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## ML Lab Mini-Project 1

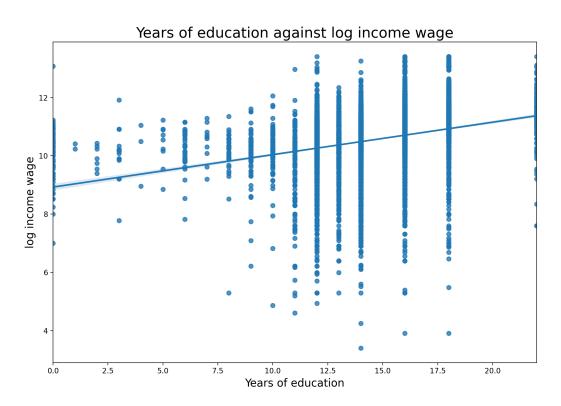
## 4 Data Analysis

1. Compute descriptive (summary) statistics for the following variables: *year*, *incwage*, *lnincwage*, *educdc*, *female*, *age*, *age*<sup>2</sup>, *white*, *black*, *hispanic*, *married*, *nchild*, *vet*, *hsdip*, *coldip*, and the interaction terms. In other words, compute sample means, standard deviations, etc.

```
Age square summary
                                               8665.000000
                                    count
                                    mean
                                               1916.814080
                                               1105.097898
                                    std
                                                324.000000
                                    min
                                    25%
                                                961.000000
                                    50%
                                               1764.000000
                                    75%
                                               2809.000000
                                               4225.000000
                                    max
                                    Name: ageSq, dtype: float64
                                    White summary
                                               8665.000000
                                    count
               in case you're curious
                                    mean
                                                  0.767340
         8665.0
[count
                                    std
                                                  0.422552
         2019.0
mean
std
           0.0
                                    min
                                                  0.000000
         2019.0
min
                                    25%
                                                  1.000000
         2019.0
25%
                                    50%
                                                  1.000000
50%
         2019.0
                                    75%
                                                  1.000000
75%
         2019.0
        2019.0
                                                  1.000000
max
                                    max
Name: YEAR, dtype: float64
                                    Name: white, dtype: float64
Income wage summary
                                    Black summary
count
          8665.000000
                                               8665.000000
                                    count
mean
         58128.161570
std
         66595.450579
                                    mean
                                                  0.092672
            30.000000
                                    std
                                                  0.289989
         23000.000000
25%
                                    min
                                                  0.000000
50%
         41000.000000
                                    25%
                                                  0.000000
75%
         70000.000000
max
        665000.000000
                                    50%
                                                  0.000000
Name: INCWAGE, dtype: float64
                                    75%
                                                  0.000000
                                    max
                                                  1.000000
Log income wage summary
                                    Name: black, dtype: float64
count
        8665.000000
mean
          10.510626
std
           1.070592
                                    Hispanic summary
           3.401197
                                    count
                                               8665.000000
          10.043249
50%
          10.621327
                                    mean
                                                  0.150952
          11.156251
                                    std
                                                  0.358023
max
          13.407542
                                    min
                                                  0.000000
Name: LNincwage, dtype: float64
                                                  0.000000
                                    25%
                                    50%
                                                  0.000000
Education year count summarized
count
        8665.000000
                                    75%
                                                  0.000000
mean
          14.218927
                                                  1.000000
           2.940894
std
                                    Name: hispan, dtype: float64
           0.000000
          12.000000
50%
          14.000000
                                    Married sum
75%
          16.000000
                                               8665.000000
                                    count
max
          22.000000
                                                  0.016157
                                    mean
Name: EDUCDC, dtype: float64
                                                  0.126086
                                    std
Female summary
count 8665.000000
                                    min
                                                  0.000000
                                    25%
                                                  0.000000
           0.487248
mean
                                    50%
                                                  0.000000
           0.499866
std
                                    75%
                                                  0.000000
           0.000000
min
                                                  1.000000
           0.000000
                                    max
50%
           0.000000
                                    Name: married, dtype: float64
75%
           1.000000
           1.000000
max
                                    Number of children
Name: female, dtype: float64
                                               8665.000000
                                    count
Age summary
                                    mean
                                                  0.801039
        8665.000000
count
                                                  1.098086
                                    std
mean
          41.754183
                                    min
                                                  0.000000
          13.168988
std
                                    25%
                                                  0.000000
min
          18.000000
                                    50%
25%
50%
                                                  0.000000
          31.000000
          42.000000
                                    75%
                                                  1.000000
7.5%
          53.000000
                                    max
                                                  9.000000
max
          65.000000
                                    Name: NCHILD, dtype: float64
Name: AGE, dtype: float64
```

```
Veteran status summary
count
         8665.000000
mean
            0.047086
std
            0.211835
            0.000000
min
25%
            0.000000
50%
            0.000000
75%
            0.000000
max
            1.000000
Name: vet, dtype: float64
Highschool diploma summary
         8665.000000
count
mean
            0.244893
            0.430049
std
min
            0.000000
25%
            0.000000
50%
            0.000000
75%
            0.000000
            1.000000
max
Name: hsdip, dtype: float64
College diploma summary
count
         8665.000000
            0.242816
mean
            0.428809
std
min
            0.000000
25%
            0.000000
50%
            0.000000
75%
            0.000000
            1.000000
max
Name: coldip, dtype: float64
Interaction term summary
count
         8665.000000
mean
            2.938719
std
            5.160584
            0.000000
min
25%
            0.000000
50%
            0.000000
75%
            0.000000
           12.000000
max
Name: educXhs, dtype: float64
count
         8665.000000
            3.885055
mean
std
            6.860952
            0.000000
min
25%
            0.000000
50%
            0.000000
75%
            0.000000
           16.000000
max
Name: educXcol, dtype: float64
```

2. Scatter plot ln(incwage)and education. Include a linear fit line. Be sure to label all axes and include an informative title.



3. Estimate the following model:

 $ln(incwage) = \beta_0 + \beta_1 educdc + \beta_2 f \ emale + \beta_3 age + \beta_4 age_2 + \beta_5 white + \beta_6 black + \beta_8 hispanic + \beta_9 married + \beta_{10} nchild + \beta_{11} vet + \varepsilon$ , and report your results.

ULS Regression Results								
Dan Vaniabla						Z LLI VAL	0.206	
Dep. Variable:		LNino	_		quared:		0.296	
Model:		1	OLS		R-squared:		0.295	
Method:		Least Squ			tatistic:	ж.	363.5	
Date:	m.	on, 01 Feb			) (F-statistic	91	0.00	
Time:		17:4	4:11	-	·Likelihood:		-11366.	
No. Observatio	ns:		8665	AIC:			2.275e+04	
Df Residuals:			8654	BIC			2.283e+04	
Df Model:			10					
Covariance Typ	e:	nonro	Dust					
_========			:=====:	====			0.0751	
	coef	std err		t	P> t	[0.025	0.975]	
Intercept	5.4635	0.115	47	.314	0.000	5,237	5.690	
EDUCDC	0.0997	0.003		.151	0.000	0.093	0.106	
female	-0.4007	0.020		.321	0.000	-0.439	-0.362	
AGE	0.1753	0.020		.078	0.000	0.164	0.186	
ageSq	-0.0018	6.71e-05		. 247	0.000	-0.002	-0.002	
white	0.0424	0.029		. 480	0.139	-0.014	0.099	
black	-0.1775	0.042	_	. 247	0.139	-0.259	-0.096	
hispan	-0.0775	0.029		.713	0.007	-0.134	-0.022	
married	-0.0983	0.025		. 276	0.202	-0.249	0.053	
NCHILD	0.0133	0.010		.379	0.168	-0.006	0.032	
vet	-0.0450	0.046		.969	0.333	-0.136	0.032	
=========	=======	========	:=====:		:========	=======	=======	
Omnibus:		2698	.134	Durt	oin-Watson:		1.863	
Prob(Omnibus):		6	.000	Jaro	que-Bera (JB):		13300.836	
Skew:			. 424		(JB):		0.00	
Kurtosis:			.359		i. No.		2.67e+04	
=========			=====	====				

- (a) What fraction of the variation in log wages does the model explain?
  - a. The R-Squared is .296, which means that the fraction of the variation in log wages is explained by approximately 30 percent of the model.
- (b) Test the hypothesis that:

H<sub>0</sub>:
$$\beta_1 = \beta_2 = ... = \beta_{11} = 0$$
  
H<sub>A</sub>: $\beta_j \neq 0$  for some j with  $\alpha = 0.10$ .

With an alpha of 0.1, we are able to reject the null at a 10 percent significance level. The F-Statistic is 363.5, as well as our p-value. Thus, we are certain that we are able to reject the null hypothesis. Furthermore, this means that our X variables all have predictive values; the predictors we should be careful about are **white**, **married**, **NCHILD**, and **vet**.

- (c) What is the return to an additional year of education? Is this statistically significant? Is it practically significant? Briefly explain.
  - a. Because this is the log income wage, an additional year of education yields a 9.97 percent increase in one's wages. This is statistically

significant, with certainty in our p-values, confidence intervals, and t-statistic. Given that this is an econometric measure, it is also practically significant when one's income is at a certain threshold. The magnitude at which the amount of years of education one has affecting their log wages will have a practical and realistic significance whenever the amount one gains in income is substantial to a 9.97 percent increase.

