Why Propensity Scores Should Not Be Used For Matching

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Yale University, 3/10/2016

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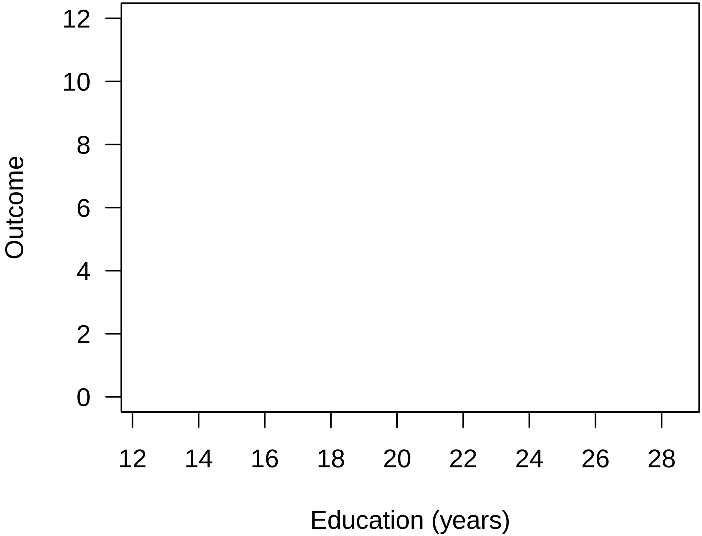

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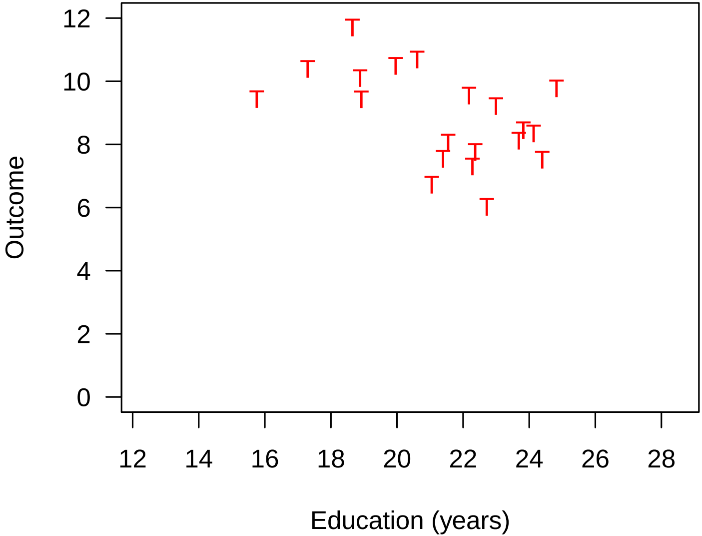

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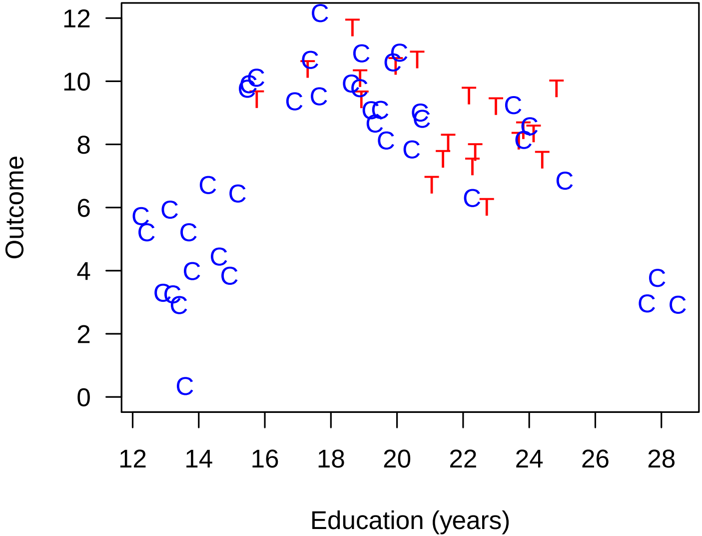

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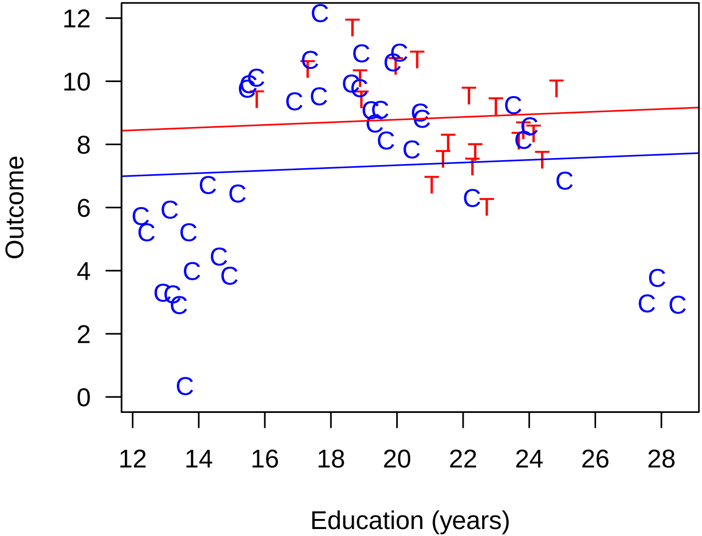

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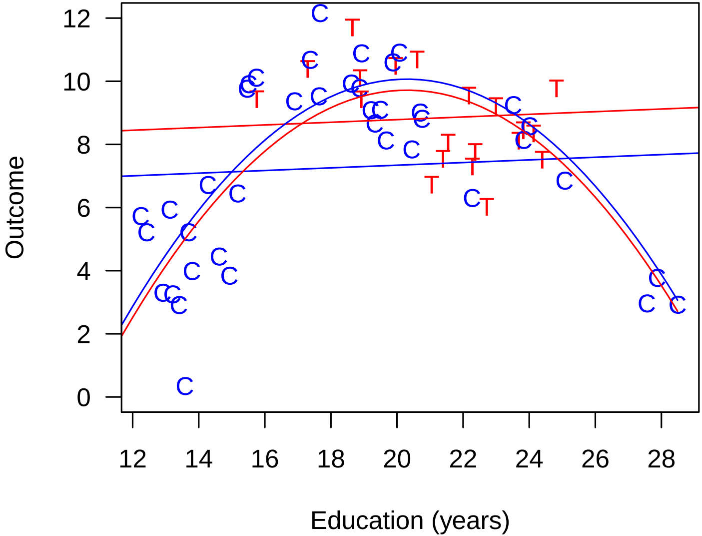

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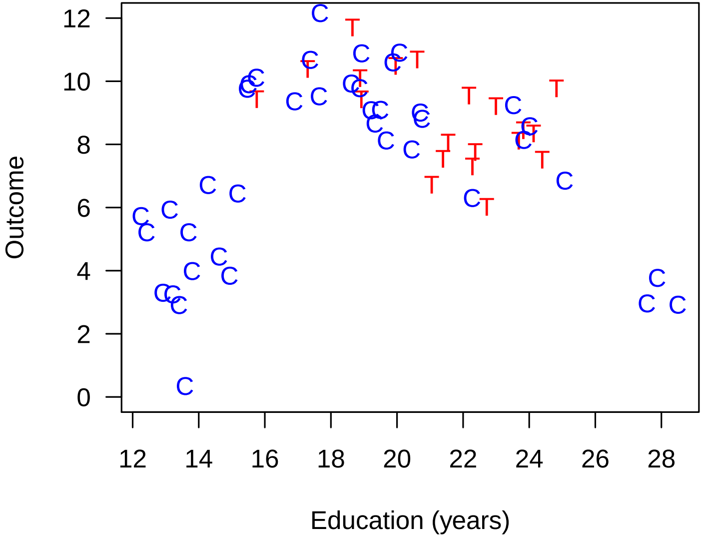

