Machine learning final project

生醫三辛明峯

Report abstract

- Data introduction
- Data statistical analysis
- Data initial introduction
- Data preprocessing
- Model training
- conclusion

Data introduction

This data is from the Korea Sports promotion foundation

https://www.bigdata-culture.kr/bigdata/user/data_market/detail.do?id=ace0aea7-5eee-48b9-b616-637365d665c1

body_perform = pd.read_csv("C:\\Users\\User\\Desktop\\ML_final\\bodyPerformance.csv")

The name of each column:

1. age	7.systolic
2 gandar	0 grinFa

2. gender 8.gripForce3.height_cm 9.sit and bend forward_cm

4.weight_kg 10.sit-ups counts in 2 min

5.body fat_% 11.broad jump_cm

6.diastolic 12.class {"A","B","C","D"} A the best

	age	gender	height_cm	weight_kg	body fat_%	diastolic	systolic	gripForce	sit and bend forward_cm	sit- ups counts	broad jump_cm	class
0	27.0	М	172.3	75.24	21.3	80.0	130.0	54.9	18.4	60.0	217.0	С
1	25.0	М	165.0	55.80	15.7	77.0	126.0	36.4	16.3	53.0	229.0	Α
2	31.0	М	179.6	78.00	20.1	92.0	152.0	44.8	12.0	49.0	181.0	С
3	32.0	М	174.5	71.10	18.4	76.0	147.0	41.4	15.2	53.0	219.0	В
4	28.0	М	173.8	67.70	17.1	70.0	127.0	43.5	27.1	45.0	217.0	В

Data introduction

```
A 25.08 %
B 25.07 %
C 25.09 %
D 25.09 %
13393
```

There is no missing values
And the data seem vary good?

```
body perform.info()
 ✓ 0.1s
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13393 entries, 0 to 13392
Data columns (total 12 columns):
    Column
                             Non-Null Count Dtype
                             13393 non-null float64
    age
    gender
                             13393 non-null object
    height cm
                             13393 non-null float64
    weight kg
                             13393 non-null float64
    body fat %
                             13393 non-null float64
                             13393 non-null float64
    diastolic
     systolic
                             13393 non-null float64
    gripForce
                             13393 non-null float64
    sit and bend forward cm 13393 non-null float64
    sit-ups counts
                             13393 non-null float64
    broad jump_cm
                             13393 non-null float64
    class
                             13393 non-null object
```

```
body_perform.isnull().sum()
 ✓ 0.0s
age
gender
height cm
weight_kg
body fat %
diastolic
systolic
gripForce
sit and bend forward cm
sit-ups counts
broad jump cm
class
dtype: int64
```

Data introduction

But these people definitely pass away

bo ✓ 0.	dy_perform.de 3s	scribe()						sit and bend forward_cm	sit-ups counts	broad jump_cm
	age	height_cm	weight_kg	body fat_%	distolic	systolic	gripForce	13393.000000	13393.000000	13393.000000
				, -				15.209268	39.771224	190.129627
count	13393.000000	13393.000000	13393.000000	13393.000000	13393.	1339 .000000	13393.000000	0.456677	44076600	22.25222
mean	36.775106	168.559807	67.447316	23.240165	78.7 <mark>-</mark> 96842	13(<mark>234817</mark>	36.963877	8.456677	14.276698	39.868000
std	13.625639	8.426583	11.949666	7.256844	10.7 2033	14 13954	10.624864	-25.000000	0.000000	0.000000
min	21.000000	125.000000	26.300000	3.000000	0.000000	0.000000	0.000000	10.90000	30.000000	162.000000
25%	25.000000	162.400000	58.200000	18.000000	71.000000	120.000000	27.500000	16.200000	41.000000	193.000000
50%	32.000000	169.200000	67.400000	22.800000	79.000000	130.000000	37.900000	10.200000	41.000000	133.000000
75%	48.000000	174.800000	75.300000	28.000000	86.000000	141.000000	45.200000	20.700000	50.000000	221.000000
max	64.000000	193.800000	138.100000	78.400000	156.200000	201.000000	70.500000	213.000000	80.000000	303.000000

