K-Nearest Neighbors

In [1]:
```
import os
import sys

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy

from mlxtend.plotting import plot_decision_regions
from sklearn.datasets import load_breast_cancer, load_iris
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.neighbors import KNeighborsClassifier as KNC, kneighbors_graph
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

%matplotlib inline
```

In [2]:
```
f1_values_set1 = np.random.randint(low=12, high=17,size=50)
f2_values_set1 = np.random.randint(low=20, high=25,size=50)

f1_values_set2 = np.random.randint(low=2, high=7,size=50)
f2_values_set2 = np.random.randint(low=10, high=15,size=50)
```

In [3]:
```
dummy_dataset1 = pd.DataFrame({'f1':f1_values_set1,
                               'f2':f2_values_set1})

dummy_dataset2 = pd.DataFrame({'f1':f1_values_set2,
                               'f2':f2_values_set2})

dummy_data = pd.concat([dummy_dataset1,dummy_dataset2],axis=0).reset_index(drop=True
```

In [4]:
```
dummy_data['label'] = dummy_data['f1'].apply(lambda val: 1 if val > 7 else 0)
```

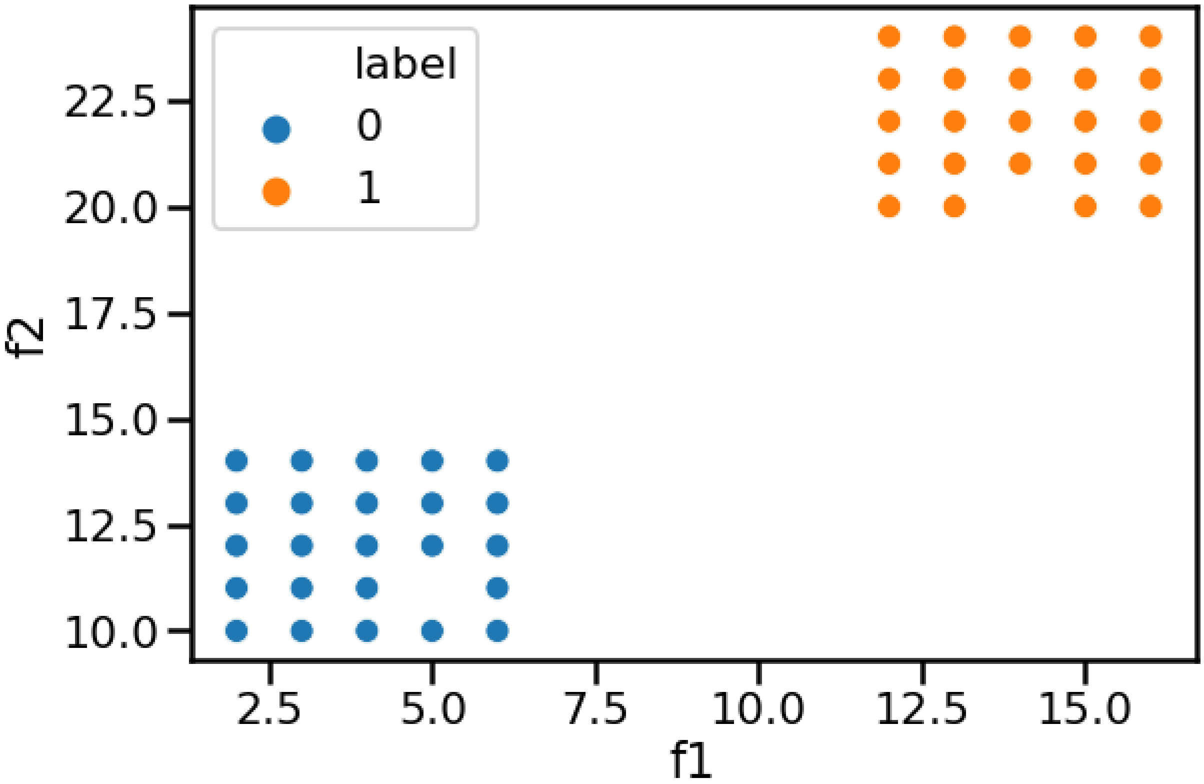
In [5]:
```
dummy_data.head()
```

Out[5]:

	f1	f2	label
0	12	22	1
1	13	23	1
2	12	20	1
3	12	21	1
4	16	24	1

In [6]:
```
sns.set_context(context='poster')
plt.figure(figsize=(9,6))
sns.scatterplot(x='f1',y='f2',hue='label',data=dummy_data)
```

Out[6]:
```
<AxesSubplot:xlabel='f1', ylabel='f2'>
```



In [7]:
```
X_train, X_test, y_train, y_test = train_test_split(dummy_data.iloc[:,0:-1],dummy_da
```

In [8]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[8]: ((60, 2), (40, 2), (60,), (40,))

K=1

In [9]:
```
knc = KNC(n_neighbors=1)
```

In [10]:
```
knc_model = knc.fit(X_train,y_train)
```

In [11]:
```
y_predict = knc.predict(X_test)
```

In [12]:
```
accuracy_score(y_test,y_predict), precision_score(y_test,y_predict), recall_score(y_
```

Out[12]: (1.0, 1.0, 1.0)

K=1, Weighted KNN with distance metric as Canberra

In [13]:
```
knc2 = KNC(n_neighbors=1, weights='distance',algorithm='ball_tree',metric=scipy.spat
```

In [14]:
```
knc_model2 = knc2.fit(X_train,y_train)
```

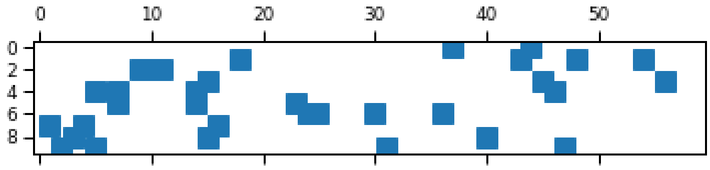
In [15]:
```
y_predict2 = knc_model2.predict(X_test)
```

In [16]:
```
accuracy_score(y_test,y_predict2), precision_score(y_test,y_predict2), recall_score(
```

Out[16]: (1.0, 1.0, 1.0)

