Why Propensity Scores Should Not Be Used For Matching

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The Scholarly Influence of Propensity Score Matching

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    - The mathematical theorems about propensity scores

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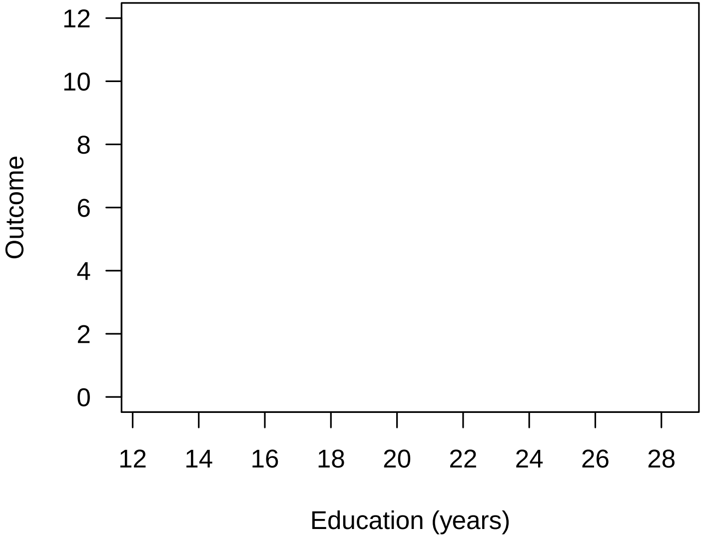

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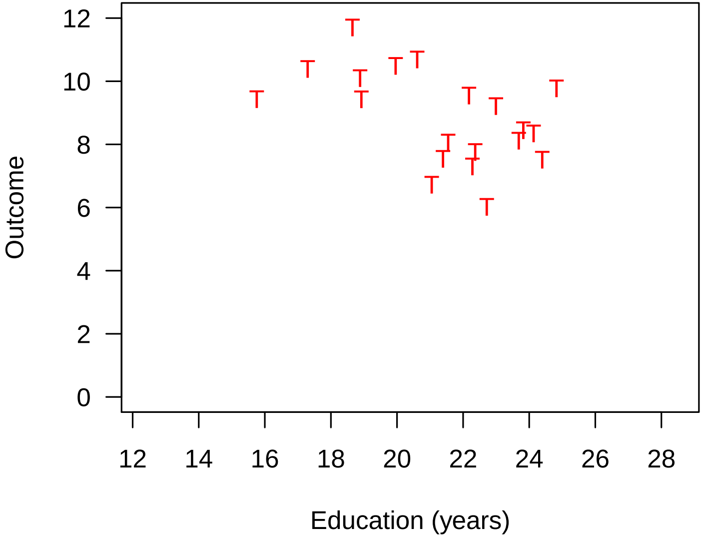

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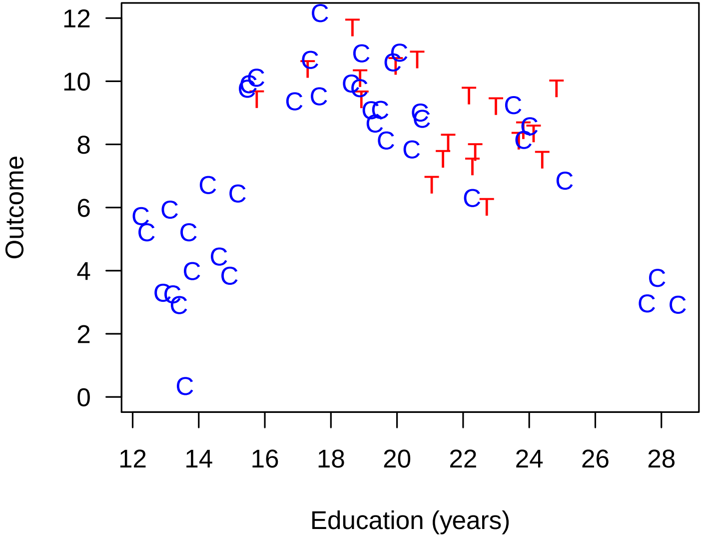

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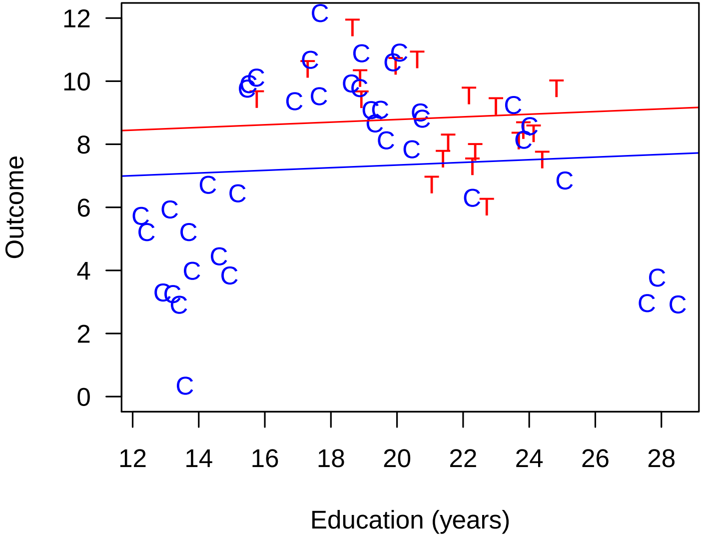

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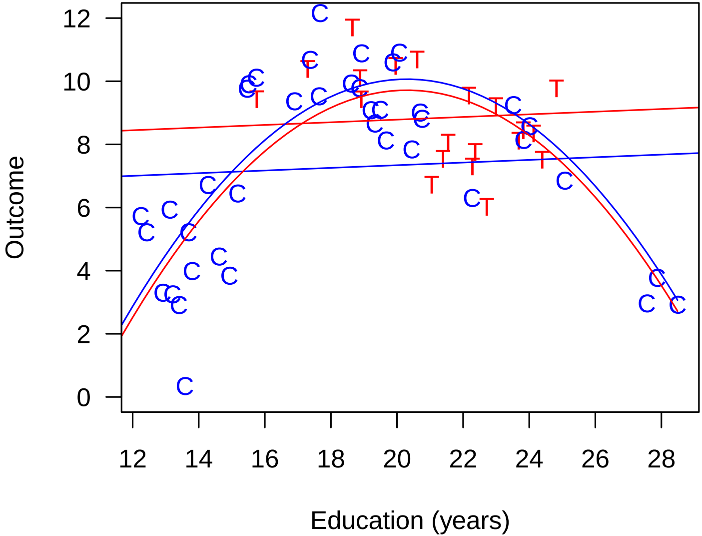

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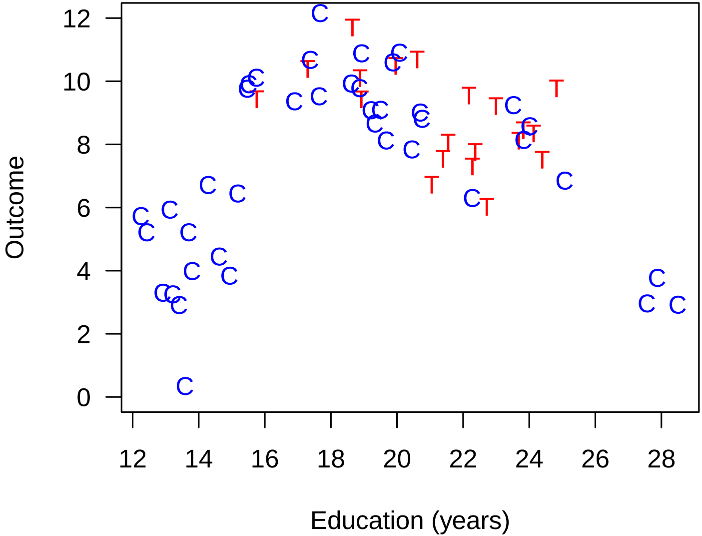

