Matching Methods for Causal Inference & 21 Other Topics

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3 Problems, 3 Solutions

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Matching to Reduce Model Dependence

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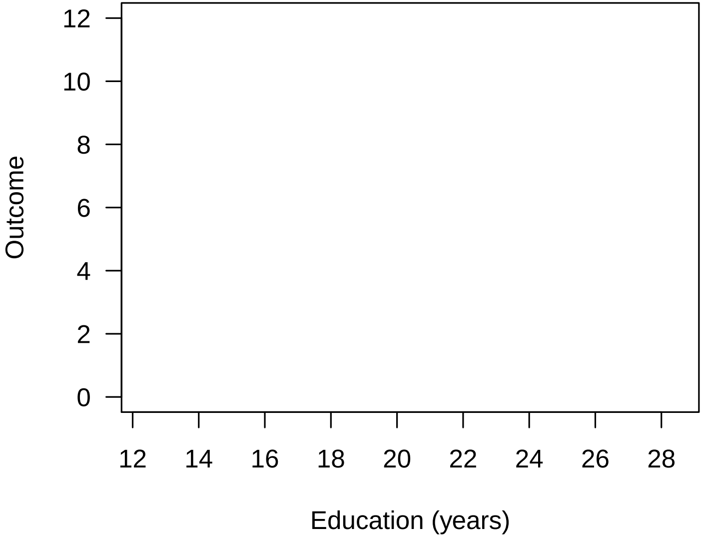

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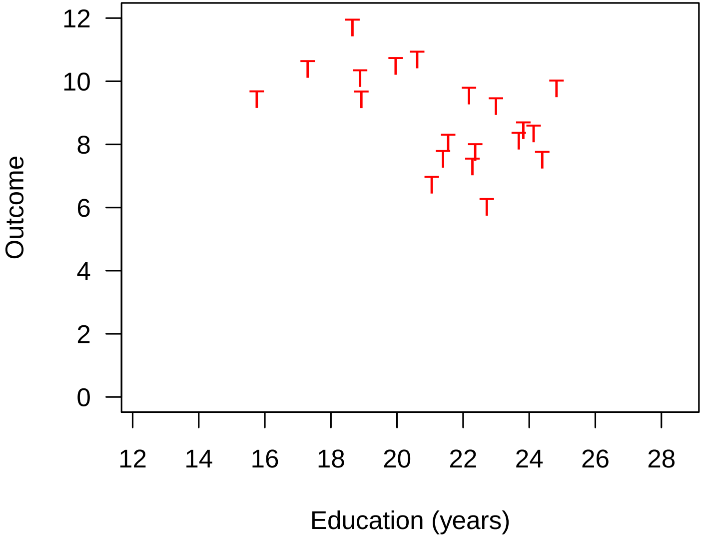

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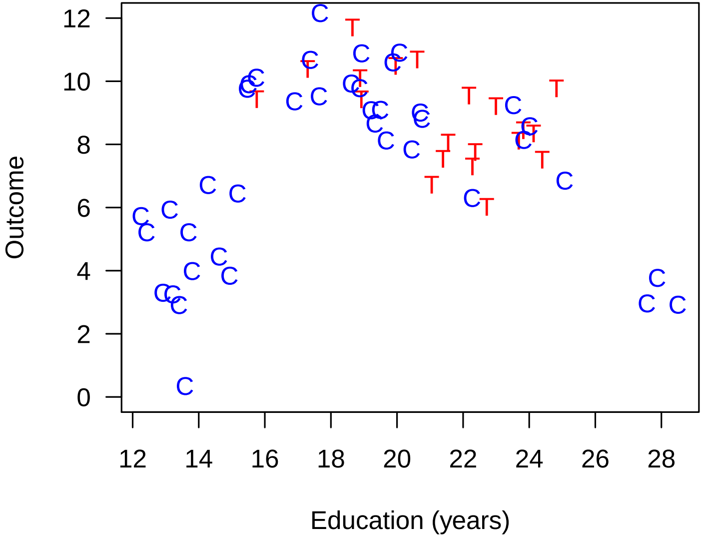

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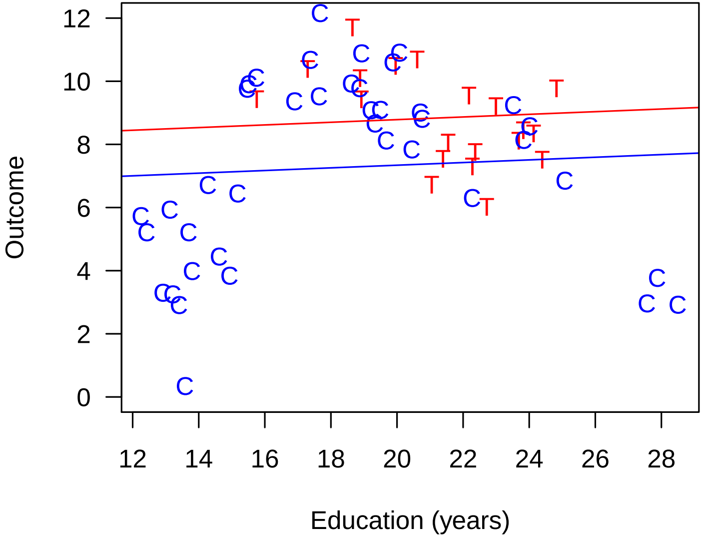

