

In []:

```
1 X = [[ 1,  2,  3, 0],  
2      [11, 12, 13, 1]]
```

In [11]:

```
1 from sklearn.ensemble import RandomForestClassifier  
2  
3 clf = RandomForestClassifier(random_state=123)  
4  
5 X = [[ 1,  2,  3],  
6      [11, 12, 13],  
7      [23, 33, 45]]  
8 y = [0, 1, 0] # classes of each sample  
9  
10 clf.fit(X, y)  
11  
12 clf.predict(X)
```

Out[11]:

```
array([0, 1, 0])
```

In [14]:

```
1 clf.predict([234, 23, 456])
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-14-40ed47e22509> in <module>
----> 1 clf.predict([234, 23, 456])

~Wanaconda3\lib\site-packages\sklearn\ensemble\_forest.py in predict(self, X)
    627         """
    628         The predicted classes.
--> 629         proba = self.predict_proba(X)
    630
    631         if self.n_outputs_ == 1:

~Wanaconda3\lib\site-packages\sklearn\ensemble\_forest.py in predict_proba(self, X)
    671         check_is_fitted(self)
    672         # Check data
--> 673         X = self._validate_X_predict(X)
    674
    675         # Assign chunk of trees to jobs

~Wanaconda3\lib\site-packages\sklearn\ensemble\_forest.py in _validate_X_predict(self, X)
    419         check_is_fitted(self)
    420
--> 421         return self.estimators_[0]._validate_X_predict(X, check_input
=True)
    422
    423     @property

~Wanaconda3\lib\site-packages\sklearn\tree\_classes.py in _validate_X_predict(self, X, check_input)
    386         """Validate X whenever one tries to predict, apply, predict_proba"""
    387         if check_input:
--> 388             X = check_array(X, dtype=DTYPE, accept_sparse="csr")
    389             if issparse(X) and (X.indices.dtype != np.intc or
    390                               X.indptr.dtype != np.intc):

~Wanaconda3\lib\site-packages\sklearn\utils\validation.py in inner_f(*args, **kwargs)
    70         FutureWarning)
    71         kwargs.update({k: arg for k, arg in zip(sig.parameters, args)})
--> 72         return f(**kwargs)
    73     return inner_f
    74

~Wanaconda3\lib\site-packages\sklearn\utils\validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator)
    617         # If input is 1D raise error
    618         if array.ndim == 1:
--> 619             raise ValueError(
    620                 "Expected 2D array, got 1D array instead:Wnarr
```

```
ay={}.Wn"
```

```
621
```

```
"Reshape your data either using array.reshape
```

```
(-1, 1) if "
```

ValueError: Expected 2D array, got 1D array instead:

array=[234. 23. 456.].

Reshape your data either using array.reshape(-1, 1) if your data has a single feature or array.reshape(1, -1) if it contains a single sample.

In []:

1

(실습)

1. 영어, 수학, 과학 학습시간으로 합격, 불합격을 예측하시오.

- 기존데이터
- 영어(80), 수학(95), 과학(80) --> 합격(1)
- 영어(67), 수학(88), 과학(75) --> 합격(1)
- 영어(75), 수학(64), 과학(55) --> 불합격(0)
- 영어(100), 수학(46), 과학(65) --> 불합격(0)

2. 영어(76), 수학(75), 과학(68) 시간 학습시 합격? 불합격?

3. 알고리즘은 RandomForestClassifier 를 사용.

