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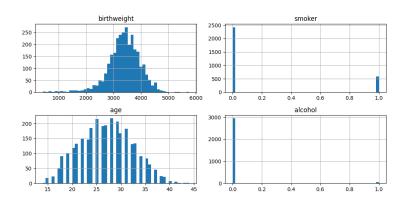
Statistical Methods and Data Analysis (EN.625.603) Project 2

Question 1

Get to know your data. Make histograms and summary statistics of your data to get a sense of distributions.

(a) What is the average value of birthweight for mothers who smoke? For mothers who don't smoke?

Solution



	birthweight	smoker	age	alcohol
coun	t 3000.000000	3000.000000	3000.000000	3000.000000
mean	3382.933667	0.194000	26.889000	0.019333
std	592.162889	0.395495	5.362487	0.137717
min	425.000000	0.000000	14.000000	0.000000
25%	3062.000000	0.000000	23.000000	0.000000
50%	3420.0000000	0.000000	27.000000	0.000000
75%	3750.000000	0.000000	31.000000	0.000000
max	5755.000000	1.000000	44.000000	1.000000
smok				
0	3432.059967			
ĭ	3178.831615			
	31701031013			

From Python and Pandas, we can see that the average value of birthweight for mothers who smoke is 3178.83 and for mothers who don't smoke is 3432.06.

Question 2

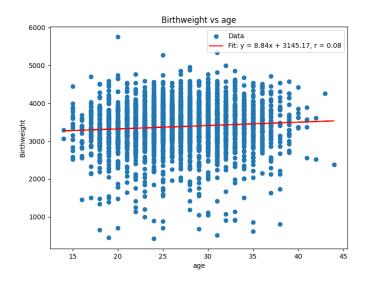
Consider associations. Plot each predictor (variables 2 through 11 in the pdf data description) against the response (birthweight). You could also do a quick line fit or get its correlation. Correlation is with "cor()". A line fit can be achieved using the linear model function. Try for regressions 2 through 11.

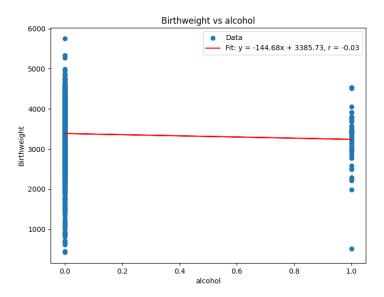
(a) What does a regression of birthweight on the binary variable smoker suggest about the relationship between maternal smoking and infant birthweight?

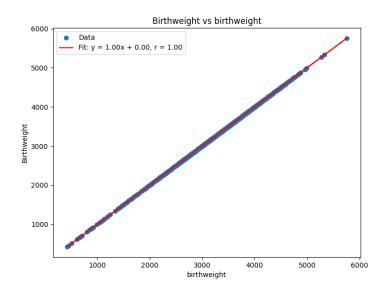
- (b) Do you think the regression above accurately captures the impact of smoking on birthweight? (Consider the assumptions of the linear regression model and whether they are met. Hint: do you think smoking is uncorrelated with other factors that cause low birthweight?)
- (c) Regress birthweight on smoker, alcohol, and nprevist. Explain why the exclusion of these variables could lead to a biased regression coefficient in (a) above. Is the estimated effect of smoking on birthweight substantially different from the regression in (a) above?
- (d) Jane smoked during her pregnancy, did not drink alcohol, and had 8 prenatal care visits. Use the regression in (c) to predict the birthweight of Jane's infant.

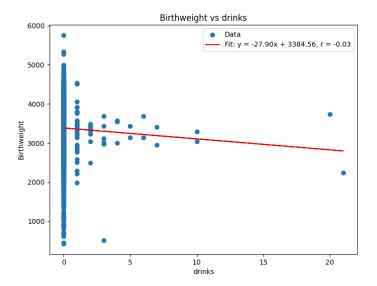
Solution

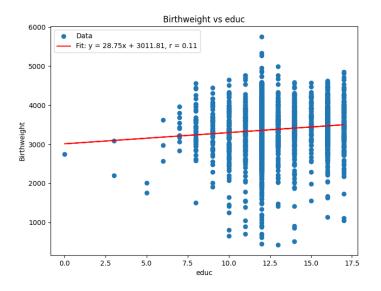
All plots and regression lines and fitting model for each predictor against birthweight are shown below.

