Unit5HW

May 19, 2020

1 Unit5作业

[18]:
```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = 'all'
import scipy.stats as stats
import numpy as np
import statsmodels.stats.proportion as proportion
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
sns.set_style('darkgrid')
```

HW-U5-1：对于Diabetes.csv数据，请利用协方差和pearson 相关系数分析Glucose与Blood-Pressure的关系 （0.5分），并画出血糖-血压散点图（0.5分）

[19]:
```
diabetes=pd.read_csv('Diabetes.csv')
diabetes.head(5)
```

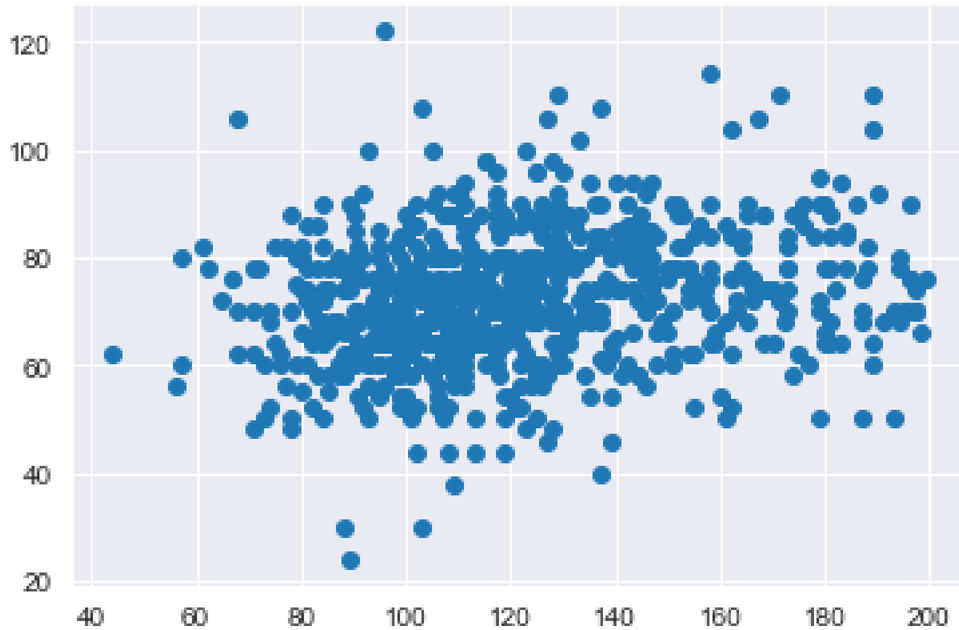
[19]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

[20]:
```
diabetes=diabetes[diabetes['Glucose']!=0]
diabetes=diabetes[diabetes['BloodPressure']!=0]
glu=diabetes['Glucose']
bp=diabetes['BloodPressure']
```

```
plt.scatter(glu,bp)
```

[20]: <matplotlib.collections.PathCollection at 0x1f489300508>



[21]:
```
np.cov(glu,bp)
stats.pearsonr(glu,bp)
```

```
[21]: array([[941.21371888,  84.81198513],
       [ 84.81198513, 153.4157062 ]])
```

```
[21]: (0.223191778249542, 1.138581203805524e-09)
```

pearson’ s r$=0.22$,p$=1.14\times10^{-9}$.该结果显示Glucose与BloodPressure之间没有明显的相关关系。

HW-5-2: 对于Titantic.csv数据（参见前面单元作业），请用分别用pearson r, spearman rho, kendall’ s tau分别计算乘客年龄与买的票的等级的相关系数 (1分)

[22]:
```
titantic=pd.read_csv('Titanic.csv')
titantic.head(5)
titantic=titantic.dropna()
```

```
[22]:                                          Name PClass    Age     Sex  \
0                  Allen, Miss Elisabeth Walton    1st  29.00  female
1                   Allison, Miss Helen Loraine    1st   2.00  female
2           Allison, Mr Hudson Joshua Creighton    1st  30.00    male
3 Allison, Mrs Hudson JC (Bessie Waldo Daniels)    1st  25.00  female
```

```
4                  Allison, Master Hudson Trevor    1st   0.92    male

   Survived
0         1
1         0
2         0
3         0
4         1
```

