

Propensity Score Methods Using SAS®

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Observational Research

- Key strength: estimate effect of exposures or treatment in “real world” conditions
- Advantages
 - Data readily available, inexpensive
 - Generate quick results
 - Results more generalizable than controlled trials
 - Offer solution to limitations of RCT
 - Ethics
 - Feasibility- Costs/resources
 - Time- results lag
 - Hawthorne effect
 - External validity- patient mix
 - Small samples

Observational Research

- Key limitation: comparison groups not randomized
- Consequence: biased estimate of treatment
- Disadvantages
 - Lack of randomization
 - Differential selection- leads to differences in observed and unobserved characteristics
 - Heterogeneity of populations
 - Varying statistical analyses

Bias in Observational Studies

- Is outcome due to treatment? Or other factors?
- Limited by bias
 - Selection bias
 - Confounding
 - Reverse causality
- Selection bias
 - General definition by Rothman- a distortion resulting from the manner in which subjects are selected into the study population
 - Specified by Faries- differential probability of an individual assigned to a treatment condition and the characteristics of that individual are confounded with treatment outcomes
 - Overt (observed) and hidden (unobserved)

Rothman KJ, Greenland S. *Modern Epidemiology*, 3rd Edition. Lippincott Williams & Wilkins. 2008.
Faries et al, *Analysis of Observational Health Care Data Using SAS*, SAS Institute. 2010.



**Patients eligible for
Drug A or Drug B**



Drug A

Drug B

Patient Characteristics
Younger, More females,
Taking less medications,
Poorer medication use behavior

Patient Characteristics
Older, More male,
Taking more medications,
Better medication use behavior

Guidance on Observational Research

- Good practices for observational studies
 - The International Society of Pharmacoepidemiology (ISPE)
 - International Society for Pharmacoeconomics and Outcomes Research (ISPOR)
- Methods for CER reviews
 - The Effective Health Care Program working document. Effective Healthcare Methods Guide for CER Reviews
 - Guide on evaluating quality CER - The GRACE Initiative (Good Research for Comparative Effectiveness)
- Guidelines on reporting observational CER studies
 - The STROBE (Strengthening the Reporting of Observational Studies) Guidelines
- Guidelines when working with patient registries – AHRQ, Registries for Evaluating Patient Outcomes: A User's Guide
- Guidelines on Systematic Reviews - Cochrane Handbook for Systematic Reviews of Interventions

Methods to Estimate Effects

- Design stage
 - Match subjects
 - Exclusion and inclusion criteria
- Analysis stage- Use statistical techniques
 - Regression, ANCOVA, propensity scoring
- Goal = **balance groups** on characteristics
 - → mimic randomization or simulate random treatment assignment , “quasi randomization”
 - → more confident stating outcome is due to treatment vs. explained by other factors

Propensity Score Methods as a Potential Fix

- Traditional techniques (e.g., regression adjustment) may be limited if using too few covariates in adjustment process
- Propensity score techniques avoids limitation
 - Summarizes covariate information into a single score
- Editorial by D'Agostino (Jr. and Sr.) in JAMA
 - Use 2 methods to adjust for group differences
 - Propensity scoring- balance groups
 - Analysis of covariance- add precision

What is the Propensity Score?

- The propensity score is the conditional probability of being treated based on individual covariates
 - Rosenbaum and Rubin demonstrated p scores can account for imbalances in treatment groups and reduce bias by resembling randomization of subjects into treatment groups
- Propensity score techniques used to compare groups while adjusting for group differences
 - Regression adjustment
 - Matching
 - Stratification (subclassification)

Rosenbaum P.R. and Rubin D.B. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects", *Biometrika*, 70, 41-55.

