

# 2019 ECT Project

## 第1- 4題

- ☒ 從 data\_new.csv 選取 Crossing ~ GKReflexes 欄位（共 34 個屬性）
- ☒ 計算以上所有欄位的平均
- ☒ 加標籤（大於平均：'Above-average Players'，小於平均：'Below-average Players'）
- ☒ 訓練模型，可針對所需的模型進行屬性挑選
- ☒ 切分資料集（test\_size=0.33），並用測試集測試模型
- ☒ 分析結果需印出 accuracy、classification report、confusionmatrix
- ☒ 調整模型，讓 accuracy 達到 0.9 以上
- ☒ 加分題（每大題至多 2.5%）嘗試使用 matplotlib 等套件將各個演算法結果視覺化

步驟過程

1. 首先，import 所需套件。

```
import pandas as pd
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
```

2. 依各步驟進行實作。

```
1 # 讀取CSV檔案
2 data = pd.read_csv('datanew.csv', index_col=0)
3
4 # 從 data_new.csv 選取Crossing ~ GKReflexes欄位（共34個屬性）
5 df = data.loc[:, 'Crossing': 'GKReflexes']
6
7 # 計算以上所有欄位的平均
8 array_data = np.array(df)
9 column_data_mean = np.mean(array_data, axis=0)
10 all_data_mean = np.mean(column_data_mean)
11
12 # 加標籤（大於平均：'Above-average Players'，小於平均：'Below-average Players'）
13 df['all_mean'] = df[:].mean(axis=1)
14 df.loc[df.all_mean > all_data_mean, 'label'] = 'Above-average Players'
15 df.loc[df.all_mean <= all_data_mean, 'label'] = 'Below-average Players'
16 df.drop('all_mean', axis=1, inplace=True)
17
18 data['label'] = df['label']
19
20 feature = df.iloc[:, 0:34]
21
22 #將屬性轉為數字Label
23 from sklearn import preprocessing
24 le = preprocessing.LabelEncoder()
25 target = le.fit_transform(data['label'])
26
27 # 切分訓練與測試資料
28 from sklearn.model_selection import train_test_split
29 X_train, X_test, y_train, y_test = train_test_split(feature, target, test_size = 0.33, random_state=1)
30
31 # 定義 target_name 用於顯示圖表使用
32 target_names = ['Above-average Players', 'Below-average Players']
```

## 1. Naive Bayes (20%)

模型建立與訓練，並進行預測，透過 seaborn 顯示 confusion matrix

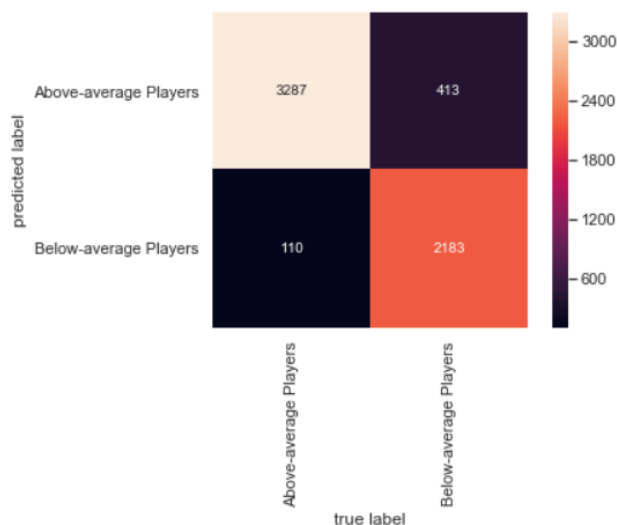
```
1 from sklearn.naive_bayes import GaussianNB
2
3 # 建立 Naive Bayes 模型
4 nb = GaussianNB()
5
6 # 僅挑選 Crossing ~ SlidingTackle 的屬性
7 feature = data.loc[:, 'Crossing': 'SlidingTackle']
8 X_train, X_test, y_train, y_test = train_test_split(feature, target, test_size = 0.33, random_state=1)
9
10 datanew_nb = nb.fit(X_train, y_train)
11
12 # 預測
13 y_test_pred = datanew_nb.predict(X_test)
14 y_train_pred = datanew_nb.predict(X_train)
15 # 績效
16 test_accuracy = accuracy_score(y_test, y_test_pred)
17 train_accuracy = accuracy_score(y_train, y_train_pred)
18
19 cm_train = confusion_matrix(y_train, y_train_pred)
20 cm_test = confusion_matrix(y_test, y_test_pred)
21
22 print('訓練集準確度為:', train_accuracy)
23 print('測試集準確度為:', test_accuracy)
24 print('\nclassification_report:\n', classification_report(y_test, y_test_pred, target_names=target_names))
25
26 mat = confusion_matrix(y_test, y_test_pred)
27 sns.heatmap(mat.T, square=True, annot=True, fmt='d',
28             xticklabels=target_names, yticklabels=target_names)
29 plt.xlabel('true label')
30 plt.ylabel('predicted label');
```

顯示結果如下

```
classification_report:
              precision    recall  f1-score   support

Above-average Players      0.89      0.97      0.93      3397
Below-average Players      0.95      0.84      0.89      2596

   accuracy                   0.91      5993
  macro avg                   0.92      5993
 weighted avg                   0.92      5993
```



## 2. Decision Trees (20%)

模型建立與訓練，並進行預測，透過 seaborn 顯示 confusion matrix

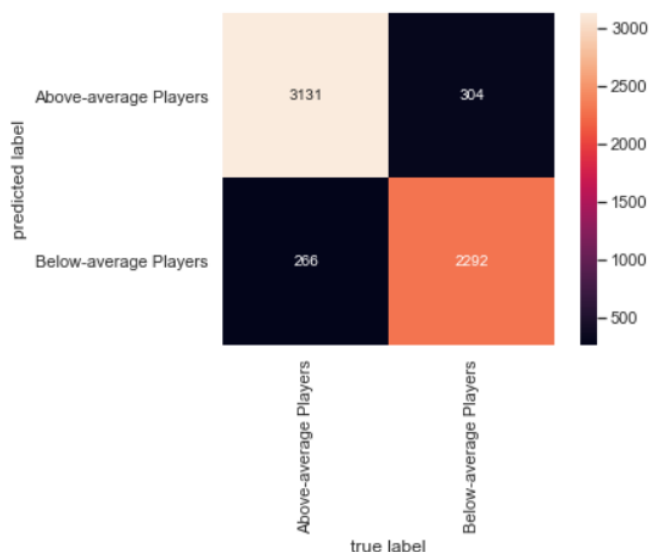
```
1 from sklearn.tree import DecisionTreeClassifier
2
3 # 建立 DecisionTree 模型
4 clf = DecisionTreeClassifier(criterion = 'gini', max_depth=7)
5
6 datanew_clf = clf.fit(X_train, y_train)
7 # 預測
8 y_test_pred = datanew_clf.predict(X_test)
9 y_train_pred = datanew_clf.predict(X_train)
10 # 績效
11 test_accuracy = accuracy_score(y_test, y_test_pred)
12 train_accuracy = accuracy_score(y_train, y_train_pred)
13
14 cm_train = confusion_matrix(y_train, y_train_pred)
15 cm_test = confusion_matrix(y_test, y_test_pred)
16
17 print('訓練集準確度為:', train_accuracy)
18 print('測試集準確度為:', test_accuracy)
19 print('\nclassification_report:\n', classification_report(y_test, y_test_pred, target_names=target_names))
20
21 mat = confusion_matrix(y_test, y_test_pred)
22 sns.heatmap(mat.T, square=True, annot=True, fmt='d',
23             xticklabels=target_names, yticklabels=target_names)
24 plt.xlabel('true label')
25 plt.ylabel('predicted label');
```

