



# Propensity Score [brief introduction]



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## Reference

Austin, P. C. (2011).

*A tutorial and case study in propensity score analysis: an application to estimating the effect of in-hospital smoking cessation counseling on mortality.*

Multivariate behavioral research, 46(1), 119-151.

# Propensity score

1. **Definition:** the propensity score is
  - Probability of receiving treatment (exposure,  $A$ ) given covariates ( $L$ ).
  - $P(L) = \Pr(A=1|L)$
2. **Properties**
  - Balancing score.
  - $P(L)=0.5$  in RCT.
3. **Assumes**
  - no unmeasured confounding  $Y(1), Y(0) \perp A \mid P(L)$ .
  - positivity:  $0 < P(L) < 1$ .
  - Sufficient overlap. If there is no overlap, can't compare  $Y(0), Y(1)$

# Propensity score

- Modelling  $P(L) = \Pr(A=1|L)$ 
  - Any method that gives good predictions is useful.
    - i. **Logistic regression** typically used
    - ii. **Machine learning** methods also reasonable
  - only the predictions matter, the coefficients (in the PS model) don't
  - model can be rich

# Propensity score

- Variables to include (requires subject area-expertise)
  - Include only pre-baseline measures
  - **Confounders**: important to include
  - **Risk factors** /Predictors of  $Y$ : include to reduce SE
  - **Instruments**/Predictors of  $A$  only: avoid
  - **Noise**: avoid (increases SE)
  - Don't look at outcome data while modelling PS

# Various Propensity score analyses approaches

How can I use propensity scores?

- Matching ✓
- Weighting ✓
- Stratification (will not cover)
- Propensity score as a covariate (will not cover)

[A tutorial and case study in propensity score analysis: an application to estimating the effect of in-hospital smoking cessation counseling on mortality.](#)

PC Austin - Multivariate behavioral research, 2011 - Taylor & Francis

**Propensity score** methods allow investigators to estimate causal treatment effects using observational or nonrandomized data. In this article we provide a practical illustration of the appropriate steps in conducting **propensity score** analyses. For illustrative purposes, we use ...

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# Propensity score Matching (ATT)

# Propensity score matching

## How to conduct propensity score matching?



For the purposes of illustration, we will first assume that our data was collected via SRS.



# Propensity score matching: step 1

## Step 1: Specify PS

Model and  
fit that model

PS.model/formula specification:  $A \sim L$

PS.fit = logistic( $A \sim L$ )

Predict from PS.fit

Get the predicted values from the fitted logistic regression

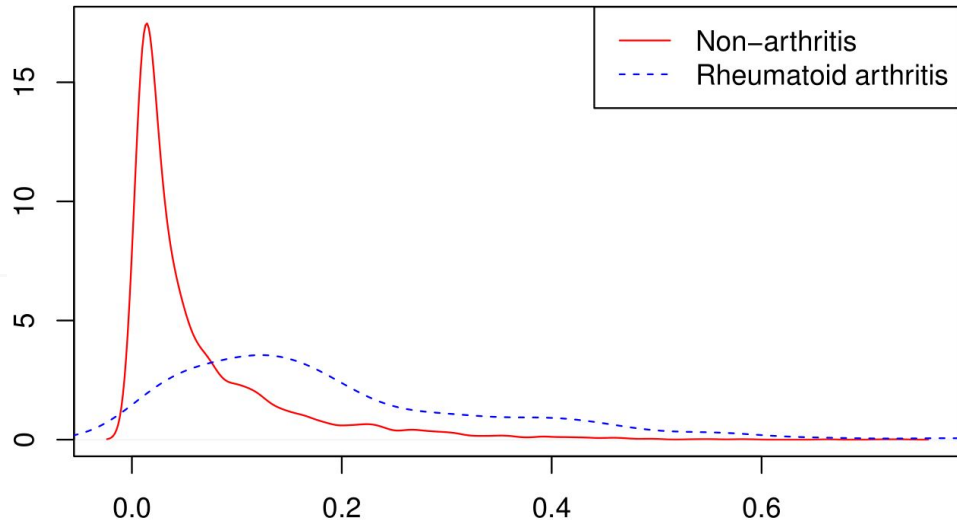
# Propensity score matching: step 1

## Step 1:

Plot the predicted values / propensity scores

Numerical summary of PS distribution

```
## $`Non-arthritis`  
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.  
## 0.001809 0.013710 0.031450 0.064314 0.080949 0.733198  
##  
## $`Rheumatoid arthritis`  
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.  
## 0.006047 0.087135 0.148875 0.190836 0.270072 0.792427
```



# Propensity score matching: step 2

## Step 2: Match subjects by PS

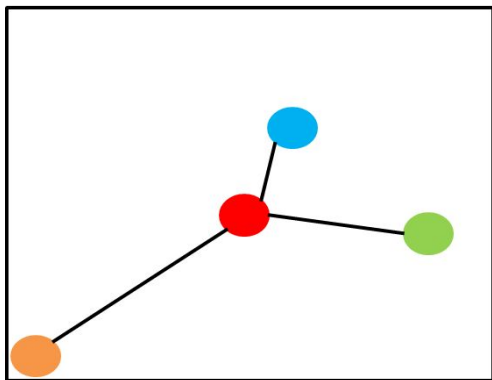
Different algorithms are available to match propensity scores

- Nearest Neighbor (NN) matching: selects the closet PS in the control
- NN & caliper matching: pre-defined bound
- Optimal matching
- Coarsened exact matching / CEM
- Full Matching

# Propensity score matching: step 2

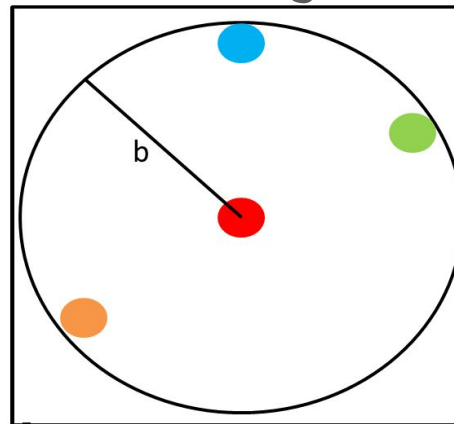
**Step 2:** Match subjects by PS

Nearest Neighbor



Treated ●  
Control ● ● ●

Nearest Neighbor + caliper



Treated ●  
Control ● ● ●

Randomness involved if tied

# Propensity score matching: step 2

## Step 2:

Match subjects  
by PS

Good idea to set seed because some randomness is involved.

Match with the following criteria:

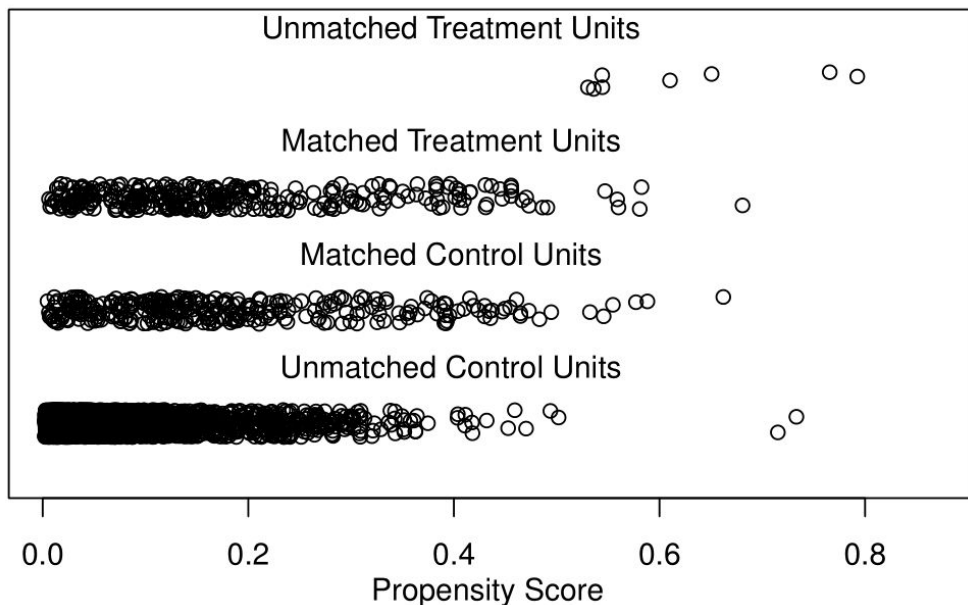
- First get PS from a logistic regression (logit link)
- Using those PS, perform nearest-neighbor matching
- Match without replacement
- Pair matching (ratio = 1:1 for RA vs. non-arthritis)
- Caliper =  $0.2 * \text{sd}(\text{PS})$

Summarize the PS

# Propensity score matching: step 2

**Step 2:** Match subjects by PS

**Distribution of Propensity Scores**

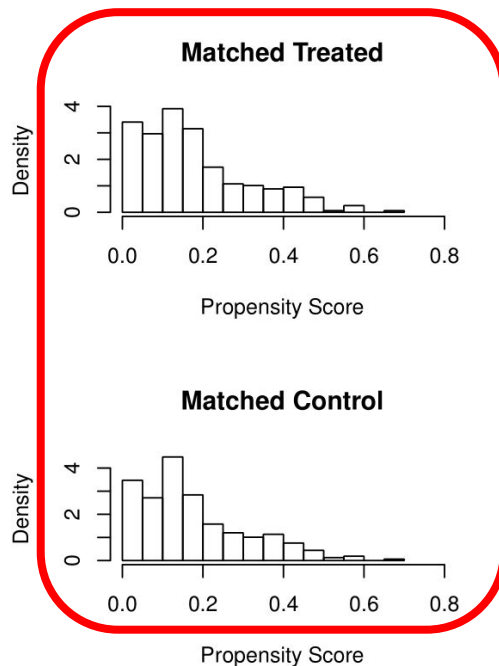
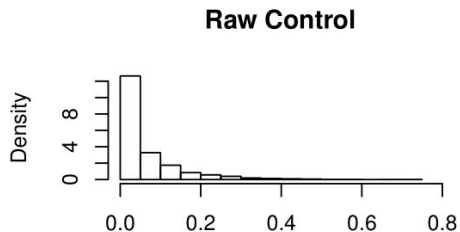
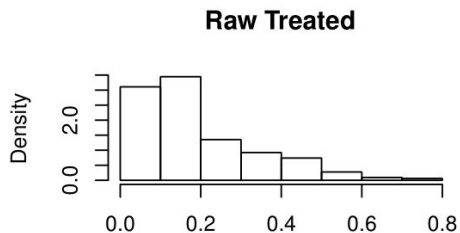


## Sample sizes:

##	Control	Treated
## All	4089	325
## Matched	317	317
## Unmatched	3772	8
## Discarded	0	0

# Propensity score matching: step 3

**Step 3:** Covariate balance in matched sample, **check graphically**



step 3

Step 3

Covariate  
balance  
checking  
using  
**SMD**  
( $<0.2$ ,  
Or  
 $<0.1$ )

Unmatched		Stratified by arthritis.type		
		Non-arthritis	Rheumatoid arthritis	SMD
##	n	4089	325	
##	gender = Female (%)	1960 (47.9)	194 (59.7)	0.238
##	bmi = (25,80] (%)	2745 (67.1)	245 (75.4)	0.183
##	diabetes = Yes (%)	358 ( 8.8)	87 (26.8)	0.485
##	smoke = Yes (%)	1796 (43.9)	177 (54.5)	0.212
##	age (%)			0.891
##	(0,50]	2577 (63.0)	74 (22.8)	
##	(50,70]	1046 (25.6)	169 (52.0)	
##	70+	466 (11.4)	82 (25.2)	
##	race (%)			0.347
##	White	1739 (42.5)	127 (39.1)	
##	Black	843 (20.6)	114 (35.1)	
##	Other	1507 (36.9)	84 (25.8)	
##	born = USborn (%)	2912 (71.2)	262 (80.6)	0.221
##	education (%)			0.160
##	School	495 (12.1)	52 (16.0)	
##	College	1892 (46.3)	127 (39.1)	
##	High.School	1702 (41.6)	146 (44.9)	
##	marriage = Married (%)	2468 (60.4)	152 (46.8)	0.275
##	annualincome (%)			0.531
##	<20k	820 (20.1)	135 (41.5)	
##	20kto54k	1737 (42.5)	126 (38.8)	
##	55k+	1532 (37.5)	64 (19.7)	
##	physical.activity (%)			0.266
##	No	2309 (56.5)	223 (68.6)	
##	High	871 (21.3)	43 (13.2)	
##	Moderate	909 (22.2)	59 (18.2)	
##	medical.access = Yes (%)	3312 (81.0)	310 (95.4)	0.457
##	blood.pressure = Yes (%)	1057 (25.8)	204 (62.8)	0.801
##	healthy.diet (%)			0.213
##	Poor	210 ( 5.1)	34 (10.5)	
##	Fair	951 (23.3)	81 (24.9)	
##	Good	2928 (71.6)	210 (64.6)	
##	covered.health = Yes (%)	2900 (70.9)	279 (85.8)	0.369

Table 1 in unmatched data  
and corresponding SMD

	Non-Ar	RA	SMD
Diabetes	8.8%	26.8%	<b>0.485</b>
Smoke	43.9%	54.5%	<b>0.212</b>

## Sample sizes:

##	Control	Treated
## All	4089	325
## Matched	317	317
## Unmatched	3772	8
## Discarded	0	0



step 3

Unmatched

Table 1 in matched data  
and corresponding SMD

Step 3:

	Non-Ar	RA	SMD
Diabetes	21.8%	25.2%	<b>0.082</b>
Smoke	53.6%	53.6%	<b>&lt;0.001</b>

SMD  
(<0.2,  
Or  
<0.1)

```
## Sample sizes:
##           Control Treated
## All           4089     325
## Matched           317     317
## Unmatched        3772         8
## Discarded           0         0
```

Matched

SMD	##	Stratified by arthritis.type		SMD
		Non-arthritis	Rheumatoid arthritis	
	n	317	317	
0.238	gender = Female (%)	173 (54.6)	186 (58.7)	0.083
0.183	bmi = (25,80] (%)	241 (76.0)	238 (75.1)	0.022
0.485	diabetes = Yes (%)	69 (21.8)	80 (25.2)	0.082
0.212	smoke = Yes (%)	170 (53.6)	170 (53.6)	<0.001
0.891	age (%)			0.052
	(0,50]	77 (24.3)	74 (23.3)	
	(50,70]	166 (52.4)	162 (51.1)	
	70+	74 (23.3)	81 (25.6)	
0.347	race (%)			0.110
	White	139 (43.8)	126 (39.7)	
	Black	108 (34.1)	107 (33.8)	
	Other	70 (22.1)	84 (26.5)	
0.221	born = USborn (%)	252 (79.5)	254 (80.1)	0.016
0.160	education (%)			0.066
	School	52 (16.4)	51 (16.1)	
	College	133 (42.0)	124 (39.1)	
	High.School	132 (41.6)	142 (44.8)	
0.275	marriage = Married (%)	150 (47.3)	149 (47.0)	0.006
0.531	annualincome (%)			0.034
	<20k	125 (39.4)	127 (40.1)	
	20kto54k	131 (41.3)	126 (39.7)	
	55k+	61 (19.2)	64 (20.2)	
0.266	physical.activity (%)			0.083
	No	205 (64.7)	215 (67.8)	
	High	52 (16.4)	43 (13.6)	
	Moderate	60 (18.9)	59 (18.6)	
0.457	medical.access = Yes (%)	300 (94.6)	302 (95.3)	0.029
0.801	blood.pressure = Yes (%)	202 (63.7)	196 (61.8)	0.039
0.213	healthy.diet (%)			0.049
	Poor	28 ( 8.8)	31 ( 9.8)	
	Fair	74 (23.3)	78 (24.6)	
	Good	215 (67.8)	208 (65.6)	
0.369	covered.health = Yes (%)	265 (83.6)	272 (85.8)	0.061

# Propensity score matching: step 4

**Step 4:** Estimate treatment effect

Logistic regression

(Y ~ A) OR = 1.55

fit in matched data

# Propensity score matching vs. regression

Estimates of the OR/CI from matching are not very different than what we got from regression. Why would we do this then?

- **Intuitive**: compare two similar groups
- **Diagnostics** (balance checking) much easier compared to residual plot/influence
- Exposure and outcome models are **seperate**
- Non-parametric (ML) approaches can be used to relax linearity assumption in estimating PS.

# Propensity score matching directly gives you

ATT

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# Thanks!



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