In []:

1

In []:

1

In []:

1

In [7]:

```
1 from sklearn.ensemble import RandomForestClassifier
2
3 clf = RandomForestClassifier(random_state=123)
4
5 X = [[ 80, 95, 80],
6      [67, 88, 75],
7      [75, 64, 55],
8      [100, 46, 65]]
9 y = [1, 1, 0, 0] # classes of each sample
10
11 clf.fit(X, y)
12
13 clf.predict([[76,75,68]])
```

Out[7]:

array([0])

In []:

1

In []:

1

(Scikit-Learn의 데이터 표현 방식)

Numpy 배열을 이용한 특징 행렬(X), 대상 벡터(y)의 생성

In [33]:

```
1 import numpy as np
2
3 rs = np.random.RandomState(10)
4
5 x = 10 * rs.rand(5)
6 y = 2 * x - 1 * rs.rand(5)
7 x.shape, y.shape
```

Out[33]:

((5,), (5,))

In [34]:

```
1 X = x.reshape(-1,1)
2 X.shape
```

Out[34]:

(5, 1)

In [35]:

```
1 X
```

Out[35]:

```
array([[7.71320643],
       [0.20751949],
       [6.33648235],
       [7.48803883],
       [4.98507012]])
```

In [18]:

```
1 x
```

Out[18]:

```
array([7.71320643, 0.20751949, 6.33648235, 7.48803883, 4.98507012])
```

In [38]:

```
1 rs = np.random.RandomState(10)
2
3 x = 10 * rs.rand(12)
4 x
```

Out[38]:

```
array([7.71320643, 0.20751949, 6.33648235, 7.48803883, 4.98507012,
       2.24796646, 1.98062865, 7.60530712, 1.69110837, 0.88339814,
       6.85359818, 9.53393346])
```

In [39]:

```
1 x.shape
```

Out[39]:

```
(12,)
```

In [45]:

```
1 x.reshape(4,3)
```

Out[45]:

```
array([[7.71320643, 0.20751949, 6.33648235],
       [7.48803883, 4.98507012, 2.24796646],
       [1.98062865, 7.60530712, 1.69110837],
       [0.88339814, 6.85359818, 9.53393346]])
```

In [52]:

```
1 X = x.reshape(-1,1)
```

In [53]:

```
1 | X
```

Out [53]:

```
array([[7.71320643],  
       [0.20751949],  
       [6.33648235],  
       [7.48803883],  
       [4.98507012],  
       [2.24796646],  
       [1.98062865],  
       [7.60530712],  
       [1.69110837],  
       [0.88339814],  
       [6.85359818],  
       [9.53393346]])
```

In []:

```
1 |
```

In [55]:

```
1 | x.shape
```

Out [55]:

```
(12,)
```

In [54]:

```
1 | X.shape
```

Out [54]:

```
(12, 1)
```

In []:

```
1 |
```

In []:

```
1 |
```

In [15]:

```
1 | y
```

Out [15]:

```
array([15.20161622,  0.21697612, 11.91243399, 14.80696681,  9.88180043])
```

In []:

1

(Scikit-Learn의 데이터 표현 방식)

Pandas DataFrame을 이용한 특징 행렬(X), 대상벡터(y)의 생성

In [8]:

```
1 import seaborn as sns
2 iris = sns.load_dataset("iris")
3 iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   sepal_length    150 non-null   float64
1   sepal_width     150 non-null   float64
2   petal_length    150 non-null   float64
3   petal_width     150 non-null   float64
4   species         150 non-null   object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [9]:

```
1 iris.head()
```

Out[9]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In []:

1

In []:

1

(실습.species 컬럼을 제외한 나머지 컬럼으로 X를 만들기)

In [16]:

```
1 X = iris.drop("species",axis=1) ;X.head()
```

Out[16]:

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

In []:

```
1 X = iris.drop("species", axis=1) ;X.head()
```

In [11]:

```
1 X1 = iris["sepal_length"];X1
```

Out[11]:

```
0    5.1
1    4.9
2    4.7
3    4.6
4    5.0
...
145   6.7
146   6.3
147   6.5
148   6.2
149   5.9
```

Name: sepal_length, Length: 150, dtype: float64

In [23]:

```
1 X2 = iris[["sepal_length", "sepal_width", "petal_length", "petal_width"]];X2.head()
```

Out[23]:

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

In [28]:

```
1 iris.iloc[:,0:4].head(3)
```

Out[28]:

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2

In []:

```
1
```

In []:

```
1
```

(실습.species 컬럼만 있는 y 를 만들기)

In [26]:

```
1 y = iris["species"]  
2 y.shape
```

Out[26]:

```
(150,)
```

In [17]:

```
1 X.shape
```

Out[17]:

```
(150, 4)
```

In [22]:

```
1 iris.shape
```

Out[22]:

```
(150, 5)
```

In [18]:

```
1 iris.head(3)
```

Out[18]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa

In [22]:

```
1 iris["species"].unique()
2 #iris.species
```

Out[22]:

```
array(['setosa', 'versicolor', 'virginica'], dtype=object)
```

In []:

```
1
```

In [23]:

```
1 # 컬럼 조회
2 iris.columns
```

Out[23]:

```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',
      'species'],
      dtype='object')
```

In [24]:

```
1 # 결측치 확인
2 iris.isnull().sum()
```

Out[24]:

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

In []:

```
1
```

In []:

1

(Scikit-Learn의 데이터 표현 방식)

Bunch 객체를 이용한 특징 행렬(X), 대상벡터(y) 의 생성

In [29]:

```
1 from sklearn.datasets import load_iris
2
3 iris = load_iris()
4 type(iris)
```

Out[29]:

sklearn.utils.Bunch

In [31]:

```
1 iris.keys()
```

Out[31]:

```
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'fil
ename'])
```

In []:

1

In [30]:

```
1 iris
```

```
sWn      :Attribute Information:Wn      - sepal length in cmWn      - sepal wid
th in cmWn      - petal length in cmWn      - petal width in cmWn      - cl
ass:Wn      - Iris-SetosaWn      - Iris-VersicolourWn
- Iris-VirginicaWn      Wn      :Summary Statistics:WnWn      =====
=====Wn      Min Max Me
an      SD      Class CorrelationWn      =====
=====Wn      sepal length:  4.3 7.9  5.84  0.83  0.7826Wn      sepal wid
th:      2.0 4.4  3.05  0.43  -0.4194Wn      petal length:  1.0 6.9  3.76  1.
76  0.9490 (high!)Wn      petal width:  0.1 2.5  1.20  0.76  0.9565 (hig
h!)Wn      =====WnWn      :Miss
ing Attribute Values: NoneWn      :Class Distribution: 33.3% for each of 3 classe
s.Wn      :Creator: R.A. FisherWn      :Donor: Michael Marshall (MARSHALL%PLU@io.arc.
nasa.gov)Wn      :Date: July, 1988WnWn      The famous Iris database, first used by Sir
R.A. Fisher. The dataset is takenWn      from FisherW's paper. Note that itW's the same
as in R, but not as in the UCIWn      Machine Learning Repository, which has two wrong
data points.WnWn      This is perhaps the best known database to be found in theWn      patte
rn recognition literature. FisherW's paper is a classic in the field andWn      is ref
erenced frequently to this day. (See Duda & Hart, for example.) TheWn      data set c
ontains 3 classes of 50 instances each, where each class refers to aWn      type of iri
s plant. One class is linearly separable from the other 2; theWn      latter are NOT l
```

In []:

1

In [32]:

1 iris.feature_names

Out[32]:

```
['sepal length (cm)',  
'sepal width (cm)',  
'petal length (cm)',  
'petal width (cm)']
```

In [33]:

1 iris.data[:5]

Out[33]:

```
array([[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]])
```

In []:

1

In [34]:

1 type(iris.data)

Out[34]:

numpy.ndarray

In [35]:

1 iris.data.shape

Out[35]:

(150, 4)

In [36]:

```
1 iris.target
```

Out[36]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [37]:

```
1 type(iris.target)
```

Out[37]:

```
numpy.ndarray
```

In []:

```
1
```

In [37]:

```
1 iris.target.shape
```

Out[37]:

```
(150,)
```

In [38]:

```
1 iris.target_names
```

Out[38]:

```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

In [44]:

```
1 X = iris.data
2 y = iris.target
```

In [45]:

```
1 X.shape
```

Out[45]:

```
(150, 4)
```

In [46]:

```
1 type(y)
```

Out[46]:

numpy.ndarray

In [47]:

```
1 y.shape
```

Out[47]:

(150,)

In []:

```
1
```

In []:

```
1
```

(Scikit-Learn Estimator API 기본 활용 절차)

1. 데이터 준비

In [48]:

```
1 import numpy as np
2 import matplotlib.pyplot as plt
```

In [49]:

```
1 rs = np.random.RandomState(10)
2 x = 10 * rs.rand(100)
3 y = 3 * x + 2 * rs.rand(100)
```

In [54]:

```
1 x.shape
```

Out[54]:

(100,)

In [55]:

```
1 x[:5]
```

Out[55]:

array([7.71320643, 0.20751949, 6.33648235, 7.48803883, 4.98507012])

In [60]:

```
1 x.reshape(-1,2,5)[:5]
```

Out[60]:

```
array([[7.71320643, 0.20751949, 6.33648235, 7.48803883, 4.98507012],
       [2.24796646, 1.98062865, 7.60530712, 1.69110837, 0.88339814]],

       [[6.85359818, 9.53393346, 0.03948266, 5.12192263, 8.12620962],
       [6.12526067, 7.21755317, 2.91876068, 9.17774123, 7.14575783]],

       [[5.42544368, 1.42170048, 3.7334076 , 6.74133615, 4.41833174],
       [4.34013993, 6.17766978, 5.13138243, 6.50397182, 6.01038953]],

       [[8.05223197, 5.21647152, 9.08648881, 3.19236089, 0.90459349],
       [3.00700057, 1.13984362, 8.28681326, 0.46896319, 6.26287148]],

       [[5.47586156, 8.19286996, 1.9894754 , 8.56850302, 3.51652639],
       [7.54647692, 2.95961707, 8.8393648 , 3.25511638, 1.65015898]]])
```

In []:

```
1
```

In []:

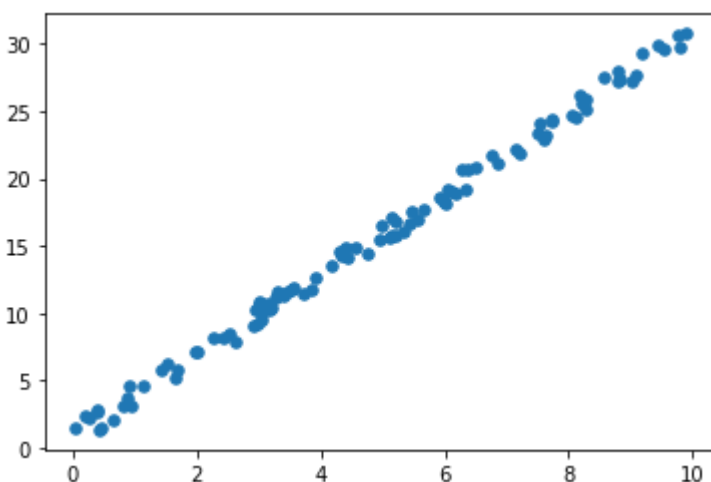
```
1
```

In [51]:

```
1 plt.scatter(x, y, s=30)
```

Out[51]:

<matplotlib.collections.PathCollection at 0x2398cd22f70>



In []:

```
1
```

2. 모델 클래스 선택
3. 모델 인스턴스 생성과 하이퍼파라미터 선택

In [52]:

```
1 from sklearn.linear_model import LinearRegression
2 regr = LinearRegression()
```

In [10]:

```
1 from sklearn.linear_model import LinearRegression
2 regr = LinearRegression(fit_intercept=True)
```

In []:

```
1
```

4. 특징 행렬과 대상벡터 준비

In [53]:

```
1 X = x.reshape(-1, 1)
2 X.shape, y.shape
```

Out[53]:

```
((100, 1), (100,))
```

In []:

```
1
```

5. 모델을 데이터에 적합

In [64]:

```
1 regr.fit(X,y)
```

Out[64]:

```
LinearRegression()
```

In [63]:

```
1 regr.get_params()
```

Out[63]:

```
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize': False}
```


In []:

1

In []:

1

In [65]:

1 regr.coef_

Out[65]:

array([2.9855087])

In [66]:

1 regr.intercept_

Out[66]:

0.9878534341975644

In []:

1

6. 새로운 데이터를 이용해 예측

In [68]:

1 x_new = np.linspace(-1, 11, num=100)

In [69]:

1 x_new[:5]

Out[69]:

array([-1. , -0.87878788, -0.75757576, -0.63636364, -0.51515152])

In [16]:

1 x_new.shape

Out[16]:

(100,)

In [70]:

```
1 X_new = x_new.reshape(-1, 1)
2 X_new.shape
```

Out[70]:

(100, 1)

In [71]:

```
1 y_pred = regr.predict(X_new)
```

In [74]:

```
1 x_new[:5]
```

Out[74]:

array([-1. , -0.87878788, -0.75757576, -0.63636364, -0.51515152])

In [72]:

```
1 y_pred[:5]
```

Out[72]:

array([-1.99765526, -1.63577542, -1.27389558, -0.91201574, -0.5501359])

In []:

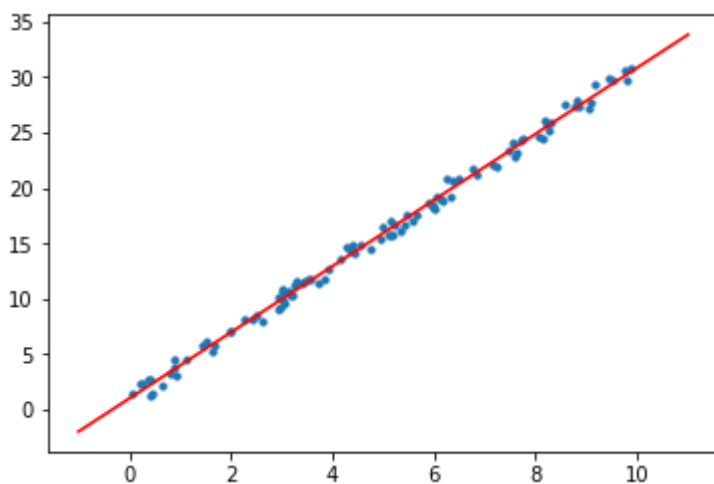
```
1
```

In [75]:

```
1 plt.plot(x_new, y_pred, c="red")
2 plt.scatter(x,y,s=10)
```

Out[75]:

<matplotlib.collections.PathCollection at 0x2398e6dab80>



In []:

1

7. 모델 평가

In [72]:

```
1 from sklearn.metrics import mean_squared_error
2
3 rmse = np.sqrt(mean_squared_error(y, y_pred))
4 rmse
```

Out[72]:

13.708237122486333

In []:

1

(훈련 데이터와 테스트 데이터)

정확도가 정말 1.0 인가?

In [87]:

```
1 # 데이터 읽어 오기
2 from sklearn.datasets import load_iris
3
4 iris = load_iris()
5
6 X = iris.data
7 y = iris.target
```

In [89]:

1 X[5]

Out[89]:

array([5.4, 3.9, 1.7, 0.4])

In [91]:

1 y[5]

Out[91]:

0

In []:

1

In []:

1

In [81]:

```

1 # KNN 모델 선택
2 from sklearn.neighbors import KNeighborsClassifier
3 knn = KNeighborsClassifier(n_neighbors=1)

```

In [82]:

```

1 # 모델 훈련(학습)
2 knn.fit(X, y)

```

Out[82]:

KNeighborsClassifier(n_neighbors=1)

In [92]:

```
1 y_pred = knn.predict(X)
```

In [97]:

```
1 np.mean(y == y_pred)
```

Out[97]:

1.0

In [94]:

1 y

Out[94]:

```

array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])

```

1	y_pred
---	--------

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

```
1 # 실제값과 예측결과값 비교
2 y == y_pred
```

[illegible]

```
1 from sklearn.model_selection import train_test_split
2
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=25)
```

In []:

1

In [100]:

```
1 X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

Out[100]:

```
((120, 4), (120,), (30, 4), (30,))
```

In [101]:

```
1 X_train[:5]
```

Out[101]:

```
array([[6.5, 2.8, 4.6, 1.5],
       [5.7, 2.5, 5. , 2. ],
       [7.7, 3. , 6.1, 2.3],
       [5. , 3.6, 1.4, 0.2],
       [6.4, 3.2, 5.3, 2.3]])
```

In []:

1

In [102]:

```
1 from sklearn.neighbors import KNeighborsClassifier
2 knn = KNeighborsClassifier(n_neighbors=5)
3
4 knn.fit(X_train, y_train)
```

Out[102]:

```
KNeighborsClassifier(n_neighbors=1)
```

In [103]:

```
1 y_pred = knn.predict(X_test)
2 y_pred
```

Out[103]:

```
array([0, 2, 2, 1, 2, 1, 2, 0, 1, 1, 0, 0, 0, 1, 0, 1, 2, 2, 1, 1, 1, 1,
       1, 0, 0, 2, 1, 2, 2, 0])
```

In [104]:

```
1 np.mean(y_test == y_pred)
```

Out[104]:

```
0.9
```

In [84]:

```
1 knn.score(X_test, y_test)
```

Out[84]:

0.9

In [85]:

```
1 from sklearn.metrics import accuracy_score
2 accuracy_score(y_test, y_pred)
```

Out[85]:

0.9

In []:

```
1
```

In [129]:

```
1 from sklearn.datasets import load_iris
2 iris = load_iris()
3
4 X = iris.data
5 y = iris.target
6
7 from sklearn.model_selection import train_test_split
8 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=250)
9 #X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5)
10
11 from sklearn.neighbors import KNeighborsClassifier
12 knn = KNeighborsClassifier(n_neighbors=5)
13
14 knn.fit(X_train, y_train)
15 y_pred = knn.predict(X_test)
16
17 from sklearn.metrics import accuracy_score
18 accuracy_score(y_test, y_pred)
```

Out[129]:

0.9866666666666667

In []:

```
1
```

In [137]:

```
1 from sklearn.neighbors import KNeighborsClassifier
2 from sklearn.datasets import load_iris
3 from sklearn.model_selection import train_test_split
4 from sklearn.metrics import accuracy_score
5
6 iris = load_iris()
7
8 X = iris.data
9 y = iris.target
10
11 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=250)
12 #X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5)
13
14 knn = KNeighborsClassifier(n_neighbors=2)
15
16 knn.fit(X_train, y_train)
17 y_pred = knn.predict(X_test)
18
19 accuracy_score(y_test, y_pred)
```

Out[137]:

0.9333333333333333

In []:

```
1 1 .. 0.95
2 2 .. 0.93
```

(하이퍼파라미터의 선택)

하이퍼파라미터의 선택

In [156]:

```

1 train_accuracy = []
2 test_accuracy = []
3
4 neighbors = range(1, 30) # range(1,20,2)
5
6 for n in neighbors:
7     knn = KNeighborsClassifier(n_neighbors = n)
8     knn.fit(X_train, y_train)
9
10    print("n = ", n , " train = ", knn.score(X_train, y_train), " test = ", knn.score(X_test, y
11
12    train_accuracy.append(knn.score(X_train, y_train))
13    test_accuracy.append(knn.score(X_test, y_test))

```