In [17]:
```
# pd.DataFrame(knc2.kneighbors_graph(X=X_train,n_neighbors=1,mode='connectivity').to
sns.set_context('paper')
```

```
plt.spy(knc2.kneighbors_graph(X=X_train.iloc[0:10,],n_neighbors=5,mode='distance'))
plt.show()
```



KNN on Breast Cancer Dataset

In [18]:
```
cancer = load_breast_cancer()
```

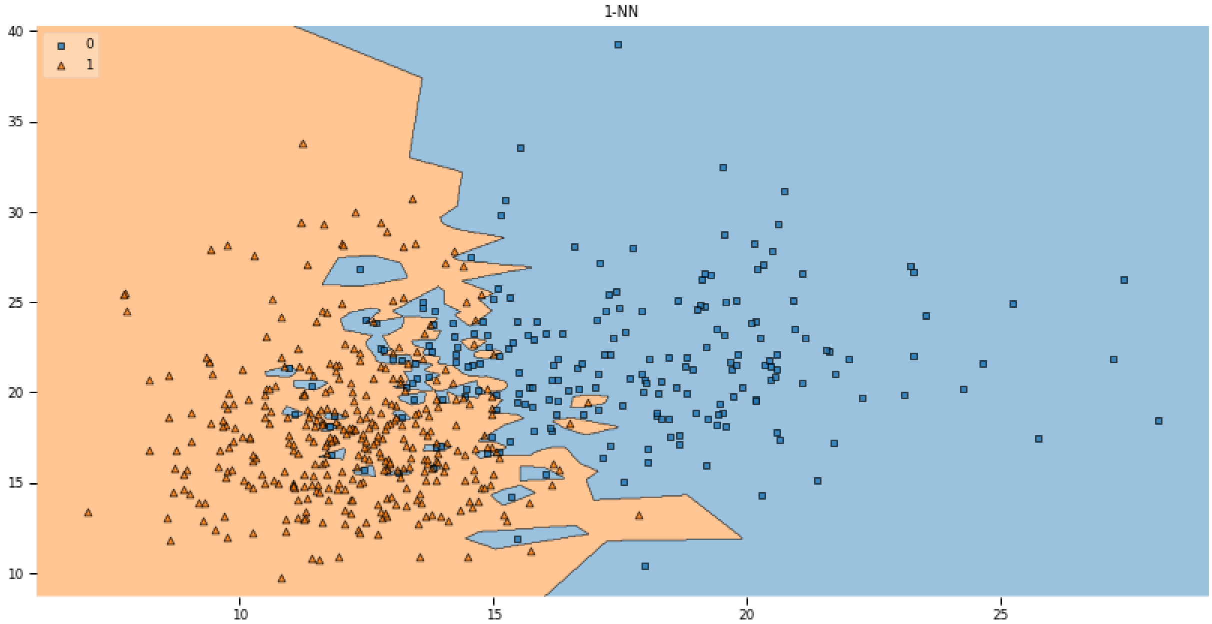
In [19]:
```
cancer_df = pd.concat([pd.DataFrame(cancer.data,columns=cancer.feature_names),pd.Dat
cancer_df
```

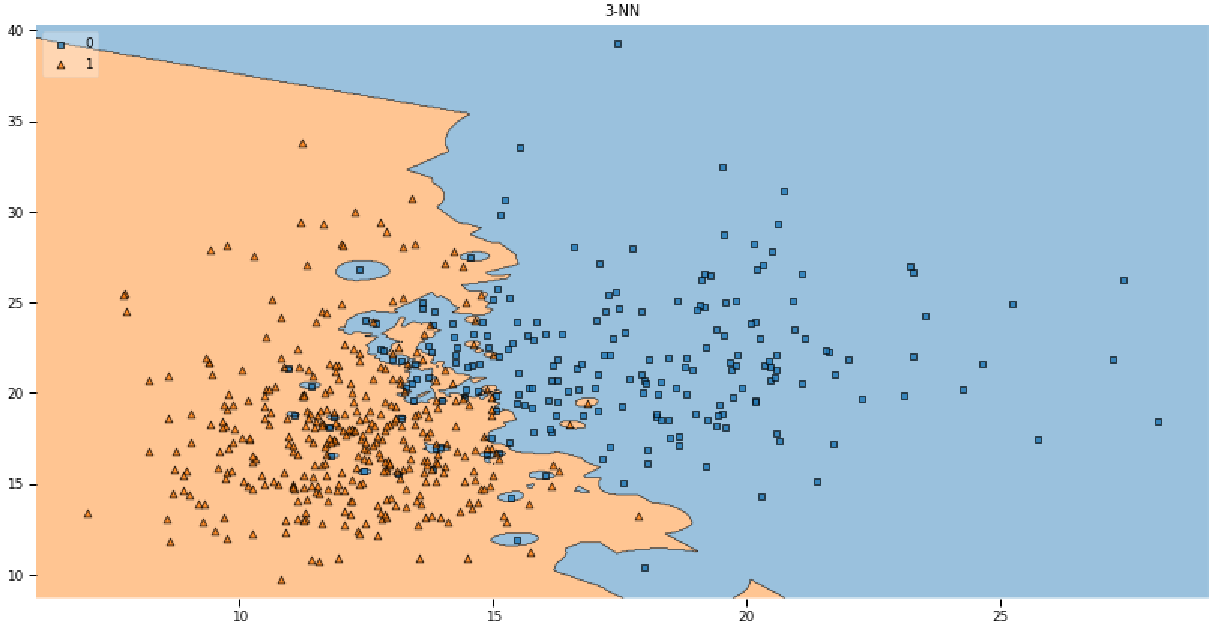
Out[19]:

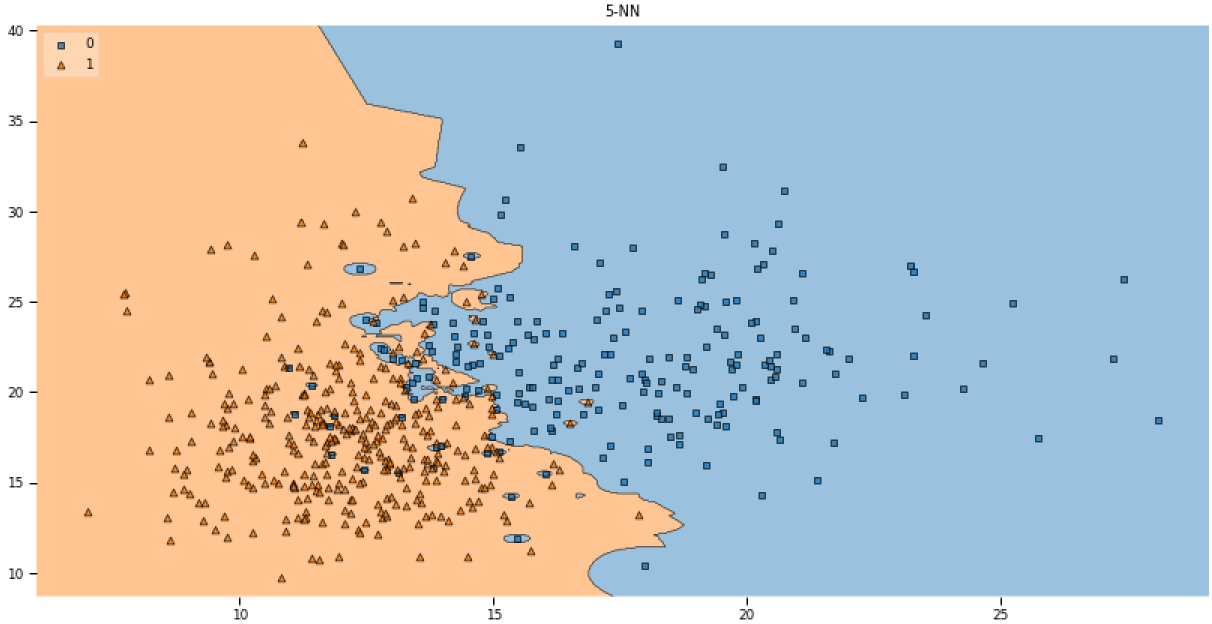
	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809
...	...	...	...	...	...	...	...	...	...
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587

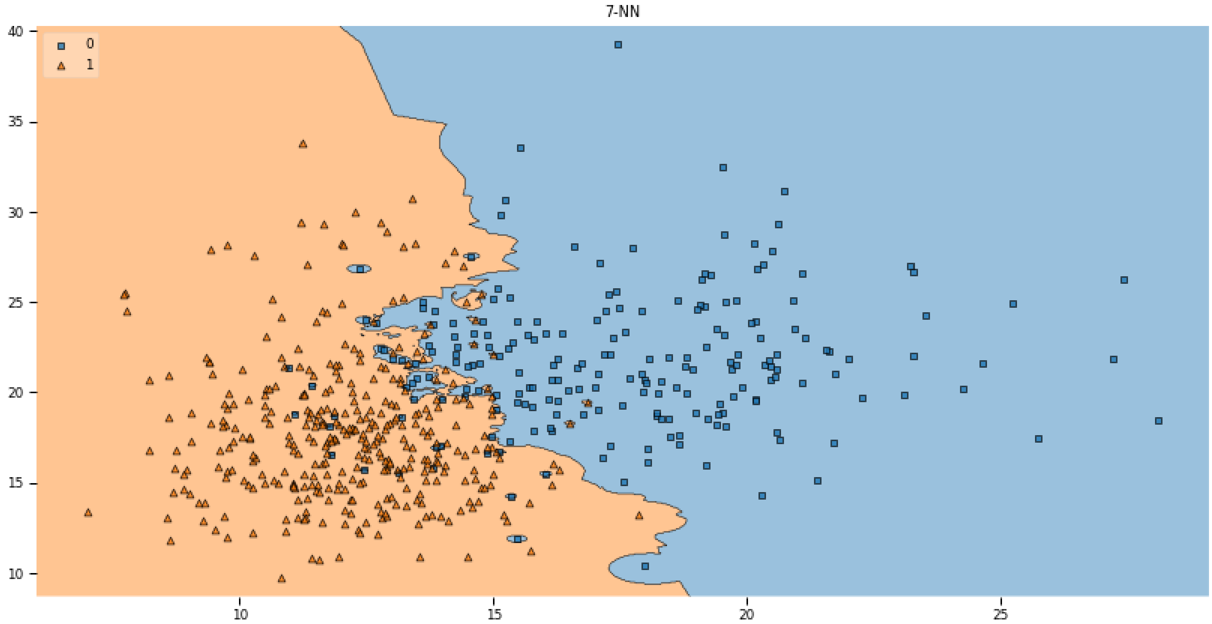
569 rows × 31 columns

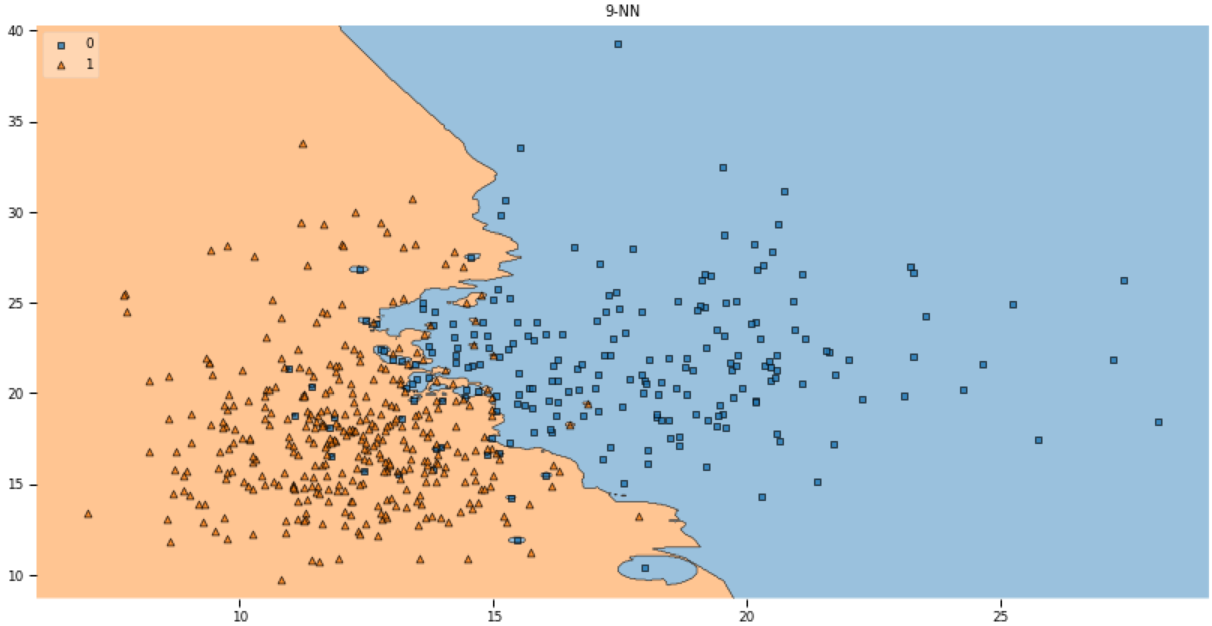
In [49]:
```
for k in range(1,21)[::2]:
    knn_dec_reg = KNC(n_neighbors=k,weights='distance',algorithm='kd_tree',leaf_size
    knn_dec_reg.fit(cancer_df.iloc[:,0:2],y=cancer_df['Label'])
    with plt.style.context('seaborn-bright'):
        plt.figure(figsize=(14,7))
        plot_decision_regions(X=cancer_df.iloc[:,0:2].values,y=cancer_df['Label'].va
        plt.title("{}-NN".format(k))
        plt.show()
```

