PSet1_Q5a_ARE213

October 2, 2023

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[1]: import numpy as np
import pandas as pd
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
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[3]: df = pd.read_csv("clean_pset1.csv")
     ################
     #5.a
     ################
     #Logit to estimate propensity score
     y_log_reg = df['tobacco']
     #outcome
     y = ['dbrwt']
     #treatment
     D = ['tobacco']
     #cor with y and D
     x1 = ['alcohol', 'mrace3_2', 'mrace3_3', 'ormothhis', 'adeq_2.0', 'adeq_3.0', 'adeq_3.0']

¬'cardiac', 'pre4000', 'phyper',
           'diabetes', 'anemia', 'lung', 'dlivord', 'educ_0.0', 'educ_1.0', 'educ_2.
      \rightarrow 0', 'dmage', 'dmar', 'tot_2.0',
            'tot_3.0', 'tot_4.0', 'tot_5.0', 'tot_6.0', 'tot_7.0', 'tot_8.0', 'live_1.0', _

¬'live_2.0', 'live_3.0', 'live_4.0',
           'live_5.0', 'live_6.0', 'live_7.0', 'live_8.0', 'live_9.0']
     #cor with D not y
     x2 = \prod
     #cor with y not D
     x3 = ['dgestat', 'csex', 'plur_1']
     X_{\log_{reg}} = df[x1+x3]
     model = LogisticRegression(solver='liblinear', random_state=0)
     model.fit(X_log_reg, y_log_reg)
     #2nd column gives us predictions
     predictions = model.predict_proba(X_log_reg)[:,1]
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df['predictions'] = model.predict_proba(X_log_reg)[:,1]
#Calculate weights
wt = (df['tobacco'] / predictions) + (1 - df['tobacco']) /(1 - predictions)
#Demeaned X matrix
for item in x1+x3:
    df[item+'demeaned'] = df[item].sub(df[item].mean())
#multiply by D
for item in x1+x3:
    df['tobacco*'+item] = df[item+'demeaned']*df['tobacco']
#concatenate
d_times_demeaned_X = df[['tobacco*alcohol',
       'tobacco*mrace3_2', 'tobacco*mrace3_3', 'tobacco*ormothhis',
       'tobacco*adeq_2.0', 'tobacco*adeq_3.0', 'tobacco*cardiac',
       'tobacco*pre4000', 'tobacco*phyper',
       'tobacco*diabetes', 'tobacco*anemia', 'tobacco*lung', 'tobacco*dlivord',
       'tobacco*educ_0.0', 'tobacco*educ_1.0', 'tobacco*educ_2.0',
       'tobacco*dgestat', 'tobacco*dmage', 'tobacco*dmar', 'tobacco*csex',
       'tobacco*tot_2.0', 'tobacco*tot_3.0', 'tobacco*tot_4.0',
       'tobacco*tot_5.0', 'tobacco*tot_6.0', 'tobacco*tot_7.0',
       'tobacco*tot_8.0', 'tobacco*live_1.0', 'tobacco*live_2.0',
       'tobacco*live_3.0', 'tobacco*live_4.0', 'tobacco*live_5.0',
       'tobacco*live_6.0', 'tobacco*live_7.0', 'tobacco*live_8.0',
       'tobacco*live_9.0', 'tobacco*plur_1']]
#Outcome: birthweight
y_log_reg = df['dbrwt']
#Create final covariates matrix:
double_robust_reg_X = pd.concat([df['tobacco'],
                                 X_log_reg,
                                 d_times_demeaned_X], axis=1)
fit_wls = sm.WLS(y_log_reg, double_robust_reg_X, weights=wt).fit()
print(fit_wls.summary())
```

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WLS Regression Results
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Dep. Variable: dbrwt R-squared (uncentered): 0.981
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Model: WLS Adj. R-squared (uncentered):

0.981

Method: Least Squares F-statistic:

7.849e+04

Date: Sun, 01 Oct 2023 Prob (F-statistic):

0.00

Time: 11:46:32 Log-Likelihood:

-8.8421e+05

No. Observations: 114610 AIC:

1.769e+06

Df Residuals: 114535 BIC:

1.769e+06

Df Model: 75
Covariance Type: nonrobust

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====	coef	std err	t	P> t	[0.025	
0.975]						
tobacco -201.701	-207.0867	2.748	-75.358	0.000	-212.473	
alcohol -1.008	-41.5588	20.689	-2.009	0.045	-82.109	
mrace3_2 -176.692	-204.0738	13.970	-14.608	0.000	-231.455	
mrace3_3 -135.994	-149.2118	6.744	-22.125	0.000	-162.430	
ormothhis -85.555	-106.5636	10.719	-9.942	0.000	-127.573	
adeq_2.0 -30.849	-40.6022	4.976	-8.159	0.000	-50.355	
adeq_3.0 -63.509	-83.0854	9.988	-8.319	0.000	-102.661	
cardiac 20.828	-25.1022	23.434	-1.071	0.284	-71.032	
pre4000 428.454	396.3398	16.385	24.189	0.000	364.226	
phyper -80.067	-102.1757	11.280	-9.058	0.000	-124.284	