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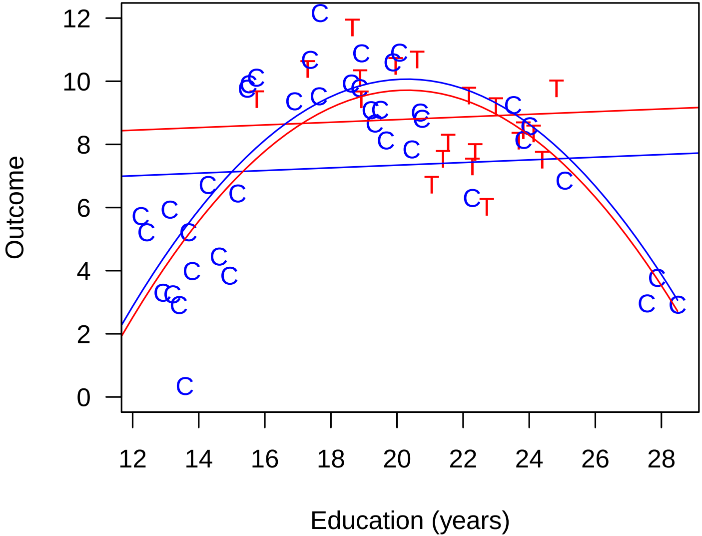

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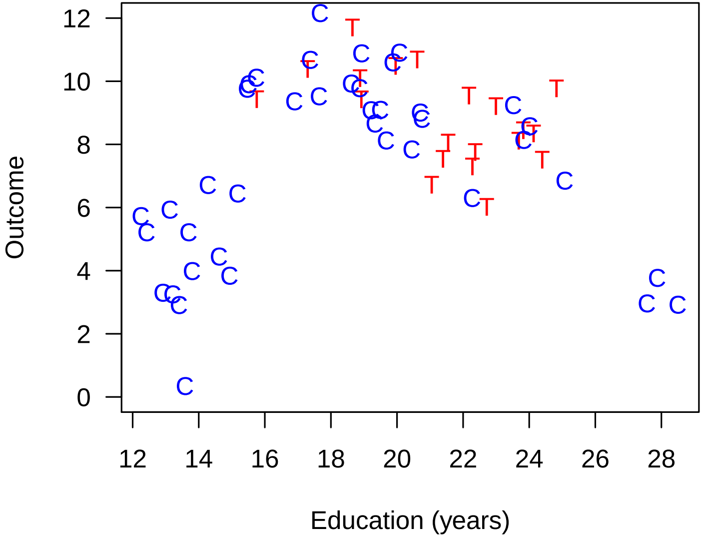

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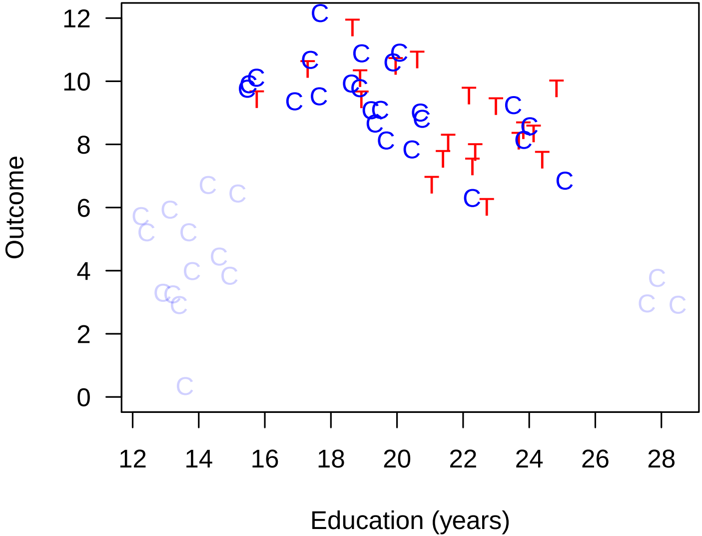

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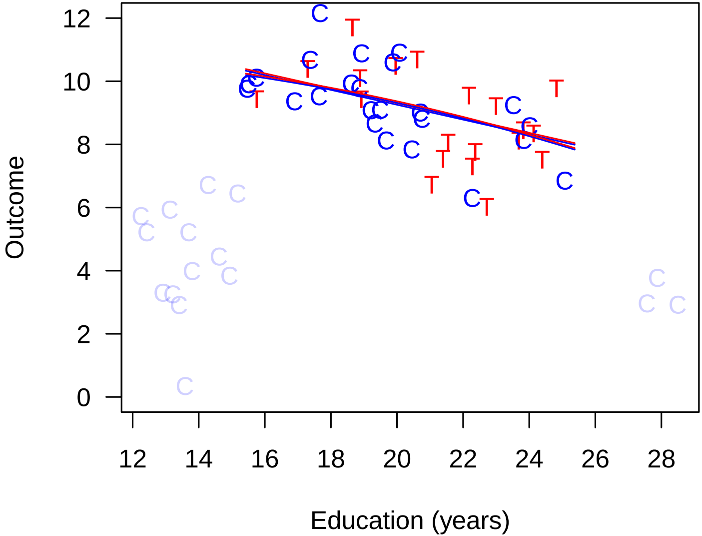

The Problems Matching Solves

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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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   - (Many adjustments available to this basic method)
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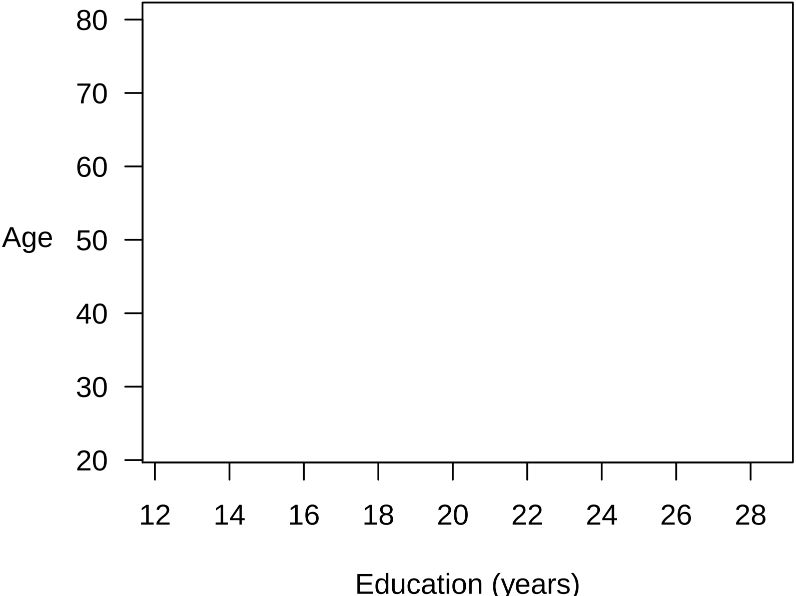

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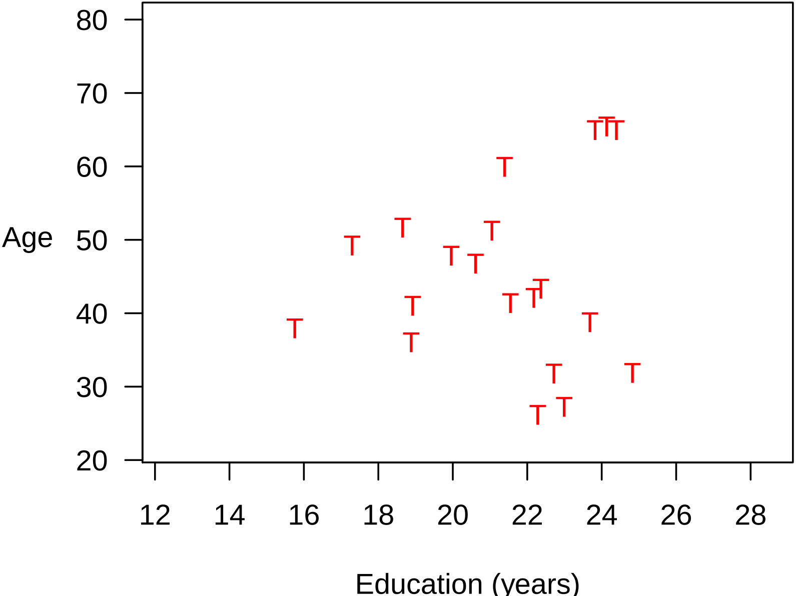

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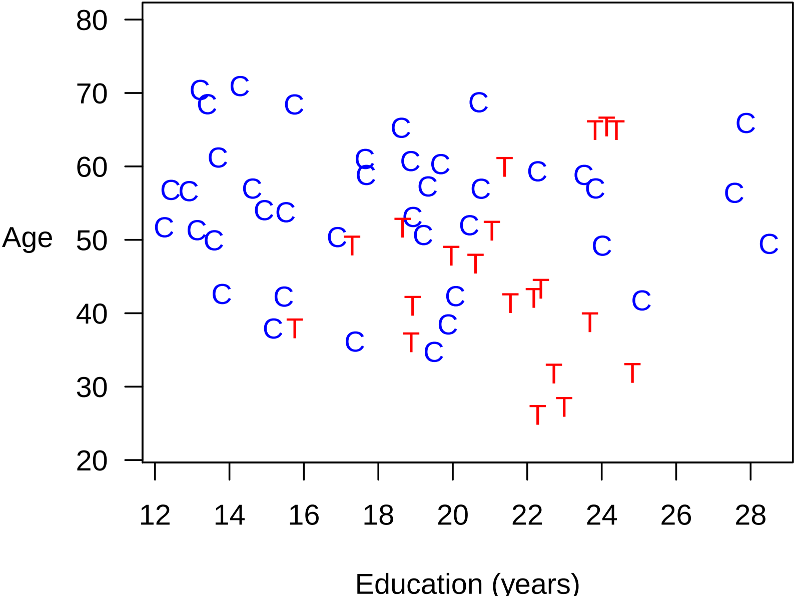

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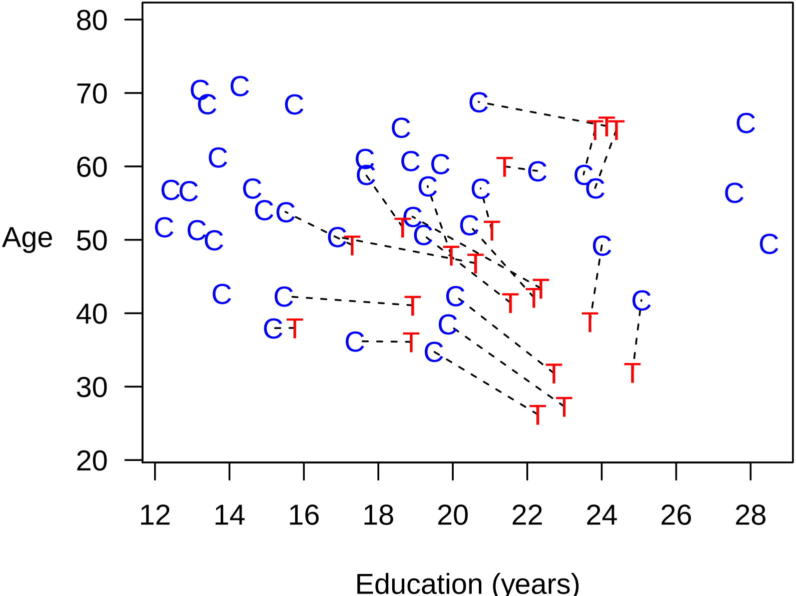

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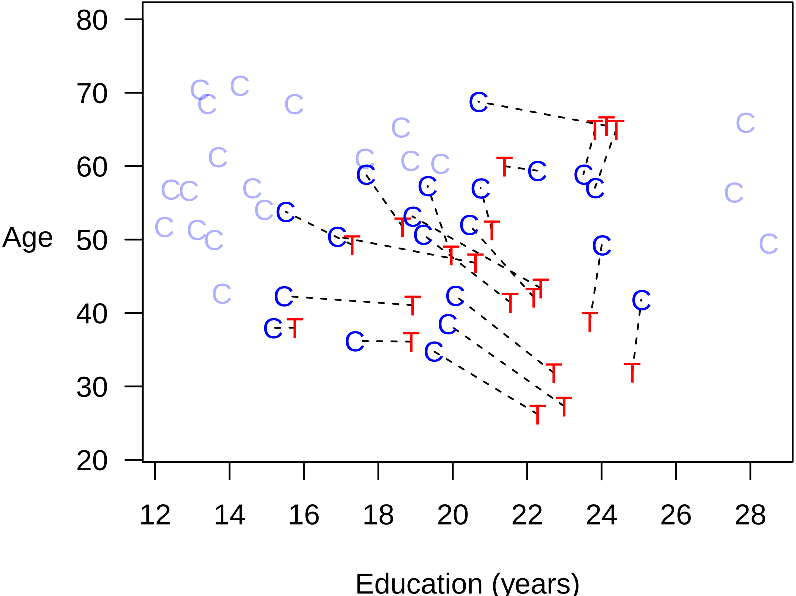

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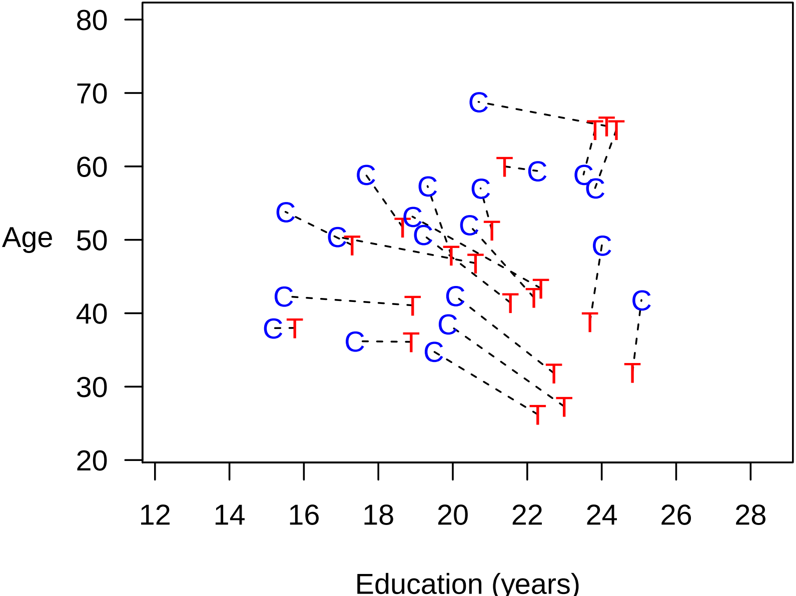

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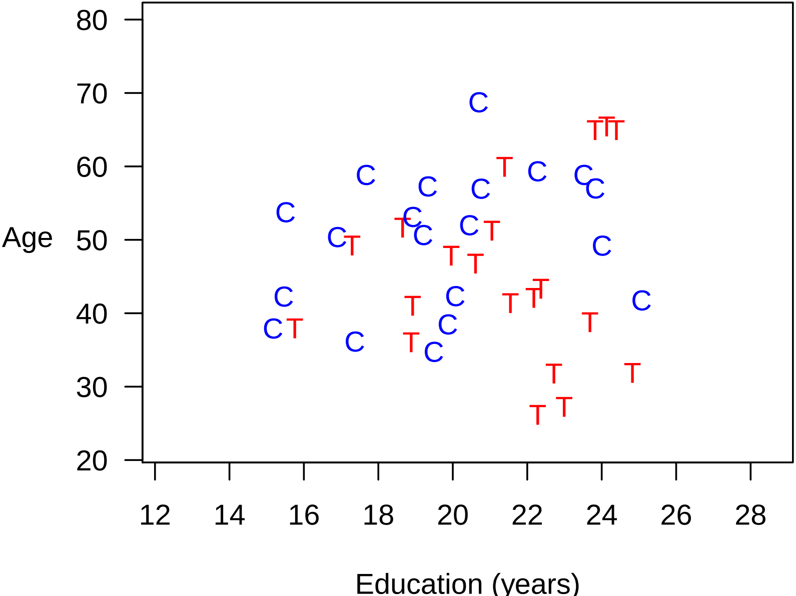

Best Case: Mahalanobis Distance Matching

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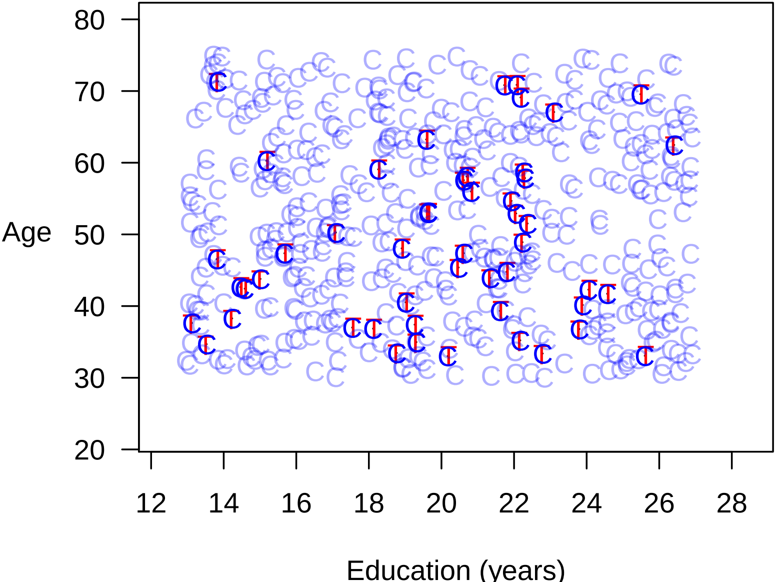

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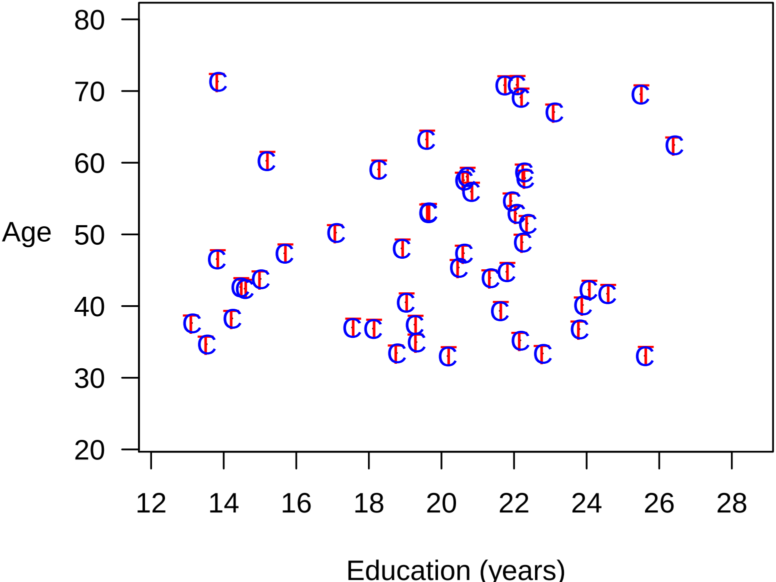

Method 2: Coarsened Exact Matching

Method 2: Coarsened Exact Matching

(Approximates Fully Blocked Experiment)

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1. Preprocess (Matching)

2. Estimation Difference in means or a model

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   - Weight controls in each stratum to equal treateds

Coarsened Exact Matching

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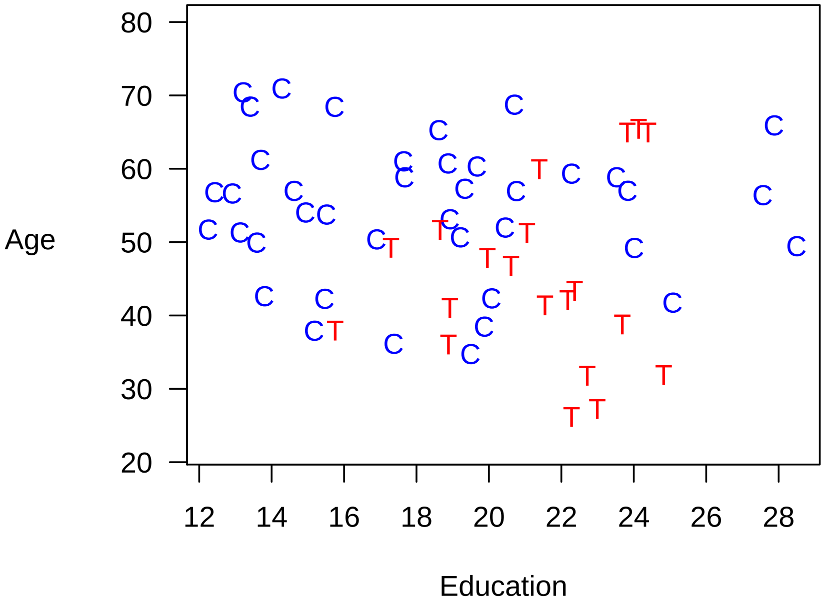

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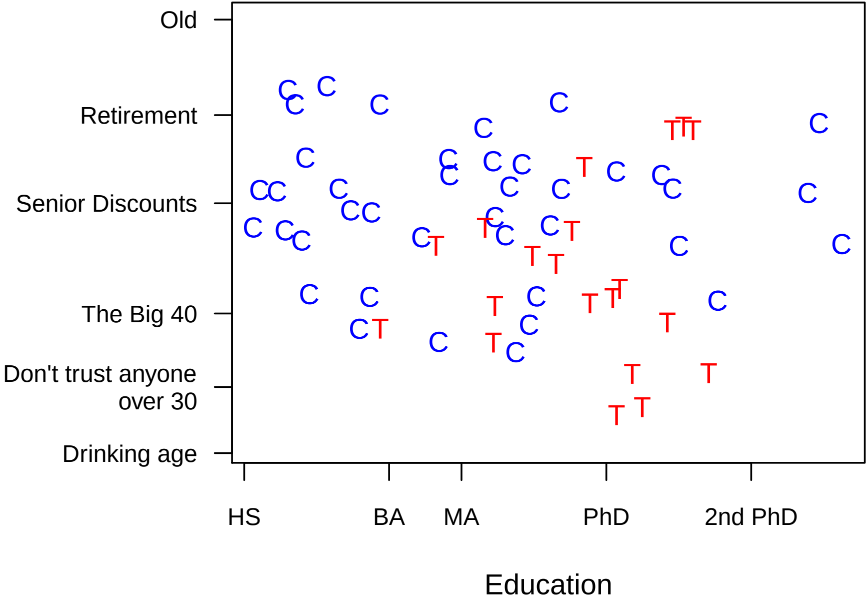

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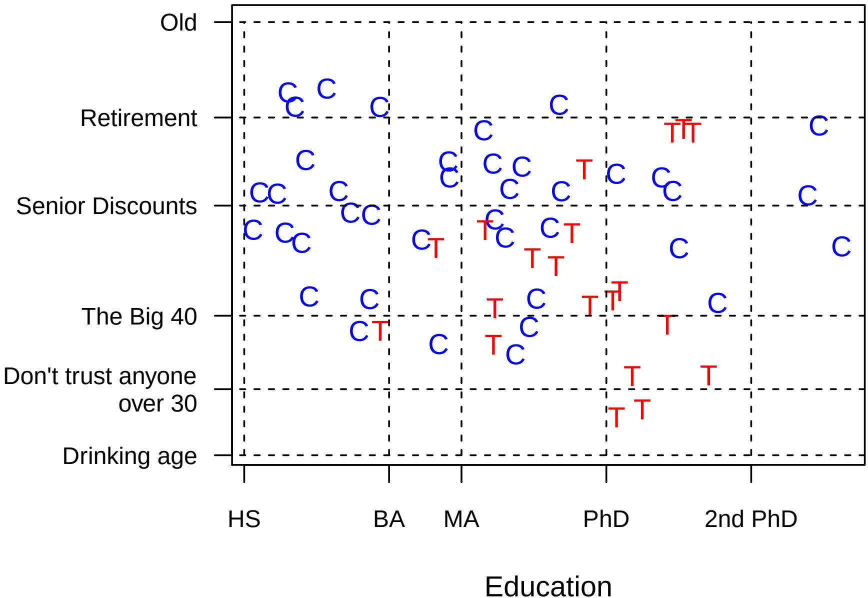

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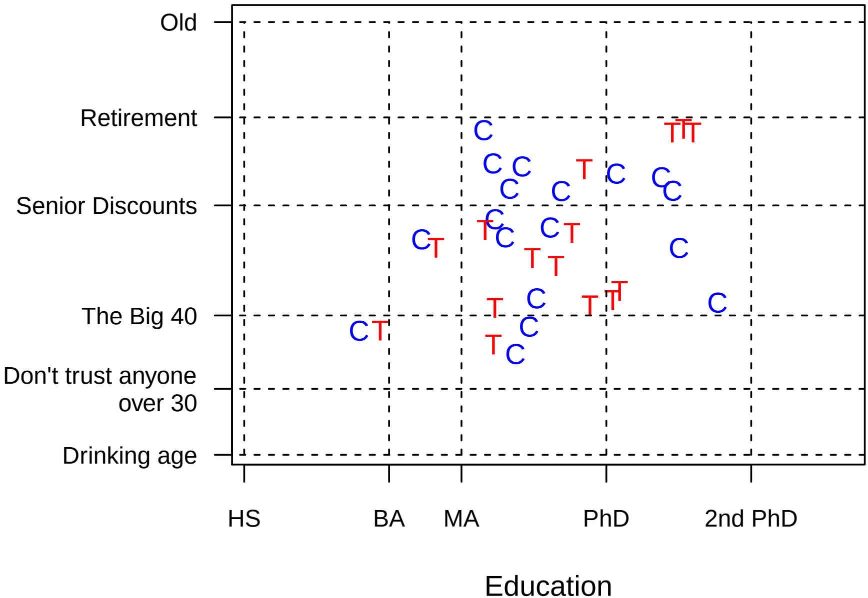

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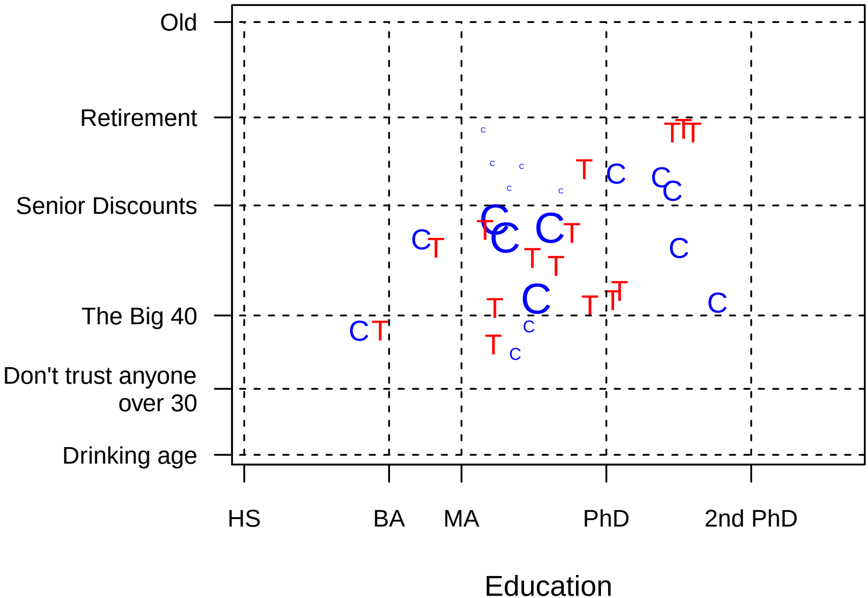