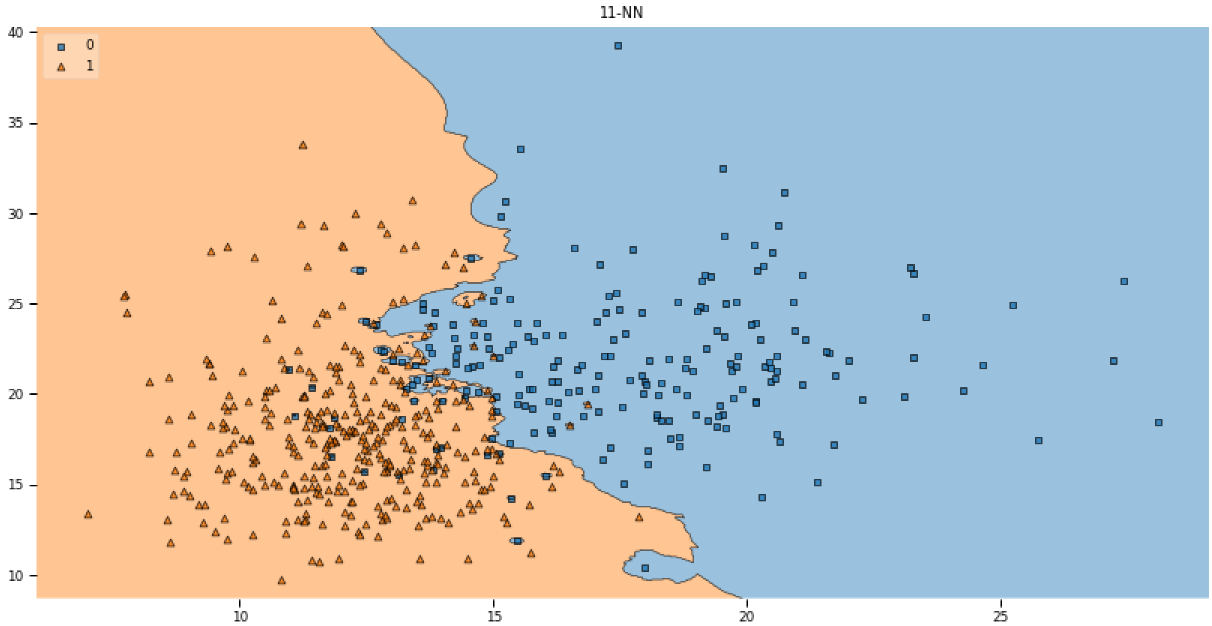

1-NN
0
1
40
35
30
25
20
15
10
10
15
20
25

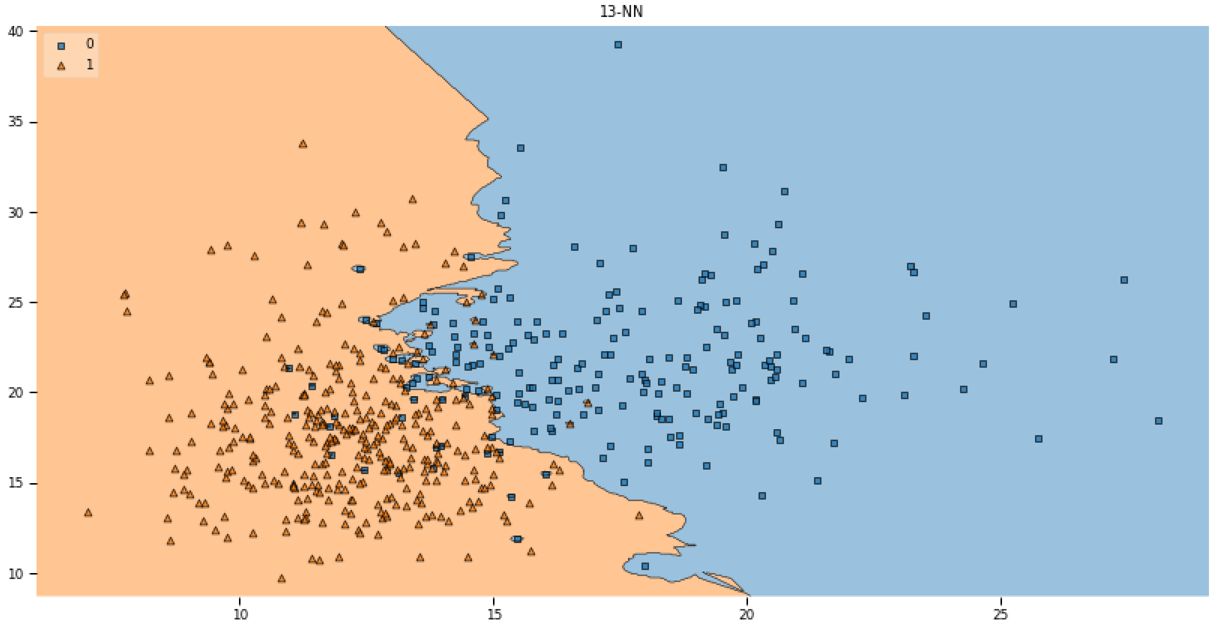

3-NN
0
1
40
35
30
25
20
15
10
10
15
20
25

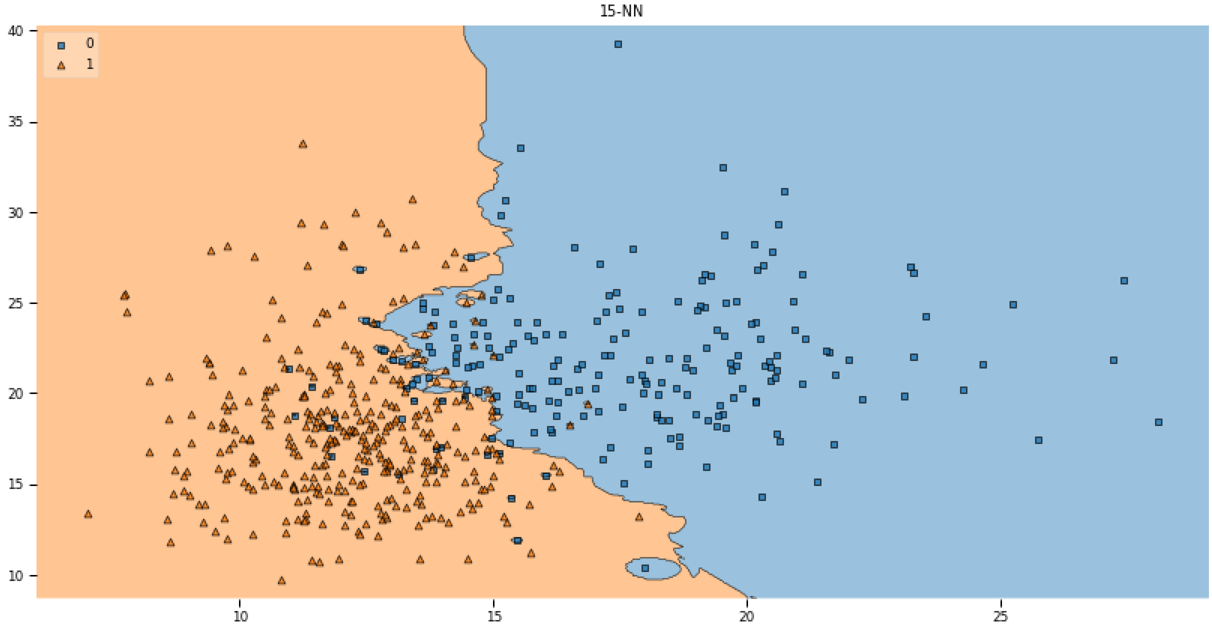

5-NN
0
1
40
35
30
25
20
15
10
10
15
20
25

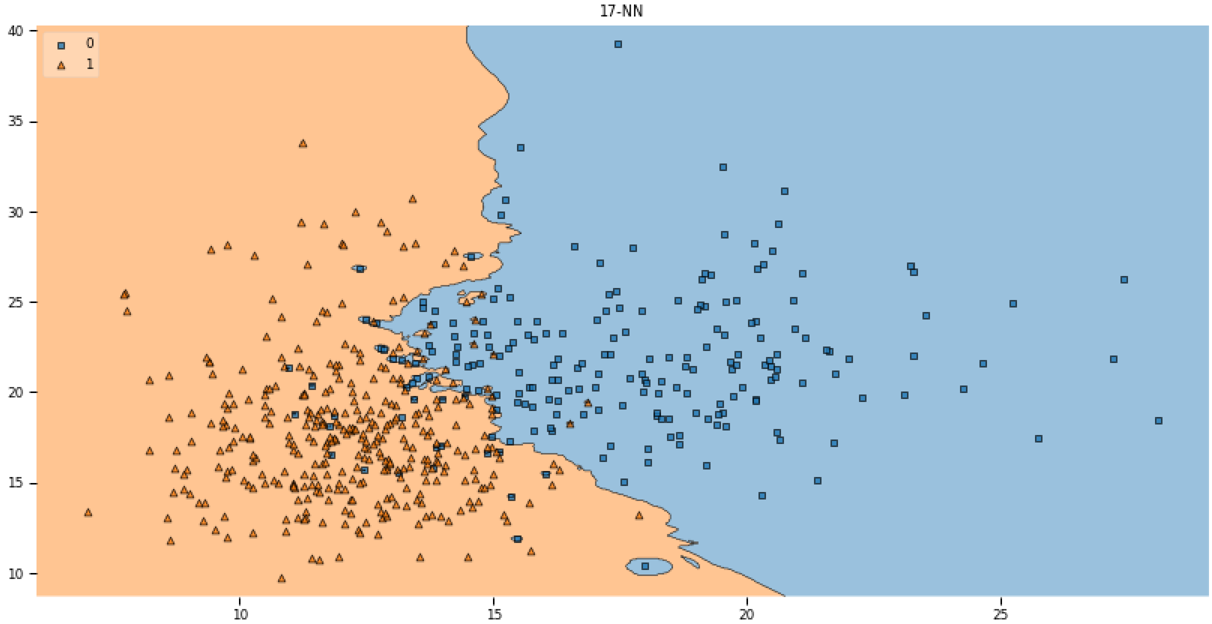

7-NN
0
1
40
35
30
25
20
15
10
10
15
20
25

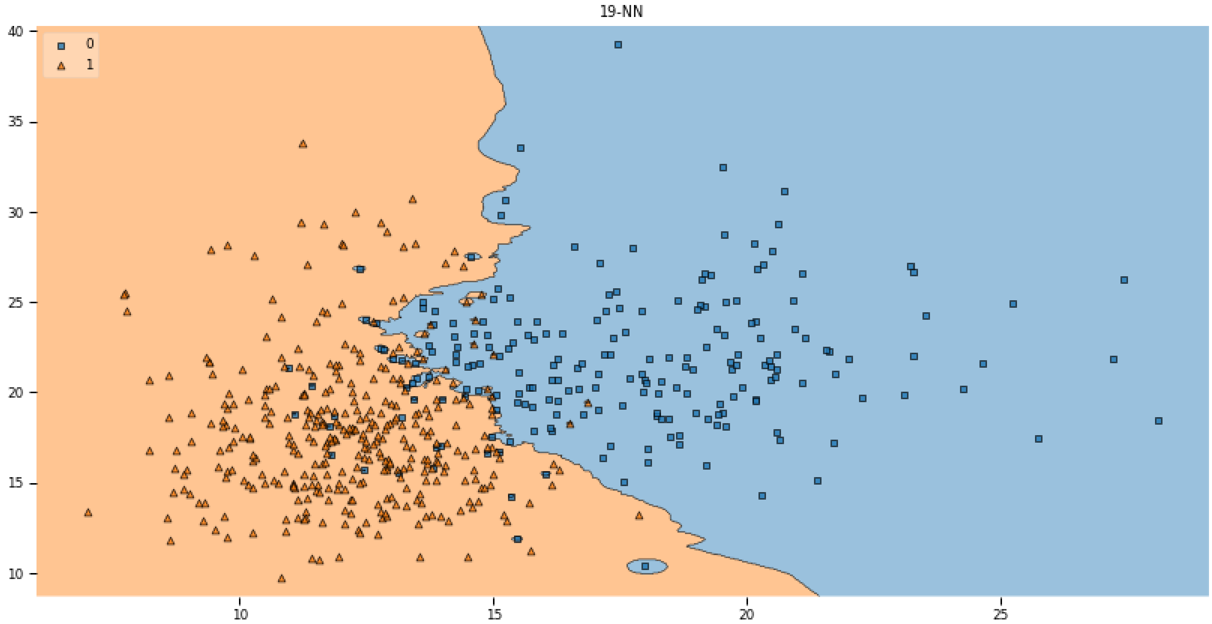

9-NN
0
1
40
35
30
25
20
15
10
10
15
20
25


11-NN
0
1
40
35
30
25
20
15
10
10
15
20
25


13-NN
0
1
40
35
30
25
20
15
10
10
15
20
25


15-NN
0
1
40
35
30
25
20
15
10
10
15
20
25


17-NN
0
1
40
35
30
25
20
15
10
10
15
20
25



Only TRAIN and TEST

In [36]:
```
X_train, X_test, y_train, y_test = train_test_split(cancer_df.iloc[:,0:-1],cancer_df