Creating Propensity Scores Using PROC LOGISTIC

- Logistic regression: Used to predict probability of event occurring as a function of independent variables (continuous and/or dichotomous)


- Logistic model:

$$P(Y) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i x_i)}}$$

- Propensity scores created using PROC LOGISTIC or PROC GENMOD
 - The propensity score is the conditional probability of each patient receiving a particular treatment based on pre-treatment variables
 - Creates data set with predicted probabilities as a variable
 - Or use logit of p score $\log(1/1-p)$

Creating Propensity Scores: Code

```
proc logistic data = indsn;  
class naive0;  
model tx (event='Drug A') = age female b_hmo  
  pre_drug_cnt_subset naive0 pre_refill_pct  
  copay_idxdrug pre_sulf pre_htn pre_asthma  
  pre_pain pre_lipo pre_depress  
  /link=logit rsquare;  
output out = psdataset pred = ps  
  xbeta=logit_ps;  
run;
```



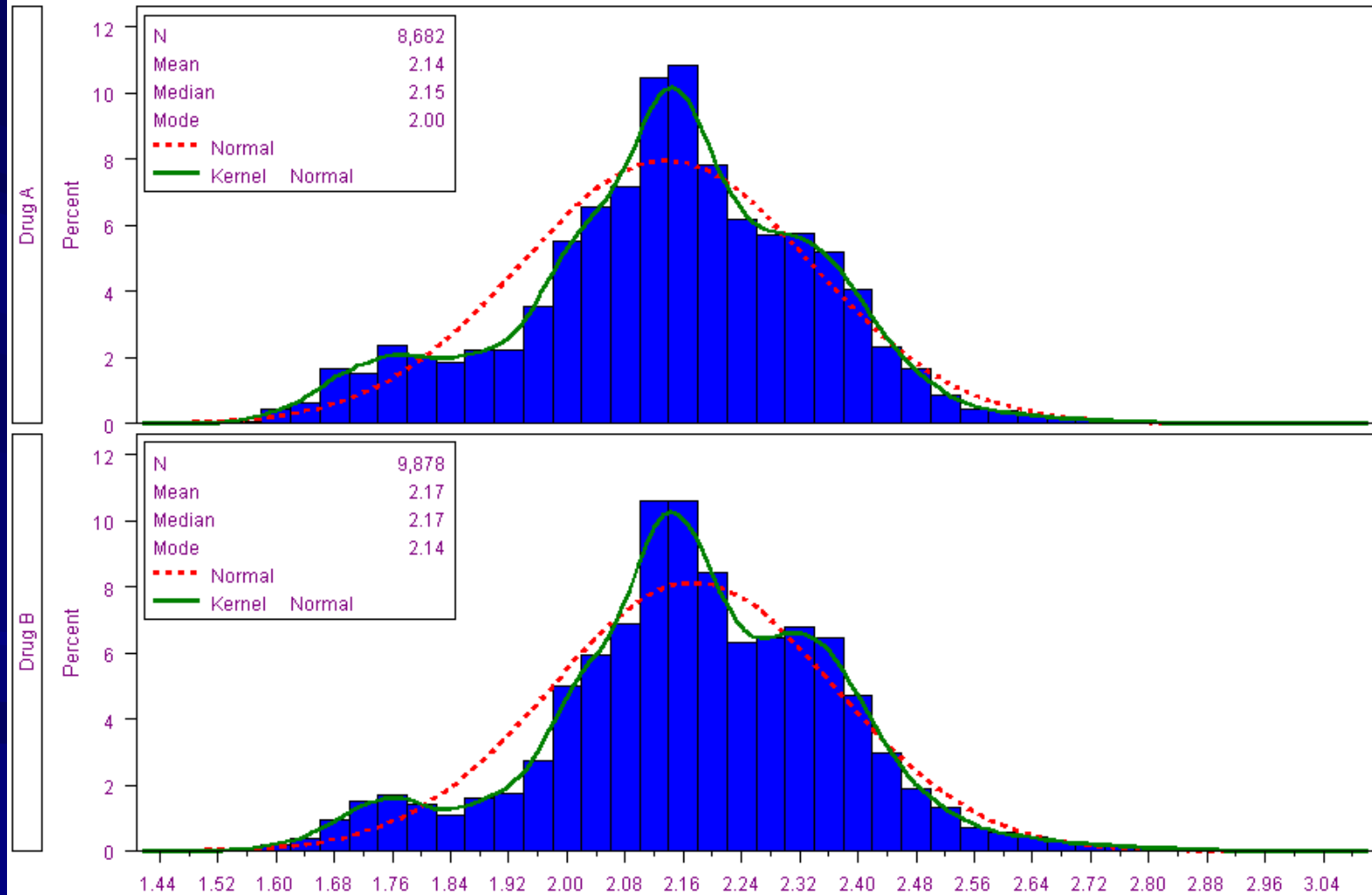
PS= predicted event probability of
receiving treatment based on specified
factors

