Why Propensity Scores Should Not Be Used For Matching

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(Society for Political Methodology talk, University of Rochester, 7/24/2015)

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The Scholarly Influence of Propensity Score Matching
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- The most commonly used matching method

Maybe even “the most developed and popular strategy for causal analysis in observational studies” (Pearl, 2010)

This paper is about: propensity score matching, as used in practice.

Not implicated by our results:
- Other uses of propensity scores: E.g., regression adjustment, inverse weighting, stratification, pscores used in other methods, such as GenMatch or CBPS
- The mathematical theorems about propensity scores
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![Graph showing the relationship between Education (years) and Outcome. The graph includes data points and a trend line to illustrate matching to reduce model dependence.](image-url)
The Problems Matching Solves

• Qualitative choice from unbiased estimates = biased estimator
e.g., Choosing from results of 50 randomized experiments
• Choosing based on "plausibility" is probably worse
• Conscientious effort doesn't avoid biases (Banaji 2013)
• People do not have easy access to their own mental processes or feedback to avoid the problem (Wilson and Brekke 1994)
• Experts overestimate their ability to control personal biases more than nonexperts, and more prominent experts are the most overconfident (Tetlock 2005)
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Imbalance $\leadsto$ Model Dependence $\leadsto$ Researcher discretion
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A central project of statistics: Automating away human discretion
What’s Matching?

• \( Y_i \) dep var, \( T_i \) (1=treated, 0=control), \( X_i \) confounders

• Treatment Effect for treated observation \( i \):

\[
TE_i = Y_i - Y_i(0) = \text{observed} - \text{unobserved}
\]

• Estimate \( Y_i(0) \) with \( Y_j \) with a matched (\( X_i \approx X_j \)) control

• Quantities of Interest:
  1. SATT: Sample Average Treatment effect on the Treated:
     \[
     SATT = \text{Mean} \{ i \in \{ T_i = 1 \} \}(TE_i)
     \]
  2. FSATT: Feasible SATT (prune badly matched treateds too)

• Big convenience: Follow preprocessing with whatever statistical method you’d have used without matching

• Pruning nonmatches makes control vars matter less: reduces imbalance, model dependence, researcher discretion, & bias
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Matching: Finding Hidden Randomized Experiments

Types of Experiments

- Balance
- Covariates:
  - Complete Randomization
  - Fully Blocked
  - Observed
  - Unobserved

On average, Fully blocked dominates complete randomization for:
- imbalance,
- model dependence,
- power,
- efficiency,
- bias,
- research costs,
- robustness.

E.g., Imai, King, Nall 2009: SEs 600% smaller!
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Goal of Each Matching Method (in Observational Data):
- PSM: complete randomization
- Other methods: fully blocked
- Other matching methods dominate PSM
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Complete Randomization

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$\Rightarrow$ *Fully blocked* dominates *complete randomization* for:

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E.g., Imai, King, Nall 2009: SEs 600% smaller!
Matching: Finding Hidden Randomized Experiments

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Goal of Each Matching Method (in Observational Data)
Matching: Finding Hidden Randomized Experiments

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Goal of Each Matching Method (in Observational Data)

- PSM: complete randomization
Matching: Finding Hidden Randomized Experiments

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Goal of Each Matching Method (in Observational Data)

- PSM: complete randomization
- Other methods: fully blocked
## Matching: Finding Hidden Randomized Experiments

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### Goal of Each Matching Method (in Observational Data)

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### Goal of Each Matching Method (in Observational Data)

- PSM: *complete randomization*
- Other methods: *fully blocked*
- Other matching methods dominate PSM (wait, it gets worse)
Method 1: Mahalanobis Distance Matching

1. Preprocess (Matching)
   - Distance($X_c$, $X_t$) = $\sqrt{\left((X_c - X_t)S^{-1}(X_c - X_t)\right)}$
   - (Mahalanobis is for methodologists; in applications, use Euclidean!)
   - Match each treated unit to the nearest control unit
   - Control units: not reused; pruned if unused
   - Prune matches if Distance $> \text{caliper}$
   - (Many adjustments available to this basic method)

2. Estimation Difference in means or a model
Method 1: Mahalanobis Distance Matching
(Approximates Fully Blocked Experiment)
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2. **Estimation** Difference in means or a model
Mahalanobis Distance Matching

Education (years)

Age

12 14 16 18 20 22 24 26 28

20

30

40

50

60

70

80

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8/23
Best Case: Mahalanobis Distance Matching
Best Case: Mahalanobis Distance Matching
Method 2: Coarsened Exact Matching

1. Preprocess (Matching)
   - Temporarily coarsen $X$ as much as you're willing
     - e.g., Education (grade school, high school, college, graduate)
   - Apply exact matching to the coarsened $X$, $C(X)$
   - Sort observations into strata, each with unique values of $C(X)$
   - Prune any stratum with 0 treated or 0 control units
   - Pass on original (uncoarsened) units except those pruned

2. Estimation
   - Difference in means or a model
   - Weight controls in each stratum to equal treateds
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   - Weight controls in each stratum to equal treateds
Coarsened Exact Matching
Coarsened Exact Matching

![Coarsened Exact Matching Graph]

- **Age** values: 12, 14, 16, 18, 20, 22, 24, 26, 28
- **Education** values: 20, 30, 40, 50, 60, 70, 80

Legend:
- **C** for Coarsened
- **T** for Exact
Coarsened Exact Matching

Drinking age
Don't trust anyone over 30
The Big 40
Senior Discounts
Retirement
Old
Education
HS BA MA PhD 2nd PhD

11/23
Coarsened Exact Matching

Drinking age
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Coarsened Exact Matching

Education

Age

12 14 16 18 20 22 24 26 28

20

30

40

50

60

70

80

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CC

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Best Case: Coarsened Exact Matching
Best Case: Coarsened Exact Matching
Best Case: Coarsened Exact Matching

Educational attainment vs. age

Education: 12 14 16 18 20 22 24 26 28
Age: 20 30 40 50 60 70 80

C C C C C C C C C C C C C C C C

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Method 3: Propensity Score Matching

1. Preprocess (Matching)
   • Reduce $k$ elements of $X$ to scalar $\pi_i \equiv \Pr(T_i = 1 | X) = \frac{1}{1 + e^{-X_i \beta}}$
   • Distance($X_c, X_t$) = $|\pi_c - \pi_t|$
   • Match each treated unit to the nearest control unit
   • Control units: not reused; pruned if unused
   • Prune matches if Distance $>$ caliper
   • (Many adjustments available to this basic method)

2. Estimation Difference in means or a model
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   - Distance \((X_c, X_t) = |\pi_c - \pi_t|\)
   - Match each treated unit to the nearest control unit
   - Control units: not reused; pruned if unused
   - Prune matches if Distance > *caliper*
   - (Many adjustments available to this basic method)

2. **Estimation** Difference in means or a model
Propensity Score Matching

Education (years) vs. Age

- Education (years): 12, 16, 20, 24, 28
- Age: 20, 30, 40, 50, 60, 70, 80

Points on the graph represent matched pairs, with C and T indicating different groups or conditions.
Propensity Score Matching

Education (years)

Age

12 16 20 24 ...

Propensity Score

0 1
Propensity Score Matching

Age

12 16 20 24 28

20

30

40

50

60

70

80

Education (years)

Propensity Score

0 1
Propensity Score Matching

Education (years)

0 10 20 30 40 50 60 70 80
Age

12 16 20 24 28

Propensity Score

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Education (years)

0 1

Propensity Score
Propensity Score Matching

Propensity Score

Education (years)

Age

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Propensity Score Matching

Education (years)

Age

12 16 20 24 28

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Best Case: Propensity Score Matching
Best Case: Propensity Score Matching
Best Case: Propensity Score Matching
Best Case: Propensity Score Matching

![Graph showing data points across education years and age.](image-url)
Best Case: Propensity Score Matching is Suboptimal
Random Pruning Increases Imbalance

"Random pruning": pruning process is independent of \( X \).

**Discrete example**

Sex-balanced dataset: treated males \( M_t \), females \( F_t \), controls males \( M_c \), females \( F_c \).

Randomly prune 1 treated & 1 control \( \Rightarrow \) 4 possible datasets:
- 2 balanced: \{\( M_t \), \( M_c \)\}, \{\( F_t \), \( F_c \)\}
- 2 imbalanced: \{\( M_t \), \( F_c \)\}, \{\( F_t \), \( M_c \)\}

\[ \Rightarrow \text{random pruning increases imbalance} \]

**Continuous example**

Dataset: \( T \in \{0, 1\} \) randomly assigned; \( X \) any fixed variable; with \( n \) units.

Measure of imbalance: squared difference in means \( d^2 \), where \( d = \bar{X}_t - \bar{X}_c \).

\[ \mathbb{E}(d^2) = \mathbb{V}(d) \propto \frac{1}{n} \text{(note: } \mathbb{E}(d) = 0) \]

Random pruning \( \Rightarrow n \) declines \( \Rightarrow \mathbb{E}(d^2) \) increases.

\[ \Rightarrow \text{random pruning increases imbalance} \]
Random Pruning Increases Imbalance

Deleting data only helps if you’re careful!

• “Random pruning”: pruning process is independent of X

• Discrete example

• Sex-balanced dataset: treateds M_t, F_t, controls M_c, F_c

• Randomly prune 1 treated & 1 control ⇝ 4 possible datasets:
  {2 balanced} {M_t, M_c}, {F_t, F_c}
  {2 imbalanced} {M_t, F_c}, {F_t, M_c}

• =⇒ random pruning increases imbalance

• Continuous example

• Dataset: T ∈ {0, 1} randomly assigned; X any fixed variable; with n units

• Measure of imbalance: squared difference in means \( d^2 \), where \( d = \bar{X}_t - \bar{X}_c \)

• \( E(d^2) = V(d) \propto \frac{1}{n} \) (note: \( E(d) = 0 \))

• Random pruning ⇝ n declines ⇝ \( E(d^2) \) increases

• =⇒ random pruning increases imbalance
Random Pruning Increases Imbalance
Deleting data only helps if you’re careful!

- “Random pruning”: pruning process is independent of $X$

- Discrete example
  - Sex-balanced dataset: treated $M_t$, $F_t$, controls $M_c$, $F_c$
  - Randomly prune 1 treated & 1 control
    - 4 possible datasets:
      - 2 balanced: $\{M_t, M_c\}$, $\{F_t, F_c\}$
      - 2 imbalanced: $\{M_t, F_c\}$, $\{F_t, M_c\}$
    - $= \Rightarrow$ random pruning increases imbalance

- Continuous example
  - Dataset: $T \in \{0, 1\}$ randomly assigned; $X$ any fixed variable; with $n$ units
  - Measure of imbalance: squared difference in means $d^2$, where $d = \bar{X}_t - \bar{X}_c$
  - $E(d^2) = V(d) \propto 1/n$ (note: $E(d) = 0$)
  - Random pruning $\Rightarrow n$ declines $\Rightarrow E(d^2)$ increases
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\[
\begin{align*}
\text{Randomly prune 1 treated & 1 control} & \Rightarrow 4 \text{ possible datasets:} \\
\quad & \{M_t, M_c\}, \{F_t, F_c\} \\
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\]

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  - Sex-balanced dataset: treateds \( M_t, F_t \), controls \( M_c, F_c \)
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  • Dataset: $T \in \{0, 1\}$ randomly assigned; $X$ any fixed variable; with $n$ units
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  • Sex-balanced dataset: treateds $M_t, F_t$, controls $M_c, F_c$
  
  • Randomly prune 1 treated & 1 control $\leadsto$ 4 possible datasets:
    - 2 balanced $\{M_t, M_c\}, \{F_t, F_c\}$
    - 2 imbalanced $\{M_t, F_c\}, \{F_t, M_c\}$

• $\implies$ random pruning increases imbalance

• **Continuous example**
  
  • Dataset: $T \in \{0, 1\}$ randomly assigned; $X$ any fixed variable; with $n$ units
  
  • Measure of imbalance: squared difference in means $d^2$, where $d = \bar{X}_t - \bar{X}_c$
  
  • $E(d^2) = V(d) \propto 1/n$ (note: $E(d) = 0$)
  
  • Random pruning $\leadsto n$ declines $\leadsto E(d^2)$ increases

• $\implies$ random pruning increases imbalance
PSM’s Statistical Properties

1. Low Standards:
   - Sometimes helps, never optimizes
     • Efficient relative to complete randomization, but
     • Inefficient relative to (the more powerful) full blocking
     - Other methods dominate:
       \[
       X_c = X_t \Rightarrow \pi_c = \pi_t \neq \pi_t \Rightarrow X_c = X_t
       \]

2. The PSM Paradox:
   - When you do “better,” you do worse
     • When PSM approximates complete randomization (to begin
       with or, after some pruning)
       \[
       \Rightarrow \forall \hat{\pi} \approx 0 \text{ (or constant within strata)}
       \Rightarrow \text{pruning at random}
       \Rightarrow \text{Imbalance}
       \Rightarrow \text{Inefficency}
       \Rightarrow \text{Model dependence}
       \Rightarrow \text{Bias}
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   - If the data have no good matches, the paradox won’t be a
     problem but you’re cooked anyway.
   - Doesn’t PSM solve the curse of dimensionality problem?
     Nope.
   - The PSM Paradox gets worse with more covariates
   - What if I match on a few important covariates and then use
     PSM?
     The low standards will be raised some, but the PSM
     Paradox will kick in earlier.
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1. **Low Standards:** Sometimes helps, never optimizes
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   - *Inefficient* relative to (the more powerful) full blocking

2. **The PSM Paradox:** When you do “better,” you do worse
   - When PSM approximates complete randomization (to begin with or, after some pruning)
     - $\hat{\pi}_c \approx \pi_c$ (or constant within strata)
     - Pruning at random
     - Imbalance
     - Inefficency
     - Model dependence
     - Bias
   - If the data have no good matches, the paradox won’t be a problem but you’re cooked anyway.
   - Doesn’t PSM solve the curse of dimensionality problem?
   - No.
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3. What if I match on a few important covariates and then use PSM?
   - The low standards will be raised some, but the PSM Paradox will kick in earlier
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\[ x_c = x_t \Rightarrow \pi_c = \pi_t \]

2. The PSM Paradox: When you do “better,” you do worse
   - When PSM approximates complete randomization (to begin with or, after some pruning)
     \[ \hat{\pi} \approx 0 \text{ (or constant within strata)} \]
     \[ \Rightarrow \text{pruning at random} \Rightarrow \text{Imbalance} \Rightarrow \text{Inefficency} \Rightarrow \text{Model dependence} \Rightarrow \text{Bias} \]
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   - When PSM approximates complete randomization (to begin with or, after some pruning)
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   - When PSM approximates complete randomization (to begin with or, after some pruning) \[ \sim \] all \( \hat{\pi} \approx 0.5 \) (or constant within strata) \[ \sim \] pruning at random \[ \sim \] Imbalance
PSM’s Statistical Properties

1. **Low Standards:** Sometimes helps, never optimizes
   - *Efficient* relative to complete randomization, but
   - *Inefficient* relative to (the more powerful) full blocking
   - Other methods dominate:
     $$X_c = X_t \implies \pi_c = \pi_t$$ but
     $$\pi_c = \pi_t \nRightarrow X_c = X_t$$

2. **The PSM Paradox:** When you do “better,” you do worse
   - When PSM approximates complete randomization (to begin with or, after some pruning) \(\leadsto\) all \(\hat{\pi} \approx 0.5\) (or constant within strata) \(\leadsto\) pruning at random \(\leadsto\) Imbalance \(\leadsto\) Inefficiency
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   - Doesn’t PSM solve the curse of dimensionality problem?
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PSM is Blind Where Other Methods Can See
PSM is Blind Where Other Methods Can See
PSM is Blind Where Other Methods Can See
What Does PSM Match?

MDM Matches

PSM Matches

Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$
Treated: $X_1, X_2 \sim \text{Uniform}(1,6)$
PSM Increases Model Dependence & Bias

Model Dependence

Bias

\[ Y_i = 2T_i + X_{1i} + X_{2i} + \epsilon_i \]
\[ \epsilon_i \sim N(0, 1) \]
The Propensity Score Paradox in Real Data

Finkel et al. (JOP, 2012)

Nielsen et al. (AJPS, 2011)
Conclusions

• Why propensity scores should not be used for matching
• Low Standards: sometimes helps, never optimizes
• The PSM Paradox: When you do "better," you do worse
• Some mistakes with PSM: Controlling for irrelevant covariates; adjusting experimental data; reestimating propensity score after eliminating noncommon support; 1/4 caliper on propensity score; not switching to other methods.

• A warning for any matching method:
  • Pruning discards information; you must overcome this.
  • Other methods can generate a "paradox" if you prune after approximating full blocking (rare, but possible)
  • If you're not doing positive good, you may be hurting yourself

• Matching methods still highly recommended; choose one with higher standards
Conclusions

- Why propensity scores should not be used for matching
Conclusions

• Why propensity scores should not be used for matching
  • Low Standards: sometimes helps, never optimizes
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Conclusions

• Why propensity scores should not be used for matching
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  • The PSM Paradox: When you do “better,” you do worse
  • Some mistakes with PSM: Controlling for irrelevant covariates; Adjusting experimental data;
Conclusions

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• Matching methods still highly recommended; choose one with higher standards
For more information, papers, & software

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