顯示結果如下

訓練集準確度為： 0.9473943777741246  
測試集準確度為： 0.9048890372100784

classification\_report:

	precision	recall	f1-score	support
Above-average Players	0.91	0.92	0.92	3397
Below-average Players	0.90	0.88	0.89	2596
accuracy			0.90	5993
macro avg	0.90	0.90	0.90	5993
weighted avg	0.90	0.90	0.90	5993



### 3. Logistic Regression (20%)

模型建立與訓練，並進行預測，透過 seaborn 顯示 confusion matrix

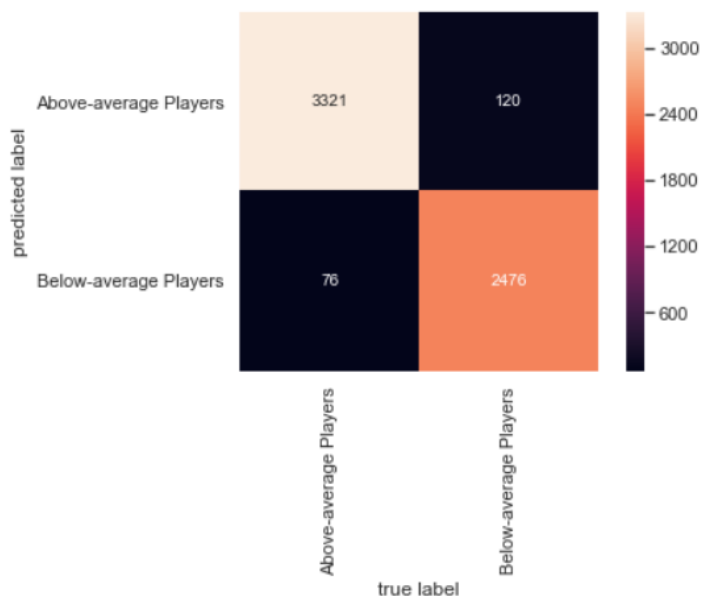
```
1 from sklearn.linear_model import LogisticRegression
2
3 # 建立 LinearRegression 模型
4 lr = LogisticRegression(solver='liblinear')
5
6 datanew_lr = lr.fit(X_train, y_train)
7 # 預測
8 y_test_pred = datanew_lr.predict(X_test)
9 y_train_pred = datanew_lr.predict(X_train)
10 # 績效
11 test_accuracy = accuracy_score(y_test, y_test_pred)
12 train_accuracy = accuracy_score(y_train, y_train_pred)
13
14 cm_train = confusion_matrix(y_train, y_train_pred)
15 cm_test = confusion_matrix(y_test, y_test_pred)
16
17 print('訓練集準確度為：', train_accuracy)
18 print('測試集準確度為：', test_accuracy)
19 print('\nclassification_report:\n', classification_report(y_test, y_test_pred, target_names=target_names))
20
21 mat = confusion_matrix(y_test, y_test_pred)
22 sns.heatmap(mat.T, square=True, annot=True, fmt='d',
23             xticklabels=target_names, yticklabels=target_names)
24 plt.xlabel('true label')
25 plt.ylabel('predicted label');
```

顯示結果如下

訓練集準確度為： 0.9660529344073648  
測試集準確度為： 0.9672951777073252

classification\_report:

	precision	recall	f1-score	support
Above-average Players	0.97	0.98	0.97	3397
Below-average Players	0.97	0.95	0.96	2596
accuracy			0.97	5993
macro avg	0.97	0.97	0.97	5993
weighted avg	0.97	0.97	0.97	5993