```

In [21]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

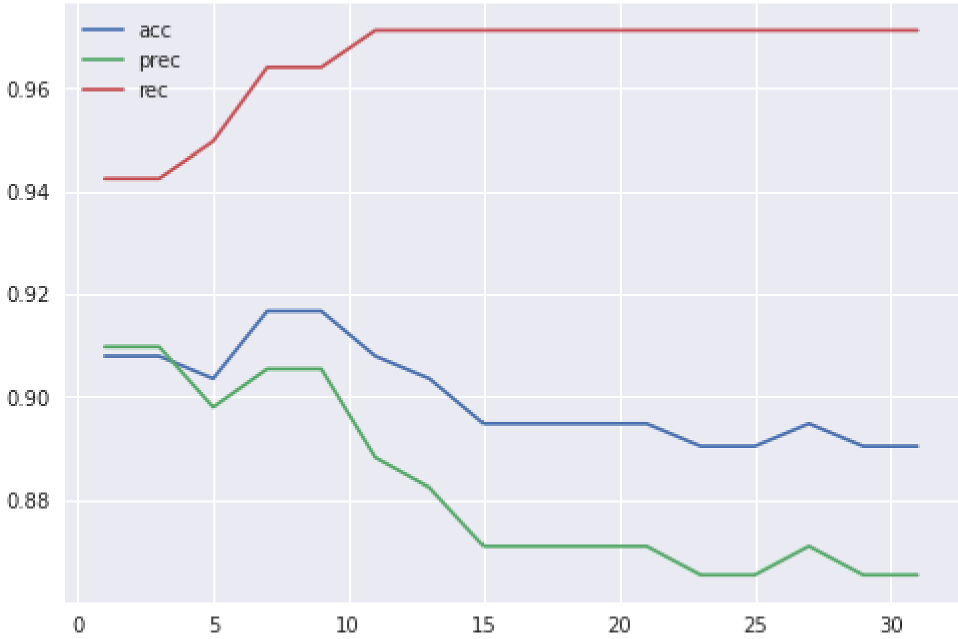
Out[21]:
```
((341, 30), (228, 30), (341,), (228,))
```

In [22]:
```
def filt(val):
    if val%2 != 0:
        return val
```

In [23]:
```
neighbors = list(filter(filt, [val for val in range(0,32)]))
neighbors
```

Out[23]:
```
[1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31]
```

In [24]:
```
acc_scr = []
rec_scr = []
prec_scr = []

for neighbor in neighbors:
    knn_model = KNC(n_neighbors=neighbor)
    knn_model.fit(X_train, y_train)
    knn_y_predict = knn_model.predict(X_test)
    acc_scr.append(accuracy_score(y_test,knn_y_predict))