diabetes 164.131	140.5447	12.034	11.679	0.000	116.959	
anemia 56.395	18.2205	19.477	0.936	0.350	-19.954	
lung 20.270	-24.6043	22.895	-1.075	0.283	-69.479	
dlivord 33.138	25.6250	3.833	6.685	0.000	18.112	

educ_0.0 -1725.582	-1796.3924	36.128	-49.723	0.000	-1867.202
educ_1.0	-1811.8350	33.714	-53.742	0.000	-1877.913
-1745.757 educ_2.0	-1781.7611	34.195	-52.107	0.000	-1848.782
-1714.740	1,01.,011	01.100	02.101	0.000	1010.102
dgestat 115.692	114.1372	0.793	143.880	0.000	112.582
dmage 1.528	0.6116	0.468	1.308	0.191	-0.305
dmar	47.1451	5.822	8.098	0.000	35.735
58.555	136.2566	3.873	35.177	0.000	128.665
csex 143.849	130.2300	3.013	33.177	0.000	120.005
tot_2.0	9.3572	7.222	1.296	0.195	-4.799
23.513					
tot_3.0	12.6626	8.451	1.498	0.134	-3.902
29.227	0.5400	40.400	0.040	0 504	40.400
tot_4.0 26.523	6.5466	10.192	0.642	0.521	-13.430
tot_5.0	-1.1584	12.878	-0.090	0.928	-26.400
24.083					
tot_6.0 29.845	-3.1789	16.849	-0.189	0.850	-36.202
tot_7.0	-19.5211	23.197	-0.842	0.400	-64.987
25.945					
tot_8.0 -9.022	-60.7119	26.373	-2.302	0.021	-112.402
live_1.0	-45.1494	26.526	-1.702	0.089	-97.141
6.842					
live_2.0 -12.969	-58.9822	23.476	-2.512	0.012	-104.995
live_3.0	48.8789	11.649	4.196	0.000	26.048
71.710					
live_4.0	97.5953	10.632	9.179	0.000	76.756
118.434	99.3367	0 427	10 506	0.000	90 940
live_5.0 117.833	99.3367	9.437	10.526	0.000	80.840
live_6.0	91.4001	9.968	9.169	0.000	71.863
110.938					
live_7.0	87.3700	11.276	7.748	0.000	65.269
109.471 live_8.0	67.5009	12.922	5.224	0.000	42.174
92.828	07.3009	12.922	3.224	0.000	42.174
live_9.0	56.7237	10.326	5.493	0.000	36.485
76.962		4.4.5=6	08	0.000	F00 000
plur_1 586.625	557.5078	14.856	37.527	0.000	528.390

tobacco*alcohol	-37.3531	28.791	-1.297	0.195	-93.784
19.078 tobacco*mrace3_2	168.2648	22.364	7.524	0.000	124.431
212.099 tobacco*mrace3_3	29.6411	9.041	3.279	0.001	11.921
47.361 tobacco*ormothhis	63.4584	15.282	4.152	0.000	33.505
93.411 tobacco*adeq_2.0	-10.4443	6.998	-1.493	0.136	-24.160
3.271 tobacco*adeq_3.0 50.403	22.6612	14.154	1.601	0.109	-5.081
tobacco*cardiac	40.0302	33.516	1.194	0.232	-25.661
tobacco*pre4000 -35.460	-81.6672	23.575	-3.464	0.001	-127.875
tobacco*phyper 106.066	75.7972	15.444	4.908	0.000	45.528
tobacco*diabetes	108.0868	16.720	6.465	0.000	75.316
tobacco*anemia 29.901	-23.6158	27.305	-0.865	0.387	-77.133
tobacco*lung 53.208	-9.3116	31.898	-0.292	0.770	-71.831
tobacco*dlivord -10.229	-20.9621	5.476	-3.828	0.000	-31.695
tobacco*educ_0.0 2553.411	2020.2018	272.047	7.426	0.000	1486.993
tobacco*educ_1.0 2659.062	2127.1097	271.407	7.837	0.000	1595.157
tobacco*educ_2.0 2674.057	2141.9499	271.485	7.890	0.000	1609.843
tobacco*dgestat -5.716	-7.9058	1.117	-7.076	0.000	-10.095
tobacco*dmage -1.507	-2.7495				
tobacco*dmar 6.186		7.804			
tobacco*csex 13.747		5.484		0.584	
tobacco*tot_2.0 31.545					
tobacco*tot_3.0 12.728					
tobacco*tot_4.0 69.696					
tobacco*tot_5.0 37.639	1.9808	18.193	0.109	0.913	-33.677

tobacco*tot_6.0	14.1254	23.972	0.589	0.556	-32.860
61.111 tobacco*tot_7.0 114.757	50.9782	32.540	1.567	0.117	-12.800
114.757 tobacco*tot_8.0 189.118	116.8786	36.857	3.171	0.002	44.639
tobacco*live_1.0 91.372	17.3771	37.753	0.460	0.645	-56.618
tobacco*live_2.0 67.198	2.8142	32.849	0.086	0.932	-61.569
tobacco*live_3.0 41.539	8.9669	16.619	0.540	0.589	-23.605
tobacco*live_4.0 28.982	-0.7858	15.188	-0.052	0.959	-30.554
tobacco*live_5.0	-23.2003	13.411	-1.730	0.084	-49.486
tobacco*live_6.0 27.944	0.2926	14.108	0.021	0.983	-27.359
tobacco*live_7.0 58.713	27.2405	16.057	1.696	0.090	-4.232
tobacco*live_8.0 35.763	-0.0084	18.251	-0.000	1.000	-35.780
tobacco*live_9.0 33.667	5.3063	14.470	0.367	0.714	-23.054
tobacco*plur_1 41.714	0.3808	21.088	0.018	0.986	-40.952
Omnibus:	1	 9870.950	Durbin-Watso	on:	1.963
<pre>Prob(Omnibus):</pre>		0.000	Jarque-Bera	(JB):	451511.094
Skew:		0.126	Prob(JB):		0.00
Kurtosis:	:========	12.720 =======	Cond. No.		1.65e+04

Notes:

- [1] \mathbb{R}^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 1.65e+04. This might indicate that there are strong multicollinearity or other numerical problems.

[]: