Why Propensity Scores Should Not Be Used For Matching

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Talk Department of Statistics, Harvard University, 11/18/2015

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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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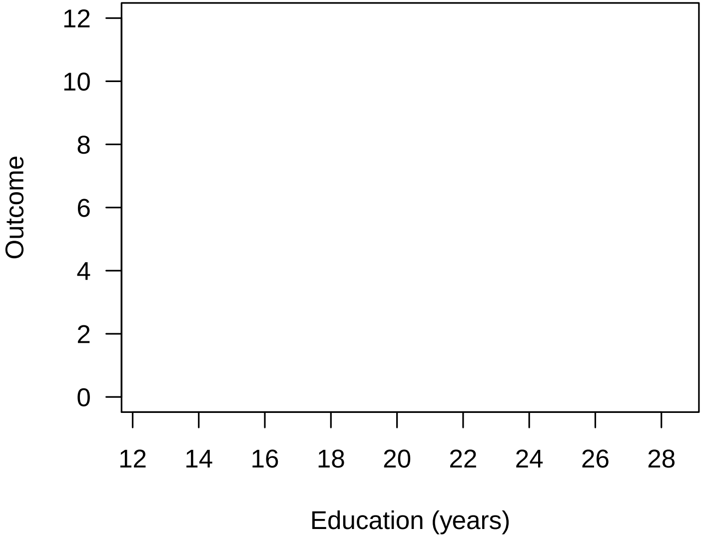

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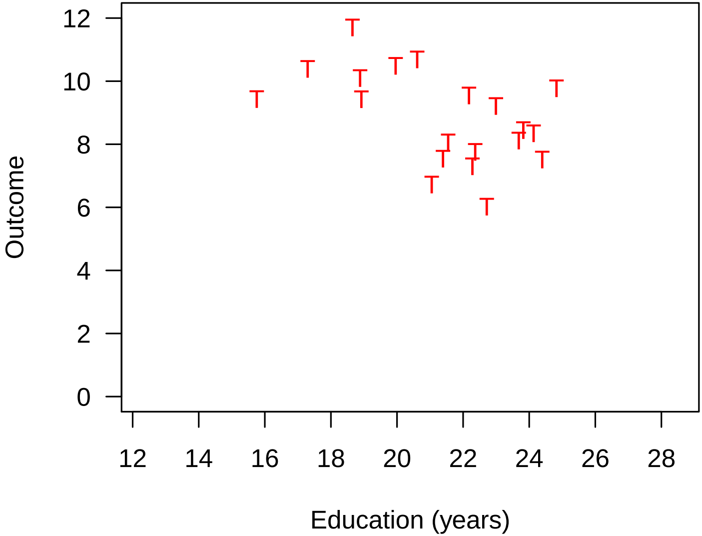

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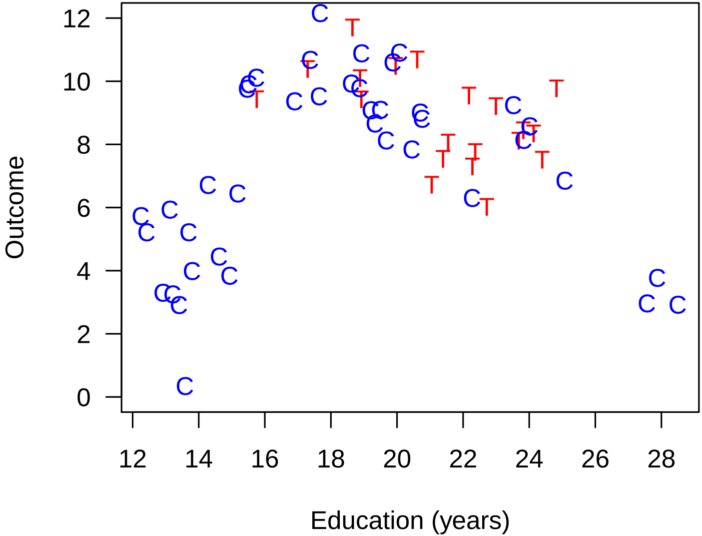

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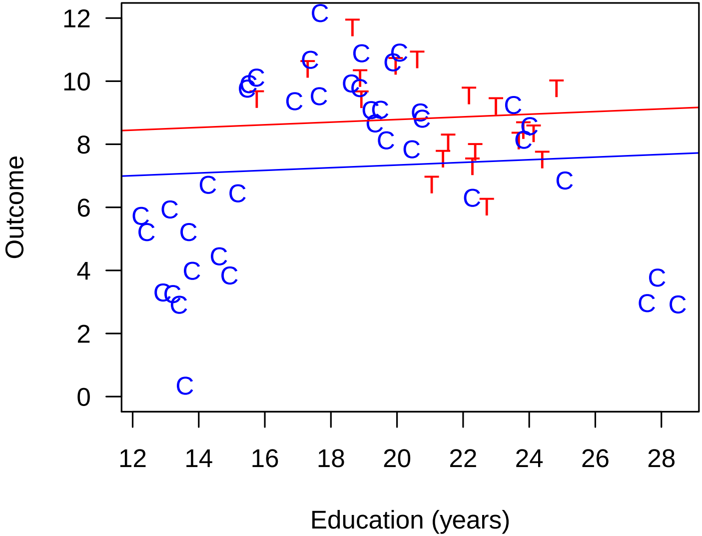

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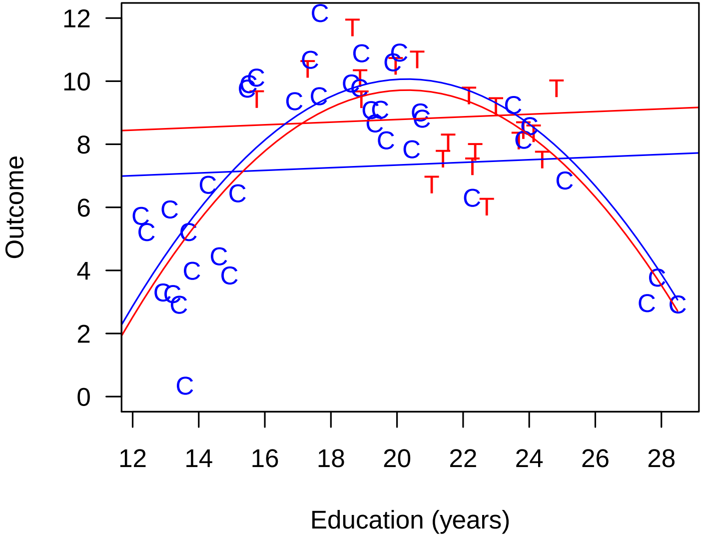

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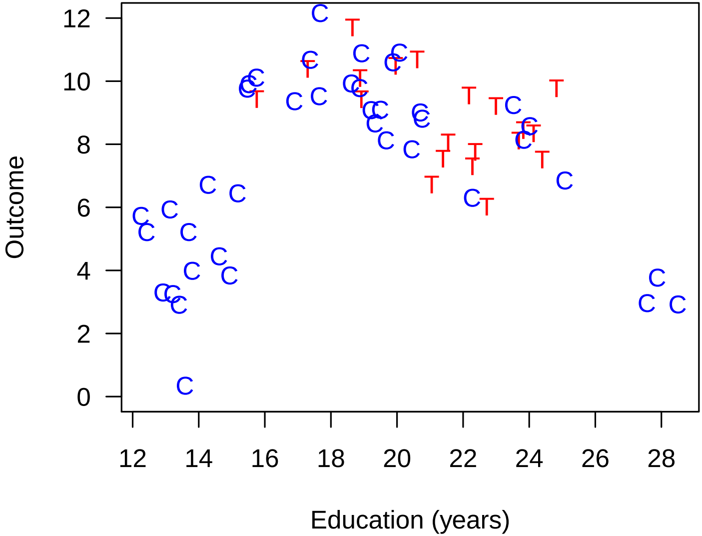

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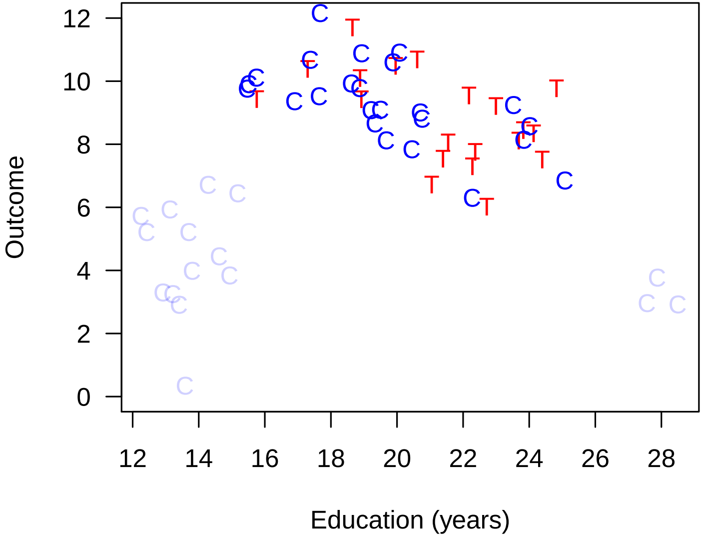

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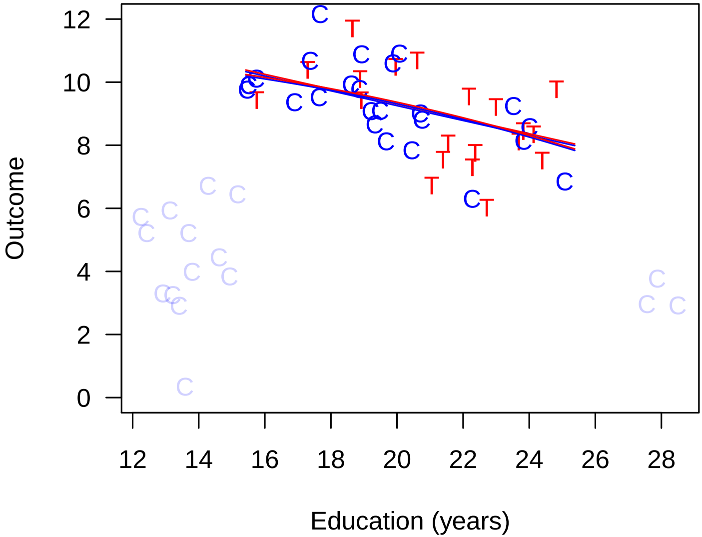

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- "Teaching psychology is mostly a waste of time" (Kahneman 2011)

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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

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Types of Experiments

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Complete Randomization

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- Other matching methods dominate PSM (wait, it gets worse)

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   - (Many adjustments available to this basic method)
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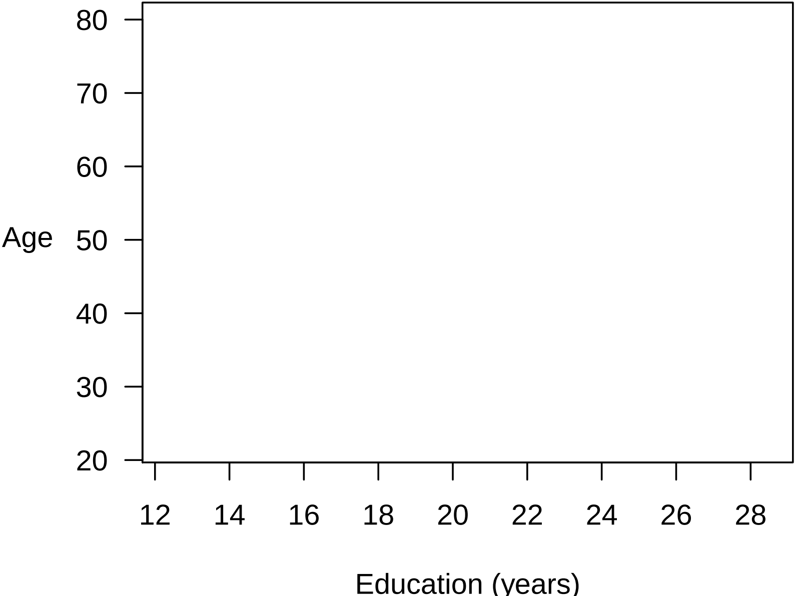

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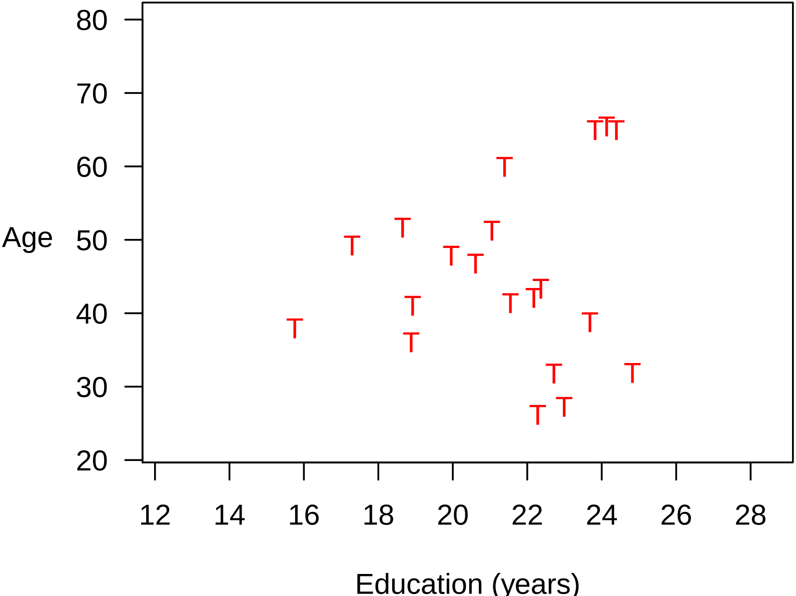

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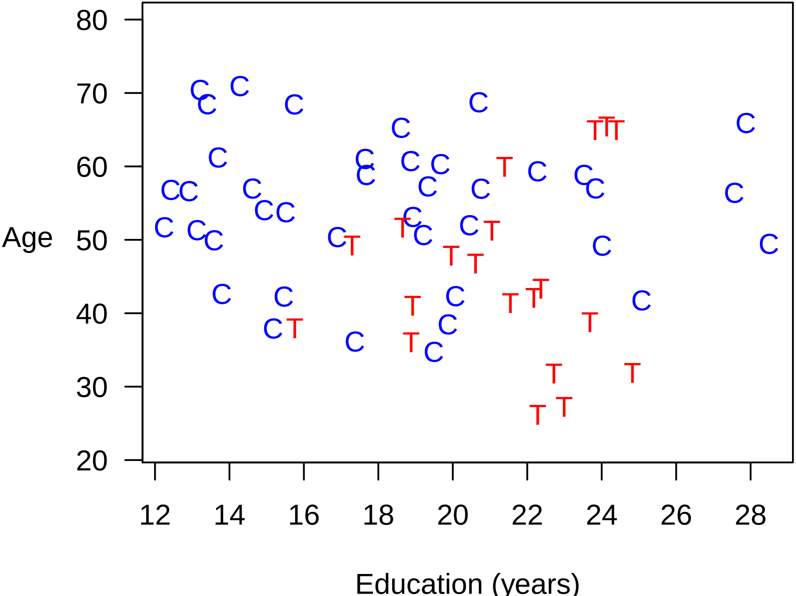

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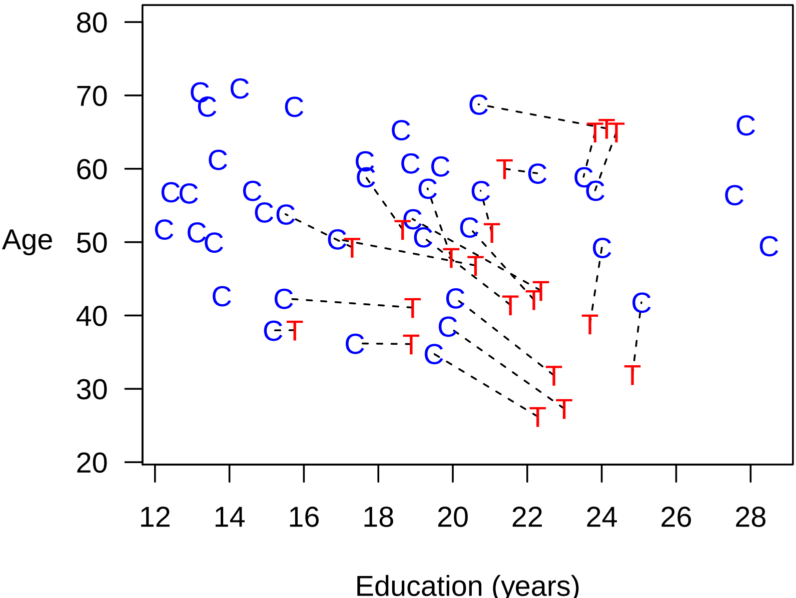

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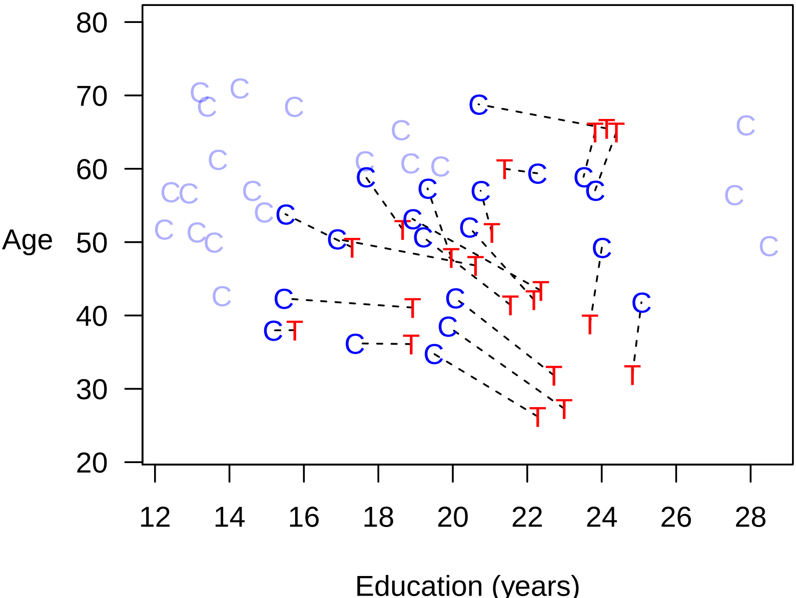

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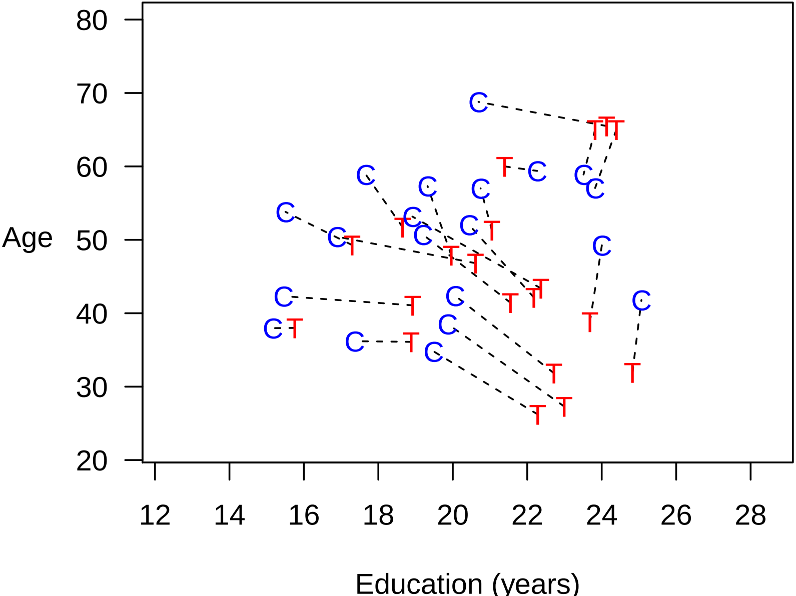

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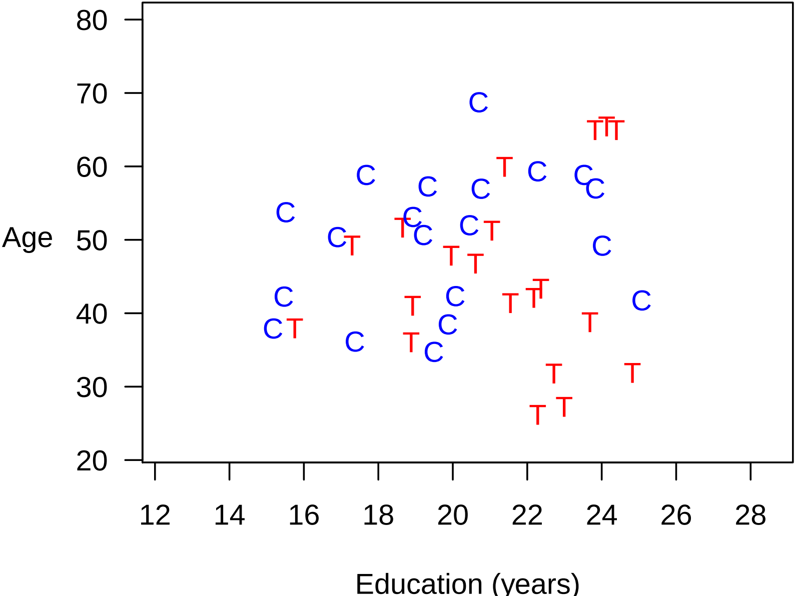

Best Case: Mahalanobis Distance Matching

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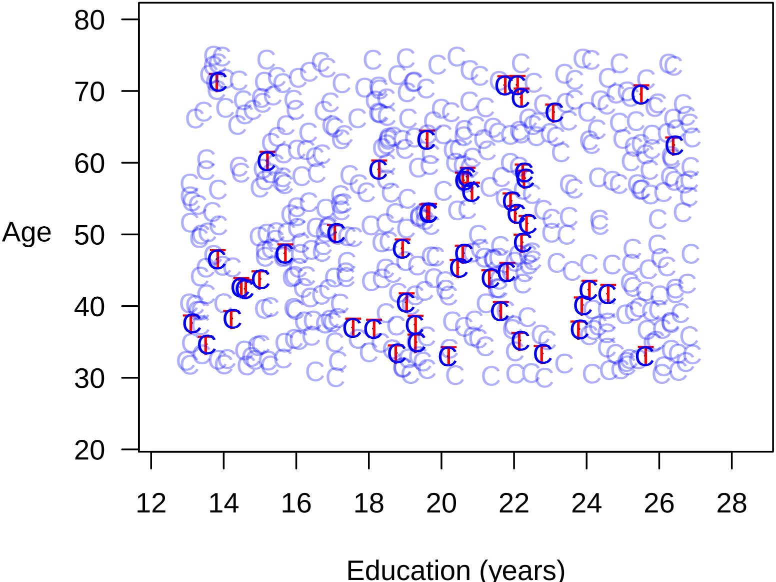

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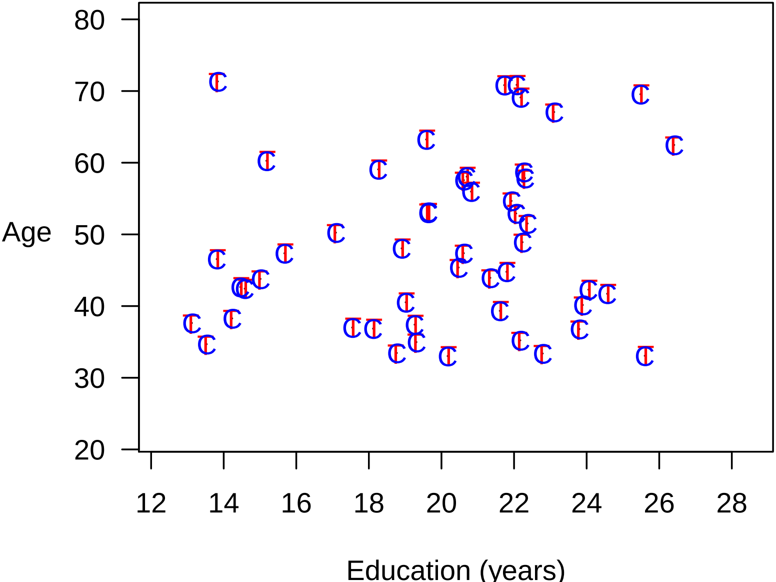

Method 2: Coarsened Exact Matching

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(Approximates Fully Blocked Experiment)

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1. Preprocess (Matching)

2. Estimation Difference in means or a model

Method 2: Coarsened Exact Matching

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    - 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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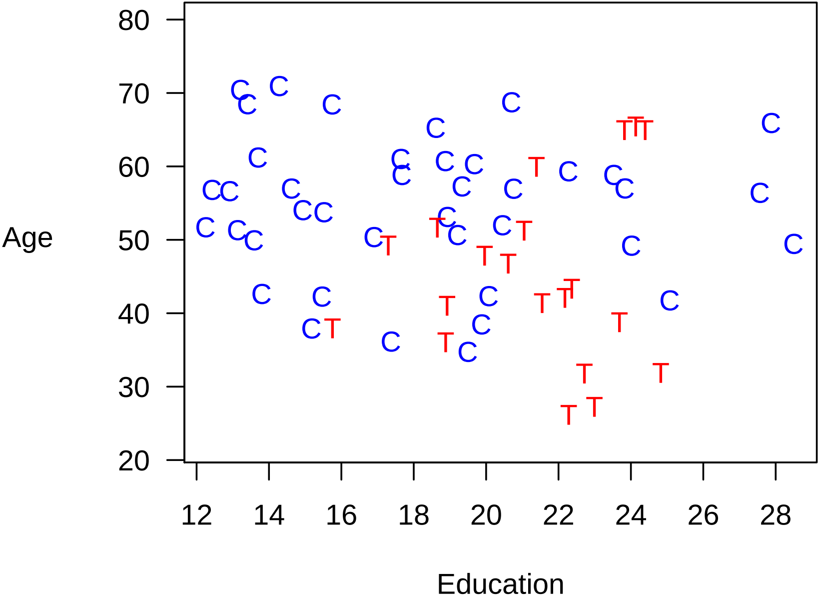

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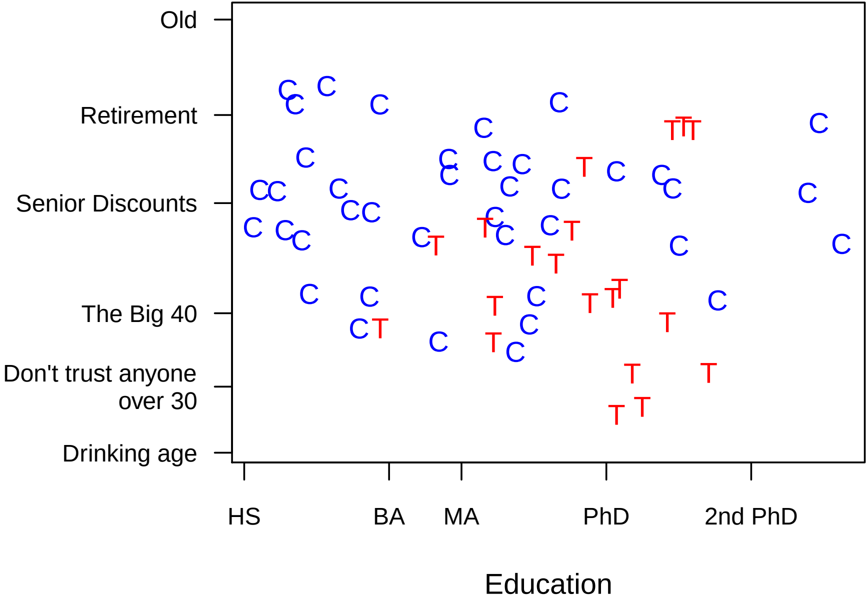

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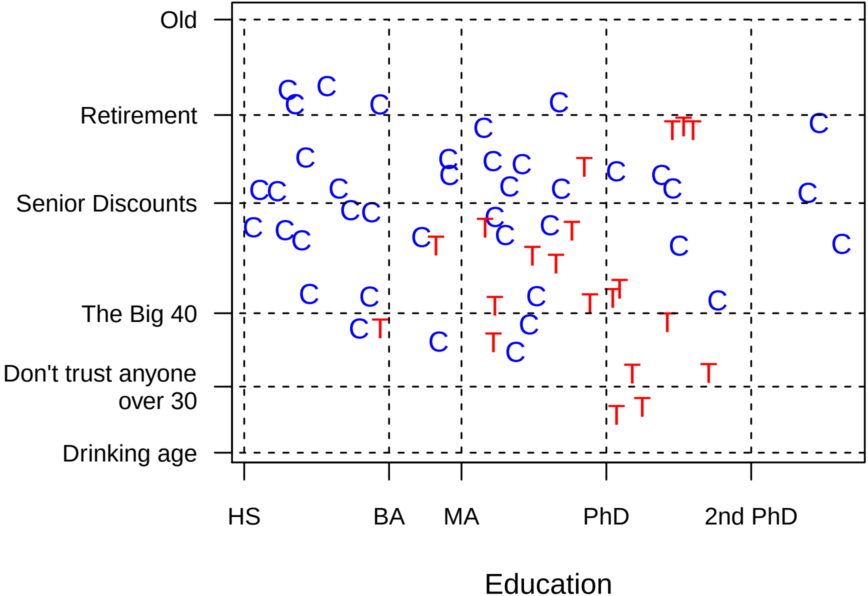

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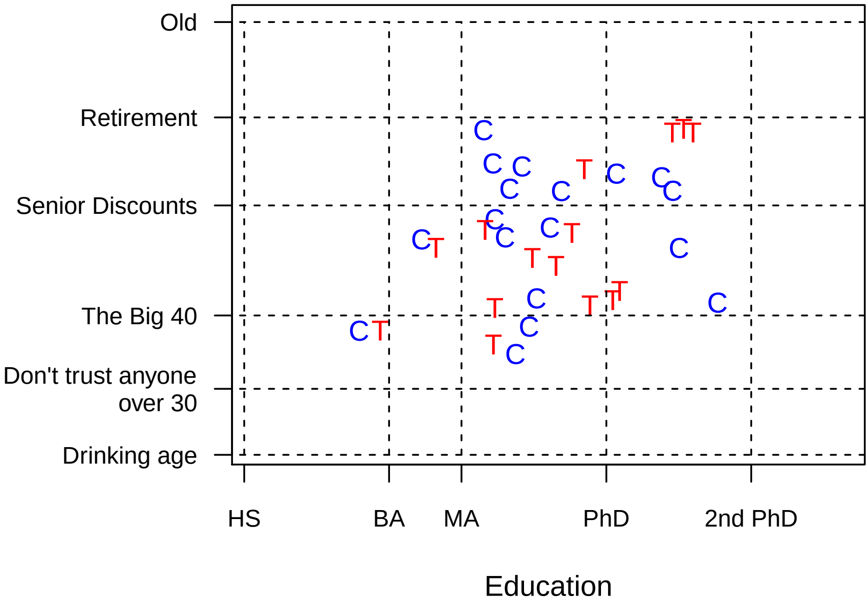

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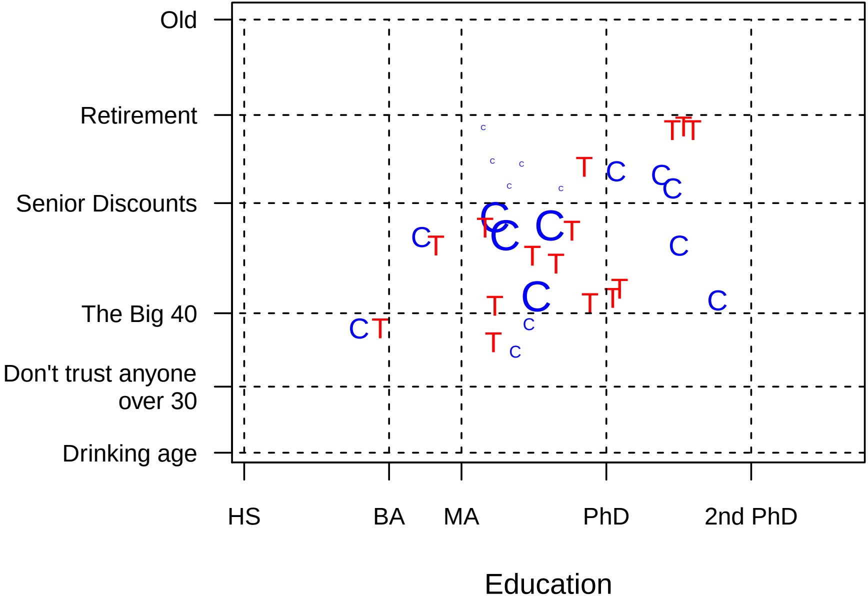

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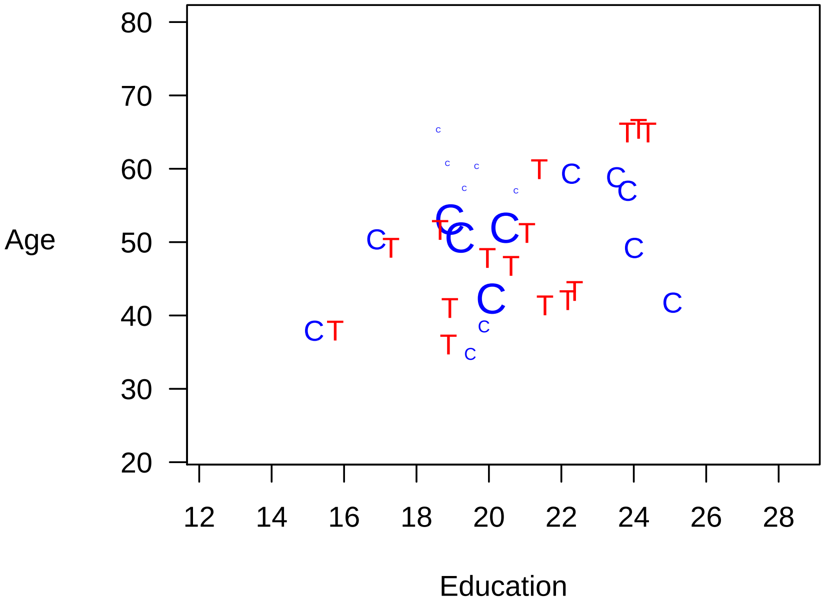

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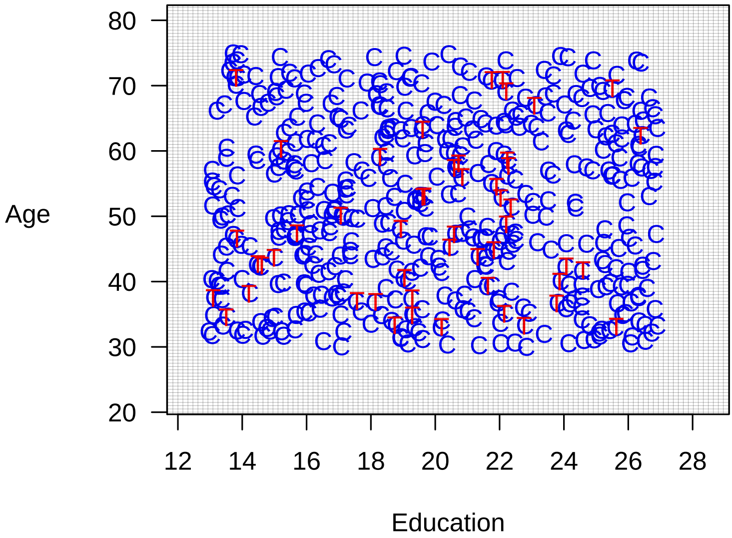

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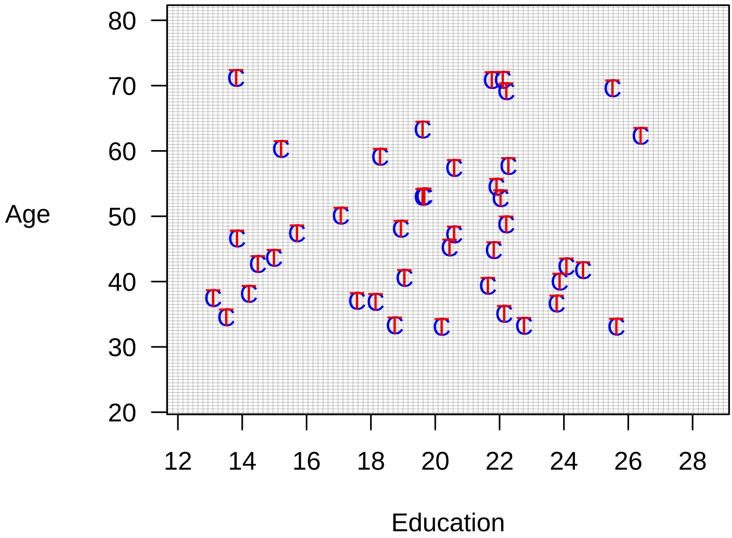

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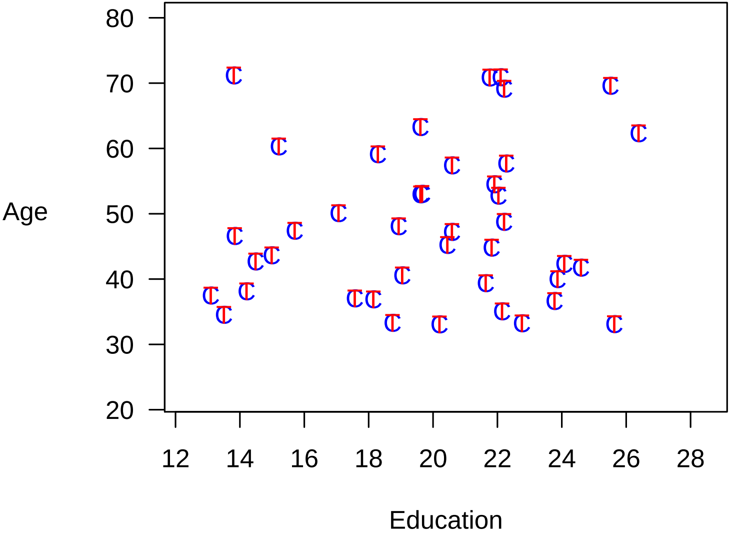

Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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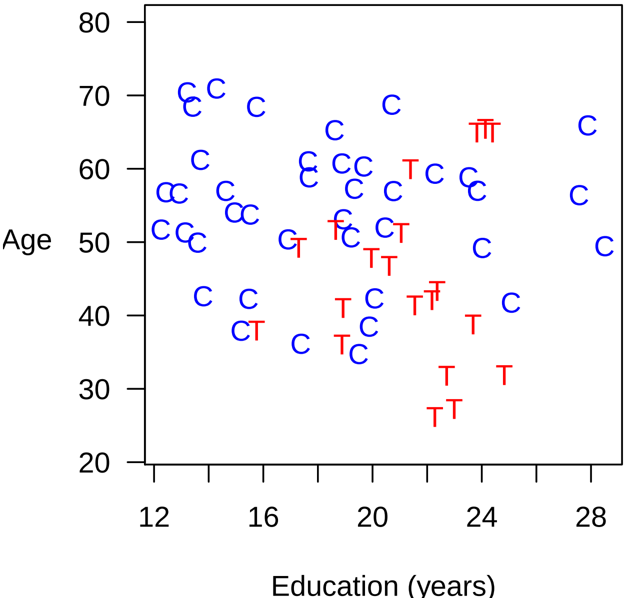
    - (Many adjustments available to this basic method)
2. Estimation Difference in means or a model

Propensity Score Matching



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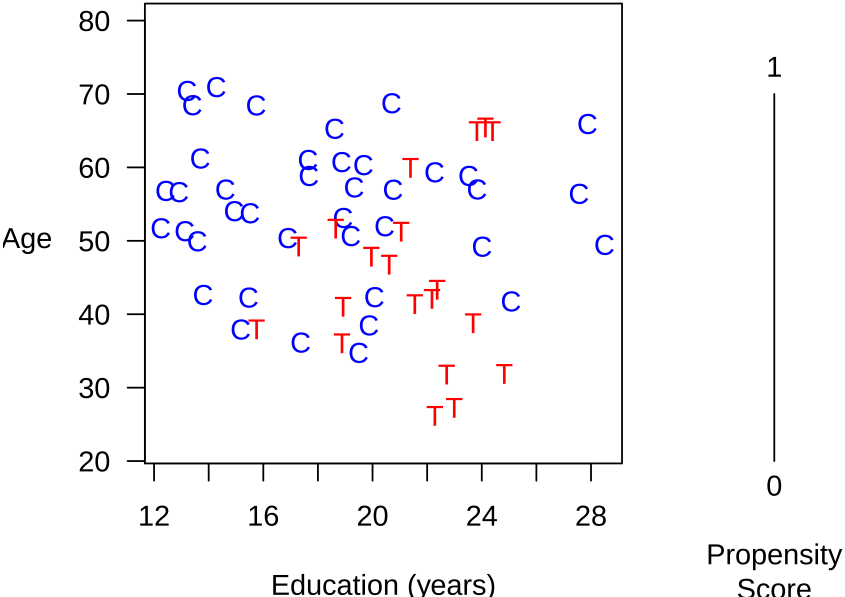

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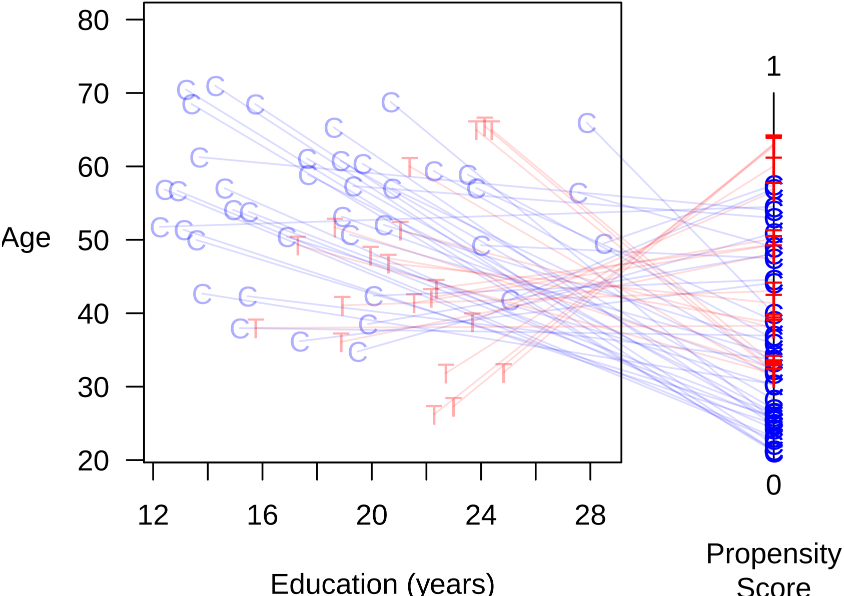

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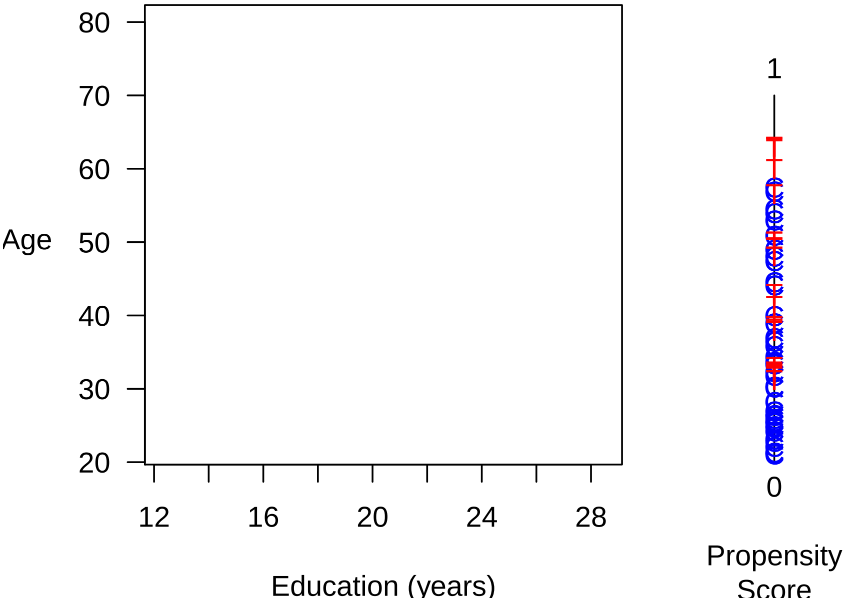

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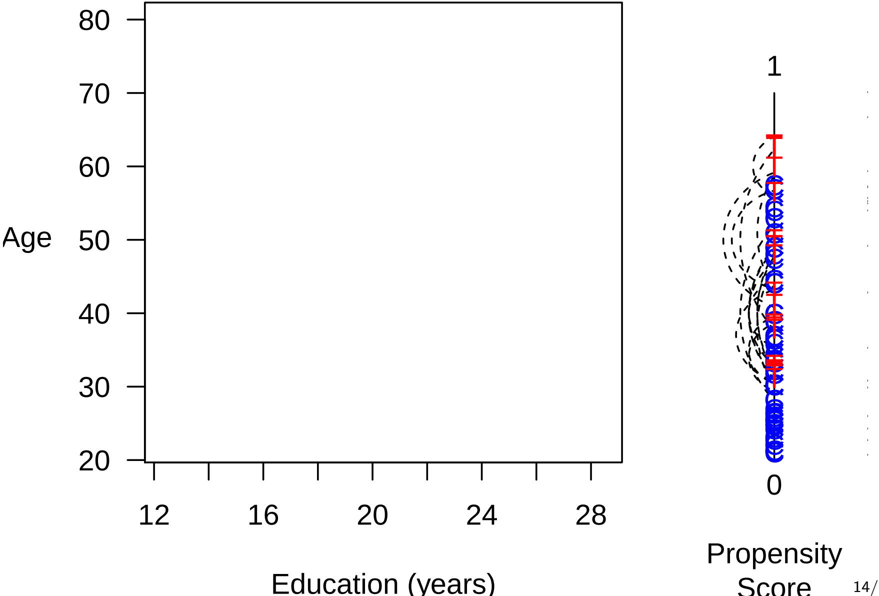

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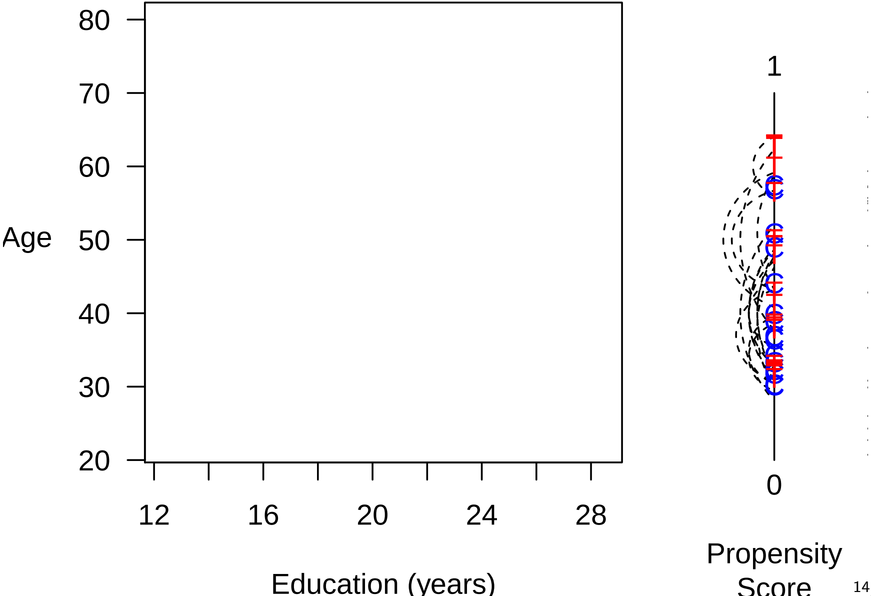

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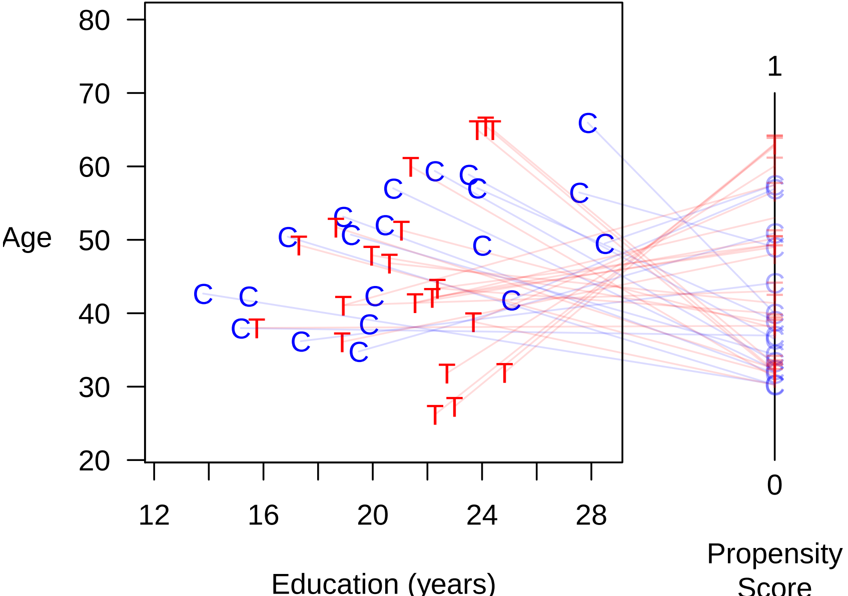

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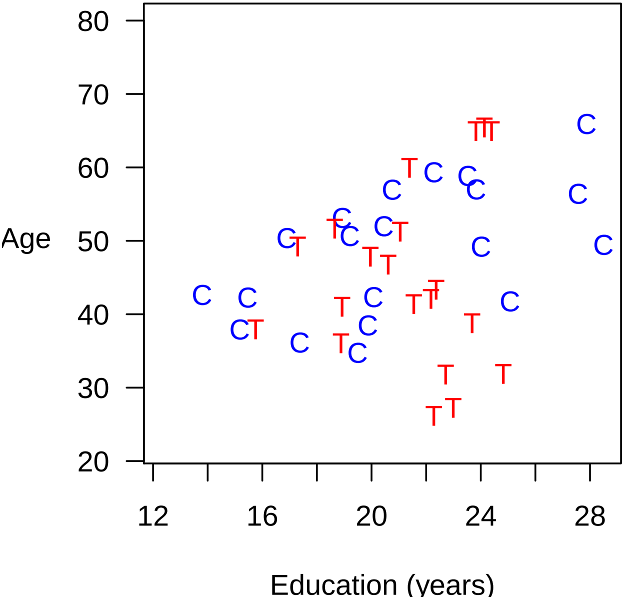

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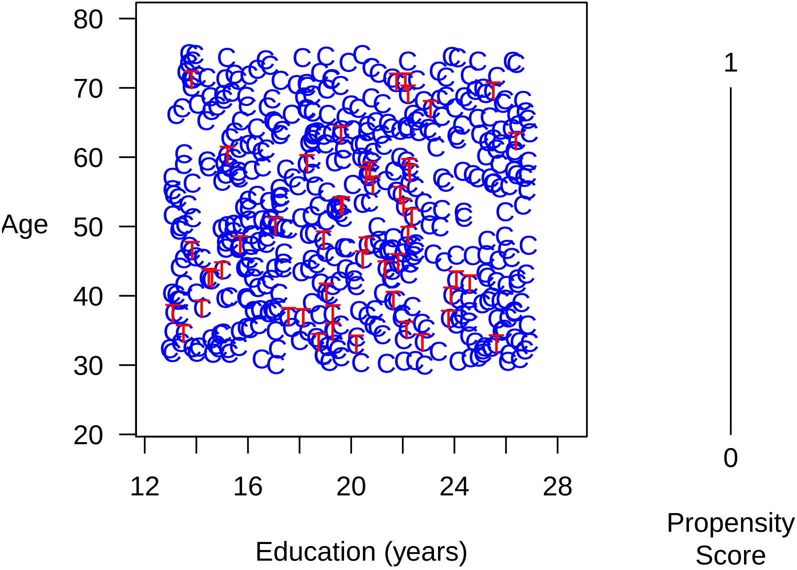

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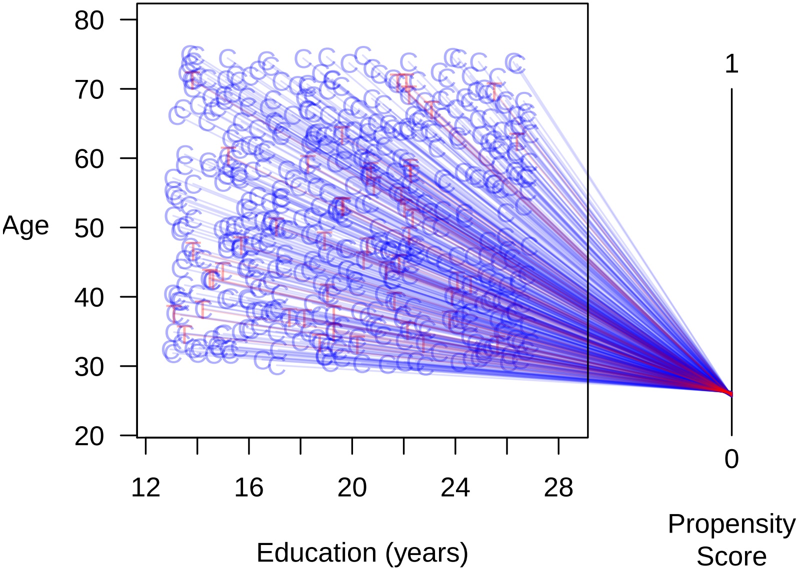