[23]:
```
age=titantic['Age']
pclass=titantic['PClass']
pclass=pclass.replace(['1st','2nd','3rd'],[1,2,3])
```

[24]:
```
stats.pearsonr(age,pclass)
stats.spearmanr(age,pclass)
stats.kendalltau(age,pclass)
```

[24]:
```
(-0.4141214595264922, 1.0969903610990536e-32)
```

[24]:
```
SpearmanrResult(correlation=-0.39366216507025165, pvalue=1.9756955531661058e-29)
```

[24]:
```
KendalltauResult(correlation=-0.3103724477828569, pvalue=8.600565143832718e-28)
```

以上三个结果的p-value均很小，均反映了Age与PClass之间没有显著的相关关系.

HW-5-3：针对汽车数据mtcars.csv

（1）画出wt~ mpg散点图；用简单线性回归分析mpg（因变量），和wt(自变量）的关系，并根据回归结果中的截距和斜率及其显著性水平（p值),对结果进行解释；并解释Rsquare.（1.5分）

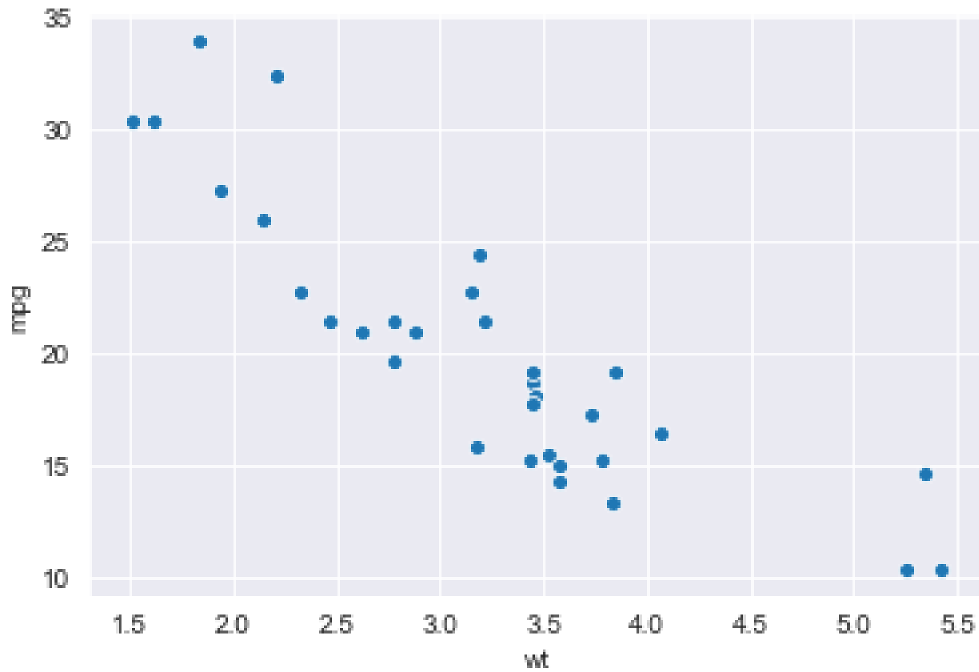
[25]:
```
df=pd.read_csv('mtcars.csv')
df.head(5)
```

[25]:
```
          Unnamed: 0   mpg  cyl   disp   hp  drat     wt   qsec  vs  am  gear  \
0          Mazda RX4  21.0    6  160.0  110  3.90  2.620  16.46   0   1     4
1      Mazda RX4 Wag  21.0    6  160.0  110  3.90  2.875  17.02   0   1     4
2         Datsun 710  22.8    4  108.0   93  3.85  2.320  18.61   1   1     4
3     Hornet 4 Drive  21.4    6  258.0  110  3.08  3.215  19.44   1   0     3
4  Hornet Sportabout  18.7    8  360.0  175  3.15  3.440  17.02   0   0     3

   carb
0     4
1     4
2     1
3     1
4     2
```

