hw5nk_ipynb

September 29, 2024

[1]:
```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

[10]:
```
#Question 1
kbbdata=pd.read_csv('../data/KelleyBlueBookData.csv')
kbbdata.sample(10)
```

[10]:
```
            Price  Mileage       Make        Model             Trim  \
69   21831.82292    25564      Buick  Park Avenue         Sedan 4D
712  30443.87990    15050       SAAB          9_5   Linear Wagon 4D
654  30731.94165    22479       SAAB       9_3 HO      Aero Conv 2D
53   21575.45683    20137      Buick      Lesabre  Limited Sedan 4D
479  20221.80881    26223  Chevrolet  Monte Carlo       SS Coupe 2D
225  11726.00297    23103  Chevrolet     Cavalier          Coupe 2D
333  14194.82360     9561  Chevrolet       Cobalt          Sedan 4D
85   43892.46788    23371   Cadillac        CST-V          Sedan 4D
292  13135.90503    21796  Chevrolet       Cobalt          Coupe 2D
764  14739.06724     1737     Saturn          Ion          Sedan 4D

            Type  Cylinder  Liter  Doors  Cruise  Sound  Leather
69         Sedan         6    3.8      4       1      1        1
712        Wagon         4    2.3      4       1      0        1
654  Convertible         4    2.0      2       1      0        0
53         Sedan         6    3.8      4       1      1        0
479        Coupe         6    3.8      2       1      1        1
225        Coupe         4    2.2      2       0      1        1
333        Sedan         4    2.2      4       0      1        1
85         Sedan         8    5.7      4       1      0        1
292        Coupe         4    2.2      2       1      1        1
764        Sedan         4    2.2      4       0      0        1
```

[3]:
```
kbbdata['Type'] = kbbdata['Type'].astype('category')
kbbdata['Cylinder'] = kbbdata['Cylinder'].astype('category')
kbbdata = sm.add_constant(kbbdata)
```

```python
formula = 'Price ~ Mileage + C(Type) + C(Cylinder) + Liter + Cruise + Sound +␣
  ↪Leather'
model = smf.ols(formula=formula, data=kbbdata).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Price   R-squared:                       0.738
Model:                            OLS   Adj. R-squared:                  0.734
Method:                 Least Squares   F-statistic:                     202.6
Date:                Sun, 29 Sep 2024   Prob (F-statistic):         1.51e-221
Time:                        16:01:02   Log-Likelihood:                -7998.0
No. Observations:                 804   AIC:                         1.602e+04
Df Residuals:                     792   BIC:                         1.608e+04
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
========
                           coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
--------
Intercept             2.943e+04   1608.357     18.300      0.000    2.63e+04
3.26e+04
C(Type)[T.Coupe]     -1.857e+04    874.134    -21.244      0.000   -2.03e+04
-1.69e+04
C(Type)[T.Hatchback] -1.831e+04   1085.146    -16.873      0.000   -2.04e+04
-1.62e+04
C(Type)[T.Sedan]     -1.547e+04    799.994    -19.336      0.000    -1.7e+04
-1.39e+04
C(Type)[T.Wagon]     -9452.1225   1000.020     -9.452      0.000   -1.14e+04
-7489.120
C(Cylinder)[T.6]      1360.1311   1075.453      1.265      0.206    -750.943
3471.205
C(Cylinder)[T.8]      1.416e+04   1959.004      7.231      0.000    1.03e+04
1.8e+04
Mileage                 -0.1871      0.022     -8.505      0.000      -0.230
-0.144
Liter                 1115.8414    621.236      1.796      0.073    -103.622
2335.305
Cruise                4650.7921    473.626      9.820      0.000    3721.081
5580.504
Sound                   14.7921    404.338      0.037      0.971    -778.909
808.493
Leather               1677.9449    433.225      3.873      0.000     827.541
2528.349
==============================================================================
Omnibus:                       50.373   Durbin-Watson:                   0.341
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               68.521
Skew:                           0.531   Prob(JB):                     1.32e-15
Kurtosis:                       3.958   Cond. No.                     3.17e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.17e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[11]:
```python
full_model = smf.ols(formula='Price ~ Mileage + C(Type) + C(Cylinder) + Liter +
 ↪Cruise + Sound + Leather', data=kbbdata).fit()

reduced_model = smf.ols(formula='Price ~ Mileage + C(Type) + Liter + Cruise +
 ↪Sound + Leather', data=kbbdata).fit()

anova_results = sm.stats.anova_lm(reduced_model, full_model)

print("ANOVA Results for the F-test:")
print(anova_results)
```

```
ANOVA Results for the F-test:
   df_resid           ssr  df_diff        ss_diff           F        Pr(>F)
0     794.0  2.592209e+10      0.0            NaN         NaN           NaN
1     792.0  2.057353e+10      2.0   5.348559e+09  102.949252  1.807044e-40
```

