Tucil2_13515096

November 7, 2017

1 TUGAS KECIL 2 - INTELIGENSI BUATAN

1.1 Eksplorasi Scikit-Learn

1.2 Anggota

1.2.1 Gilang Ardyamandala Al Assyifa (13515096)

1.2.2 Rio Dwi Putra Perkasa (13515012)

1.3 A. Membaca Dataset

1.3.1 Membaca dataset Iris dari sklearn.datasest

In [1]:
```
from sklearn import datasets

df_iris = datasets.load_iris()

print('Isi dataframe iris:')
for x in df_iris: print(x)
```

```
Isi dataframe iris:
data
feature_names
target_names
target
DESCR
```

In [2]:
```
print(df_iris.DESCR)
print()
print('Sampel data dan target')
print(df_iris.feature_names)
print(df_iris.data[:10])
print(df_iris.target_names)
print(df_iris.target[:10])
```

Iris Plants Database
====================

Notes

Data Set Characteristics:

:Number of Instances: 150 (50 in each of three classes)

:Number of Attributes: 4 numeric, predictive attributes and the class

:Attribute Information:

- sepal length in cm
- sepal width in cm
- petal length in cm
- petal width in cm
- class:
    - Iris-Setosa
    - Iris-Versicolour
    - Iris-Virginica

:Summary Statistics:

	Min	Max	Mean	SD	Class Correlation
sepal length:	4.3	7.9	5.84	0.83	0.7826
sepal width:	2.0	4.4	3.05	0.43	-0.4194
petal length:	1.0	6.9	3.76	1.76	0.9490 (high!)
petal width:	0.1	2.5	1.20	0.76	0.9565 (high!)

:Missing Attribute Values: None

:Class Distribution: 33.3% for each of 3 classes.

:Creator: R.A. Fisher

:Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)

:Date: July, 1988

This is a copy of UCI ML iris datasets.
http://archive.ics.uci.edu/ml/datasets/Iris

The famous Iris database, first used by Sir R.A Fisher

This is perhaps the best known database to be found in the pattern recognition literature. Fisher's paper is a classic in the field and is referenced frequently to this day. (See Duda & Hart, for example.) The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant. One class is linearly separable from the other 2; the latter are NOT linearly separable from each other.

References

```
   - Fisher,R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
     Mathematical Statistics" (John Wiley, NY, 1950).
   - Duda,R.O., & Hart,P.E. (1973) Pattern Classification and Scene Analysis.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...


Sampel data dan target
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
[[ 5.1  3.5  1.4  0.2]
 [ 4.9  3.   1.4  0.2]
 [ 4.7  3.2  1.3  0.2]
 [ 4.6  3.1  1.5  0.2]
 [ 5.   3.6  1.4  0.2]
 [ 5.4  3.9  1.7  0.4]
 [ 4.6  3.4  1.4  0.3]
 [ 5.   3.4  1.5  0.2]
 [ 4.4  2.9  1.4  0.2]
 [ 4.9  3.1  1.5  0.1]]
['setosa' 'versicolor' 'virginica']
[0 0 0 0 0 0 0 0 0 0]
```

1.3.2 Membaca dataset play-tenis dari dataset eksternal (dalam .csv)

In [3]:
```python
import pandas as pd

df_tennis = pd.read_csv('tennis.csv')

df_tennis
```

Out[3]:

	outlook	temp	humidity	windy	play
0	sunny	hot	high	False	no
1	sunny	hot	high	True	no
2	overcast	hot	high	False	yes
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes
5	rainy	cool	normal	True	no
6	overcast	cool	normal	True	yes

```
7      sunny  mild    high  False   no
8      sunny  cool  normal  False  yes
9      rainy  mild  normal  False  yes
10     sunny  mild  normal   True  yes
11  overcast  mild    high   True  yes
12  overcast   hot  normal  False  yes
13     rainy  mild    high   True   no
```

1.4 MELAKUKAN PEMBELAJARAN

Pada tugas ini, algoritma yang digunakan untuk pembelajaran, antara lain: - Naive Bayes (GaussianNB) - DecisionTree, catatan: default DTL pada sklearn.tree adalah Optimized CART, bukan ID3 - kNN - Neural Network MLP

```
In [4]: from sklearn.naive_bayes import GaussianNB
        from sklearn import tree
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.neural_network import MLPClassifier
```

1.5 B. Pembelajaran dengan Skema *Full Training*

- Melakukan pembelajaran
- Menampilkan setiap modelnya
- Tidak disuruh menampilkan kinerjanya

```
In [5]: X_train_full = df_iris.data
        y_train_full = df_iris.target
```

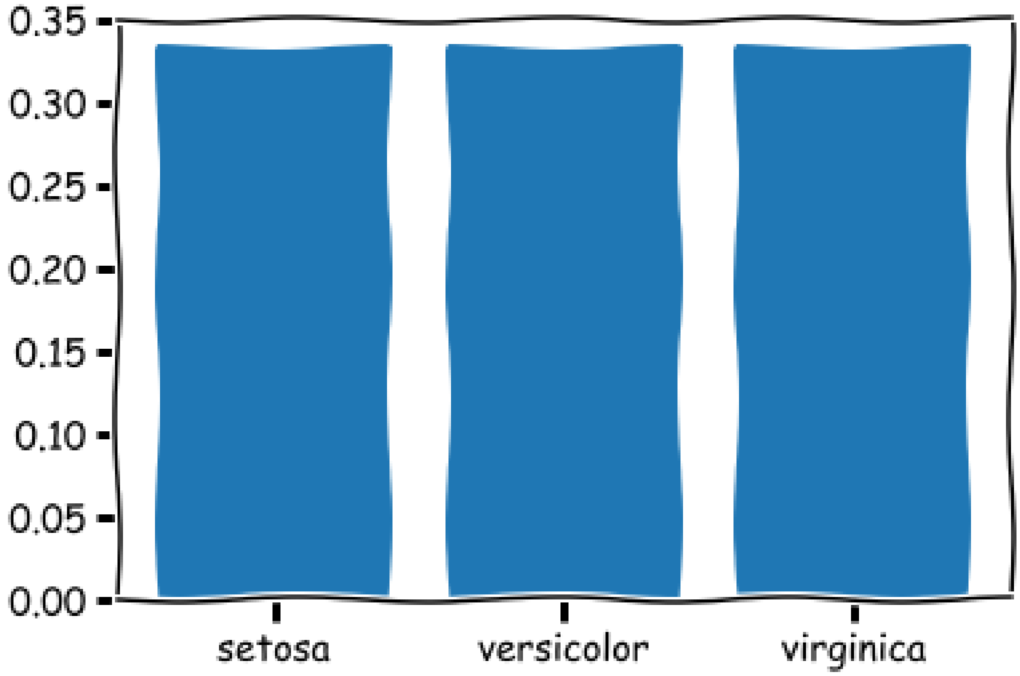
1.5.1 Gaussian Naive Bayes (GNB)

```
In [6]: clf_GNB = GaussianNB()
        clf_GNB.fit(X_train_full, y_train_full)

Out[6]: GaussianNB(priors=None)
```