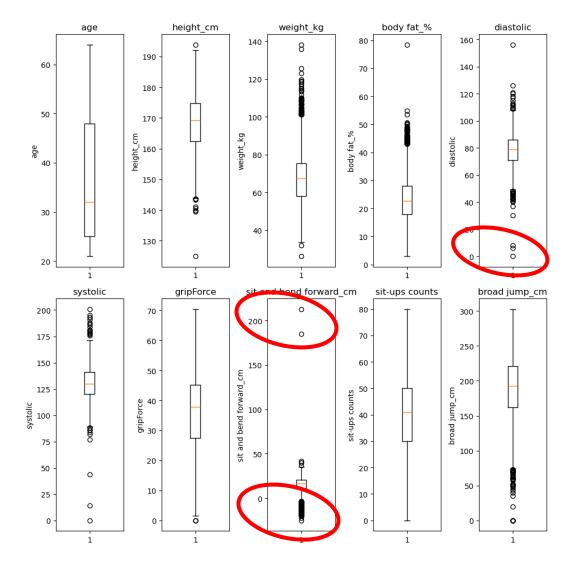
In my experience, I believe that this could be possible

In addition, there are some people who can decrease there size!!!

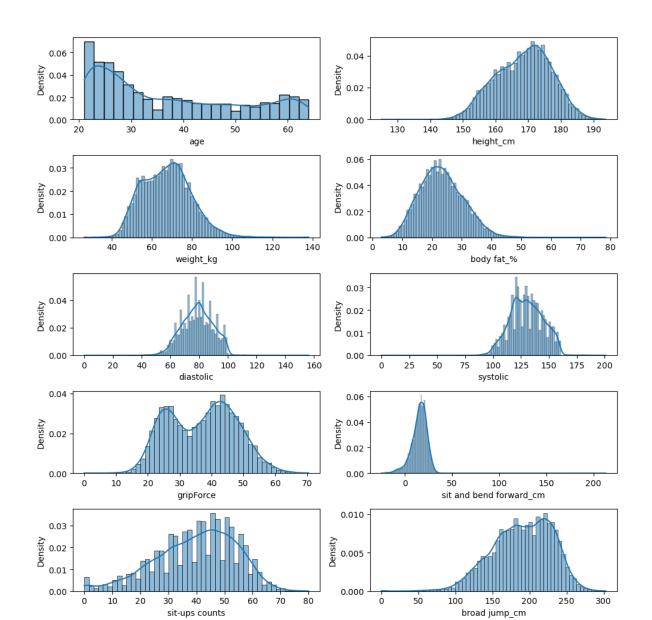
多拉A夢縮小燈~

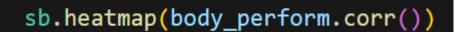
Data statistical analysis

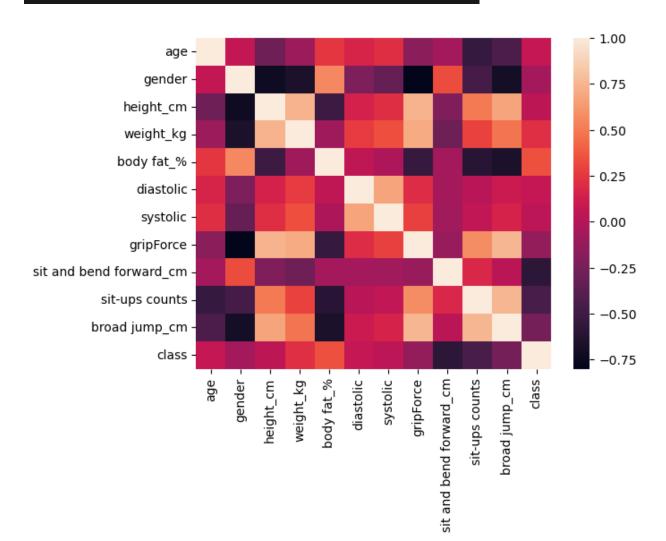
Box_plot of each column



skewness of each column

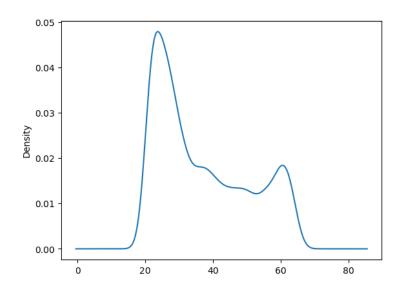






body_perfor()["	class"]
age gender height_cm weight_kg body fat_% diastolic systolic gripForce sit and bend forward_cm sit-ups counts broad jump_cm	0.065612 -0.075605 0.037753 0.214129 0.341956 0.066761 0.035484 -0.136088 -0.588123 -0.452832 -0.262154
class Name: class, dtype: float	1.000000 :64

```
body_perform['age'].plot(kind = 'density')
0.7s
```



Data initial introduction

```
# 先看看完全沒有Data cleaning 的資料
   from sklearn.neighbors import KNeighborsClassifier
   from sklearn.model selection import GridSearchCV
   X = body perform.drop("class",axis = 1)
   y = body perform["class"]
   knn_params = {'n_neighbors':[1, 2, 3, 4, 5, 6, 7]}
   knn = KNeighborsClassifier()
   grid = GridSearchCV(knn, knn params)
   grid.fit(X, y)
   print(grid.best_score_, grid.best_params_)
✓ 7.1s
0.5732846767419877 {'n_neighbors': 7}
```

```
# 初步cleaning 測試 drop unqualified data
   from sklearn.neighbors import KNeighborsClassifier
   from sklearn.model selection import GridSearchCV
   X = body drop.drop("class",axis = 1)
   y = body_drop["class"]
   y.shape
   knn params = \{' \text{n neighbors'}: [1, 2, 3, 4, 5, 6, 7]\}
   knn = KNeighborsClassifier()
   grid = GridSearchCV(knn, knn params)
   grid.fit(X, y)
   print(grid.best score , grid.best params )

√ 6.2s

0.5463913950824559 {'n neighbors': 7}
```

Data initial introduction

```