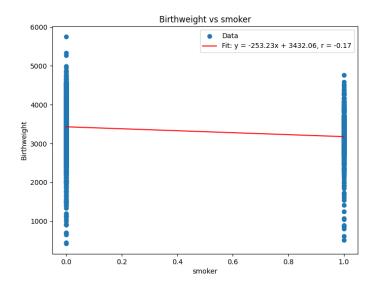


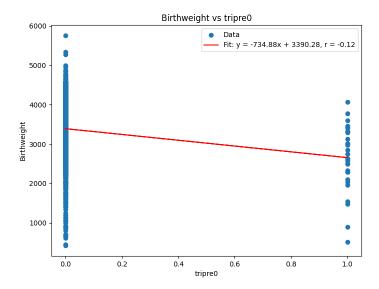


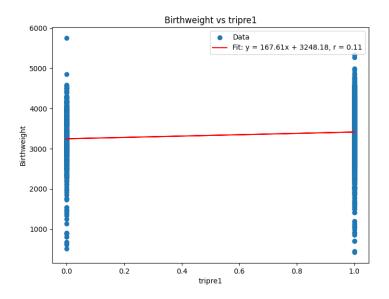


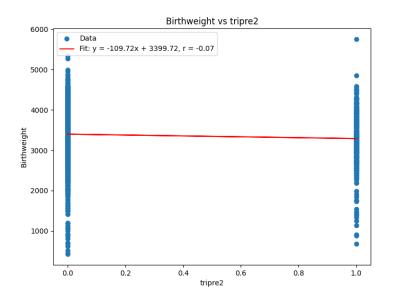


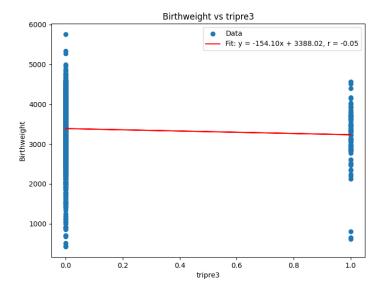


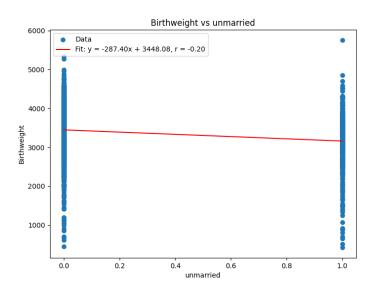










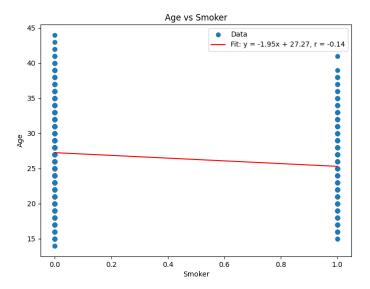


(a) The fitting model for the regression of birthweight on the binary variable smoker is

birthweight =
$$3369.58 - 254.47 \times \text{smoker}$$

The regression suggests that the birthweight of infants whose mothers smoke is 254.47 grams less than the birthweight of infants whose mothers don't smoke.

(b) It might not be accurate because the assumptions of the linear regression model might not be met. For example, smoking might be correlated with other factors that cause low birthweight, one example is age of mother. The younger the mother is, the more likely she is to smoke and the more likely her infant is to have low birthweight. Plot and regression line and fitting model of age of mother against birthweight are shown below



(c) Regressing birthweight on smoker, alcohol, and nprevist, we have

birthweight =
$$3051.2486 - 217.5801 \times \text{smoker} - 30.4913 \times \text{alcohol} + 34.0699 \times \text{nprevist}$$

The exclusion of these variables could lead to a biased regression coefficient in (a) above because

- i. The estimated effect of smoking on birthweight is -254.47 grams if regress birthweight against smoker only
- ii. The estimated effect of smoking on birthweight is -217.58 grams if regress birthweight against smoker, alcohol, and nprevist

And the estimated effect of smoking on birthweight is substantially different.

