knn

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1 Name: Sourabh Barala

2 Course: M.Sc. Data Science

3 Year: 1st

4 Reg. No.: 23MSD7044

5 Subject: Machine Learning and its Applications

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[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.base import TransformerMixin
import numpy as np
from sklearn.metrics import␣
↪f1_score,recall_score,precision_score,accuracy_score,confusion_matrix
```

[2]:
```
cancer=load_breast_cancer()
```

[3]:
```
cancer_df=pd.DataFrame(cancer.data,columns=cancer.
↪feature_names,index=range(len(cancer.data)))
```

[4]:
```
cancer_df.describe()
```

[4]:

	mean radius	mean texture	mean perimeter	mean area	\
count	569.000000	569.000000	569.000000	569.000000	
mean	14.127292	19.289649	91.969033	654.889104	
std	3.524049	4.301036	24.298981	351.914129	
min	6.981000	9.710000	43.790000	143.500000	
25%	11.700000	16.170000	75.170000	420.300000	
50%	13.370000	18.840000	86.240000	551.100000	
75%	15.780000	21.800000	104.100000	782.700000	
max	28.110000	39.280000	188.500000	2501.000000	

	mean smoothness	mean compactness	mean concavity	mean concave points	\
count	569.000000	569.000000	569.000000	569.000000	
mean	0.096360	0.104341	0.088799	0.048919	
std	0.014064	0.052813	0.079720	0.038803	
min	0.052630	0.019380	0.000000	0.000000	
25%	0.086370	0.064920	0.029560	0.020310	
50%	0.095870	0.092630	0.061540	0.033500	
75%	0.105300	0.130400	0.130700	0.074000	
max	0.163400	0.345400	0.426800	0.201200	

	mean symmetry	mean fractal dimension	…	worst radius	\
count	569.000000	569.000000	…	569.000000	
mean	0.181162	0.062798	…	16.269190	
std	0.027414	0.007060	…	4.833242	
min	0.106000	0.049960	…	7.930000	
25%	0.161900	0.057700	…	13.010000	
50%	0.179200	0.061540	…	14.970000	
75%	0.195700	0.066120	…	18.790000	
max	0.304000	0.097440	…	36.040000	

	worst texture	worst perimeter	worst area	worst smoothness	\
count	569.000000	569.000000	569.000000	569.000000	
mean	25.677223	107.261213	880.583128	0.132369	
std	6.146258	33.602542	569.356993	0.022832	
min	12.020000	50.410000	185.200000	0.071170	
25%	21.080000	84.110000	515.300000	0.116600	
50%	25.410000	97.660000	686.500000	0.131300	
75%	29.720000	125.400000	1084.000000	0.146000	
max	49.540000	251.200000	4254.000000	0.222600	

	worst compactness	worst concavity	worst concave points	\
count	569.000000	569.000000	569.000000	
mean	0.254265	0.272188	0.114606	
std	0.157336	0.208624	0.065732	
min	0.027290	0.000000	0.000000	

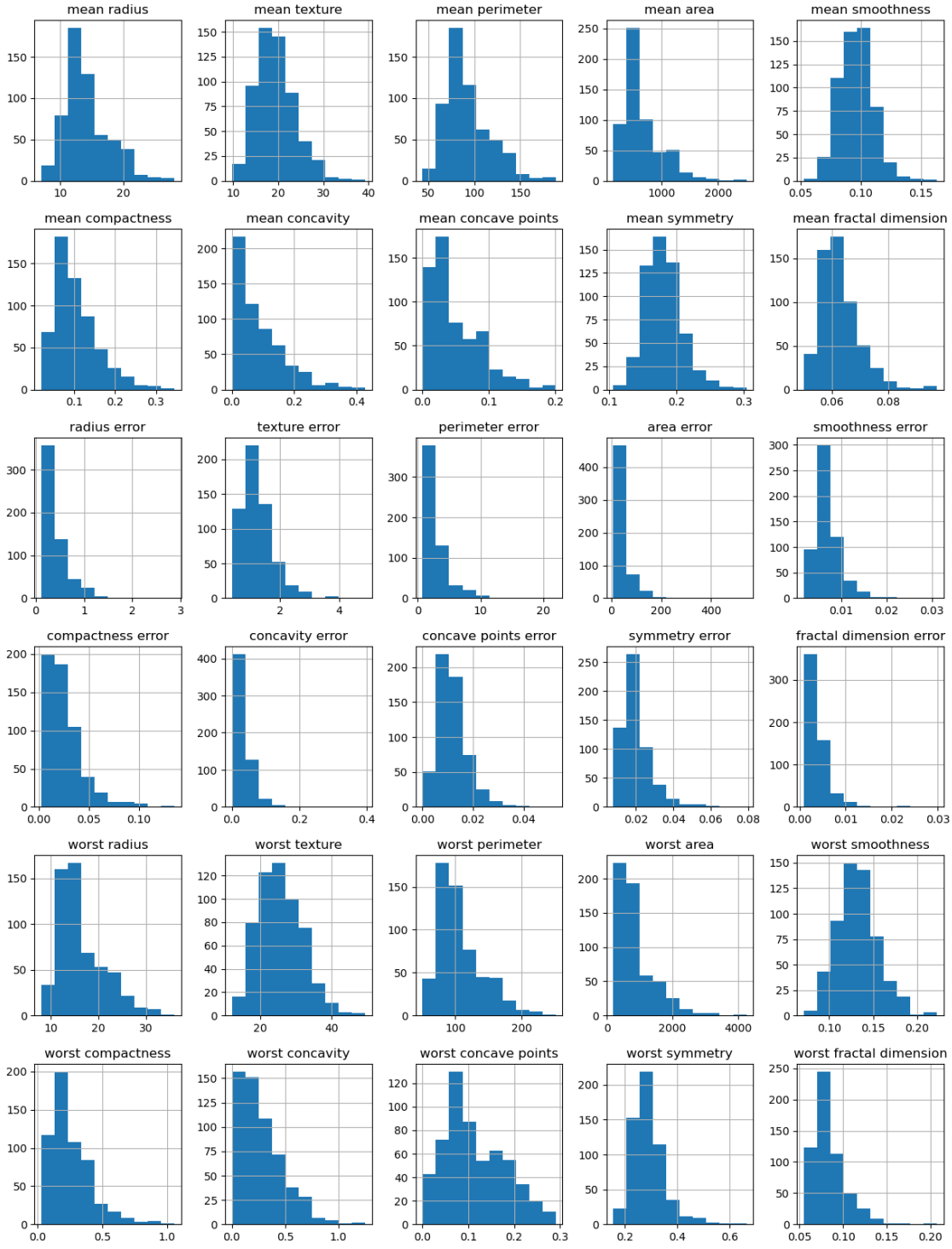
```
25%             0.147200         0.114500              0.064930
50%             0.211900         0.226700              0.099930
75%             0.339100         0.382900              0.161400
max             1.058000         1.252000              0.291000

       worst symmetry  worst fractal dimension
count      569.000000               569.000000
mean         0.290076                 0.083946
std          0.061867                 0.018061
min          0.156500                 0.055040
25%          0.250400                 0.071460
50%          0.282200                 0.080040
75%          0.317900                 0.092080
max          0.663800                 0.207500

[8 rows x 30 columns]
```

[5]:
```
cancer_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 30 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   mean radius              569 non-null    float64
 1   mean texture             569 non-null    float64
 2   mean perimeter           569 non-null    float64
 3   mean area                569 non-null    float64
 4   mean smoothness          569 non-null    float64
 5   mean compactness         569 non-null    float64
 6   mean concavity           569 non-null    float64
 7   mean concave points      569 non-null    float64
 8   mean symmetry            569 non-null    float64
 9   mean fractal dimension   569 non-null    float64
 10  radius error             569 non-null    float64
 11  texture error            569 non-null    float64
 12  perimeter error          569 non-null    float64
 13  area error               569 non-null    float64
 14  smoothness error         569 non-null    float64
 15  compactness error        569 non-null    float64
 16  concavity error          569 non-null    float64
 17  concave points error     569 non-null    float64
 18  symmetry error           569 non-null    float64
 19  fractal dimension error  569 non-null    float64
 20  worst radius             569 non-null    float64
 21  worst texture            569 non-null    float64
 22  worst perimeter          569 non-null    float64
```

