20160674-code

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1 Tasks

- Formulate the learning problem
- Choose a way to deal with missing value
- Choose a Machine Learning model
- Do training / evaluation
- Make prediction for 10 testing samples

2 Solving

2.1 Import needed libraries

[0]:
```
import re
import sys

import pandas as pd
import pandas.util.testing as tm
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")

from sklearn import preprocessing

from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score

from sklearn import tree
```

```
from sklearn.model_selection import GridSearchCV

from sklearn import metrics
from sklearn.metrics import accuracy_score, mean_squared_error,␣
 ↪mean_absolute_error, r2_score, f1_score
```

2.2 Read file from Drive

[0]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
··········
Mounted at /content/drive
```

[0]:
```
training_data = pd.read_csv("/content/drive/My Drive/Colab Notebooks/Homework1/
 ↪1-training-data.csv")
testing_data = pd.read_csv("/content/drive/My Drive/Colab Notebooks/Homework1/
 ↪20160674-test.csv",
                            names=['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7',␣
 ↪'A8', 'y'])
```

2.3 Data analyzing

[0]:
```
training_data.head()
```

[0]:

	A1	A2	A3	A4	A5	A6	A7	A8	y
0	?	3.683393747	?	-0.634417312	1	0.409611744	7	30	5
1	?	?	60	1.573617763	0	0.639813727	7	30	5
2	?	3.096229013	67	0.249917163	0	0.089343498	?	80	3
3	2.887677333	3.870994828	68	-1.347755064	?	1.276985638	?	60	5
4	2.731273335	3.945024383	79	1.967319655	1	2.487831092	?	100	4

[0]:
```
training_data.tail()
```

[0]:

	A1	A2	A3	A4	A5	A6	A7	A8	y
995	3.125917	3.245430	68.0	-0.142998	0.0	2.540562	7.0	15.0	4.0
996	2.566080	3.567651	65.5	-0.618728	1.0	2.414309	7.0	70.0	4.0

```
997  1.783414  3.596953  65.5  0.411349  0.0  1.234720  7.0  60.0  3.0
998  1.633291  4.130596  65.5  1.938254  0.0 -1.389201  6.0   0.0  4.0
999  1.417296  4.138071  65.0  2.107206  0.0 -0.751386  6.0   0.0  3.0
```

[0]:
```
training_data.shape
```

[0]:
```
(1000, 9)
```

[0]:
```
training_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   A1      1000 non-null   object
 1   A2      1000 non-null   object
 2   A3      1000 non-null   object
 3   A4      1000 non-null   object
 4   A5      1000 non-null   object
 5   A6      1000 non-null   object
 6   A7      1000 non-null   object
 7   A8      1000 non-null   object
 8   y       1000 non-null   int64
dtypes: int64(1), object(8)
memory usage: 70.4+ KB
```

[0]:
```
training_data.describe()
```

[0]:
```
                A1           A2  …          A8            y
count  1000.000000  1000.000000  …  1000.000000  1000.000000
mean      1.387968     3.613840  …    23.085000     3.351000
std       1.127265     0.419025  …    24.818818     1.289753
min      -1.448874     2.484787  …     0.000000     1.000000
25%       0.926002     3.381371  …     0.000000     2.000000
50%       1.417296     3.596953  …    15.000000     4.000000
75%       1.984458     3.851148  …    35.000000     4.000000
max       3.983271     4.912296  …   100.000000     6.000000

[8 rows x 9 columns]
```

[0]:
```
testing_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15 entries, 0 to 14
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
```

```
 0   A1      15 non-null     float64
 1   A2      15 non-null     float64
 2   A3      15 non-null     int64
 3   A4      15 non-null     float64
 4   A5      15 non-null     int64
 5   A6      15 non-null     float64
 6   A7      15 non-null     int64
 7   A8      15 non-null     int64
 8   y       15 non-null     int64
dtypes: float64(4), int64(5)
memory usage: 1.2 KB
```

2.4 Data cleaning

We need to change all that missing values to NaN (standing for not a number).

[0]:
```python
# replace all the value '?' by NaN
for column in training_data:
    training_data[column] = pd.to_numeric(training_data[column],␣
 ↪errors='coerce')
```

[0]:
```python
training_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   A1      1000 non-null   float64
 1   A2      1000 non-null   float64
 2   A3      1000 non-null   float64
 3   A4      1000 non-null   float64
 4   A5      1000 non-null   float64
 5   A6      1000 non-null   float64
 6   A7      1000 non-null   float64
 7   A8      1000 non-null   float64
 8   y       1000 non-null   int64
dtypes: float64(8), int64(1)
memory usage: 70.4 KB
```

Then, we replace all the missing values by the median values

[0]:
```python
# fill all the NaN values
training_data.fillna(training_data.median(), inplace = True)
```

[0]:
```python
# View the training dataset
training_data
```

[0]:
```
           A1        A2    A3        A4   A5        A6   A7     A8  y
0    1.417296  3.683394  65.5 -0.634417  1.0  0.409612  7.0   30.0  5
1    1.417296  3.596953  60.0  1.573618  0.0  0.639814  7.0   30.0  5
2    1.417296  3.096229  67.0  0.249917  0.0  0.089343  7.0   80.0  3
3    2.887677  3.870995  68.0 -1.347755  0.0  1.276986  7.0   60.0  5
4    2.731273  3.945024  79.0  1.967320  1.0  2.487831  7.0  100.0  4
..        …         …   …        …   …       …  …     … ..
995  3.125917  3.245430  68.0 -0.142998  0.0  2.540562  7.0   15.0  4
996  2.566080  3.567651  65.5 -0.618728  1.0  2.414309  7.0   70.0  4
997  1.783414  3.596953  65.5  0.411349  0.0  1.234720  7.0   60.0  3
998  1.633291  4.130596  65.5  1.938254  0.0 -1.389201  6.0    0.0  4
999  1.417296  4.138071  65.0  2.107206  0.0 -0.751386  6.0    0.0  3