    rec_scr.append(recall_score(y_test,knn_y_predict))
    prec_scr.append(precision_score(y_test,knn_y_predict))

with plt.style.context('seaborn'):
    sns.lineplot(x=neighbors,y=acc_scr,label='acc')
    sns.lineplot(x=neighbors,y=prec_scr,label='prec')
    sns.lineplot(x=neighbors,y=rec_scr,label='rec')
```



TRAIN, CV and TEST

In [25]:
```
X1, X_test, y1, y_test = train_test_split(cancer_df.iloc[:,0:-1],cancer_df['Label'],
```

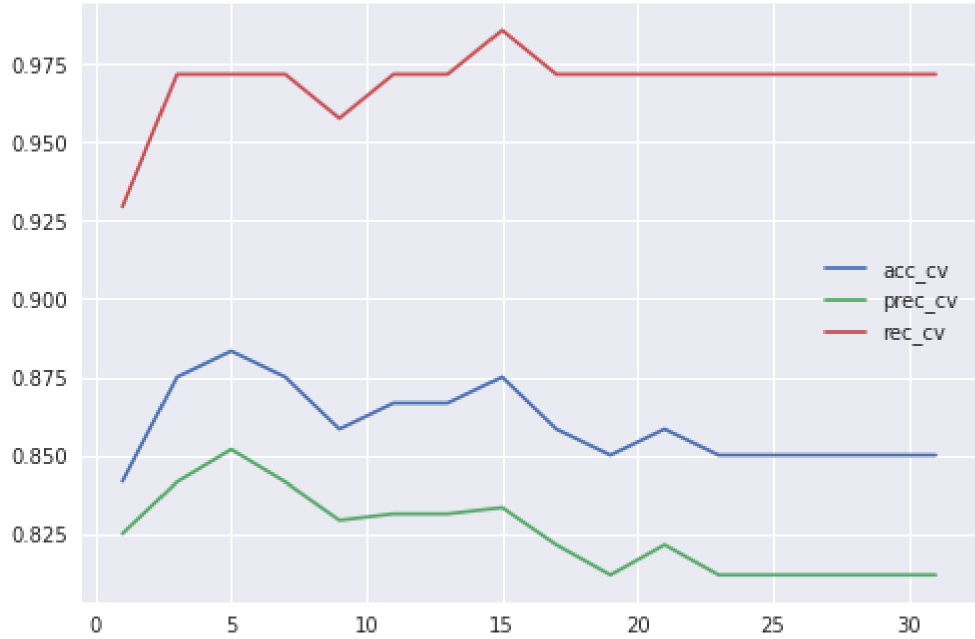
In [26]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X1,y1,test_size=0.30,random_state=42
```

In [27]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape, X_cv.shape, y_cv.shape
```