## 4. SVM (20%)

模型建立與訓練，並進行預測，透過 seaborn 顯示 confusion matrix

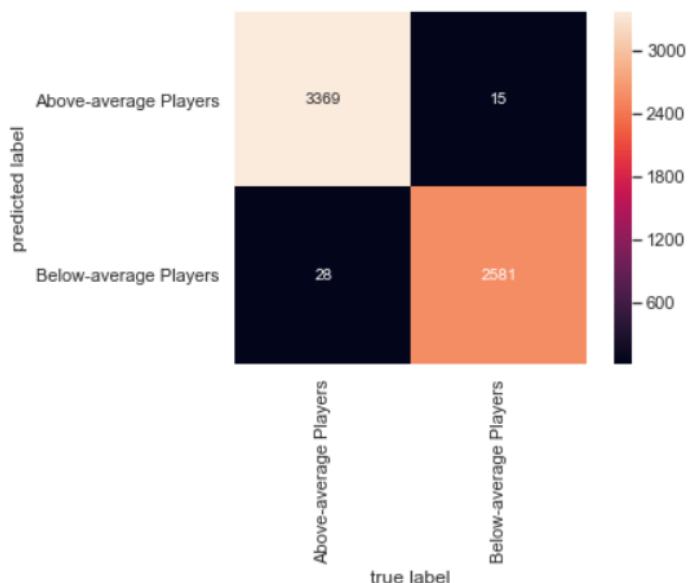
```
1 from sklearn.svm import SVC
2
3 # 建立 SVM 模型
4 svc = SVC(gamma = 0.0001, C=1.0)
5
6 datanew_svc = svc.fit(X_train, y_train)
7 # 預測
8 y_test_pred = datanew_svc.predict(X_test)
9 y_train_pred = datanew_svc.predict(X_train)
10 # 績效
11 test_accuracy = accuracy_score(y_test, y_test_pred)
12 train_accuracy = accuracy_score(y_train, y_train_pred)
13
14 cm_train = confusion_matrix(y_train, y_train_pred)
15 cm_test = confusion_matrix(y_test, y_test_pred)
16
17 print('訓練集準確度為:', train_accuracy)
18 print('測試集準確度為:', test_accuracy)
19 print('\nclassification_report:\n', classification_report(y_test, y_test_pred, target_names=target_names))
20
21 mat = confusion_matrix(y_test, y_test_pred)
22 sns.heatmap(mat.T, square=True, annot=True, fmt='d',
23             xticklabels=target_names, yticklabels=target_names)
24 plt.xlabel('true label')
25 plt.ylabel('predicted label');
```

顯示結果如下

訓練集準確度為： 0.9958901857636034  
測試集準確度為： 0.9928249624561989

classification\_report:

	precision	recall	f1-score	support
Above-average Players	1.00	0.99	0.99	3397
Below-average Players	0.99	0.99	0.99	2596
accuracy			0.99	5993
macro avg	0.99	0.99	0.99	5993
weighted avg	0.99	0.99	0.99	5993



## 第5題

取data\_new.csv，進行KNN分析

可針對所需的模型進行屬性挑選

選取Crossing ~ GKReflexes欄位，並加上Skill Moves欄位。

```
feature = data.iloc[:,6:40]
feature['Skill Moves'] = data['Skill Moves']
```

### 5. KNN (20%)

(a) 推薦與 "Neymar Jr" 相像的前五名足球選手

```
1 from sklearn.neighbors import NearestNeighbors
2
3 # 找出 Neymar Jr 資料的 index
4 Neymar_Jr = data[data['Name'] == 'Neymar Jr']
5 Neymar_Jr_index = Neymar_Jr.index.tolist()[0]
6 # 找出 Neymar Jr 的資料
7 Neymar_Jr = feature[Neymar_Jr_index:Neymar_Jr_index+1]
8
9 # 將 feature 進行標準化 (以 Neymar Jr 為中心)
10 normalized_feature=(feature-Neymar_Jr.mean())/(feature.std())
11
12 # 找出標準化後的 Neymar Jr 資料
13 normalized_Neymar_Jr = normalized_feature[Neymar_Jr_index:Neymar_Jr_index+1]
14
15 nbrs = NearestNeighbors(n_neighbors=6).fit(normalized_feature)
16 distances, indices = nbrs.kneighbors(normalized_Neymar_Jr)
17 for x in indices:
18     print(data['Name'][x])
19 distances
```

2          Neymar Jr  
5          E. Hazard  
0          L. Messi  
65        Douglas Costa  
84          R. Mahrez  
15          P. Dybala  
Name: Name, dtype: object

```
array([[0.                   , 2.51869119, 2.65644407, 3.00039668, 3.0243212 ,  
       3.03490117]])
```

1. 先透過原始 data 找出 Neymar Jr 資料的 index
2. 將feature以Neymar Jr為中心進行標準化，不同於一般標準化的方法，每筆feature中的資料會減去Neymar Jr的資料，再除以feature的標準差。
3. 利用步驟1. 找出的 index 找出標準化後的feature中Neymar Jr的資料。(此資料將用於後續

kneighbors演算法中)

4. 得出E. Hazard、L. Messi、Douglas Costa、R. Mahrez、P. Dybala為與Neymar Jr相像的前五名足球選手

**(b) 推薦與 " L. Messi " 相像的前五名足球選手**

```
1 from sklearn.neighbors import NearestNeighbors
2
3 # 找出 L. Messi 的 index
4 L_Messi = data[data['Name'] == 'L. Messi']
5 L_Messi_index = L_Messi.index.tolist()[0]
6 # 找出 L_Messi 的資料
7 L_Messi = feature[L_Messi_index:L_Messi_index+1]
8
9 # 將 feature 進行標準化 (以 Neymar Jr 為中心)
10 normalized_feature=(feature-L_Messi.mean())/(feature.std())
11
12 # 找出標準化後的 L_Messi 資料
13 normalized_L_Messi = normalized_feature[L_Messi_index:L_Messi_index+1]
14
15 nbrs = NearestNeighbors(n_neighbors=6).fit(normalized_feature)
16 distances, indices = nbrs.kneighbors(normalized_L_Messi)
17 for x in indices:
18     print(data['Name'][x])
19 distances
```

```
0      L. Messi
2      Neymar Jr
5      E. Hazard
15     P. Dybala
154    A. Robben
68      M. Reus
Name: Name, dtype: object
```

```
array([[0.          , 2.65644407, 2.66905995, 2.7565991 , 3.26975065,
        3.43961592]])
```

1. 先透過原始 data 找出 L. Messi 資料 的 index
2. 將feature以L. Messi為中心進行標準化，不同於一般標準化的方法，每筆feature中的資料會減去L. Messi的資料，再除以feature的標準差。
3. 利用步驟1. 找出的 index 找出 標準化後的feature中L. Messi的資料。(此資料將用於後續kneighbors演算法中)
4. 得出Neymar Jr、E. Hazard、P. Dybala、A. Robben、M. Reus為與L. Messi相像的前五名足球選手

**第6題**

**6. 加分題 (10%)**



## 對資料額外進行有趣的分析

透過將 attribute 之間的相關性視覺化，可以更佳了解到屬性之間的相互關係，能做更加深的應用

```
1 # 讀取CSV檔案
2 data = pd.read_csv('datanew.csv', index_col=0)
3
4 # correlation
5 corr = data.corr()
6
7 # 設定 figure 大小
8 fig = plt.figure(figsize=(20,10))
9
10 ax = fig.add_subplot()
11
12 # matshow 矩陣視覺化
13 cax = ax.matshow(corr,cmap='coolwarm', vmin=-1, vmax=1)
14 fig.colorbar(cax)
15 ticks = np.arange(0,len(data.columns),1)
16 ax.set_xticks(ticks)
17 plt.xticks(rotation=90)
18 ax.set_yticks(ticks)
19 ax.set_xticklabels(data.columns)
20 ax.set_yticklabels(data.columns)
21 plt.show()
```

