

Лабораторное занятие 5. Задачи для реализации метода ближайших соседей. Работа с библиотекой sklearn.neighbors import KNeighborsClassifier

5-зертханалық сабақ. Жақын көршілер әдісіне есептер.

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In [ ]: %matplotlib inline
import matplotlib.pyplot as plt

import pandas
data = pandas.read_csv("http://archive.ics.uci.edu/ml/machine-learning-databases/spambase/spambase.data", header=None)

In [ ]: data.head()

In [5]: names = []
for line in text.split("\n"):
    if len(line) > 0:
        if (line[0] != "*" and line[0] != "1"):
            names.append(line.split(":")[0])
names.append("spam/not")

In [6]: print(names)

['word_freq_make', 'word_freq_address', 'word_freq_all', 'word_freq_3d', 'word_freq_out', 'word_freq_over', 'word_freq_remove', 'word_freq_internet', 'word_freq_order', 'word_freq_mail', 'word_freq_receive', 'word_freq_will', 'word_freq_people', 'word_freq_report', 'word_freq_addresses', 'word_freq_free', 'word_freq_business', 'word_freq_small', 'word_freq_you', 'word_freq_credit', 'word_freq_your', 'word_freq_font', 'word_freq_000', 'word_freq_money', 'word_freq_hp', 'word_freq_hpl', 'word_freq_george', 'word_freq_650', 'word_freq_lab', 'word_freq_lake', 'word_freq_telnet', 'word_freq_857', 'word_freq_data', 'word_freq_415', 'word_freq_85', 'word_freq_technology', 'word_freq_1999', 'word_freq_parts', 'word_freq_ga', 'word_freq_direct', 'word_freq_cs', 'word_freq_meeting', 'word_freq_original', 'word_freq_project', 'word_freq_re', 'word_freq_edu', 'word_freq_table', 'word_freq_conference', 'char_freq_:', 'char_freq_!', 'char_freq_(', 'char_freq_)', 'char_freq_<', 'char_freq_>', 'capital_run_length_average', 'capital_run_length_longest', 'capital_run_length_total', 'spam/not']

In [7]: data.columns = names

In [8]: data.head()

Out[8]:
```

	word_freq_make	word_freq_address	word_freq_all	word_freq_3d	word_freq_out	word_freq_over	word_freq_remove	word_freq_internet	word_freq_order
0	0.00	0.84	0.84	0.0	0.32	0.00	0.00	0.00	0.00
1	0.21	0.28	0.50	0.0	0.14	0.19	0.21	0.07	0.00
2	0.06	0.00	0.71	0.0	1.23	0.19	0.19	0.12	0.64
3	0.00	0.00	0.00	0.0	0.63	0.00	0.31	0.63	0.31
4	0.00	0.00	0.00	0.0	0.63	0.00	0.31	0.63	0.31

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In [9]: features = data.iloc[:, 1:-1]
response = data.iloc[:, -1]

In [10]: import numpy as np
X = features.values
Y = response.values

In [11]: print(X)
print(Y)

[[ 0.00000000e+00  6.40000000e-01  6.40000000e-01 ...,  0.00000000e+00
  3.75000000e+00  6.10000000e+01]
 [ 2.10000000e-01  2.80000000e-01  5.00000000e-01 ...,  4.80000000e-02
  5.11400000e+00  1.01000000e+02]
 [ 6.00000000e-02  0.00000000e+00  7.10000000e-01 ...,  1.00000000e-02
  9.82100000e+00  4.85000000e+02]
 ...,
 [ 0.00000000e-01  0.00000000e+00  3.00000000e-01 ...,  0.00000000e+00
  1.40400000e+00  6.00000000e+00]
 [ 9.60000000e-01  0.00000000e+00  0.00000000e+00 ...,  0.00000000e+00
  1.14700000e+00  5.00000000e+00]
 [ 0.00000000e+00  0.00000000e+00  6.50000000e-01 ...,  0.00000000e+00
  1.25000000e+00  5.00000000e+00]]
[1 1 1 ..., 0 0 0]

In [12]: #print out shape of data code
data.shape[0]

Out[12]: 4601

In [13]: #print out shape of data code
(data.iloc[data["spam/not"] == 1].shape[0] / data.shape[0])

Out[13]: 0.30404477207546186

In [14]: for i in data.columns:
    print(i)

word_freq_make
word_freq_address
word_freq_all
word_freq_3d
word_freq_out
```

```
In [15]: #Hyperparameter tuning
# cross_freq 1000
# class_freq 1
# capital_run_length_average, length, total

#Note: hyperparameters space
#Note: hyperparameters dimension
#Parameter Types: (integer hyperparameters, float hyperparameters, string)

In [16]: from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size= X.shape[0] - 3000, random_state=42)

In [17]: from sklearn.preprocessing import scale
X_test_norm = scale(X_test)
X_train_norm = scale(X_train)

In [18]: from sklearn.neighbors import KNeighborsClassifier

kifknn = KNeighborsClassifier()

In [19]: kifknn.fit(X_train_norm, Y_train)
Y_pred = kifknn.predict(X_test_norm)

In [20]: from sklearn import metrics

In [21]: print("recall = " + str(metrics.recall_score(Y_test, Y_pred)))
print("precision = " + str(metrics.precision_score(Y_test, Y_pred)))
print("f1 = " + str(metrics.f1_score(Y_test, Y_pred)))
print("accuracy = " + str(metrics.accuracy_score(Y_test, Y_pred)))

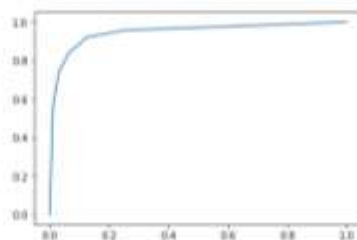
recall = 0.839150227618
precision = 0.900451463798
f1 = 0.869813825409
accuracy = 0.895690103429

In [22]: Y_pred_proba = kifknn.predict_proba(X_test_norm)[1,1]

In [23]: fprknn, tprknn, thresholdsknn = metrics.roc_curve(Y_test, Y_pred_proba)
roc_aucknn = metrics.auc(fprknn, tprknn)
print(roc_aucknn)
```

0.94893461687

```
In [24]: plt.plot(fprknn, tprknn)
Out[24]: [matplotlib.lines.Line2D at 0x2c9a648c50]
```



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In [27]: from sklearn.model_selection import GridSearchCV

knn = KNeighborsClassifier()
tuned_parametersknn = [{"n_neighbors": np.arange(1, 5),
                        "p": [1, 2],
                        "weights": ["uniform", "distance"]}
gsknn = GridSearchCV(knn, tuned_parametersknn)

In [28]: gsknn.fit(X_train, Y_train)

Out[28]: GridSearchCV(cv=Base, error_score='raise',
                    estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=1, n_neighbors=3, p=2,
                    weights='uniform'),
                    fit_params={}, iid=True, n_jobs=1,
                    param_grid=[{"n_neighbors": array([1, 2, 3, 4]), "p": [1, 2], "weights": ['uniform', 'distance']}],
                    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                    scoring=None, verbose=0)

In [29]: gsknn.best_params_
Out[29]: {'n_neighbors': 4, 'p': 1, 'weights': 'distance'}
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