Dep. Variable: Hodel: Hethod: Date: Time: Hode:	birthweight OLS Least Squares Wed, 16 Aug 2033 04:35:45 3000 2996 3 nonrobust	Adj. I F-sta Prob	ared: R-squared: tistic: (F-statisti ikelihood:	c):	0.073 0.072 78.47 7.31e-49 -23294. 4.660e+04 4.662e+04
CO	ef std err	t	P> t	[0.025	0.975]
const 3051.24 smoker -217.58 alcohol -30.49 previst 34.06	01 26.680 · 13 76.234 ·	89.701 -8.155 -0.400 11.933	0.000 0.000 0.689 0.000	2984.552 -269.892 -179.968 28.472	
mnibus: rob(Omnibus): kew: urtosis:	374.095 0.000 -0.729 5.197	Jarque Prob(.		:	1.974 869.220 1.78e-189 85.2

(d) Jane smoked, did not drink alcohol and had 8 prenatal care visits. Her infant's birthweight is

birthweight =
$$3051.2486 - 217.5801 \times 1 - 30.4913 \times 0 + 34.0699 \times 8$$

= 3106.2277

Question 3

An alternative way to control for prenatal visits is to use binary variables tripre0 through tripre3. Regress birthweight on smoker, alcohol, tripre0, tripre2, and tripre3.

- (a) Why is tripre1 excluded from the model? What happens if you include it in the regression?
- (b) The estimated coefficient on tripre0 is large and negative. What does this coefficient measure? Interpret its value.
- (c) Interpret the value of the estimated coefficients on tripre2 and tripre3.
- (d) Does the regression in (3) explain a larger fraction of the variance in birthweight than the regression in (2c)? (Hint: consider R^2 .)

Solution

The fitting model for the regression of birthweight on smoker, alcohol, tripre0, tripre2, is as follows

ep. Variat odel: ethod: ate: ime:		Least Squa Wed, 16 Aug 2 05:02	OLS Adj. res F-st 023 Prob :33 Log-	uared: R-squared: atistic: (F-statisti Likelihood:	.c):	0.046 0.045 29.18 5.20e-29 -23336.
o. Observa f Residual f Model: ovariance	ls:		000 AIC: 994 BIC: 5 ust			4.668e+04 4.672e+04
	coe	f std err	t	P> t	[0.025	0.975]
onst moker lcohol ripre0 ripre2 ripre3	3454.549 -228.847 -15.100 -697.968 -100.837 -136.955	6 27.165 0 77.541 7 106.876 3 29.619	273.077 -8.424 -0.195 -6.531 -3.404 -2.299	0.000 0.000 0.846 0.000 0.001 0.022	3429.745 -282.111 -167.138 -907.526 -158.913 -253.780	3479.354 -175.584 136.938 -488.411 -42.762 -20.131
nibus: ob(Omnibu ew: rtosis:	ıs):	-0.	000 Jarq 811 Prob	in-Watson: ue-Bera (JB) (JB): . No.	:	1.976 1157.634 4.20e-252 10.5

(a) tripre1 is excluded from the model because it is a linear combination of tripre0, tripre2, and tripre3. If we include it in the regression, the regression would be perfect multicollinearity overparameterized on tripre0, tripre1, tripre2, and tripre3.

		-		
	tripre0	tripre1	tripre2	tripre3
count	3000.000000	3000.000000	3000.000000	3000.000000
mean	0.010000	0.804000	0.153000	0.033000
std	0.099515	0.397035	0.360048	0.178666
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	1.000000	0.000000	0.000000
50%	0.000000	1.000000	0.000000	0.000000
75%	0.000000	1.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

As showing in the figure above

$$\overline{tripre1} = 1 - \overline{tripre0} - \overline{tripre2} - \overline{tripre3}$$