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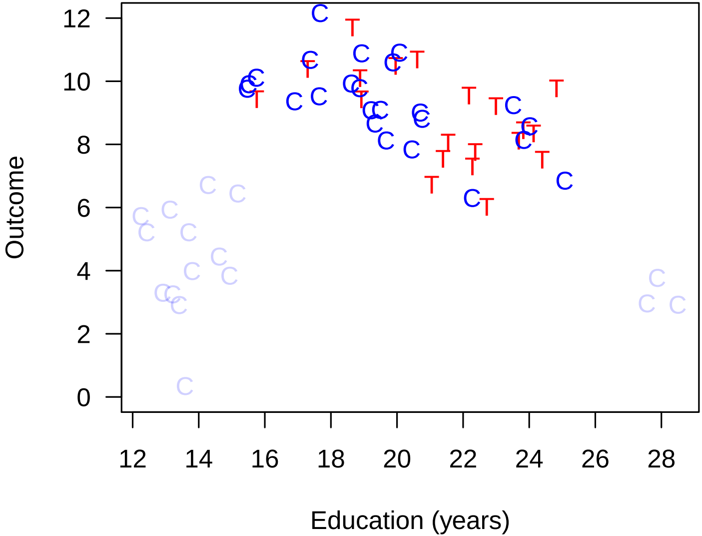

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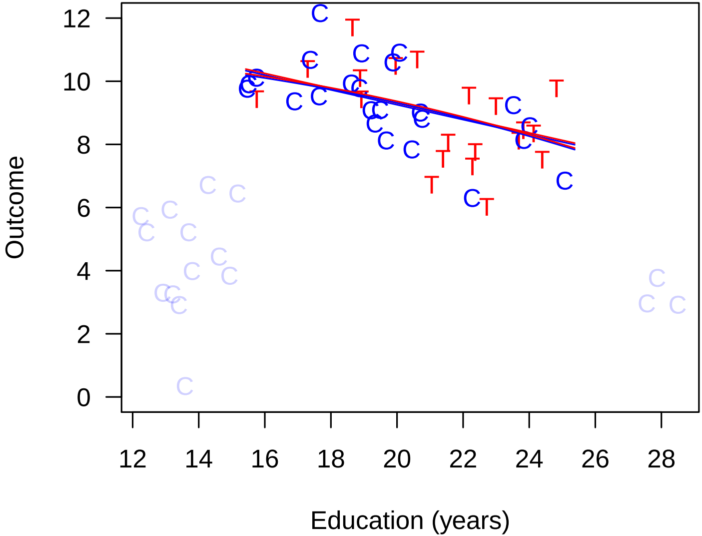

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- "Teaching psychology is mostly a waste of time" (Kahneman 2011)

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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

Matching: Finding Hidden Randomized Experiments

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Types of Experiments

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Complete Randomization

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- Other methods: *fully blocked*
- Other matching methods dominate PSM (wait, it gets worse)

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   - (Many adjustments available to this basic method)
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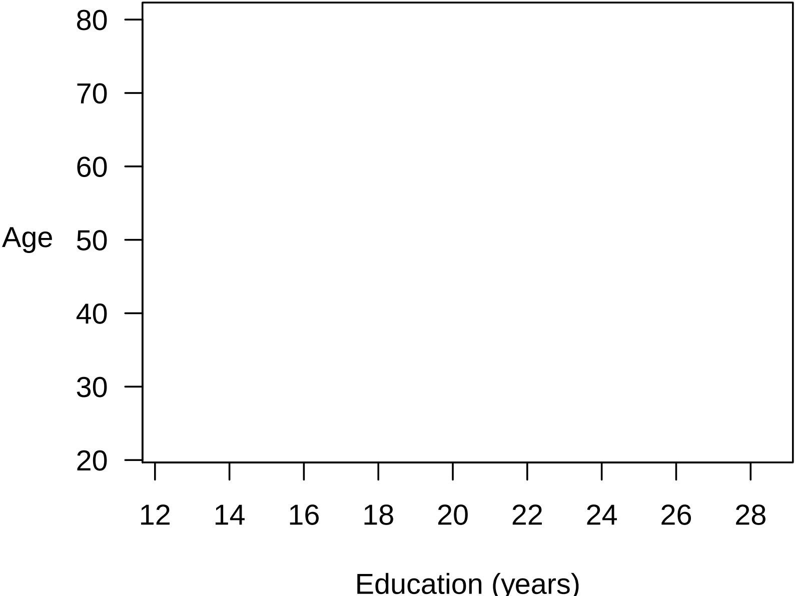
Mahalanobis Distance Matching



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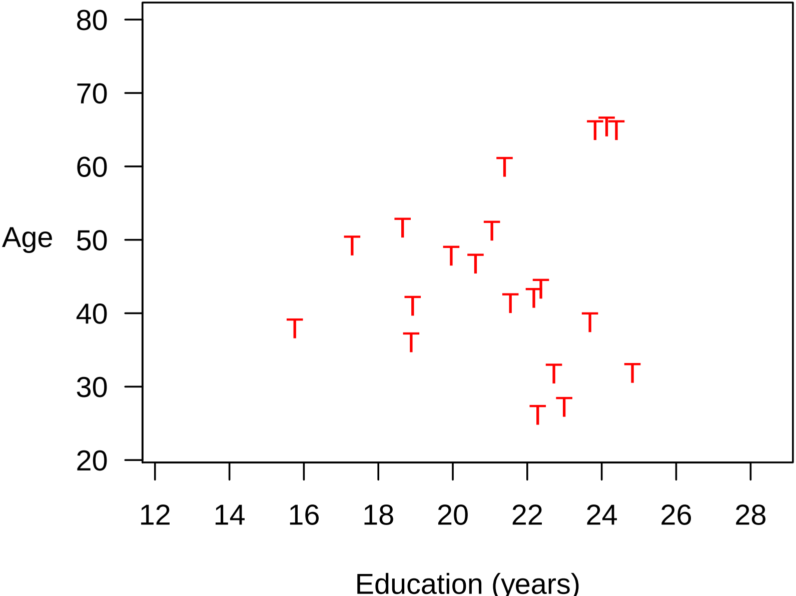

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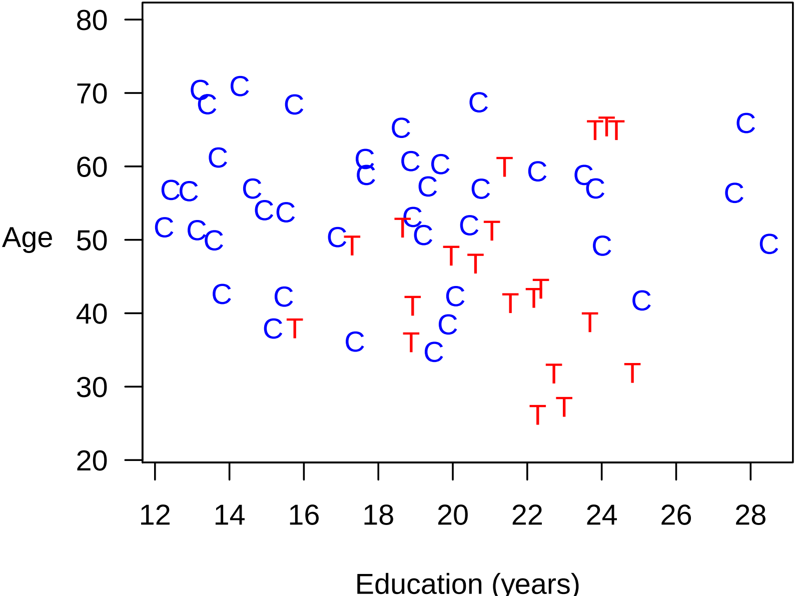