# use imputer
   from sklearn.impute import SimpleImputer
   imputer = SimpleImputer(strategy='mean')
   raw col = ["age", "gender", "height cm", "weight kg", "body
   body imputed = imputer.fit transform(body perform)
   body imputed = pd.DataFrame(body imputed, columns = raw of
   X imputed = body imputed.drop("class",axis = 1)
   y imputed = body imputed['class']
   knn_params = {'n_neighbors':[1, 2, 3, 4, 5, 6, 7]}
   knn = KNeighborsClassifier()
   grid = GridSearchCV(knn, knn params)
   grid.fit(X_imputed, y_imputed)
   print(grid.best_score_, grid.best_params_)
 ✓ 7.7s
0.5470771338273702 {'n neighbors': 7}
```

```
# use 0 to fill None
   body_zero = body_perform.fillna(0)
   X_zero = body_zero.drop('class', axis = 1)
   y_zero = body_zero['class']
   grid.fit(X zero, y zero)
   print("learning from {} rows".format(X_zero.
   print(grid.best_score_, grid.best_params_)
    6.5s
learning from 13393 rows
0.5711939821269125 {'n_neighbors': 7}
```

Data initial introduction

I also use some basic strategy to build model, here I make a table to show the performance

Pipeline description	Cross-validated accuracy				
Original data	0.57 % n_neighbor = 7				
Drop unqualified data	0.54 % n_neighbor = 7				
Impute with mean or zero	0.55 % n_neighbor = 7, 0.57 % n_neighbor = 7				
logistic regression	0.57 %				
{'classifierC': 1.0, 'classifierpenalty': 'l1', 'cla 'mean', 'scalar': MinMaxScaler()}	ssifiersolver': 'liblinear', 'imputerstrategy':				
knn	0.59 %				
{'classifyn_neighbors': 7, 'imputerstrategy':	'median', 'scalar': StandardScaler()}				
decisiontree	0.67 %				
{'classifymax_depth': 12, 'imputerstrategy':	'mean', 'scalar': StandardScaler()}				
randomforest	0.73 %				
{'classifymax_depth': None, 'classifyn_estimators': 100, 'imputerstrategy': 'mean', 'scalar': StandardScaler()}					

