## 操作報告

DataSet using: duke\_gpa.csv

First I load my data using pandas.

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.linear_model import LogisticRegression

# Load your data
df = pd.read_csv('duke_gpa.csv')
print(df)
```

```
gpa studyweek sleepnight out gender
0
   3.890 50 6.0 3.0 female
   3.900
              15
                      6.0 1.0 female
1
             15
10
2
   3.750
                       7.0 1.0 female
3
   3.600
                       6.0 4.0
                                male
             25
                       7.0 3.0 female
4
   4.000
             20
5
                      7.0 3.0
   3.150
                               male
  3.250
             15
                      6.0 1.0 female
6
             10
7
  3.925
                      8.0 3.0 female
8
  3.428
             12
                      8.0 2.0 female
             2
9
   3.800
                      8.0 4.0
                               male
10 3.900
                      8.0 1.0 female
             10
            30
11 2.900
                      6.0 2.0 female
            30
21
10
12
  3.925
                       7.0 2.0 female
13
   3.650
                      9.0
                           3.0 female
14 3.750
                      8.5 3.5 female
             14
                      6.5 3.0
15 4.670
                               male
16 3.100
             12
                      7.5 3.5 male
             12
                      8.0 1.0 female
17 3.800
18 3.400
             4
                      9.0 3.0 female
            45
19 3.575
                      6.5 1.5 female
              6
20 3.850
                      7.0 2.5 female
             10
21 3.400
                       7.0 3.0 female
             12
13
35
22 3.500
                       8.0 2.0
                                male
23
   3.600
                       6.0
                           3.5 female
24 3.825
                      8.0 4.0 female
             10
                      8.0 3.0 female
25 3.925
26 4.000
            40
                      8.0 3.0 female
             14
27 3.425
                      9.0 3.0 female
28 3.750
             30
                      6.0 0.0 female
             8
29 3.150
                      6.0 0.0 female
              8
30 3.400
                      6.5 2.0 female
            20
40
15
31 3.700
                      7.0 1.0 female
32
   3.360
                       7.0 1.0 female
33 3.700
                      7.0 1.5
            15
25
10
34 3.700
                      5.0 1.0 female
35 3.600
                      7.0 2.0 female
36 3.825
             18
                      7.0 1.5 female
             15
                      6.0 1.0 female
37 3.200
38 3.500
             30
                      8.0 3.0
                               male
39 3.500
             11
                      7.0 1.5 female
40 3.000
             28
                      6.0 1.5 female
             4
4
41 3.980
                       7.0 1.5 female
42 3.700
43 3.810
                       5.0 1.0
                                male
              25
                       7.5
                           2.5 female
            42
44 4.000
                      5.0 1.0 female
                      7.0 2.0
45 3.100
              3
                               male
             42
46 3.400
                      9.0 2.0 male
47 3.500
             25
                      8.0 2.0 male
48 3.650
             20
                      6.0 2.0 female
             7
49 3.700
                      8.0 2.0 female
50 3.100
              6
                      8.0 1.0 female
51 4.000
              20
                       7.0 3.0 female
52
   3.350
              45
                       6.0 2.0 female
53
  3.541
              30
                       7.5
                           1.5
                              female
54 2.900
                       6.0 3.0 female
              20
```

We can observe that there is a gender column which is nominal data. We convert it into binary data, 1 stands for male and 0 for female.

```
In []: # Load the data
df = pd.read_csv('duke_gpa.csv')

df['gender'] = df['gender'].map({'male': 1, 'female': 0})
print(df)
```

	ana	ctudywook	clooppight	out	gondon
0	gpa 3.890	studyweek 50	sleepnight 6.0	out 3.0	gender 0
	3.900	15	6.0		0
1				1.0	
2	3.750	15	7.0	1.0	0
3	3.600	10	6.0	4.0	1
4	4.000	25	7.0	3.0	0
5	3.150	20	7.0	3.0	1
6	3.250	15	6.0	1.0	0
7	3.925	10	8.0	3.0	0
8	3.428	12	8.0	2.0	0
9	3.800	2	8.0	4.0	1
10	3.900	10	8.0	1.0	0
11	2.900	30	6.0	2.0	0
12	3.925	30	7.0	2.0	0
13	3.650	21	9.0	3.0	0
14	3.750	10	8.5	3.5	0
15	4.670	14	6.5	3.0	1
16	3.100	12	7.5	3.5	1
17	3.800	12	8.0	1.0	0
18	3.400	4	9.0	3.0	0
19	3.575	45	6.5	1.5	0
20	3.850	6	7.0	2.5	0
21	3.400	10	7.0	3.0	0
22	3.500	12	8.0	2.0	1
23	3.600	13	6.0	3.5	0
24	3.825	35	8.0	4.0	0
25	3.925	10	8.0	3.0	0
26	4.000	40	8.0	3.0	0
27	3.425	14	9.0	3.0	0
28	3.750	30	6.0		0
				0.0	
29	3.150	8	6.0	0.0	0
30	3.400	8	6.5	2.0	0
31	3.700	20	7.0	1.0	0
32	3.360	40	7.0	1.0	0
33	3.700	15	7.0	1.5	1
34	3.700	25	5.0	1.0	0
35	3.600	10	7.0	2.0	0
36	3.825	18	7.0	1.5	0
37	3.200	15	6.0	1.0	0
38	3.500	30	8.0	3.0	1
39	3.500	11	7.0	1.5	0
40	3.000	28	6.0	1.5	0
41	3.980	4	7.0	1.5	0
42	3.700	4	5.0	1.0	1
43	3.810	25	7.5	2.5	0
44	4.000	42	5.0	1.0	0
45	3.100	3	7.0	2.0	1
46	3.400	42	9.0	2.0	1
47	3.500	25	8.0	2.0	1
48	3.650	20	6.0	2.0	0
49	3.700	7	8.0	2.0	0
50	3.100	6	8.0	1.0	0
51	4.000	20	7.0	3.0	0
52	3.350	45	6.0	2.0	0
53	3.541	30	7.5	1.5	0
54	2.900	20	6.0	3.0	0
				-	_

Next, I want to know what other features are related to gpa, so I will do feature selection using SelectKBest method.

I noticed that different features have different scales, like gpa may be using 4.0 scaling. Studyweek should be hours but is the accumulate study hours of a week. Sleep night should be the hours a student sleep at night...

They are all on different scales, so I would be doing Standarizing first. The method I'm using is MinMaxScaler.