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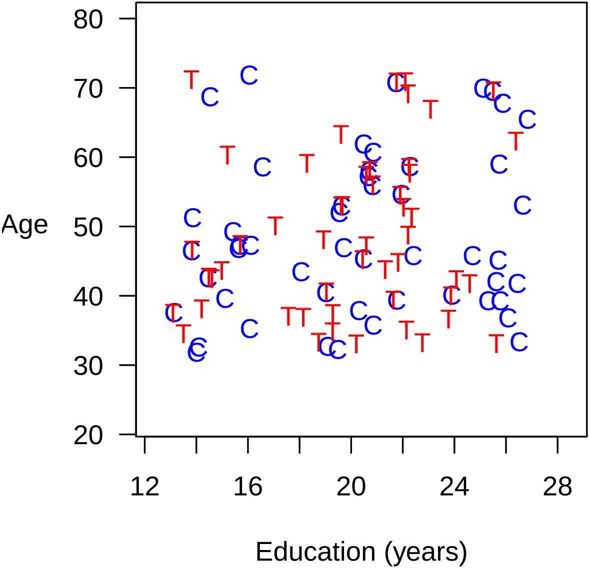
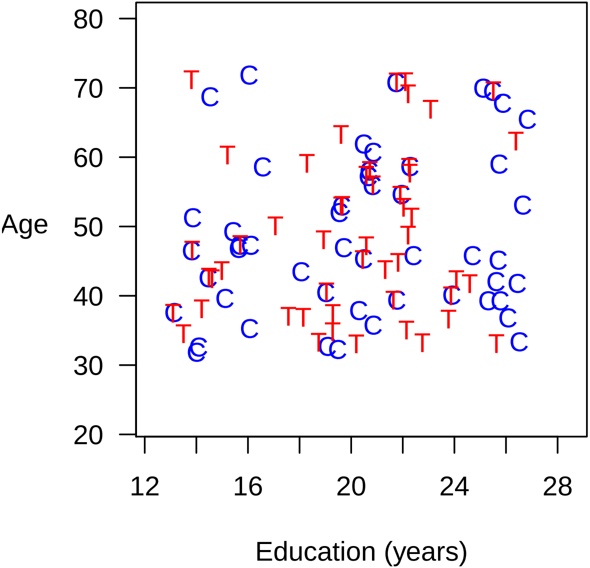


Best Case: Propensity Score Matching is Suboptimal



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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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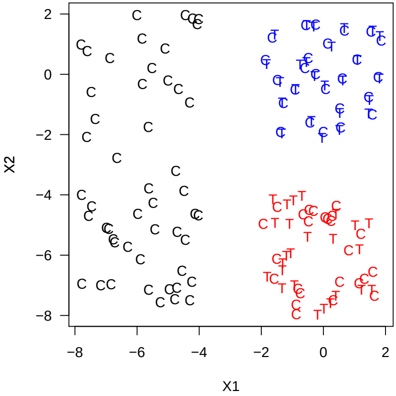

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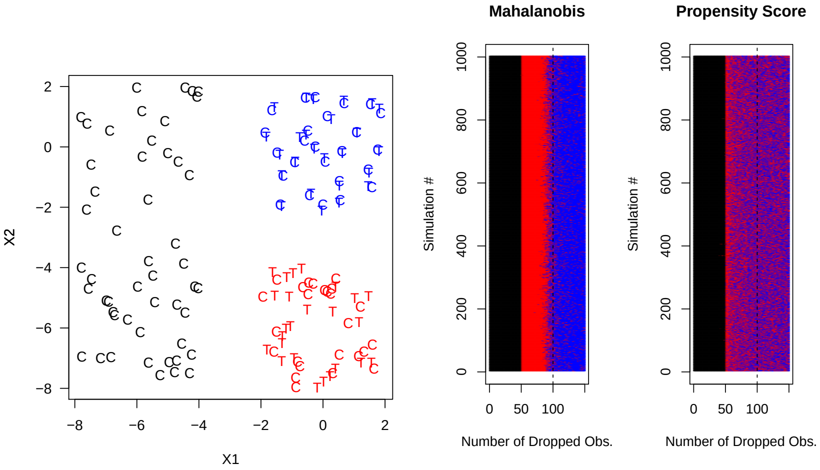
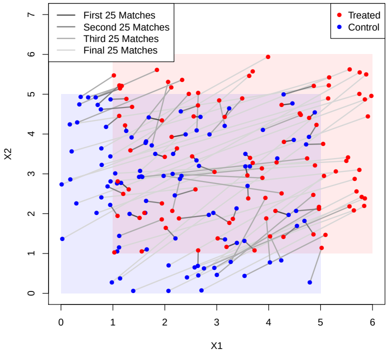


What Does PSM Match?

MDM Matches



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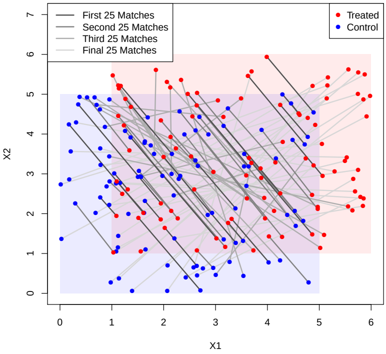
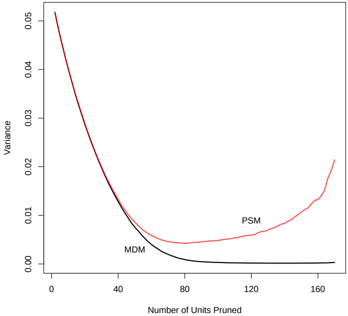
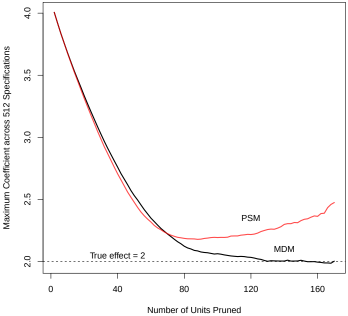


Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$

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

PSM Increases Model Dependence & Bias


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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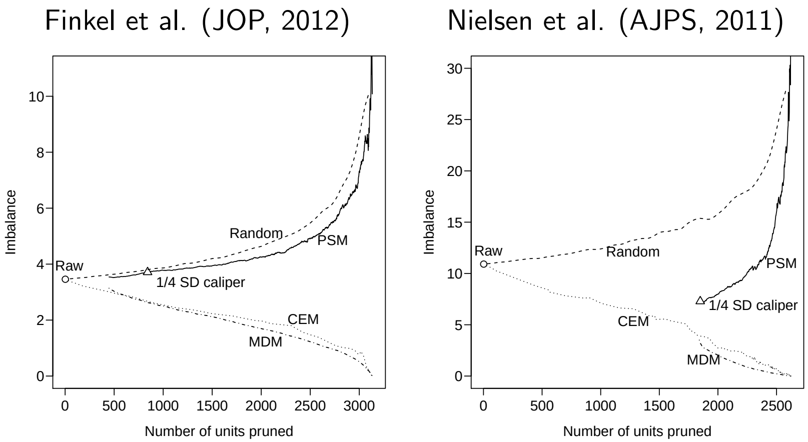

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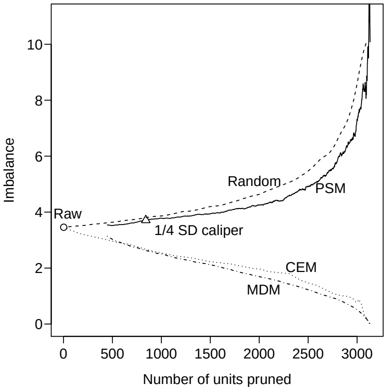
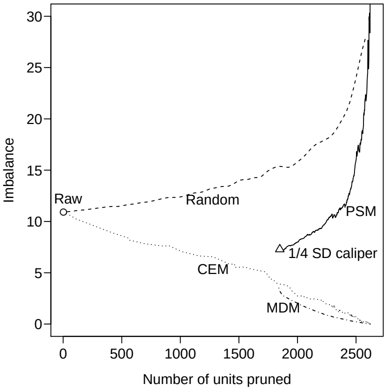
Finkel et al. (JOP, 2012)



Nielsen et al. (AJPS, 2011)



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