Data preprocessing

And bend forward = negative

I replace every quantitative value be divided into 5 bins

```
Work flow 1 :    pipe = Pipeline([("remover",UN),("imputer",ID)])

Work flow 2 :    pipe = Pipeline([("remover",UN),("imputer",ID),("rank",PR)])

Work flow 3 :    pipe = Pipeline([("remover",UN),("imputer",ID),("addBMI",ALB)])

I replace unqualified data to None, including systolic or diastolic pressure = 0
```

```
class addleanBMI(TransformerMixin):
    def __init__(self,fat='body fat_%',height="he
        self.fat = fat
        self.weight = height
        self.weight = weight
    def fit(self,*_):
        return self
    def transform(self,df):
        X = df.copy()
        body_fat = X['body fat_%'] / 100
        height_m = X['height_cm'] / 100
        lean_mass = X['weight_kg'] * (1-body_fat)
```

I add a new data here which is called Lean_BMI(瘦體組織) 類似BMI但體重的計算要去除脂肪重量

```
Workflow 1: pipe = Pipeline([("remover",UN),("imputer",ID)])
```

```
('scalar', StandardScaler()), ('classify',
```

```
logistic regression
                                                       0.57 %
{'classifier__C': 1.0, 'classifier__penalty': 'l1', 'classifier__solver': 'liblinear',
'scalar': StandardScaler()}
                                                       0.62 %
knn
{'classify n neighbors': 7, 'scalar': MinMaxScaler()}
decisiontree
                                                       0.67 %
{'classify__max_depth': 11, 'scalar': StandardScaler()}
randomforest
                                                       0.72 %
{'classify max depth': None, 'classify n estimators': 100, 'scalar':
MinMaxScaler()}
```

randomforest

```
Best Accuracy: 0.7276187624767191
Best Parameters: {'classify_max_c
Average Time to Fit (s): 0.469
Average Time to Score (s): 0.013
```

logistic regression

```
Best Accuracy: 0.5705219502444956
Best Parameters: {'classifier__C': 1.0, 'c
Average Time to Fit (s): 0.374
Average Time to Score (s): 0.003
```

knn

```
Best Accuracy: 0.6223398261754843
Best Parameters: {'classify_n_nei;
Average Time to Fit (s): 0.016
Average Time to Score (s): 0.196
```

decisiontree

```
Best Accuracy: 0.6665433943812704
Best Parameters: {'classify_max_
Average Time to Fit (s): 0.046
Average Time to Score (s): 0.002
```

```
Pipeline([('select_feature',SL),('scalar', StandardScaler()), ('classify',
logistic regression
                                              0.53 %
{'classifier C': 1.0, 'classifier penalty': 'l1', 'classifier solver':
'liblinear', 'scalar': MinMaxScaler(), 'select my feature threshold': 0}
knn
                                              0.55 %
{'classify n neighbors': 7, 'scalar': MinMaxScaler(),
select feature threshold': 0}
                                              0.57%
decisiontree
{'classify max depth': 9, 'scalar': StandardScaler(),
'select feature threshold': 0}
randomforest
                                              0.59 %
{'classify max depth': 12, 'classify n estimators': 100, 'scalar':
MinMaxScaler(), 'select feature threshold': 0}
                         randomforest
                         Best Accuracy: 0.5930719693263318
                         Best Parameters: {'classify max dep
                         Average Time to Fit (s): 0.304
                         Average Time to Score (s): 0.015
```