[1000 rows x 9 columns]
```

The data contains discreted value with 1000 rows and 9 columns, some values of parameters are missing. We found that the data type of column 'y' aka the result of the problem is discrete integer values, so this is classification problem.

2.5 Training model

We will use two popular approaches which are appropriate with the problem: Random Forest and SVM. At first, I will split the dataset into train and test using sklearn with the popular ratio 70/30.

[0]:
```
X = np.array(training_data[training_data.columns[:-1]])
Y = np.array(training_data[training_data.columns[-1]])

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3,␣
↪random_state=6)
print (X_train.shape, X_test.shape, Y_train.shape, Y_test.shape)
```

```
(700, 8) (300, 8) (700,) (300,)
```

2.5.1 Training with Random Forest model

With Random Forest model, we will use the RandomForestClassifier that is the Random Forest model for classification problem

Find the best parameters for Random Forest by using Grid Search Cross-Validation The parameters that we choose to train this model are the number of decision trees, maximum depth of each tree and the minimum samples leaf.

[0]:
```
rf_param_grid = {
               "n_estimators":[50, 100, 200, 300, 400, 500, 600, 800, 1000],
               'max_depth': [3, 4, 5, 6, 8],
               'min_samples_leaf': [3, 4, 5, 6, 8]
              }
```

```
rf_grid = GridSearchCV(estimator=RandomForestClassifier(random_state=6),
                 param_grid = rf_param_grid,
                 scoring="accuracy",
                 cv = 5,
                 n_jobs = 1)

rf_grid.fit(X_train,Y_train)
rf_grid_best = rf_grid.best_estimator_

print("Best Model Parameter: ", rf_grid.best_params_)
```

```
Best Model Parameter:  {'max_depth': 8, 'min_samples_leaf': 3, 'n_estimators':
800}
```

Training model with the found parameters

[0]:
```
rf_model = RandomForestClassifier (n_estimators = 800,
                                   criterion = 'gini',
                                   bootstrap = True,
                                   max_depth=8,
                                   min_samples_leaf=3,
                                   random_state=6)

rf_model.fit (X_train, Y_train)
rf_predict = rf_model.predict(X_test)
```

[0]:
```
print ("Accuracy: ", metrics.accuracy_score(Y_test, rf_predict))
```

```
Accuracy:  0.8433333333333334
```

2.5.2 Training with SVM model

Find the best parameters for SVM by using Grid Search Cross-Validation Some parameters will be used in SVM: - Kernel: RBF (Radial Basis Function). RBF can map an input space in infinite dimensional space. - gamma - C

[0]:
```
svm_param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [0.1, 0.2, 0.3, 0.5, 1.0],
              'kernel': ['rbf']
             }

svm_grid = GridSearchCV(SVC(),
                        param_grid = svm_param_grid,
                        refit = True,
                        scoring="accuracy",
                        verbose = 3,
                        cv = 5)
```

```
svm_grid.fit(X_train, Y_train)

print("Best Model Parameter: ", svm_grid.best_params_)
```

Training model with the found parameters After using Grid Search CV, we found the best parameters are: gamma = 0.3, C = 1000

[0]:
```
svm_model = SVC (kernel = 'rbf' , gamma = 0.3, C = 1000.0, random_state=6)

svm_model.fit(X_train, Y_train)
svm_predict = svm_model.predict(X_test)
```

[0]:
```
print ("Accuracy: ", metrics.accuracy_score(Y_test, svm_predict))
```

```
Accuracy:  0.92
```

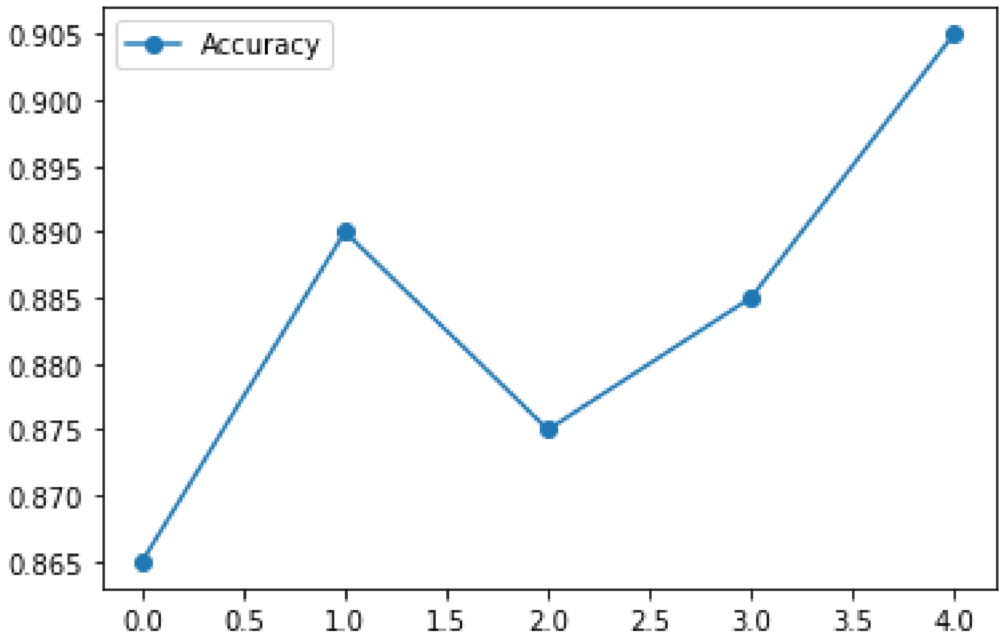
2.6 Evaluation model

We will evaluate the model using Cross-Validation

2.6.1 Random Forest model

[0]:
```
cv_rf_model = RandomForestClassifier (n_estimators = 800,
                                      criterion = 'gini',
                                      bootstrap = True,
                                      max_depth=8,
                                      min_samples_leaf=3,
                                      random_state=6)
rf_scores = cross_val_score(cv_rf_model, X, Y, cv=5)
```

[0]:
```
linear_score_data = np.array(rf_scores)
plt.plot(linear_score_data, '-o')
plt.legend(['Accuracy'])
plt.show()
```

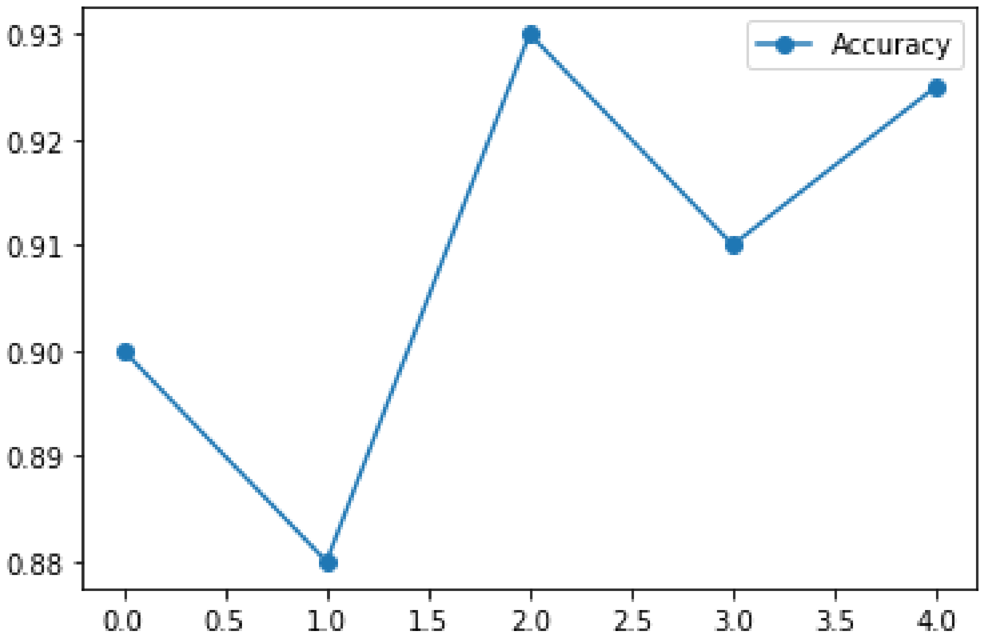


2.6.2 SVM model

[0]:
```
cv_svm_model = SVC (kernel = 'rbf' , gamma = 0.3, C = 1000.0, random_state=6)

svm_scores = cross_val_score(cv_svm_model, X, Y, cv=5)
```

[0]:
```
linear_score_data = np.array(svm_scores)
plt.plot(linear_score_data, '-o')
plt.legend(['Accuracy'])
plt.show()
```



As we can see, the SVM model has better accuacy. Therefore, we will choose the SVM model to predict the testing data.

2.7 Predict the result of testing data

[0]:
```
testing_X = np.array (testing_data[testing_data.columns[:-1]])
testing_Y = np.array (testing_data[testing_data.columns[-1]])
Y_prediction = svm_model.predict (testing_X)
print ("Initial value of y: ", testing_Y)
print ("Prediction: ", Y_prediction)
```

```
Initial value of y:  [5 4 4 1 2 0 0 0 0 0 0 0 0 0 0]
Prediction:  [5 4 4 1 2 5 4 4 3 5 5 5 4 2 5]
```

We can see that, the accuracy in the first 5 rows is 100% so the result of the predicted values might be really good.