Estimating P Scores

- Propensity score is the conditional probability of each patient receiving a particular treatment based on pre-treatment variables
 - More covariates better than less (Austin, 2007)
 - Include characteristics that are unbalanced b/w treatment groups
 - Success: Did it balance treatment groups?
 - Michael Doherty SAS paper/macro

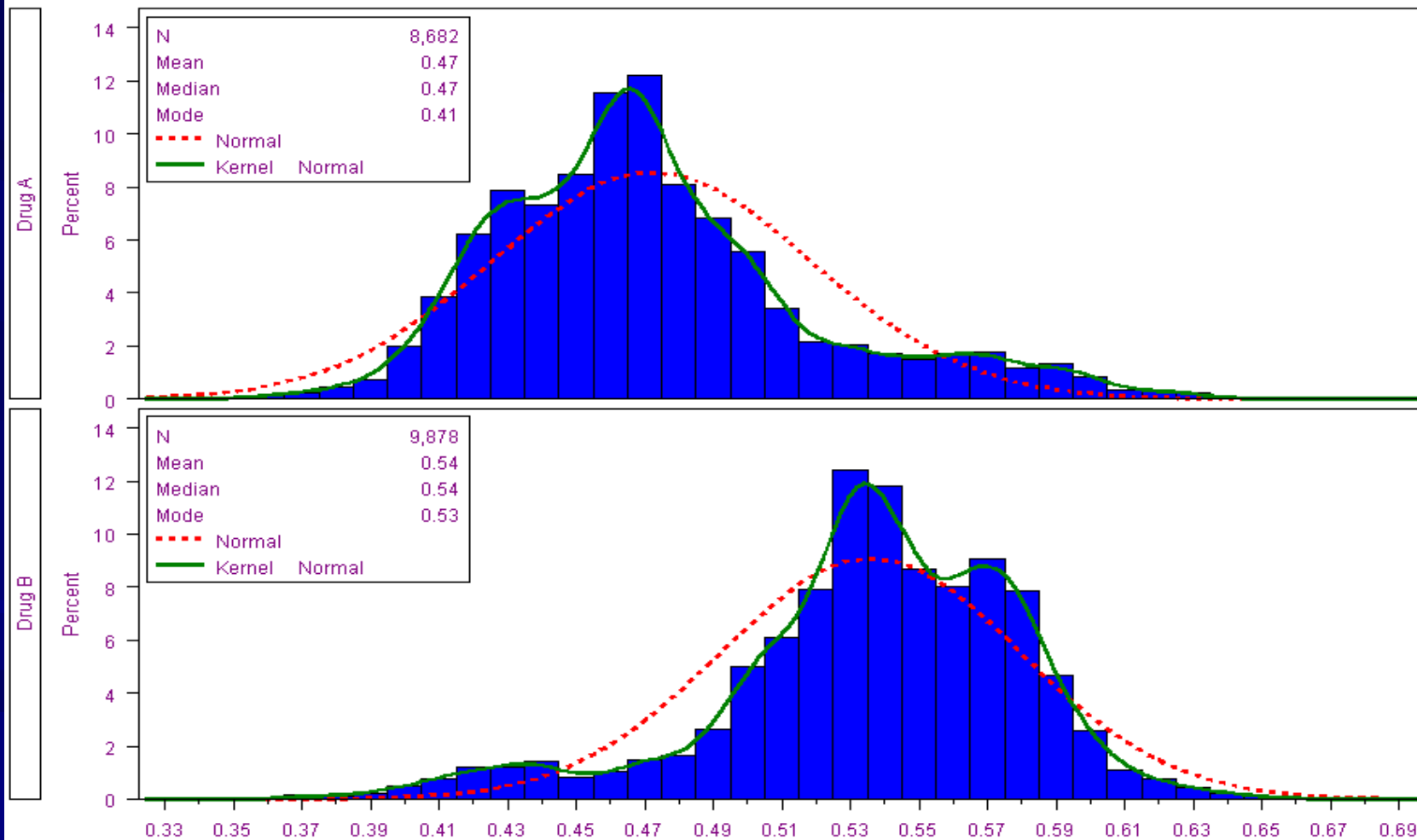
Distribution of Propensity Scores

Histograms of Propensity Scores by Treatment Group



Distribution of Propensity Scores

Histograms of Propensity Scores by Treatment Group



Distribution of P Scores: Code

```
proc univariate data=psds plot;  
title 'Histograms of Propensity Scores by Treatment Group';  
var ps;  
class tx;  
histogram ps / ctext=purple cfill=blue  
    kernel (k=normal color=green w=3 l=1)  
    normal (color = red w=3 l= 2)  
    ncols=1 nrows=2;  
inset n='N' (comma6.0) mean='Mean' (6.2)  
    median='Median' (6.2) mode='Mode'(6.2)  
    normal kernel(type) / position=NW;  
run;
```


Propensity Score Methods

- Once the propensity score is calculated what to do you with them?
- 3 common methods as stated by Rosenbaum and Rubin, 1984
 - Regression adjustment
 - Stratification (subclassification)
 - Matching

Rosenbaum P.R. and Rubin D.B. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects", *Biometrika*, 70, 41-55.

Regression Adjustment Method

- Use p score as a covariate outcome model
 - Or use propensity score weights as the inverse of propensity score

- Use PROC GLM or PROC LOGISTIC to model outcome
 - Add independent variables believed to confound outcome

- Second step of 2 stage process
 1. Use propensity scores to balance groups
 2. Use ANCOVA modeling to create precisions

Regression Adjustment: Code

- Model continuous outcome adjusting for p scores

```
/*create p score*/
```

```
proc logistic data = indsn;
```

```
class naive0;
```

```
model tx (event='Drug A') = /*pre_tx_vars*/ ivar1 ivar2
```

```
  /link=logit rsquare;
```

```
output out = ps_dataset pred = ps xbeta=logit_ps;
```

```
run;
```

```
/*outcome model adjusting for p score*/
```

```
proc glm data = ps_dataset ;
```

```
class tx;
```

```
model pdc = tx ps /solution;
```

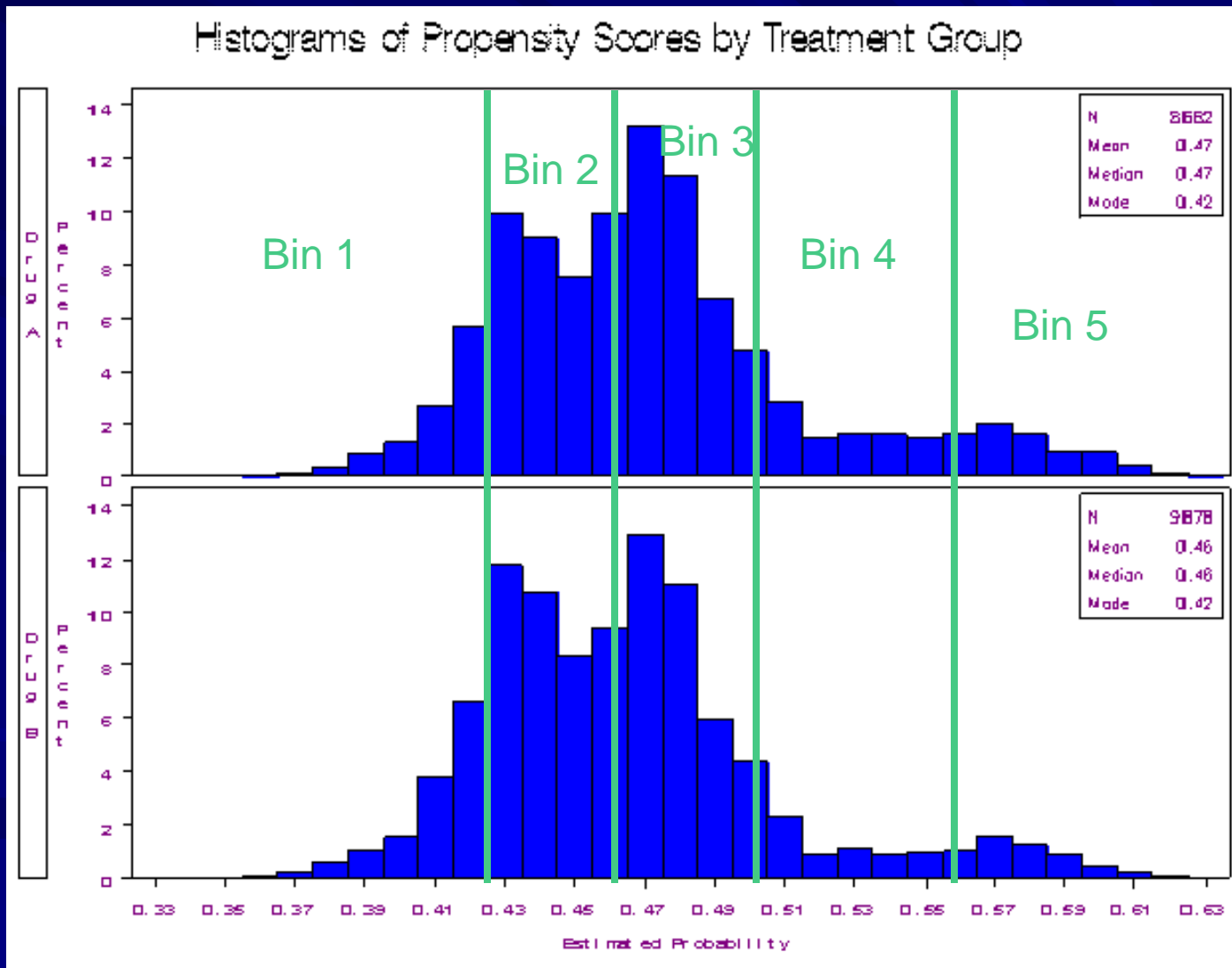
```
lsmeans tx / om adjust = tukey pdiff cl;
```

```
quit;
```

Stratifying by P Score: Objective

- Stratification, subclassification or binning involves grouping subjects into strata based on subject's observed characteristics
- Use calculated p scores to place subjects into strata
- Objective = subjects in the same stratum are similar in the characteristics used in the propensity score development process

Stratifying Propensity Scores



Cochran, Biometrics, 1968 - 5 strata can remove 90% of the bias

Stratifying by P Score: Code

```
/*create 5 quintiles of p scores */  
  
proc rank data = psdataset groups=5  
  out = rank_ds;  
ranks rank;  
var ps;  
  
data quintile;  
set rank_ds;  
quintile = rank + 1;  
run;
```

Stratifying by P Score: Estimate Effect

- Result of code is 5 bins of homogenous subjects
 - Check differences between treatment groups
 - Sensitivity analysis if distributions don't overlap