```
 23  worst area               569 non-null    float64
 24  worst smoothness         569 non-null    float64
 25  worst compactness        569 non-null    float64
 26  worst concavity          569 non-null    float64
 27  worst concave points     569 non-null    float64
 28  worst symmetry           569 non-null    float64
 29  worst fractal dimension  569 non-null    float64
dtypes: float64(30)
memory usage: 133.5 KB
```

[6]:
```
cancer_df.hist(figsize=(15,20))
plt.show()
```



[7]:
```
target=pd.DataFrame(cancer.target,columns=['Target'],index=range(len(cancer.
↪target)))
```

[8]:
```
target_names=cancer.feature_names
```

[9]:
```
target.value_counts()
```

[9]:
```
Target
1          357
0          212
dtype: int64
```

[10]:
```
X_train, X_test, y_train,␣
↪y_test=train_test_split(cancer_df,target,stratify=target,random_state=100)
```

[11]:
```
class KNN(TransformerMixin):
    def __init__(self,k=3,metric='euclidean'):
        self.k=k
        self.metric=metric

    def cal_dist(self,point,train_para,train_label):
        '''takes a point (data point) and calculates its distance (euclidean)␣
↪with all other data pointes
        input:
            point: one data point
            train_para: all other data points
            train_label: labels of ecach data points in train_para␣
↪(1-dimensional)

        output:
            DataFrame with distances from a given point to all points, with␣
↪labels

        example:
            input:
                temp_cls.cal_dist(point=X_train.
↪iloc[0],train_para=X_train,train_label=y_train.values.ravel())

            output:
                        dist        class
                0        0.000000        1
                1        38.449169        1
                2        271.548671        1
                3        109.262951        1
                4        160.529340        1
                ...        ...        ...
                421        1252.334390        0
                422        574.286256        0
                423        1519.622517        0
                424        1552.695208        0
```

```
                425         184.725959         1
        '''

        dist_ls=list()

        for i in range(len(train_para)):
            dims=train_para.iloc[i]
            dist_sqr=0
            for j in range(len(dims)):
                # calculate squared euclidean distance
                dist_sqr+=(dims[j]-point[j])**2

            dist=np.sqrt(dist_sqr)
            dist_ls.append(dist)


        dist_df=pd.DataFrame({'dist':dist_ls,'class':
↪train_label},index=range(len(dist_ls)))



        return dist_df

    def get_closest_class(self,dist_df):
        '''takes DataFrame given by cal_dist function --> sorts the DataFrame␣
↪according to diatance --> selects top 'k' smallest distances --> returns␣
↪label with max count
        input:
            dist_df: DataFrame given by cal_dist function

        output:
            label with max count

        example:
            input:
                temp=temp_cls.cal_dist(point=X_train.
↪iloc[0],train_para=X_train,train_label=y_train.values.ravel())

                temp_cls.get_closest_k_classes(temp)

            output:
                1
        '''
        sorted_df=dist_df.sort_values(by=['dist'])
        top_k=sorted_df.iloc[:self.k]
        top_k['class'].value_counts()
        closest_class=top_k['class'].value_counts().keys()[0]
        return closest_class
```

```
    def fit(self,train_para,train_label):
        self.train_para=train_para
        self.train_label=train_label

    def predict(self,test_para):
        '''predicts class of each point and appends in a list
        input:
            test_para: points to be classified

        output:
            list with predicted classes for each point

        example:
            input:
                temp_cls.fit(X_train,y_train.values.ravel())
                pred=temp_cls.predict(X_test)
                pred=np.array(pred)

            output:
                array([1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, ....])
        '''
        predictions=list()
        for i in range(len(test_para)):
            dist_df=self.cal_dist(test_para.iloc[i],self.train_para,self.
↪train_label)
            pred=self.get_closest_class(dist_df)
            predictions.append(pred)
        return predictions
```

[12]:
```
temp_cls=KNN(k=10)
```

[13]:
```
temp_cls.fit(X_train,y_train.values.ravel())
pred=temp_cls.predict(X_test)
pred=np.array(pred)
```

[14]:
```
print(confusion_matrix(y_true=y_test,y_pred=pred))
scores=pd.Series({'accuracy':accuracy_score(y_true=y_test,y_pred=pred),
                  'recall':recall_score(y_true=y_test,y_pred=pred),
                  'precision':precision_score(y_true=y_test,y_pred=pred),
                  'f1':f1_score(y_true=y_test,y_pred=pred)})
scores
```