- (d) At what age does the model predict an individual will achieve the highest wage?
  - a. When we take the derivative with respects to age in our regression model and maximize, we find that the model predicts that an individual will achieve the highest wage at 46.36 years old.

In (incwage) = 
$$B_0 + B_1$$
 educed  $C + B_2$  female  $C + B_3$  age  $C + B_4$  age  $C + B_5$  white  $C + B_6$  black  $C + B_6$  hispanic  $C + B_6$  married  $C + B_6$  nothild  $C + B_6$  vet  $C + B_6$  married  $C + B_6$  age  $C + B_6$  age

(coefficient values may differ from work shown above due to time screenshot was taken, but same practice applies).

- (e) Does the model predict that men or women will have higher wages, all else equal? Briefly explain why we might observe this pattern in the data.
  - a. Seeing as how the coefficient for female is negative, the model predicts that those who identify as female will reportedly have lower wages, even if we hold all else equal. Since the model does not account for tax or tax credits, the data would otherwise support the predicted values the model produced.
- (f) Interpret the coefficients on the white, black, and Hispanic variables.
  - a. The coefficient on the white variable is statistically insignificant, even at the alpha = .1 level. Black and hispanic variables, however, are statistically significant, both with negative effects. Therefore this would translate into receiving negative wages solely from the fact that one identifies as black or hispanic.

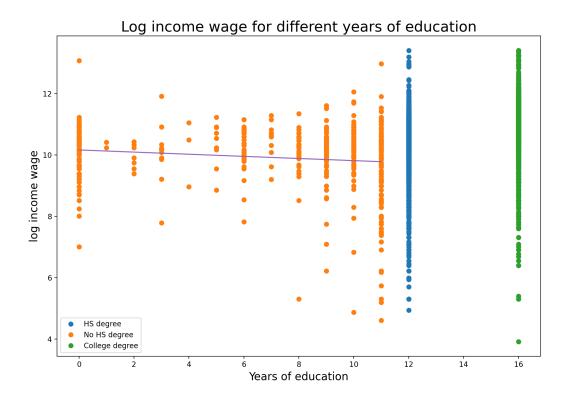
- (g) Test the hypothesis that race has no effect on wages. Be sure to explicitly state the null and alternative hypotheses and show your calculations.
  - a. Considering the rhetoric that some would argue Hispanic not being a race, but more so an ethnicity, I will proceed with the assumption that race is equal to white and black for this question.

The Null Hypothesis would be that race has no effect on wages, namely that Beta 5 + Beta 6 = 0; thus the indicator variable would have a 0 percent change in one's wages. Based off of my model's predictions, I will take a one sided approach.

The Alternative Hypothesis would state that race does have a negative non-zero effect on one's wage, namely that Beta 5 + Beta 6 =/= 0. In my calculations, I conducted a linear regression of the influence race had on the response. Based on my model's predictions, we are able to statistically reject the null hypothesis, for we see that race still does have an effect on one's wages.

OLS Regression Results									
Dep. Variabl Model: Method: Date: Time: No. Observat Df Residuals Df Model: Covariance T	Mo ions:	Least Squa on, 01 Feb 20 18:07 80	DLS Adj. res F-sta 021 Prob :05 Log-l 565 AIC: 562 BIC: 2	lared: R-squared; litistic: (F-statistic likelihood:	):	0.009 0.009 41.15 1.63e-18 -12845. 2.570e+04 2.572e+04			
=======	coef	std err	t	P> t	[0.025	0.975]			
Intercept white black	10.4095 0.1534 -0.1787	0.031 0.033 0.048	4.611	0.000 0.000 0.000	10.349 0.088 -0.274	10.469 0.219 -0.084			
Omnibus: Prob(Omnibus Skew: Kurtosis: ========	·):	-1.0	900 Jarqu			1.773 5010.290 0.00 6.66			

4. Graph In(incwage) and education. Include three distinct linear fit lines specific to individuals with no high school diploma, a high school diploma, and a college degree. Be sure to label all axis and include an informative title.



5. Since the President is considering new education legislation, she asks you to determine whether a college degree is a strong predictor of wages. Write down a model that will allow the returns to education to vary by degree acquired (use the three categories in the previous question). Be sure to include the controls from question 3. Explain/justify why you think your model is the best possible

representation of the way the world works.

representation of the way the world works.								
Inserting our interaction terms to our model OLS Regression Results								
=========	=======	 	:====== :ce.c33.	-===		=======	=======	
Dep. Variable	2:	LNind	wage	R-sa	uared:		0.300	
Model:			_	Adj. R-squared:			0.299	
Method:		Least Squ		F-statistic:			309.1	
Date:		Mon, 01 Feb 202		Prob (F-statistic)			0.00	
Time:		18:4	4:41	Log-Likelihood:			-11340.	
No. Observati	ions:		8665	AIC:			2.271e+04	
Df Residuals:				BIC:			2.280e+04	
Df Model:			12					
Covariance Ty	/pe:	nonro	bust					
========			======	====				
	coef	std err		t	P> t	[0.025	0.975]	
T	F 6400	0.130	47	420	0 000	F 41 F	F 00F	
Intercept EDUCDC	5.6499 0.0880	0.120 0.004		138 896	0.000 0.000	5.415 0.080	5.885 0.096	
female	-0.4034		-20.		0.000	-0.442	-0.365	
AGE	0.1731	0.026		735	0.000	0.162	0.184	
ageSq	-0.0018	6.71e-05	-26.		0.000	-0.002	-0.002	
white	0.0427	0.029		493	0.135	-0.013	0.099	
black	-0.1663	0.042		989	0.000	-0.248	-0.085	
hispan	-0.0749	0.029		625	0.009	-0.131	-0.019	
married	-0.0836			087	0.277	-0.234	0.067	
NCHILD	0.0130	0.010		349	0.177	-0.006	0.032	
vet	-0.0400	0.046		863	0.388	-0.131	0.051	
educXhs	-0.0064	0.002	-3.	038	0.002	-0.011	-0.002	
educXcol	0.0090	0.002	5.	848	0.000	0.006	0.012	
========		========		====	========			
Omnibus:					in-Watson:		1.869	
Prob(Omnibus)	):				ue-Bera (JB):		13671.480	
Skew:					(JB):		0.00	
Kurtosis:		-			. No.		2.77e+04	
========		========	======	====	========		========	

Taking our formula from 3 and adding on the two interaction terms, we still can see that white, married, NCHILD, and vet variables are insignificant. However, we see that there is a statistical significance at the  $\alpha = .1$  level with the addition of the two interaction terms. I believe this new model explains, despite the statistical insignificance of some variables, a realistic view of the way the world works; each of these variables contribute to one's income wage. When we incorporate the interaction terms, we see that having a college degree is positive, which the President could interpret as being a strong predictor of wages. Also,  $R^2$  is higher (slightly), which means our predictors explain the variation in log income wages based on the model.

- 6. Estimate the model you proposed in the previous question and report your results.
  - a. Predict the wages of a 22 year old, female individual (who is neither white, black, nor Hispanic, is not married, has no children, and is not a veteran) with a high school diploma and an all else equal individual with a college diploma. Assume that it takes someone 12 years to graduate high school and 16 years to graduate college

6a

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 \ln(incwage) = \beta_0 + \beta_1 educdc + \beta_2 female + \beta_3 age + \beta_4 age^2 \\ + \beta_5 whife + \beta_6 black + \beta_8 hispanic \\ + \beta_9 married + \beta_{10} nchild + \beta_{11} yet + \epsilon, \\ + \beta_3 educdc \times h.s. + \beta_4 educdc \times col \\ + \epsilon \\ = 5. (449.4 + (0.088) (12) + (-0.4034) (1) \\ + (0.0090)(0) \\ + (0.0090)(0) \\ + (0.0090)(16)   \ln(incwage) = \beta_0 + \beta_1 educdc + \beta_2 female + \beta_3 age + \beta_4 age^2 \\ + \beta_5 whife + \beta_6 black + \beta_8 hispanic \\ + \beta_9 married + \beta_{10} nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_{10} nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_{10} nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_{10} nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_9 married + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\ + \beta_1 nchild + \beta_1 yet + \epsilon, \\
```

b. The President wants to know, given your results, do individuals with college degrees have higher predicted wages than those without? By how much? Briefly explain.

By my models predictions, my estimate results show that individuals with college degrees have nearly identically, yet still slightly higher percent predicted wages than those who have only received a high school diploma, by nearly a few percentage points (5-10%).

- c. The President asked you to look into this question because she is considering legislation that will expand access to college education (for instance, by increasing student loan subsidies). She will only support the legislation if there are cost offsets (if college education increases wages and therefore, future income tax revenues that help reduce the net cost of the subsidy). Given that criteria, how would you advise the President?
  - i. If I were the president, I would study or investigate the longevity of one's involvement in the workforce for those pursuing college education. If there remains a positive slope coefficient, then it might be worthwhile to pursue increasing student loan subsidies.

7. There are many ways that this model could be improved. How would you do things differently if you were asked to predict the returns to education given the data available on IPUMS?

Depending on what parameters I would use to predict the returns to education, I would ensure some geographical context is also provided. Using data like proximal distance to city center, communal health indexes, and other more contextual specifiers that are identifiable like mental disabilities or other handicaps.