1.5.2 Model GNB

```
In [7]: %matplotlib inline
        import matplotlib.pyplot as plt
        plt.xkcd()

        print('Prior probability')
        for i in range(3):
            print(df_iris.target_names[i] + ':', clf_GNB.class_prior_[i])
        plt.bar([0,1,2], clf_GNB.class_prior_)
        plt.xticks([0,1,2],df_iris.target_names)
        plt.show()
```

```
Prior probability
setosa: 0.333333333333
versicolor: 0.333333333333
virginica: 0.333333333333
```

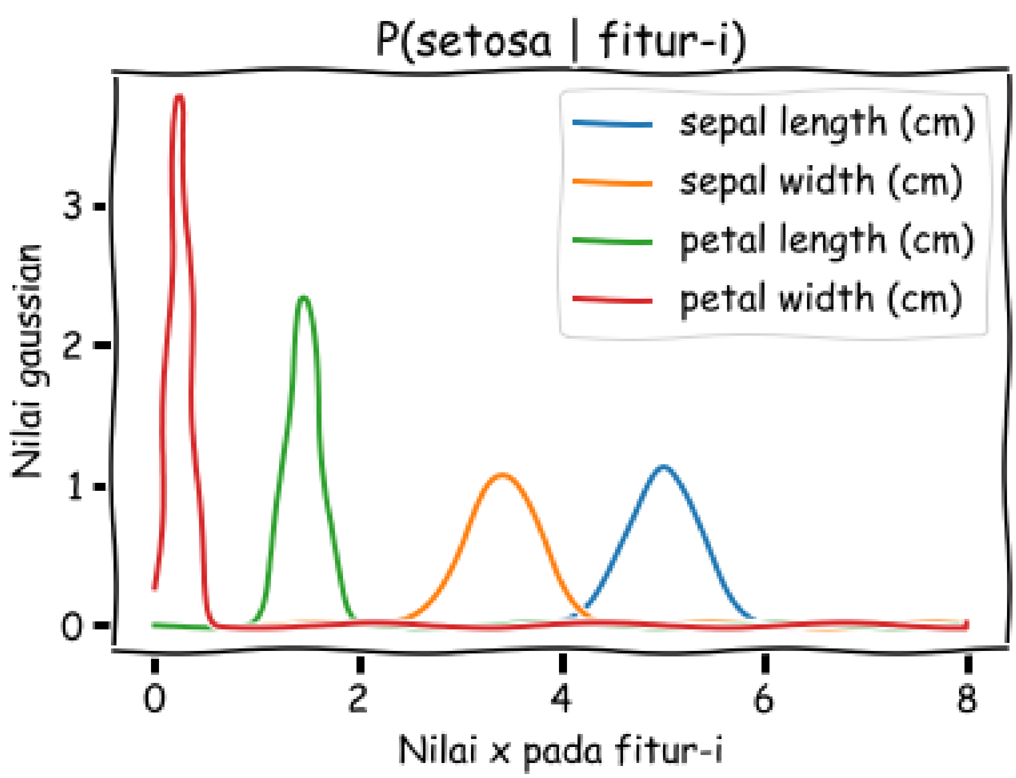



```
In [8]: from math import exp, sqrt, pi
        import numpy as np

        # Untuk mengeluarkan nilai gaussian
        def gaussian(x, theta, sigma):
            return 1/sqrt(2*pi*sigma) * exp((-(x-theta)**2)/(2*sigma))

        # Untuk menggambar grafik Gaussian
        def model_gnb(lot, los, tar):
            print('Untuk kelas', df_iris.target_names[tar])
            print('Nilai theta')
            for j in range(4): print(df_iris.target_names[tar] + ' | ' + df_iris.feature_names[j

            print('\nNilai sigma')
            for j in range(4): print(df_iris.target_names[tar] + ' | ' + df_iris.feature_names[j

            eks = list(np.arange(0.0, 8.0, 0.01))
            plt.xlabel('Nilai x pada fitur-i')
            plt.ylabel('Nilai gaussian')
```

```
            for feat in range(4):
                ye = [gaussian(elem, lot[tar][feat], los[tar][feat]) for elem in eks]
                plt.title('P(' + df_iris.target_names[tar] + ' | fitur-i)')
                plt.plot(eks, ye, label = df_iris.feature_names[feat])
            plt.legend(loc='upper right')
            plt.show()
```

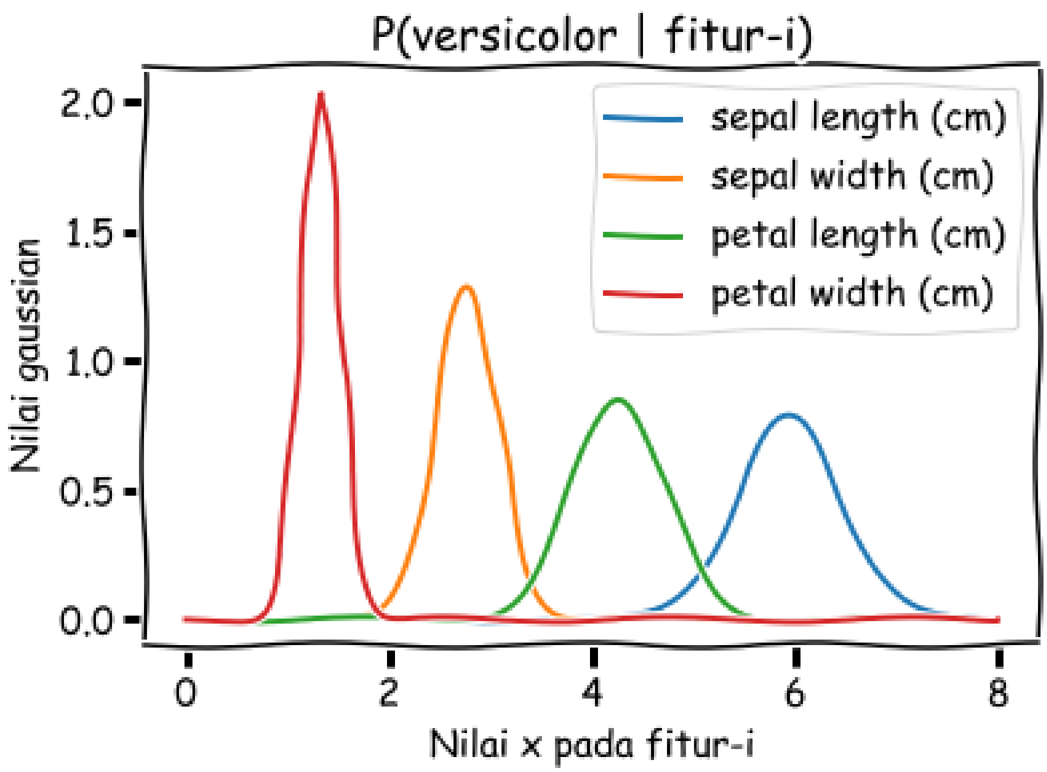
```
In [9]: model_gnb(clf_GNB.theta_, clf_GNB.sigma_, 0)
```

```
Untuk kelas setosa
Nilai theta
setosa | sepal length (cm): 5.006
setosa | sepal width (cm): 3.418
setosa | petal length (cm): 1.464
setosa | petal width (cm): 0.244

Nilai sigma
setosa | sepal length (cm): 0.121764003092
setosa | sepal width (cm): 0.142276003092
setosa | petal length (cm): 0.0295040030924
setosa | petal width (cm): 0.0112640030924
```



```
In [10]: model_gnb(clf_GNB.theta_, clf_GNB.sigma_, 1)
```

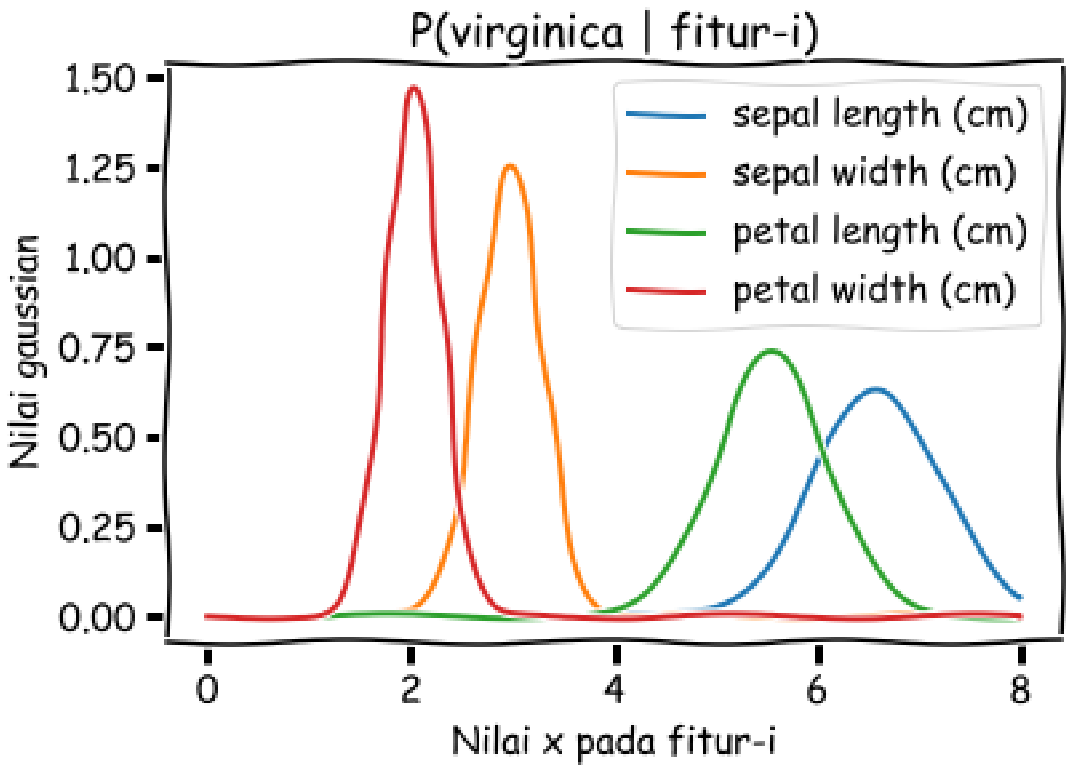
```
Untuk kelas versicolor
Nilai theta
versicolor | sepal length (cm): 5.936
versicolor | sepal width (cm): 2.77
versicolor | petal length (cm): 4.26
versicolor | petal width (cm): 1.326

Nilai sigma
versicolor | sepal length (cm): 0.261104003092
versicolor | sepal width (cm): 0.0965000030924
versicolor | petal length (cm): 0.216400003092
versicolor | petal width (cm): 0.0383240030924
```




```
In [11]: model_gnb(clf_GNB.theta_, clf_GNB.sigma_, 2)
```

```
Untuk kelas virginica
Nilai theta
virginica | sepal length (cm): 6.588
virginica | sepal width (cm): 2.974
virginica | petal length (cm): 5.552
```

```
virginica | petal width (cm): 2.026

Nilai sigma
virginica | sepal length (cm): 0.396256003092
virginica | sepal width (cm): 0.101924003092
virginica | petal length (cm): 0.298496003092
virginica | petal width (cm): 0.0739240030924
```



1.5.3 DecisionTree CART

Perhatikan bahwa DTL pada sklearn.tree adalah CART, bukan ID3.

