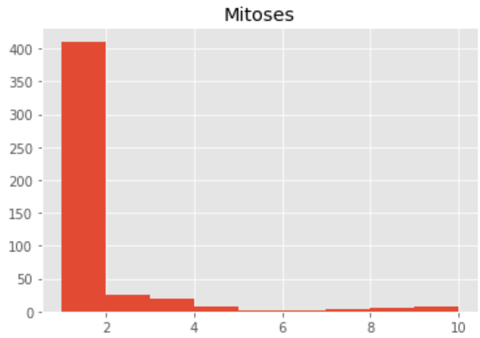


Bare Nuclei









IMPLEMENTATION OF k-NN

In my implementation of k-NN, I first created a class called 'Datapoint'. An object of this class holds all the feautres of our dataset. Also the class has a couple of helper functions to make things easier.

Solution to 2(a.iii)

> As part of further data exploration, I next randomly selected 5 pairs of datapoints. Then plotted these points. This helps to judge the possible correlation between features. From my observation I could not see too much correlation between any of the features that I had chosen. Also the scatter plot helped to show that the data was not linearly seperable and hence something simple like a perceptron would be unable to classify this data.

The dataset is parsed and the corresponding datapoints are then created. To compute the nearest neighbors I have used 3 different distance metrics; euclidean distance, hamming distance and cosine similarity. Having used the training and test data I finally compare the performance of the 3 distance metrics and for different values of 'k'.

Solution to 2(b.i)

> To perform nearest neighbor classification the following steps were followed.
>
> 1. Find the neighbors of the datapoint being classified
> 2. Of the neighbors find the neighbor neighbor closest to the datapoint in question. Here is where the value of 'k' comes into play. The number 'k' tells us how many of the nearest neighbors to a given point we consider. The nearness of a point in the space and the datapoint can be measured by different metrics.
> 3. Each of the 'k' nearest neighbors get to vote to steer the results toward the class they belong to. Once all the neighbors vote, the datapoint is said to belong to the class which got the most votes.

> In this question the euclidean distance metric was used. The code for this can be found from line 85 to 153 below.

Solution to 2(b.ii),2(b.iii) and 2(b.iv)

Now, that it is clear how a k-NN works, the next step was to train the k-NN to classify a given point. To ensure this is done accurately we use a development set to train a model while varying the values of k. Also, we ran 3 different models for 3 different distance metrics i.e. Euclidean Distance, Cosine Similarity and the Hamming distance. Using the Acc and B.Acc performance metrics we compared the trained models and chose the best model of this to use on our test data.

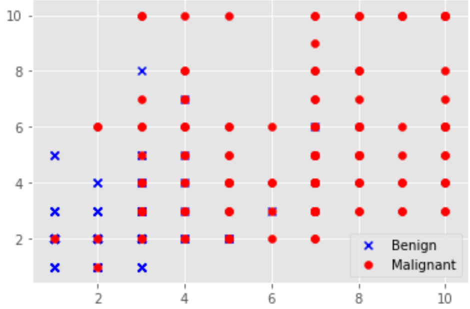
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics.pairwise import cosine_similarity
from scipy.spatial import distance
from scipy import spatial
import csv
import math as m
import operator

#Creating a class for representing the Datapoints.

class Datapoint(object):

  def __init__ (self, feats):
      self.feature_1 = feats['Clump_Thick']
      self.feature_2 = feats['U_CSize']
      self.feature_3 = feats['CShape']
      self.feature_4 = feats['M_Adh']
      self.feature_5 = feats['E_CSize']
      self.feature_6 = feats['B_Nuclei']
      self.feature_7 = feats['Bl_Chroma']
      self.feature_8 = feats['Norm_Nucleoli']
      self.feature_9 = feats['Mitoses']
      self.type_of_tumor = feats['type_of_tumor']
  #Returns the features as a Numpy Array.
  def feature_vector (self):
      return np.array([self.feature_1, self.feature_2, self.feature_3,\
                       self.feature_4, self.feature_5, self.feature_6,\
                       self.feature_7, self.feature_8, self.feature_9, self.type_of_tumor])

  def __str__(self):
    return "\nClump Thickness:{}, \nCell Size:{}, \nCell Shape:{}, \nMarginal Adhesion:{},\
     \nEpithelial Cell Size:{}, \nBare Nuclei:{}, \nBland Chromatin:{}, \
     \nNormal Nucleoli:{}, \nMitoses:{}, \nType of Tumor:{}".format(self.feature_1, self.feature_2, self.feature_3, self.feature_4, self.feature_5,\
                                                                  self.feature_6, self.feature_7, self.feature_8,  self.feature_9, self.type_of_tumor)
#Function that creates the datapoints and writes the corresponding feature value to the datapoints.
def parse_dataset(filename):
    with open(filename) as csvfile:
      dataset = []
      readCSV = csv.reader(csvfile)
      for row in readCSV:
        a=Datapoint({'Clump_Thick':int(row[0]), 'U_CSize':int(row[1]), 'CShape':int(row[2]), 'M_Adh':int(row[3]), \
                                 'E_CSize':int(row[4]), 'B_Nuclei':int(row[5]), 'Bl_Chroma':int(row[6]), 'Norm_Nucleoli':int(row[7]),
                                 'Mitoses':int(row[8]),'type_of_tumor':int(row[9])})

        dataset.append(a.feature_vector())


    return dataset

#PARSE the training , development and testing  dataset.
dataset_train = parse_dataset('hw1_question1_train.csv')
dataset_test  = parse_dataset('hw1_question2_test.csv')
dataset_dev = parse_dataset('hw1_question2_dev.csv')
#Printing some statistics about the data.
print("Total Number of Data Points in Training set: {0}".format(len(dataset_train)))
print("Total Number of Data Points in Dev set: {0}".format(len(dataset_dev)))
print("Total Number of Data Points in Testing set: {0}".format(len(dataset_test)))

#Function to plot.
def plot_data(dataset,x,y):

  benign_feat1 = [data[x] for data in dataset if data[9] == 2]
  benign_feat2 = [data[y] for data in dataset if data[9] == 2]
  malign_feat1 = [data[x] for data in dataset if data[9] == 4]
  malign_feat2 = [data[y] for data in dataset if data[9] == 4]
  plt.scatter(benign_feat1,benign_feat2, c='b',marker ='x', label = 'Benign')
  plt.scatter(malign_feat1,malign_feat2, c='r',marker ='o', label = 'Malignant')
  plt.legend()
  plt.show()
#Plotting 5 random sets of features. It is not really random, but just different combinations
#features
plot_data(dataset_train, 6, 4)
plot_data(dataset_train, 0, 2)
plot_data(dataset_train, 1, 3)
plot_data(dataset_train, 3, 5)
plot_data(dataset_train, 4, 2)

print("The Datapoints are not linearly sperable.")

#-------------------------------------------------------------CLASSIFICATION----------------------------------------------------------------------------------
'''
As a first step in classification, I define a function that can compute the eucledian distance between two datapoints
'''
#DISTANCE METRICS-------------------------------------------------
def EuclidDistance (instance1, instance2, length):
  distance = 0
```

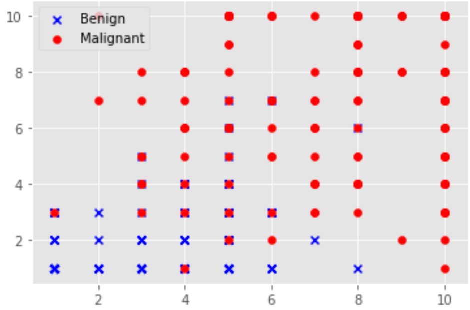
```
  for x in range(length):
    distance += pow((instance1[x]-instance2[x]),2)
  return m.sqrt(distance)

def hamming_distance(instance1, instance2, length):
  return(distance.hamming(instance1, instance2))

def cosine_similarity(instance1, instance2, length):
  return(spatial.distance.cosine(instance1, instance2))
#------------------------------------------------------------------
# Function to compute the neighbors to the test point.
def getNeighbors(dataset, testcase, k):
  distances = []
  length = len(testcase) - 1
  for x in range((len(dataset))):
    dist = EuclidDistance(testcase,dataset[x],length)
    distances.append((dataset[x],dist))
  distances.sort(key=operator.itemgetter(1))
  neighbors = []
  for x in range (k):
      neighbors.append(distances[x][0])
  return neighbors

def getNeighbors_hamming(dataset, testcase, k):
  distances = []
  length = len(testcase) - 1
  for x in range((len(dataset))):
    dist = hamming_distance(testcase,dataset[x],length)
    distances.append((dataset[x],dist))
  distances.sort(key=operator.itemgetter(1))
  neighbors = []
  for x in range (k):
      neighbors.append(distances[x][0])
  return neighbors

def getNeighbors_cosine(dataset, testcase, k):
  distances = []
  length = len(testcase) - 1
  for x in range((len(dataset))):
    dist = cosine_similarity(testcase,dataset[x],length)
    distances.append((dataset[x],dist))
  distances.sort(key=operator.itemgetter(1))
  neighbors = []
  for x in range (k):
      neighbors.append(distances[x][0])
  return neighbors
#------------------------- End of Distance Metrics-------------------------------
#Function that calculates the final class based on a vote.
def getResponse(neighbors):
    votes = []
    four = 0
    two = 0
    for x in range (len(neighbors)):
      response = neighbors [x][-1]
      votes.append(neighbors[x][-1])
    for x in votes:
      if x == 2:
        two += 1
      else:
        four += 1
    if (two>four):
      result = 2
    else:
      result = 4
    return (result)
#-------------------------------------------------------------------------------
#Accuracy calculations
def Acc (classified,dataset):
  count = 0
  for x in range (len(dataset)):
    if (classified[x]==dataset[x][-1]):
      count += 1
  acc = float(count/(len(dataset)))
  return(acc)

def bAcc (classified,dataset):
  one = 0
  two = 0
  count1 = 0
  count2 = 0
  for x in range (len(dataset)):
    if (dataset[x][-1]== 2):
      one += 1
    else:
      two += 1
  for x in range (len(dataset)):
    if (classified[x]==dataset[x][-1] & classified [x]==2):
      count1 += 1
```

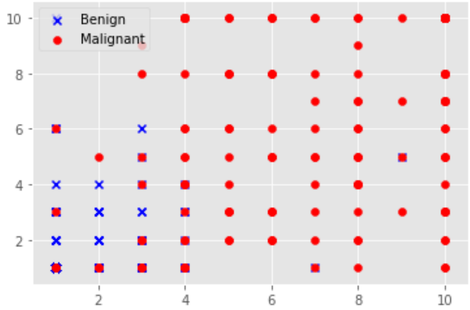
```
    elif (classified[x]==dataset[x][-1] & classified [x]==4):
      count2 += 1
  bacc = 0.5*((count1/one) + (count2/two))
  return(bacc)
#-----------------------------------------------------------------------------
#KNN CLASSIFICATION (EUCLIDEAN Distance)
print("\nTRAINING MODEL WITH EUCLIDEAN DISTANCE AS THE DISTANCE METRIC")
k_values = [1,3,5,7,9,11,13,15,17,19]
acc_values = []
bacc_values = []
for k in k_values:
  neighbors = []
  classified = []
  print("\nRunning for K =", k)
  for data in dataset_dev:
    neighbors= (getNeighbors(dataset_train, data, k))
    classified.append(getResponse (neighbors))
  print('Accuracy:',Acc(classified,dataset_dev),'\nBalanced Accuracy:',\
        bAcc(classified,dataset_dev))
  acc_values.append(Acc(classified, dataset_dev))
  bacc_values.append(bAcc(classified,dataset_dev))
plt.title('Accuracy')
plt.bar(k_values,acc_values)
plt.show()