[26]:
```
sns.scatterplot(x='wt',y='mpg',data=df)
```

[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f489864948>
```



[27]:
```
result1=smf.ols('mpg~wt',data=df).fit()
result1.summary()
```

[27]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                    mpg   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.745
Method:                 Least Squares   F-statistic:                     91.38
Date:                Tue, 19 May 2020   Prob (F-statistic):           1.29e-10
Time:                        20:04:26   Log-Likelihood:                -80.015
No. Observations:                  32   AIC:                             164.0
Df Residuals:                      30   BIC:                             167.0
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     37.2851      1.878     19.858      0.000      33.450      41.120
wt            -5.3445      0.559     -9.559      0.000      -6.486      -4.203
```

```
==============================================================================
Omnibus:                        2.988   Durbin-Watson:                   1.252
Prob(Omnibus):                  0.225   Jarque-Bera (JB):                2.399
Skew:                           0.668   Prob(JB):                        0.301
Kurtosis:                       2.877   Cond. No.                         12.7
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

回归结果$mpg = -5.3445wt + 37.2851$，截距和斜率的p值均很小，说明截距和斜率均有显著意义.$R^2 = 0.753$说明mpg与wt之间有比较强的线性关系(strong).

（2）用多元线性回归分析mpg（因变量），和wt(自变量）、hp(自变量）的关系，并根据回归结果中的各个自变量的系数及其显著性水平（p值)，　对回归结果进行解释；　并解释R-square（1.5分）

[28]:
```python
result2=smf.ols('mpg~wt+hp',data=df).fit()
result2.summary()
```

[28]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                    mpg   R-squared:                       0.827
Model:                            OLS   Adj. R-squared:                  0.815
Method:                 Least Squares   F-statistic:                     69.21
Date:                Tue, 19 May 2020   Prob (F-statistic):           9.11e-12
Time:                        20:04:26   Log-Likelihood:                -74.326
No. Observations:                  32   AIC:                             154.7
Df Residuals:                      29   BIC:                             159.0
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     37.2273      1.599     23.285      0.000      33.957      40.497
wt            -3.8778      0.633     -6.129      0.000      -5.172      -2.584
hp            -0.0318      0.009     -3.519      0.001      -0.050      -0.013
==============================================================================
Omnibus:                        5.303   Durbin-Watson:                   1.362
Prob(Omnibus):                  0.071   Jarque-Bera (JB):                4.046
Skew:                           0.855   Prob(JB):                        0.132
Kurtosis:                       3.332   Cond. No.                         588.
==============================================================================
```

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

回归结果$mpg = -3.8778wt - 0.0318hp + 37.2273$，三个系数的p值均小于0.05，说明结果具有显著意义。mpg与wt和hp都成负相关，但且wt对mpg的影响要高于hp。

$R^2 = 0.827$, 说明mpg与wt和hp之间有很强的二元线性关系。相比单变量回归，R^2值提高了，结合$Adj-R^2$，也没有出现明显的过拟合现象，因此模型较单变量效果更好。

HW-5-4：mtcars.csv 数据），汽车的离合（am: 手动（1）/自动（0））与汽车的油耗（mpg)，马力（hp)是很相关的，请：

（1）基于全部数据用mpg,hp作为自变量，am作为因变量，建立对应的逻辑回归模型，并作出解释 (1.0分)

[29]:
```python
log_res=smf.logit('am~mpg+hp',data=df).fit()
log_res.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.300509
         Iterations 9
```