```
[[47  6]
 [ 4 86]]
```

[14]:
```
accuracy     0.930070
recall       0.955556
precision    0.934783
f1           0.945055
dtype: float64
```

11.1 Elbow Method

[15]:
```
accuracies_with_k=[]
f1_with_k=[]
precision_with_k=[]
recall_with_k=[]

k_range=range(1,15)
for i in k_range:
    temp_cls=KNN(k=i)
    temp_cls.fit(X_train,y_train.values.ravel())
    pred=temp_cls.predict(X_test)

    accuracies_with_k.append(accuracy_score(y_true=y_test,y_pred=pred))
    f1_with_k.append(f1_score(y_true=y_test,y_pred=pred))
    precision_with_k.append(precision_score(y_true=y_test,y_pred=pred))
    recall_with_k.append(recall_score(y_true=y_test,y_pred=pred))
```

[16]:
```
metric_df=pd.DataFrame({'k':k_range,'accuracy':accuracies_with_k,'f1':
↪f1_with_k,'precision':precision_with_k,'recall':recall_with_k},index=k_range)
```

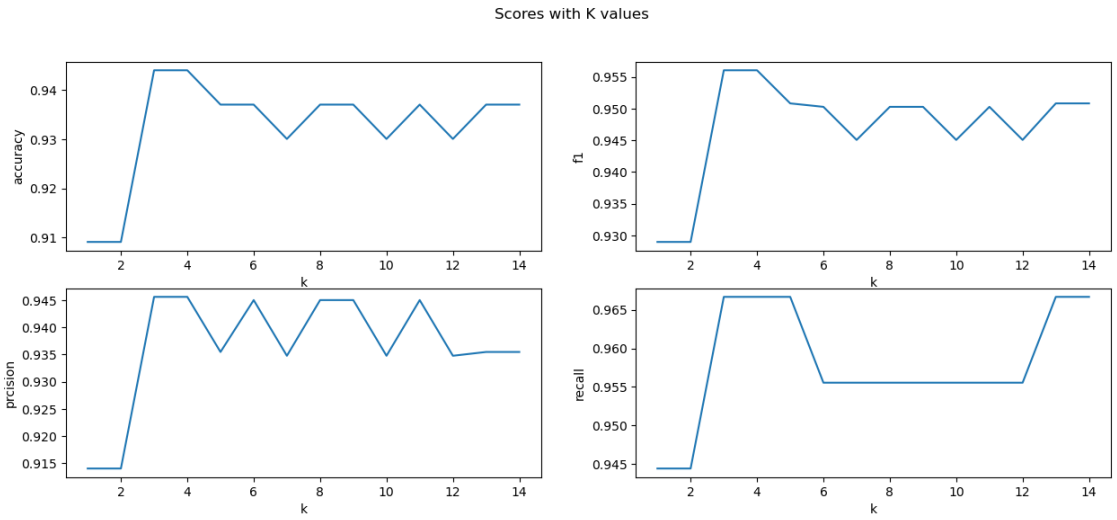
[17]:
```
metric_df
```

[17]:

	k	accuracy	f1	precision	recall
1	1	0.909091	0.928962	0.913978	0.944444
2	2	0.909091	0.928962	0.913978	0.944444
3	3	0.944056	0.956044	0.945652	0.966667
4	4	0.944056	0.956044	0.945652	0.966667
5	5	0.937063	0.950820	0.935484	0.966667
6	6	0.937063	0.950276	0.945055	0.955556
7	7	0.930070	0.945055	0.934783	0.955556
8	8	0.937063	0.950276	0.945055	0.955556
9	9	0.937063	0.950276	0.945055	0.955556
10	10	0.930070	0.945055	0.934783	0.955556
11	11	0.937063	0.950276	0.945055	0.955556
12	12	0.930070	0.945055	0.934783	0.955556
13	13	0.937063	0.950820	0.935484	0.966667
14	14	0.937063	0.950820	0.935484	0.966667

[18]:
```
plt.figure(figsize=(15,6))
plt.subplot(2,2,1)
```

```
plt.plot(metric_df['k'],metric_df['accuracy'])
plt.ylabel('accuracy')
plt.xlabel('k')

plt.subplot(2,2,2)
plt.plot(metric_df['k'],metric_df['f1'])
plt.ylabel('f1')
plt.xlabel('k')

plt.subplot(2,2,3)
plt.plot(metric_df['k'],metric_df['precision'])
plt.ylabel('prcision')
plt.xlabel('k')

plt.subplot(2,2,4)
plt.plot(metric_df['k'],metric_df['recall'])
plt.ylabel('recall')
plt.xlabel('k')

plt.suptitle('Scores with K values')
plt.show()
```



[ ]:

[ ]: