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PREPARING DATA

1. Education

```
#Create continuous for EDUCD
acs_data = pd.merge(acs_data, crosswalk, left_on='EDUCD', right_on='educd')
acs_data
```

	YEAR	SAMPLE	SERIAL	CBSERIAL	HHWT	CLUSTER	STRATA	GQ	PERNUM	PERWT	NCHILD	NCHLT5	SEX	AGE	MARST	RACE
0	2019	201901	2611	2019000016124	19504.8	2019000026111	80001	1	1	19659.6	1	1	1	29	1	1
1	2019	201901	6016	2019000247422	1702.8	2019000060161	230001	1	1	1702.8	3	1	1	41	1	1
2	2019	201901	6790	2019000301008	8668.8	2019000067901	190001	1	3	20278.8	0	0	1	21	6	1
3	2019	201901	9577	2019000497180	42105.6	2019000095771	10001	1	1	42105.6	0	0	1	20	6	1
4	2019	201901	9731	2019000507929	7430.4	2019000097311	270201	1	1	7275.6	0	0	1	33	6	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9049	2019	201901	1220732	2019000282619	26006.4	2019012207321	230548	1	1	25851.6	2	1	1	47	1	1
9050	2019	201901	1222589	2019000308283	33746.4	2019012225891	680448	1	2	39628.8	0	0	1	43	6	1
9051	2019	201901	1237295	2019000512472	20433.6	2019012372951	670248	1	2	21207.6	2	0	2	59	1	1
9052	2019	201901	1302776	2019001404140	27554.4	2019013027761	461548	1	1	27554.4	0	0	2	49	3	7
9053	2019	201901	1308039	2019000485767	13312.8	2019013080391	5700249	1	1	13312.8	2	0	1	61	1	1

RACED	HISPAN	HISPAND	EDUC	EDUCD	EMPSTAT	EMPSTATD	INCWAGE	VETSTAT	VETSTATD	educd	educdc
100	0	0	8	81	1	10	59000	1	11	81	14.0
100	0	0	8	81	1	10	50000	2	20	81	14.0
100	0	0	8	81	1	10	10000	1	11	81	14.0
100	0	0	8	81	1	10	800	1	11	81	14.0
200	0	0	8	81	1	10	45000	1	11	81	14.0
...	...	...	...	...	...	...	...	...	...	...	...
100	1	100	2	22	1	10	25000	1	11	22	5.0
100	1	100	2	22	1	10	21600	1	11	22	5.0
100	1	100	2	22	1	10	18000	1	11	22	5.0
700	4	416	2	22	1	10	17000	1	11	22	5.0
100	1	100	1	14	1	10	38000	1	11	14	1.0

2. Dummy Variables

```
#Get Dummies
acs_data['hsdip'] = np.where(acs_data['EDUCD'] == 63, 1, 0)
acs_data['coldip'] = np.where(acs_data['EDUCD'] == 101,  1, 0)
acs_data['white'] = np.where(acs_data['RACE'] == 1,  1, 0)
acs_data['black'] = np.where(acs_data['RACE'] == 2,  1, 0)
acs_data['hispanic'] = np.where(acs_data['RACE'] != 0,  1, 0)
acs_data['married'] = np.where(acs_data['MARST'] == 1,  1, 0)
acs_data['female'] = np.where(acs_data['SEX'] == 2,  1, 0)
acs_data['vet'] = np.where(acs_data['VETSTAT'] == 2,  1, 0)
acs_data.head()
```

educd	educdc	hsdip	coldip	white	black	hispanic	married	female	vet
81	14.0	0	0	1	0	1	1	0	0
81	14.0	0	0	1	0	1	1	0	1
81	14.0	0	0	1	0	1	0	0	0
81	14.0	0	0	1	0	1	0	0	0
81	14.0	0	0	0	1	1	0	0	0

3. Interaction Terms

```
#Interaction
acs_data['EDUC:educdc'] = acs_data['EDUC'].mul(acs_data['educdc'])
acs_data.head()
```

EDUC:educdc
112.0
112.0
112.0
112.0
112.0

4. Created Variables

```
#Age Squared
acs_data['AGE^2'] = np.power(acs_data['AGE'],2)
acs_data.head()
```

AGE^2
841
1681
441
400
1089

```
#Log of Wage
acs_data = acs_data[acs_data['INCWAGE'] != 0] #Only one row had a 0 so needed to remove it
acs_data['LNINCWAGE'] = np.log(acs_data['INCWAGE'])
acs_data.head()
```