```

n = 1  train = 1.0  test = 0.9555555555555556
n = 2  train = 0.9904761904761905  test = 0.9333333333333333
n = 3  train = 0.9714285714285714  test = 0.9555555555555556
n = 4  train = 0.9714285714285714  test = 0.9333333333333333
n = 5  train = 0.9809523809523809  test = 0.9777777777777777
n = 6  train = 0.9714285714285714  test = 0.9555555555555556
n = 7  train = 0.9809523809523809  test = 0.9777777777777777
n = 8  train = 0.9714285714285714  test = 0.9555555555555556
n = 9  train = 0.9714285714285714  test = 0.9555555555555556
n = 10 train = 0.9619047619047619  test = 0.9555555555555556
n = 11 train = 0.9619047619047619  test = 0.9555555555555556
n = 12 train = 0.9619047619047619  test = 0.9555555555555556
n = 13 train = 0.9809523809523809  test = 0.9777777777777777
n = 14 train = 0.9619047619047619  test = 0.9777777777777777
n = 15 train = 0.9809523809523809  test = 0.9777777777777777
n = 16 train = 0.9619047619047619  test = 0.9555555555555556
n = 17 train = 0.9714285714285714  test = 0.9777777777777777
n = 18 train = 0.9619047619047619  test = 0.9333333333333333
n = 19 train = 0.9619047619047619  test = 0.9333333333333333
n = 20 train = 0.9523809523809523  test = 0.9111111111111111
n = 21 train = 0.9523809523809523  test = 0.9111111111111111
n = 22 train = 0.9523809523809523  test = 0.9111111111111111
n = 23 train = 0.9523809523809523  test = 0.9333333333333333
n = 24 train = 0.9428571428571428  test = 0.9333333333333333
n = 25 train = 0.9523809523809523  test = 0.9333333333333333
n = 26 train = 0.9619047619047619  test = 0.9333333333333333
n = 27 train = 0.9523809523809523  test = 0.9333333333333333
n = 28 train = 0.9428571428571428  test = 0.9333333333333333
n = 29 train = 0.9428571428571428  test = 0.9333333333333333

```

In [141]:

```

1 # neighbors
2 list(range(1, 11))

```

Out[141]:

[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

In []:

1

In []:

1

In [151]:

1 neighbors

Out[151]:

range(1, 30, 2)

In []:

1

In []:

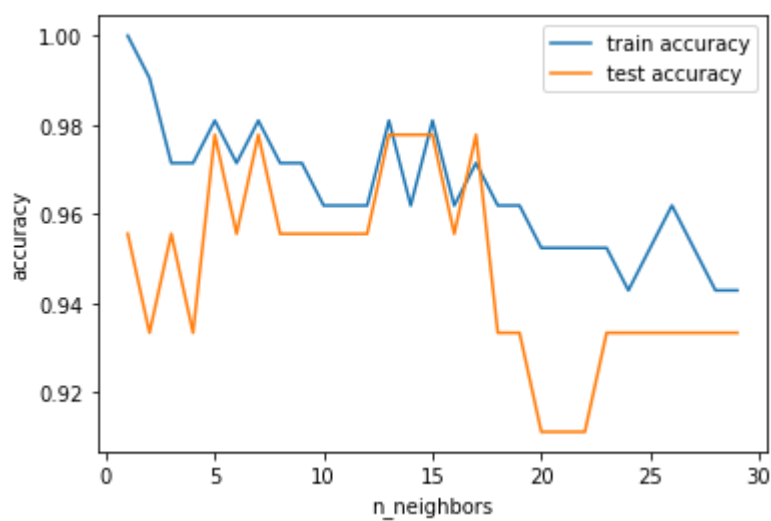
1

In [157]:

```
1 import matplotlib.pyplot as plt
2 #%matplotlib inline
3
4 plt.plot(neighbors, train_accuracy, label="train accuracy")
5 plt.plot(neighbors, test_accuracy, label="test accuracy")
6 plt.xlabel("n_neighbors")
7 plt.ylabel("accuracy")
8 plt.legend()
```

Out[157]:

<matplotlib.legend.Legend at 0x2398e4ce160>



In []:

1