Workflow 2:

pipe = Pipeline([("remover",UN),("imputer",ID),("rank",PR)])

logistic regression

```
Best Accuracy: 0.534532352841967
Best Parameters: {'classifier C':
Average Time to Fit (s): 0.13
Average Time to Score (s): 0.003
```

knn

```
Best Accuracy: 0.5464038474780056
Best Parameters: {'classify n neighb
Average Time to Fit (s): 0.019
Average Time to Score (s): 0.122
```

decisiontree

```
Best Accuracy: 0.5667145036729397
Best Parameters: {'classify__max_d
Average Time to Fit (s): 0.027
Average Time to Score (s): 0.003
```

Workflow 3: pipe = Pipeline([("remover",UN),("imputer",ID),("addBMI",ALB)]) Pipeline([('select_feature',SL),('scalar', StandardScaler()), ('classify',

```
logistic regression
                                                      0.57 %
{'classifier__C': 1.0, 'classifier__penalty': 'l1', 'classifier solver': 'liblinear',
'imputer strategy': 'mean', 'scalar': MinMaxScaler()}
                                                      0.59 %
knn
{'classify n neighbors': 7, 'imputer strategy': 'median', 'scalar':
decisiontree
                                                      0.67 %
{'classify__max_depth': 12, 'imputer__strategy': 'mean', 'scalar':
randomforest
                                                      0.73 %
{'classify max depth': None, 'classify n estimators': 100,
'imputer strategy': 'mean', 'scalar': StandardScaler()}
```

randomforest

```
Best Accuracy: 0.7246321554446234
Best Parameters: {'classify_max_depth': None,
Average Time to Fit (s): 0.398
Average Time to Score (s): 0.014
```

logistic regression

```
Best Accuracy: 0.5741060180682268
Best Parameters: {'classifier__C':
Average Time to Fit (s): 0.957
Average Time to Score (s): 0.003
```

knn

```
Best Accuracy: 0.6165158100469421

Best Parameters: {'classify_n_neighborderage Time to Fit (s): 0.018

Average Time to Score (s): 0.125
```

decisiontree

```
Best Accuracy: 0.6684843613968741
Best Parameters: {'classify_max_depth'
Average Time to Fit (s): 0.04
Average Time to Score (s): 0.002
```