Classifier ini menggunakan konfigurasi criterion='entropy' agar lebih mirip dengan ID3 (dibanging criterion='gini')

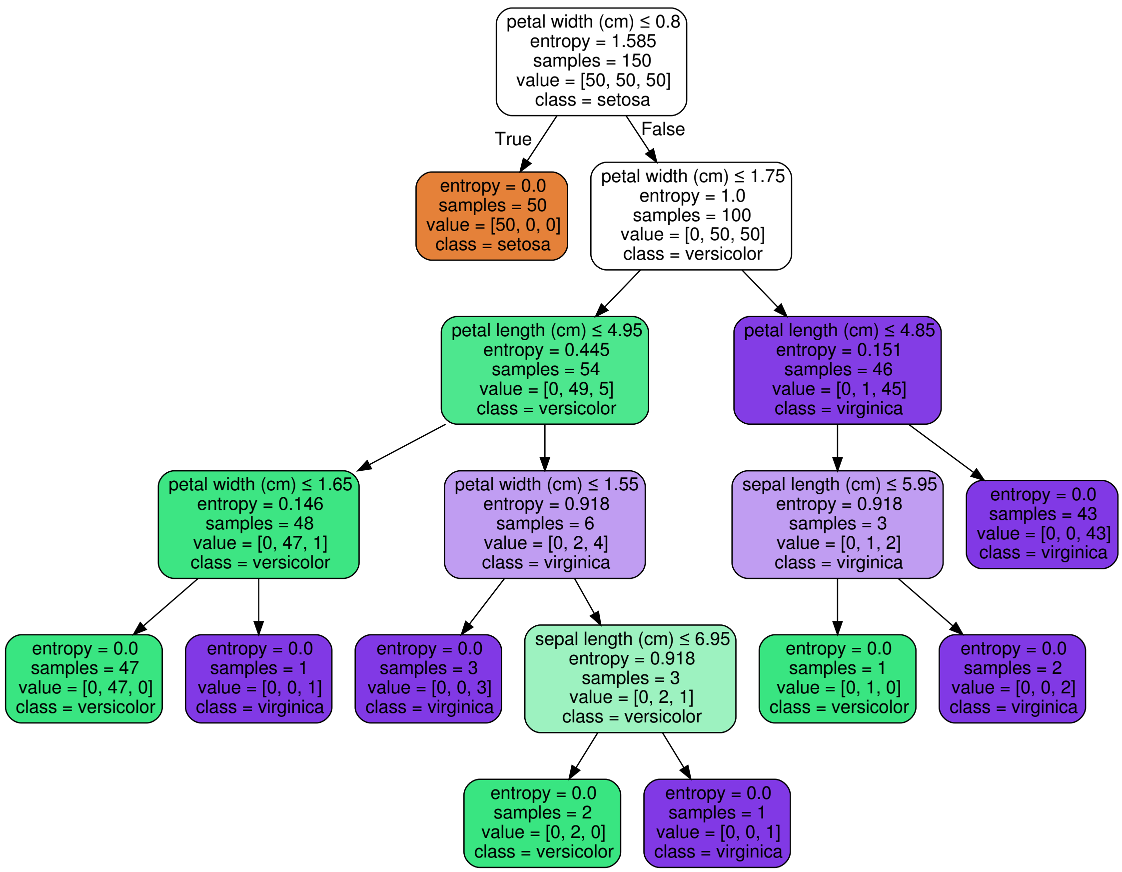
In [12]:
```
clf_DT = tree.DecisionTreeClassifier(criterion='entropy')
clf_DT.fit(X_train_full, y_train_full)
```

Out[12]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

1.5.4 Model DecisionTree

```
In [13]: import graphviz

         dot_data = tree.export_graphviz(clf_DT, out_file=None,
                                         feature_names=df_iris.feature_names,
                                         class_names=df_iris.target_names,
                                         filled=True, rounded=True,
                                         special_characters=True)
         graph = graphviz.Source(dot_data)
         graph
```

Out[13]:



1.5.5 K Nearest Neighbors (KNN)

Dengan K = 5

```
In [14]: clf_KNN = KNeighborsClassifier()
         clf_KNN.fit(X_train_full, y_train_full)
```

```
Out[14]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=1, n_neighbors=5, p=2,
                    weights='uniform')
```

1.5.6 Model KNN

Tidak ada

1.5.7 Multilayer Perceptron (MLP)

default configuration

```
In [15]: clf_MLP = MLPClassifier(hidden_layer_sizes=(10,))
         clf_MLP.fit(X_train_full, y_train_full)
```

```
/home/gilang20/anaconda3/lib/python3.5/site-packages/sklearn/neural_network/multilayer_perceptro
  % self.max_iter, ConvergenceWarning)
```

```
Out[15]: MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
                beta_2=0.999, early_stopping=False, epsilon=1e-08,
                hidden_layer_sizes=(10,), learning_rate='constant',
                learning_rate_init=0.001, max_iter=200, momentum=0.9,
                nesterovs_momentum=True, power_t=0.5, random_state=None,
                shuffle=True, solver='adam', tol=0.0001, validation_fraction=0.1,
                verbose=False, warm_start=False)
```

1.5.8 Model MLP

```
In [16]: print('Weight')
         print(clf_MLP.coefs_)

         print()
         print('Loss')
         print(clf_MLP.loss_curve_)
```

```
Weight
[array([[  5.20784970e-01,   4.60285762e-01,   2.83164461e-01,
         -5.64594688e-02,   3.75719547e-02,   5.19286300e-01,
          3.54356662e-04,   8.95836363e-03,   3.70065751e-01,
         -9.74668499e-02],
       [ -2.75374730e-01,   5.29397619e-01,   5.76636481e-01,
          4.77814551e-01,  -6.74433847e-02,   3.40232985e-01,
         -3.08113833e-01,   5.68589080e-01,  -4.41450600e-01,
          5.59329418e-02],
       [ -4.94994947e-01,   6.37106885e-01,  -8.05642508e-02,
         -7.69774480e-01,  -2.43867721e-01,   2.99185047e-01,
          1.17236231e-01,  -3.07297895e-01,   5.47922300e-01,
          3.49089561e-01],
```

```
[  1.91346872e-01,   3.45772072e-01,  -6.83267199e-01,
  -5.39049914e-01,  -4.82072480e-01,  -4.55863449e-01,
  -4.41557547e-01,  -2.96734430e-01,   1.16108764e-01,
   3.52514922e-01]]), array([[-0.47089794,  0.0281882 , -0.05611221],
[-0.28429539,  0.41278706,  0.24832723],
[-0.08487305, -0.31931439, -0.54865803],
[-0.41488019,  0.23949029,  0.140002  ],
[-0.31887008,  0.45360329, -0.43441085],
[ 0.67606998,  0.29907845,  0.21433811],
[ 0.18373797, -0.29596702,  0.12398637],
[ 0.71931726, -0.463342  , -0.32534352],
[ 0.36725406, -0.35574876, -0.12376887],
[-0.15513308, -0.38308346,  0.67723058]])]

Loss
[4.6356687956934, 4.5812168690320094, 4.5267020771469184, 4.4719968136795414, 4.4171619227409771
```

1.6 C. Pembelajaran dengan Skema 90:10

1.6.1 Persiapan untuk melakukan split dan menggambar visualisasi confusion matrix

In [17]:
```python
import itertools
from sklearn import metrics
from sklearn.model_selection import train_test_split

def plot_confusion_matrix(cm, classes,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
#     print(cm)
#     plt.xkcd()
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="black" if cm[i, j] > thresh else "black")
```

```
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

def kinerja(y_test, y_predict, title):
    print("Akurasi: {0:.4f}".format(metrics.accuracy_score(y_test, y_predict)))
    print()
    print("Classification Report")
    print(metrics.classification_report(y_test, y_predict, target_names=df_iris.target_
    print()
    plt.figure()
    # print(metrics.confusion_matrix(y_test, y_predict, labels=[0,1,2]))
    plot_confusion_matrix(metrics.confusion_matrix(y_test, y_predict), classes=df_iris.
                          title= title + ' Confusion Matrix')
    plt.show()
```

1.6.2 Split Dataset, 90% Train : 10% Test

```
In [18]: X_train_90, X_test_90, y_train_90, y_test_90 = train_test_split(df_iris.data, df_iris.t
```

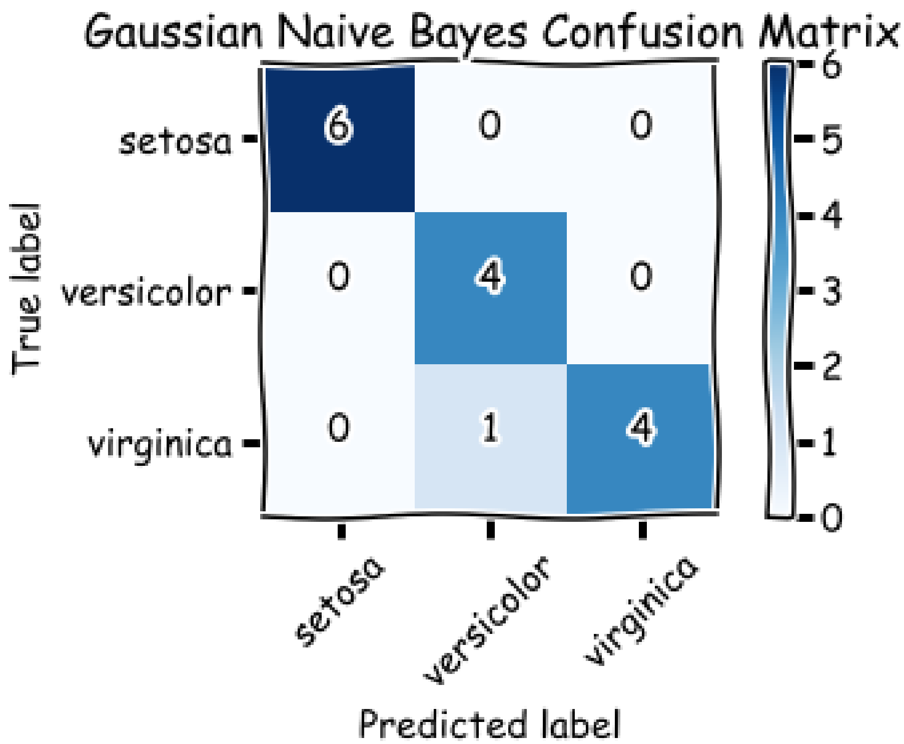
1.6.3 Gaussian Naive Bayes (GNB)

```
In [19]: clf_GNB_90 = GaussianNB()
         clf_GNB_90.fit(X_train_90, y_train_90)

Out[19]: GaussianNB(priors=None)
```

1.6.4 Kinerja dan Confusion Matrix GNB

```
In [20]: kinerja(y_test_90, clf_GNB_90.predict(X_test_90), 'Gaussian Naive Bayes')
```

```
Akurasi: 0.9333

Classification Report
             precision    recall  f1-score   support

     setosa       1.00      1.00      1.00         6
 versicolor       0.80      1.00      0.89         4
  virginica       1.00      0.80      0.89         5

avg / total       0.95      0.93      0.93        15
```



1.6.5 DecisionTree

```
In [21]: clf_DT_90 = tree.DecisionTreeClassifier(criterion='entropy')
         clf_DT_90.fit(X_train_90, y_train_90)
```

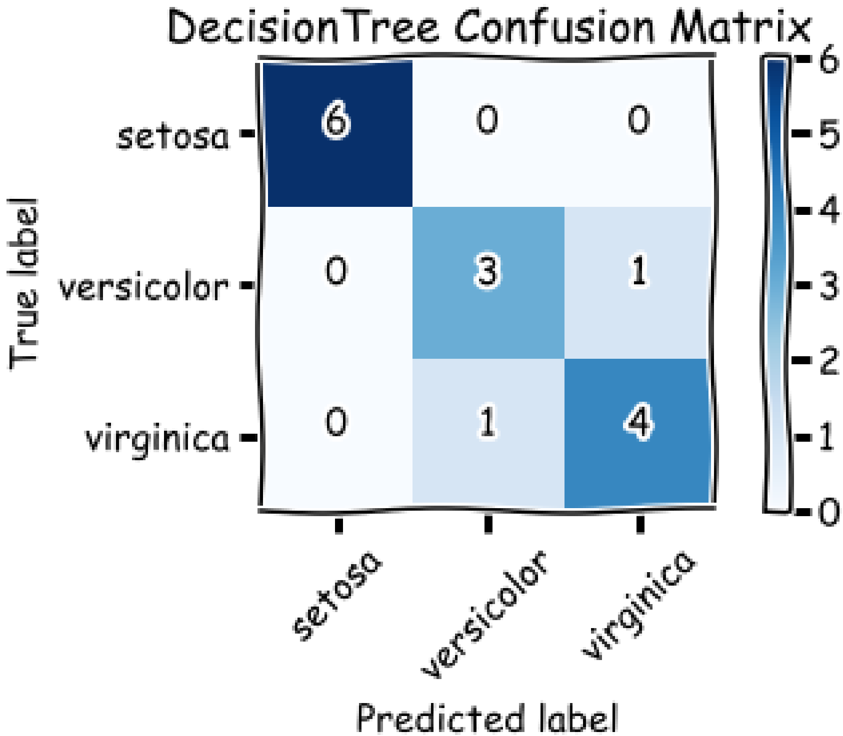
```
Out[21]: DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=None,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                     splitter='best')
```

1.6.6 Kinerja dan Confusion Matrix DecisionTree

```
In [22]: kinerja(y_test_90, clf_DT_90.predict(X_test_90), 'DecisionTree')
```

```
Akurasi: 0.8667

Classification Report
             precision    recall  f1-score   support

     setosa       1.00      1.00      1.00         6
 versicolor       0.75      0.75      0.75         4
```

```
  virginica       0.80      0.80      0.80         5

avg / total       0.87      0.87      0.87        15
```



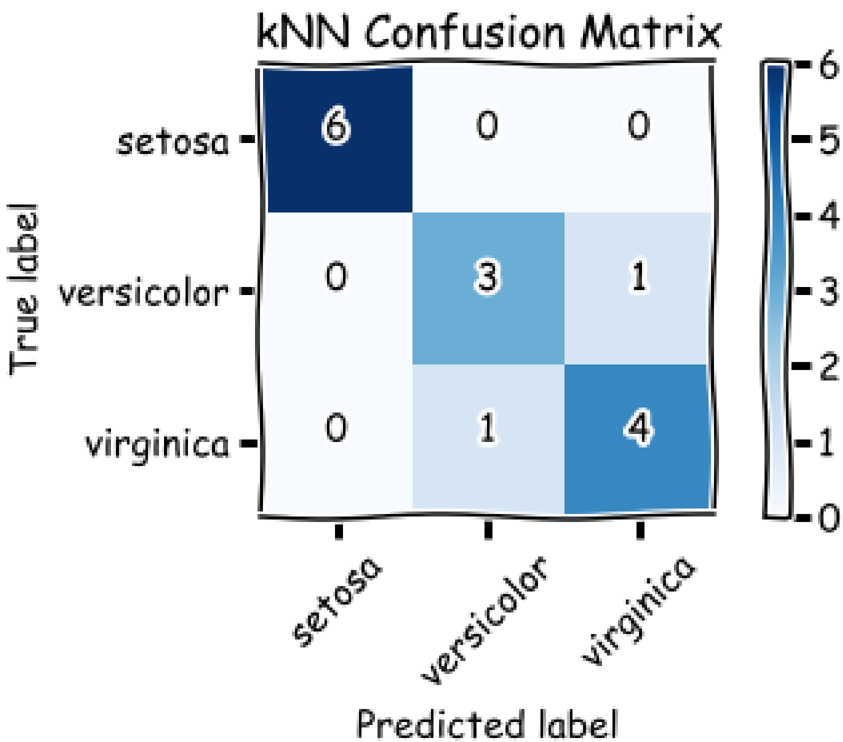
1.6.7 K Nearest Neighbors

```
In [23]: clf_KNN_90 = KNeighborsClassifier(n_neighbors=1)
         clf_KNN_90.fit(X_train_90, y_train_90)

Out[23]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=1, n_neighbors=1, p=2,
                    weights='uniform')
```

1.6.8 Kinerja dan Confusion Matrix kNN

```
In [24]: kinerja(y_test_90, clf_KNN_90.predict(X_test_90), 'kNN')

Akurasi: 0.8667

Classification Report
```

```
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00         6
  versicolor       0.75      0.75      0.75         4
   virginica       0.80      0.80      0.80         5

avg / total        0.87      0.87      0.87        15
```