Out[27]:
```
((278, 30), (171, 30), (278,), (171,), (120, 30), (120,))
```

CV performance metrics

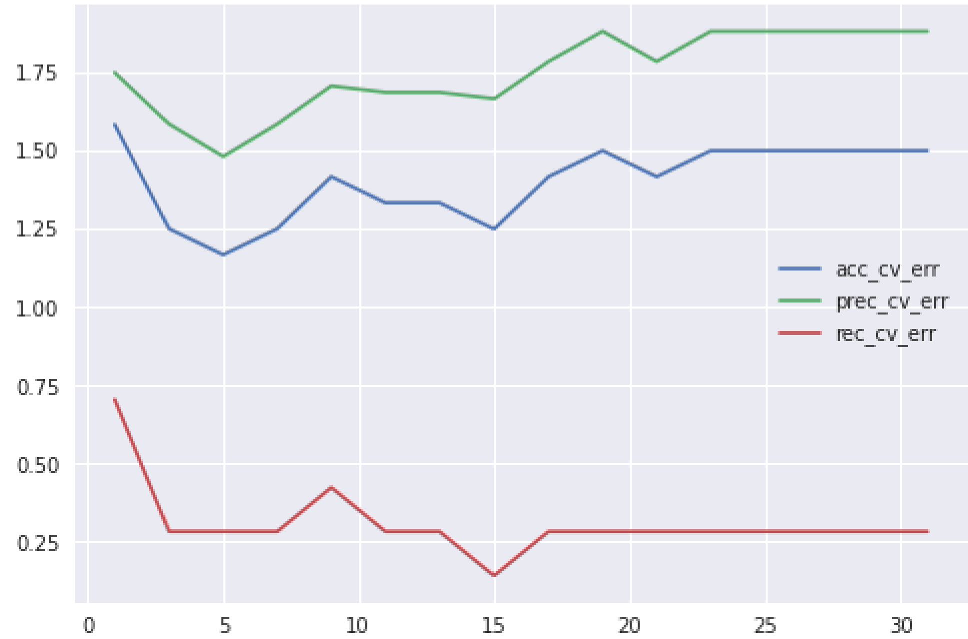
In [28]:
```
acc_scr_cv = []
rec_scr_cv = []
prec_scr_cv = []

for neighbor in neighbors:
    knn_model = KNC(n_neighbors=neighbor,weights='distance',algorithm='kd_tree',leaf
    knn_model.fit(X_train, y_train)
    y_cv_pred = knn_model.predict(X_cv)
    acc_scr_cv.append(accuracy_score(y_cv,y_cv_pred))
    rec_scr_cv.append(recall_score(y_cv,y_cv_pred))
    prec_scr_cv.append(precision_score(y_cv,y_cv_pred))

with plt.style.context('seaborn'):
    sns.lineplot(x=neighbors,y=acc_scr_cv,label='acc_cv')
    sns.lineplot(x=neighbors,y=prec_scr_cv,label='prec_cv')
    sns.lineplot(x=neighbors,y=rec_scr_cv,label='rec_cv')
```



CV Error

In [29]:
```
acc_scr_cv_err = [(1 - val)*10 for val in acc_scr_cv]
prec_scr_cv_err = [(1 - val)*10 for val in prec_scr_cv]
rec_scr_cv_err = [(1 - val)*10 for val in rec_scr_cv]
```

In [30]:
```
with plt.style.context('seaborn'):
    sns.lineplot(x=neighbors,y=acc_scr_cv_err,label='acc_cv_err')
    sns.lineplot(x=neighbors,y=prec_scr_cv_err,label='prec_cv_err')
    sns.lineplot(x=neighbors,y=rec_scr_cv_err,label='rec_cv_err')
```



TEST set performance metrics

In [31]:
```
knn_cancer_model = KNC(n_neighbors=neighbor,weights='distance',algorithm='kd_tree',l
knn_cancer_model.fit(X_train,y_train)
knn_cancer_ypred = knn_cancer_model.predict(X_test)
```

In [32]:
```
accuracy_score(y_test,knn_cancer_ypred), precision_score(y_test,knn_cancer_ypred), r
```

Out[32]:
```
(0.9415204678362573, 0.9152542372881356, 1.0)
```

Predicting Class Probability

In [33]:
```
print(knn_cancer_model.predict_proba(X_test))
```

```
[[0.10727533 0.89272467]
 [1.         0.        ]
 [0.90987962 0.09012038]
 [0.01882241 0.98117759]
 [0.01403691 0.98596309]
 [1.         0.        ]
 [1.         0.        ]
 [0.96872456 0.03127544]
 [0.02335353 0.97664647]
 [0.12278102 0.87721898]
 [0.03116392 0.96883608]
 [0.98430656 0.01569344]
 [0.12262872 0.87737128]
 [0.57084654 0.42915346]
 [0.02223204 0.97776796]
 [1.         0.        ]
 [0.11867577 0.88132423]
 [0.         1.        ]
 [0.         1.        ]
 [1.         0.        ]
 [0.28898917 0.71101083]
 [0.0501302  0.9498698 ]
 [1.         0.        ]
 [0.         1.        ]
 [0.         1.        ]
 [0.0243354  0.9756646 ]
 [0.02509231 0.97490769]
 [0.         1.        ]
 [0.         1.        ]
 [1.         0.        ]
 [0.         1.        ]
 [0.01898134 0.98101866]
 [0.         1.        ]
 [0.19632132 0.80367868]
 [0.         1.        ]
 [0.01658878 0.98341122]
 [0.92674356 0.07325644]
 [0.03880247 0.96119753]
 [1.         0.        ]
 [0.15321879 0.84678121]
 [0.         1.        ]
 [0.80984493 0.19015507]
 [0.         1.        ]
 [0.02596695 0.97403305]
 [0.         1.        ]
 [0.05303708 0.94696292]
 [0.         1.        ]
 [0.         1.        ]
 [0.05255506 0.94744494]
 [0.01350674 0.98649326]
 [1.         0.        ]
 [1.         0.        ]
 [0.04146001 0.95853999]
 [0.05088521 0.94911479]
 [0.         1.        ]
 [0.09863321 0.90136679]
 [0.         1.        ]
 [1.         0.        ]
 [0.20776767 0.79223233]
 [0.01592945 0.98407055]
 [0.02672009 0.97327991]
 [1.         0.        ]
 [1.         0.        ]
 [0.0593718  0.9406282 ]
 [0.01424098 0.98575902]
```

```
 [0.03313167 0.96686833]
 [0.9668277  0.0331723 ]
 [1.         0.        ]
 [0.         1.        ]
 [0.04307508 0.95692492]
 [0.25743538 0.74256462]
 [0.98509099 0.01490901]
 [0.05410487 0.94589513]
 [0.56849597 0.43150403]
 [0.         1.        ]
 [0.05490436 0.94509564]
 [0.11694131 0.88305869]
 [0.21835167 0.78164833]
 [0.0187632  0.9812368 ]
 [0.04211452 0.95788548]
 [0.95263292 0.04736708]
 [0.05722965 0.94277035]
 [0.16149533 0.83850467]
 [1.         0.        ]
 [1.         0.        ]
 [0.4904376  0.5095624 ]
 [0.23756747 0.76243253]
 [1.         0.        ]
 [0.         1.        ]
 [0.01563645 0.98436355]
 [0.05989591 0.94010409]
 [0.19446449 0.80553551]
 [0.25130616 0.74869384]
 [0.01627946 0.98372054]
 [0.         1.        ]
 [0.         1.        ]
 [1.         0.        ]
 [0.87381559 0.12618441]
 [0.01393219 0.98606781]
 [1.         0.        ]
 [0.96537113 0.03462887]
 [0.         1.        ]
 [1.         0.        ]
 [1.         0.        ]
 [0.13782438 0.86217562]
 [0.06321966 0.93678034]
 [0.0183746  0.9816254 ]
 [1.         0.        ]
 [0.11049027 0.88950973]
 [0.16877216 0.83122784]
 [0.9697765  0.0302235 ]
 [0.01915967 0.98084033]
 [0.08137518 0.91862482]
 [1.         0.        ]
 [0.         1.        ]
 [1.         0.        ]
 [0.         1.        ]
 [0.05219805 0.94780195]
 [0.         1.        ]
 [0.57208783 0.42791217]
 [0.09643647 0.90356353]
 [0.02692151 0.97307849]
 [0.04566413 0.95433587]
 [1.         0.        ]
 [0.04912859 0.95087141]
 [1.         0.        ]
 [0.84654748 0.15345252]
 [0.         1.        ]
 [0.05269405 0.94730595]
 [1.         0.        ]
 [1.         0.        ]
 [0.4721521  0.5278479 ]
 [0.19556569 0.80443431]
 [0.         1.        ]
```

```
[0.48016319 0.51983681]
[0.7242847  0.2757153 ]
[0.08481298 0.91518702]
[0.         1.        ]
[0.13835626 0.86164374]
[0.75779242 0.24220758]
[0.04599738 0.95400262]
[1.         0.        ]
[0.         1.        ]
[0.         1.        ]
[0.43795616 0.56204384]
[0.02604189 0.97395811]
[1.         0.        ]
[1.         0.        ]
[0.68907434 0.31092566]
[0.11228702 0.88771298]
[0.78476206 0.21523794]
[0.02011579 0.97988421]
[0.         1.        ]
[0.11952399 0.88047601]
[0.0162412  0.9837588 ]
[1.         0.        ]
[1.         0.        ]
[0.         1.        ]
[0.14078314 0.85921686]
[0.         1.        ]
[0.         1.        ]
[0.         1.        ]
[0.0233792  0.9766208 ]
[0.         1.        ]
[0.50005405 0.49994595]
[0.02265209 0.97734791]
[0.         1.        ]
[0.18478532 0.81521468]
[0.         1.        ]
[0.19417011 0.80582989]
[0.0505732  0.9494268 ]]
```

Locality Sensitive Hashing

In [34]:

```
import numpy as np

class HashTable:
    def __init__(self, hash_size, inp_dimensions):
        self.hash_size = hash_size
        self.inp_dimensions = inp_dimensions
        self.hash_table = dict()
        self.projections = np.random.randn(self.hash_size, inp_dimensions)

    def generate_hash(self, inp_vector):
        bools = (np.dot(inp_vector, self.projections.T) > 0).astype('int')
        return ''.join(bools.astype('str'))

    def __setitem__(self, inp_vec, label):
        hash_value = self.generate_hash(inp_vec)
        self.hash_table[hash_value] = self.hash_table\
            .get(hash_value, list()) + [label]

    def __getitem__(self, inp_vec):
        hash_value = self.generate_hash(inp_vec)
        return self.hash_table.get(hash_value, [])

hash_table = HashTable(hash_size=4, inp_dimensions=20)
```

In [35]:

```
class LSH:
```

```python
    def __init__(self, num_tables, hash_size, inp_dimensions):
        self.num_tables = num_tables
        self.hash_size = hash_size
        self.inp_dimensions = inp_dimensions
        self.hash_tables = list()
        for i in range(self.num_tables):
            self.hash_tables.append(HashTable(self.hash_size, self.inp_dimensions))

    def __setitem__(self, inp_vec, label):
        for table in self.hash_tables:
            table[inp_vec] = label

    def __getitem__(self, inp_vec):
        results = list()
        for table in self.hash_tables:
            results.extend(table[inp_vec])
        return list(set(results))
```

In [ ]:

In [ ]:

In [ ]: