Tugas Kecil 1 Machine Learning

Dataset breast cancer Jon Felix Germinian - 13518025 Filbert Wijaya - 13518077

Import semua library yang diperlukan

agak banyak library yang diminta, dimaklumin

```
import pandas as pd
import sklearn
import sklearn.datasets
import sklearn.model_selection
import sklearn.metrics
```

Import dataset yang digunakan

```
In [2]: breast_cancer = sklearn.datasets.load_breast_cancer()
```

Make dataframe for given dataset

```
In [3]:
    df_breast_cancer = pd.DataFrame(breast_cancer.data, columns=breast_cancer.feature_names
    df_breast_cancer.head()
```

Out[3]:		mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	m fra dimen
	0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07
	1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	20.0
	2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05
	3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09
	4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05

5 rows × 30 columns

```
'smoothness error', 'compactness error', 'concavity error',
'concave points error', 'symmetry error', 'fractal dimension error',
'worst radius', 'worst texture', 'worst perimeter', 'worst area',
'worst smoothness', 'worst compactness', 'worst concavity',
'worst concave points', 'worst symmetry', 'worst fractal dimension'],
dtype='object')
```

Feature engineering

```
In [5]:
    X, y = sklearn.datasets.load_breast_cancer(return_X_y=True)
    X_train, X_test, y_train, y_test = sklearn.model_selection.train_test_split(X, y, rando
```

Training

Decision Tree

```
In [6]:
                            from sklearn import tree
                            clf1 = tree.DecisionTreeClassifier()
                            clf1 = clf1.fit(X train, y train)
                            tree.plot tree(clf1)
Out[6]: [Text(187.32857142857142, 205.3599999999999, 'X[7] <= 0.049\ngini = 0.468\nsamples = 42
                          6\nvalue = [159, 267]'),
                            Text(119.57142857142857, 181.2, X[20] <= 17.59  ngini = 0.095 \nsamples = 260 \nvalue =
                          [13, 247]'),
                            Text(79.71428571428572, 157.04, 'X[13] <= 42.19\ngini = 0.054\nsamples = 252\nvalue =
                          [7, 245]'),
                             Text(47.82857142857143, 132.88, 'X[25] <= 0.454 | ngini = 0.032 | nsamples = 247 | nvalue = 0.032 | nsamples = 247 | nvalue = 0.032 | nsamples =
                           [4, 243]'),
                             Text(31.885714285714286, 108.72, 'X[21] <= 30.145\ngini = 0.024\nsamples = 246\nvalue =
                           [3, 243]'),
                             Text(15.942857142857143, 84.56, 'gini = 0.0\nsamples = 215\nvalue = [0, 215]'),
                             Text(47.82857142857143, 84.56, 'X[14] <= 0.004 / ngini = 0.175 / nsamples = 31 / nvalue = [3, 1.25]
                             Text(31.885714285714286, 60.400000000000000, 'gini = 0.0 \nsamples = 2 \nvalue = [2, ]
