Why Propensity Scores Should Not Be Used For Matching

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Talk at Department of Epidemiology,
Harvard T.H. Chan School of Public Health, 10/15/2015

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The Scholarly Influence of Propensity Score Matching

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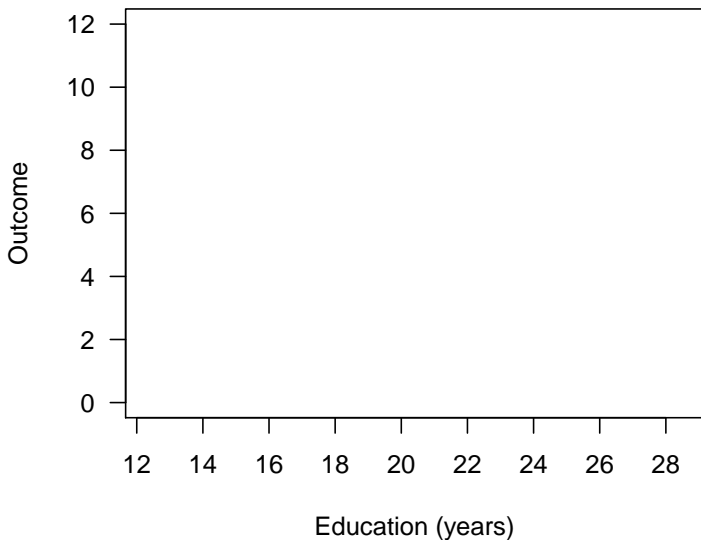 - The mathematical theorems about propensity scores

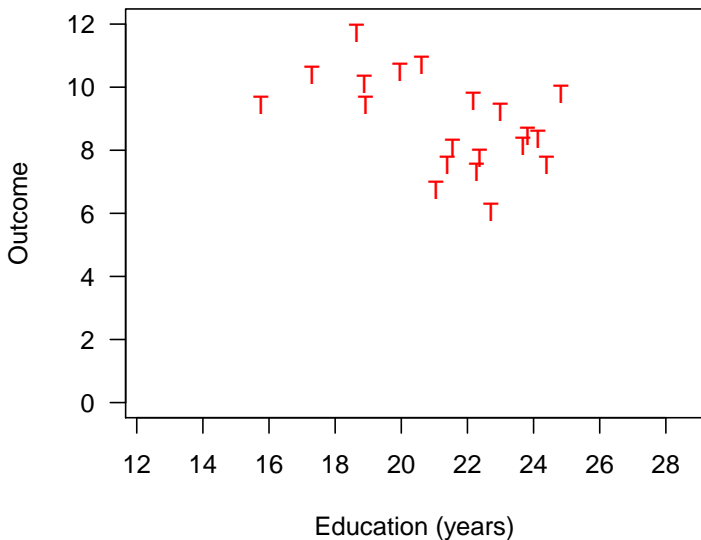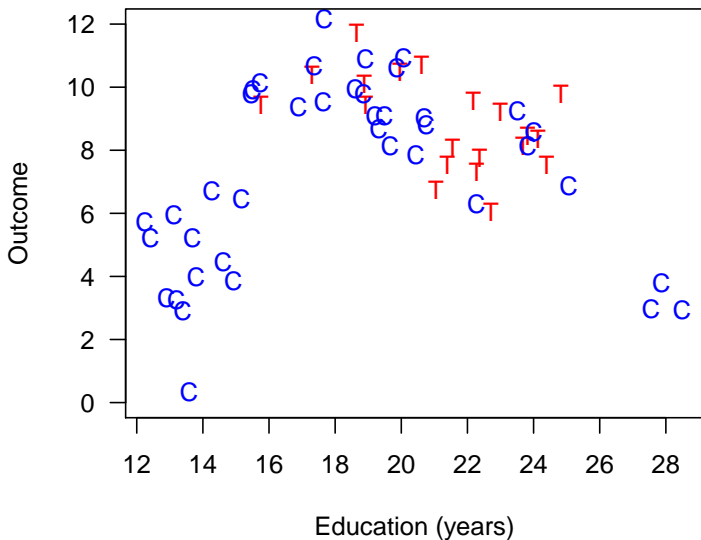# Matching to Reduce Model Dependence

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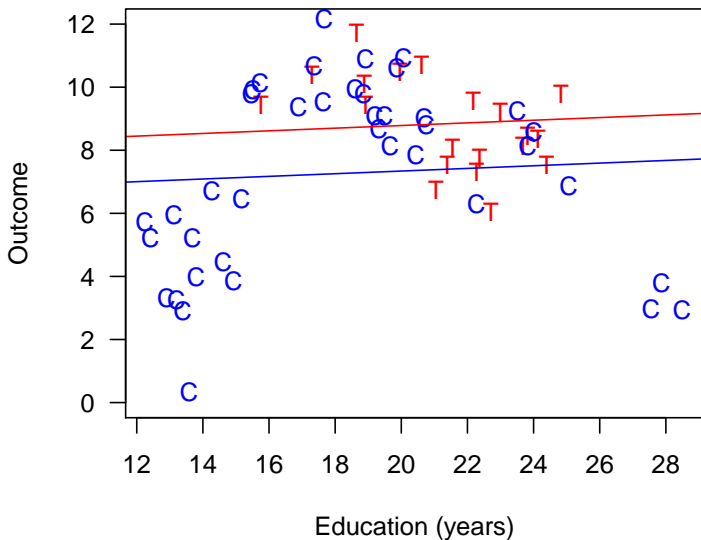(Ho, Imai, King, Stuart, 2007: fig.1, *Political Analysis*)

