Assignment 1 (k-NN Classification)

Ref

Summery:

KNN Vanilla & Ball Models

List of HyperPrameters

- methods = ["vanilla" , "ball"]
- metrics = ["euclidean", "cityblock", "cosine", "chebyshev", "sqeuclidean"]
- k_values = [1 , 3 , 5 , 7 , 9 , 11 , 13 , 15 , 17 , 19])
- e_values = [0.1 , 0.5, 0.8 , 1 , 2 , 5 , 7 , 10 , 15 ,20]

Prediction on the validation dataset:

The accuracy and optimum hyper prameters were achived as below:

- methods vanilla
- metrics euclidean
- k_values 19.0
- Accuracy 0.637
- methods ball
- metrics euclidean
- e_values 0.500
- Accuracy 0.500

Prediction was conducted on validation dataset using different combinations of hyperprameters, to choose the optimum one. As a result, the above combinations were achive for each of Vanilla and Ball methods.

Prediction on the train dataset:

The accuracy and optimum hyper prameters were achived as below:

- methods vanilla
- metrics euclidean
- k_values 1.0
- Accuracy 1.000
- methods ball
- metrics euclidean
- e_values 0.100
- Accuracy 0.440

As expected training dataset has higher accuracy than test and validation dataset, because model can memorize datapoints and prediction accuracy does not represent the accuracy on unseen data.

Prediction on the test dataset:

The accuracy and optimum hyper prameters were achived as below:

- methods vanilla
- metrics euclidean
- k_values 1.0
- Accuracy 0.470
- methods ball
- metrics euclidean

- e_values 0.5
- Accuracy 0.441

As could be seen above, vanilla should a better accuracy than ball method and euclidean function performed the best for both models. I conducted the predictions on the test dataset with different hyperpropeters to see if the optimum here will be the same as valid dataset (as expected) or not. Results showed the same optimum hyper prameters which was satisfactory expriment.

KNN KD-Tree Model

Prediction on the train dataset:

- kd_methods k_nearest
- kd_metrics euclidean
- leaf_sizes 1
- k_values 1.0
- Accuracy 0.999
- kd_methods radius
- kd_metrics euclidean
- leaf_sizes 1
- r_values 0.1
- Accuracy 0.996

KD Tree was exprimented to ovbserve change of speed by using this model compared to the previous two models. As a result, prediction time on the training dataset was considerably improved compared to the prediction time of train dataset on Vanilla and Ball methods. I chose prediction on train dataset due to its much longer prediction time than prediction on validation or test sets.

Importing Required Libraries

In [3]:

```
import numpy as np
from scipy.spatial.distance import cdist
from scipy.stats import mode
import pandas as pd
from sklearn.model_selection import train_test_split #Split Data
from sklearn.model_selection import cross_val_score #cross validation
import matplotlib.pyplot as plt
import matplotlib
from sklearn.neighbors import KDTree
from sklearn.neighbors import NearestNeighbors
from sklearn.preprocessing import RobustScaler
```

Defining KNN Class

In [4]:

```
class KNN:

    def __init__(self, arg1 , selected_metric = 'euclidean' , method = 'vanilla'):

#         super(KNN , self).__init__()

        if (method == "vanilla" ):

            self.k = arg1 #IndexError: index 0 is out of bounds for axis 0 with size 0

            self.selected_metric = selected_metric

            self.method = method

        elif (method == "ball" ):
```

```
            self.e = arg1

            self.selected_metric = selected_metric

            self.method = method

    def fit(self, data, target):

        self.data = data

        self.target = target

#         print(self.target.shape)

    def predict(self, tedata):

        pred = np.zeros((tedata.shape[0], 1))#?????????????????????????????????????????

        distances = cdist(self.data, tedata , self.selected_metric).T

#         print(distances.shape) #(240 , 1119)

        #                 print(boolArr.shape) #(240, 1119) // Checking the shape of boo
lean array
#     self.target is  Y_train with shape(1119, )   I change the dimension to (1119 , 1)
in 2 lines below

#                 boolArr = boolArr.T #Changing shape of boolarray to (1119, 240)

#         print(self.target.shape)#(1119,)

        if (method == 'vanilla'):

            one_comb_240predic= []

            for i in range(distances.shape[0]): #range(240)

                top_k = self.target[np.argsort(distances[i])[:self.k]].tolist()
                #index 876 is out of bounds for axis 0 with size 240

                pred[i] = mode(top_k, axis=None).mode[0]

        elif (method == 'ball'):#selecting distances which are smaller than k (here k is
radius of ball)

            self.target = self.target.reshape(-1,1119) #It is not updated in place, I ne
ed to reassign

#             print(self.target.shape) #(1 , 1119)

            repetitions = distances.shape[0]

            self.target = np.tile(self.target, (repetitions, 1))#Tiling a row 240 times
in the next rows

            for i in range(distances.shape[0]):

                boolArr = distances < self.e

                top_e = self.target[boolArr].tolist()#changing shape of Y_train from (11
19,) to (1,1119)

                if(len(top_e)==0):

                    pred[i] = -1#so it will not be equal to any candidate labels

                else:

#                 if statement for the case top_e is empty. the stop to avoid error

                    pred[i] = mode(top_e, axis=None).mode[0]#???????????????????????????
?????????
```

```
#                   print(pred[i])
# which train samples each test sample like to consider

#                   print(len(top_k))#33
    #is it a matrix with 240 rows and different numbers of columns?



        return pred.astype(int)# 240 cases
```

Loading CSV data Into a Dataframe

In [5]:

```
df = pd.read_csv("winequality-red.csv" , sep = ";") #Reading CSV data as seperating them with ";"
df.head()  #Taking a look at the data format
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

Scaling

In [6]:

```
scaler = RobustScaler() #Initilization of scaler object
features = np.array(df.columns)
features =  features[:-1]#Removing labels (last column) from the list of candidate columns for scaling
features = features.reshape(-1 , 1)
# features.shape#Shape of features candidate for scaling

for feature in features:

    df[feature] = scaler.fit_transform(df[feature])

df.head()#Representation of DF after scaling by "RobustScaler"
```

Out[6]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	-0.238095	0.72	-0.787879	-0.428571	-0.15	-0.214286	-0.100	0.469799	1.052632	-0.333333	-0.50	5
1	-0.047619	1.44	-0.787879	0.571429	0.95	0.785714	0.725	0.022371	-0.578947	0.333333	-0.25	5
2	-0.047619	0.96	-0.666667	0.142857	0.65	0.071429	0.400	0.111857	-0.263158	0.166667	-0.25	5
3	1.571429	-0.96	0.909091	-0.428571	-0.20	0.214286	0.550	0.559284	-0.789474	-0.222222	-0.25	6
4	-0.238095	0.72	-0.787879	-0.428571	-0.15	-0.214286	-0.100	0.469799	1.052632	-0.333333	-0.50	5

total

Splitting Data To Train, Validation And Test (x,y) Datasets

In [7]:

```
# Split data into 70% train and 30% test subsets (15% val and 15% test)
X_train, X_test, Y_train, Y_test = train_test_split(df.values[:,:-1],df.values[:,-1] ,test_size=0.3, shuffle=False)
X_valid, X_test, Y_valid, Y_test = train_test_split(X_test, Y_test, test_size=0.5, shuffle=False)
print(X_train.shape, X_valid.shape, X_test.shape)
print(Y_train.shape, Y_valid.shape, Y_test.shape)
```

```
(1119, 11) (240, 11) (240, 11)
(1119,) (240,) (240,)
```

List of Candidate Hyper Parameters

In [37]:

```
methods = ["vanilla" , "ball"] #List of candidate KNN methods
metrics = ["euclidean", "cityblock", "cosine", "chebyshev", "sqeuclidean"] #List of candidate distance functions
k_values = [1 , 3 , 5 , 7 , 9 , 11 , 13 , 15 , 17 , 19] #List of candidate number of neighbors (exclusively for vanilla)
e_values = [0.1 , 0.5, 0.8 , 1 , 2 , 5 , 7 , 10 , 15 ,20 ]#List of candidate radius of neighborhood (exclusively for ball)
```

Validation Dataset Accuracy

In [38]:

```
all_combo_pred_lst = []

for method in methods:

    for metric in metrics:

        if(method == "vanilla"):

            for k_value in k_values: #We need two different for loop here for vanilla and ball

                each_combo = []

                obj_knn = KNN(k_value , metric , method)#making the KNN obj with vanilla consructor
                #We ccan not pass e_value to the costructor above, since we still dont have it
#                 should I call self.k instead of k_value?
#constructor checks the methods, and since it is vanilla,it assihnes self.k = k_value

                obj_knn.fit(X_train, Y_train) #trainig obj

                prediction = obj_knn.predict(X_valid)#it returns a list of 240 predictions for a comb

                accuracy = sum(prediction.flatten() == Y_valid)/len(Y_valid)

                each_combo.append(method )
                each_combo.append( metric )
                each_combo.append( k_value)
                each_combo.append(accuracy)

                all_combo_pred_lst.append(each_combo)  #list of lists of all 100 comb eac
```

```
h containing above appends

        elif(method == "ball"):

            for e_value in e_values:

                each_combo = []

                obj_knn = KNN(e_value , metric , method)#making the KNN obj with ball co
nsructor

                obj_knn.fit(X_train, Y_train) #trainig obj

                prediction = obj_knn.predict(X_valid)#it returns a list of 240 predictio
ns for a comb

                accuracy = sum(prediction.flatten() == Y_valid)/len(Y_valid)

                each_combo.append(method )
                each_combo.append( metric )
                each_combo.append( e_value)
                each_combo.append(accuracy)

                all_combo_pred_lst.append(each_combo) #list of lists of all 100 comb eac
h containing above appends
```

In [39]:

```
## DF of Validation-Accuracy ( Different Hyperprameter Combinations)
df2 = pd.DataFrame(all_combo_pred_lst ,columns=[ 'methods', 'metrics', 'k_values' ,'Accu
racy'])
df2.head()
```

Out[39]:

	methods	metrics	k_values	Accuracy
0	vanilla	euclidean	1.0	0.475000
1	vanilla	euclidean	3.0	0.479167
2	vanilla	euclidean	5.0	0.562500
3	vanilla	euclidean	7.0	0.595833
4	vanilla	euclidean	9.0	0.583333

In [40]:

```
# Statistical description of Validation-Accuracy DF, Grouped by method
df2.groupby(["methods"]).describe()
```

Out[40]:

	k_values								Accuracy						
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%
methods															
ball	50.0	6.14	6.607849	0.1	0.8	3.5	10.0	20.0	50.0	0.329167	0.136892	0.000000	0.341667	0.341667	0.341
vanilla	50.0	10.00	5.802885	1.0	5.0	10.0	15.0	19.0	50.0	0.562167	0.060204	0.395833	0.537500	0.579167	0.600

In [41]:

```
## Splitting original DF to DFs of vanilla and ball
df_ball =  df2[df2.methods == 'ball'].rename(columns={'k_values':'e_values'})
df_vanilla =  df2[df2.methods == 'vanilla']
df_ball.head()
# df_vanilla.head()
```

Out[41]:

	methods	metrics	e_values	Accuracy
50	ball	euclidean	0.1	0.000000
51	ball	euclidean	0.5	0.500000
52	ball	euclidean	0.8	0.500000
53	ball	euclidean	1.0	0.500000
54	ball	euclidean	2.0	0.341667

In [42]:

```
## Maximum Accuracy (Vanilla method) Hyperprameter Configuration
df_vanilla.loc[df_vanilla['Accuracy'].idxmax()]
```

Out[42]:

```
methods        vanilla
metrics      euclidean
k_values          19.0
Accuracy        0.6375
Name: 9, dtype: object
```

In [43]:

```
## Maximum Accuracy (Ball method) Hyperprameter Configuration
df_ball.loc[df_ball['Accuracy'].idxmax()]
```

Out[43]:

```
methods           ball
metrics      euclidean
e_values           0.5
Accuracy           0.5
Name: 51, dtype: object
```

Train Dataset Accuracy

In [44]:

```
train_all_combo_pred_lst = []

for method in methods:

    for metric in metrics:

        if(method == "vanilla"):

            for k_value in k_values: #We need two different for loop here for vanilla and
ball

                each_combo = []

                train_obj_knn = KNN(k_value , metric , method)#making the KNN obj with v
anilla consructor
                #We ccan not pass e_value to the costructor above, since we still dont ha
ve it
#                 should I call self.k instead of k_value?
#constructor checks the methods, and since it is vanilla,it assihnes self.k = k_value

                train_obj_knn.fit(X_train, Y_train) #trainig obj

                train_prediction = train_obj_knn.predict(X_train)#it returns a list of 2
40 predictions for a comb

                train_accuracy = sum(train_prediction.flatten() == Y_train)/len(Y_train)

                each_combo.append(method )
```

```
                each_combo.append( metric )
                each_combo.append( k_value)
                each_combo.append(train_accuracy)

                train_all_combo_pred_lst.append(each_combo) #list of lists of all 100 co
mb each containing above appends

        elif(method == "ball"):

            for e_value in e_values:

                each_combo = []

                train_obj_knn = KNN(e_value , metric , method)#making the KNN obj with b
all consructor

                train_obj_knn.fit(X_train, Y_train) #trainig obj

                train_prediction = train_obj_knn.predict(X_train)#it returns a list of 2
40 predictions for a comb

                train_accuracy = sum(train_prediction.flatten() == Y_train)/len(Y_train)

                each_combo.append(method )
                each_combo.append( metric )
                each_combo.append( e_value)
                each_combo.append(train_accuracy)

                train_all_combo_pred_lst.append(each_combo) #list of lists of all 100 co
mb each containing above appends
```

In [45]:

```
## DF of Train-Accuracy ( Different Hyperprameter Combinations)
train_df2 = pd.DataFrame(train_all_combo_pred_lst ,columns=[ 'methods', 'metrics', 'k_va
lues' ,'Accuracy'])
train_df2.head()
```

Out[45]:

	methods	metrics	k_values	Accuracy
0	vanilla	euclidean	1.0	1.000000
1	vanilla	euclidean	3.0	0.787310
2	vanilla	euclidean	5.0	0.729223
3	vanilla	euclidean	7.0	0.672922
4	vanilla	euclidean	9.0	0.630920

In [46]:

```
# Statistical description of Train-Accuracy DF, Grouped by method
train_df2.groupby(["methods"]).describe()
```

Out[46]:

	k_values								Accuracy						
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%
methods															
ball	50.0	6.14	6.607849	0.1	0.8	3.5	10.0	20.0	50.0	0.440572	5.607473e-17	0.440572	0.440572	0.440572	0.4
vanilla	50.0	10.00	5.802885	1.0	5.0	10.0	15.0	19.0	50.0	0.695353	1.141437e-01	0.613047	0.626005	0.641197	0.7

In [47]:

```python
## Splitting original DF to DFs of vanilla and ball
train_df_ball =  train_df2[train_df2.methods == 'ball'].rename(columns={'k_values':'e_va
lues'})
train_df_vanilla =  train_df2[train_df2.methods == 'vanilla']
# df_ball.shape
# train_df_ball.head()
train_df_vanilla.head()
```

Out[47]:

	methods	metrics	k_values	Accuracy
0	vanilla	euclidean	1.0	1.000000
1	vanilla	euclidean	3.0	0.787310
2	vanilla	euclidean	5.0	0.729223
3	vanilla	euclidean	7.0	0.672922
4	vanilla	euclidean	9.0	0.630920

In [48]:

```python
## Maximum Accuracy (Vanilla method) Hyperprameter Configuration
train_df_vanilla.loc[train_df_vanilla['Accuracy'].idxmax()]
```

Out[48]:

```
methods        vanilla
metrics      euclidean
k_values           1.0
Accuracy           1.0
Name: 0, dtype: object
```

In [49]:

```python
## Maximum Accuracy (Ball method) Hyperprameter Configuration
train_df_ball.loc[train_df_ball['Accuracy'].idxmax()]
```

Out[49]:

```
methods           ball
metrics      euclidean
e_values           0.1
Accuracy      0.440572
Name: 50, dtype: object
```

Test Dataset Accuracy

In [50]:

```python
test_all_combo_pred_lst = []

for method in methods:

    for metric in metrics:

        if(method == "vanilla"):

            for k_value in k_values: #We need two different for loop here for vanilla and
ball

                each_combo = []

                test_obj_knn = KNN(k_value , metric , method)#making the KNN obj with va
nilla consructor
                #We ccan not pass e_value to the costructor above, since we still dont ha
ve it
#                 should I call self.k instead of k_value?
#constructor checks the methods, and since it is vanilla,it assihnes self.k = k_value
```

```
                test_obj_knn.fit(X_train, Y_train) #trainig obj

                test_prediction = test_obj_knn.predict(X_test)#it returns a list of 240
predictions for a comb

                test_accuracy = sum(test_prediction.flatten() == Y_test)/len(Y_test)

                each_combo.append(method )
                each_combo.append( metric )
                each_combo.append( k_value)
                each_combo.append(test_accuracy)

                test_all_combo_pred_lst.append(each_combo) #list of lists of all 100 com
b each containing above appends

        elif(method == "ball"):

            for e_value in e_values:

                each_combo = []

                test_obj_knn = KNN(e_value , metric , method)#making the KNN obj with ba
ll consructor

                test_obj_knn.fit(X_train, Y_train) #trainig obj

                test_prediction = test_obj_knn.predict(X_test)#it returns a list of 240
predictions for a comb

                test_accuracy = sum(test_prediction.flatten() == Y_test)/len(Y_test)

                each_combo.append(method )
                each_combo.append( metric )
                each_combo.append( e_value)
                each_combo.append(test_accuracy)

                test_all_combo_pred_lst.append(each_combo) #list of lists of all 100 com
b each containing above appends
```

In [51]:

```
## DF of Test-Accuracy ( Different Hyperprameter Combinations)
test_df2 = pd.DataFrame(test_all_combo_pred_lst ,columns=[ 'methods', 'metrics', 'k_value
s' ,'Accuracy'])
test_df2.head()
```

Out[51]:

	methods	metrics	k_values	Accuracy
0	vanilla	euclidean	1.0	0.470833
1	vanilla	euclidean	3.0	0.470833
2	vanilla	euclidean	5.0	0.479167
3	vanilla	euclidean	7.0	0.520833
4	vanilla	euclidean	9.0	0.595833

In [52]:

```
# Statistical description of Train-Accuracy DF, Grouped by method
test_df2.groupby(["methods"]).describe()
```

Out[52]:

	k_values								Accuracy						
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%
methods															
ball	50.0	6.14	6.607849	0.1	0.8	3.5	10.0	20.0	50.0	0.377167	0.153989	0.0000	0.441667	0.441667	0.44166

	k_values								Accuracy						
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%
vanilla	50.0	10.00	5.802885	1.0	5.0	10.0	15.0	19.0	50.0	0.532417	0.051026	0.3875	0.489583	0.545833	0.57500

In [53]:

```
## Splitting original DF to DFs of vanilla and ball
test_df_ball =  test_df2[test_df2.methods == 'ball'].rename(columns={'k_values':'e_value
s'})
test_df_vanilla =  test_df2[test_df2.methods == 'vanilla']
# df_ball.shape
# test_df_ball.head()
test_df_vanilla.head()
```

Out[53]:

	methods	metrics	k_values	Accuracy
0	vanilla	euclidean	1.0	0.470833
1	vanilla	euclidean	3.0	0.470833
2	vanilla	euclidean	5.0	0.479167
3	vanilla	euclidean	7.0	0.520833
4	vanilla	euclidean	9.0	0.595833

In [54]:

```
## Maximum Accuracy (Vanilla method) Hyperprameter Configuration
test_df_vanilla.loc[train_df_vanilla['Accuracy'].idxmax()]
```

Out[54]:

```
methods        vanilla
metrics      euclidean
k_values           1.0
Accuracy      0.470833
Name: 0, dtype: object
```

In [55]:

```
## Maximum Accuracy (Ball method) Hyperprameter Configuration
test_df_ball.loc[test_df_ball['Accuracy'].idxmax()]
```

Out[55]:

```
methods           ball
metrics      euclidean
e_values           0.5
Accuracy      0.441667
Name: 51, dtype: object
```

Generating two heatmaps for each vanilla and ball

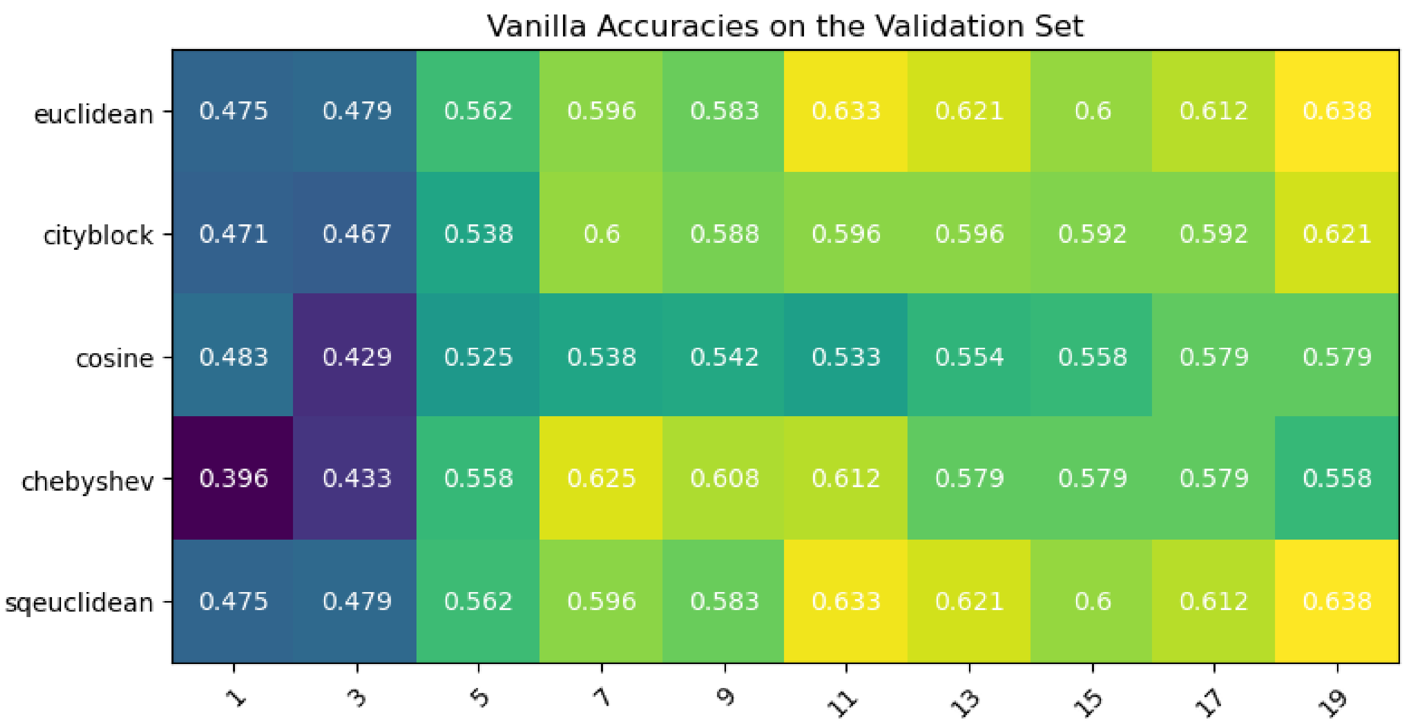
Validation Heatmaps

Vanilla

In [67]:

```
#Making a Numpy array of vanilla accuracy
vanilla_accuracy = df_vanilla["Accuracy"].values
vanilla_accuracy = vanilla_accuracy.reshape(5,10) #Reshape to prepare for the desired hea
tmap
vanilla_accuracy = np.around(vanilla_accuracy, decimals=3)#Rounding accuracies to 3 deci
mal places
```

```python
fig, ax = plt.subplots(figsize=(8,8), ncols=1)
im = ax.imshow(vanilla_accuracy)

# We want to show all ticks...
ax.set_xticks(np.arange(len(k_values)))
ax.set_yticks(np.arange(len(metrics)))

# ... and label them with the respective list entries
ax.set_xticklabels(k_values)
ax.set_yticklabels(metrics)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
for i in range(len(metrics)):
    for j in range(len(k_values)):
        text = ax.text(j, i, vanilla_accuracy[i, j],
                       ha="center", va="center", color="w")

ax.set_title("Vanilla Accuracies on the Validation Set")
fig.tight_layout()
plt.show()
```

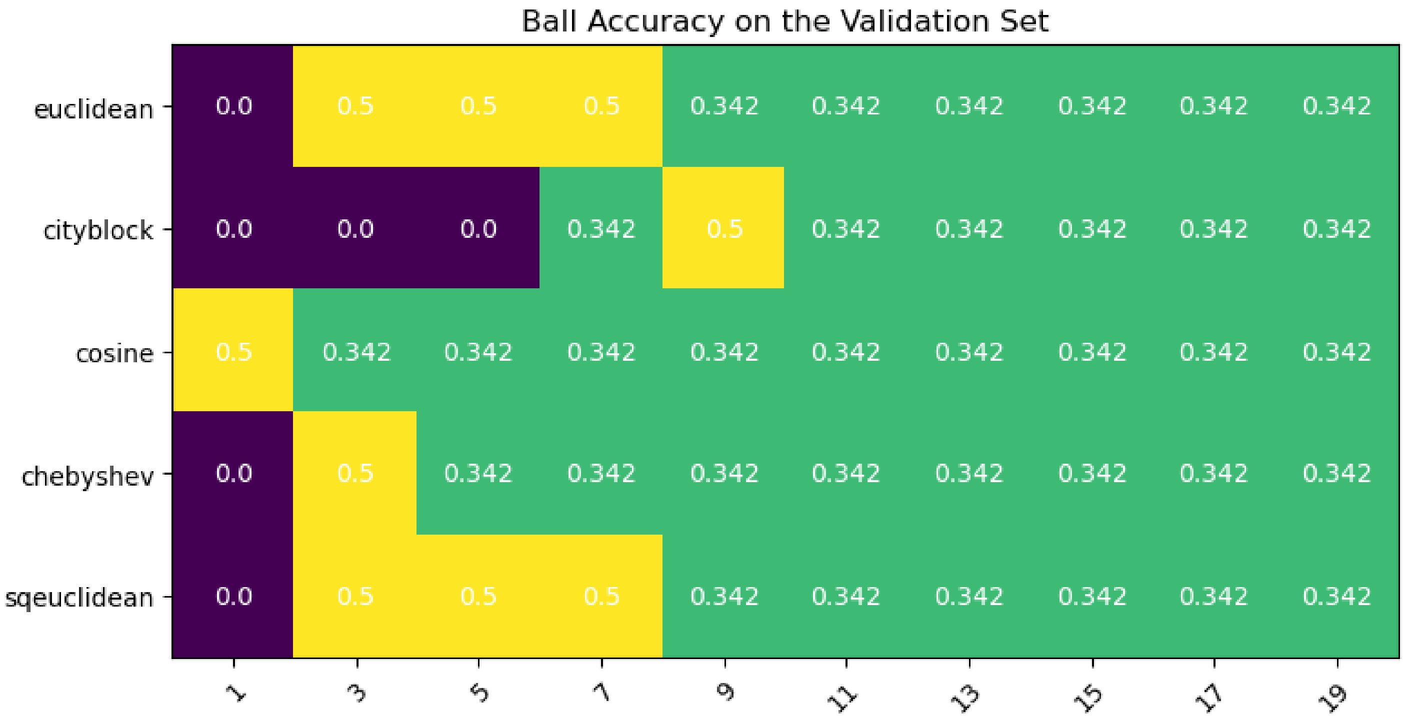


Ball

In [66]:

```python
#Making a Numpy array of Ball accuracy
ball_accuracy = df_ball["Accuracy"].values
ball_accuracy = ball_accuracy.reshape(5,10) #Reshape to prepare for the desired heatmap
ball_accuracy = np.around(ball_accuracy, decimals=3) #Rounding accuracies to 3 decimal pla
ces

fig, ax = plt.subplots(figsize=(8,8), ncols=1)
im = ax.imshow(ball_accuracy)

# We want to show all ticks...
ax.set_xticks(np.arange(len(k_values)))
ax.set_yticks(np.arange(len(metrics)))

# ... and label them with the respective list entries
ax.set_xticklabels(k_values)
ax.set_yticklabels(metrics)
```

```
# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
for i in range(len(metrics)):
    for j in range(len(k_values)):
        text = ax.text(j, i, ball_accuracy[i, j],
                       ha="center", va="center", color="w")

ax.set_title("Ball Accuracy on the Validation Set")
fig.tight_layout()
plt.show()
```



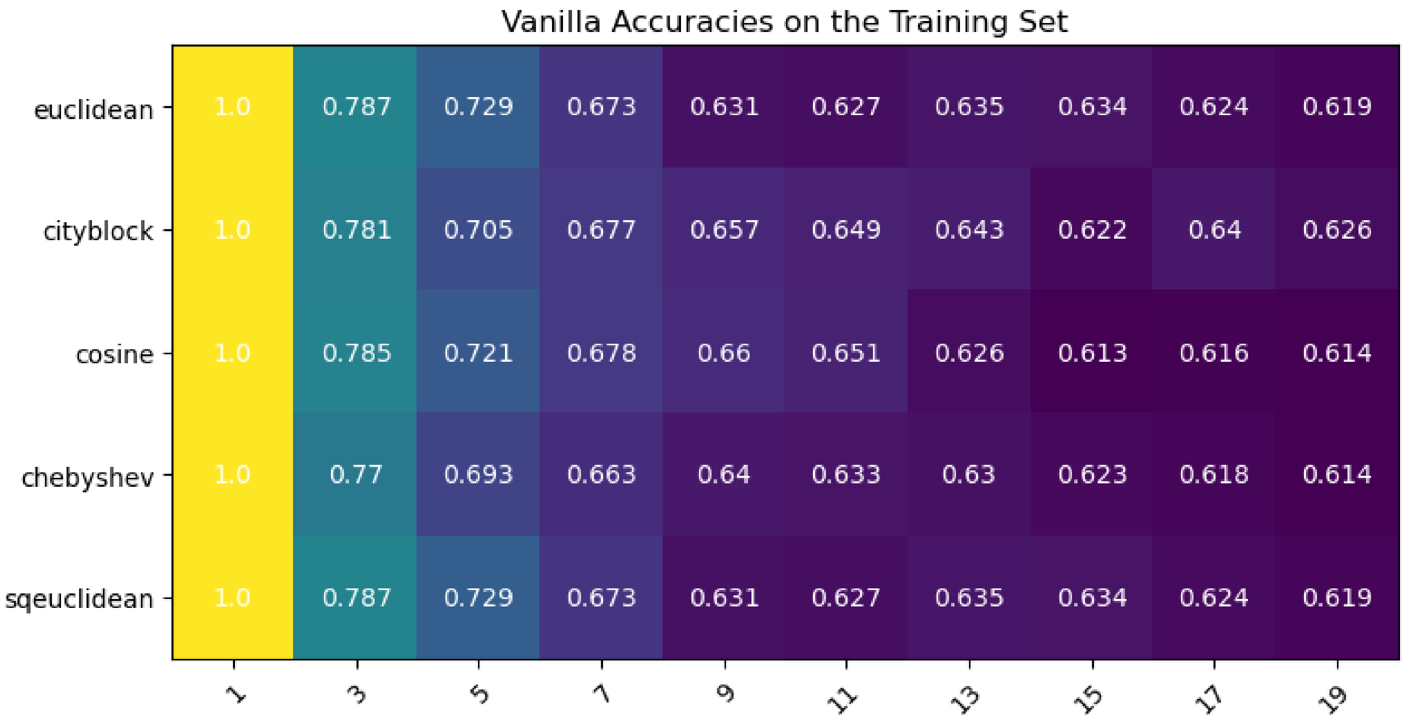
Train Heatmap

Vanilla

In [58]:

```
#Making a Numpy array of vanilla accuracy
train_vanilla_accuracy = train_df_vanilla["Accuracy"].values
train_vanilla_accuracy = train_vanilla_accuracy.reshape(5,10) #Reshape to prepare for the
desired heatmap
train_vanilla_accuracy = np.around(train_vanilla_accuracy, decimals=3) #Rounding accuraci
es to 3 decimal places

fig, ax = plt.subplots(figsize=(8,8), ncols=1)
im = ax.imshow(train_vanilla_accuracy)

# We want to show all ticks...
ax.set_xticks(np.arange(len(k_values)))
ax.set_yticks(np.arange(len(metrics)))

# ... and label them with the respective list entries
ax.set_xticklabels(k_values)
ax.set_yticklabels(metrics)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
```

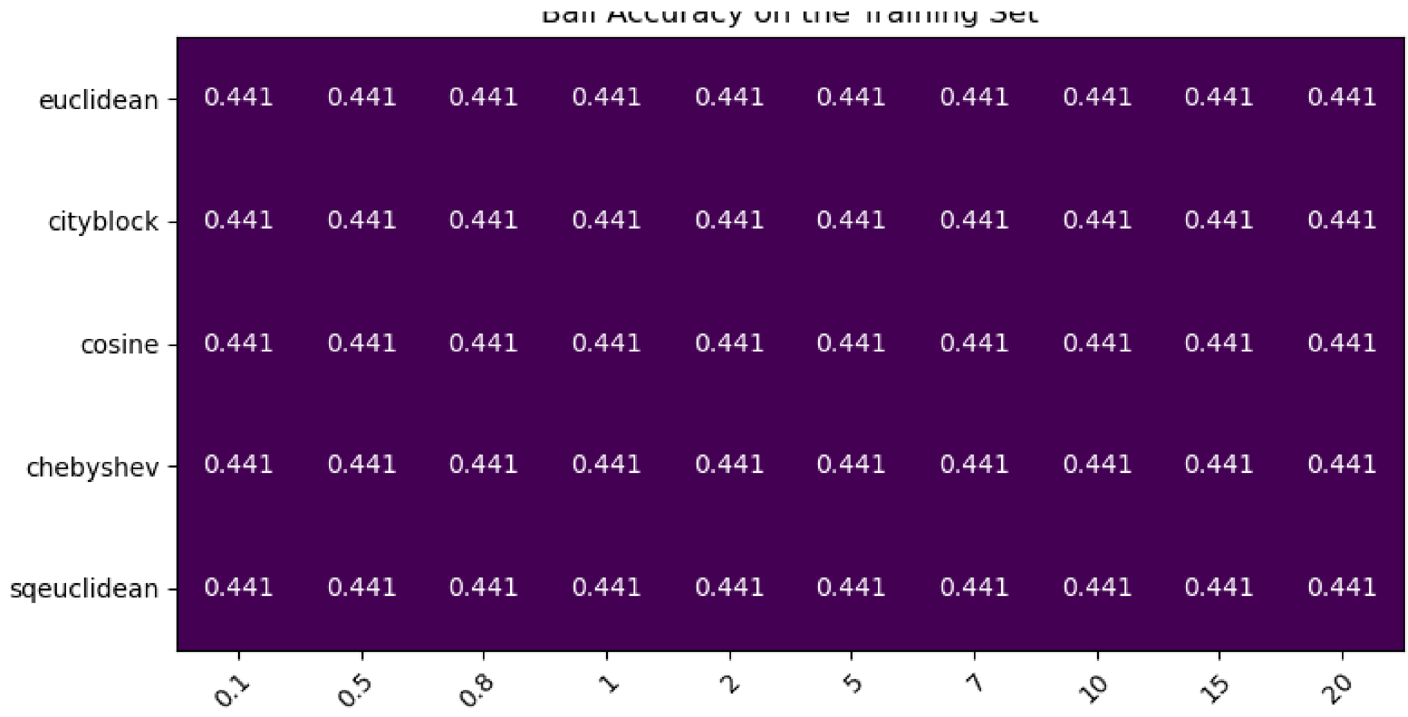
```
for i in range(len(metrics)):
    for j in range(len(k_values)):
        text = ax.text(j, i, train_vanilla_accuracy[i, j],
                       ha="center", va="center", color="w")

ax.set_title("Vanilla Accuracies on the Training Set")
fig.tight_layout()
plt.show()
```



Ball

In [59]:

```
#Making a Numpy array of Ball accuracy
train_ball_accuracy = train_df_ball["Accuracy"].values
train_ball_accuracy = train_ball_accuracy.reshape(5,10) #Reshape to prepare for the desire
d heatmap
train_ball_accuracy = np.around(train_ball_accuracy, decimals=3) #Rounding accuracies to 3
decimal places

fig, ax = plt.subplots(figsize=(8,8), ncols=1)
im = ax.imshow(train_ball_accuracy)

# We want to show all ticks...
ax.set_xticks(np.arange(len(e_values)))
ax.set_yticks(np.arange(len(metrics)))

# ... and label them with the respective list entries
ax.set_xticklabels(e_values)
ax.set_yticklabels(metrics)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
for i in range(len(metrics)):
    for j in range(len(k_values)):
        text = ax.text(j, i, train_ball_accuracy[i, j],
                       ha="center", va="center", color="w")

ax.set_title("Ball Accuracy on the Training Set")
fig.tight_layout()
plt.show()
```

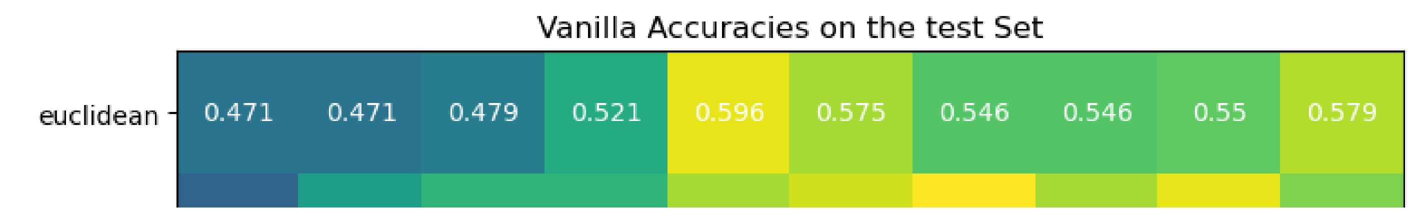


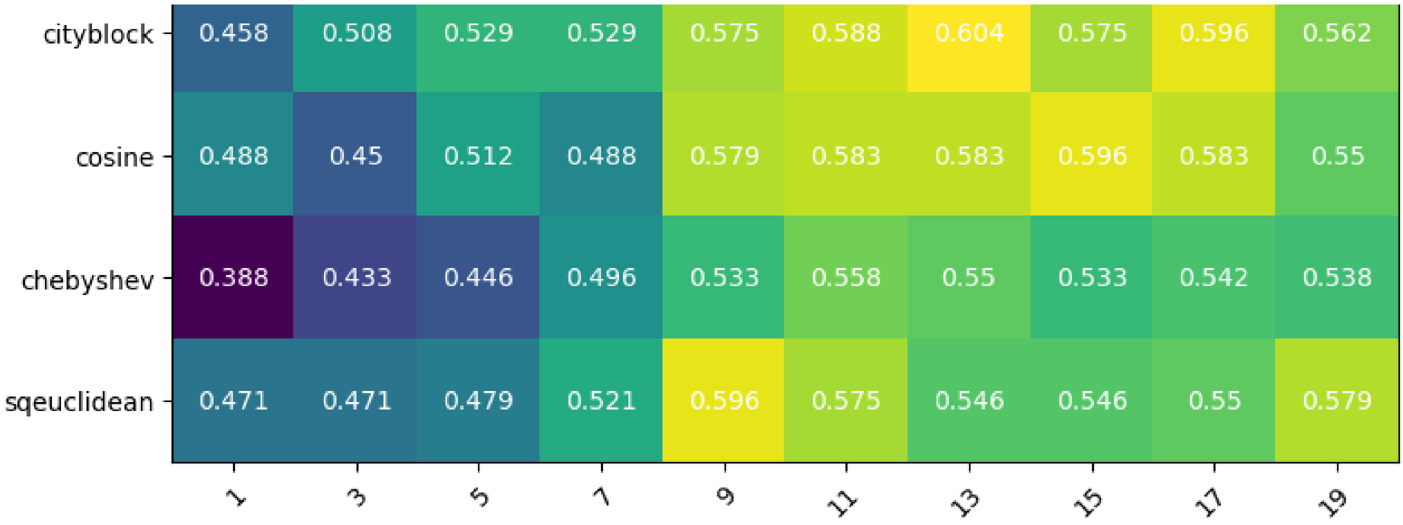
test Heatmap

Vanilla

In [68]:

```
#Making a Numpy array of Vanilla accuracy
test_vanilla_accuracy = test_df_vanilla["Accuracy"].values
test_vanilla_accuracy = test_vanilla_accuracy.reshape(5,10) #Reshape to prepare for the de
sired heatmap
test_vanilla_accuracy = np.around(test_vanilla_accuracy, decimals=3) #Rounding accuracies
to 3 decimal places

fig, ax = plt.subplots(figsize=(8,8), ncols=1)
im = ax.imshow(test_vanilla_accuracy)

# We want to show all ticks...
ax.set_xticks(np.arange(len(k_values)))
ax.set_yticks(np.arange(len(metrics)))

# ... and label them with the respective list entries
ax.set_xticklabels(k_values)
ax.set_yticklabels(metrics)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
for i in range(len(metrics)):
    for j in range(len(k_values)):
        text = ax.text(j, i, test_vanilla_accuracy[i, j],
                       ha="center", va="center", color="w")

ax.set_title("Vanilla Accuracies on the test Set")
fig.tight_layout()
plt.show()
```

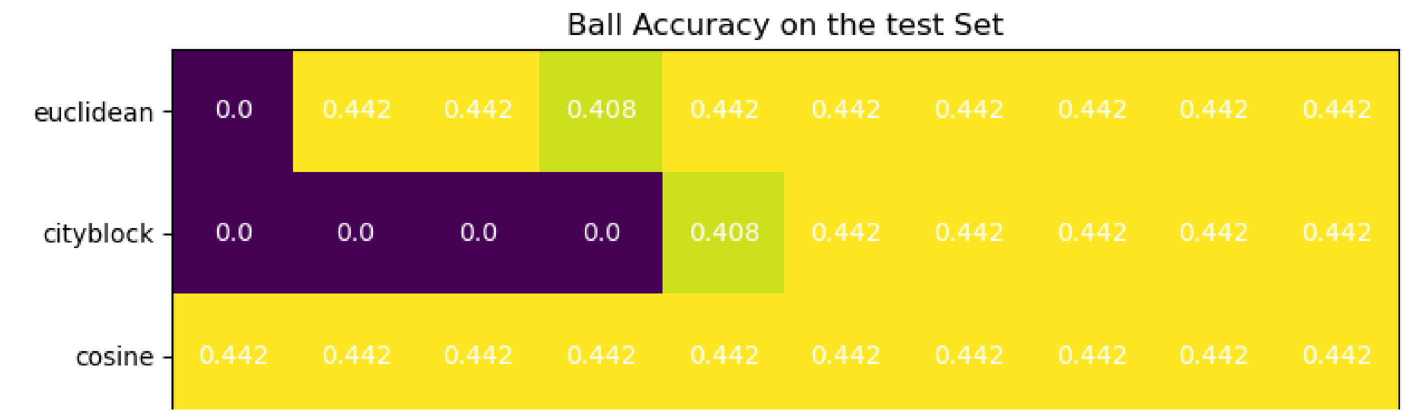


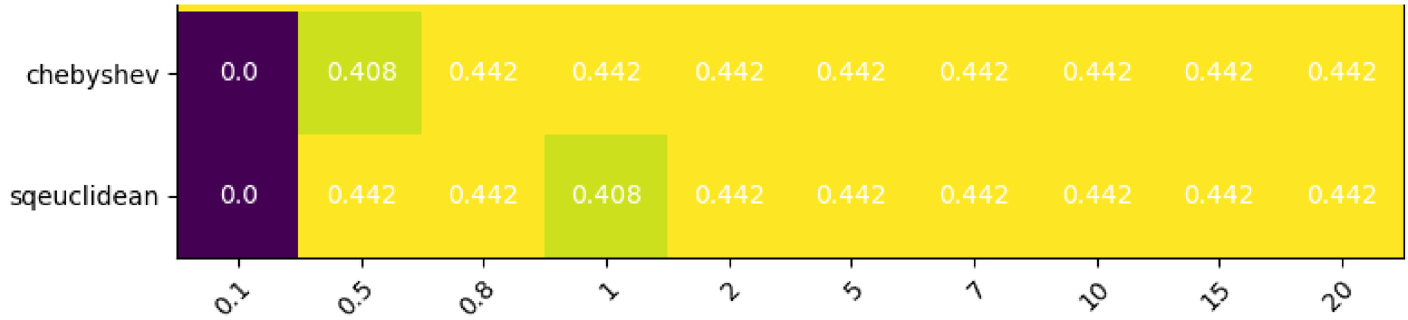


Ball

In [69]:

```
#Making a Numpy array of Ball accuracy
test_ball_accuracy = test_df_ball["Accuracy"].values
test_ball_accuracy = test_ball_accuracy.reshape(5,10) #Reshape to prepare for the desired
heatmap
test_ball_accuracy = np.around(test_ball_accuracy, decimals=3) #Rounding accuracies to 3 d
ecimal places

# fig = plt.figure(figsize=(15,5),facecolor='w')
# ax = fig.add_subplot(111)
# ax.imshow(ball_accuracy, cmap=cm.jet)
fig, ax = plt.subplots(figsize=(8,8), ncols=1)
im = ax.imshow(test_ball_accuracy)

# We want to show all ticks...
ax.set_xticks(np.arange(len(e_values)))
ax.set_yticks(np.arange(len(metrics)))

# ... and label them with the respective list entries
ax.set_xticklabels(e_values)
ax.set_yticklabels(metrics)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

# Loop over data dimensions and create text annotations.
for i in range(len(metrics)):
    for j in range(len(k_values)):
        text = ax.text(j, i, test_ball_accuracy[i, j],
                       ha="center", va="center", color="w")

ax.set_title("Ball Accuracy on the test Set")
fig.tight_layout()
plt.show()
```





A faster version of the k-NN classifier by using a kd-tree data structure

Hyper Prameters

In [143]:

```
KDTree.valid_metrics
```

Out[143]:

```
['euclidean',
 'l2',
 'minkowski',
 'p',
 'manhattan',
 'cityblock',
 'l1',
 'chebyshev',
 'infinity']
```

In [144]:

```
kd_methods = ["k_nearest" , "radius"]
kd_metrics = ["euclidean", "cityblock", "minkowski", "chebyshev", "manhattan" , "infinit
y"] #List of candidate distance functions
k_sizes = [1 , 3 , 5 , 7 , 9 , 11 , 13 , 15 , 17 , 19] #List of candidate number of neig
hbors (exclusively for vanilla)
r_sizes = [0.1 , 0.5, 0.8 , 1 , 2 , 5 , 7 , 10 , 15 ,20 ]#List of candidate radius of ne
ighborhood (exclusively for ball)
leaf_sizes = [1,2,3,4,5,6,7,8,9,10]
```

- **Trying different leaf_size , k and r on the model**
- **getting the mode of selected neighbors for both k and e methods**
- **comparing detected label woth real label for accuracy**

Train Dataset kdTree Prediction

Query for neighbors within a given radius

Query for Nearest Neighbors

In [152]:

```
train_all_combo_pred_lst = []

for method in kd_methods:

    for metric in kd_metrics:

        for leaf_size in leaf_sizes:
```

```
            tree = KDTree(X_train, metric = metric, leaf_size=leaf_size)#Initialization
of the tree object. The same for both methods



            if(method == "k_nearest"):

                for k_size in k_sizes: #We need two different for loop here for vanilla
and ball

                    each_combo = []# 1-d list

                    nearest_ind = tree.query(X_train, k=k_size , return_distance = False
)
                    #nearest neigh indexes type (numpy ndarray), shape (1119, 1) because
in this loop k=1
#                     number of columns could be as large as maximum k


                    prediction = np.zeros((X_train.shape[0], 1)) #we need to initialize
the array #shape(1, 1119)
#                     prediction is type numpy.ndarray shape (1119, 1) all filled with z
ero
                    # it is constant for all k


                    for i in range(nearest_ind.shape[0] - 1):#finding each sample k pred
ictions labels

                        temp_top_k = [] #1-d list

                        for j in range(k_size):#if k=1 it should iterate one time

                            temp_top_k.append(Y_train[nearest_ind[i][j ]])

                        prediction[i] = mode(temp_top_k, axis=None).mode[0]





    #                 The function above gave me top k neighbors, while in my KNN class
I had to find between 1118 neighbors
    #                 prediction = mode(top_k, axis=None).mode[0]
        #one mode for the k predictions of each 1119 samples as prediction

                    accuracy = sum(prediction.flatten() == Y_train)/len(Y_train)

                    each_combo.append(method )
                    each_combo.append( metric )
                    each_combo.append(leaf_size)
                    each_combo.append(k_size)
                    each_combo.append(accuracy)

                    train_all_combo_pred_lst.append(each_combo) #list of lists of all 10
0 comb each containing above appends

            elif(method == "radius"):

                for r_size in r_sizes:

                    each_combo = []

                    ind = tree.query_radius(X_train, r = r_size , count_only = False, re
turn_distance = False)#ind will be shape(1119 , variable)

                    ind = ind.reshape(1119 , -1)#rows with number of samples, columns va
riable
                    # Query for 1119*k_size rows of indexes of neighbors within a given
radius
```

```
#                         print(ind.shape)
                        prediction = np.zeros((X_train.shape[0], 1))

                        for i in range(ind.shape[0]):

                            temp_top_k = []

                            for j in range(len(ind[i])):

                                temp_top_k.append(Y_train[ind[i][j]])

                            prediction[i] = mode(temp_top_k, axis=None).mode[0]

                        accuracy = sum(prediction.flatten() == Y_train)/len(Y_train)
                        #accuracy type: numpy array

                        each_combo.append(method )
                        each_combo.append( metric )
                        each_combo.append(leaf_size)
                        each_combo.append(r_size)
                        each_combo.append(accuracy)

                        train_all_combo_pred_lst.append(each_combo) #list of lists of all 10
0 comb each containing above appends
```

In [153]:

```
## DF of Test-Accuracy ( Different Hyperprameter Combinations)
train_df3 = pd.DataFrame(train_all_combo_pred_lst ,columns=[ 'kd_methods', 'kd_metrics',
'leaf_sizes' , 'k_values' ,'Accuracy'])
train_df3 = train_df3.round(3)
train_df3.head()
```

Out[153]:

	kd_methods	kd_metrics	leaf_sizes	k_values	Accuracy
0	k_nearest	euclidean	1	1.0	0.999
1	k_nearest	euclidean	1	3.0	0.787
2	k_nearest	euclidean	1	5.0	0.728
3	k_nearest	euclidean	1	7.0	0.672
4	k_nearest	euclidean	1	9.0	0.630

In [154]:

```
# Statistical description of Train-Accuracy DF, Grouped by method
train_df3.groupby(["kd_methods"]).describe()
```

Out[154]:

	leaf_sizes								k_values					Accuracy			
	count	mean	std	min	25%	50%	75%	max	count	mean	...	75%	max	count	mean	std	mi
kd_methods																	
k_nearest	600.0	5.5	2.874678	1.0	3.0	5.5	8.0	10.0	600.0	10.00	...	15.0	19.0	600.0	0.693970	0.112425	0.6
radius	600.0	5.5	2.874678	1.0	3.0	5.5	8.0	10.0	600.0	6.14	...	10.0	20.0	600.0	0.676267	0.235667	0.4

2 rows × 24 columns

In [155]:

```
## Splitting original DF to DFs of vanilla and ball
train_df3_radius =  train_df3[train_df3.kd_methods == 'radius'].rename(columns={'k_value
s':'r_values'})
train_df3_k_nearest =  train_df3[train_df3.kd_methods == 'k_nearest']
```

```
# df_ball.shape
# test_df_ball.head()
train_df3_radius.head()
```

Out[155]:

	kd_methods	kd_metrics	leaf_sizes	r_values	Accuracy
600	radius	euclidean	1	0.1	1.000
601	radius	euclidean	1	0.5	0.987
602	radius	euclidean	1	0.8	0.939
603	radius	euclidean	1	1.0	0.881
604	radius	euclidean	1	2.0	0.633

In [156]:

```
## Maximum Accuracy (Vanilla method) Hyperprameter Configuration
train_df3_k_nearest.loc[train_df3_k_nearest['Accuracy'].idxmax()]
```

Out[156]:

```
kd_methods     k_nearest
kd_metrics     euclidean
leaf_sizes             1
k_values             1.0
Accuracy           0.999
Name: 0, dtype: object
```

In [157]:

```
## Maximum Accuracy (Ball method) Hyperprameter Configuration
train_df3_radius.loc[train_df3_radius['Accuracy'].idxmax()]
```

Out[157]:

```
kd_methods        radius
kd_metrics     euclidean
leaf_sizes             1
r_values             0.1
Accuracy             1.0
Name: 600, dtype: object
```

In [150]:

```
## Maximum Accuracy (Ball method) Hyperprameter Configuration
train_df3_radius.loc[train_df3_radius['Accuracy'].idxmax()]
```

Out[150]:

```
kd_methods        radius
kd_metrics     euclidean
leaf_sizes             1
r_values             0.1
Accuracy             1.0
Name: 600, dtype: object
```