LNINCWAGE
10.985293
10.819778
9.210340
6.684612
10.714418

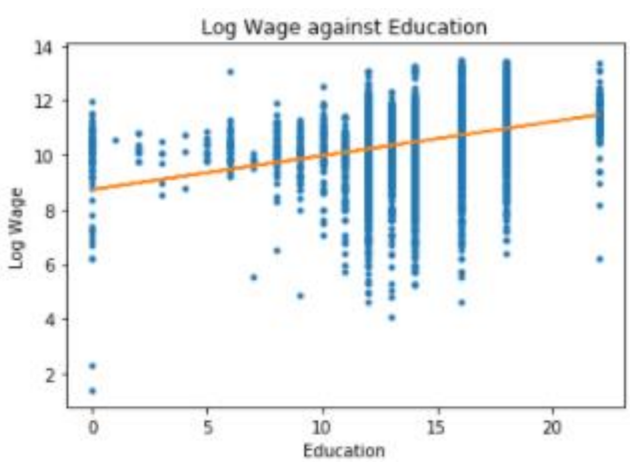
DATA ANALYSIS

1.

	YEAR	INCWAGE	LNINCWAGE	educdc	female	AGE	AGE^2	white	black	hispanic	married
count	8606.0	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.000000	8606.0	8606.000000
mean	2019.0	58420.063212	10.496826	14.187427	0.486521	41.849059	1931.513479	0.773298	0.090286	1.0	0.525912
std	0.0	68115.268196	1.097734	2.857626	0.499847	13.423513	1126.920775	0.418723	0.286607	0.0	0.499357
min	2019.0	4.000000	1.386294	0.000000	0.000000	18.000000	324.000000	0.000000	0.000000	1.0	0.000000
25%	2019.0	22725.000000	10.031219	12.000000	0.000000	30.000000	900.000000	1.000000	0.000000	1.0	0.000000
50%	2019.0	41300.000000	10.628615	14.000000	0.000000	42.000000	1764.000000	1.000000	0.000000	1.0	1.000000
75%	2019.0	70750.000000	11.166889	16.000000	1.000000	54.000000	2916.000000	1.000000	0.000000	1.0	1.000000
max	2019.0	717000.000000	13.482831	22.000000	1.000000	65.000000	4225.000000	1.000000	1.000000	1.0	1.000000

NCHILD	vet	hsdip	coldip	EDUC:educdc
8606.000000	8606.000000	8606.000000	8606.000000	8606.000000
0.784801	0.049733	0.210783	0.236812	117.493028
1.100708	0.217405	0.407888	0.425150	51.649895
0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	72.000000
0.000000	0.000000	0.000000	0.000000	98.000000
1.000000	0.000000	0.000000	0.000000	160.000000
9.000000	1.000000	1.000000	1.000000	242.000000

2.



3.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              LNINCWAGE   R-squared:                       0.309
Model:                            OLS   Adj. R-squared:                  0.308
Method:                 Least Squares   F-statistic:                     426.4
Date:                Sat, 30 Jan 2021   Prob (F-statistic):               0.00
Time:                        19:24:58   Log-Likelihood:                -11425.
No. Observations:                8606   AIC:                         2.287e+04
Df Residuals:                    8596   BIC:                         2.294e+04
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
educdc         0.1112      0.004     31.564      0.000       0.104       0.118
female        -0.4338      0.020    -21.577      0.000      -0.473      -0.394
AGE            0.1567      0.006     27.646      0.000       0.146       0.168
AGE^2         -0.0016    6.7e-05    -24.270      0.000      -0.002      -0.001
white         -0.0297      0.029     -1.024      0.306      -0.087       0.027
black         -0.1875      0.043     -4.410      0.000      -0.271      -0.104
hispanic       5.6555      0.114     49.594      0.000       5.432       5.879
married        0.1955      0.023      8.450      0.000       0.150       0.241
NCHILD        -0.0063      0.010     -0.616      0.538      -0.026       0.014
vet           -0.0396      0.046     -0.856      0.392      -0.130       0.051
==============================================================================
Omnibus:                     2437.163   Durbin-Watson:                   1.867
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            10300.166
Skew:                          -1.335   Prob(JB):                         0.00
Kurtosis:                       7.647   Cond. No.                     2.60e+04
==============================================================================
```

a) The fraction of variation is the R^2 which from our results is 0.309 which indicates that around 30.9% of the log wage as the dependent variable can be explained by the predictor
b) The F-statistics: 426.4 and Prob(F-statistic): 0 indicates that we reject the null hypothesis that ln(wage) is not affected by any of the predictors
c) An additional year of education increased the log wage by (e^(0.112)-1)*100 =11.85129 ~ 11.985% and is statistically significant because we have a p-value of 0 which is less than 0.05.
d) According to the model, the ln(wage) will achieve the highest wage at Age 50.

```
d = {'AGE': [50]}
df = pd.DataFrame(data=d)
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	10.923088	0.06992	10.786029	11.060148	8.99937	12.846806

Intercept	8.5613	0.088	96.999	0.000	8.388	8.734
C(AGE)[T.19]	0.1403	0.118	1.192	0.233	-0.090	0.371
C(AGE)[T.20]	0.5995	0.119	5.020	0.000	0.365	0.834
C(AGE)[T.21]	0.8163	0.120	6.803	0.000	0.581	1.052
C(AGE)[T.22]	0.8900	0.113	7.889	0.000	0.669	1.111
C(AGE)[T.23]	1.2769	0.117	10.936	0.000	1.048	1.506
C(AGE)[T.24]	1.5024	0.116	12.901	0.000	1.274	1.731
C(AGE)[T.25]	1.5190	0.115	13.157	0.000	1.293	1.745
C(AGE)[T.26]	1.7094	0.115	14.859	0.000	1.484	1.935
C(AGE)[T.27]	1.8766	0.118	15.876	0.000	1.645	2.108
C(AGE)[T.28]	1.8940	0.114	16.649	0.000	1.671	2.117
C(AGE)[T.29]	1.7146	0.113	15.213	0.000	1.494	1.936
C(AGE)[T.30]	2.0496	0.111	18.489	0.000	1.832	2.267
C(AGE)[T.31]	1.9967	0.114	17.552	0.000	1.774	2.220
C(AGE)[T.32]	2.0790	0.115	18.134	0.000	1.854	2.304
C(AGE)[T.33]	1.9255	0.116	16.658	0.000	1.699	2.152
C(AGE)[T.34]	2.1251	0.112	18.928	0.000	1.905	2.345
C(AGE)[T.35]	1.9479	0.115	16.892	0.000	1.722	2.174
C(AGE)[T.36]	2.0875	0.112	18.593	0.000	1.867	2.308
C(AGE)[T.37]	2.2044	0.117	18.855	0.000	1.975	2.434
C(AGE)[T.38]	2.1583	0.114	18.868	0.000	1.934	2.382
C(AGE)[T.39]	2.3228	0.112	20.689	0.000	2.103	2.543
C(AGE)[T.40]	2.1019	0.115	18.313	0.000	1.877	2.327
C(AGE)[T.41]	2.1998	0.114	19.295	0.000	1.976	2.423
C(AGE)[T.42]	2.1307	0.114	18.770	0.000	1.908	2.353
C(AGE)[T.43]	2.1793	0.115	18.988	0.000	1.954	2.404
C(AGE)[T.44]	2.0735	0.115	17.960	0.000	1.847	2.300
C(AGE)[T.45]	2.2876	0.115	19.931	0.000	2.063	2.513
C(AGE)[T.46]	2.2064	0.115	19.134	0.000	1.980	2.432
C(AGE)[T.47]	2.1709	0.115	18.870	0.000	1.945	2.396
C(AGE)[T.48]	2.2629	0.115	19.738	0.000	2.038	2.488
C(AGE)[T.49]	2.3234	0.115	20.196	0.000	2.098	2.549
C(AGE)[T.50]	2.3618	0.113	20.975	0.000	2.141	2.583
C(AGE)[T.51]	2.2763	0.112	20.389	0.000	2.057	2.495
C(AGE)[T.52]	2.2442	0.112	19.989	0.000	2.024	2.464
C(AGE)[T.53]	2.1435	0.112	19.217	0.000	1.925	2.362
C(AGE)[T.54]	2.2303	0.111	20.085	0.000	2.013	2.448
C(AGE)[T.55]	2.1614	0.114	19.040	0.000	1.939	2.384
C(AGE)[T.56]	2.1321	0.108	19.776	0.000	1.921	2.343
C(AGE)[T.57]	2.3128	0.114	20.373	0.000	2.090	2.535
C(AGE)[T.58]	2.1994	0.111	19.736	0.000	1.981	2.418
C(AGE)[T.59]	2.1471	0.114	18.792	0.000	1.923	2.371
C(AGE)[T.60]	2.1243	0.116	18.355	0.000	1.897	2.351
C(AGE)[T.61]	2.0855	0.113	18.448	0.000	1.864	2.307
C(AGE)[T.62]	2.1106	0.116	18.192	0.000	1.883	2.338
C(AGE)[T.63]	1.9634	0.120	16.336	0.000	1.728	2.199
C(AGE)[T.64]	1.9695	0.120	16.439	0.000	1.735	2.204
C(AGE)[T.65]	2.0175	0.126	16.063	0.000	1.771	2.264

e) The model predicts that men will have a slightly higher wage than females and according to our results the coefficient for females is -0.4338. We might investigate this pattern to see when males start to have a higher wage gap than females at a certain age, married status, or birth to a child

```
d = {'SEX': [1]}
df = pd.DataFrame(data=d)
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	10.69294	0.016234	10.661118	10.724762	8.577313	12.808567

```
d = {'SEX': [2]}
df = pd.DataFrame(data=d)
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	10.289845	0.016677	10.257153	10.322536	8.174204	12.405485

f) Interpreting the coefficients White: -0.0297, Black:-0.1875, Hispanic: 5.655 indicates that Hispanics have the highest percentage increase in wages controlling for all variables, whites had a small decrease, but is NOT statistically significant, and blacks have the highest decrease in wages in 2019.

g) Null Hypothesis: $H_0 : B_{race} = 0$

Alternative Hypothesis: $H_A : B_{race} \neq 0$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              LNINCWAGE   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     12.56
Date:                Sun, 31 Jan 2021   Prob (F-statistic):           0.000397
Time:                        17:10:32   Log-Likelihood:                -13007.
No. Observations:                8606   AIC:                         2.602e+04
Df Residuals:                    8604   BIC:                         2.603e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     10.5374      0.016    639.840      0.000      10.505      10.570
RACE          -0.0225      0.006     -3.543      0.000      -0.035      -0.010
==============================================================================
Omnibus:                     1902.558   Durbin-Watson:                   1.627
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6042.310
Skew:                          -1.122   Prob(JB):                         0.00
Kurtosis:                       6.437   Cond. No.                         3.89
==============================================================================

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

Running an OLS of LNWAGE on RACE. We reject the null hypothesis that race has nothing to do with wages because it is not statistically significant , but the variation is very small of R^2 at 0.001.

4.

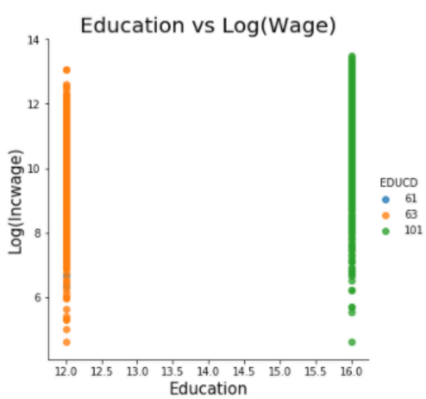
```
#Question 4

new_df = acs_data[acs_data.EDUCD.isin([61,63,101])]

sns.lmplot(x='educdc', y='LNINCWAGE',hue='EDUCD', data=new_df)
plt.xlabel("Education", fontsize=15)
plt.ylabel("Log(Incwage)", fontsize=15)
plt.title('Education vs Log(Wage)', fontsize=20)

#Source:https://www.machinelearningplus.com/plots/top-50-matplotlib-visualizations-the-master-plots-python/
```

```
Text(0.5, 1, 'Education vs Log(Wage)')
```



5. **LNINCWAGE = $B_0 + B_1$ (educdc = [61 (No High School), 63 (High School) , 101(college Degree)]+ B_3 (female) + B_4 (AGE) + B_5 (AGE^2) + B_6 (white) + B_7 (black) + B_8 (Hispanic) + B_9 (married) + B_{10} (NCHILD)**

   Probability = e^(LNINCWAGE Regression)/(1+e^(LNINCWAGE Regression))

   I believe this is the best model because we can control for all variables and include these three categorical variables because we are trying to find correlations between the education levels and INCWAGE not the causation. Also, the parameters B_0, B_1 etc. best explain the observed data and with this probability model we can explain more than 2 categorical variables

6.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              LNINCWAGE   R-squared:                       0.258
Model:                            OLS   Adj. R-squared:                  0.256
Method:                 Least Squares   F-statistic:                     137.1
Date:                Mon, 01 Feb 2021   Prob (F-statistic):          8.75e-247
Time:                        10:02:58   Log-Likelihood:                -5300.0
No. Observations:                3959   AIC:                         1.062e+04
Df Residuals:                    3948   BIC:                         1.069e+04
Df Model:                          10
Covariance Type:            nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Intercept           4.5332      0.053     86.174      0.000       4.430       4.636
C(educd)[T.63]      0.3830      0.092      4.146      0.000       0.202       0.564
C(educd)[T.101]     1.0429      0.092     11.276      0.000       0.862       1.224
female             -0.4540      0.030    -15.125      0.000      -0.513      -0.395
AGE                -0.0011      0.008     -0.142      0.887      -0.016       0.014
AGE ^ 2             0.0185      0.007      2.494      0.013       0.004       0.033
white               0.0650      0.045      1.441      0.150      -0.023       0.153
black              -0.0775      0.066     -1.172      0.241      -0.207       0.052
hispanic            4.5332      0.053     86.174      0.000       4.430       4.636
married             0.2460      0.035      7.010      0.000       0.177       0.315
NCHILD              0.0629      0.015      4.164      0.000       0.033       0.093
vet                 0.0053      0.071      0.075      0.940      -0.133       0.144
==============================================================================
Omnibus:                     1149.178   Durbin-Watson:                   1.900
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4226.769
Skew:                          -1.412   Prob(JB):                         0.00
Kurtosis:                       7.201   Cond. No.                     1.86e+17
==============================================================================
```

a) The wages which predict from our model which we get is 4.47871~ 4.48

```
import statsmodels.formula.api as smf

d = {'EDUCD':61,'female':1,'AGE':22,'AGE^2':22, 'white':0, 'black':0,'hispanic':0, 'married':0,'NCHILD':0,'vet':0}
df = pd.DataFrame([d])
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	4.474871	0.054332	4.36835	4.581392	2.665454	6.284289

b) Yes, the individuals do receive a higher wage, and according to our model for females it is about 0.65 dollar, and males 0.93 increase in wages.

In [401]:
```
import statsmodels.formula.api as smf

d = {'EDUCD':61,'SEX':1,'AGE':22,'AGE^2':22, 'white':0, 'black':0,'hispanic':0, 'married':0,'NCHILD':0,'vet':0}
df = pd.DataFrame([d])
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

Out[401]:

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	4.934584	0.049588	4.837363	5.031806	3.12569	6.743478

In [399]:
```
d = {'EDUCD':101,'SEX':1,'AGE':22,'AGE^2':22, 'white':0, 'black':0,'hispanic':0, 'married':0,'NCHILD':0,'vet':0}
df = pd.DataFrame([d])
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

Out[399]:

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	5.85715	0.055422	5.748493	5.965808	4.047606	7.666695

In [400]:
```
d = {'EDUCD':101,'SEX':2,'AGE':22,'AGE^2':22, 'white':0, 'black':0,'hispanic':0, 'married':0,'NCHILD':0,'vet':0}
df = pd.DataFrame([d])
predictions = result.get_prediction(df)
predictions.summary_frame(alpha=0.05)
```

Out[400]:

	mean	mean_se	mean_ci_lower	mean_ci_upper	obs_ci_lower	obs_ci_upper
0	5.397438	0.05782	5.284077	5.510798	3.587605	7.20727

c) From my point of view, it is crucial to expand college education to increase wages for male and female workers. However, allowing subsidies will increase the cost of attending college which can cause the students to fall into debt knowing college administrators can raise the prices because banks are providing easy money loans without any application.

7. To improve this model, I would probably include more interaction between education and variables such as Age, Married, and NCHILD to see where the increase or drop off is in wages. The reason why is when women give birth to a child wages tends to slip as they focus on more part-time jobs.