Effect_of_Beauty_on_Course_Ratings

September 14, 2023

[99]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import math
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.model_selection import train_test_split, GridSearchCV, KFold,␣
↪cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import classification_report
```

[100]:
```python
# Creating a function to print output in green and bold
# ANSI escape code for green color and bold font
GREEN_BOLD = '\033[1;32m'

# ANSI escape code to reset colors and font style
RESET = '\033[0m'

def print_green_bold(*args):
    text = ' '.join(str(arg) for arg in args)
    print(GREEN_BOLD + text + RESET)
```

1 Beauty Pays!

Professor Daniel Hamermesh from UT's economics department has been studying the impact of beauty in labor income (yes, this is serious research!!). First, watch the following video: http://thedailyshow.cc.com/videos/37su2t/ugly-people-prejudice It turns out this is indeed serious research and Dr. Hamermesh has demonstrated the effect of beauty into income in a variety of different situations. Here's an example: in the paper "Beauty in the Classroom" they showed that "…instructors who are viewed as better looking receive higher instructional ratings" leading to a direct impact in the salaries in the long run. By now, you should know that this is a hard effect to measure. Not only one has to work hard to figure out a way to measure "beauty" objectively (well, the video said it all!) but one also needs to "adjust for many other determinants" (gender, lower division class, native language, tenure track status). The data is in the file "BeautyData.csv" and contains for a number of UT classes, course

ratings, a relative measure of beauty for the instructors, and other potentially relevant variables.

1. Using the data, estimate the effect of "beauty" into course ratings. Make sure to think about the potential many "other determinants". Describe your analysis and your conclusions.

[167]:
```
beauty=pd.read_csv('BeautyData.csv')
beauty.head(20)
```

[167]:

	CourseEvals	BeautyScore	female	lower	nonenglish	tenuretrack
0	3.235245	0.201567	1	0	0	1
1	3.226328	-0.826081	0	0	0	1
2	3.647712	-0.660333	0	0	0	1
3	3.372062	-0.766312	1	0	0	1
4	4.292705	1.421445	1	0	0	1
5	4.239140	0.500220	0	0	0	1
6	3.005187	-0.214350	1	0	0	1
7	3.842654	-0.346539	1	0	0	1
8	3.547257	0.061344	1	0	0	1
9	4.448234	0.452568	0	0	0	0
10	3.785277	0.143264	0	0	1	1
11	3.510400	-0.155023	0	0	0	0
12	4.044416	0.128543	0	0	0	1
13	3.398674	-0.347045	0	0	1	1
14	4.247372	0.461939	1	0	0	1
15	3.727991	-0.150385	0	0	0	1
16	2.778554	-1.070734	1	0	0	0
17	3.381657	-0.142693	0	1	0	0
18	3.807480	-0.156363	1	0	0	1
19	3.723180	-0.058935	1	0	0	0

To estimate the impact of beauty on course ratings, we first run an individual regression with only BeautyScore as the independent variable. In the next step, we run a multiple regression with all variables except CourseEvals as the independent variables.

[168]:
```
# Separate the predictor (independent) and target (dependent) variables
X_beauty = beauty['BeautyScore']
y_beauty = beauty['CourseEvals']

# Add a constant term for the intercept in the simple linear regression
X_beauty = sm.add_constant(X_beauty)

# Create the simple linear regression model
lr_model_beauty = sm.OLS(y_beauty, X_beauty)

# Fit the model to the data
lr_result_beauty = lr_model_beauty.fit()
```

```python
# Print the regression results summary
print_green_bold(lr_result_beauty.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            CourseEvals   R-squared:                       0.166
Model:                            OLS   Adj. R-squared:                  0.164
Method:                 Least Squares   F-statistic:                     91.57
Date:                Sun, 30 Jul 2023   Prob (F-statistic):           6.57e-20
Time:                        15:24:35   Log-Likelihood:                -317.00
No. Observations:                 463   AIC:                             638.0
Df Residuals:                     461   BIC:                             646.3
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const           3.7134      0.022    165.119      0.000       3.669       3.758
BeautyScore     0.2715      0.028      9.569      0.000       0.216       0.327
==============================================================================
Omnibus:                        0.692   Durbin-Watson:                   1.812
Prob(Omnibus):                  0.708   Jarque-Bera (JB):                0.795
Skew:                          -0.048   Prob(JB):                        0.672
Kurtosis:                       2.821   Cond. No.                         1.29
==============================================================================

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

The above regression model shows that there is a statistically significant positive relationship between BeautyScore and CourseEvals. For each one-unit increase in BeautyScore, the CourseEvals is estimated to increase by 0.2715 units on average. However, the R-squared value of 0.166 suggests that only about 16.6% of the variance in CourseEvals can be explained by the BeautyScore. The low R-squared value indicates that BeautyScore alone may not be a strong predictor of course ratings, and there might be other factors influencing the course evaluations.

[169]:
```
# New set of independent variables
X_beauty_new = beauty[['BeautyScore', 'female', 'lower', 'nonenglish',␣
↪'tenuretrack']]

# Add a constant term for the intercept in the multiple linear regression
X_beauty_new = sm.add_constant(X_beauty_new)

# Create the multiple linear regression model
mlr_model_beauty = sm.OLS(y_beauty, X_beauty_new)

# Fit the model to the data
mlr_result_beauty = mlr_model_beauty.fit()

# Print the regression results summary
print_green_bold(mlr_result_beauty.summary())
```

```
                          OLS Regression Results
==============================================================================
Dep. Variable:            CourseEvals   R-squared:                       0.347
Model:                            OLS   Adj. R-squared:                  0.340
Method:                 Least Squares   F-statistic:                     48.58
Date:                Sun, 30 Jul 2023   Prob (F-statistic):           2.71e-40
Time:                        15:24:38   Log-Likelihood:                -260.27
No. Observations:                 463   AIC:                             532.5
Df Residuals:                     457   BIC:                             557.4
Df Model:                           5
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const           4.0654      0.051     79.020      0.000       3.964       4.167
BeautyScore     0.3041      0.025     11.959      0.000       0.254       0.354
female         -0.3320      0.041     -8.146      0.000      -0.412      -0.252
lower          -0.3426      0.043     -7.999      0.000      -0.427      -0.258
nonenglish     -0.2581      0.085     -3.044      0.002      -0.425      -0.091
tenuretrack    -0.0995      0.049     -2.035      0.042      -0.195      -0.003
==============================================================================
Omnibus:                        0.881   Durbin-Watson:                   2.094
Prob(Omnibus):                  0.644   Jarque-Bera (JB):                0.983
Skew:                          -0.075   Prob(JB):                        0.612
Kurtosis:                       2.831   Cond. No.                         6.06
==============================================================================

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

The coefficient of BeautyScore (0.3041) is still statistically significant and indicates that for each one-unit increase in BeautyScore, the CourseEvals is estimated to increase by 0.3041 units on average, controlling for the other variables in the model. In addition, the absolute value of the coefficient has actually increased.

The other predictor variables (female, lower, nonenglish, and tenuretrack) have negative coefficients, suggesting that, on average, they are associated with lower course evaluations. The pvalues indicate that female, lower and nonenglish are statistically significant at 5% level. The R-squared value of 0.347 suggests that this model explains about 34.7% of the variance in CourseEvals, which is an improvement compared to the previous model. Overall, based on these regression models, we can conclude that BeautyScore seems to have a positive effect on course ratings.

2.In his paper, Dr. Hamermesh has the following sentence:"Disentangling whether this outcome represents productivity or discrimination is, as with the issue generally,probably impossible". Using the concepts we have talked about so far,what does he mean by that?

When Dr. Hamermesh talks about productivity and discrimination, he's referring to two competing theories that could explain the relationship observed in his regression analyses -

- Productivity: In the context of this study, the productivity hypothesis suggests that an instructor's physical attractiveness (BeautyScore) contributes positively to their teaching effectiveness, thereby resulting in higher CourseEvals. This is one interpretation of the positive coefficient on BeautyScore in both regression models.
- Discrimination: The discrimination theory posits that students, either consciously or unconsciously, rate instructors they perceive as more attractive with higher CourseEvals. This has nothing do with the instructors' competence levels and is borne out of an inherent favourable bias towards physical attractiveness.
- Dr. Hamermesh's statement highlights that this is a problem of disentangling correlation from causation. While both regression models show a positive relationship between BeautyScore and CourseEvals, it's hard to definitively say if this is due to productivity or discrimination.
- From a statistical perspective, we can't directly observe either of the two. Adding other covariates in the model, such as female, lower, nonenglish, and tenuretrack, controls for potential confounding effects, but the inherent unobservability of effectiveness and bias prevents us from definitively attributing the effect on CourseEvals to productivity or discrimination.

Therefore, Dr. Hamermesh's comment reflects on the inherent difficulty in parsing out these effects.

```
[ ]:
```