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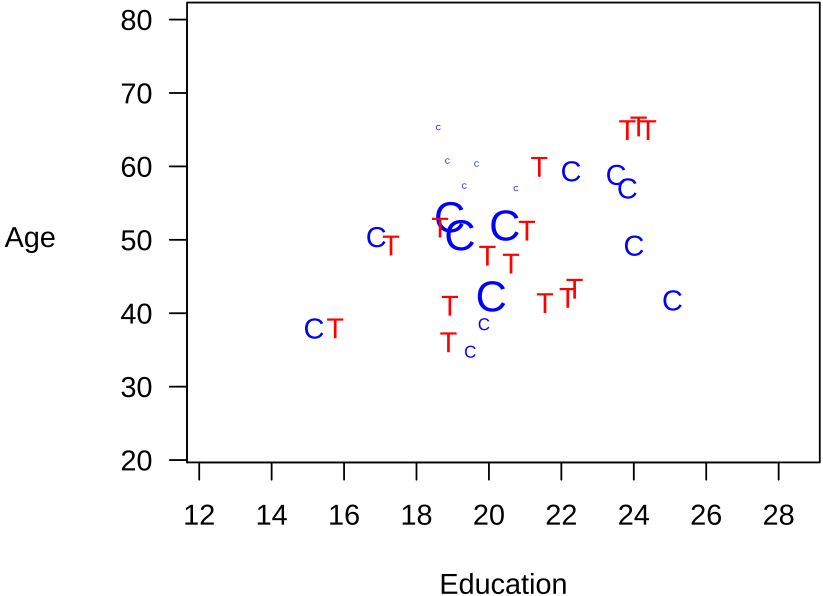

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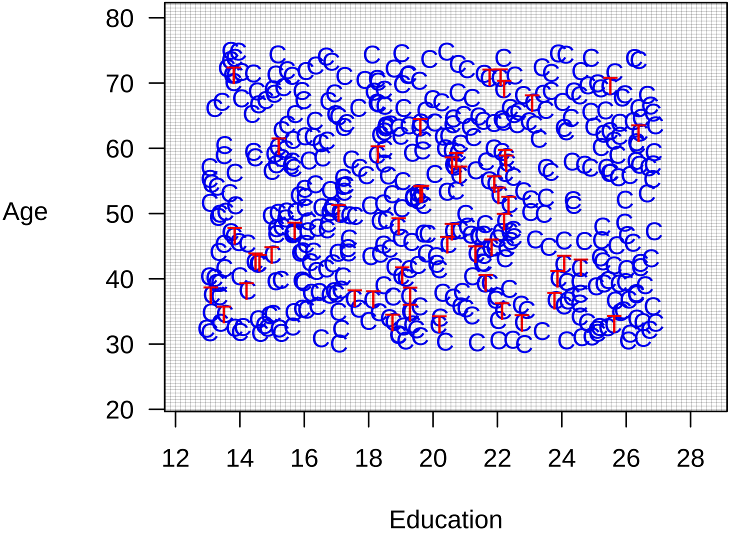

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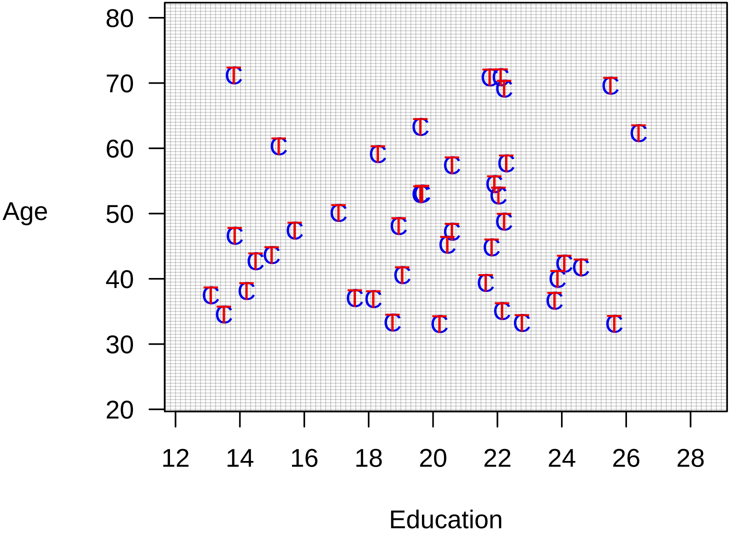

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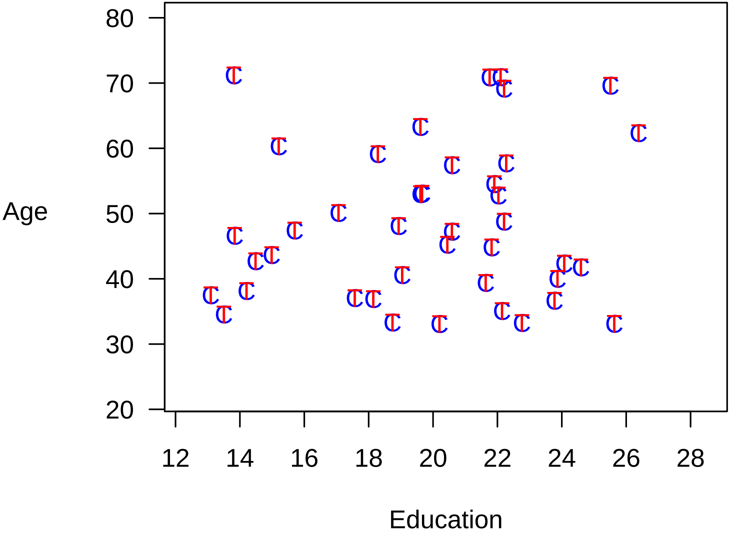

Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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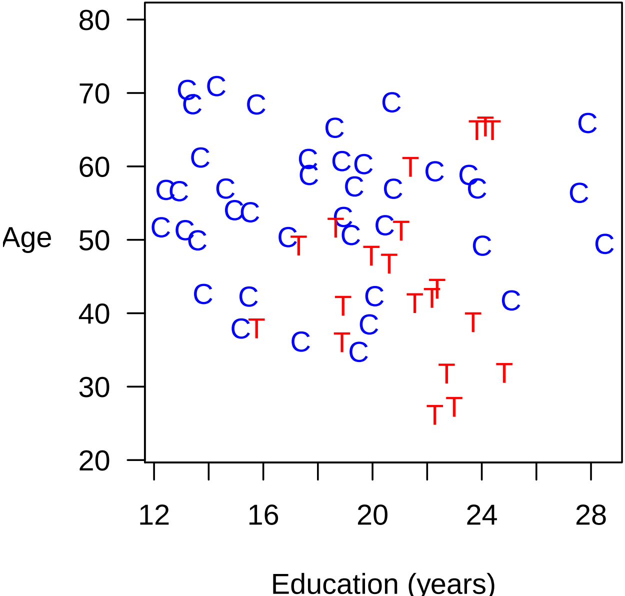
    - (Many adjustments available to this basic method)
2. Estimation Difference in means or a model

