Estimating Average Treatment Effect Using Subclassifition

Data Feature

A data frame with 614 observations on the following 9 variables.

treat: 1 if treated in the National Supported Work Demonstration, 0 if from the Current Population Survey

age: age

educ: years of education

race: factor; black, Hispanic (hispan), or white

married: 1 if married, 0 otherwise

nodegree: 1 if no degree, 0 otherwise

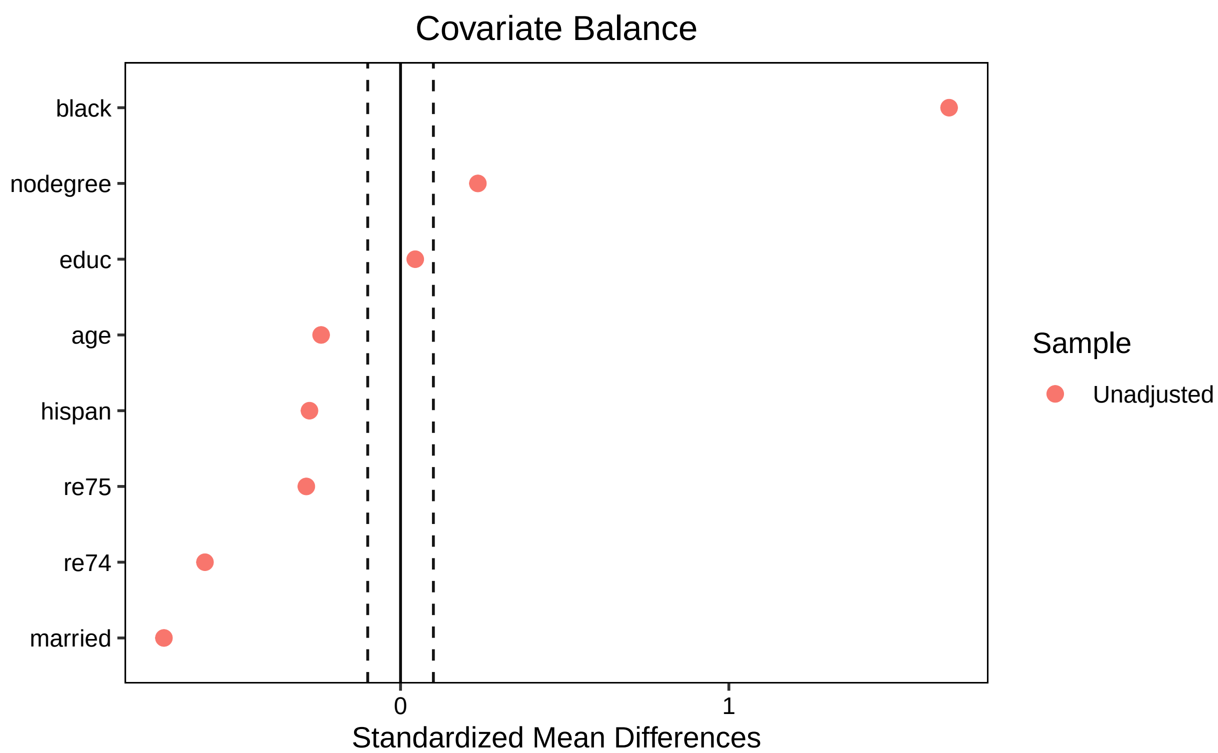
re74: earnings in 1974 (pretreatment)

re75: earnings in 1975 (pretreatment)

re78: earnings in 1978 (outcome)

Covariate Balance Check

```
##           strata():   unstrat
##           stat      Treatment Control std.diff
## vars
## age                    25.8    28.0     -0.23
## educ                   10.3    10.2      0.04
## black0                 0.157   0.797    -1.64
## black1                 0.843   0.203     1.64
## hispan0                0.941   0.858     0.26
## hispan1                0.0595  0.1422   -0.26
## married0               0.811   0.487     0.69
## married1               0.189   0.513    -0.69
## nodegree0              0.292   0.403    -0.23
## nodegree1              0.708   0.597     0.23
## re74                   2096    5619     -0.56
## re75                   1532    2466     -0.29
```

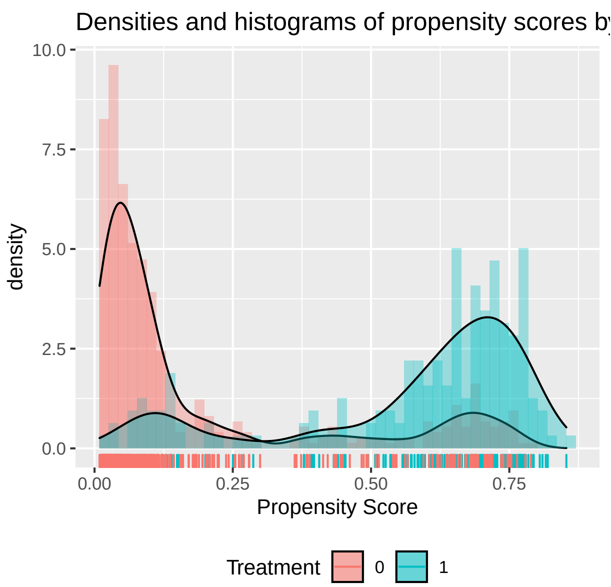


From the table and the plot above, except education, all the covariates have absolute values of the standardized mean difference larger than 0.1 (generally accepted threshold or 0.2 generously). The black variables has the standardized mean difference larger than 1. In light of these, the data have bad covariate balances.

Propensity Score Estimation & Trimming

Table 1: Summary of Propensity Score

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Summary	0.0090802	0.0485365	0.1206765	0.3013029	0.638716	0.8531528



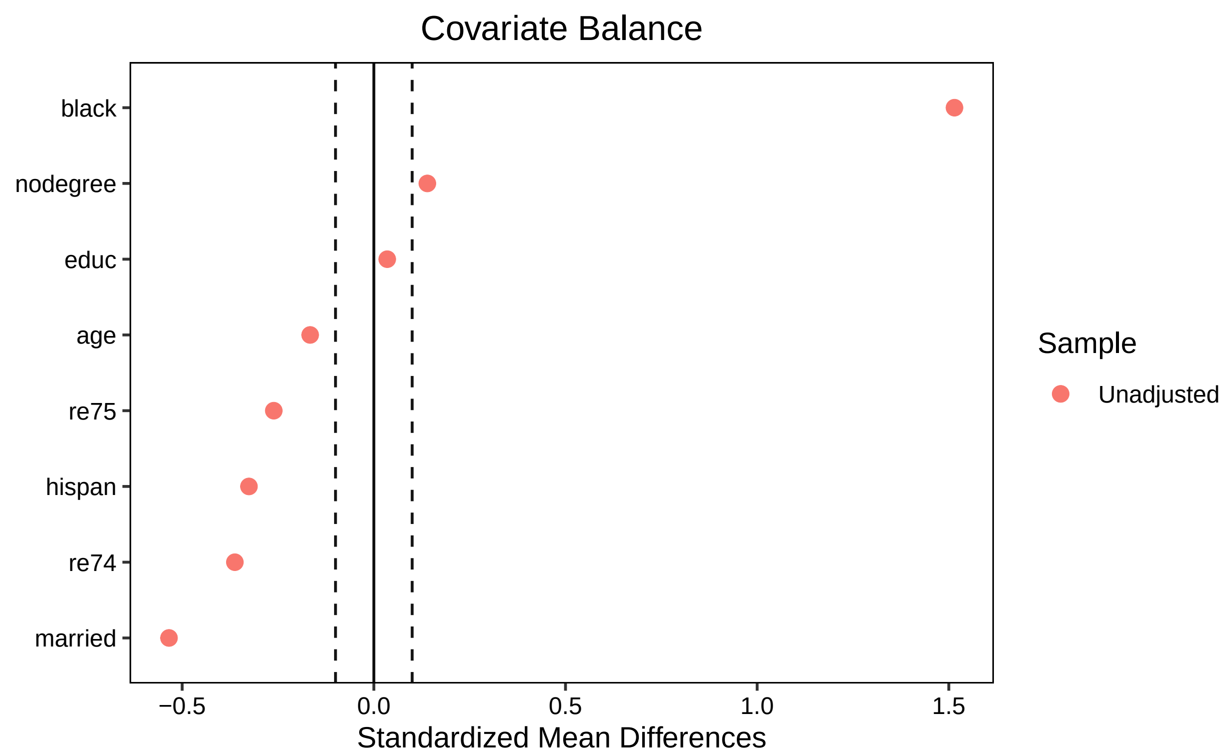

```
## [1] 614  11
```

```
## [1] 549  11
```

Originally, we had 614 observations. After trimming, we have 549 observations. From the plot on the right, it's to be observed that the observations with extreme propensity score are removed, and hence the propensity score density of the two groups (treated & not treated) overlap better compared to the plot on the left.

Checking covariate balance again

```
##            strata():   unstrat
##            stat      Treatment Control std.diff
## vars
## age                     25.4     26.9     -0.16
## educ                    10.3     10.2      0.03
## black0                  0.164    0.766    -1.48
## black1                  0.836    0.234     1.48
## hispan0                 0.938    0.836     0.30
## hispan1                 0.0621   0.1640   -0.30
## married0                0.802    0.562     0.51
## married1                0.198    0.438    -0.51
## nodegree0               0.305    0.371    -0.14
## nodegree1               0.695    0.629     0.14
## re74                    2179     4051     -0.36
## re75                    1486     2329     -0.26
```

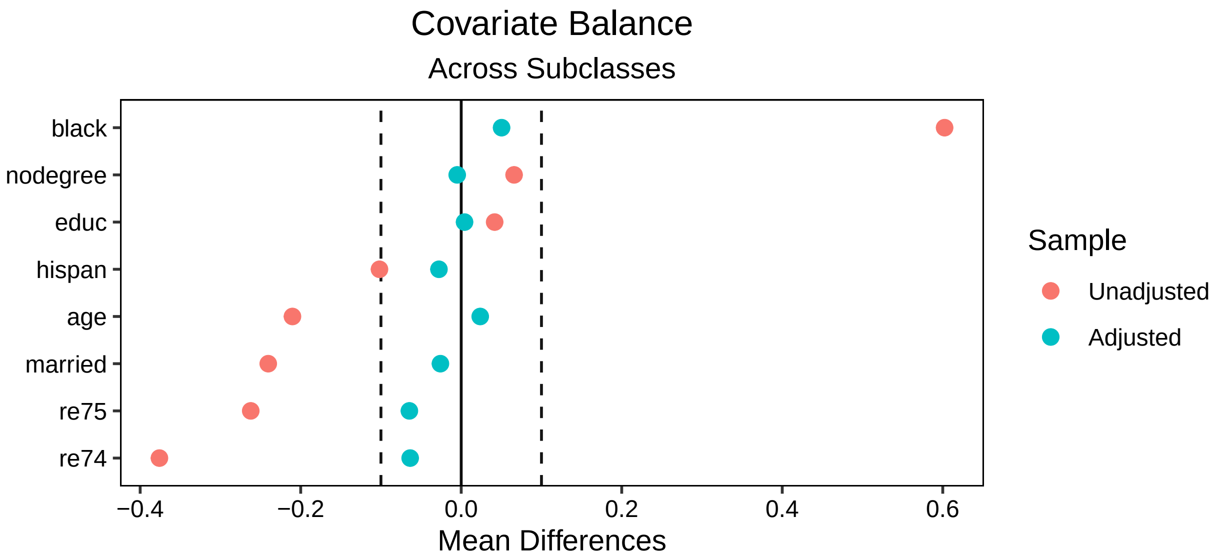


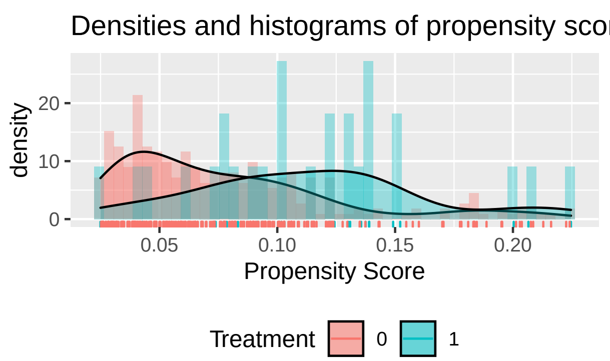
Even though we trimmed the observations with extremem propensity score, it appears that the covariate balances are still not achieved. In fact, it hasn't gotten better at all. Thus, we may want to use subclassification or matching method to improve covariates balances.

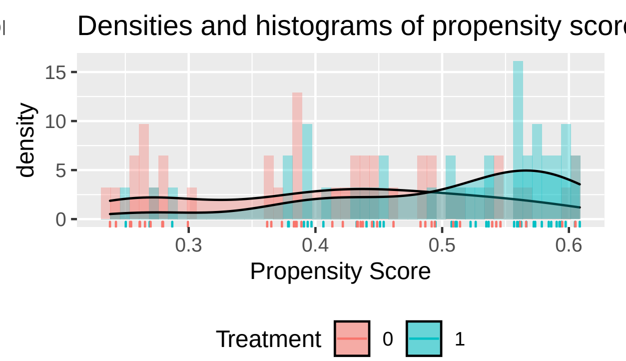
Subclassification & Covariate balance check across subclasses

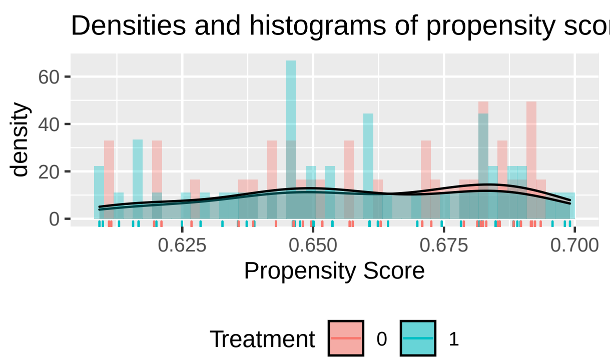
```
## Balance by subclass
##  - - - Subclass 1 - - -
##             Type Diff.Adj
## age       Contin.  -0.3997
## educ      Contin.   0.2317
## black      Binary   0.0334
## hispan     Binary   0.1145
## married    Binary  -0.2462
## nodegree   Binary  -0.0554
## re74      Contin.  -0.2553
## re75      Contin.  -0.1543
##
##  - - - Subclass 2 - - -
##             Type Diff.Adj
## age       Contin.  -0.1849
## educ      Contin.  -0.0238
## black      Binary   0.1951
## hispan     Binary  -0.1951
## married    Binary  -0.0244
## nodegree   Binary   0.0000
## re74      Contin.   0.0363
## re75      Contin.  -0.1404
##
```

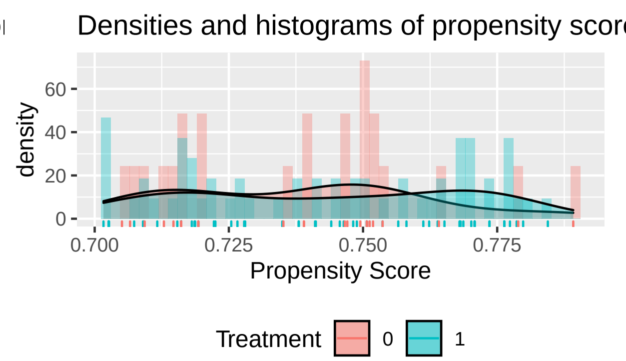
```
##  - - - Subclass 3 - - -
##             Type Diff.Adj
## age      Contin.  -0.1283
## educ     Contin.  -0.0932
## black     Binary   0.0000
## hispan    Binary   0.0000
## married   Binary   0.0625
## nodegree  Binary   0.0773
## re74     Contin.  -0.0671
## re75     Contin.  -0.0006
##
##  - - - Subclass 4 - - -
##             Type Diff.Adj
## age      Contin.   0.4808
## educ     Contin.   0.0004
## black     Binary   0.0000
## hispan    Binary   0.0000
## married   Binary   0.0000
## nodegree  Binary  -0.0529
## re74     Contin.  -0.0427
## re75     Contin.  -0.0248
##
## Balance measures across subclasses
##             Type Diff.Adj
## age      Contin.   0.0237
## educ     Contin.   0.0042
## black     Binary   0.0503
## hispan    Binary  -0.0277
## married   Binary  -0.0259
## nodegree  Binary  -0.0050
## re74     Contin.  -0.0636
## re75     Contin.  -0.0646
##
## Sample sizes by subclass
##           1  2  3  4 All
## Control 275 41 33 23 372
## Treated  27 41 49 60 177
## Total   302 82 82 83 549
```











At first, I tried different number of equally-sized propensity score subclassificaiton and compared the covariate balances in each subclass as well as balance measures across subclasses. However, equally-sized subclasses did not give ideal result for covariate balance because the sample size of the treated was very small in the first and the second subclasses. Thus, I manually set the quantile of propensity score that gives unequally-sized subclasses and then decided to use 0.5, 0.7, and 0.85 quantile after some trials. This is because not only does it improve the covariate balances in each subclass and across subclasses, but the number of both the treated and the controls in each subclass is big enough to have the ideal result in the propensity score plots. After subclassification, we can see that all the covariates have absolute values of the standardized mean difference less than 0.1. Plus, the standardized mean difference values of the variables in each subclass is much lower than those before subclassification.

Estimating Average Treatment Effect

In part 6, we categorize our data into four subclasses based on the quantile of the propensity score to improve covariate balances and ultimately estimate unbiased average causal effect. Namely, propensity score subclassification is used for the purpose of adjusting the confounding because balancing on the propensity score alone can balance all the covariates included in the propensity score model.

We estimate the average causal (treatment) effect in the following way:

$$A\hat{C}E = \sum_{j=1}^{3} \left\{ \hat{E}[Y|A=1, \psi=\psi_j] - \sum_{j=1}^{3} \hat{E}[Y|A=0, \psi=\psi_j] \right\} P(\psi=\psi_j)$$

where $\psi =$ is the proxy of the covariates (i.e. propensity score or subclass), which is the subclass in this context.

Table 2:

subclass	treat	mean	ATE
1	0	6453.3	0.0
1	1	7811.1	1357.8
2	0	5569.1	0.0
2	1	6150.8	581.7
3	0	4251.5	0.0
3	1	6189.0	1937.5
4	0	4918.3	0.0
4	1	5169.6	251.3

Table 3:

ACE	SE	CI	test_statistic	p_value
1160.7	919.3	(-641,2962)	1.26	0.208

The estimated treatment effect (taking the additional job training) on the outcome (salaries) is approximately 1,160, and we interpret that taking the additional job training increases槽 sararies by about 1,160. However, we conclude that taking the additional job training may not result in having higher salaries because we don't have enough evidence to conclude that the additional job training has a significant effect on affecting salaries given that the corresponding p-value to t test-statistic, 0.208, is larger than 0.05. Plus, the confidence interval includes 0 in the interval (-641, 2962), which aligns with the conclusion, and we are 95% confident that the effect of the additional job training on salaries is between -641 and 2,2962