Other better model

```
def print_score(clf, X_train, y_train, X_test, y_test, train=True):
   if train:
       pred = clf.predict(X train)
       clf_report = pd.DataFrame(classification_report(y_train, pred, output_dict=True))
       print("Train Result:\n=========")
       print(f"Accuracy Score: {accuracy_score(y_train, pred) * 100:.2f}%")
       print(f"CLASSIFICATION REPORT:\n{clf report}")
       print(f"Confusion Matrix: \n {confusion matrix(y train, pred)}\n")
   elif train==False:
       pred = clf.predict(X test)
       clf_report = pd.DataFrame(classification_report(y_test, pred, output_dict=True))
       print("Test Result:\n=========")
       print(f"Accuracy Score: {accuracy_score(y_test, pred) * 100:.2f}%")
       print("_
       print(f"CLASSIFICATION REPORT:\n{clf report}")
       print("
       print(f"Confusion Matrix: \n {confusion matrix(y test, pred)}\n")
```

```
Workflow 1:
```

```
pipe = Pipeline([("remover",UN),("imputer",ID)])
('scalar', StandardScaler()), ('classify',
```

```
Train Result:
                      ------
Accuracy Score: 96.70%
CLASSIFICATION REPORT:
                                                                accuracy
precision
              0.998663
                           0.983102
                                         0.958510
                                                      0.931329
                                                                 0.96704
recall.
              0.971813
                                                                 0.96704
                           0.953361
                                         0.950861
                                                      0.993068
f1-score
              0.202055
                           0.968003
                                         0.954670
                                                      0.961208
                                                                 0.96704
support
           2306.000000
                        2380.000000
                                      2381.000000
                                                                 0.96704
                                                   2308.000000
                                                                     Test Result:
             macro avg
                        weighted avg
precision
              0.967901
                            0.967938
                                                                     Accuracy Score
                                                                                    75.29%
recall
              0.967276
                            0.967040
f1-score
              0.967234
                            0.967138
                                                                     CLASSIFICATION REPORT:
support
           9375.000000
                         9375.000000
                                                                                                     1
                                                                                                                 2
                                                                                                                              3 accuracy
                                                                     precision
                                                                                  0.913866
                                                                                              0.711721
                                                                                                          0.624360
                                                                                                                       0.762697
                                                                                                                                0.752862
                                                                     recall.
                                                                                  0.834132
                                                                                              0.695562
                                                                                                          0.631470
                                                                                                                       0.837500
                                                                                                                               0.752862
                                                                     f1-score
                                                                                   872186
                                                                                              0.703549
                                                                                                          0.627895
                                                                                                                       0.798350 0.752862
                                                                                1043.000000
                                                                                            969.000000
                                                                                                                   1040.000000 0.752862
                                                                     support
                                                                                                        966.000000
                                                                                            weighted avg
                                                                                 macro avg
                                                                     precisi<u>on</u>
                                                                                  0.753161
                                                                                                0.756385
                                                                     recall
                                                                                                0.752862
                                                                                  0.749666
                                                                                  0.750494
                                                                                                0.753672
                                                                     f1-score
                                                                     support
                                                                               4018.000000
                                                                                             4018.000000
```

```
Pipeline([('select_feature',SL),('scalar', StandardScaler()), ('classify',
Train Result:
              ------
Accuracy Score 96.70%
CLASSIFICATION REPORT:
                               1
                                                          accuracy
                                            2
                         0.983102
precision
             0.998663
                                     0.958510
                                                 0.931329
                                                           0.96704
recall
             0.971813
                         0.953361
                                     0.950861
                                                           0.96704
                                                 0.993068
f1-score
                         0.968003
                                     0.954670
                                                 0.961208
                                                           0.96704
support
          2306.000000
                      2380.000000
                                              2308.000000
                                                           0.96704
                                  2381.000000
                                                             Test Result:
                      weighted avg
            macro avg
precision
             0.967901
                          0.967938
                                                             Accuracy Score 75.29%
recall
             0.967276
                          0.967040
f1-score
             0.967234
                          0.967138
                                                             CLASSIFICATION REPORT:
          9375.000000
                       9375.000000
support
                                                                                              1
                                                                                                                        accuracy
                                                             precision
                                                                           0.913866
                                                                                       0.711721
                                                                                                   0.624360
                                                                                                               0.762697
                                                                                                                         0.752862
                                                             recall.
                                                                           0.834132
                                                                                       0.695562
                                                                                                   0.631470
                                                                                                               0.837500
                                                                                                                         0.752862
                                                             f1-score
                                                                                       0.703549
                                                                                                                         0.752862
                                                                                                   0.627895
                                                                                                               0.798350
                                                             support
                                                                        1043.000000
                                                                                     969.000000
                                                                                                 966.000000
                                                                                                            1040.000000
                                                                                                                         0.752862
                                                                          macro avg weighted avg
                                                             precision
                                                                           0.753161
                                                                                         0.756385
                                                             recall.
                                                                           0.749666
                                                                                        0.752862
                                                             f1-score
                                                                           0.750494
                                                                                         0.753672
```

support

4018.000000

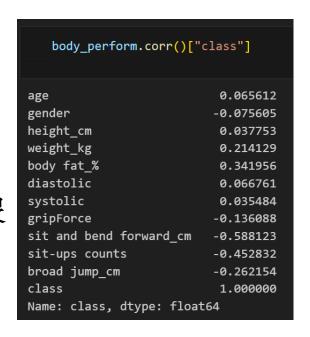
4018.000000

pipe = Pipeline([("remover",UN),("imputer",ID),("addBMI",ALB)])

Workflow 3:

conclusion

• 在查看data的correlation時有很奇妙的現象



•訓練結果發現,即便做了許多的資料處理都不夠好,我認為要不是feature或imputer做的不好,就是選定的人群,因為老年人和年輕人的分級標準應該要做區分才對

• 未來的改善方針我認為可以更換其他model來做,或是使用其他的特徵萃取方法

希望CC出道當V tuber



這應該不算暴雷吧!?

VTuber與他的中之人