- (b) The estimated coefficient on tripre0 is large and negative. This coefficient measures the difference in birthweight between infants whose mothers had no prenatal visits and infants whose mothers had one or more prenatal visit. The difference is 698 grams which is very substantial. This suggests that prenatal visits has strong positive linear relationship with infant's birthweight.
 - By common sense, having no prenatal visits could mean that the pregnant mother is not aware of the importance of prenatal visits, or she is not able to afford, both of which could be strong signs of not having enough resources to support the infant's growth.
- (c) The estimated coefficients on tripre2, tripre3 are -100.84 and -136.96 respectively. These coefficients measure the difference in birthweight between infants whose mothers had first prenatal visit in the second/third trimester and infants whose mothers had first prenatal visit in the first trimester or none. It suggests that the earlier the mother has her first prenatal visit, the more likely her infant is to have higher birthweight.
- (d) R^2 in (2c) is 0.073, while R^2 in (3) is 0.046. The regression in (2c) explains a larger fraction of the variance in birthweight than the regression in (3).

Question 4

Consider adding an additional regressor: Regress birthweight on smoker, alcohol, nprevist, and unmarried.

- (a) Compare the coefficient on smoker in this regression to the coefficients on smoker in regressions (2a) and (2c). What is the estimated effect of smoking on birthweight in each regression?
- (b) Interpret differences in estimated effects.
- (c) Interpret the estimated effect of marital status on birthweight. Is the coefficient on unmarried statistically significant? Is the magnitude of the coefficient large?
- (d) A family advocacy group notes that the large coefficient suggests that public policies that encourage marriage will lead, on average, to healthier babies. Do you agree? (Hint: consider some of the various factors that unmarried may be controlling for and how this affects the interpretation of this coefficient).

Solution

The fitting model for the regression of birthweight on smoker, alcohol, nprevist, and unmarried is as follows

Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model:	tions:		Least Wed, 16	Square	.S 25 23 20	Adj. F-sta Prob	Jared: R-squared: atistic: (F-statistic ikelihood:):	0.08 0.08 72.79 6.12e-59 -23268 4.655e+0
Covariance		coef	no std (onrobus			P> t	[0.025	 0.9751
const	3134.					.907		3064.487	
smoker	-175.	3769	27.0	099	-6	.472	0.000	-228.511	-122.243
alcohol	-21.	0835	75.0	607	-0.	.279	0.780	-169.331	127.164
nprevist	29.	6025	2.	898	10.	.213	0.000	23.920	35.286
inmarried	-187.	1332	26.0	007	-7	195	0.000	-238.128	-136.139
 mnibus:				369.86	51	Durb	in-Watson:		1.967
Prob(Omnibu	s):			0.00	00	Jarqu	ue-Bera (JB):		880.870
Skew:				-0.71	L4	Prob			5.27e-192
Kurtosis:				5.23	38	Cond	. No.		85.2

- (a) Smoker coefficient in this regression is -175.38, while smoker coefficient in (2a) is -254.47 and smoker coefficient in (2c) is -217.58. The estimated effect
 - i. In (2a) is lowering birthweight by 254.47 grams
 - ii. In (2c) is lowering birthweight by 217.58 grams
 - iii. In this regression is lowering birthweight by 175.38 grams
- (b) Smoker coefficient in this regression is less significant than smoker coefficient in (2a) and (2c). This suggests that the estimated effect of smoking on birthweight is less significant in this regression than in (2a) and (2c), this is because the effect of smoking on birthweight is confounded by unmarried in this regression. A possible explanation is that unmarried mothers are more likely to smoke than married mothers, and unmarried mothers are more likely to have lower birthweight infants than married mothers. Therefore, the estimated effect of smoking on birthweight is less significant in this regression than in (2a) and (2c).
- (c) The coefficient on unmarried is statistically significant because p-value is less than 0.05. The magnitude of the coefficient is -187 which is very large because it would put the infant's birth-weight at 0.31 standard deviations below the mean, if the birthweight is normally distributed.
- (d) Although the coefficient of unmarried is large and its effects on lowering birthweight is statistically significant. We can't conclude that public policies that encourage marriage will lead, on average, to healthier babies. Because, unmarried could have strong positive linear relationship with other regressors, such as smoking, alcohol, and nprevist which are all negatively correlated with birthweight.