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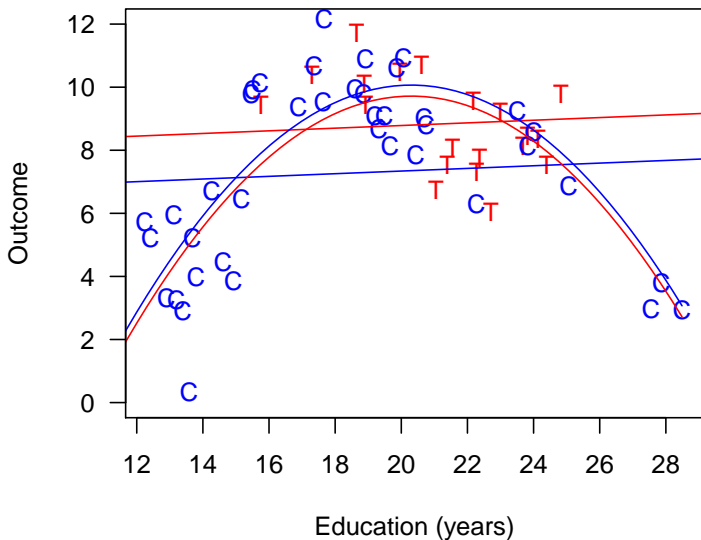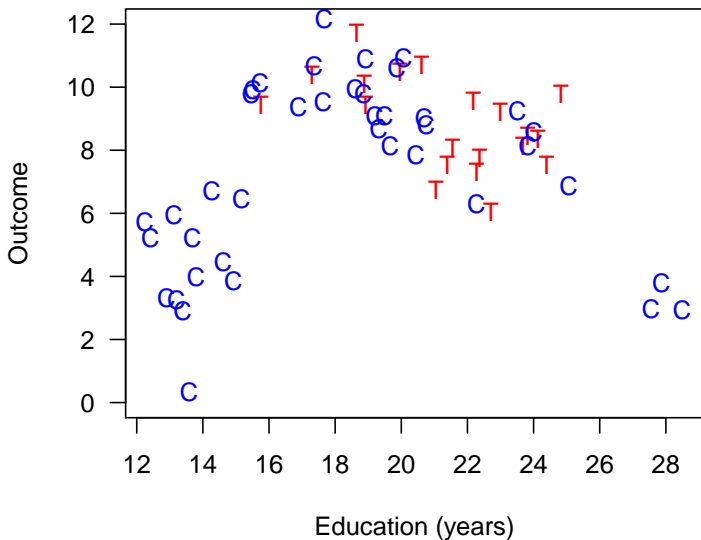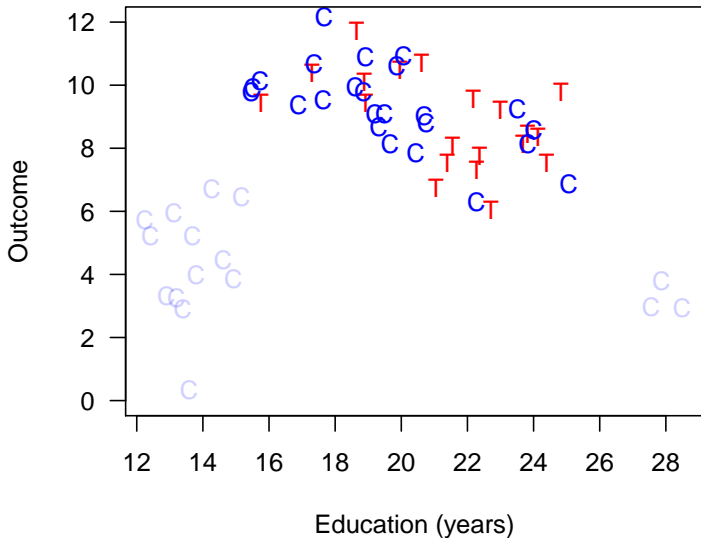
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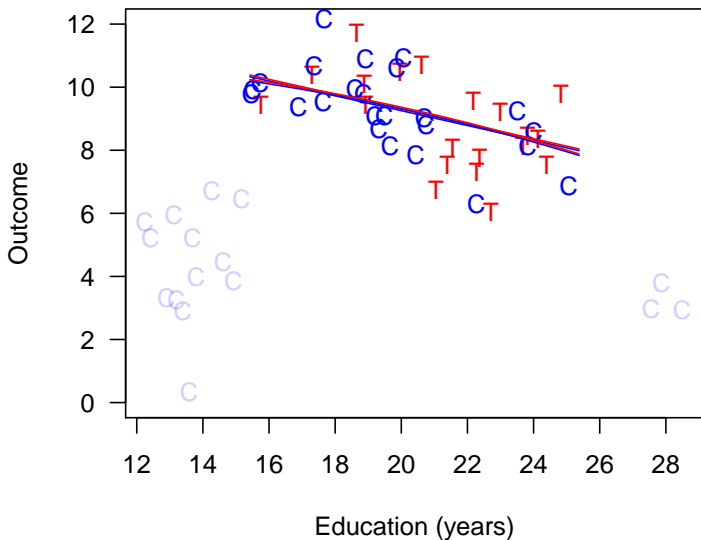
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- "Teaching psychology is mostly a waste of time" (Kahneman 2011)

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A central project of statistics: Automating away human discretion

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- Pruning nonmatches makes control vars matter less: reduces imbalance, model dependence, researcher discretion, & bias

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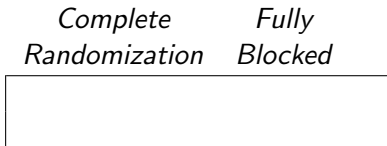
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- Other methods: *fully blocked*
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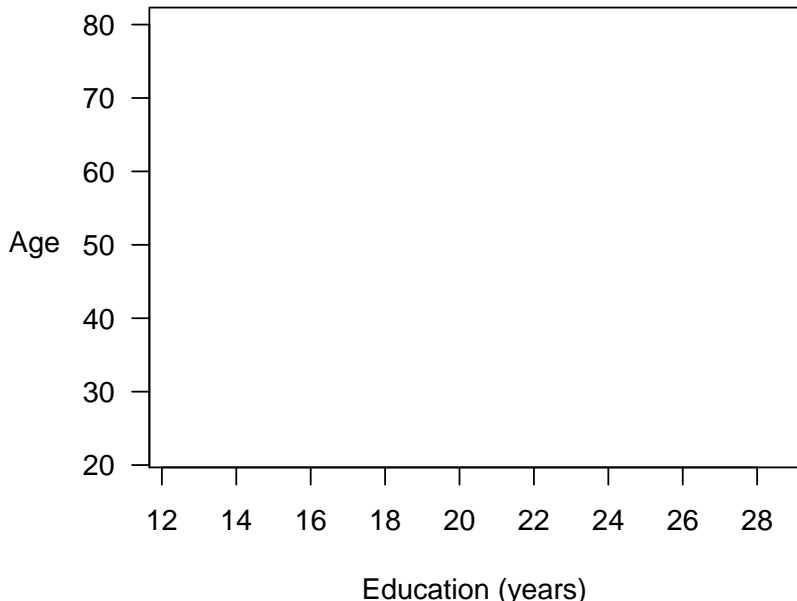
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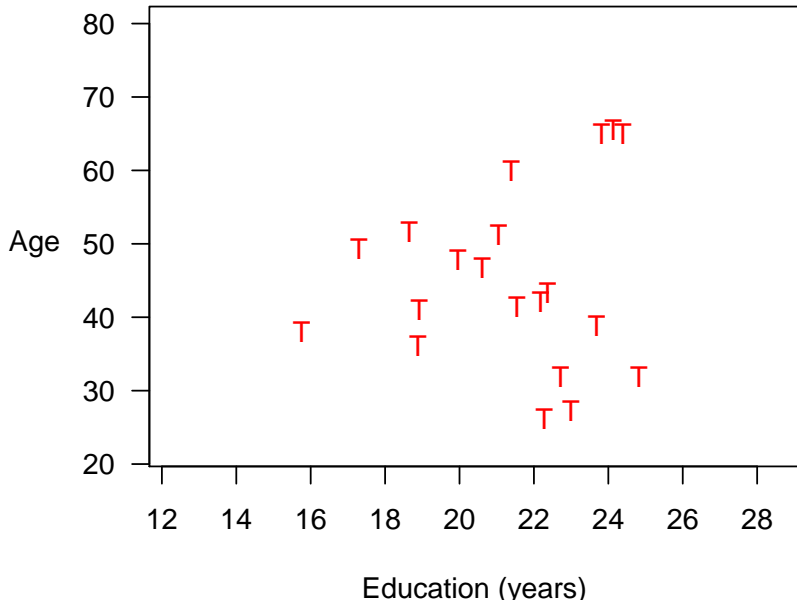
Education (years)

Mahalanobis Distance Matching

Age vs Education (years)

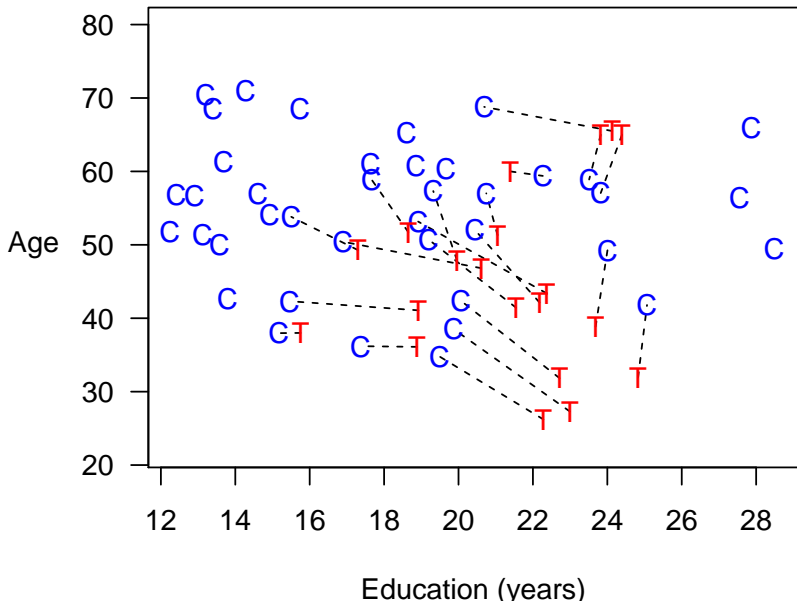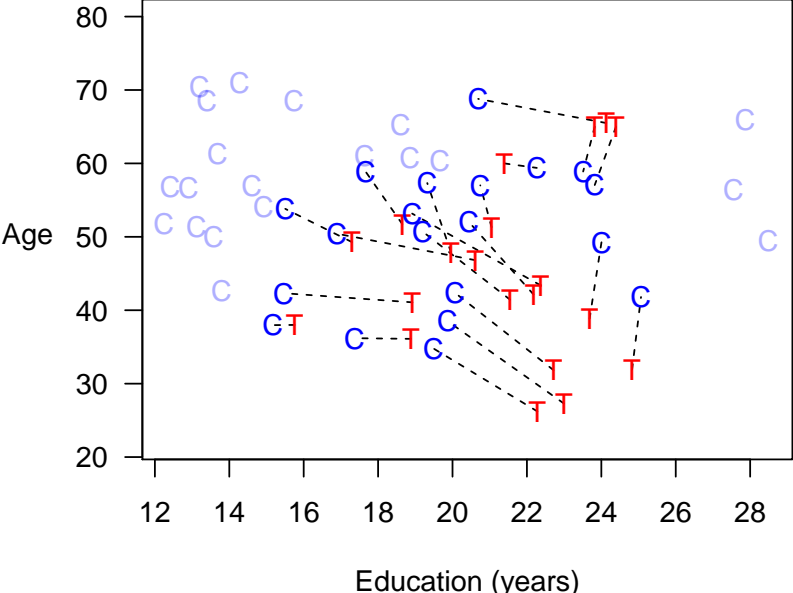**Mahalanobis Distance Matching**

Age vs. Education (years)

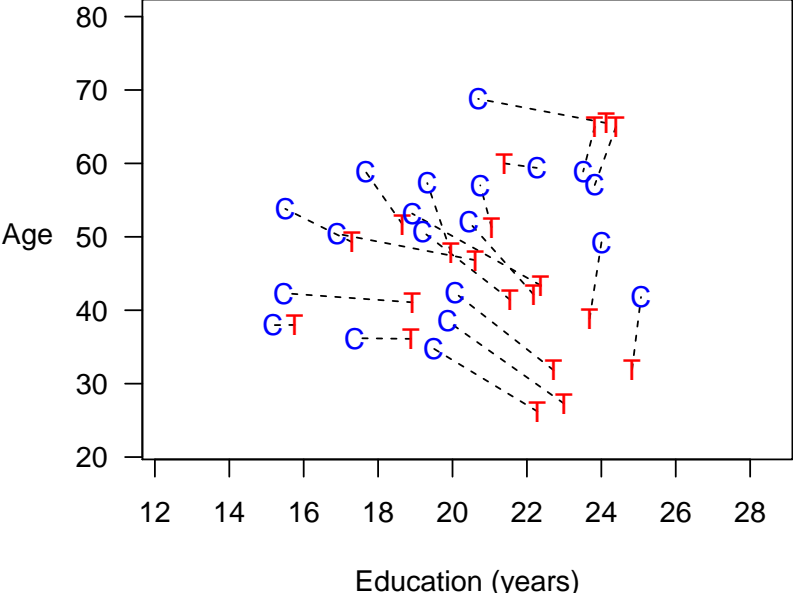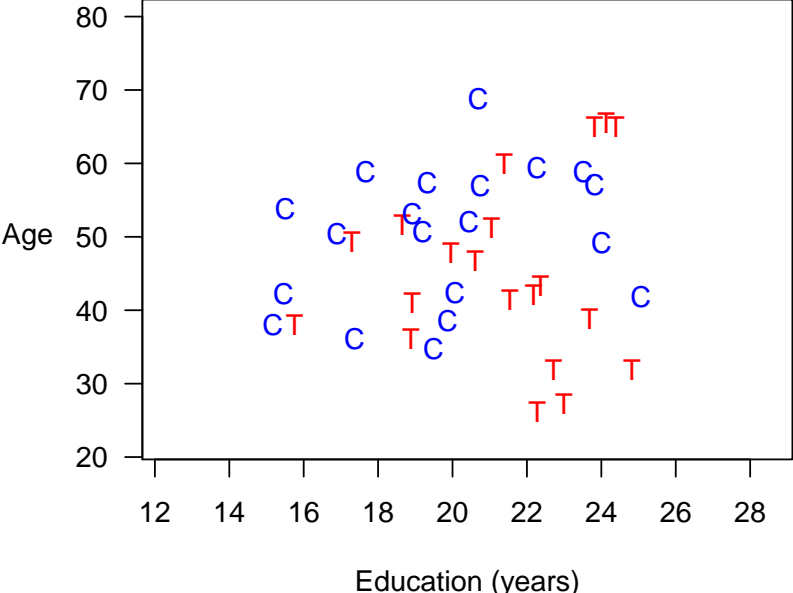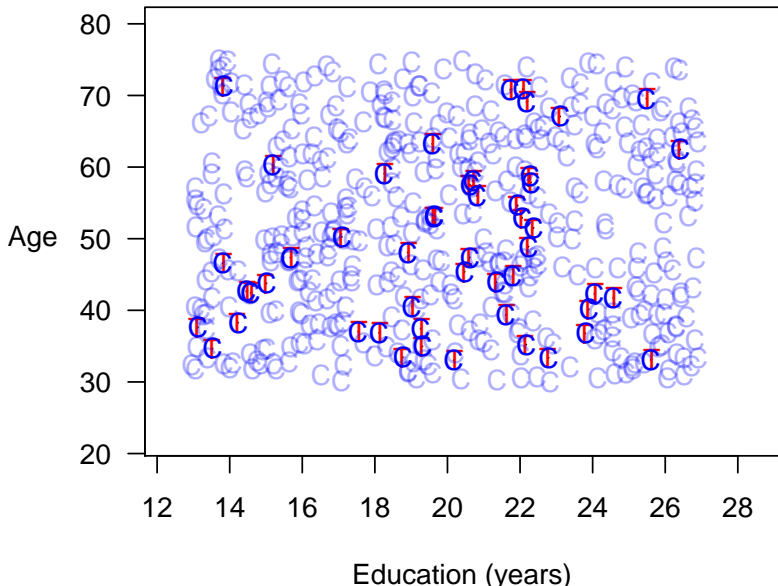# Mahalanobis Distance Matching

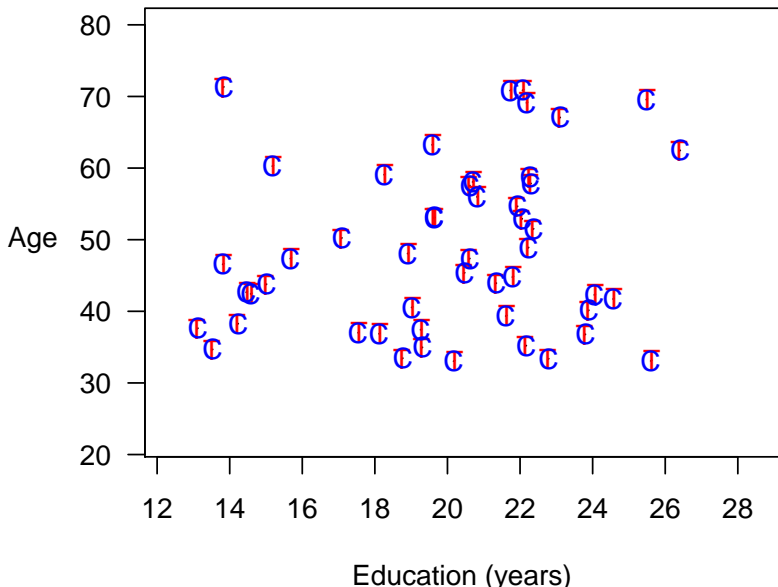# Mahalanobis Distance Matching

Mahalanobis Distance Matching

Age

Education (years)