```
In [ ]: from sklearn.preprocessing import MinMaxScaler

# Initialize the scaler
scaler = MinMaxScaler()
```

```
# Fit the scaler to the data and transform the data
df[['gpa', 'studyweek', 'sleepnight', 'out']] = scaler.fit_transform(df[['gpa', 'st
print(df)
```

```
gpa studyweek sleepnight
                                        out gender

      0.559322
      1.000000
      0.250
      0.750
      0

      0.564972
      0.270833
      0.250
      0.250
      0

 1
                                                    0
                                                    1
                                                   0
                                                   0
                                                    1
                                                    0
                                                   0
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                                                    0
                                                    1
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                                                   1
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                                                    1
                                                   0
                                                   1
                                                    1
                                                    0
                                                    0
                                                    0
                                                    0
                                                    0
```

Now we can do Feature Selection to the dataset. The scoring function I'm using is f\_regression(suitable for continuous target varriables and the predictors are binary or continuous)

```
In [ ]: from sklearn.feature_selection import SelectKBest
    from sklearn.feature_selection import f_regression

# Separate input features and target
X = df.drop('gpa', axis=1)
```

```
y = df['gpa'] # Target variable

# feature selection
selector = SelectKBest(score_func=f_regression, k=3)
fit = selector.fit(X, y)

# feature ranking
print('Top 3 features: ')
for i in range(3):
    print("%d. %s (%f)" % (i + 1, X.columns[indices[i]], fit.scores_[indices[i]]))

Top 3 features:
1. out (0.995810)
2. gender (0.215639)
3. sleepnight (0.197839)
```

From the above result we can observe that 'out' (nights going out per week) feature got a high score. Which may represent this feature has a strong relationship with gpa (target).

Next I will split the dataset for testing/training using train\_test\_split. For observing whether doing feature selection makes a difference, I'll do the training for only 'out' feature and all the features except 'gpa' respectively.

```
In []: from sklearn.linear_model import LinearRegression
    from sklearn.model_selection import train_test_split

# Separate input features and target
X = df[['out', 'gender', 'sleepnight', 'studyweek']]
y = df['gpa']

# Split the data into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
print("Training set size:", len(X_train))
print("Test set size:", len(X_test))

model = LinearRegression()
model.fit(X_train, y_train)

Training set size: 38
Test set size: 17

Out[]: v LinearRegression()
```

```
In [ ]: from sklearn.metrics import mean_squared_error

# predictions
y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
print("Mean squared error: ", mse)
```

Mean squared error: 0.021974176126192076

I trained a Linear regression model to do the prediction. The accuracy is mse = 0.021974

Now I'll be training the model with only 'out' feature.

```
In []: X = df[['out']]
y = df['gpa']

# Split the data into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
print("Training set size:", len(X_train))
print("Test set size:", len(X_test))
```

```
model = LinearRegression()
         model.fit(X_train, y_train)
       Training set size: 38
       Test set size: 17
Out[]: ▼ LinearRegression
         LinearRegression()
In [ ]: y_pred = model.predict(X_test)
         mse = mean_squared_error(y_test, y_pred)
         print("Mean squared error: ", mse)
         df_results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
         print(df_results)
       Mean squared error: 0.02041822296962972
             Actual Predicted
       31 0.451977 0.347523
       5 0.141243 0.416615
       32 0.259887 0.347523
       13 0.423729 0.416615
       19 0.381356 0.364796

      49
      0.451977
      0.382069

      41
      0.610169
      0.364796

      26
      0.621469
      0.416615

       43 0.514124 0.399342
       12 0.579096 0.382069
       52 0.254237 0.382069
       3 0.395480 0.451162
       33 0.451977 0.364796
       34 0.451977 0.347523
       8 0.298305 0.382069
       17 0.508475 0.347523
           0.197740
                       0.347523
```

The mse = 0.0204. The prediction accuracy did improved a little, but don't think it's due to feature selection.