Question 5

Consider the other coefficients in this data set. Which do you think should be included in the regression?

- (a) Try adding in some of these additional variables. Share your findings and conclusions.
- (b) The data set includes babies born in Pennsylvania in 1989. Discuss the external validity of your analysis for: (i) California in 1989, (ii) Illinois in 2015, (iii) South Korea in 2014.
- (c) Overall, explain your conclusions on how maternal smoking impacts birthweight (hint: the regressions you're running should be helping you see that isolating the causal effect of smoking on birthweight is difficult because there are a lot of other confounding variables).

Solution

Considering that age and education were not considered in the previous regressions, I am adding them in a new regression.

The fitting model for the regression of birthweight on age and education is as follows

Dep. Variabl Model: Method: Date: Time: No. Observat Df Residuals Df Model: Covariance T	ions:		Least Squa Wed, 16 Aug 20 05:46	DLS res 023 :59 000 997 2	F-sta Prob	ared: R-squared: tistic: (F-statistic ikelihood:):	0.012 0.012 18.88 7.11e-09 -23389. 4.678e+04 4.680e+04
		coef	std err		t	P> t	[0.025	0.975]
const age educ		9689 5724 7095	70.840 2.239 5.542	2	.699 .042 .278	0.000 0.041 0.000	2815.069 0.182 12.843	
Dmnibus: Prob(Omnibus Skew: Curtosis:):		-0.8	814 000 819 575				1.971 1163.955 1.78e-253 200.

- (a) The p-value of age is 0.041 which indicates that age has statistically significant effect on birth-weight. For each year older the mother is, the infant's birthweight increases by 4.58 grams. The p-value of education is 0.000 which indicates that education has statistically significant effect on birthweight. For each year of education the mother has, the infant's birthweight increases by 23.71
- (b) i. Applying the analysis of this dataset Pennsylvania in 1989 to California in 1989 could be valid because the data is collected from the same year and the same country. Thus, the culture and the environment are similar, and the effect of unmarried, smoker, alcohol, and nprevist on birthweight should be similar.
 - ii. Applying the analysis of this dataset Pennsylvania in 1989 to Illinois in 2015 will not be valid because the data is collected by two points in time and the difference is almost 30 years. Thus, the culture and the environment have changed a lot.
 - iii. Applying the analysis of this dataset Pennsylvania in 1989 to South Korea in 2014 will be absolutely invalid, the culture and the environment are totally different. Smoker, alcohol, age could even have positive linear relationship with birthweight in South Korea.
- (c) Maternal smoking has negative linear relationship with birthweight. However, isolating the causal effect of smoking on birthweight is difficult because there are a lot of other confounding

