Simplifying Matching Methods for Causal Inference

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3 Problems, 3 Solutions

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   - ⇝ "The Balance-Sample Size Frontier in Matching Methods for Causal Inference" (In press, *AJPS*; Gary King, Christopher Lucas and Richard Nielsen)

Matching to Reduce Model Dependence

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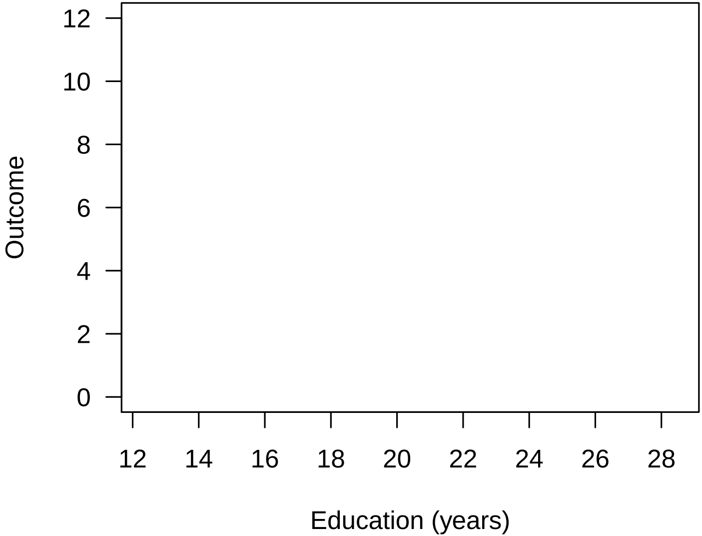

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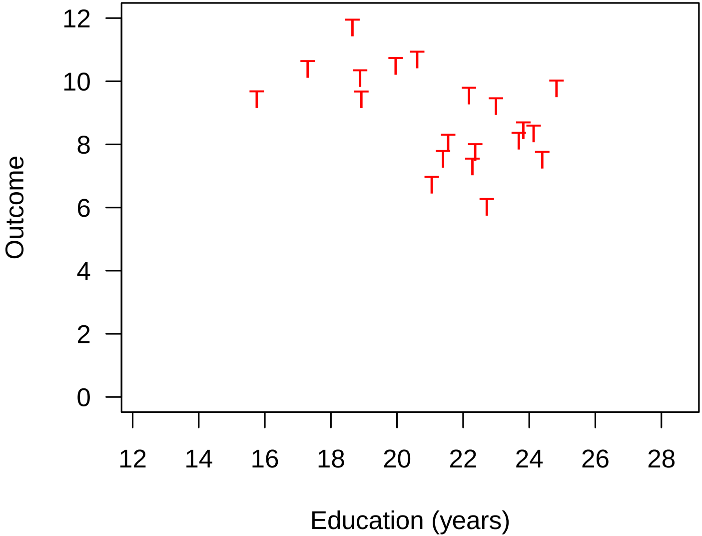

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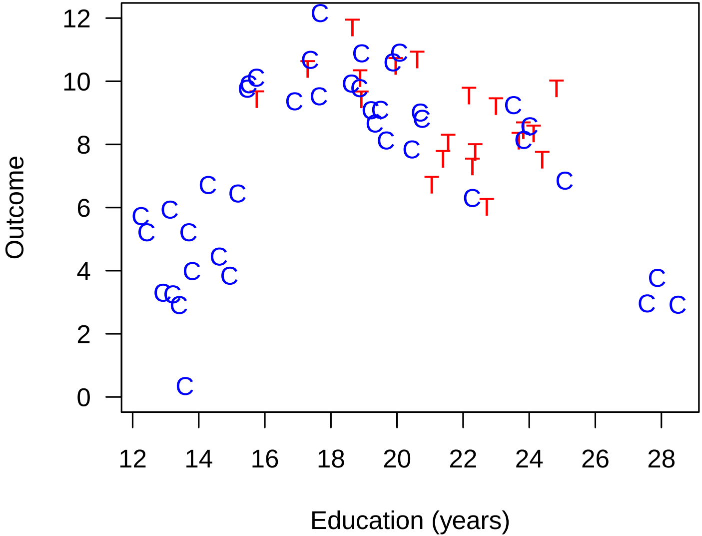

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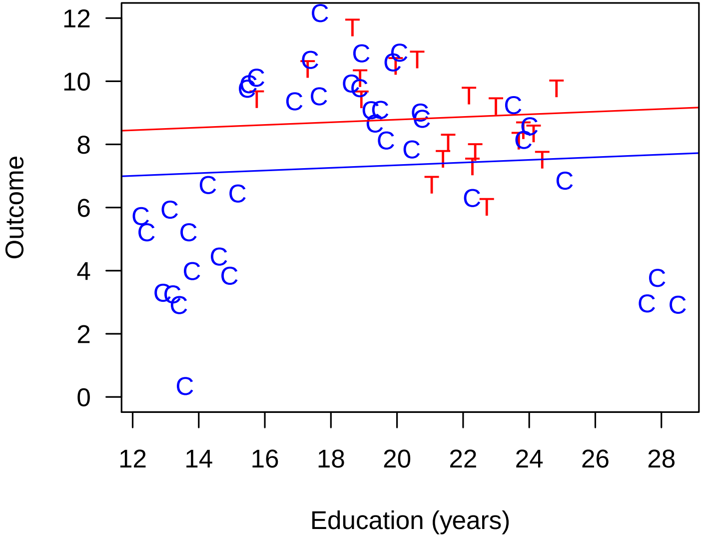

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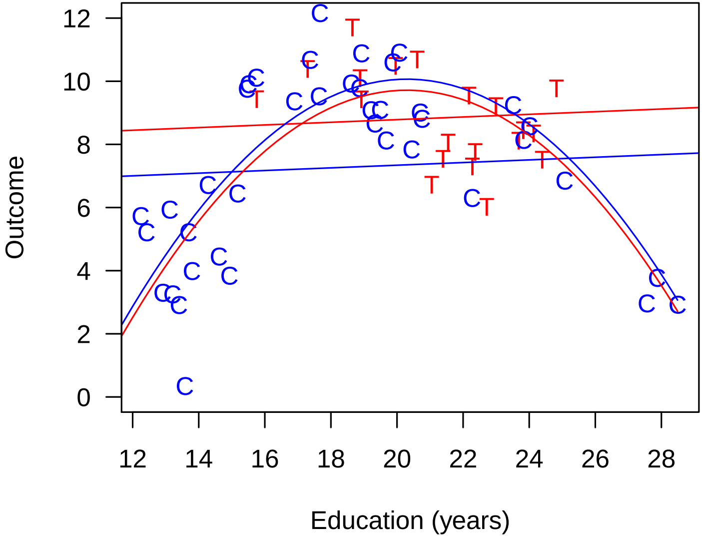

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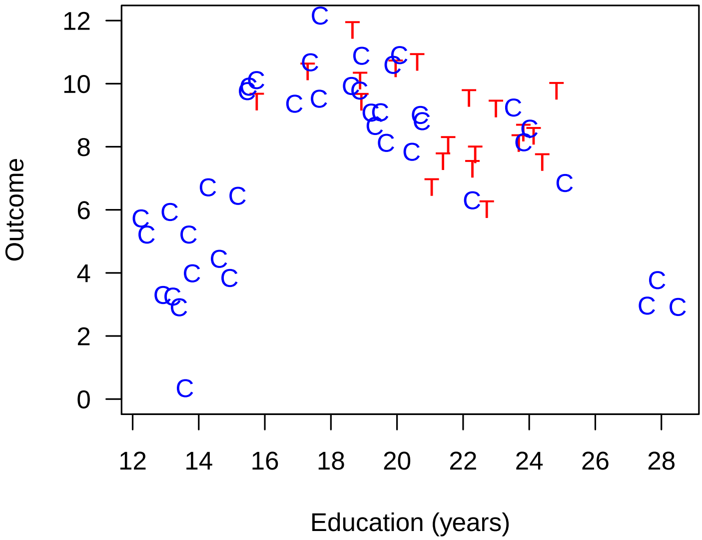

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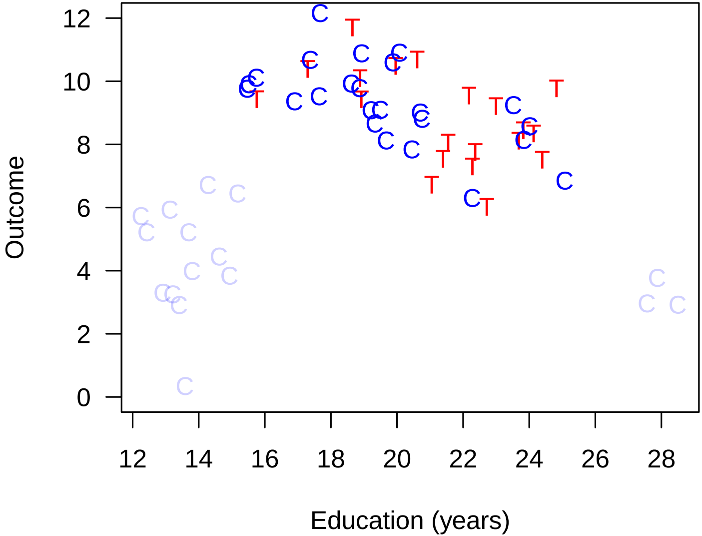

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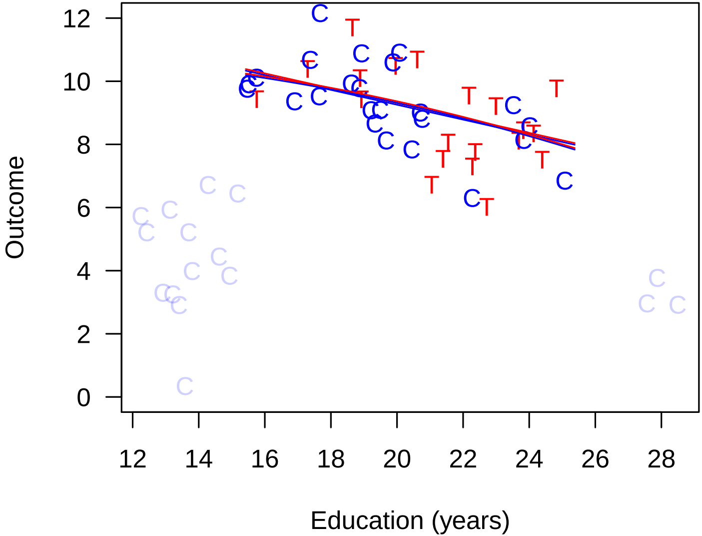

The Problems Matching Solves

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- "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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Complete Randomization

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   - (Many adjustments available to this basic method)
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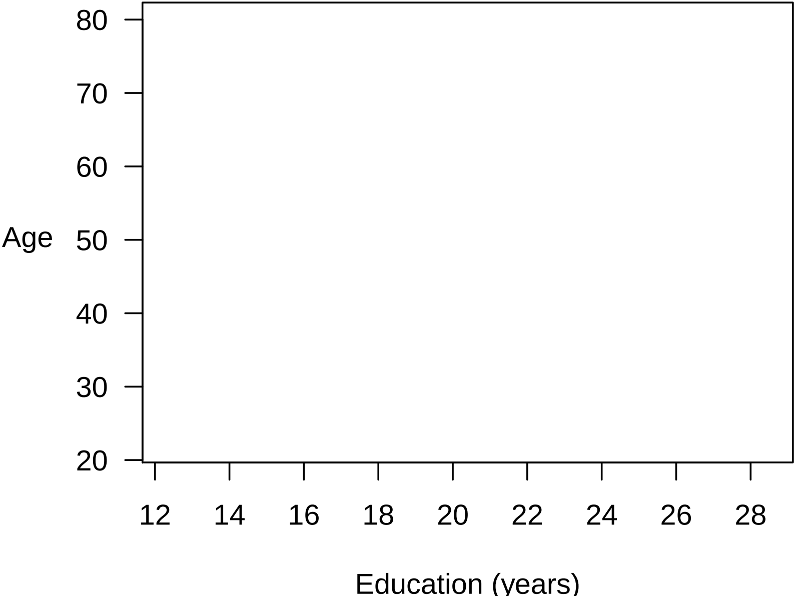

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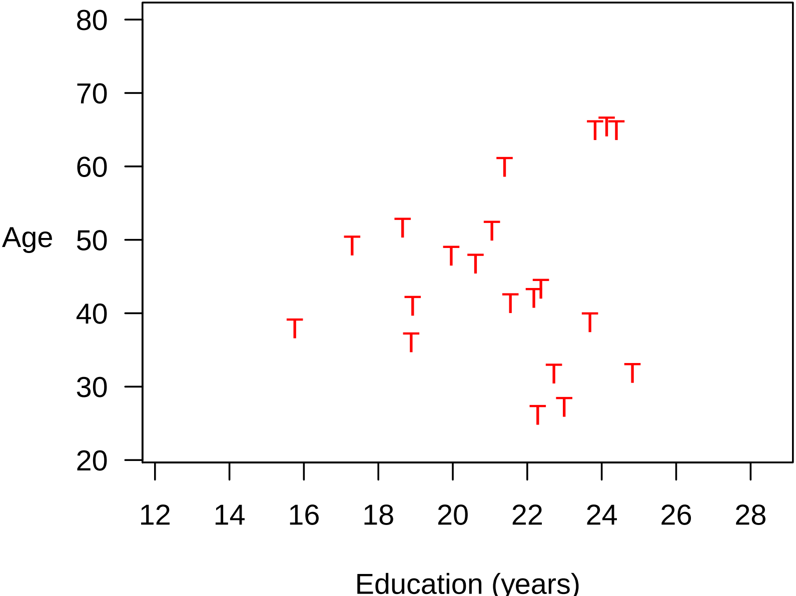

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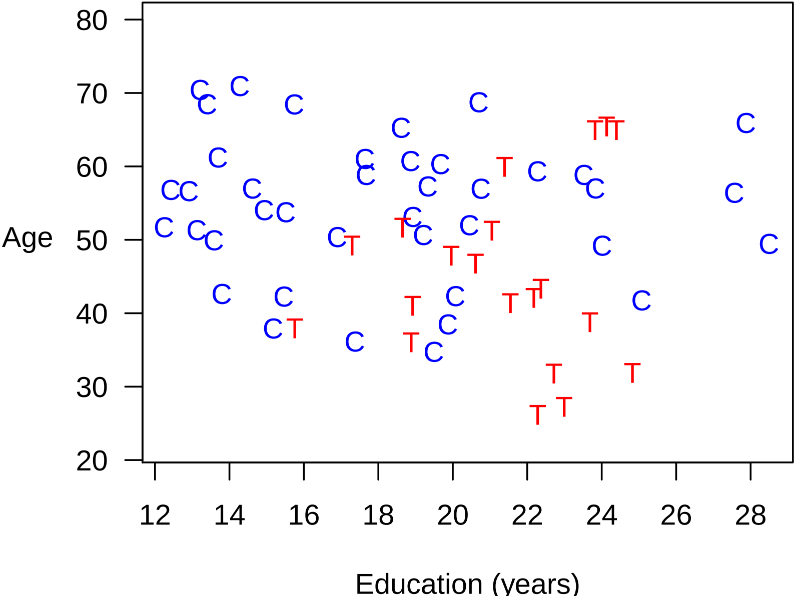

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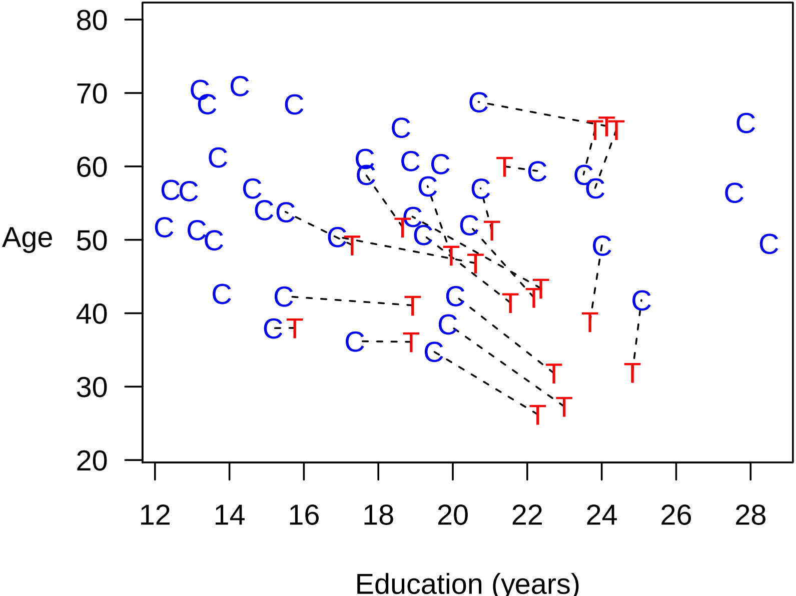

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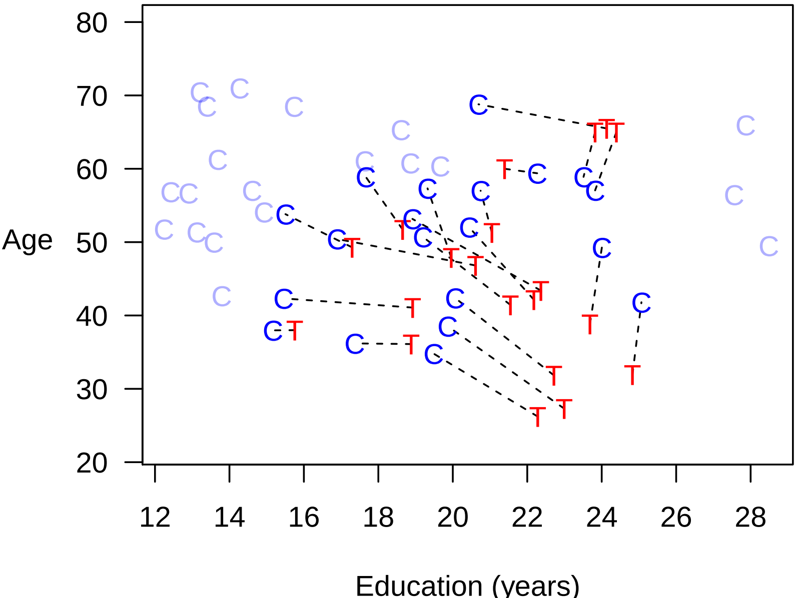

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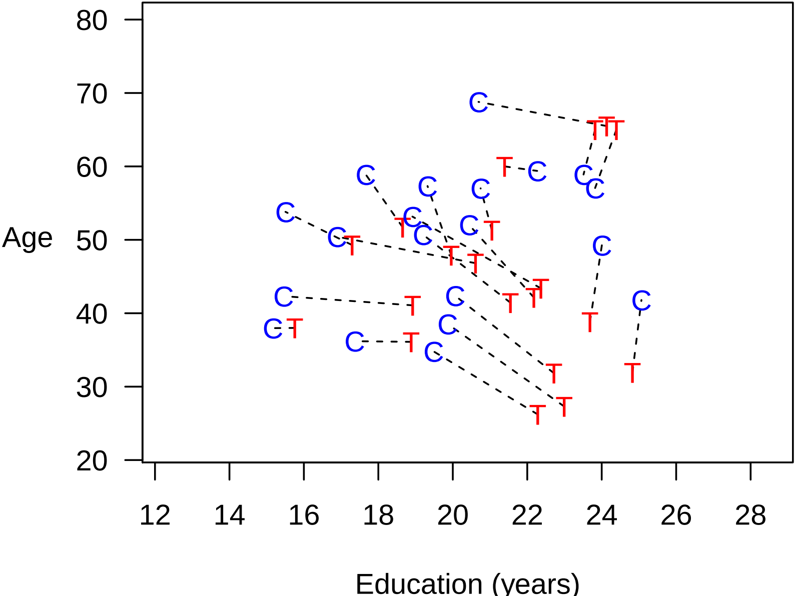

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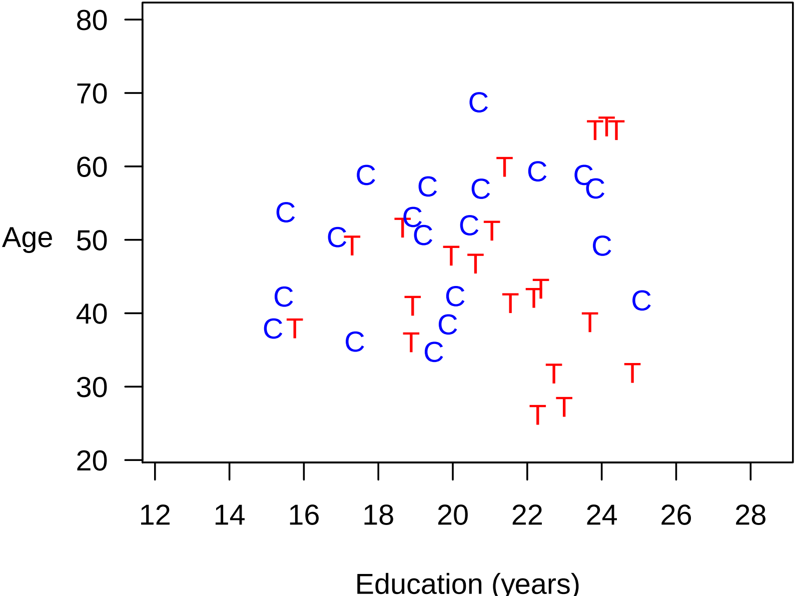

Best Case: Mahalanobis Distance Matching

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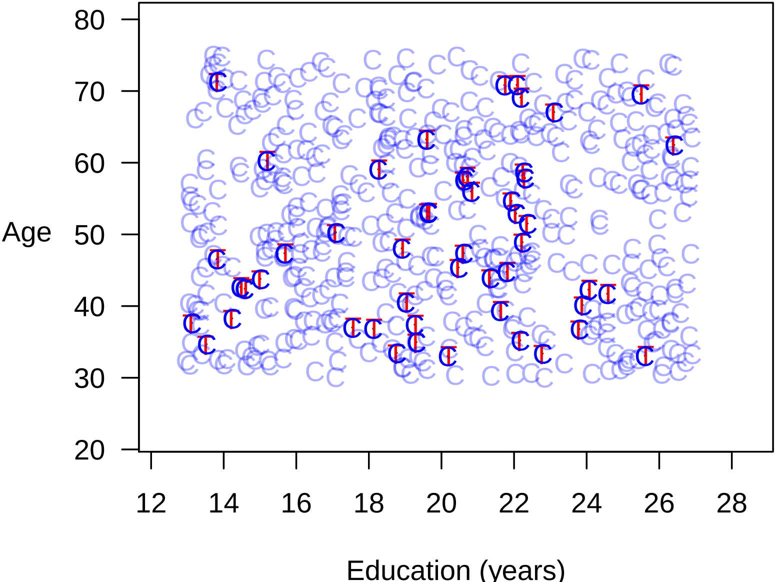

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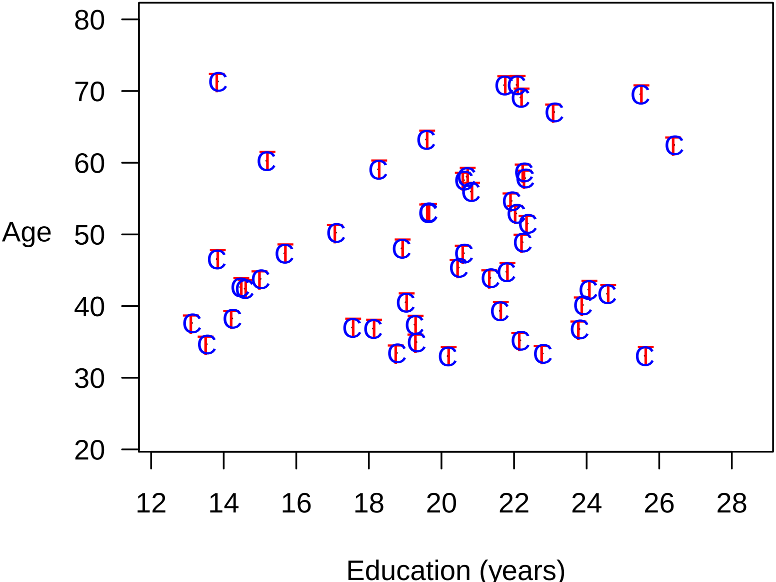

Method 2: Coarsened Exact Matching

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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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Coarsened Exact Matching

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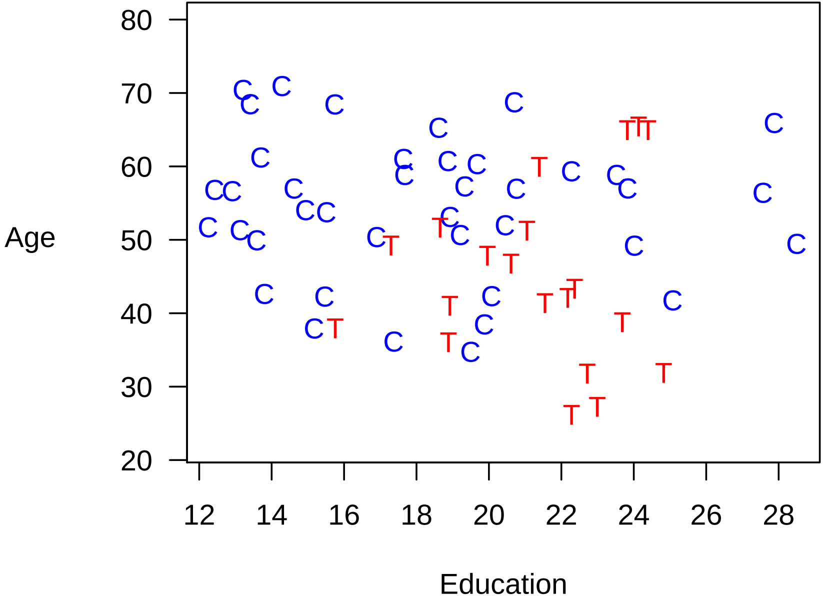

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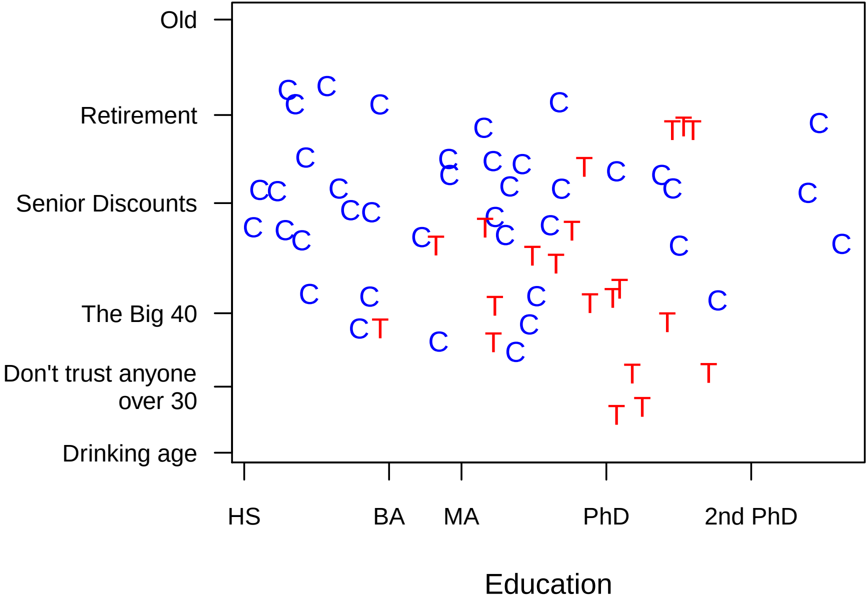

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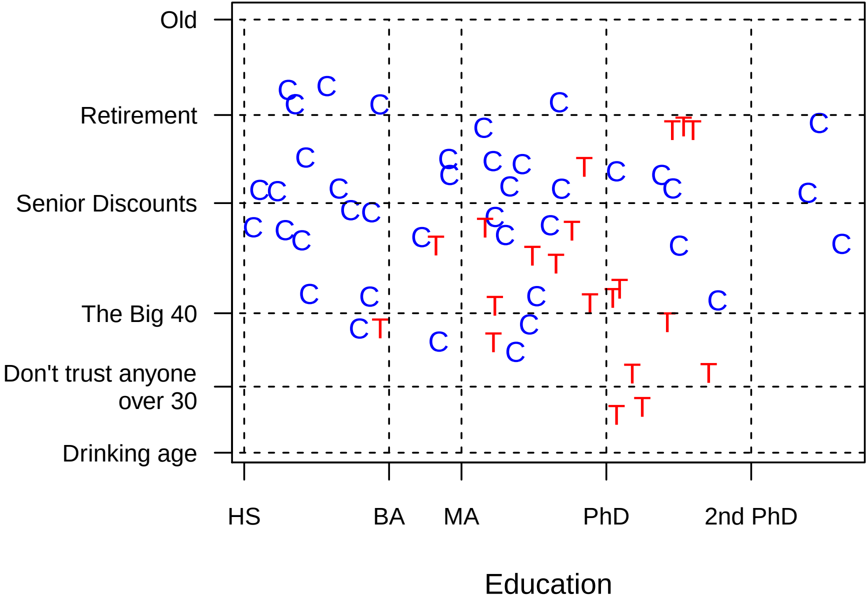

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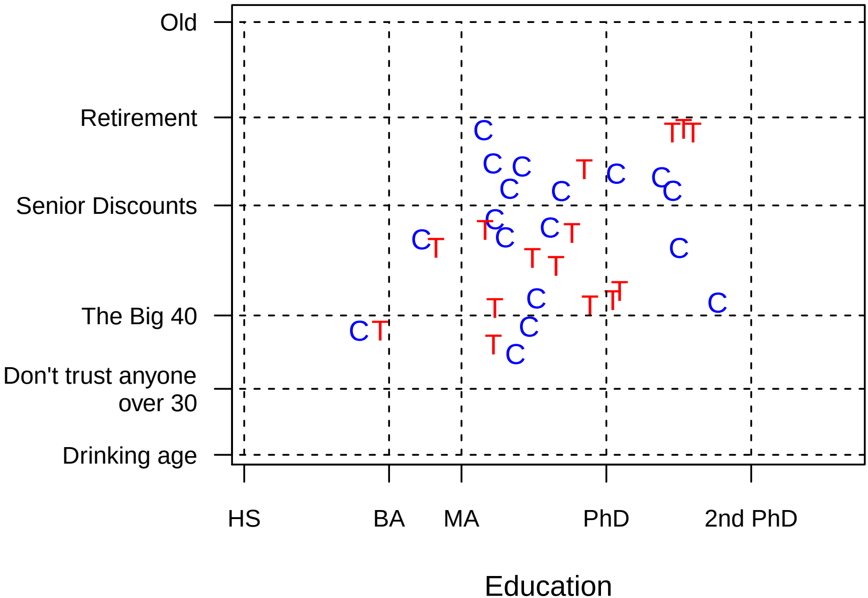

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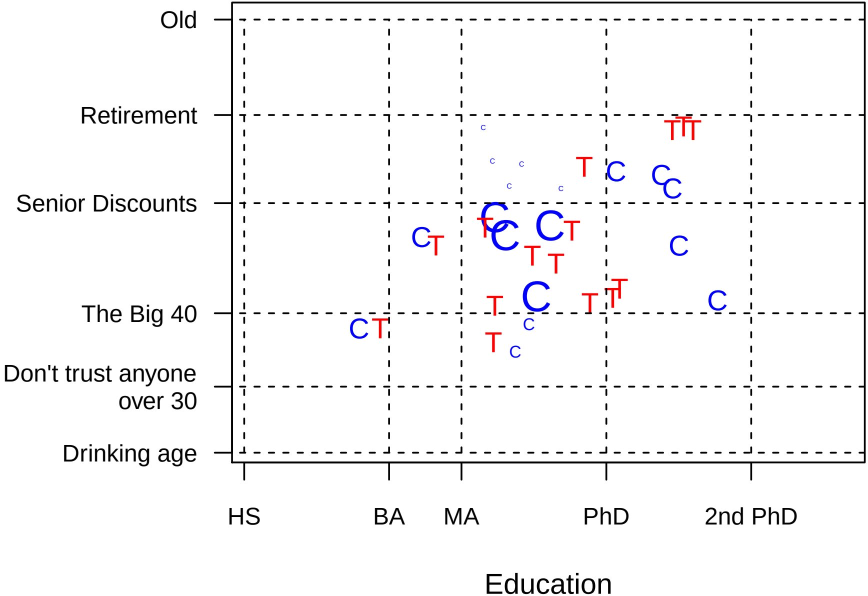

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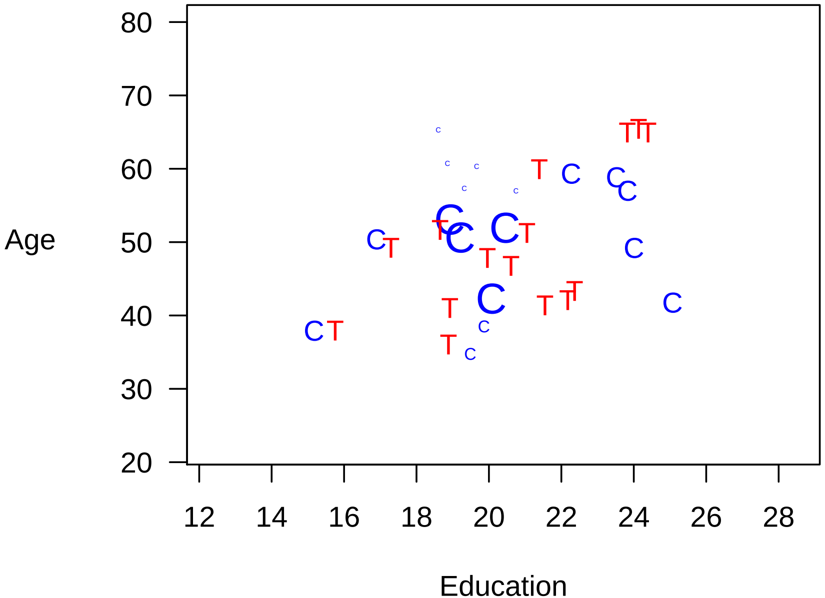

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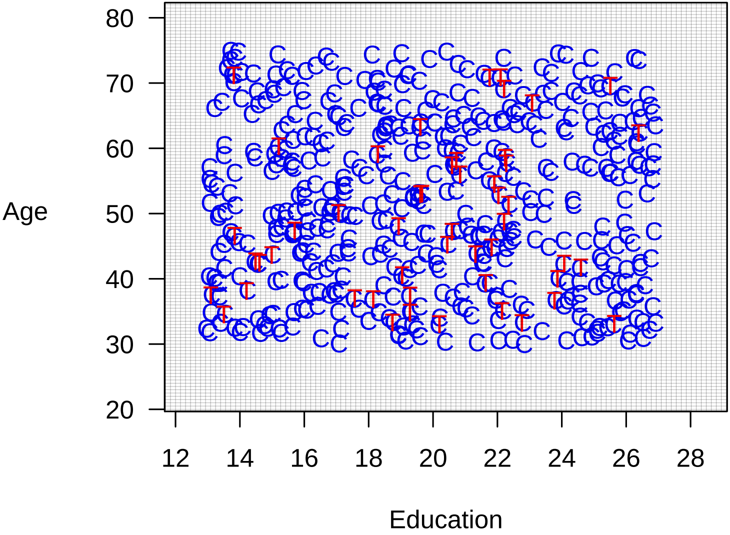

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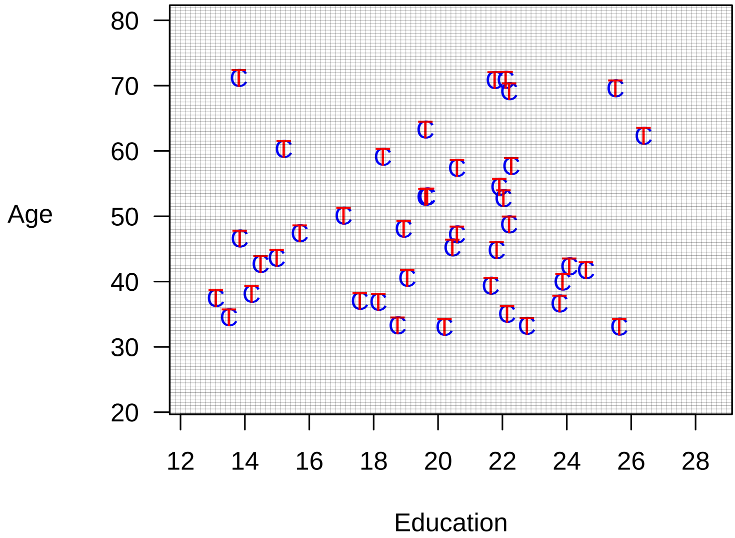

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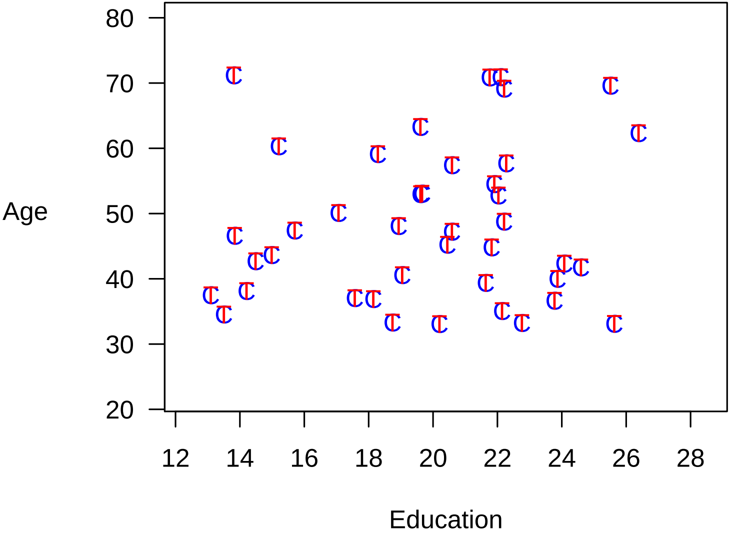

Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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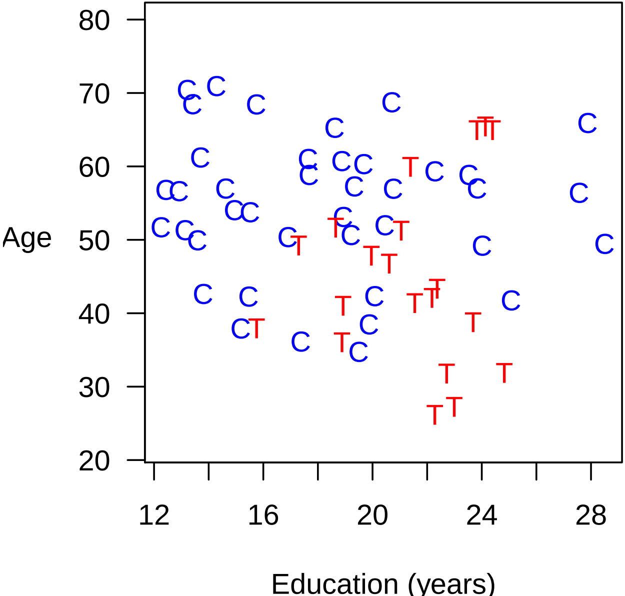
Propensity Score Matching



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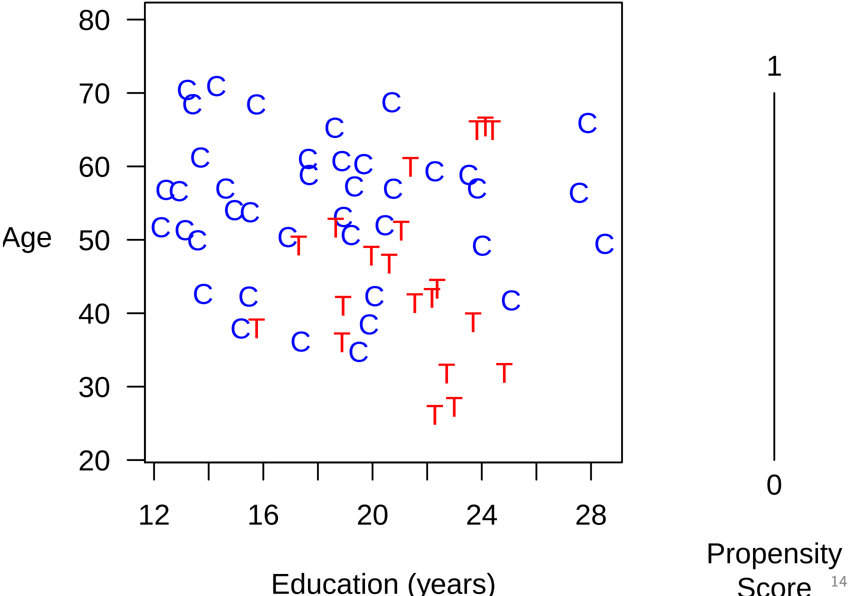

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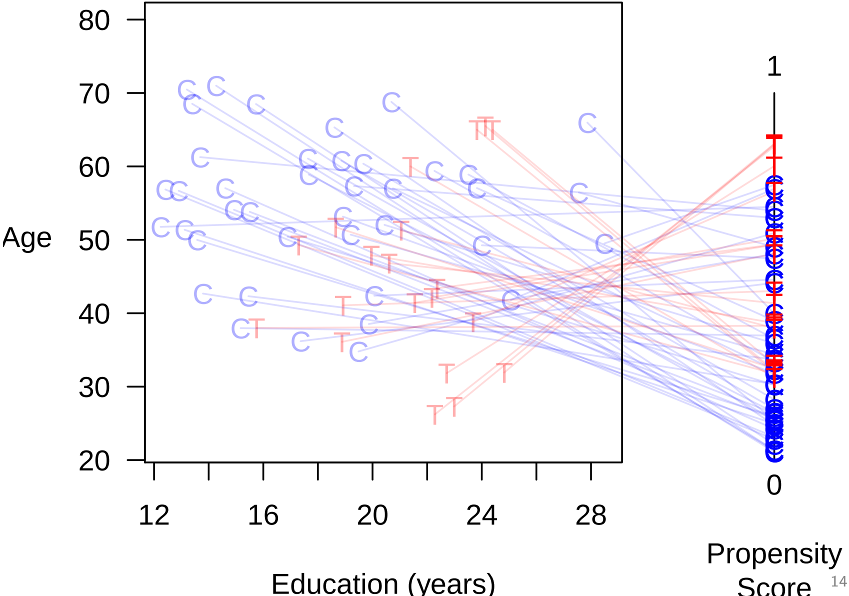

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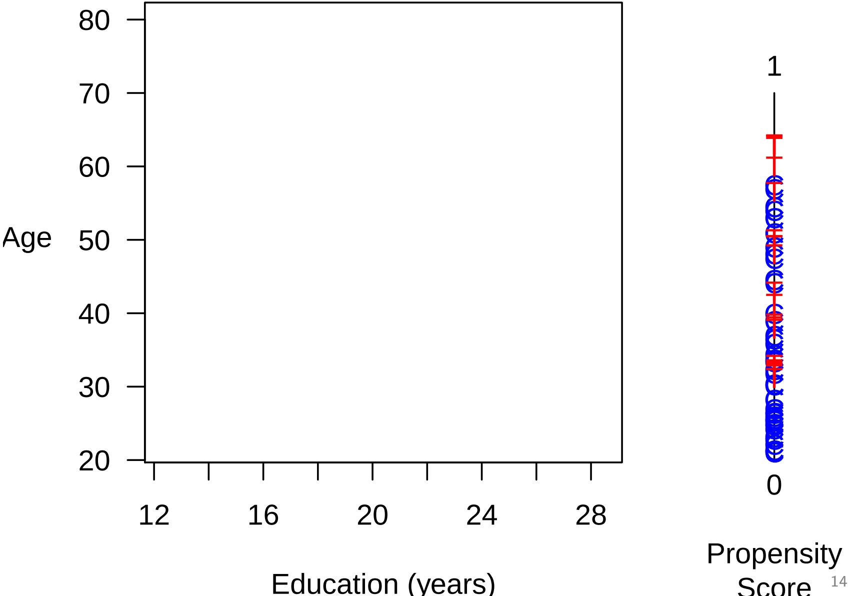

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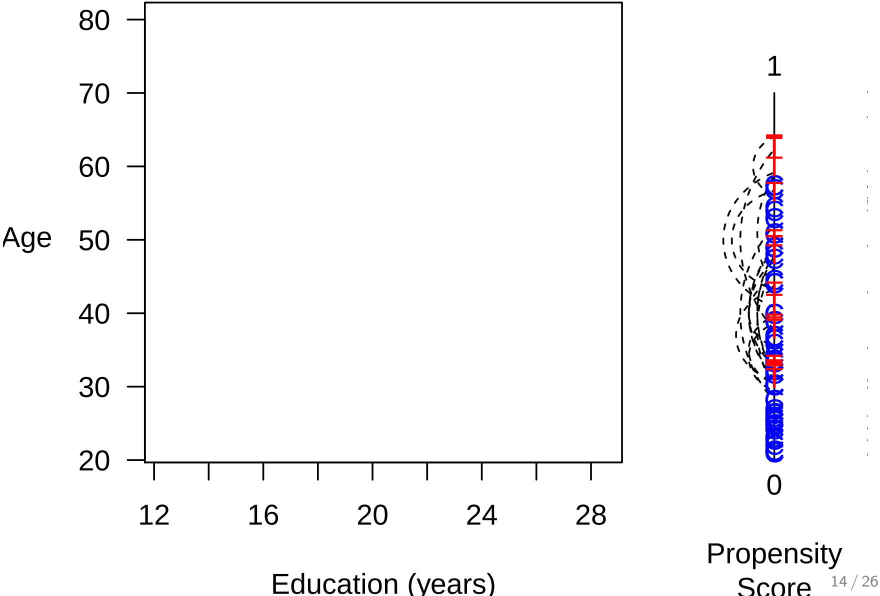

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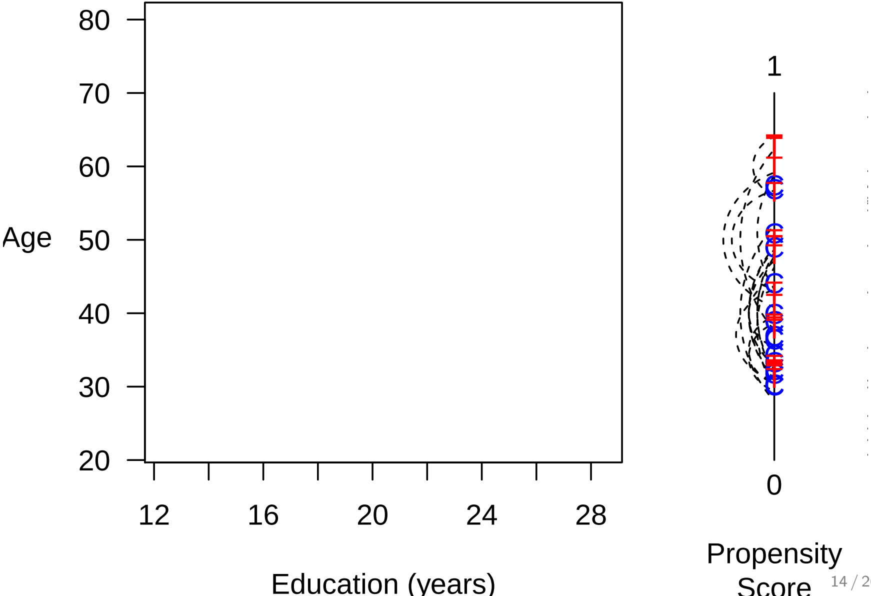

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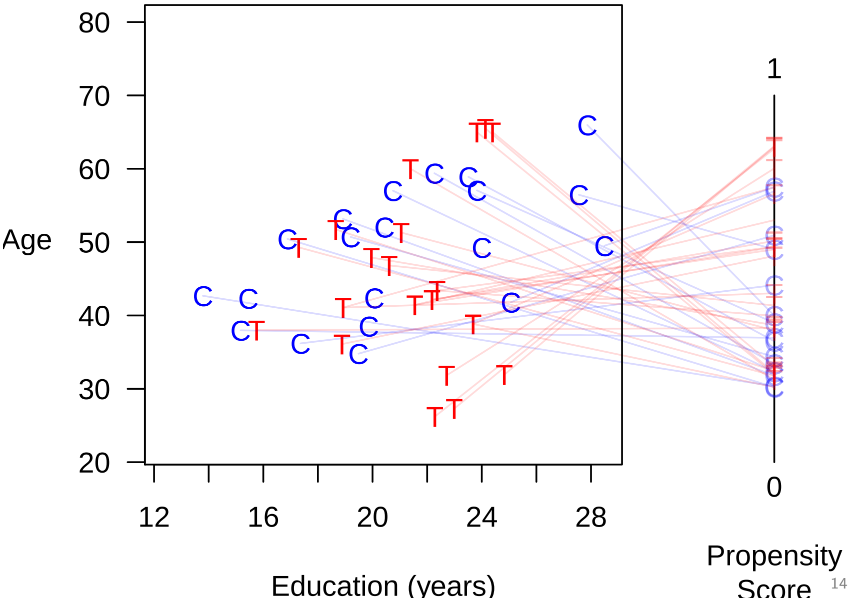

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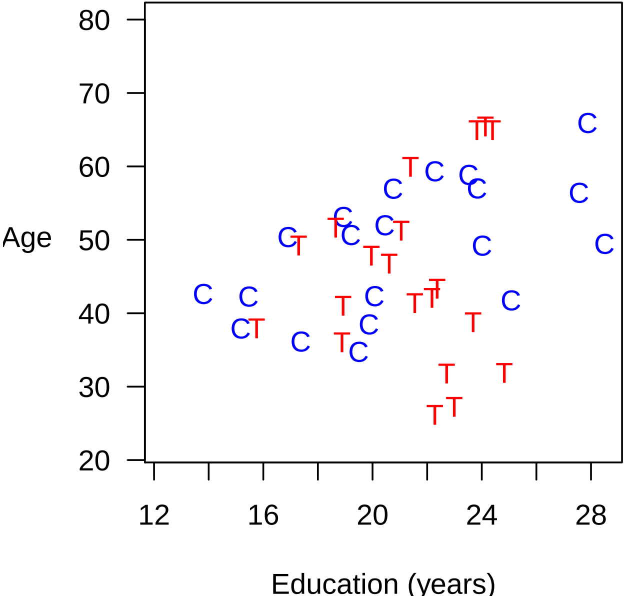

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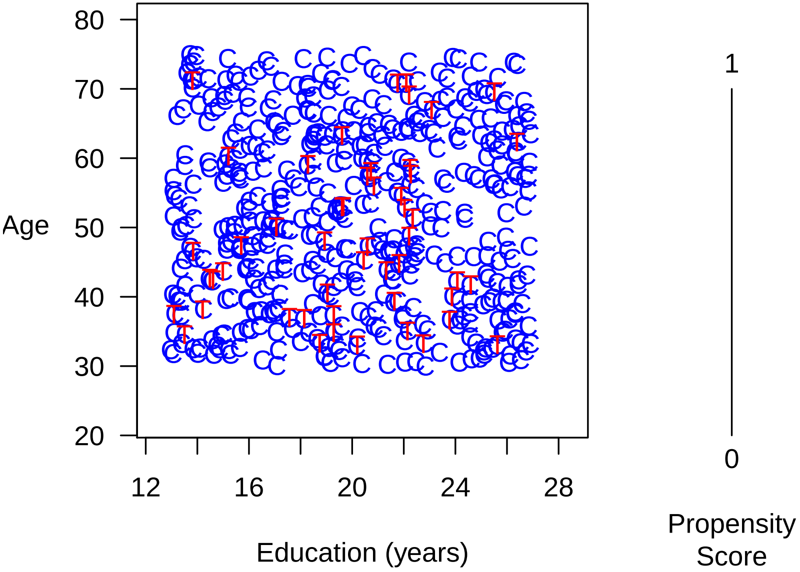

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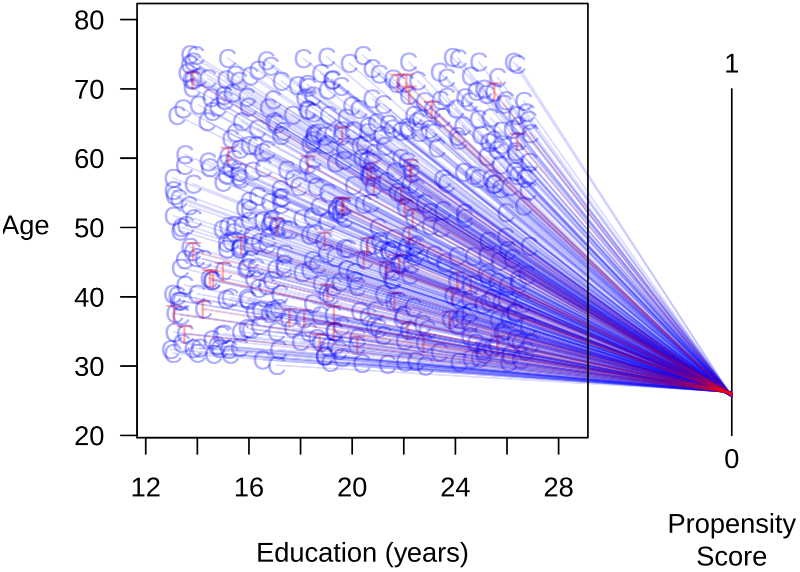

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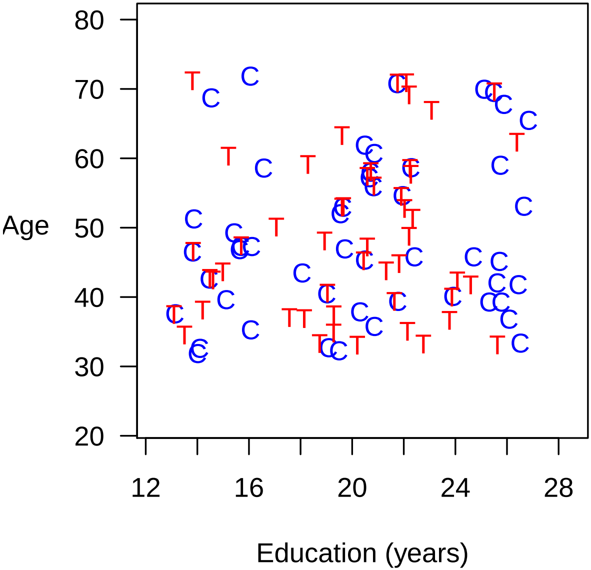
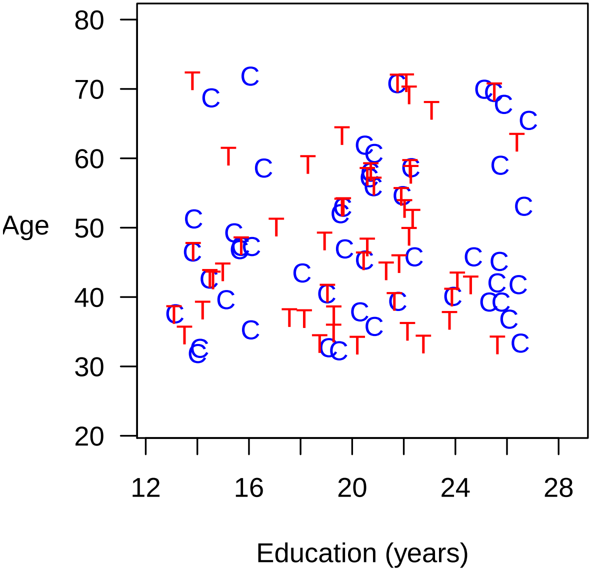


Best Case: Propensity Score Matching is Suboptimal



Random Pruning Increases Imbalance

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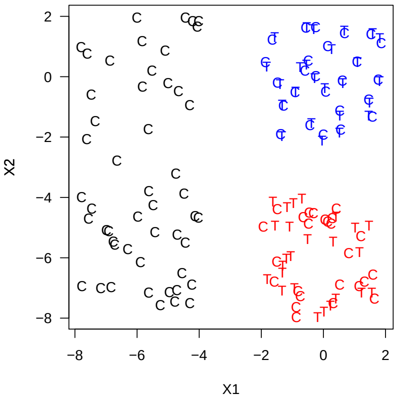

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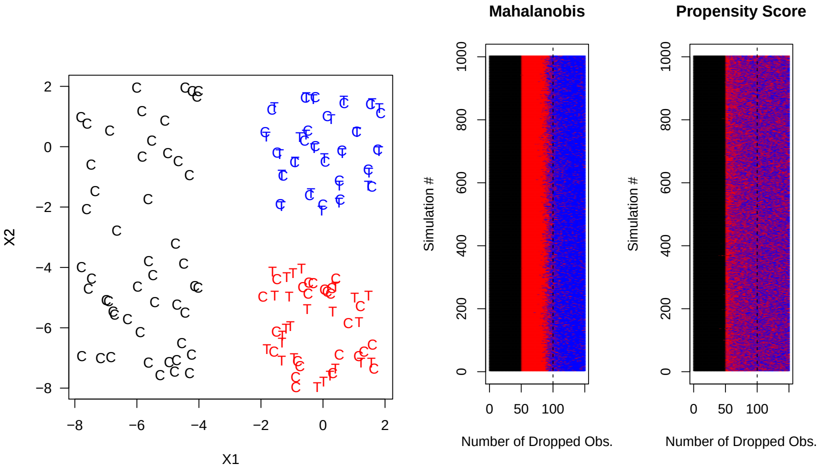
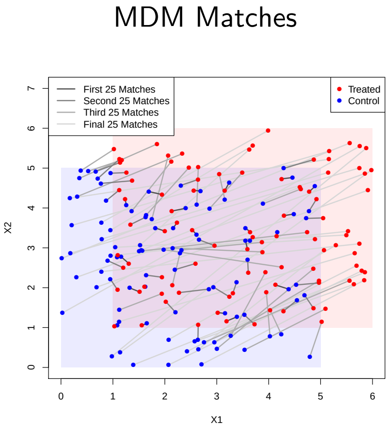
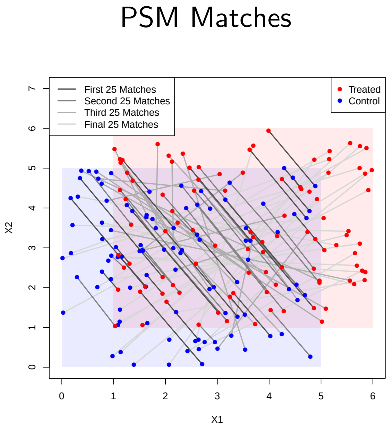


What Does PSM Match?



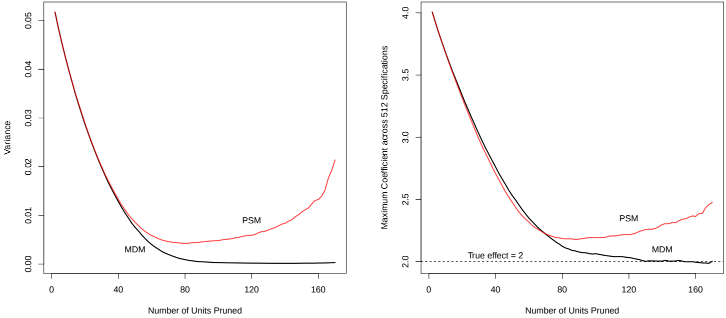


Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$
Treateds: $X_1, X_2 \sim \text{Uniform}(1,6)$

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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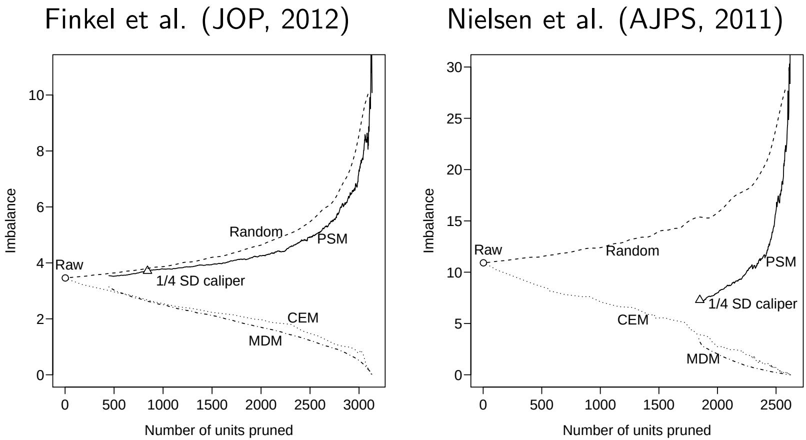

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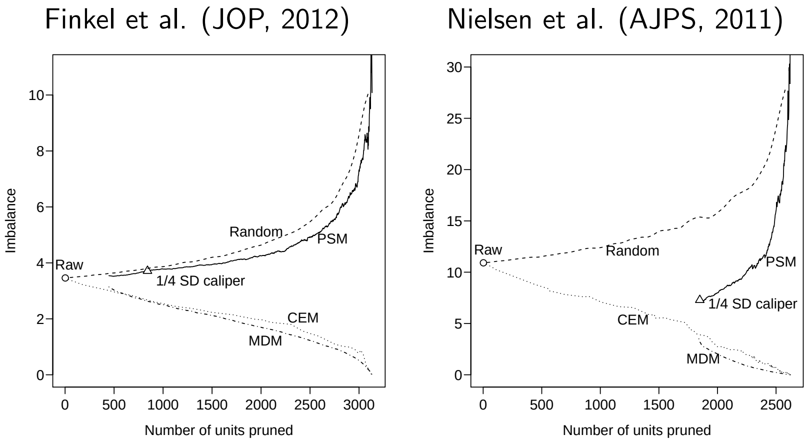

Similar pattern for $>$ 20 other real data sets we checked

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- Choose an imbalance metric, then run.

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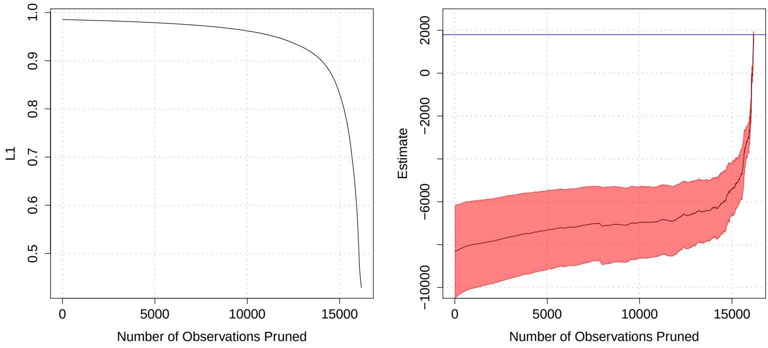
Job Training Data: Frontier and Causal Estimates



- 185 Ts; pruning most 16,252 Cs won't increase variance much
- Huge bias-variance trade-off after pruning most Cs
- Estimates converge to experiment after removing bias
- No mysteries: basis of inference clearly revealed

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For more information, articles, & software

GaryKing.org