[29]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:                     am   No. Observations:                   32
Model:                          Logit   Df Residuals:                       29
Method:                           MLE   Df Model:                            2
Date:                Tue, 19 May 2020   Pseudo R-squ.:                  0.5551
Time:                        20:04:26   Log-Likelihood:                -9.6163
converged:                       True   LL-Null:                       -21.615
Covariance Type:            nonrobust   LLR p-value:                 6.153e-06
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -33.6052     15.077     -2.229      0.026     -63.156      -4.055
mpg            1.2596      0.567      2.220      0.026       0.147       2.372
hp             0.0550      0.027      2.045      0.041       0.002       0.108
==============================================================================

Possibly complete quasi-separation: A fraction 0.12 of observations can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identified.
"""
```

mpg和hp的p值均小于0.05，说明这两者与am均有关联，且mpg在其中占的比重更大。

附加题：（2）将前20条记录作为训练数据，重新建立上面的逻辑回归模型，然后用后12条记录作为测试数据，再对该模型进行测试，并对结果作出解释。

[34]:
```
from sklearn.model_selection import train_test_split
train, test = train_test_split(df, test_size=12/32)
###Normalization
# Assuming same lines from your example
cols_to_norm = "mpg","hp"
train[cols_to_norm] = train[cols_to_norm].apply(lambda x: (x - x.mean()) / (x.
↪std()))
test[cols_to_norm] = test[cols_to_norm].apply(lambda x: (x - x.mean()) / (x.
↪std()))
```

[31]:
```
model=smf.logit('am~mpg+hp',data=train).fit()
model.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.210510
         Iterations 10
```

[31]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:                     am   No. Observations:                   20
Model:                          Logit   Df Residuals:                       17
Method:                           MLE   Df Model:                            2
Date:                Tue, 19 May 2020   Pseudo R-squ.:                  0.6941
Time:                        20:04:26   Log-Likelihood:                -4.2102
converged:                       True   LL-Null:                       -13.763
Covariance Type:            nonrobust   LLR p-value:                 7.102e-05
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.8711      1.363      1.373      0.170      -0.800       4.542
mpg           11.8868      6.970      1.705      0.088      -1.774      25.547
hp             5.6484      3.435      1.644      0.100      -1.084      12.381
==============================================================================

Possibly complete quasi-separation: A fraction 0.30 of observations can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identified.
"""
```

[32]:
```
trainingRes=pd.DataFrame(model.pred_table())
trainingRes.columns=["Predicted Outcome 0","Predicted Outcome 1"]
```

```
trainingRes=trainingRes.rename(index={0:"Actual Outcome 0", 1:"Actually Outcome␣
↪1"})
trainingRes
print("The accuracy for the train data is :",(trainingRes.iloc[1,1]+trainingRes.
↪iloc[0,0])/20)
```

[32]:

	Predicted Outcome 0	Predicted Outcome 1
Actual Outcome 0	8.0	1.0
Actually Outcome 1	1.0	10.0

```
The accuracy for the train data is : 0.9
```

[33]:

```
pred_values = model.predict(test)
bins=np.array([0,0.5,1])
cm = np.histogram2d(test['am'], pred_values, bins=bins)[0]
accuracy = (cm[0,0]+cm[1,1])/cm.sum()
print("The prediction accuracy for the test data is :", accuracy)

testRes=pd.DataFrame(cm)
testRes.columns=["Predicted Outcome 0","Predicted Outcome 1"]
testRes=testRes.rename(index={0:"Actual Outcome 0", 1:"Actually Outcome 1"})
testRes
```

```
The prediction accuracy for the test data is : 0.6666666666666666
```

[33]:

	Predicted Outcome 0	Predicted Outcome 1
Actual Outcome 0	6.0	4.0
Actually Outcome 1	0.0	2.0

从拟合的模型来看，由于训练集较之前规模减小$(32- > 20)$，因此模型精确度有所下降，三个p值均较大，可能存在一定的欠拟合情况。但从结果来看模型效果还不错，训练集的正确率为0.8，测试集的准确率有0.917。