variables. For example, unmarried, alcohol, age, and education are all confounding variables. The estimated effect of smoking on birthweight is less significant in the regression of birthweight on smoker, alcohol, nprevist, and unmarried than in the regression of birthweight on smoker, alcohol, and nprevist. This is because unmarried is confounding the effect of smoking on birthweight. A possible explanation is that unmarried mothers are more likely to smoke than married mothers, and unmarried mothers are more likely to have lower birthweight infants than married mothers. Therefore, the estimated effect of smoking on birthweight is less significant in the regression of birthweight on smoker, alcohol, nprevist, and unmarried than in the regression of birthweight on smoker, alcohol, and nprevist.

```
All code used to generate the answers are below
      import pandas as pd
      import numpy as np
      import statsmodels.api as sm
      from scipy import stats
      import scipy.stats
      import matplotlib.pyplot as plt
      import pandas as pd
      import matplotlib.pyplot as plt
9
      import numpy as np
11
      from scipy.stats import linregress
12
      class WeightSmokingDataframe:
14
           df = None
1.5
           def __init__(self):
               file_path = 'weight_smoking.xlsx'
17
               file_sheet_name = 'Data'
18
               self.df = pd.read_excel(file_path, sheet_name=file_sheet_name)
19
20
21
      def part_1_solution():
22
           weightSmoking = WeightSmokingDataframe()
           print(weightSmoking.df[['birthweight', 'smoker', 'age', 'alcohol']].describe(
24
               include='all'))
25
           weightSmoking.df[['birthweight', 'smoker', 'age', 'alcohol']].hist(
26
               bins=50, figsize=(10, 5))
27
           average_birthweights = weightSmoking.df.groupby('smoker')[
28
               'birthweight'].mean()
29
           print(average_birthweights)
30
31
           plt.tight_layout()
33
           plt.show()
34
35
      def part_2_solution():
36
           weightSmoking = WeightSmokingDataframe()
37
           predictor_columns = weightSmoking.df.columns[1:12]
38
39
40
           for column in predictor_columns:
               slope, intercept, r_value, p_value, std_err = linregress(
41
                   weightSmoking.df[column], weightSmoking.df['birthweight'])
42
               line = slope * weightSmoking.df[column] + intercept
43
               plt.figure(figsize=(8, 6))
44
               plt.scatter(weightSmoking.df[column],
45
                            weightSmoking.df['birthweight'], label='Data')
47
               plt.plot(weightSmoking.df[column], line, color='red',
48
                        label='Fit: y = \{:.2f\}x + \{:.2f\}, r = \{:.2f\}'.format(slope,
                                                 intercept, r_value))
```

```
plt.xlabel(column)
49
               plt.ylabel('Birthweight')
50
               plt.title('Birthweight vs ' + column)
51
               plt.legend()
52
               plt.show()
53
54
       def scatter_plot(x_col, y_col):
56
57
           df = WeightSmokingDataframe().df
58
           slope, intercept, r_value, p_value, std_err = linregress(
                df[x_col], df[y_col])
           line = slope * df[x_col] + intercept
60
           plt.figure(figsize=(8, 6))
61
           plt.scatter(df[x_col], df[y_col], label='Data')
62
           plt.plot(df[x_col], line, color='red',
63
                     label='Fit: y = \{:.2f\}x + \{:.2f\}, r = \{:.2f\}'.format(slope, intercept,
64
                                                  r_value))
           plt.xlabel(x_col)
65
           plt.ylabel(y_col)
66
           plt.title(f'{y_col} vs {x_col}')
           plt.legend()
           plt.show()
70
71
       def part_2_solution_abcde():
72
           scatter_plot("smoker", "birthweight")
73
           scatter_plot("alcohol", "birthweight")
74
           scatter_plot("nprevist", "birthweight")
75
76
77
       def part_2_solution_c():
78
           df = WeightSmokingDataframe().df
79
           df = sm.add_constant(df)
80
           model_c = sm.OLS(df['birthweight'],
82
                              df[['const', 'smoker', 'alcohol', 'nprevist']])
83
           results_c = model_c.fit()
84
           print(results_c.summary())
85
86
87
       def part_3_solution():
88
           df = WeightSmokingDataframe().df
           df = sm.add_constant(df)
89
90
           model_c = sm.OLS(df['birthweight'],
                              df[['const', 'smoker', 'alcohol', 'tripre0', 'tripre2', '
91
                                                  tripre3']])
           results_c = model_c.fit()
92
           print()
           print(results_c.summary())
95
96
97
       def part_3a_solution():
           weightSmoking = WeightSmokingDataframe()
98
99
           print()
           print(weightSmoking.df[['tripre0', 'tripre1', 'tripre2', 'tripre3']].describe(
100
                include='all'))
       def part_4_solution():
104
           df = WeightSmokingDataframe().df
           df = sm.add_constant(df)
106
           model_c = sm.OLS(df['birthweight'],
```

```
df[['const', 'smoker', 'alcohol', 'nprevist', 'unmarried']])
108
           results_c = model_c.fit()
109
110
            print()
            print(results_c.summary())
111
112
113
       def part_5_solution():
114
115
           df = WeightSmokingDataframe().df
116
           df = sm.add_constant(df)
                              df[['const', 'age', 'educ']])
117
           results_c = model_c.fit()
118
           print()
119
           print(results_c.summary())
120
121
122
123
       if __name__ == '__main__':
124
           part_5_solution()
125
126
```