Mahalanobis Distance Matching

Best Case: Mahalanobis Distance Matching

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Age

Education (years)
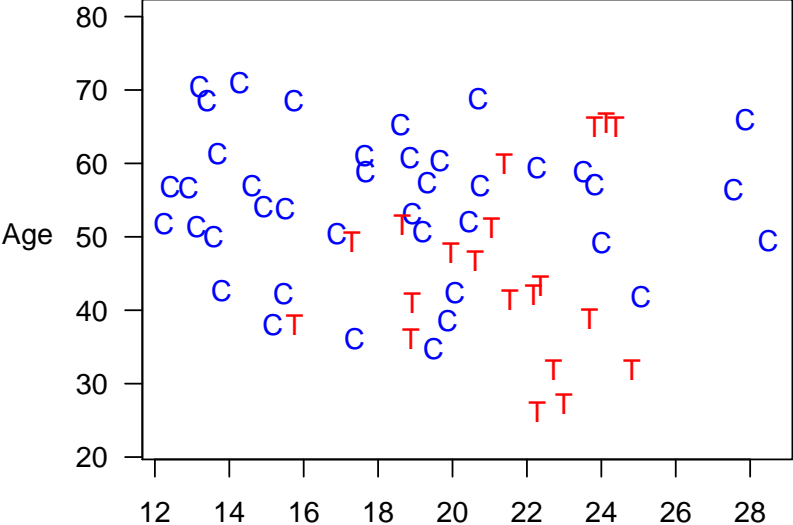
Best Case: Mahalanobis Distance Matching

Method 2: Coarsened Exact Matching

Method 2: Coarsened Exact Matching
(Approximates Fully Blocked Experiment)

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1. Preprocess (Matching)

2. Estimation Difference in means or a model

Method 2: Coarsened Exact Matching
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1. Preprocess (Matching)
   - Temporarily coarsen X as much as you're willing

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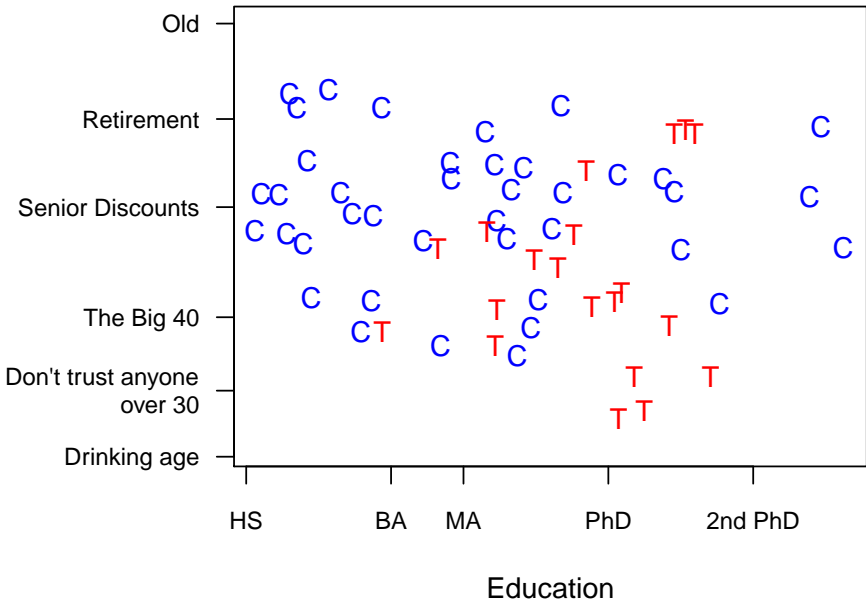2. Estimation Difference in means or a model
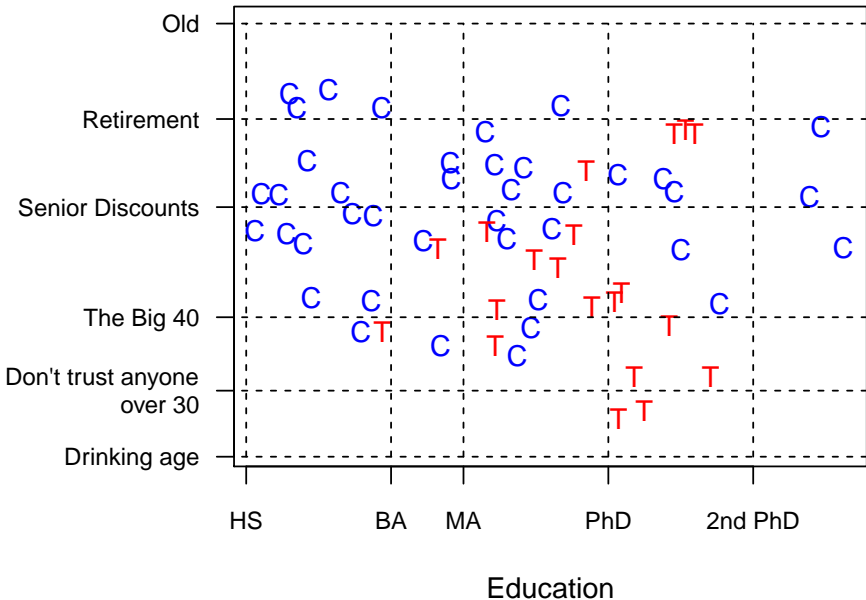   - Weight controls in each stratum to equal treateds

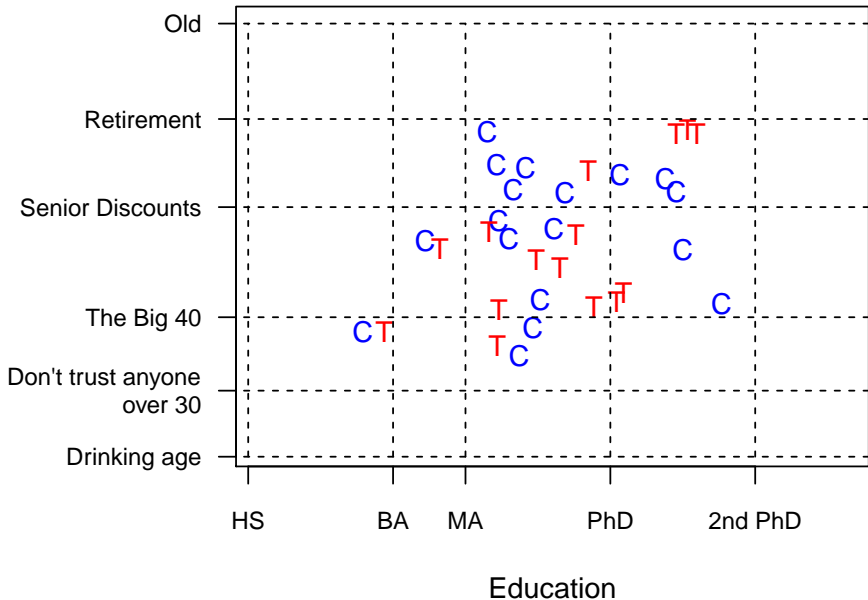# Coarsened Exact Matching
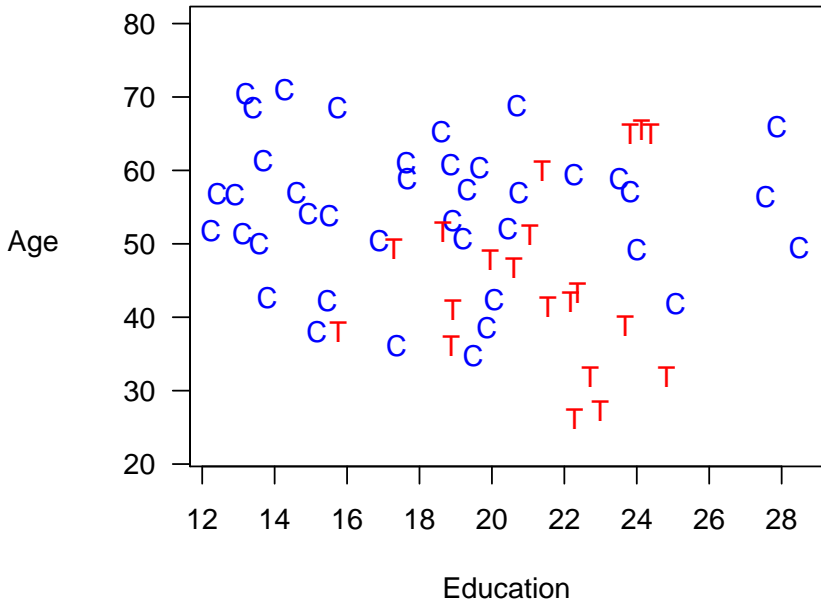
Coarsened Exact Matching

Age

Education

Coarsened Exact Matching

Education

Coarsened Exact Matching

Coarsened Exact Matching

Education

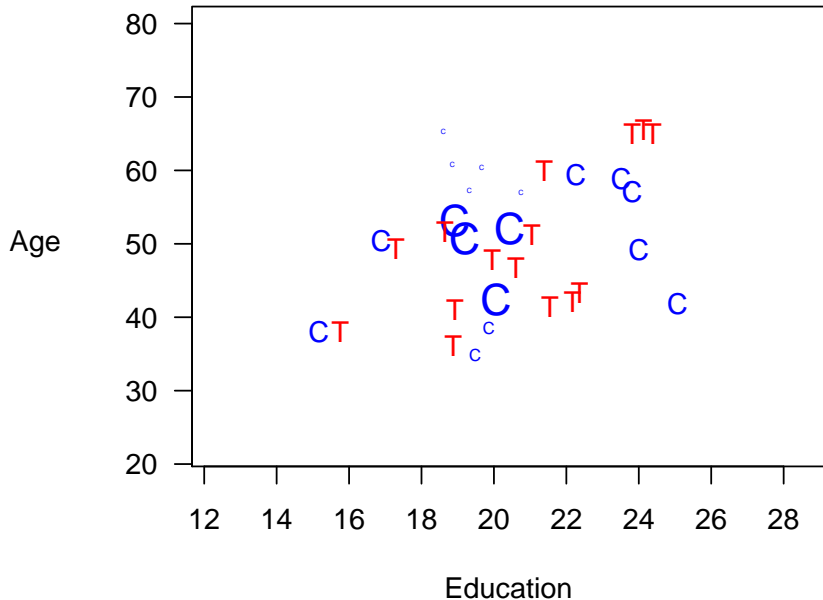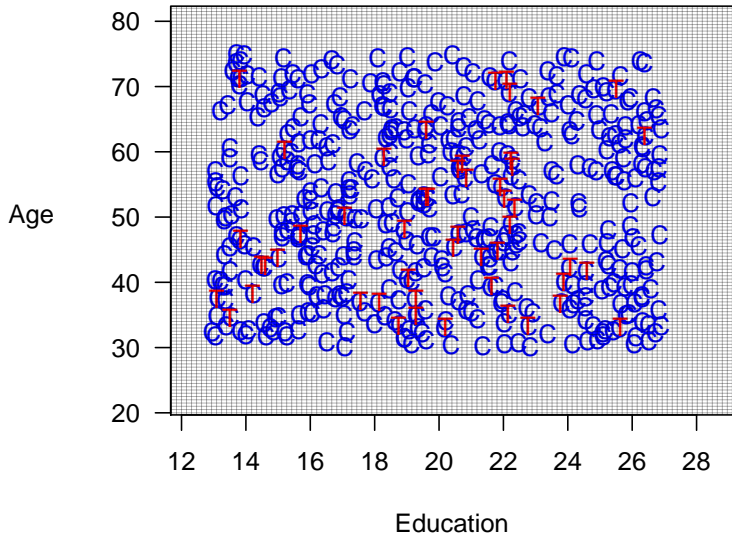**Coarsened Exact Matching**

Education

Coarsened Exact Matching

Best Case: Coarsened Exact Matching

Best Case: Coarsened Exact Matching

Age

Education

Best Case: Coarsened Exact Matching
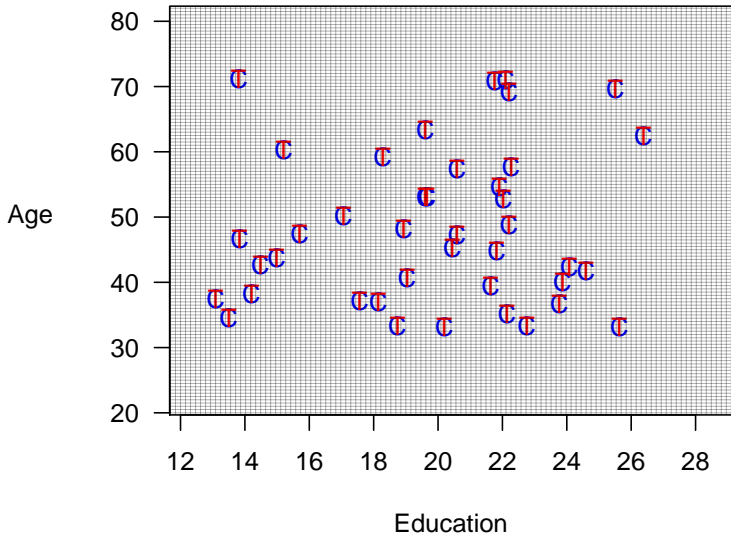
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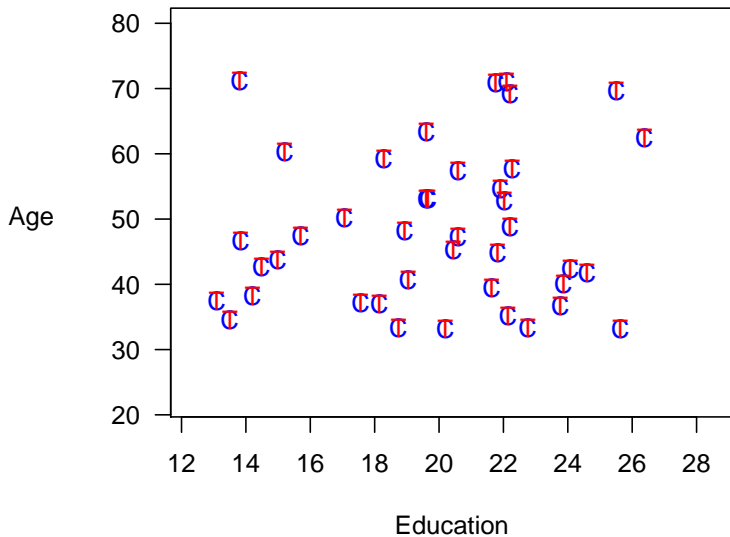
Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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1. Preprocess (Matching)

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Method 3: Propensity Score Matching

(Approximates Completely Randomized Experiment)

1. Preprocess (Matching)
   - Reduce k elements of X to scalar
   $$\pi_i \equiv \Pr(T_i = 1|X) = \frac{1}{1+e^{-X_i\beta}}$$

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    - 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
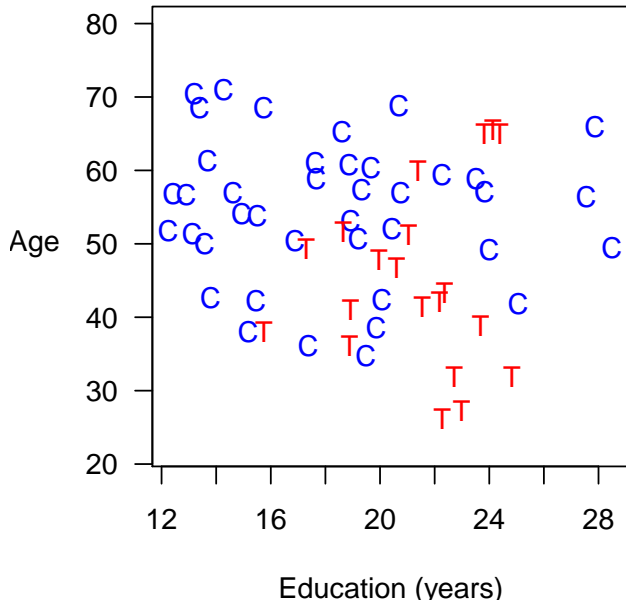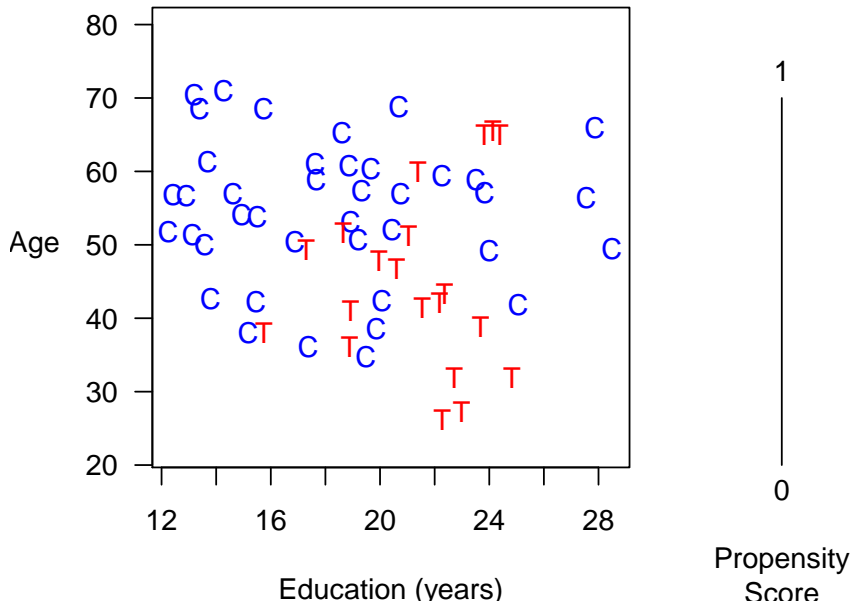
Age / Education (years)

Propensity Score Matching

Propensity Score Matching

Age

Education (years)

Propensity
Score

Propensity Score Matching

Age

Education (years)

Propensity
Score

Propensity Score Matching

Age

Education (years)

1

0

Propensity
Score

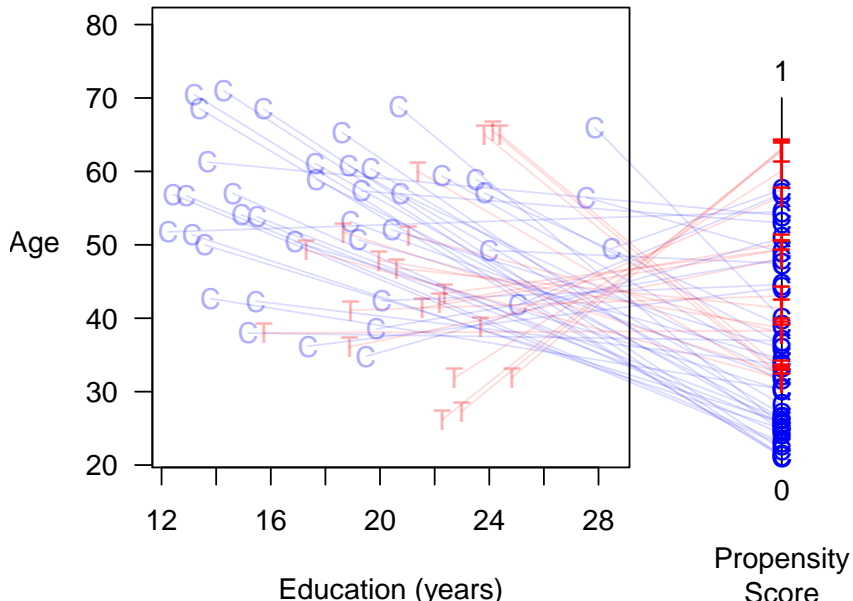**Propensity Score Matching**

Age

Education (years)

Propensity
Score

Propensity Score Matching

Propensity Score Matching

Age

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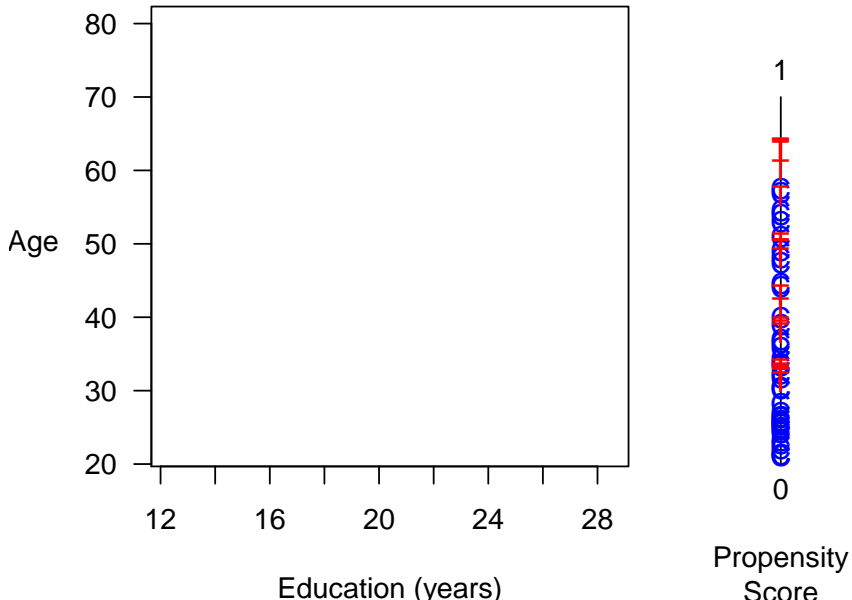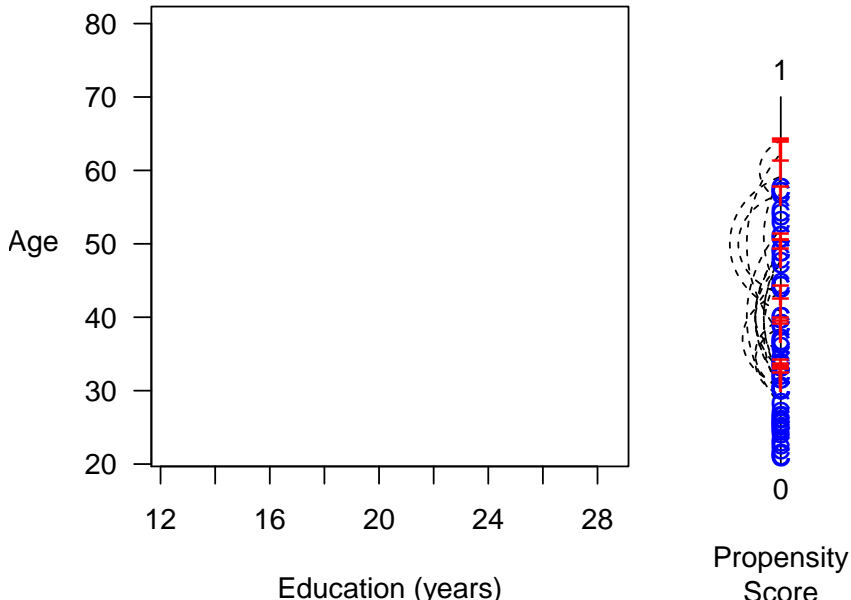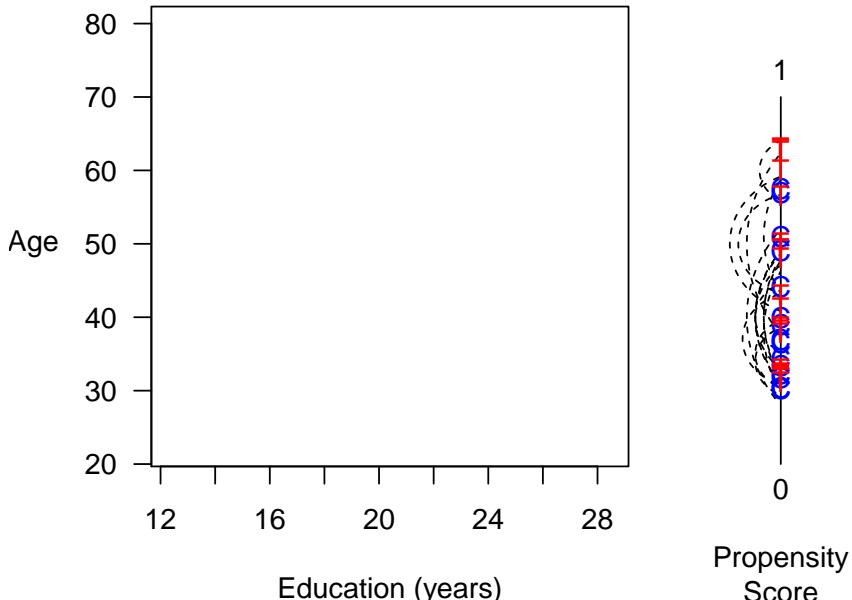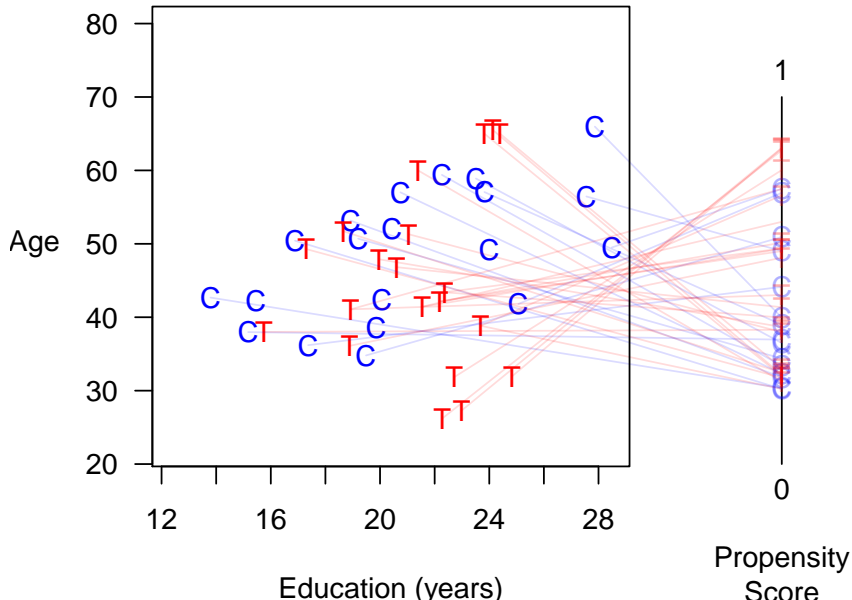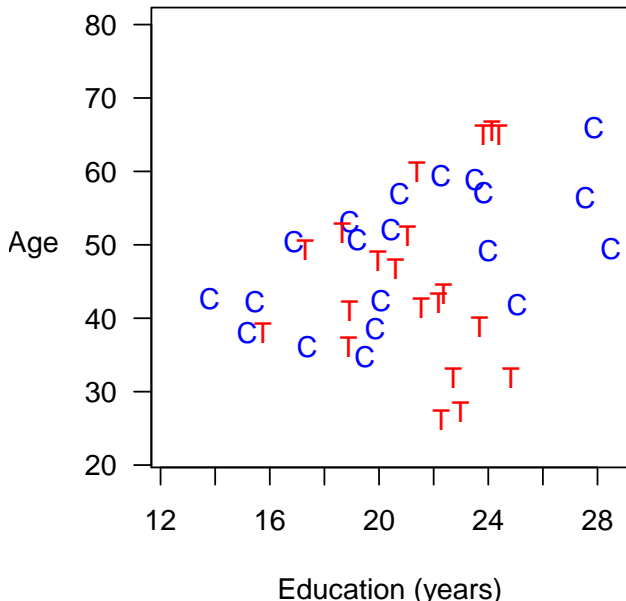
Best Case: Propensity Score Matching

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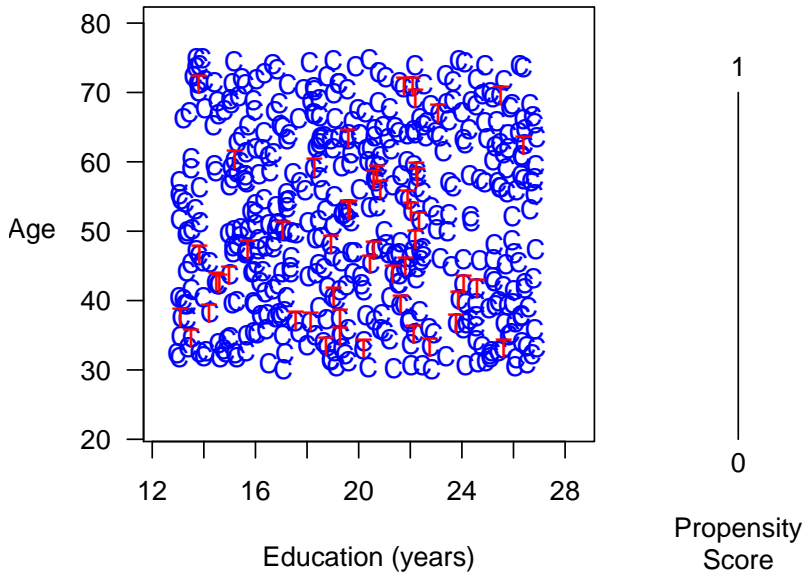
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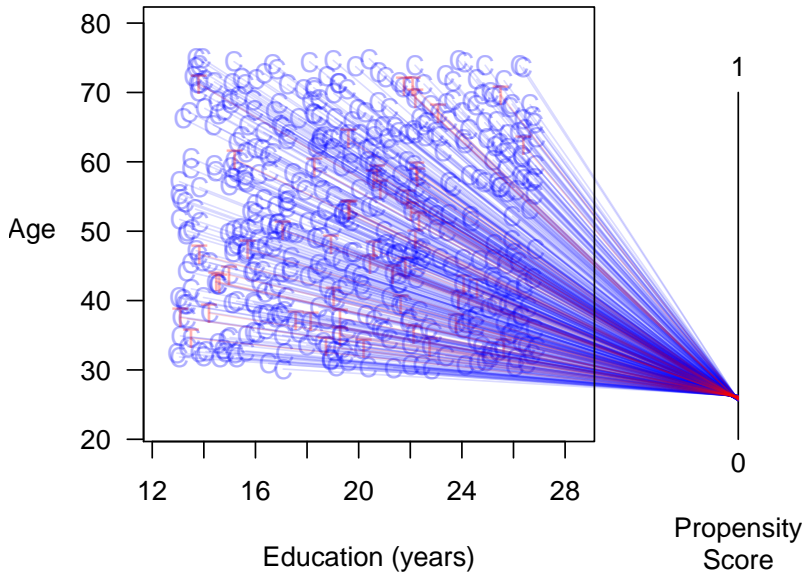
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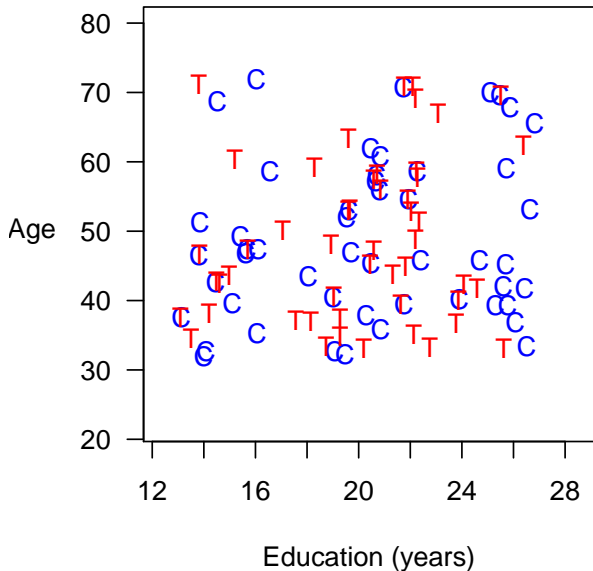
Best Case: Propensity Score Matching is Suboptimal
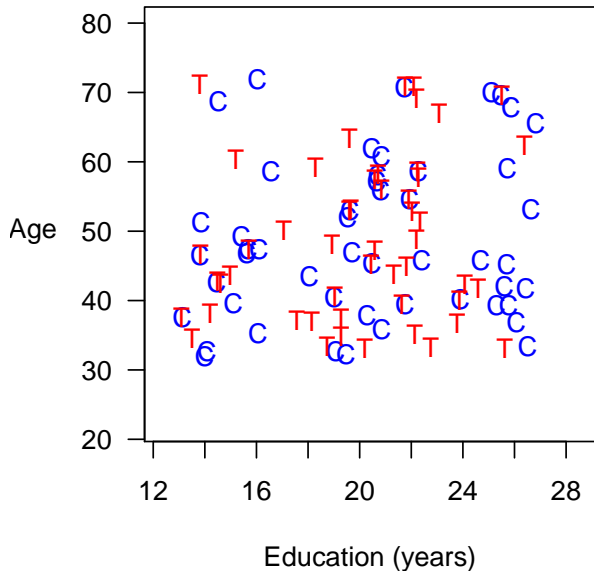
Random Pruning Increases Imbalance

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   - *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
     $\pi_c = \pi_t \;\not\!\!\!\implies X_c = X_t$
2. **The PSM Paradox:** When you do "better," you do worse
   - When PSM approximates complete randomization (to begin with or, after some pruning) $\rightsquigarrow$ all $\hat{\pi} \approx 0.5$ (or constant within strata) $\rightsquigarrow$ pruning at random $\rightsquigarrow$ Imbalance $\rightsquigarrow$ Inefficency $\rightsquigarrow$ Model dependence $\rightsquigarrow$ Bias
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PSM is Blind Where Other Methods Can See
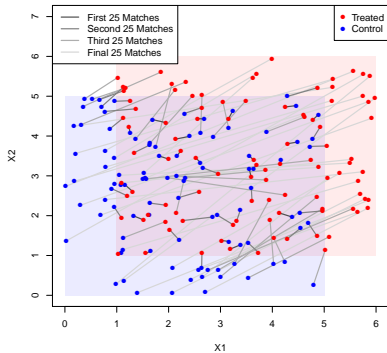
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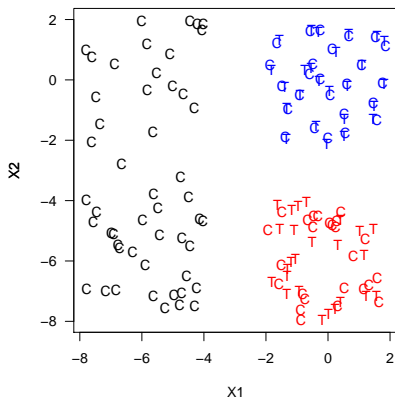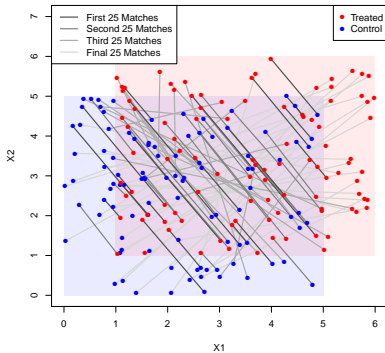
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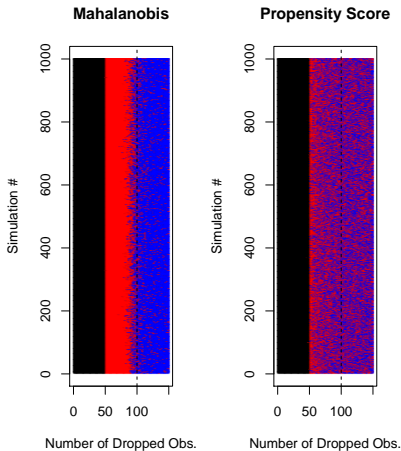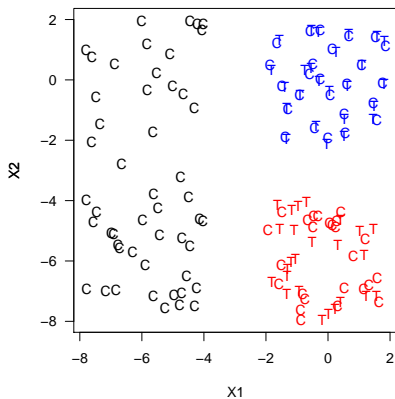
What Does PSM Match?
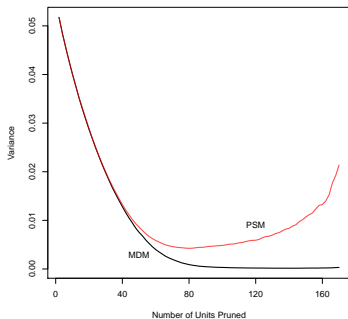
MDM Matches   PSM Matches

Controls: $X_1, X_2 \sim$ Uniform(0,5)
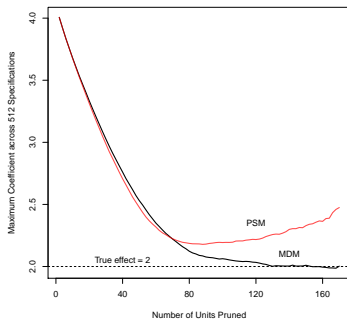Treateds: $X_1, X_2 \sim$ Uniform(1,6)

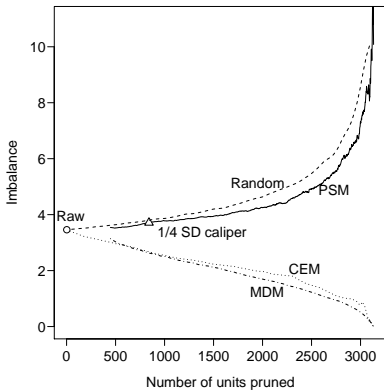# PSM Increases Model Dependence & Bias

Model Dependence

Bias

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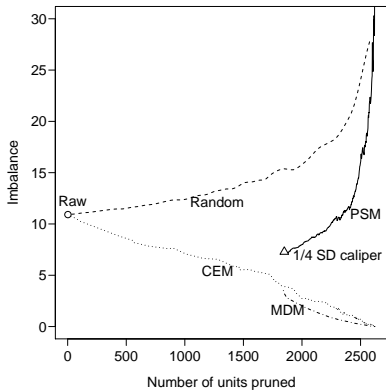
The Propensity Score Paradox in Real Data

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Finkel et al. (JOP, 2012)

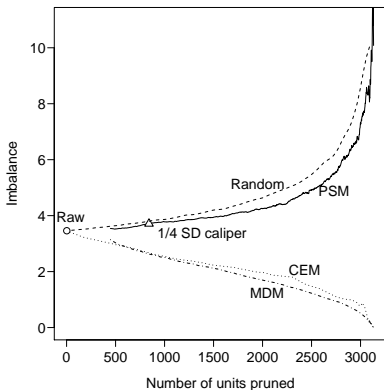Nielsen et al. (AJPS, 2011)

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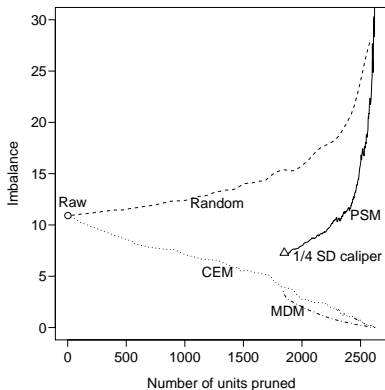
Similar pattern for > 20 other real data sets we checked

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- Matching methods still highly recommended; choose one with higher standards

For more information, papers, & software

GaryKing.org
www.mit.edu/~rnielsen