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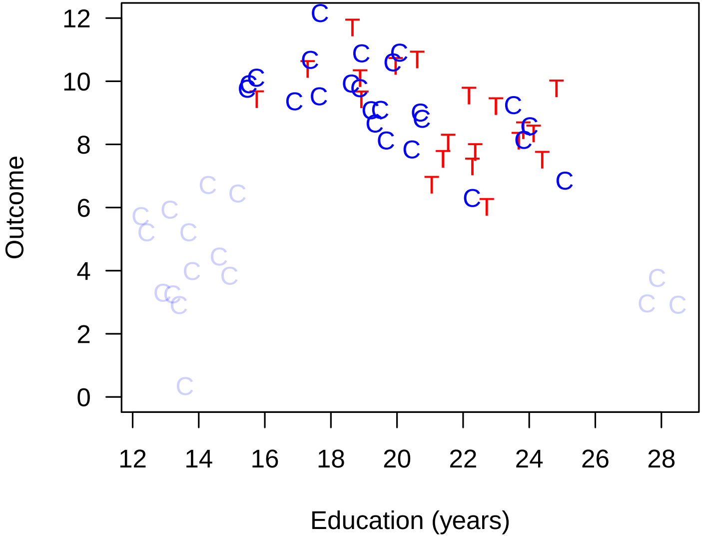

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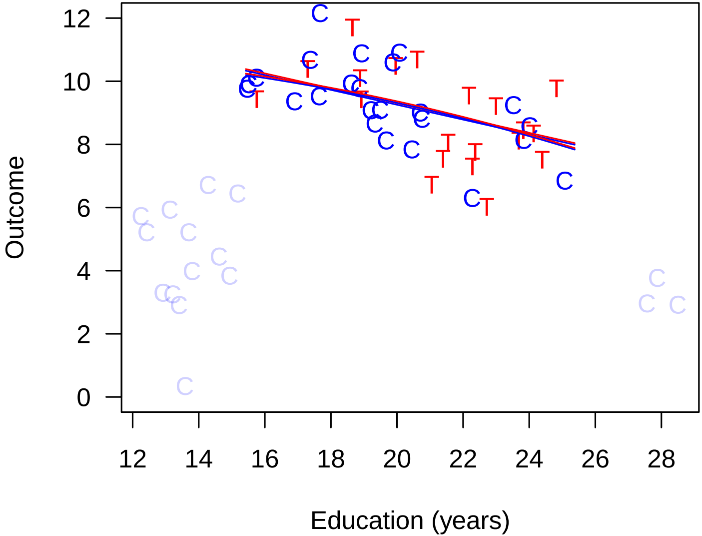

The Problems Matching Solves

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Without Matching:

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Imbalance

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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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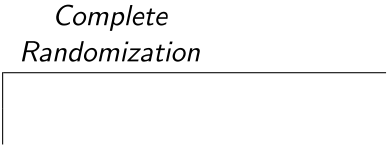

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	Complete Randomization	*Fully Blocked*

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Balance Covariates:	*Complete Randomization*	*Fully Blocked*
Observed		
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   - (Many adjustments available to this basic method)
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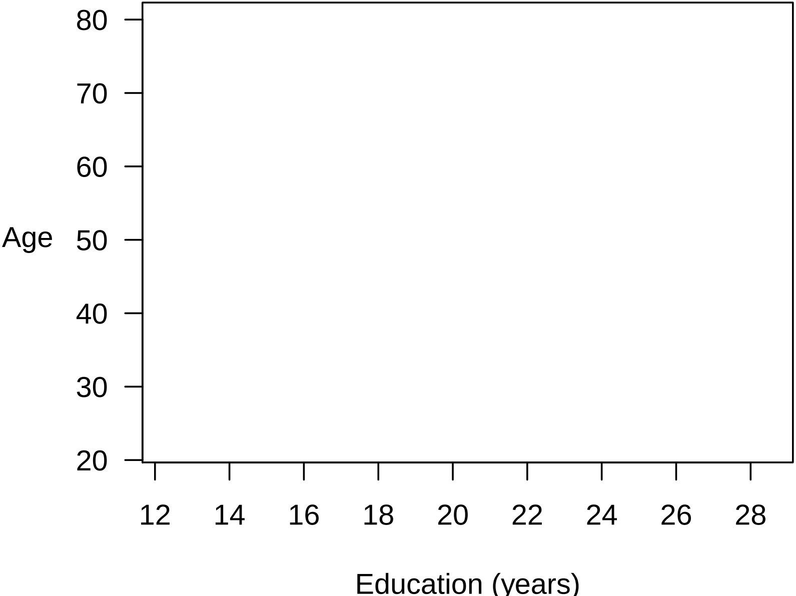
Mahalanobis Distance Matching



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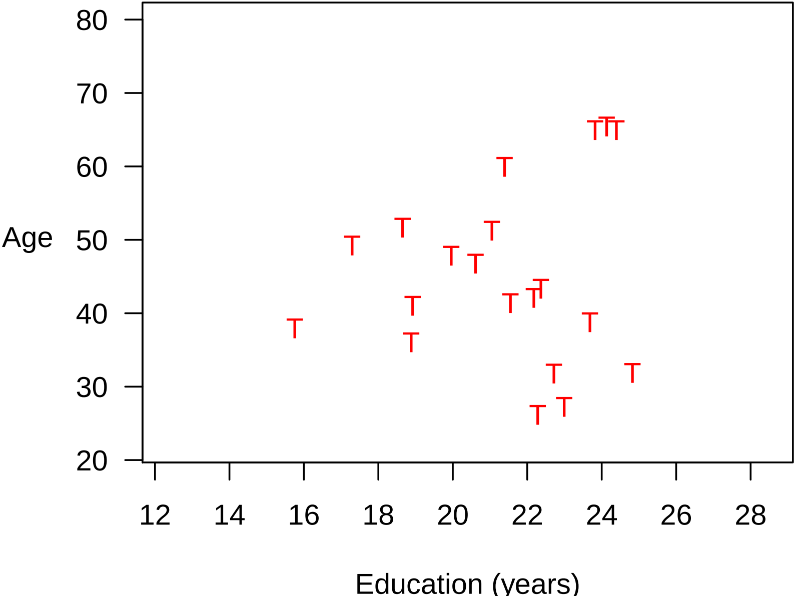

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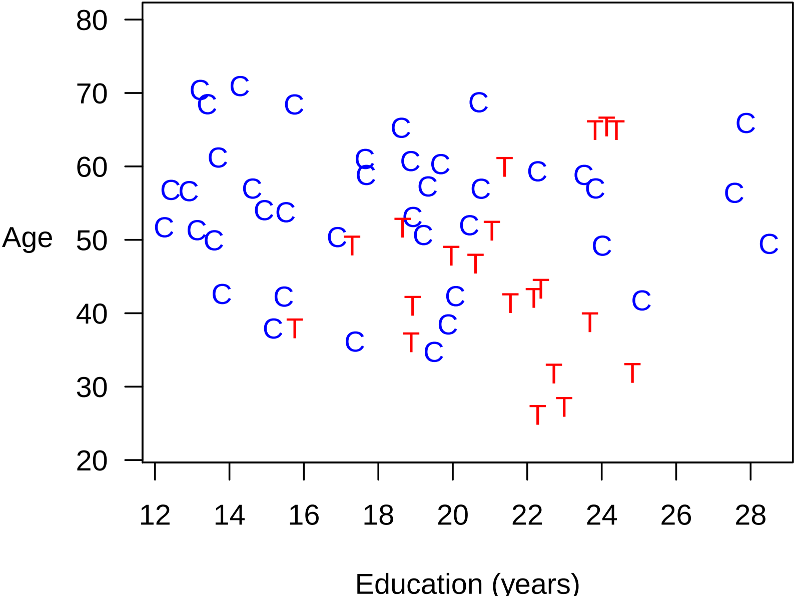

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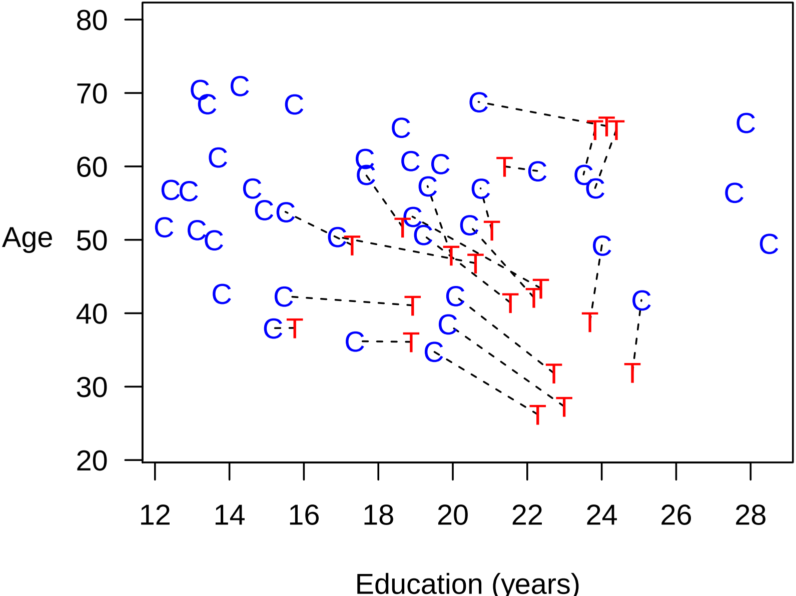

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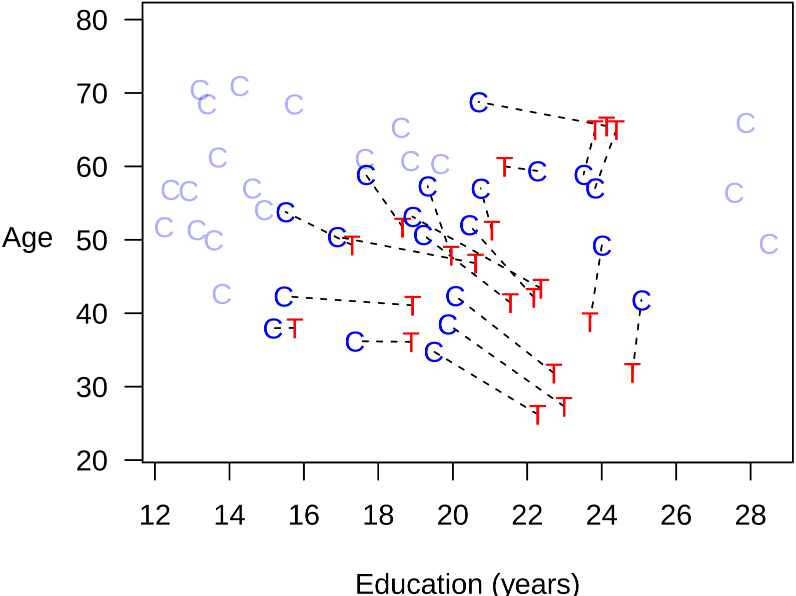

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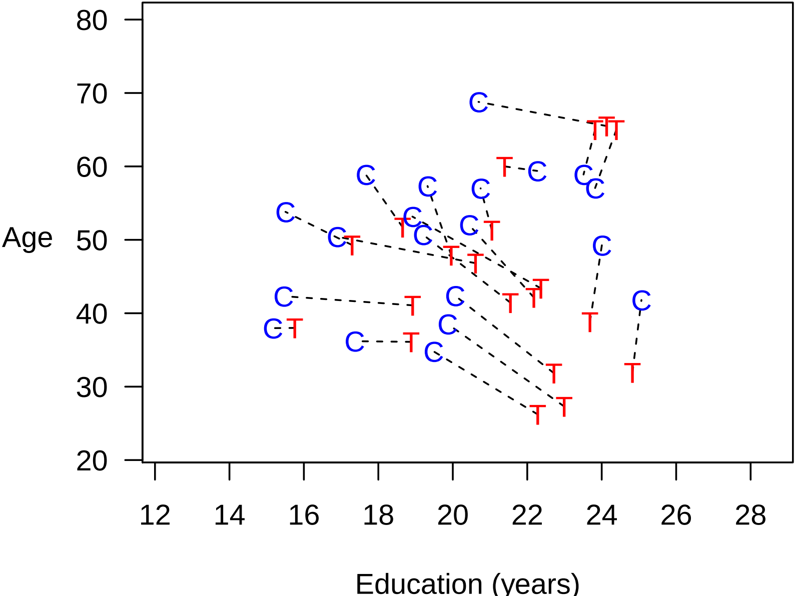

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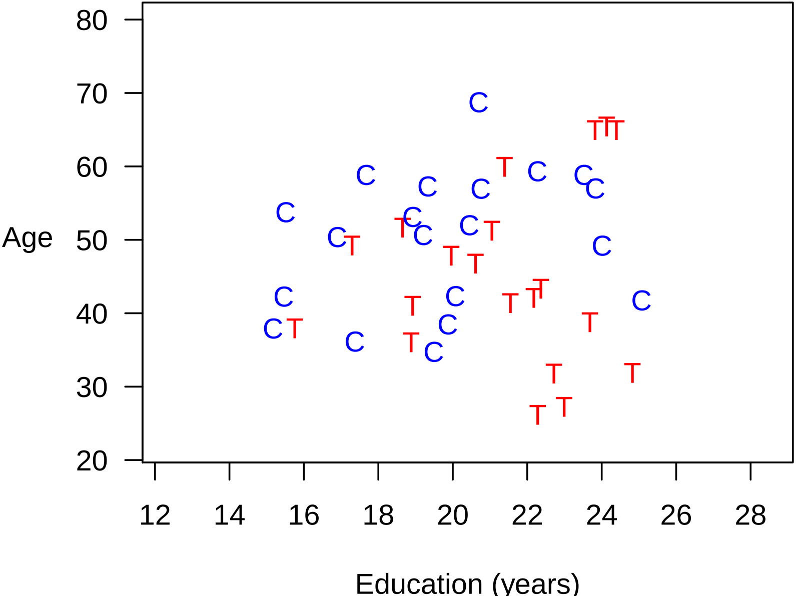

Best Case: Mahalanobis Distance Matching

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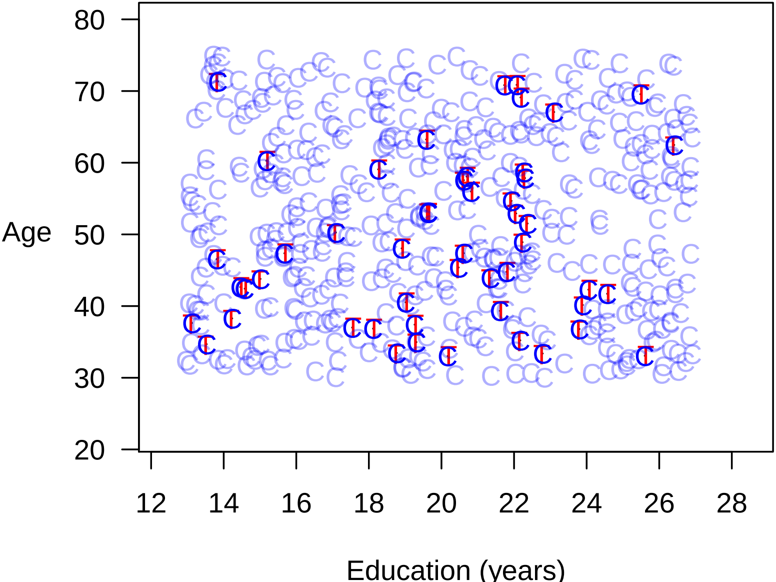

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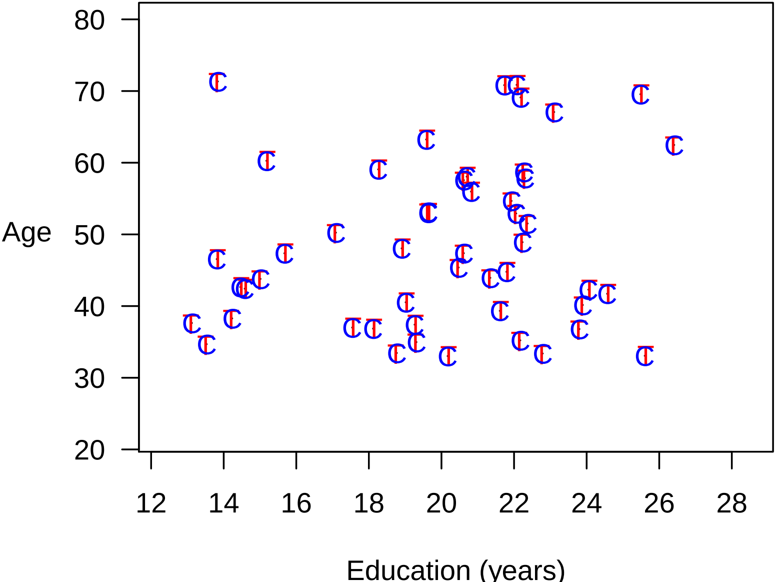

Method 2: Coarsened Exact Matching

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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   - Weight controls in each stratum to equal treateds

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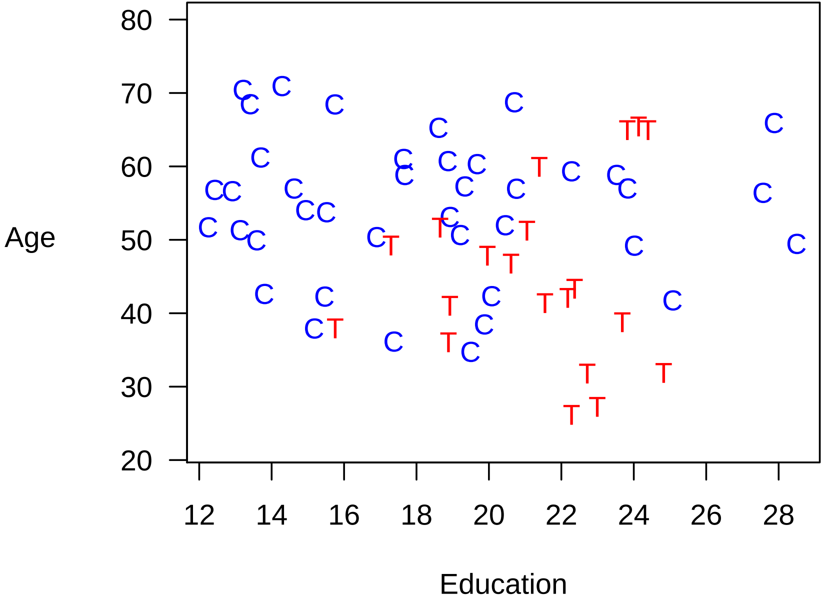

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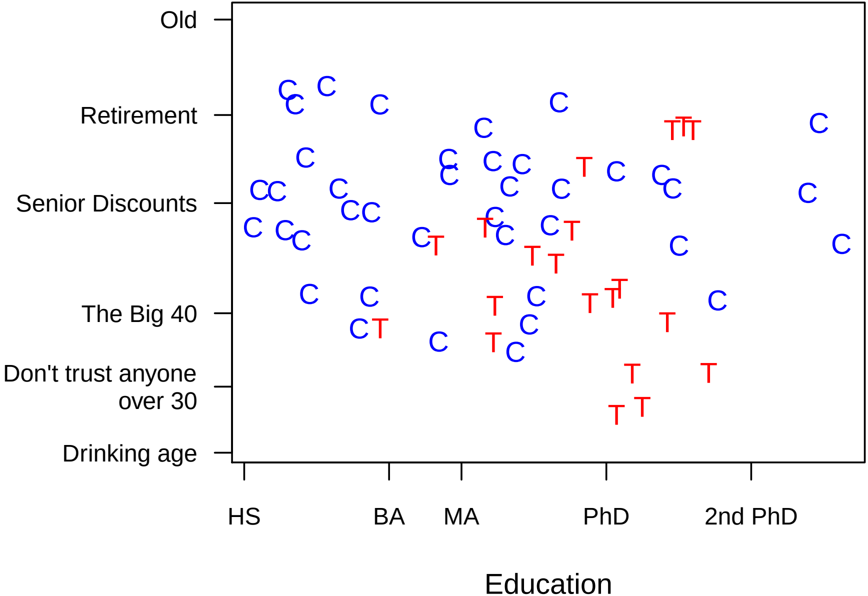

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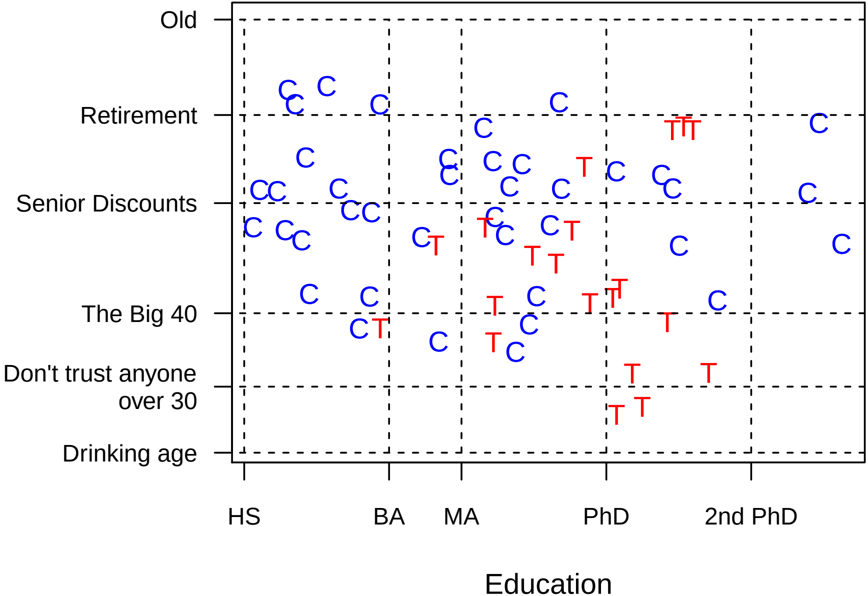

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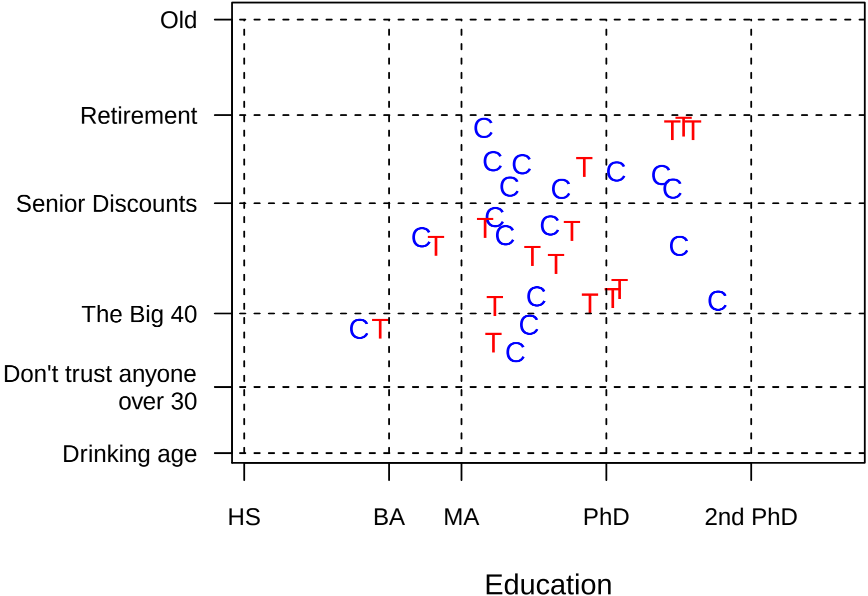

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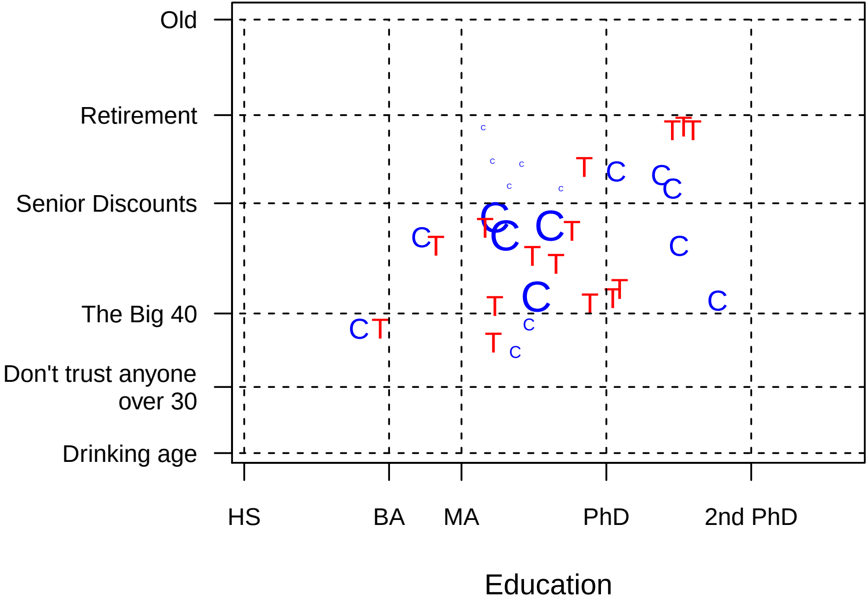

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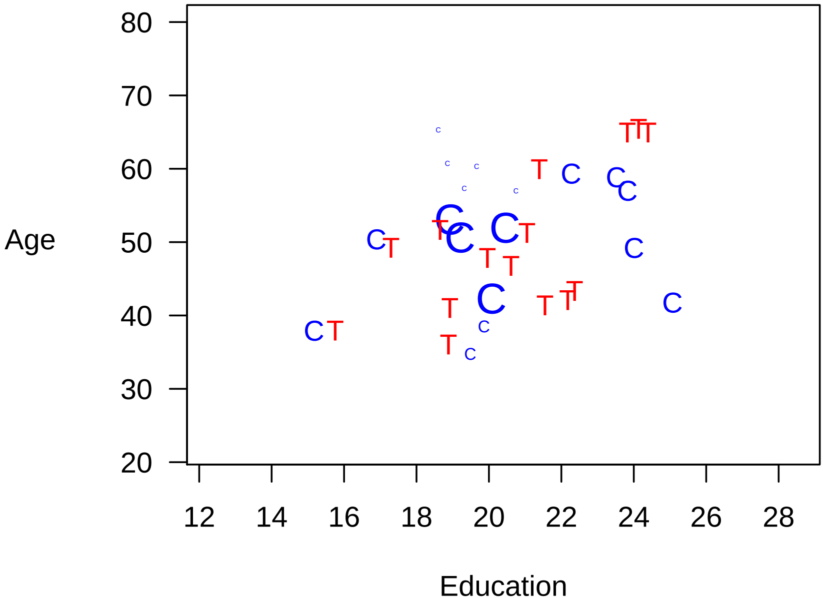

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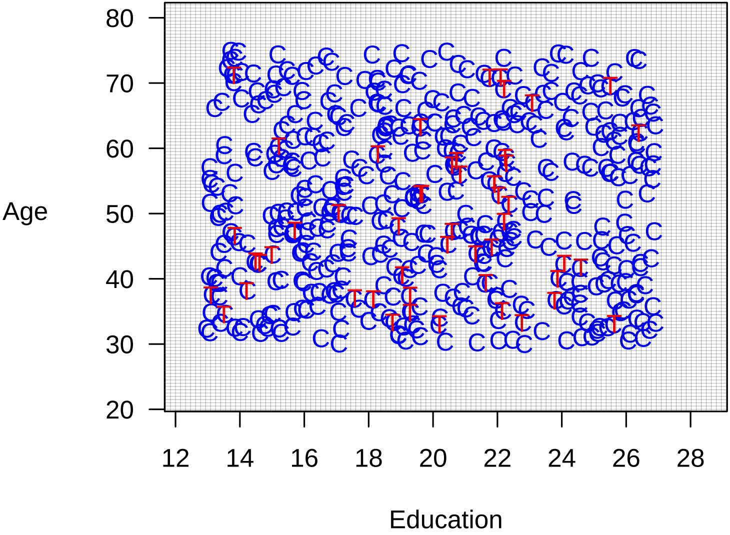

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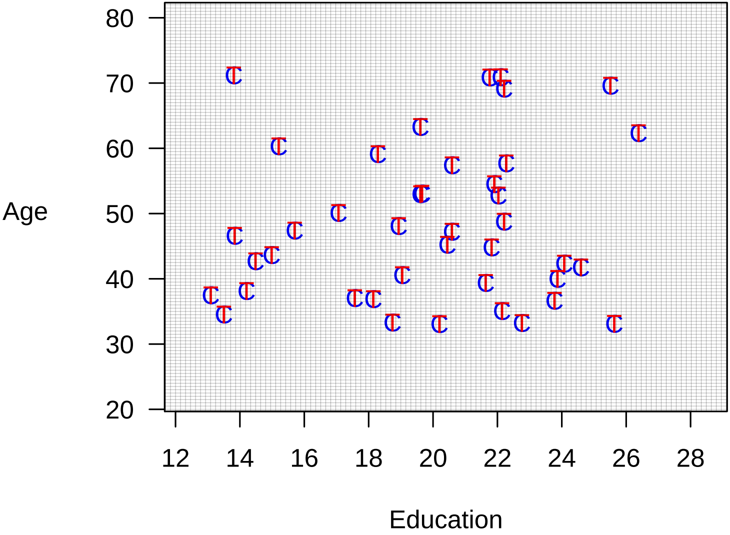

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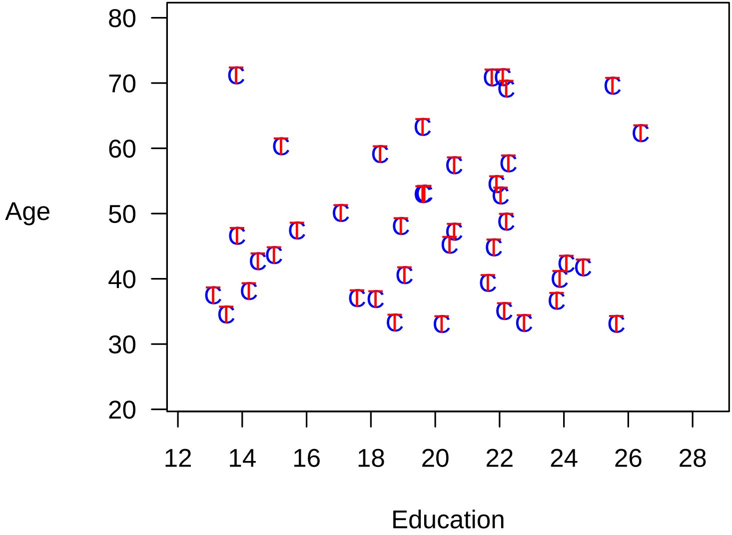

Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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1. Preprocess (Matching)

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   - 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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   - (Many adjustments available to this basic method)
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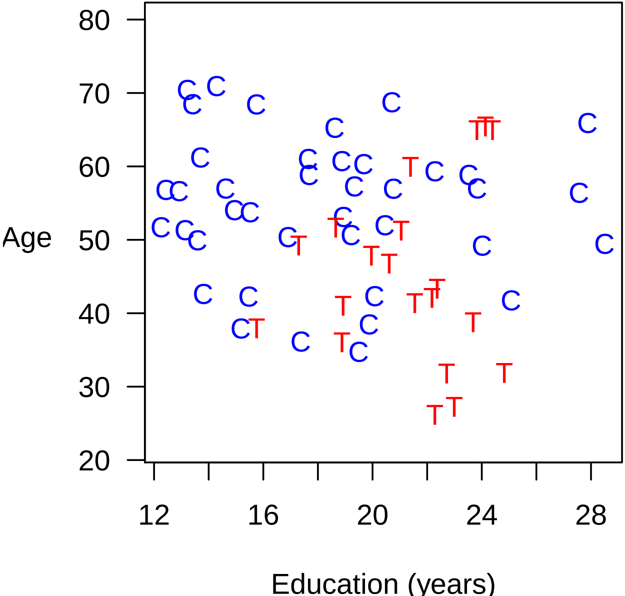
Propensity Score Matching



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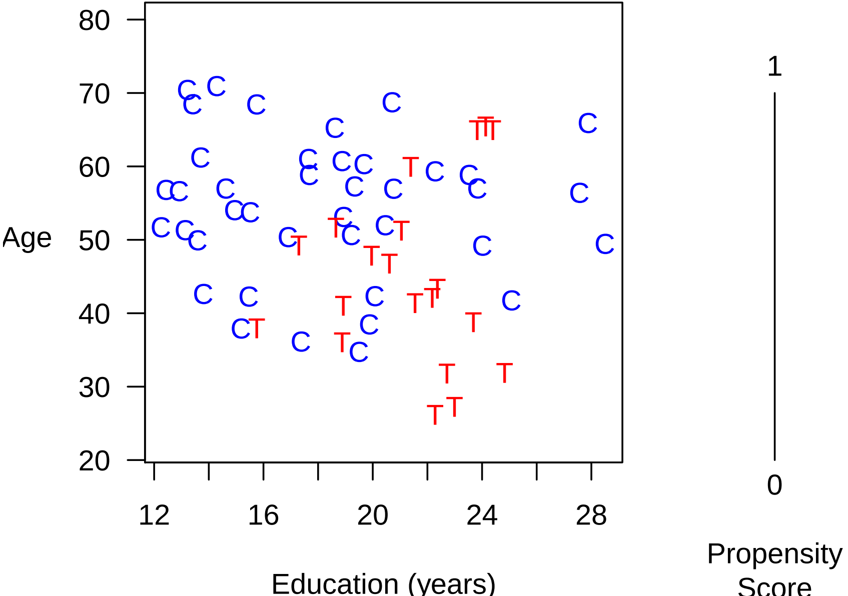

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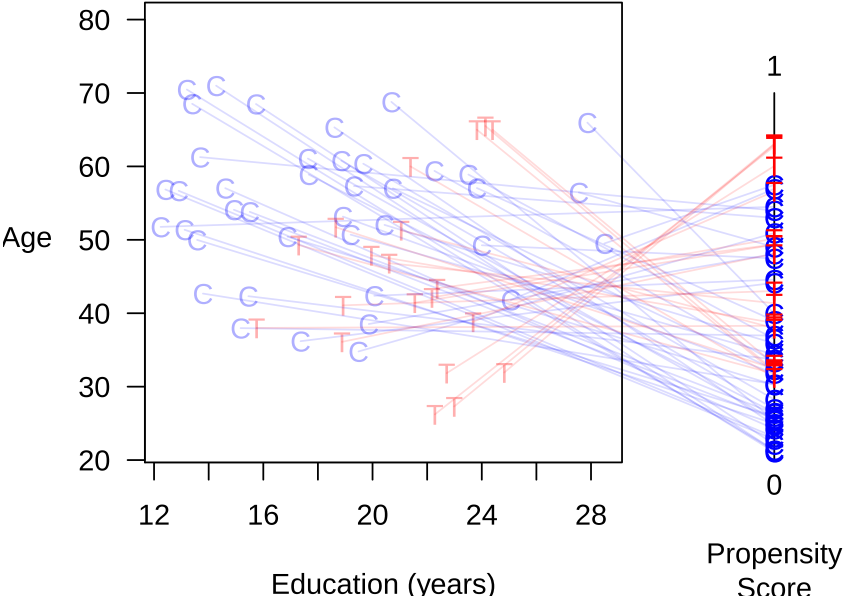

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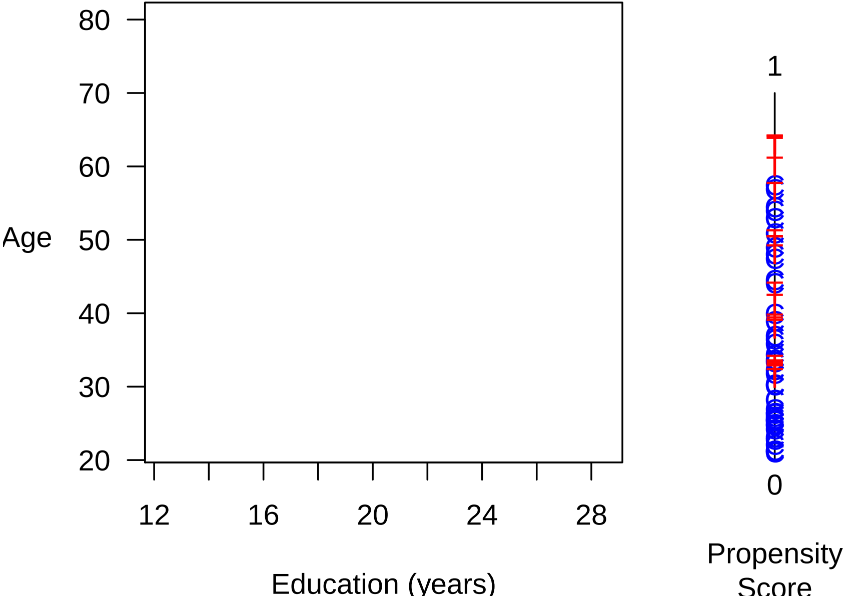

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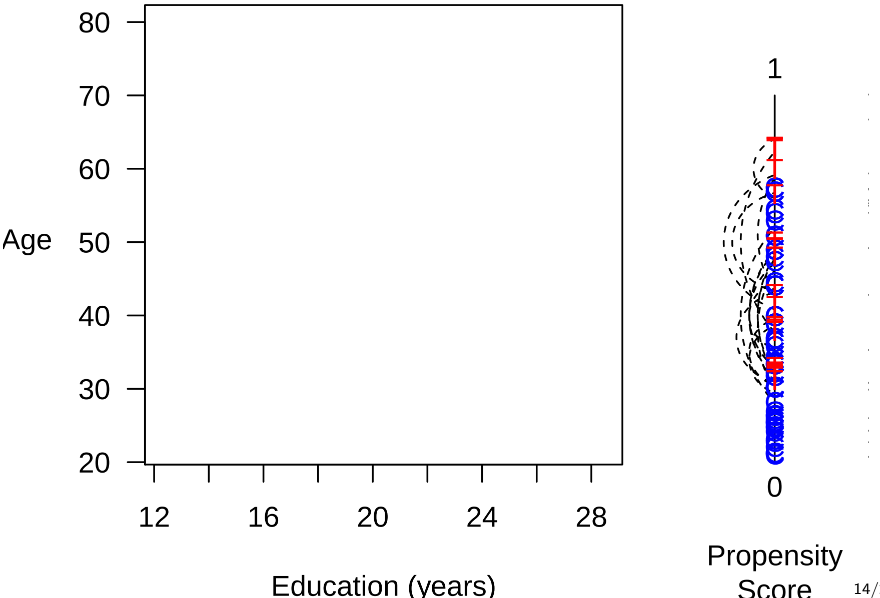

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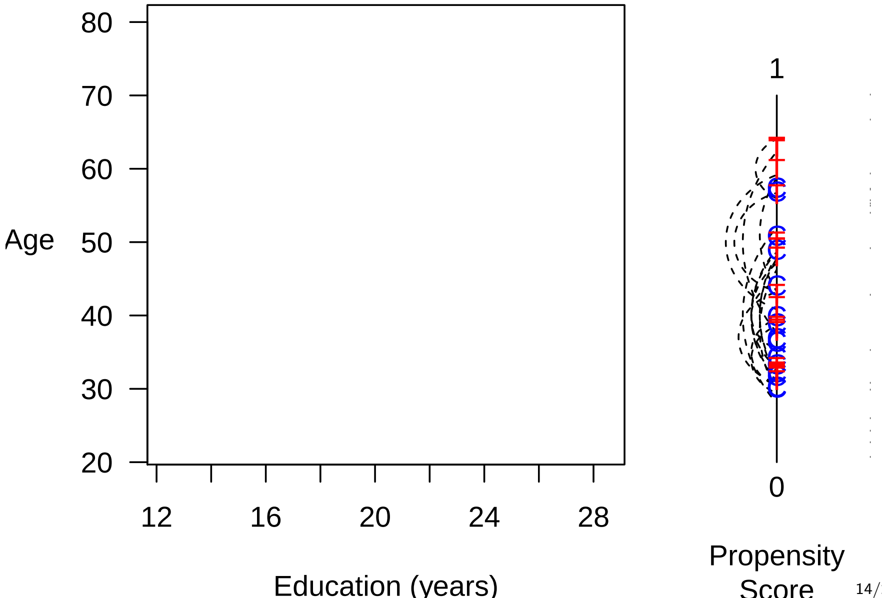

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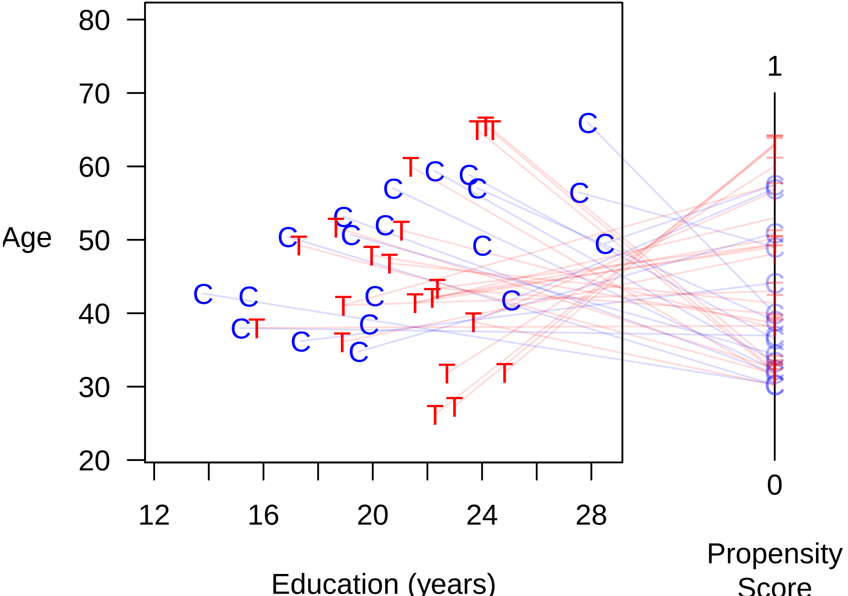

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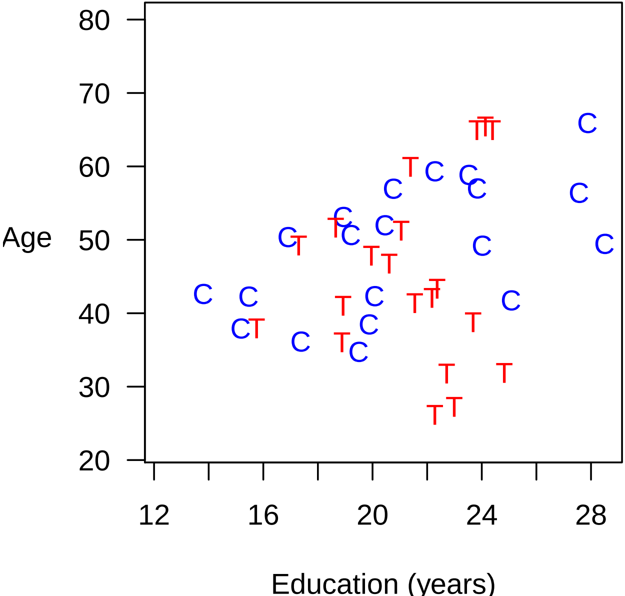

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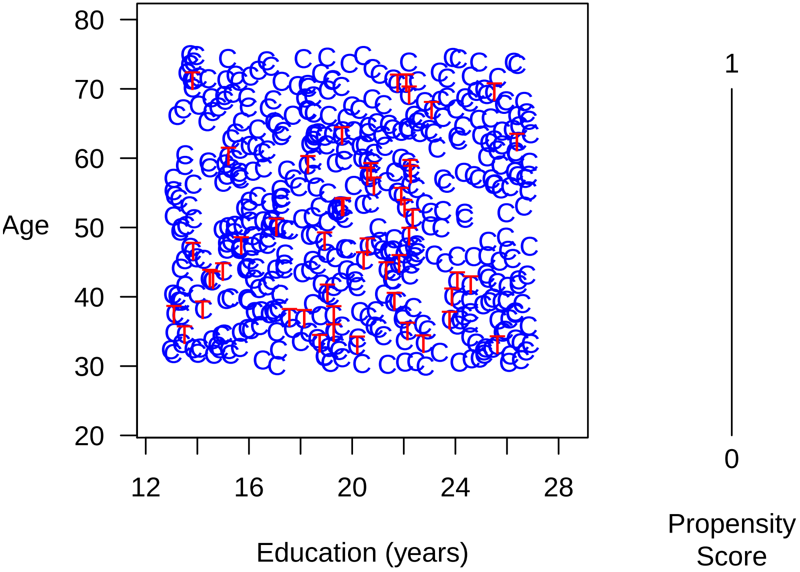

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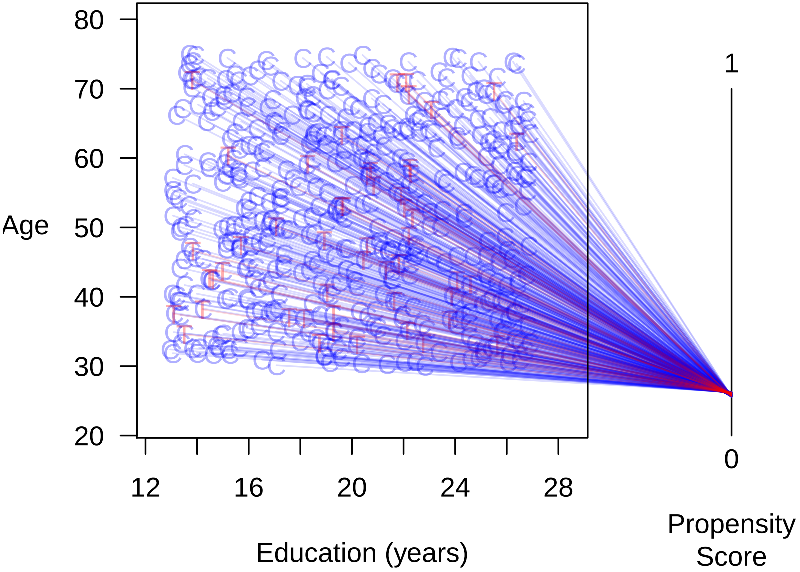

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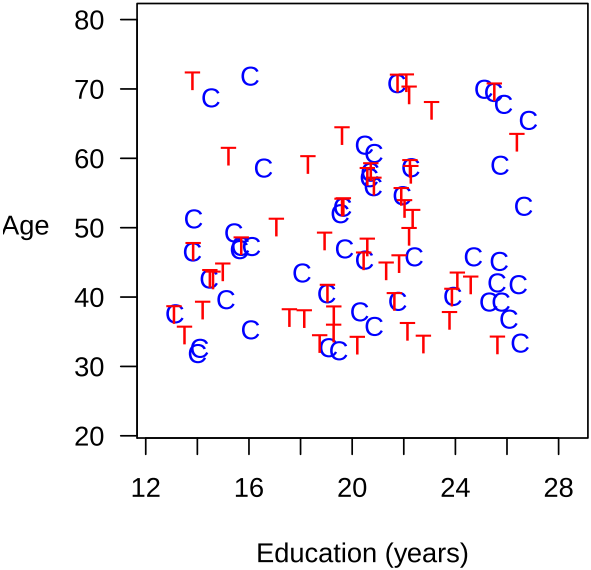
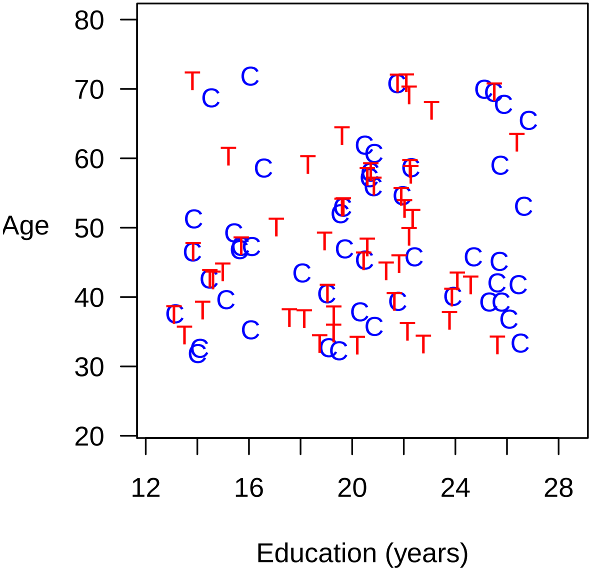


Best Case: Propensity Score Matching is Suboptimal



Random Pruning Increases Imbalance

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- Result is completely general (see math in the paper)

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   - When PSM approximates complete randomization (to begin with or, after some pruning)

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   - 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

PSM is Blind Where Other Methods Can See

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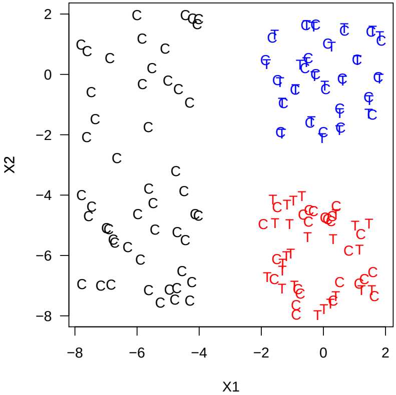

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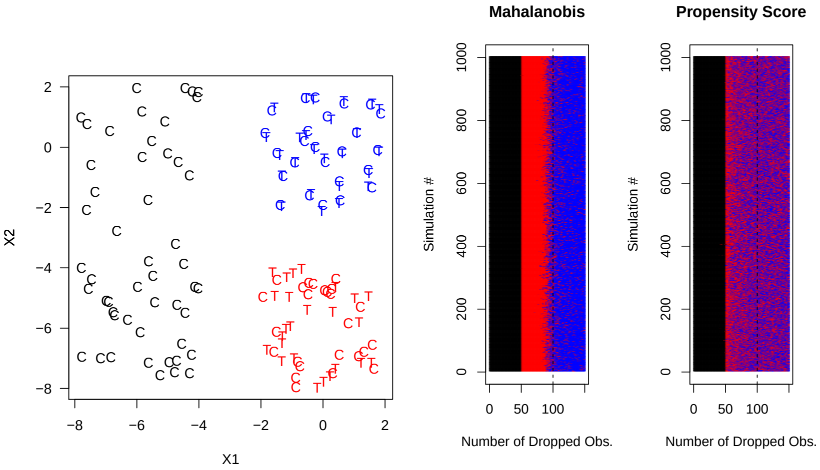
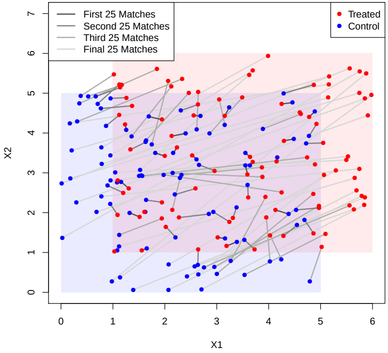


What Does PSM Match?

MDM Matches



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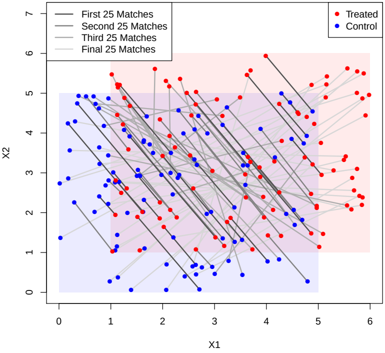
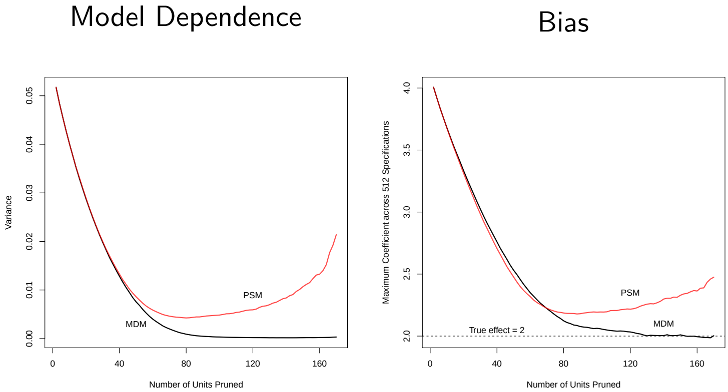


Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$

Treateds: $X_1, X_2 \sim \text{Uniform}(1,6)$

PSM Increases Model Dependence & Bias



$$Y_i = 2T_i + X_{1i} + X_{2i} + \epsilon_i$$
$$\epsilon_i \sim N(0,1)$$

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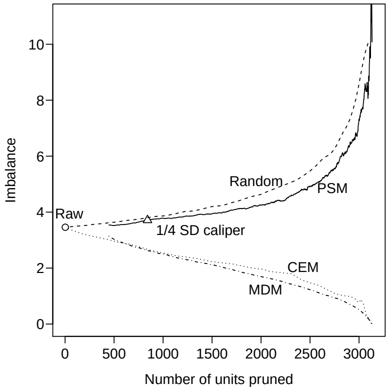

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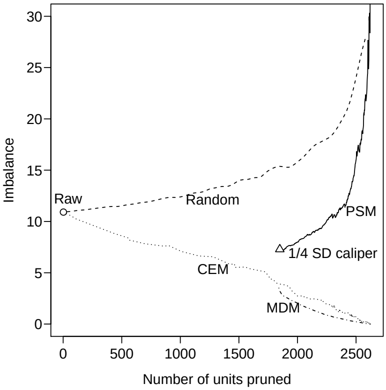

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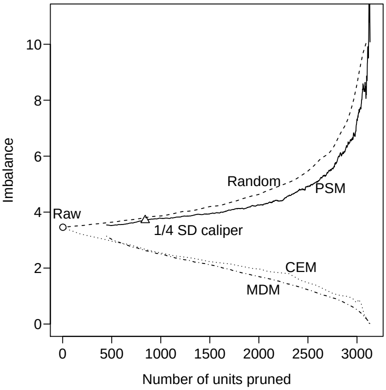

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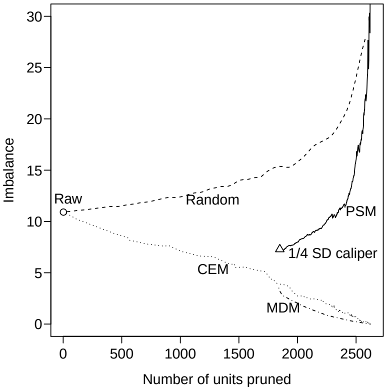

Similar pattern for $>$ 20 other real data sets we checked

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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