                          0]'),
                             Text(63.77142857142857, 60.400000000000006, 'X[1] \le 23.2 \text{ ngini} = 0.067 \text{ nsamples} = 29 \text{ ngini} = 20 \text{ ngini} = 0.067 \text{ nsamples} = 29 \text{ nsample
                          value = [1, 28]'),
                            Text(47.82857142857143, 36.24000000000000, X[1] <= 22.385 \ngini = 0.32 \nsamples = 5 \nv
                          alue = [1, 4]'),
                             Text(31.885714285714286, 12.079999999999984, 'gini = 0.0\nsamples = 4\nvalue = [0,
                          4]'),
                             Text(63.77142857142857, 12.07999999999994, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
                             Text(79.71428571428572, 36.24000000000001, 'gini = 0.0\nsamples = 24\nvalue = [0, 2
                             Text(63.77142857142857, 108.72, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
                             Text(111.6, 132.88, X[8] \le 0.166 = 0.48 = 5
                             Text(95.65714285714286, 108.72, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
                             Text(127.54285714285714, 108.72, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(159.42857142857144, 157.04, 'X[21] <= 26.005\ngini = 0.375\nsamples = 8\nvalue =
                           [6, 2]'),
                             Text(143.4857142857143, 132.88, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
                             Text(175.37142857142857, 132.88, 'gini = 0.0\nsamples = 6\nvalue = [6, 0]'),
                             Text(255.0857142857143, 181.2, 'X[23] <= 785.8\ngini = 0.212\nsamples = 166\nvalue = [1
                          46, 20]'),
                             Text(223.2, 157.04, 'X[21] \le 23.74 \text{ ngini} = 0.491 \text{ nsamples} = 30 \text{ nvalue} = [13, 17]'),
                             Text(207.25714285714287, 132.88, 'gini = 0.0\nsamples = 14\nvalue = [0, 14]'),
                             Text(239.14285714285714, 132.88, 'X[25] <= 0.263\ngini = 0.305\nsamples = 16\nvalue =
```

```
[13, 3]'),

Text(223.2, 108.72, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),

Text(255.0857142857143, 108.72, 'gini = 0.0\nsamples = 13\nvalue = [13, 0]'),

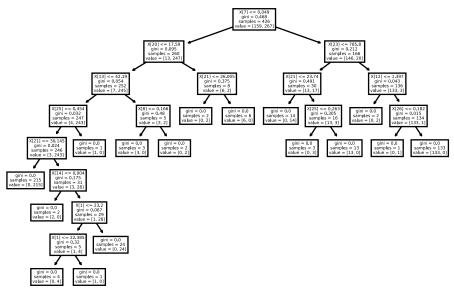
Text(286.9714285714286, 157.04, 'X[12] <= 1.397\ngini = 0.043\nsamples = 136\nvalue = [133, 3]'),

Text(271.0285714285714, 132.88, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),

Text(302.9142857142857, 132.88, 'X[26] <= 0.182\ngini = 0.015\nsamples = 134\nvalue = [133, 1]'),

Text(286.9714285714286, 108.72, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),

Text(318.8571428571429, 108.72, 'gini = 0.0\nsamples = 133\nvalue = [133, 0]')]
```



```
print("Training set score: %f" % clf1.score(X_train, y_train))
print("Test set score: %f" % clf1.score(X_test, y_test))
# overfit?
```

Training set score: 1.000000 Test set score: 0.881119

print("Accuracy score: %f" % sklearn.metrics.accuracy_score(y_test, clf1.predict(X_test
print("F1 Score : %f" % sklearn.metrics.f1_score(y_test, clf1.predict(X_test),average='

Accuracy score: 0.881119 F1 Score : 0.882642

Id3Estimator

```
import six
import sys
sys.modules['sklearn.externals.six'] = six
import mlrose

In [10]:
import id3
estimator = id3.Id3Estimator()
estimator = estimator.fit(X_train, y_train)
tree = id3.export_graphviz(estimator.tree_, 'tree.dot', breast_cancer.feature_names)
In [11]:
```

```
print("Accuracy score: %f" % sklearn.metrics.accuracy_score(y_test, estimator.predict(X
print("F1 Score : %f" % sklearn.metrics.f1_score(y_test, estimator.predict(X_test),aver
```

Accuracy score: 0.944056 F1 Score: 0.944437

KMeans

```
In [12]:
          from sklearn.cluster import KMeans
          kmeans = KMeans(n clusters=2).fit(df breast cancer)
          centroids = kmeans.cluster_centers_
          print(centroids)
          [[1.25562991e+01 1.85703653e+01 8.11234703e+01 4.96061872e+02
           9.48844977e-02 9.10998174e-02 6.24377642e-02 3.34325434e-02
           1.78057991e-01 6.34540183e-02 3.04190868e-01 1.21515320e+00
           2.15288059e+00 2.37852922e+01 7.17326256e-03 2.34746895e-02
           2.87455128e-02 1.06363242e-02 2.06135799e-02 3.74750297e-03
           1.40439018e+01 2.47095434e+01 9.19375114e+01 6.19647945e+02
           1.29959110e-01 2.23311758e-01 2.19214947e-01 9.13298425e-02
           2.83553653e-01 8.32819406e-02]
          [1.93799237e+01 2.16945802e+01 1.28231298e+02 1.18592977e+03
           1.01294580e-01 1.48612977e-01 1.76939466e-01 1.00698779e-01
           1.91539695e-01 6.06029008e-02 7.42803817e-01 1.22253817e+00
           5.25058015e+00 9.56781679e+01 6.59868702e-03 3.21766947e-02
           4.24197710e-02 1.56739847e-02 2.03039695e-02 3.95338931e-03
           2.37094656e+01 2.89126718e+01 1.58496183e+02 1.75302290e+03
           1.40424733e-01 3.57757710e-01 4.49306107e-01 1.92431069e-01
           3.11881679e-01 8.61654962e-02]]
In [13]:
          print("Accuracy score: %f" % sklearn.metrics.accuracy_score(y_test, kmeans.predict(X_te
          print("F1 Score : %f" % sklearn.metrics.f1_score(y_test, kmeans.predict(X_test),average
         Accuracy score: 0.153846
         F1 Score: 0.098834
```

Logistic Regression

Neural Network

F1 Score: 0.944437

```
from sklearn.neural_network import MLPClassifier
In [17]:
          clf4 = MLPClassifier(random state=1, max iter=300).fit(X train, y train)
In [18]:
          print("Training set score: %f" % clf4.score(X_train, y_train))
          print("Test set score: %f" % clf4.score(X_test, y_test))
         Training set score: 0.927230
         Test set score: 0.895105
In [19]:
          print("Accuracy score: %f" % sklearn.metrics.accuracy score(y test, clf4.predict(X test
          print("F1 Score : %f" % sklearn.metrics.f1 score(y test, clf4.predict(X test),average=
         Accuracy score: 0.895105
         F1 Score : 0.896232
         SVM
In [20]:
          from sklearn.pipeline import make_pipeline
          from sklearn.preprocessing import StandardScaler
          from sklearn.svm import SVC
          clf5 = make pipeline(StandardScaler(), SVC(gamma='auto'))
          clf5.fit(X_train, y_train)
Out[20]: Pipeline(steps=[('standardscaler', StandardScaler()),
                          ('svc', SVC(gamma='auto'))])
In [21]:
          print("Training set score: %f" % clf5.score(X train, y train))
          print("Test set score: %f" % clf5.score(X_test, y_test))
         Training set score: 0.985915
         Test set score: 0.965035
In [22]:
          print("Accuracy score: %f" % sklearn.metrics.accuracy score(y test, clf5.predict(X test
          print("F1 Score : %f" % sklearn.metrics.f1_score(y_test, clf5.predict(X_test),average=
```

Accuracy score: 0.965035 F1 Score : 0.964965

Abalysis

Dapat dilihat bahwa skor akurasi dari terbaik ke terburuk adalah SVM, ID3, Logistic Regression, Decision Tree, Neural Network dan KMeans.

Untuk nilai F1, skor dari terbaik ke terburuk adalah SVM, ID3, Logistic Regression, Decision Tree, Neural Network dan KMeans.

SVM mungkin terbaik dalam kasus data breast cancer karena nilai-nilai dari dataframe tersebut linearly seperable.

ID3, Logistic Regression, Decision Tree memiliki nilai baik mungkin dikarenakan algoritmanya yang cocok digunakan untuk klasifikasi dengan banyak parameter (ada 30 kolom untuk dataset ini). Performa neural network kurang dibandingkan algoritma lain karena ukuran sampel yang kurang besar.

KMeans memiliki performa yang sangat buruk untuk dataset ini, mungkin dikarenakan variasi data yang besar dan dimensi dataset.