- Outcomes can be compared within the 5 subclasses
- Calculate weighted mean of the subclasses to report an overall treatment effect

Stratifying by P Score: Code

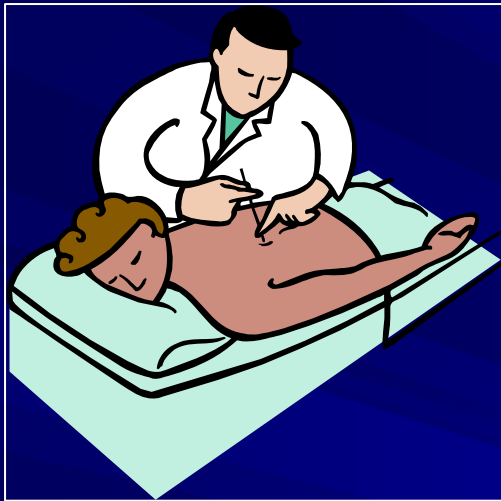
- Model continuous outcome adjusting for p scores

```
/*outcome model adjusting for quintile of p score*/  
proc glm data = quintile;  
class tx;  
model pdc = tx quintile /solution;  
lsmeans tx / om adjust = tukey pdiff cl;  
quit;
```

P Score Matching

- Matching groups by p scores can balance groups on covariates
- Subjects are matched by single score vs. by one or more variables (traditional direct matching)
- Challenges
 - incomplete matching (can't find a match)
 - inexact matching (how close is a match)

Matching by Characteristic



- Match on single or multiple characteristics
 - e.g., age, gender, disease severity, health plan, etc.
- 1:1 or 1:many

P Score Matching



I need a match! Does anyone have a propensity score near 0.824?