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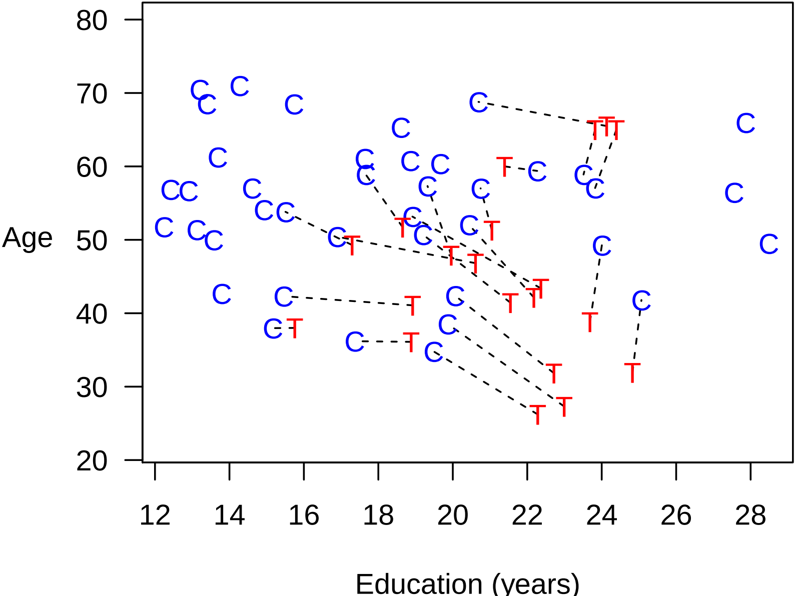

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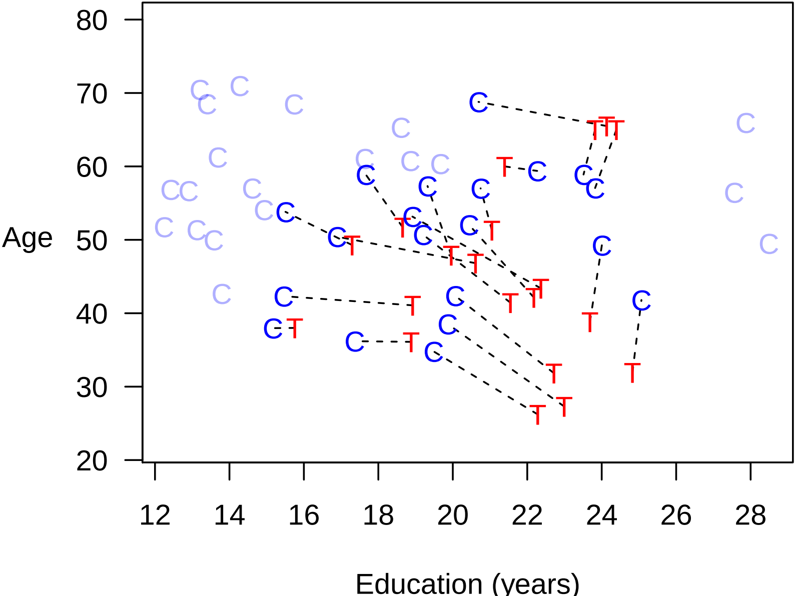

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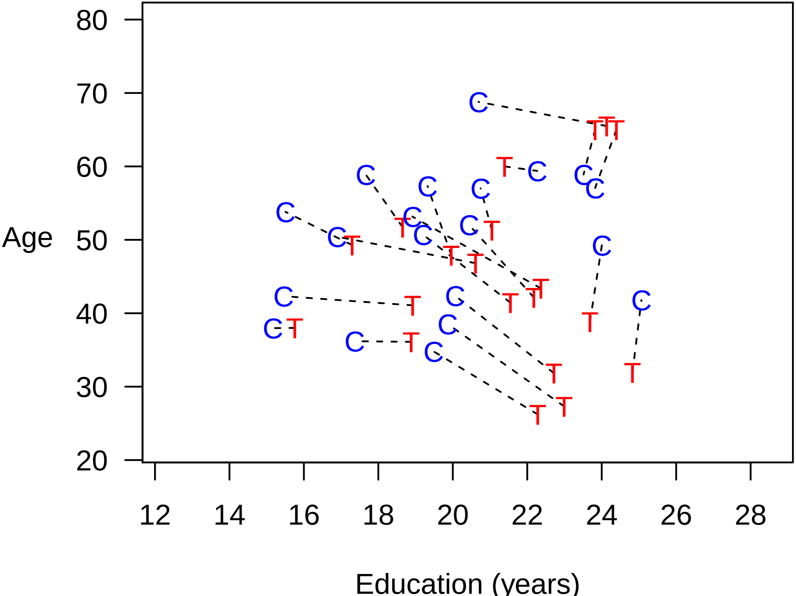

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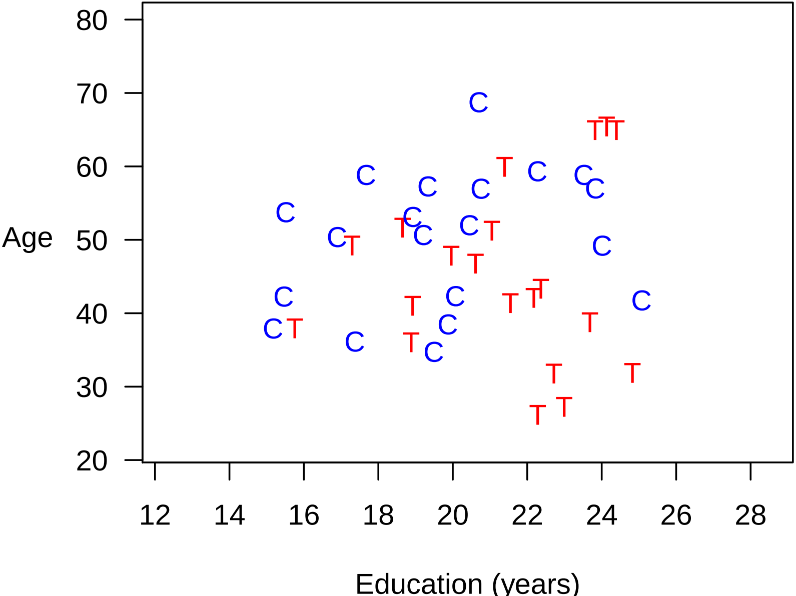

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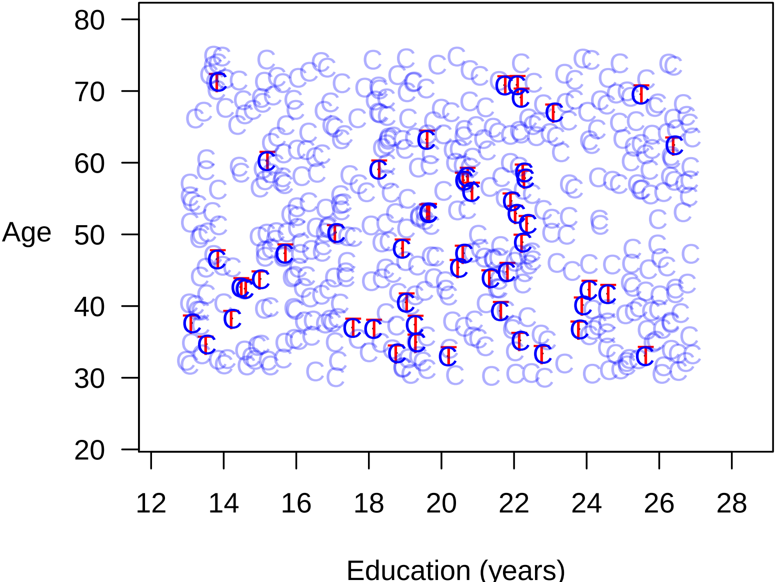

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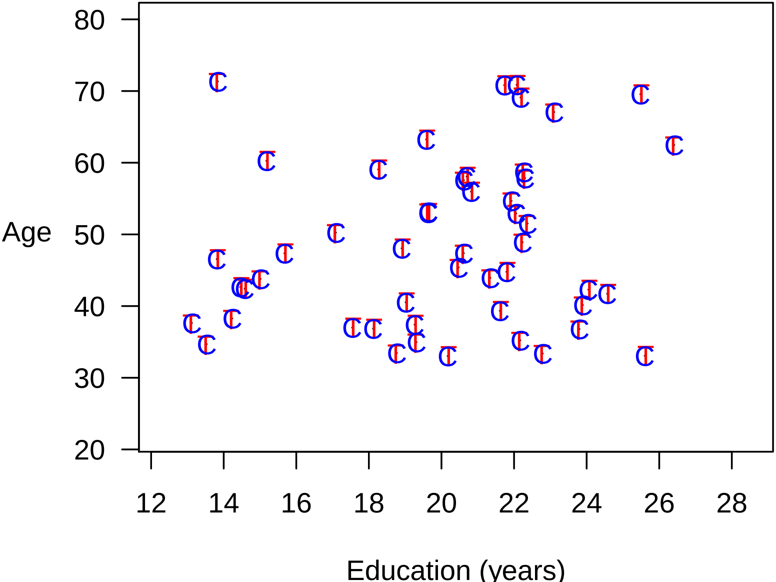

Method 2: Coarsened Exact Matching

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(Approximates Fully Blocked Experiment)

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1. Preprocess (Matching)

2. Estimation Difference in means or a model

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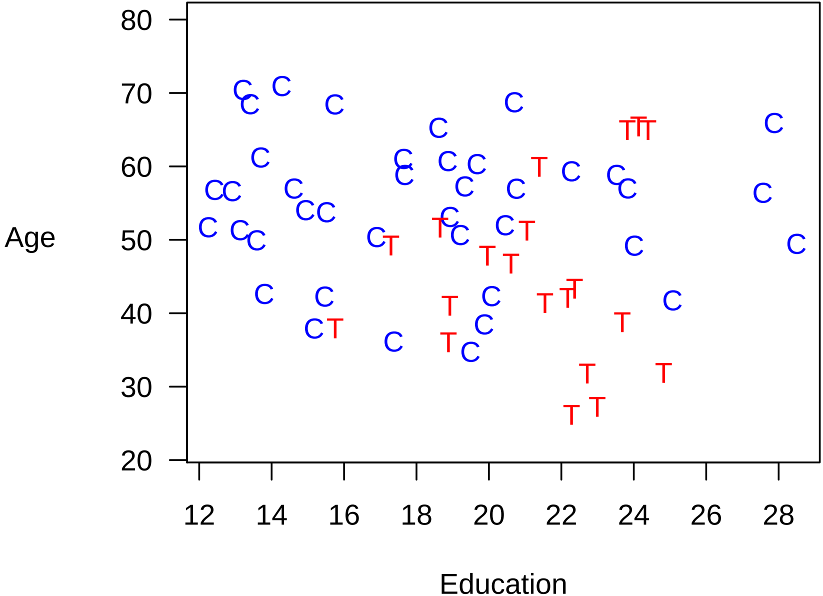

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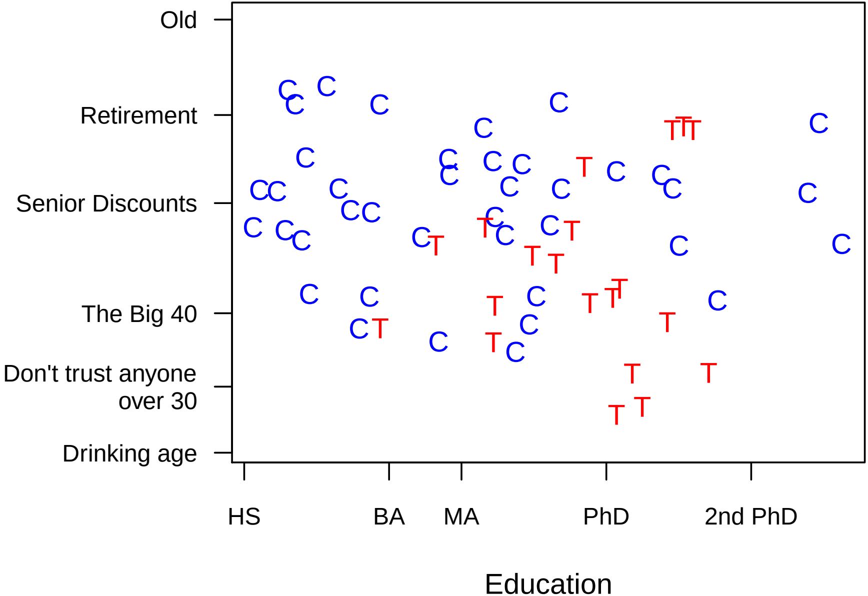

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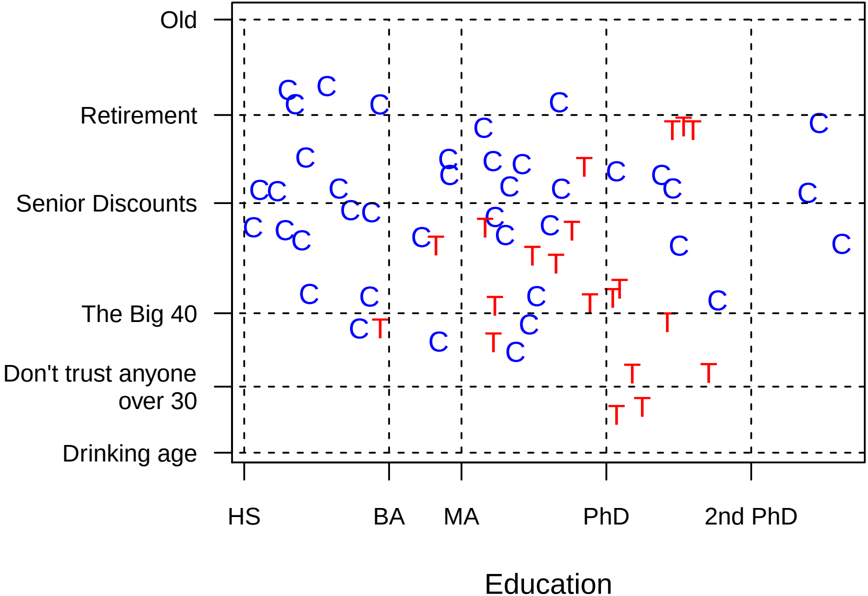

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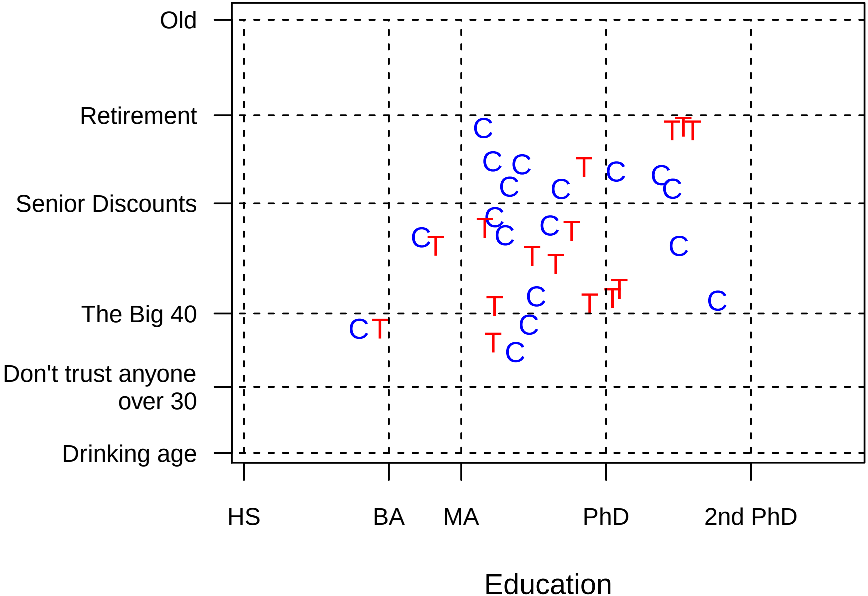

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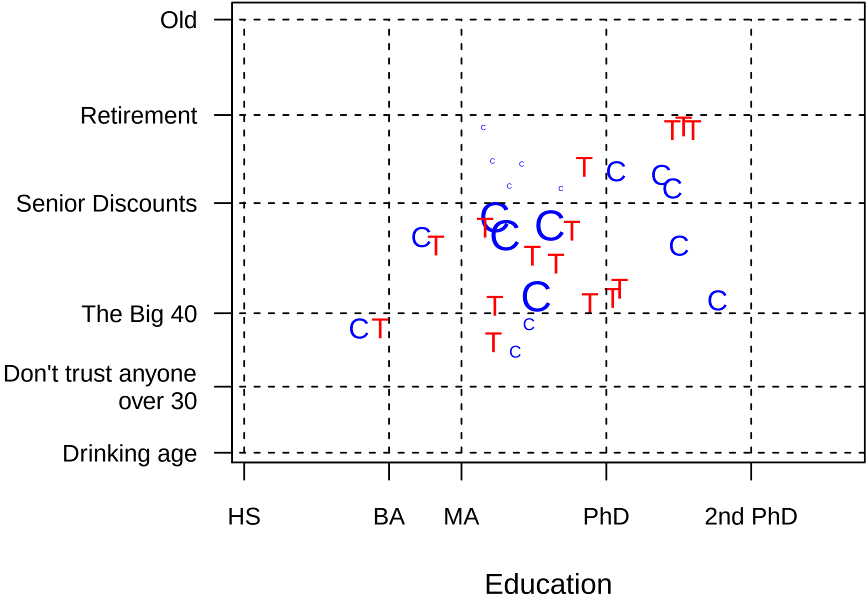

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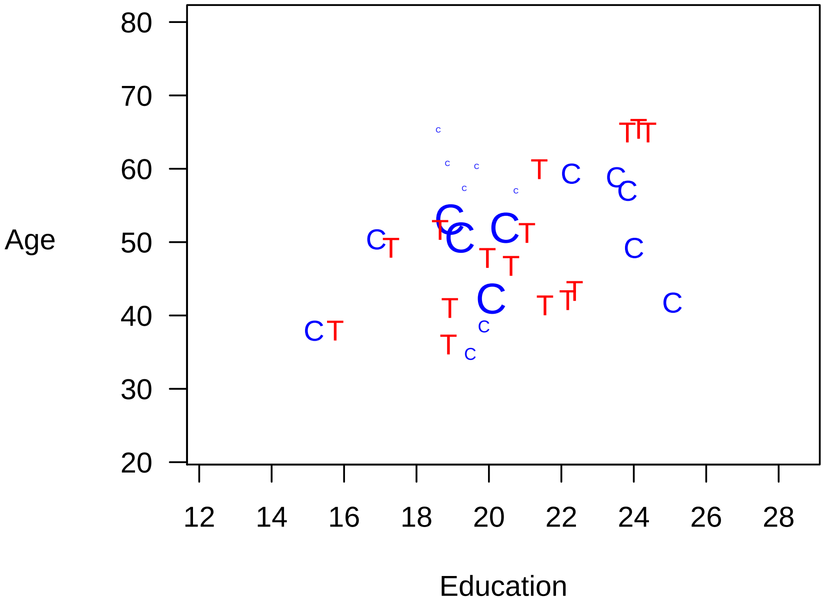

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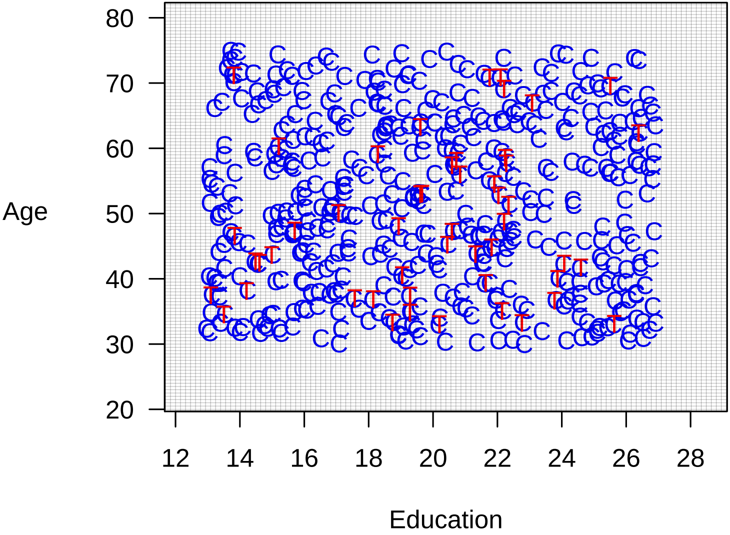

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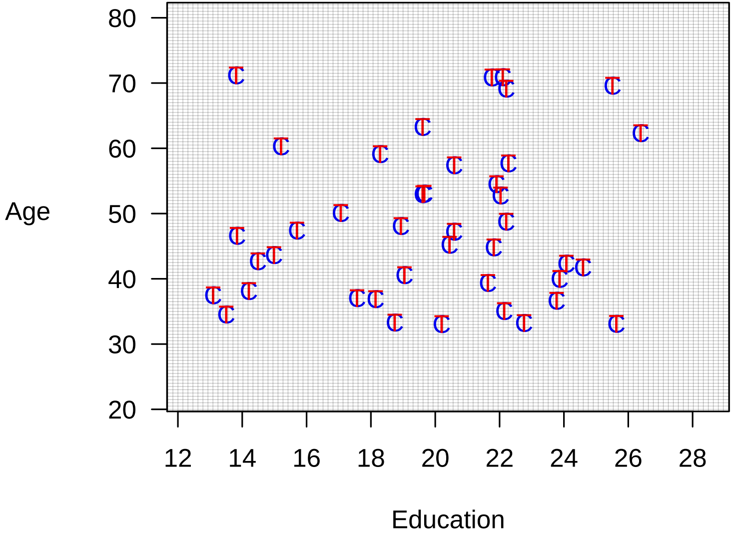

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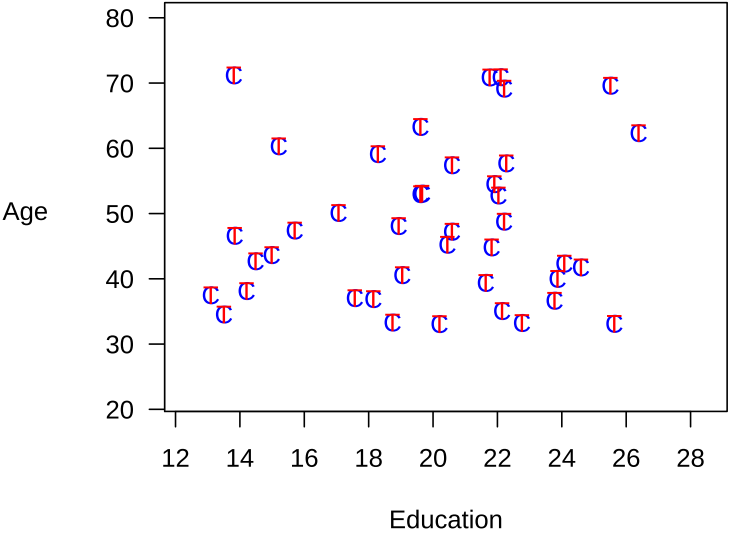

Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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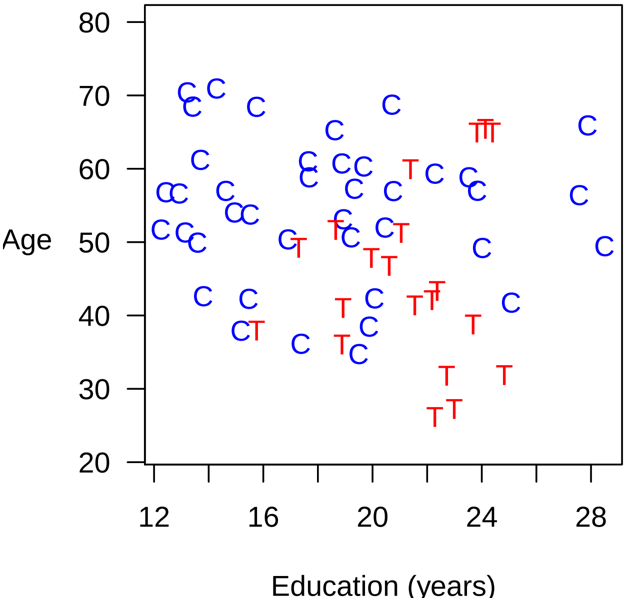
Propensity Score Matching



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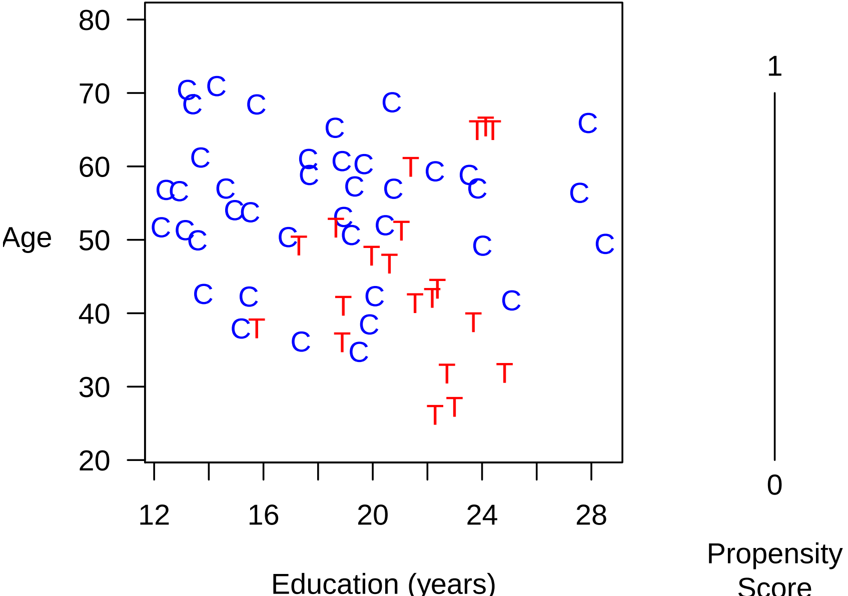

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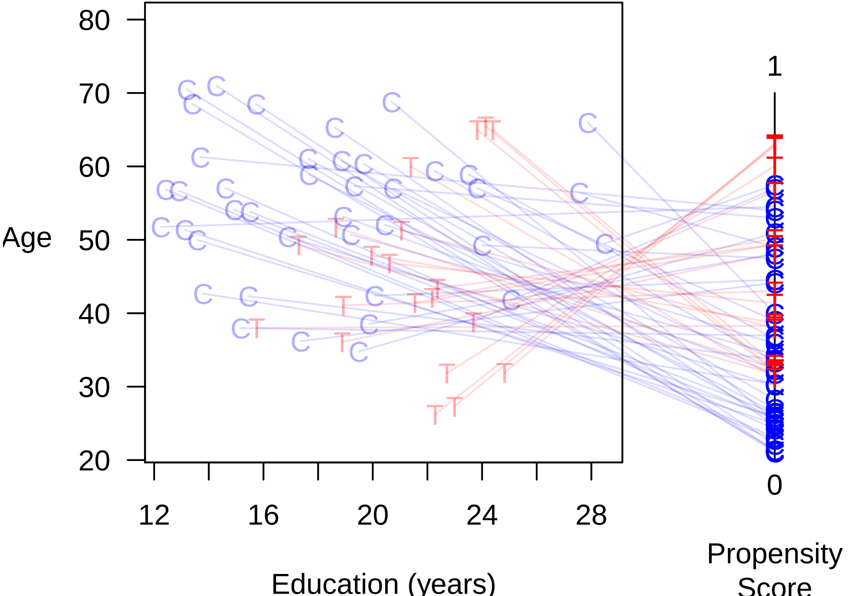

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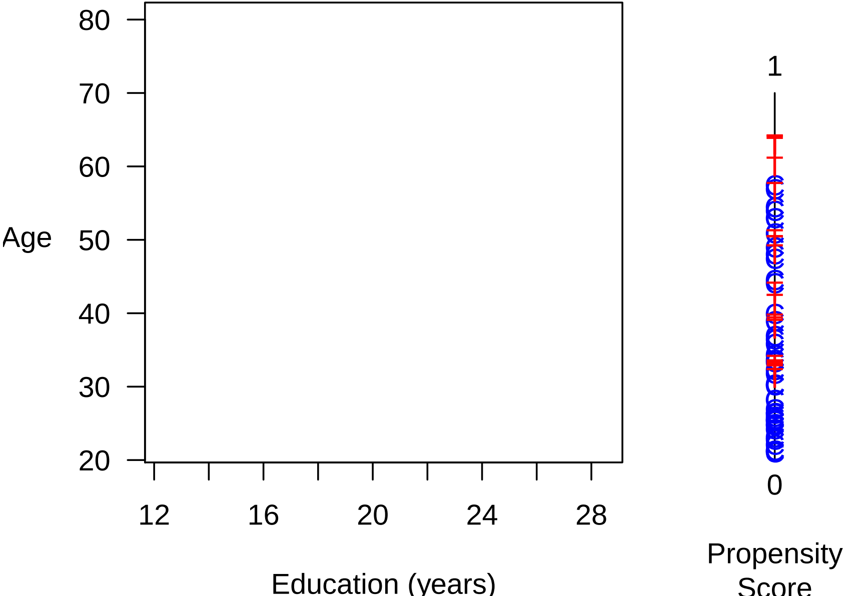

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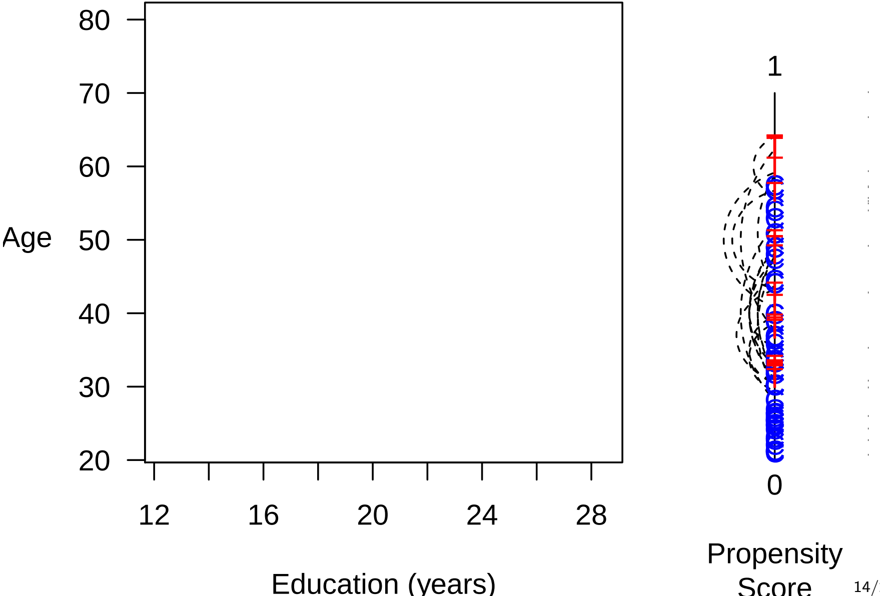

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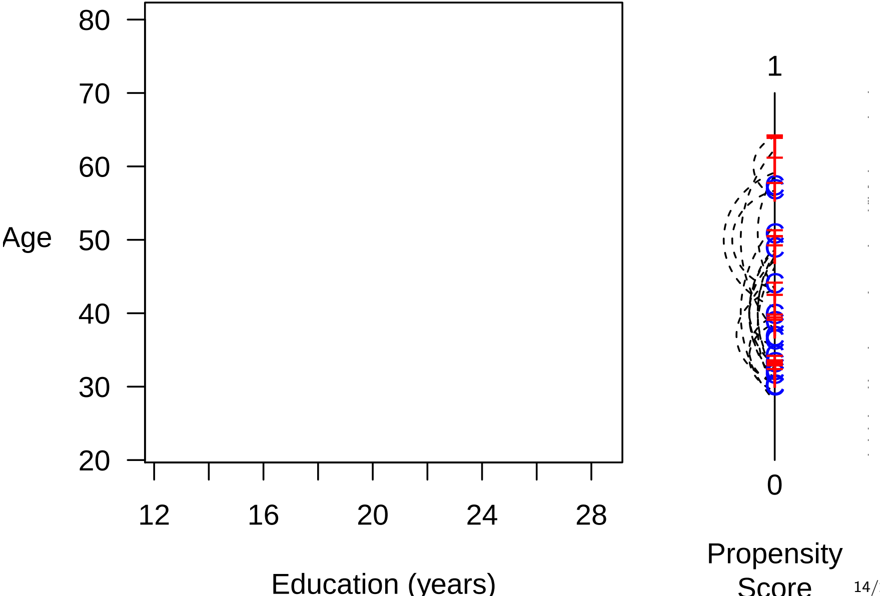

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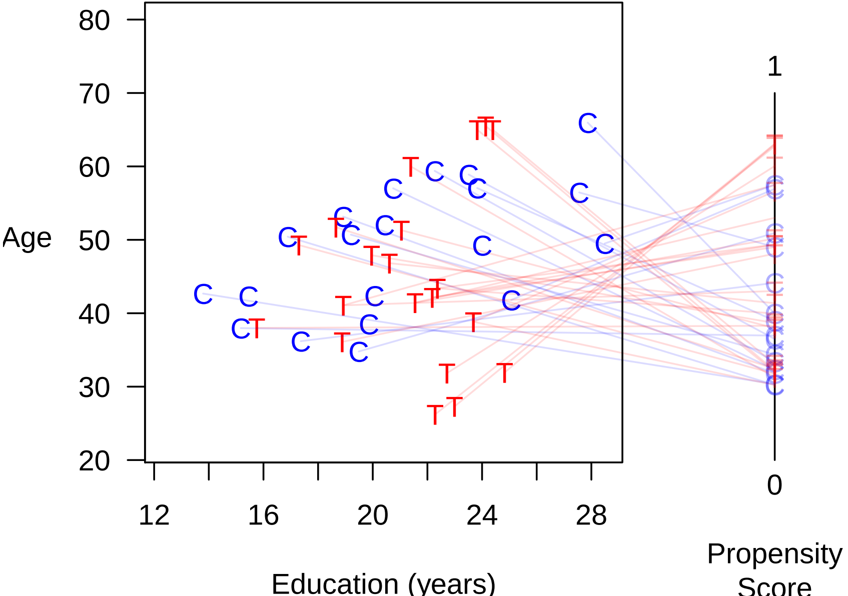

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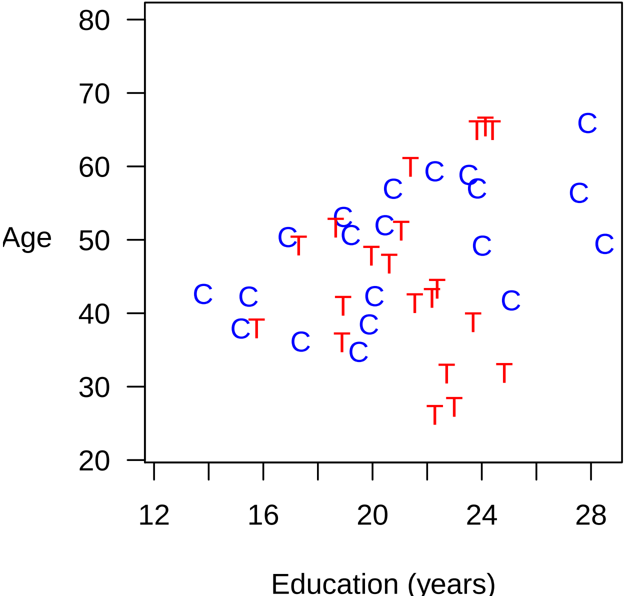

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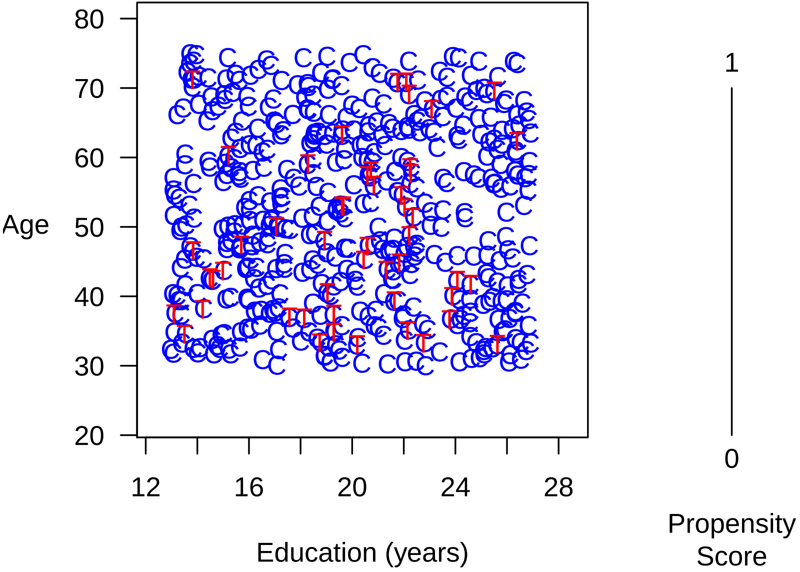

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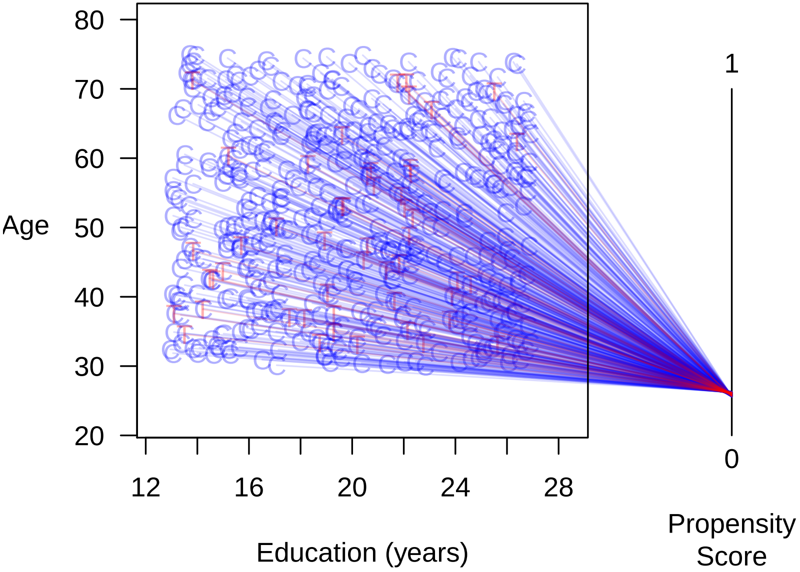

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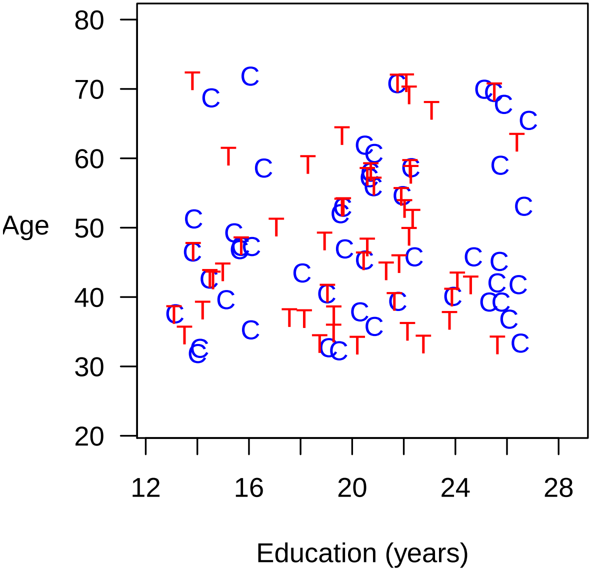
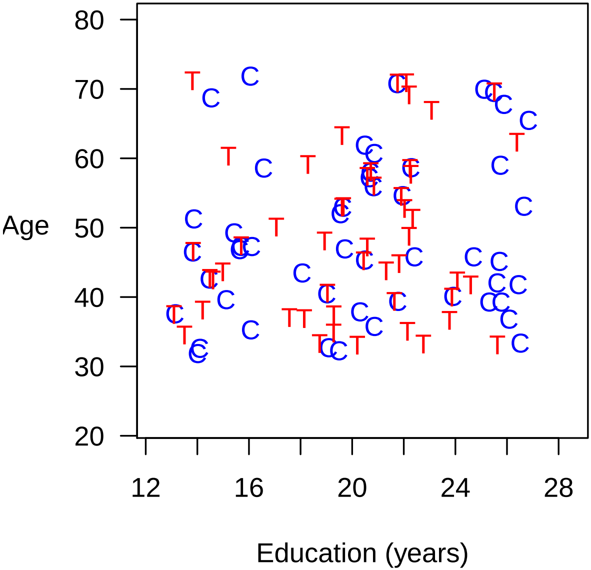


Best Case: Propensity Score Matching is Suboptimal



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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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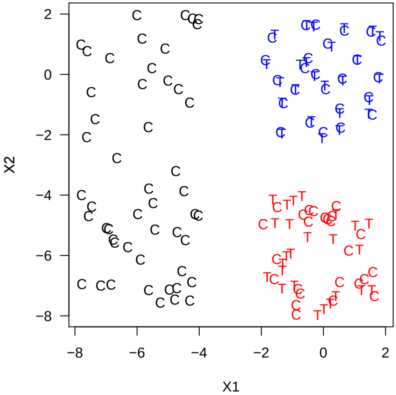

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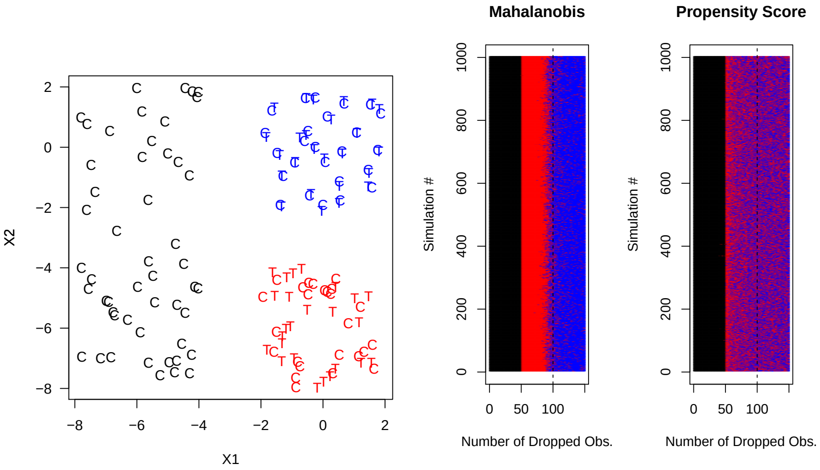
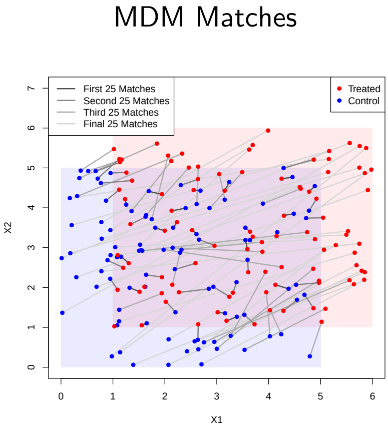
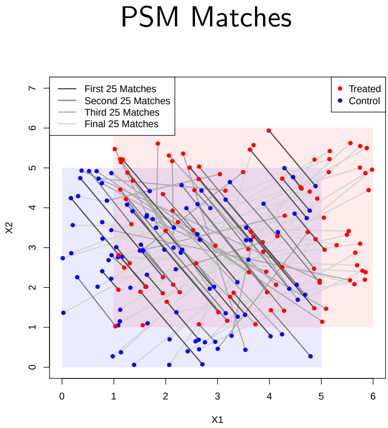


What Does PSM Match?



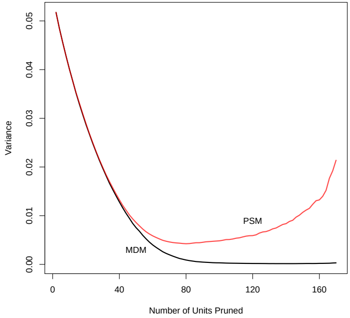


Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$

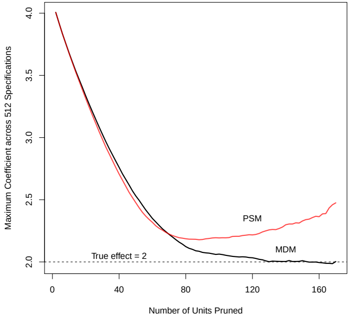
Treateds: $X_1, X_2 \sim \text{Uniform}(1,6)$

PSM Increases Model Dependence & Bias

Model Dependence



Bias



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

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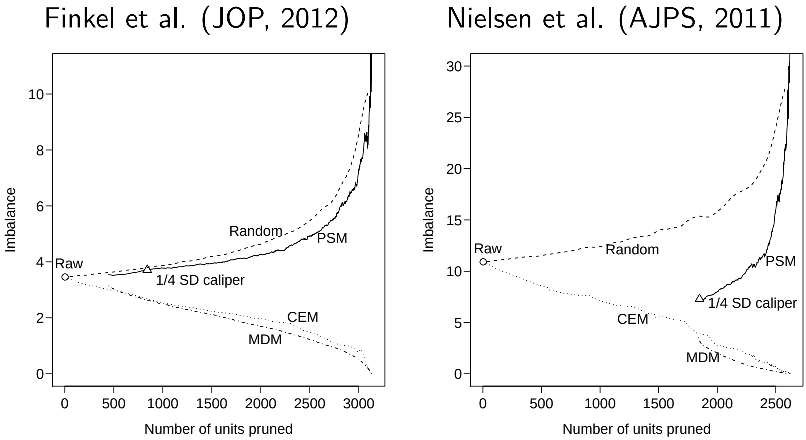

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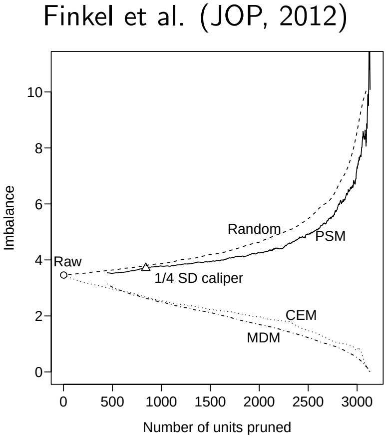

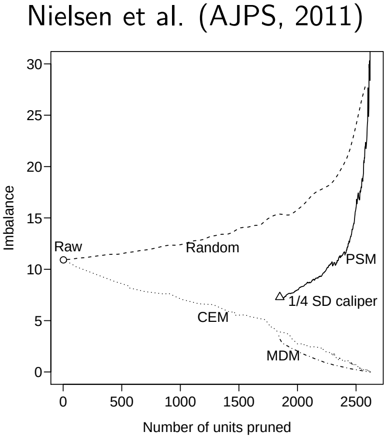

Similar pattern for $>$ 20 other real data sets we checked

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

For more information, papers, & software

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www.mit.edu/∼rnielsen