[12]:
```python
# Question 2
iccdata=pd.read_csv('../data/IceCreamConsumption.csv')
iccdata.sample(10)
```

[12]:

	cons	income	price	temp	time
24	0.309	95	0.282	28	25
11	0.298	85	0.270	26	12
8	0.269	76	0.265	32	9
27	0.416	96	0.265	52	28
18	0.386	84	0.277	67	19
7	0.288	79	0.267	47	8
16	0.470	80	0.280	72	17
0	0.386	78	0.270	41	1
17	0.443	78	0.277	72	18
20	0.319	85	0.292	44	21

[13]:
```python
predictor_corr = iccdata[['income', 'price', 'temp']].corr()
print('Predictor Correlations:')
print(predictor_corr)
```

```
Predictor Correlations:
          income     price      temp
```

```
income   1.000000 -0.107479 -0.324709
price   -0.107479  1.000000 -0.108206
temp    -0.324709 -0.108206  1.000000
```

[15]:
```python
from statsmodels.formula.api import ols

def regression_model(predictors, data):
    formula = 'cons ~ ' + ' + '.join(predictors)
    model = ols(formula, data=data).fit()
    coefs = model.params
    std_errs = model.bse
    return coefs, std_errs

coefs_income, std_errs_income = regression_model(['income'], iccdata)
coefs_price, std_errs_price = regression_model(['price'], iccdata)
coefs_temp, std_errs_temp = regression_model(['temp'], iccdata)


coefs_all, std_errs_all = regression_model(['income', 'price', 'temp'], iccdata)

print(f"Coefficient for income (individual): {coefs_income['income']:.4f},␣
 ↪Standard Error: {std_errs_income['income']:.4f}")
print(f"Coefficient for price (individual): {coefs_price['price']:.4f},␣
 ↪Standard Error: {std_errs_price['price']:.4f}")
print(f"Coefficient for temp (individual): {coefs_temp['temp']:.4f}, Standard␣
 ↪Error: {std_errs_temp['temp']:.4f}")

print(f"Coefficient for income (multiple): {coefs_all['income']:.4f}, Standard␣
 ↪Error: {std_errs_all['income']:.4f}")
print(f"Coefficient for price (multiple): {coefs_all['price']:.4f}, Standard␣
 ↪Error: {std_errs_all['price']:.4f}")
print(f"Coefficient for temp (multiple): {coefs_all['temp']:.4f}, Standard␣
 ↪Error: {std_errs_all['temp']:.4f}")
```

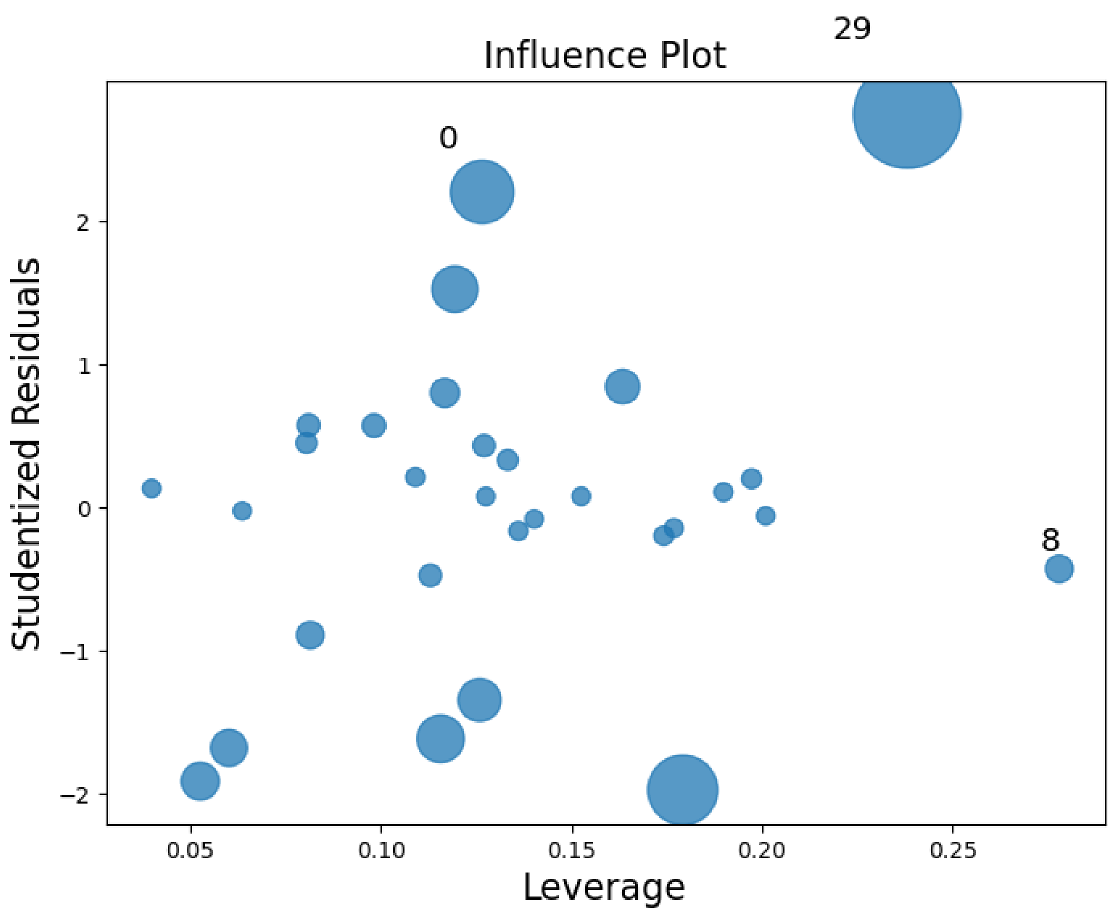
```
Coefficient for income (individual): 0.0005, Standard Error: 0.0020
Coefficient for price (individual): -2.0472, Standard Error: 1.4393
Coefficient for temp (individual): 0.0031, Standard Error: 0.0005
Coefficient for income (multiple): 0.0033, Standard Error: 0.0012
Coefficient for price (multiple): -1.0444, Standard Error: 0.8344
Coefficient for temp (multiple): 0.0035, Standard Error: 0.0004
```

[16]:
```python
def calculate_vif(target_predictor, data):
    predictors = ['income', 'price', 'temp']
    other_predictors = [p for p in predictors if p != target_predictor]
    formula = f"{target_predictor} ~ " + ' + '.join(other_predictors)
    model = ols(formula, data=data).fit()
    r_squared = model.rsquared
    vif = 1 / (1 - r_squared)
```

```
    return vif

vif_income = calculate_vif('income', iccdata)
vif_price = calculate_vif('price', iccdata)
vif_temp = calculate_vif('temp', iccdata)

print(f"VIF for income: {vif_income:.4f}")
print(f"VIF for price: {vif_price:.4f}")
print(f"VIF for temp: {vif_temp:.4f}")
```

```
VIF for income: 1.1442
VIF for price: 1.0357
VIF for temp: 1.1444
```

[17]:
```
model = smf.ols('cons ~ income + price + temp', data=iccdata).fit()

fig, ax = plt.subplots(figsize=(8, 6))
sm.graphics.influence_plot(model, ax=ax, criterion="cooks")

plt.show()
```



[19]:
```python
# Question 3
bpdata=pd.read_csv('../data/BrandPreference.csv')
bpdata.sample(10)
```

[19]:

	BrandLiking	MoistureContent	Sweetness
3	76	4	4
8	83	8	2
10	86	8	2
9	89	8	4
1	73	4	4
11	93	8	4
5	80	6	4
7	83	6	4
13	95	10	4
12	88	10	2

[20]:
```python
model = smf.ols('BrandLiking ~ MoistureContent + Sweetness', data=bpdata).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            BrandLiking   R-squared:                       0.952
Model:                            OLS   Adj. R-squared:                  0.945
Method:                 Least Squares   F-statistic:                     129.1
Date:                Sun, 29 Sep 2024   Prob (F-statistic):           2.66e-09
Time:                        16:38:04   Log-Likelihood:                -36.894
No. Observations:                  16   AIC:                             79.79
Df Residuals:                      13   BIC:                             82.11
Df Model:                           2
Covariance Type:            nonrobust
================================================================================
===
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---
Intercept          37.6500      2.996     12.566      0.000      31.177
44.123
MoistureContent     4.4250      0.301     14.695      0.000       3.774
5.076
Sweetness           4.3750      0.673      6.498      0.000       2.920
5.830
==============================================================================
Omnibus:                        0.766   Durbin-Watson:                   2.313
Prob(Omnibus):                  0.682   Jarque-Bera (JB):                0.647
Skew:                           0.049   Prob(JB):                        0.724
```

```
Kurtosis:                       2.020   Cond. No.                        35.9
==============================================================================

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

```
/opt/homebrew/anaconda3/lib/python3.12/site-
packages/scipy/stats/_axis_nan_policy.py:531: UserWarning: kurtosistest only
valid for n>=20 … continuing anyway, n=16
  res = hypotest_fun_out(*samples, **kwds)
```

[22]:

```
fitted_value_first_obs = model.fittedvalues[0]

fitted_value_first_obs
```

[22]: 64.1

[24]:

```
X = model.model.exog
y = model.model.endog

hat_matrix = X @ np.linalg.inv(X.T @ X) @ X.T

h_first_row = hat_matrix[0, :]

fitted_value_hat_matrix = np.sum(h_first_row * y)

fitted_value_hat_matrix
```

[24]: 64.10000000000026

[25]:

```
hat_matrix
```

[25]:

```
array([[ 0.2375,  0.1125,  0.2375,  0.1125,  0.1625,  0.0375,  0.1625,
         0.0375,  0.0875, -0.0375,  0.0875, -0.0375,  0.0125, -0.1125,
         0.0125, -0.1125],
       [ 0.1125,  0.2375,  0.1125,  0.2375,  0.0375,  0.1625,  0.0375,
         0.1625, -0.0375,  0.0875, -0.0375,  0.0875, -0.1125,  0.0125,
        -0.1125,  0.0125],
       [ 0.2375,  0.1125,  0.2375,  0.1125,  0.1625,  0.0375,  0.1625,
         0.0375,  0.0875, -0.0375,  0.0875, -0.0375,  0.0125, -0.1125,
         0.0125, -0.1125],
       [ 0.1125,  0.2375,  0.1125,  0.2375,  0.0375,  0.1625,  0.0375,
         0.1625, -0.0375,  0.0875, -0.0375,  0.0875, -0.1125,  0.0125,
        -0.1125,  0.0125],
       [ 0.1625,  0.0375,  0.1625,  0.0375,  0.1375,  0.0125,  0.1375,
         0.0125,  0.1125, -0.0125,  0.1125, -0.0125,  0.0875, -0.0375,
         0.0875, -0.0375],
```

```
[ 0.0375,  0.1625,  0.0375,  0.1625,  0.0125,  0.1375,  0.0125,
  0.1375, -0.0125,  0.1125, -0.0125,  0.1125, -0.0375,  0.0875,
 -0.0375,  0.0875],
[ 0.1625,  0.0375,  0.1625,  0.0375,  0.1375,  0.0125,  0.1375,
  0.0125,  0.1125, -0.0125,  0.1125, -0.0125,  0.0875, -0.0375,
  0.0875, -0.0375],
[ 0.0375,  0.1625,  0.0375,  0.1625,  0.0125,  0.1375,  0.0125,
  0.1375, -0.0125,  0.1125, -0.0125,  0.1125, -0.0375,  0.0875,
 -0.0375,  0.0875],
[ 0.0875, -0.0375,  0.0875, -0.0375,  0.1125, -0.0125,  0.1125,
 -0.0125,  0.1375,  0.0125,  0.1375,  0.0125,  0.1625,  0.0375,
  0.1625,  0.0375],
[-0.0375,  0.0875, -0.0375,  0.0875, -0.0125,  0.1125, -0.0125,
  0.1125,  0.0125,  0.1375,  0.0125,  0.1375,  0.0375,  0.1625,
  0.0375,  0.1625],
[ 0.0875, -0.0375,  0.0875, -0.0375,  0.1125, -0.0125,  0.1125,
 -0.0125,  0.1375,  0.0125,  0.1375,  0.0125,  0.1625,  0.0375,
  0.1625,  0.0375],
[-0.0375,  0.0875, -0.0375,  0.0875, -0.0125,  0.1125, -0.0125,
  0.1125,  0.0125,  0.1375,  0.0125,  0.1375,  0.0375,  0.1625,
  0.0375,  0.1625],
[ 0.0125, -0.1125,  0.0125, -0.1125,  0.0875, -0.0375,  0.0875,
 -0.0375,  0.1625,  0.0375,  0.1625,  0.0375,  0.2375,  0.1125,
  0.2375,  0.1125],
[-0.1125,  0.0125, -0.1125,  0.0125, -0.0375,  0.0875, -0.0375,
  0.0875,  0.0375,  0.1625,  0.0375,  0.1625,  0.1125,  0.2375,
  0.1125,  0.2375],
[ 0.0125, -0.1125,  0.0125, -0.1125,  0.0875, -0.0375,  0.0875,
 -0.0375,  0.1625,  0.0375,  0.1625,  0.0375,  0.2375,  0.1125,
  0.2375,  0.1125],
[-0.1125,  0.0125, -0.1125,  0.0125, -0.0375,  0.0875, -0.0375,
  0.0875,  0.0375,  0.1625,  0.0375,  0.1625,  0.1125,  0.2375,
  0.1125,  0.2375]])
```