My propensity score is 0.859. Is that close enough?

P Score Matching Methods

- Techniques
 - Stratified
 - Nearest neighbor
 - Radius matching
 - Caliber
 - Kernel matching
 - Mahalanobis metric
- Replacement- back in pool for further possible matching
- W/o replacement or greedy algorithm- find match and keep it
- Which is appropriate? Literature offers some guide
 - With replacement when matching pool is small
 - 2 to 1 match if control group is large
 - Ease of calculation
- Goal- Increase balance between groups

PS Matching Using Greedy Algorithm

- Example of case-control match using a greedy matching algorithm
- Nearest available pair method
- Reducing the non matches and inexact matches
- P scores used to balance treated and untreated groups

Parsons, Lori. 2000. "Using SAS® Software to Perform a Case Control Match on Propensity Score in an Observational Study". *Proceedings of the Twenty-Fifth Annual SAS Users Group International Conference*, Indianapolis, IN, 214-26.

PS Matching Using Greedy Algorithm

Table 1: Original Population

	Early Intervention N (%)	Conservative N (%)	p-value
Total Patients	2,402	17,735	
Age (Mean±sd)	61.3 ±12.2	68.2±13.0	<0.0001
Male Gender	1,744 (72.6)	10,914 (61.5)	<0.0001
White Race	2,079 (91.8)	15,002 (88.4)	<0.0001
Hx Angina	444 (18.5)	4,441 (25.0)	<0.0001
Hx MI	574 (23.9)	5,382 (30.3)	<0.0001

Table 2: Greedy 5 to 1 Digit Matched Population

	Early Intervention N (%)	Conservative N (%)	p-value
Total Patients	2,036	2,036	
Age (Mean±sd)	61.9 ±12.0	61.7±13.3	0.5405
Male Gender	1,452 (71.3)	1,445 (71.0)	0.8087
White Race	1,865 (91.6)	1,858 (91.3)	0.6952
Hx Angina	390 (19.2)	381 (18.7)	0.7189
Hx MI	488 (24.0)	491 (24.1)	0.9124

Summary

- Propensity score as the conditional probability of treatment (or desired event) summarizes observed values into a single score
- P scores uses:
 - Match subjects
 - Stratify subjects
 - As a covariate
- Purpose = **balancing groups** to remove bias when assessing treatment effect on outcomes

Advantages

- Summarizes observed values into a single score less sensitive to model misspecification
 - Traditional techniques may be limited if accounting for only a few covariates
- P scores can diagnose comparability of groups before modeling stage
 - Distributions overlap?
 - If comparison groups are too different >>>difficult to balance groups
- P score is more robust approach
 - Address selection bias and offers precision

Assumptions & Disadvantages

■ Assumptions

- All covariates that affect both treatment and outcome must be included in the model. How do you determine this?
- All patients have a non zero probability of receiving each treatment

■ Disadvantages

- Incorporates observed characteristics and thus doesn't account for unobserved factors, e.g., patient attitudes, socioeconomic status, and education level
 - Modified if unobserved factors are correlated to observed factors
- Large samples sizes may be needed to establish adequate variance in covariate distributions

Conclusion

- Selection bias may create biased estimate of your outcome in observational studies
- P score methods used to adjust for selection bias
- Use with traditional risk adjustment techniques to reduce bias and better describe the effect of exposure on outcomes
- Minimizes bias, not total adjustment
- Observables vs. unobservables: Instrumental variable method account for unobservables
- Use multiple methods and consistent results add robustness of research

Questions and Comments

- Thank you, BASUG and BASUG Officers
- Special thanks to,
 - Bridget Neville
 - Karen Olsen



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