plt.title('Balanced Accuracy')
plt.bar(k_values,bacc_values)
plt.show()
euclidean_metric = [acc_values,bacc_values]
print('Best K1 is', acc_values.index(max(acc_values))+2)
print('Best K2 is', bacc_values.index(max(bacc_values))+2)
#-----------------------------------------------------------------------------
#KNN using Hamming Distance
print("\nTRAINING MODEL WITH HAMMING DISTANCE AS THE DISTANCE METRIC")
k_values = [1,3,5,7,9,11,13,15,17,19]
acc_values = []
bacc_values = []
for k in k_values:
  neighbors = []
  classified = []
  print("\nRunning for K =", k)
  for data in dataset_dev:
    neighbors= (getNeighbors_hamming(dataset_train, data, k))
    classified.append(getResponse (neighbors))
  print('Accuracy:',Acc(classified,dataset_dev),'\nBalanced Accuracy:',\
        bAcc(classified,dataset_dev))
  acc_values.append(Acc(classified, dataset_dev))
  bacc_values.append(bAcc(classified,dataset_dev))
plt.title('Accuracy Hamming')
plt.bar(k_values,acc_values)
plt.show()

plt.title('Balanced Accuracy Hamming')
plt.bar(k_values,bacc_values)
plt.show()
hamming_metric = [acc_values,bacc_values]
print('Best K1 is', acc_values.index(max(acc_values))+2)
print('Best K2 is', bacc_values.index(max(bacc_values))+2)

#-----------------------------------------------------------------------------
#KNN Using Cosine Similarity
k_values = [1,3,5,7,9,11,13,15,17,19]
acc_values = []
bacc_values = []
print("\nTRAINING MODEL WITH COSINE SIMILARITY AS THE DISTANCE METRIC AND k=3")
for k in k_values:
  neighbors = []
  classified = []
  print("\nRunning for K =", k)
  for data in dataset_dev:
    neighbors= (getNeighbors_cosine(dataset_train, data, k))
    classified.append(getResponse (neighbors))
  print('Accuracy:',Acc(classified,dataset_dev),'\nBalanced Accuracy:',\
        bAcc(classified,dataset_dev))
  acc_values.append(Acc(classified, dataset_dev))
  bacc_values.append(bAcc(classified,dataset_dev))
print('\n\n\n\n\n\n')
plt.title('Accuracy (Cosine)')
plt.bar(k_values,acc_values)
plt.show()

plt.title('Balanced Accuracy (Cosine)')
plt.bar(k_values,bacc_values)
plt.show()
cosine_metric = [acc_values,bacc_values]
print('Best K1 is', acc_values.index(max(acc_values))+2)
print('Best K2 is', bacc_values.index(max(bacc_values))+2)
```

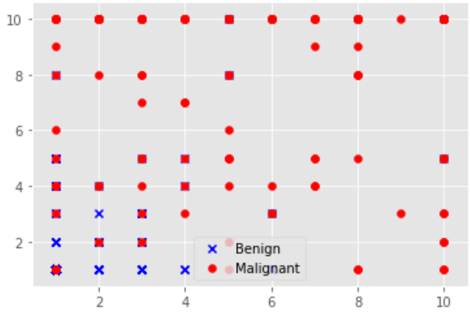
```
#-------------------------------------------------------------------------------------------
print("\nCOMPARING THE 3 DISTANCE METRICS!")
print("ACC and bACC Values for Euclidean Distance: ",euclidean_metric[0],'\n',euclidean_metric[1])
print("ACC and bACC Values for Hamming Distance: ",hamming_metric[0],'\n',hamming_metric[1])
print("ACC and bACC Values for Cosine Similarity: ",cosine_metric[0], '\n',cosine_metric[1])
#-----------------------------------TESTING--------------------------------------
#KNN using Hamming Distance
print("\nTRAINING MODEL WITH HAMMING DISTANCE AS THE DISTANCE METRIC")
k_values = [3]
acc_values = []
bacc_values = []
for k in k_values:
  neighbors = []
  classified = []
  #print("\nRunning for K =", k)
  for data in dataset_test:
    neighbors= (getNeighbors_hamming(dataset_train, data, 3))
    classified.append(getResponse (neighbors))
  print('Accuracy:',Acc(classified,dataset_test),'\nBalanced Accuracy:',\
        bAcc(classified,dataset_test))

```

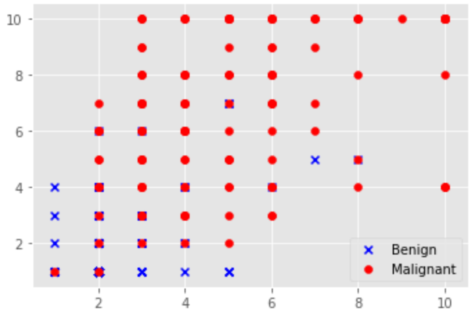
```
otal Number of Data Points in Training set: 483
otal Number of Data Points in Dev set: 100
otal Number of Data Points in Testing set: 100
```







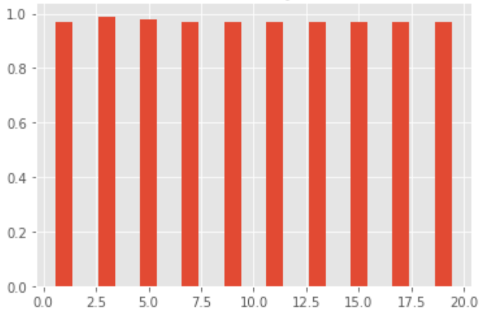




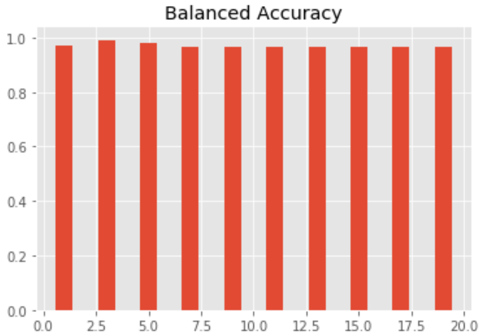

```
he Datapoints are not linearly sperable.

RAINING MODEL WITH EUCLIDEAN DISTANCE AS THE DISTANCE METRIC

unning for K = 1
ccuracy: 0.97
alanced Accuracy: 0.9708557255064076

unning for K = 3
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 5
ccuracy: 0.98
alanced Accuracy: 0.9793303017775941

unning for K = 7
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745

unning for K = 9
ccuracy: 0.97
```

```
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745

unning for K = 11
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745

unning for K = 13
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745

unning for K = 15
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745

unning for K = 17
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745

unning for K = 19
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745
```

Accuracy

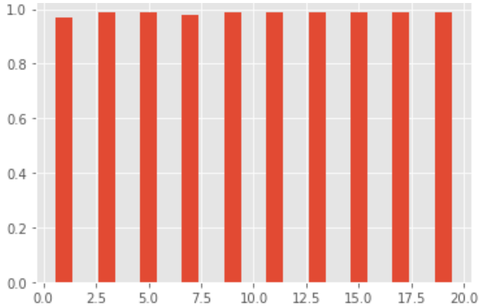


Balanced Accuracy

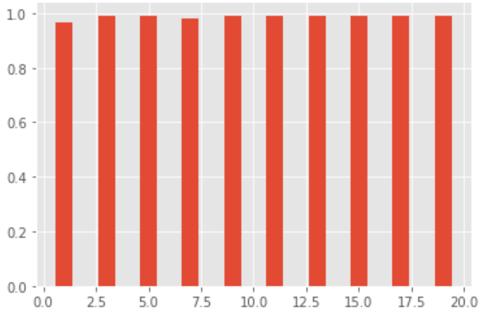



