Why Propensity Scores Should Not Be Used For Matching

Gary King\textsuperscript{1} \hspace{1cm} Richard Nielsen\textsuperscript{2}

Institute for Quantitative Social Science
Harvard University \hspace{1cm} MIT

(Talk at Harvard’s Applied Statistics Workshop, 9/16/2015)

\textsuperscript{1}GaryKing.org
\textsuperscript{2}www.mit.edu/\sim rnielsen
The Scholarly Influence of Propensity Score Matching

The most commonly used matching method
• In 49,600 articles! (according to Google Scholar)
• 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
• The mathematical theorems about propensity scores
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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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Without Matching:

Imbalance
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Without Matching:

Imbalance \xrightarrow{\sim} Model Dependence
The Problems Matching Solves

Without Matching:

Imbalance $\leadsto$ Model Dependence $\leadsto$ Researcher discretion
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Without Matching:

Imbalance $\leadsto$ Model Dependence $\leadsto$ Researcher discretion $\leadsto$ Bias
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Imbalance $\rightarrow$ Model Dependence $\rightarrow$ Researcher discretion $\rightarrow$ Bias

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Imbalance $\leadsto$ Model Dependence $\leadsto$ Researcher discretion $\leadsto$ Bias

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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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- 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
Matching: Finding Hidden Randomized Experiments

Types of Experiments

- **Balance**
  - **Covariates:**
    - Complete Randomization
    - Fully Blocked
    - Observed
    - On average
    - Unobserved
    - On average
    - On average

\[ \Rightarrow \text{Fully blocked dominates complete randomization for: imbalance, model dependence, power, efficiency, bias, research costs, robustness.} \]

- **Goal of Each Matching Method (in Observational Data)**
  - **PSM:** complete randomization
  - Other methods: fully blocked
  - Other matching methods dominate PSM

(wait, it gets worse)
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  - 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
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Goal of Each Matching Method (in Observational Data)
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- Other methods: fully blocked
- Other matching methods dominate PSM (wait, it gets worse)
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$\leadsto$ Fully blocked dominates complete randomization for: imbalance, model dependence, power, efficiency,
Matching: Finding Hidden Randomized Experiments

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Matching: Finding Hidden Randomized Experiments

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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)

- PSM: complete randomization
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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)
   - \[ \text{Distance}(X_c, X_t) = \sqrt{(X_c - X_t)'S^{-1}(X_c - X_t)} \]
   - 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 \( \text{Distance} > \text{caliper} \)
   - (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
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Mahalanobis Distance Matching

![Graph showing data points on a scatter plot with Education (years) on the x-axis and Age on the y-axis. The data points are marked with 'T'.]
Mahalanobis Distance Matching

Education (years)

Age

12 14 16 18 20 22 24 26 28

20

30

40

50

60

70

80

C

C

CC

C

C

C

C

C

CC

C

CC

C

CC

C

C

C

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CC

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Best Case: Mahalanobis Distance Matching
Best Case: Mahalanobis Distance Matching

Age
12 14 16 18 20 22 24 26 28

Education (years)
20 30 40 50 60 70 80

T TTTT T T TTT TT T T TT TTTT T T TTT TT T

C CC C CC CC C CC CCC CC C CCC CCCC C CC CC C CC CCC CCC CC CCC CC CCCC C CCC CC CCC
Best Case: Mahalanobis Distance Matching

![Graph showing age vs. education in years with data points labeled 'T' and 'C'.]
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
Method 2: Coarsened Exact Matching
(Approximates Fully Blocked Experiment)
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2. **Estimation** Difference in means or a model
   - Weight controls in each stratum to equal treateds
Coarsened Exact Matching
Coarsened Exact Matching

Education

Old
Retirement
Senior Discounts
The Big 40
Don't trust anyone over 30
Drinking age

HS BA MA PhD 2nd PhD

Senior Discounts

Don't trust anyone over 30

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

Education
Age
12 14 16 18 20 22 24 26 28
20
30
40
50
60
70
80
CC CCC CCC CC CC CCCC CCC CC C C CCCCC CCC CC CC ... C CC C CC CCC CCC CC CCC CC CCCC C CCC CC CCC
T TTTT T T TTT TT T T TT TTTT T T TTT TT T TT TTTT TTT TT TTT TT
TT TT TT

12/23
Best Case: Coarsened Exact Matching

Education vs. Age:

- Education in the range of 12 to 28
- Age in the range of 12 to 80

- Symbols represent data points
- Grid lines indicate intervals
Best Case: Coarsened Exact Matching

[Graph showing data points on a scatter plot with Age on the y-axis and Education on the x-axis. The data points are marked with 'C' and 'T' symbols.]
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 $> \text{caliper}$

(Many adjustments available to this basic method)
Method 3: Propensity Score Matching
(Approximates Completely Randomized Experiment)
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1. Preprocess (Matching)

2. Estimation Difference in means or a model
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   - (Many adjustments available to this basic method)

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

Education (years)

Age

12 16 20 24 28

20

30

40

50

60

70

80

C

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Propensity Score Matching

![Propensity Score Matching Graph]

- **Age** is represented on the y-axis.
- **Education (years)** is represented on the x-axis.
- The graph shows a scatter plot with blue and red lines indicating matching pairs.

The diagram illustrates the matching process for different educational levels and ages, with lines connecting matching pairs. The y-axis represents age, ranging from 10 to 80, while the x-axis represents education (years), ranging from 12 to 29. The plot suggests a method to match subjects based on their propensity scores, aiming to reduce selection bias in observational studies.
Propensity Score Matching

Age

Education (years)

Propensity Score
Propensity Score Matching

Education (years)

Age

12 16 20 24 28
20
30
40
50
60
70
80
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Best Case: Propensity Score Matching
Best Case: Propensity Score Matching

Education (years)

Age

12 16 20 24 28

Propensity Score

0 1
Best Case: Propensity Score Matching

Education (years)
Age
12 16 20 24 28
20
30
40
50
60
70
80
Score
1
0
Propensity Score
15/23
Best Case: Propensity Score Matching

![Graph showing education vs age with labeled axes]

- Education (years)
- Age

Anne: 12 16 20 24 28
20
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40
50
60
70
80
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C ... TT
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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 $M_t$, $F_t$, controls $M_c$, $F_c$
  - Randomly prune 1 treated & 1 control $\Rightarrow$ 4 possible datasets: 2 balanced $\{M_t, M_c\}$, $\{F_t, F_c\}$, 2 imbalanced $\{M_t, F_c\}$, $\{F_t, M_c\}$
  - $\Rightarrow$ 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
  - $\Rightarrow$ 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 $M_c$, $F_c$
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Random Pruning Increases Imbalance
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• “Random pruning”: pruning process is independent of \(X\)

\[d^2 = \bar{X}_t - \bar{X}_c\]

\[E(d^2) = V(d) \propto 1/n\] (note: \(E(d) = 0\))

\[\text{Random pruning } \Rightarrow n \text{ declines } \Rightarrow E(d^2) \text{ increases}\]

\[\Rightarrow \text{random pruning increases imbalance}\]
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: treated $m_t$, female $f_t$, controls $m_c$, female $f_c$

Randomly prune 1 treated & 1 control $\Rightarrow$ 4 possible datasets: 2 balanced $\{m_t, m_c\}, \{f_t, f_c\}$, 2 imbalanced $\{m_t, f_c\}, \{f_t, m_c\}$

$= \Rightarrow$ 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

$= \Rightarrow$ 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 $M_c, F_c$
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 $\leadsto$ 4 possible datasets:
    2 balanced $\{M_t, M_c\}, \{F_t, F_c\}$
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- **Continuous example**
  - Dataset: $T \in \{0, 1\}$ randomly assigned; $X$ any fixed variable; with $n$ units

$\Rightarrow E(d^2) = \frac{1}{n}$ (note: $E(d) = 0$)
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1. Low Standards:
   - Sometimes helps, never optimizes
   - Efficient relative to complete randomization, but
     - Inefficient relative to (the more powerful) full blocking
   - Other methods dominate:

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2. The PSM Paradox:
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![Graph showing Mahalanobis and Propensity Score distributions with number of dropped obs.]

- The left graph plots $X_1$ vs $X_2$ with different symbols representing different conditions.
- The right graphs show histograms of Mahalanobis and Propensity Score, with simulation numbers on the x-axis and number of dropped obs. on the y-axis.
What Does PSM Match?

MDM Matches

PSM Matches

Controls: \( X_1, X_2 \sim \text{Uniform}(0,5) \)
Treateds: \( X_1, X_2 \sim \text{Uniform}(1,6) \)
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
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Similar pattern for >20 other real data sets we checked
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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
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For more information, papers, & software

GaryKing.org
www.mit.edu/~rnielsen