1.6.9 Multilayer Perceptron (MLP)

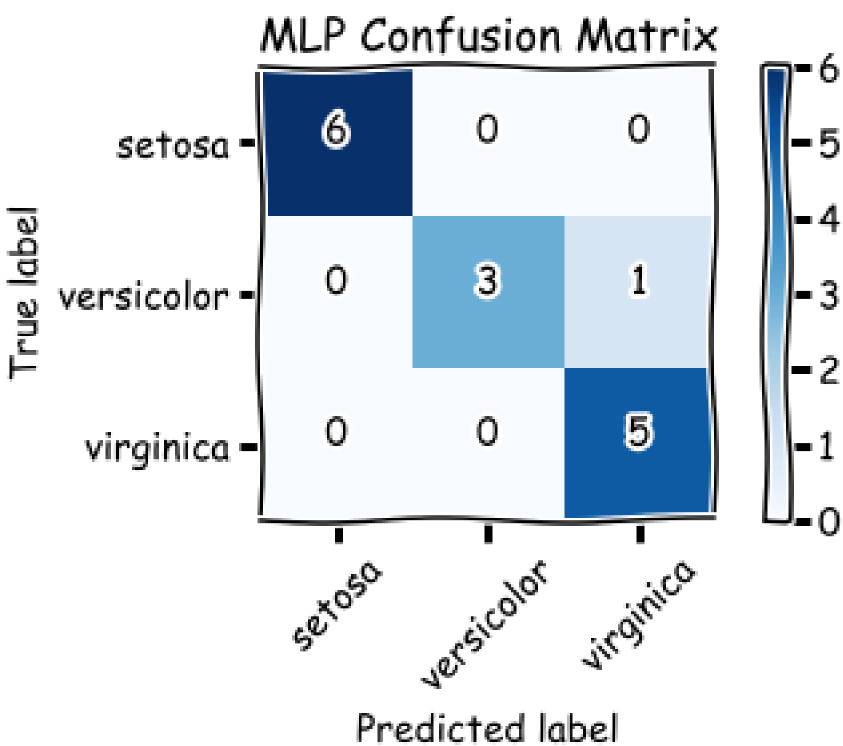
```
In [25]: clf_MLP_90 = MLPClassifier()
         clf_MLP_90.fit(X_train_90, y_train_90)

/home/gilang20/anaconda3/lib/python3.5/site-packages/sklearn/neural_network/multilayer_perceptro
  % self.max_iter, ConvergenceWarning)


Out[25]: MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
                beta_2=0.999, early_stopping=False, epsilon=1e-08,
                hidden_layer_sizes=(100,), learning_rate='constant',
```

```
learning_rate_init=0.001, max_iter=200, momentum=0.9,
nesterovs_momentum=True, power_t=0.5, random_state=None,
shuffle=True, solver='adam', tol=0.0001, validation_fraction=0.1,
verbose=False, warm_start=False)
```

1.6.10 Kinerja dan Confusion Matrix MLP

```
In [26]: kinerja(y_test_90, clf_MLP_90.predict(X_test_90), 'MLP')
```

```
Akurasi: 0.9333

Classification Report
             precision    recall  f1-score   support

     setosa       1.00      1.00      1.00         6
 versicolor       1.00      0.75      0.86         4
  virginica       0.83      1.00      0.91         5

avg / total       0.94      0.93      0.93        15
```



1.7 D. Pembelajaran dengan Skema 10-Folds Cross Validation

1.7.1 Menyiapkan Classifier

In [27]:
```
# Classifier
clf_GNB_kf = GaussianNB()
clf_DT_kf = tree.DecisionTreeClassifier(criterion='entropy')
clf_KNN_kf = KNeighborsClassifier()
clf_MLP_kf = MLPClassifier()
```

1.7.2 Melakukan Pembelajaran dengan Skema 10-Folds CV

In [28]:
```
from sklearn.model_selection import KFold

kf = KFold(10, shuffle=True)
kf
```

Out[28]:
```
KFold(n_splits=10, random_state=None, shuffle=True)
```

In [29]:
```
# Kontainer Metrik Kinerja
clf_GNB_kf_acc = []
clf_GNB_kf_prec = []
clf_GNB_kf_rec = []
clf_GNB_kf_f1 = []

clf_DT_kf_acc = []
clf_DT_kf_prec = []
clf_DT_kf_rec = []
clf_DT_kf_f1 = []

clf_KNN_kf_acc = []
clf_KNN_kf_prec = []
clf_KNN_kf_rec = []
clf_KNN_kf_f1 = []

clf_MLP_kf_acc = []
clf_MLP_kf_prec = []
clf_MLP_kf_rec = []
clf_MLP_kf_f1 = []

for train_index, test_index in kf.split(X_train_full):
#     print("TRAIN:", train_index, '\n', "TEST:", test_index, '\n\n')
    X_train, X_test = X_train_full[train_index], X_train_full[test_index]
    y_train, y_test = y_train_full[train_index], y_train_full[test_index]

    clf_GNB_kf.fit(X_train, y_train)
    y_test_predict_GNB = clf_GNB_kf.predict(X_test)
```

```
            clf_GNB_kf_acc.append(metrics.accuracy_score(y_test, y_test_predict_GNB))
            clf_GNB_kf_prec.append(metrics.precision_score(y_test, y_test_predict_GNB, average=
            clf_GNB_kf_rec.append(metrics.recall_score(y_test, y_test_predict_GNB, average='mac
            clf_GNB_kf_f1.append(metrics.f1_score(y_test, y_test_predict_GNB, average='macro'))

            clf_DT_kf.fit(X_train, y_train)
            y_test_predict_DT = clf_DT_kf.predict(X_test)
            clf_DT_kf_acc.append(metrics.accuracy_score(y_test, y_test_predict_DT))
            clf_DT_kf_prec.append(metrics.precision_score(y_test, y_test_predict_DT, average='m
            clf_DT_kf_rec.append(metrics.recall_score(y_test, y_test_predict_DT, average='macro
            clf_DT_kf_f1.append(metrics.f1_score(y_test, y_test_predict_DT, average='macro'))

            clf_KNN_kf.fit(X_train, y_train)
            y_test_predict_KNN = clf_KNN_kf.predict(X_test)
            clf_KNN_kf_acc.append(metrics.accuracy_score(y_test, y_test_predict_KNN))
            clf_KNN_kf_prec.append(metrics.precision_score(y_test, y_test_predict_KNN, average=
            clf_KNN_kf_rec.append(metrics.recall_score(y_test, y_test_predict_KNN, average='mac
            clf_KNN_kf_f1.append(metrics.f1_score(y_test, y_test_predict_KNN, average='macro'))

            clf_MLP_kf.fit(X_train, y_train)
            y_test_predict_MLP = clf_MLP_kf.predict(X_test)
            clf_MLP_kf_acc.append(metrics.accuracy_score(y_test, y_test_predict_MLP))
            clf_MLP_kf_prec.append(metrics.precision_score(y_test, y_test_predict_MLP, average=
            clf_MLP_kf_rec.append(metrics.recall_score(y_test, y_test_predict_MLP, average='mac
            clf_MLP_kf_f1.append(metrics.f1_score(y_test, y_test_predict_MLP, average='macro'))
```

```
/home/gilang20/anaconda3/lib/python3.5/site-packages/sklearn/neural_network/multilayer_perceptro
  % self.max_iter, ConvergenceWarning)
```

1.7.3 Kinerja Model

In [30]:
```
print('GNB')
print('Rerata akurasi:', np.mean(clf_GNB_kf_acc))
print('Rerata presisi:', np.mean(clf_GNB_kf_prec))
print('Rerata recall:', np.mean(clf_GNB_kf_rec))
print('Rerata f1-score:', np.mean(clf_GNB_kf_f1))

print()
print('DT')
print('Rerata akurasi:', np.mean(clf_DT_kf_acc))
print('Rerata presisi:', np.mean(clf_DT_kf_prec))
print('Rerata recall:', np.mean(clf_DT_kf_rec))
print('Rerata f1-score:', np.mean(clf_DT_kf_f1))

print()
print('KNN')
print('Rerata akurasi:', np.mean(clf_KNN_kf_acc))
```

```
print('Rerata presisi:', np.mean(clf_KNN_kf_prec))
print('Rerata recall:', np.mean(clf_KNN_kf_rec))
print('Rerata f1-score:', np.mean(clf_KNN_kf_f1))

print()
print('MLP')
print('Rerata akurasi:', np.mean(clf_MLP_kf_acc))
print('Rerata presisi:', np.mean(clf_MLP_kf_prec))
print('Rerata recall:', np.mean(clf_MLP_kf_rec))
print('Rerata f1-score:', np.mean(clf_MLP_kf_f1))
```

```
GNB
Rerata akurasi: 0.953333333333
Rerata presisi: 0.948518518519
Rerata recall: 0.948055555556
Rerata f1-score: 0.946107998755

DT
Rerata akurasi: 0.953333333333
Rerata presisi: 0.953055555556
Rerata recall: 0.95246031746
Rerata f1-score: 0.948691308691

KNN
Rerata akurasi: 0.966666666667
Rerata presisi: 0.961666666667
Rerata recall: 0.966626984127
Rerata f1-score: 0.962236282236

MLP
Rerata akurasi: 0.966666666667
Rerata presisi: 0.965555555556
Rerata recall: 0.966626984127
Rerata f1-score: 0.961851481851
```

1.8 E. Menyimpan Model ke File Eksternal

Dalam kasus ini model yang akan disimpan adalah model dari Gaussian Naive Bayes dengan skema full training

```
In [31]: from sklearn.externals import joblib
```

```
In [32]: joblib.dump(clf_GNB, 'GNB.model')
```

```
Out[32]: ['GNB.model']
```

1.9 F. Membaca Model dari File Eksternal

```
In [33]: loaded_model = joblib.load('GNB.model')
```

1.10 G. Membuat Instance Baru

```
In [34]: instance_baru = [[2.1, 2.1, 0.2, 0.2],
                          [0.2, 4.0, 1.1, 1.2],
                          [1.2, 2.2, 5.6, 7.1],
                          [1.3, 3.5, 4.6, 1.1],
                          [1.2, 0.2, 0.6, 2.1]]
```

1.11 H. Melakukan Klasifikasi terhadap Instance Baru

Model yang digunakan untuk klasifikasi kali ini adalah model yang dibentuk dengan skema Full Training

```
In [35]: def klas(i): return df_iris.target_names[i]

         hasil_GNB = clf_GNB.predict(instance_baru)
         hasil_DT = clf_DT.predict(instance_baru)
         hasil_KNN = clf_KNN.predict(instance_baru)
         hasil_MLP = clf_MLP.predict(instance_baru)

         for i in range(len(instance_baru)):
             print(instance_baru[i])
             print('GNB           :', klas(hasil_GNB[i]))
             print('Decision Tree :', klas(hasil_DT[i]))
             print('KNN           :', klas(hasil_KNN[i]))
             print('MLP           :', klas(hasil_MLP[i]))
             print()
```

```
[2.1, 2.1, 0.2, 0.2]
GNB           : setosa
Decision Tree : setosa
KNN           : setosa
MLP           : versicolor

[0.2, 4.0, 1.1, 1.2]
GNB           : versicolor
Decision Tree : versicolor
KNN           : setosa
MLP           : setosa

[1.2, 2.2, 5.6, 7.1]
GNB           : virginica
Decision Tree : virginica
KNN           : virginica
MLP           : virginica

[1.3, 3.5, 4.6, 1.1]
GNB           : virginica
Decision Tree : versicolor
```

```
KNN           : versicolor
MLP           : virginica

[1.2, 0.2, 0.6, 2.1]
GNB           : versicolor
Decision Tree : versicolor
KNN           : setosa
MLP           : virginica
```