```
est K1 is 3
est K2 is 3

RAINING MODEL WITH HAMMING DISTANCE AS THE DISTANCE METRIC

unning for K = 1
ccuracy: 0.97
alanced Accuracy: 0.9671351798263745

unning for K = 3
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 5
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 7
ccuracy: 0.98
alanced Accuracy: 0.9793303017775941

unning for K = 9
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 11
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 13
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 15
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 17
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136

unning for K = 19
ccuracy: 0.99
alanced Accuracy: 0.9915254237288136
```

Accuracy Hamming

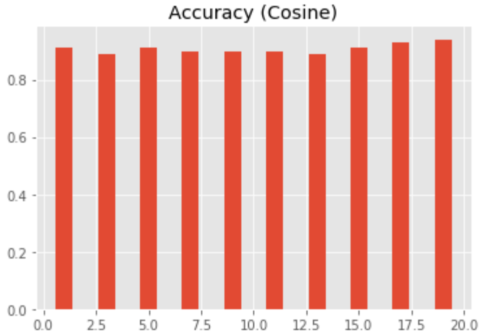


Balanced Accuracy Hamming

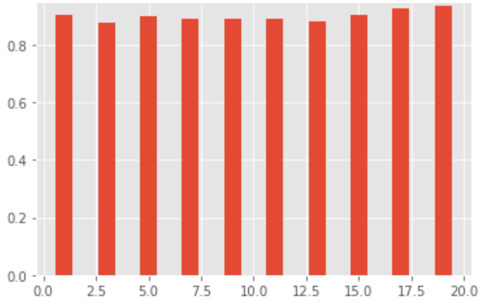



```
est K1 is 3
est K2 is 3

RAINING MODEL WITH COSINE SIMILARITY AS THE DISTANCE METRIC AND k=3

unning for K = 1
ccuracy: 0.91
alanced Accuracy: 0.9051260851591567

unning for K = 3
ccuracy: 0.89
alanced Accuracy: 0.8770152955766846

unning for K = 5
ccuracy: 0.91
alanced Accuracy: 0.9014055394791236

unning for K = 7
ccuracy: 0.9
alanced Accuracy: 0.8892104175279041

unning for K = 9
ccuracy: 0.9
alanced Accuracy: 0.8892104175279041

unning for K = 11
ccuracy: 0.9
alanced Accuracy: 0.8892104175279041

unning for K = 13
ccuracy: 0.89
alanced Accuracy: 0.8807358412567177

unning for K = 15
ccuracy: 0.91
alanced Accuracy: 0.9051260851591567

unning for K = 17
ccuracy: 0.93
alanced Accuracy: 0.9257957833815627

unning for K = 19
ccuracy: 0.94
alanced Accuracy: 0.9379909053327822
```

Accuracy (Cosine)



Balanced Accuracy (Cosine)




```
est K1 is 11
est K2 is 11

OMPARING THE 3 DISTANCE METRICS!
CC and bACC Values for Euclidean Distance:  [0.97, 0.99, 0.98, 0.97, 0.97, 0.97, 0.97, 0.97, 0.97, 0.97]
[0.9708557255064076, 0.9915254237288136, 0.9793303017775941, 0.9671351798263745, 0.9671351798263745, 0.9671351798263745, 0.9671351798263745, 0.96713517
CC and bACC Values for Hamming Distance:  [0.97, 0.99, 0.99, 0.98, 0.99, 0.99, 0.99, 0.99, 0.99, 0.99]
[0.9671351798263745, 0.9915254237288136, 0.9915254237288136, 0.9793303017775941, 0.9915254237288136, 0.9915254237288136, 0.9915254237288136, 0.99152542
CC and bACC Values for Cosine Similarity:  [0.91, 0.89, 0.91, 0.9, 0.9, 0.9, 0.89, 0.91, 0.93, 0.94]
[0.9051260851591567, 0.8770152955766846, 0.9014055394791236, 0.8892104175279041, 0.8892104175279041, 0.8892104175279041, 0.8807358412567177, 0.90512608

RAINING MODEL WITH HAMMING DISTANCE AS THE DISTANCE METRIC
ccuracy: 0.99
alanced Accuracy: 0.9864864864864865
```

Results

At the end the best set of parameters is K=3 and using Hamming distance as the distance metric. We see an Accuracy if 99% and a Balanced Accuracy of 98.6%.