Propensity Score Matching



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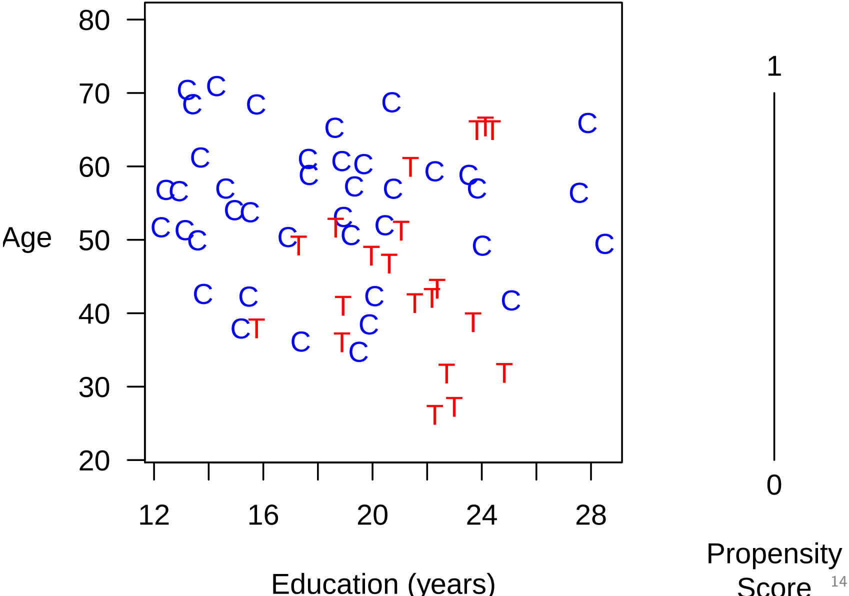

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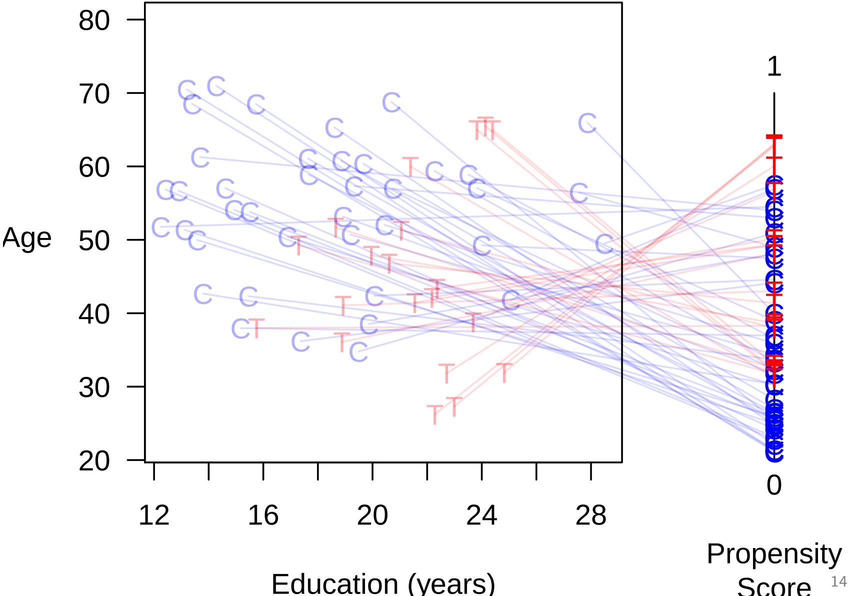

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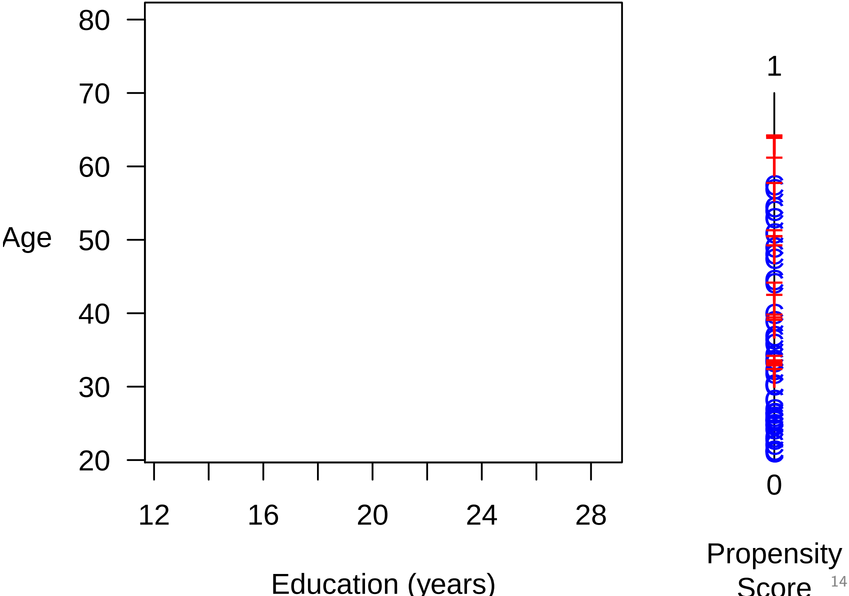

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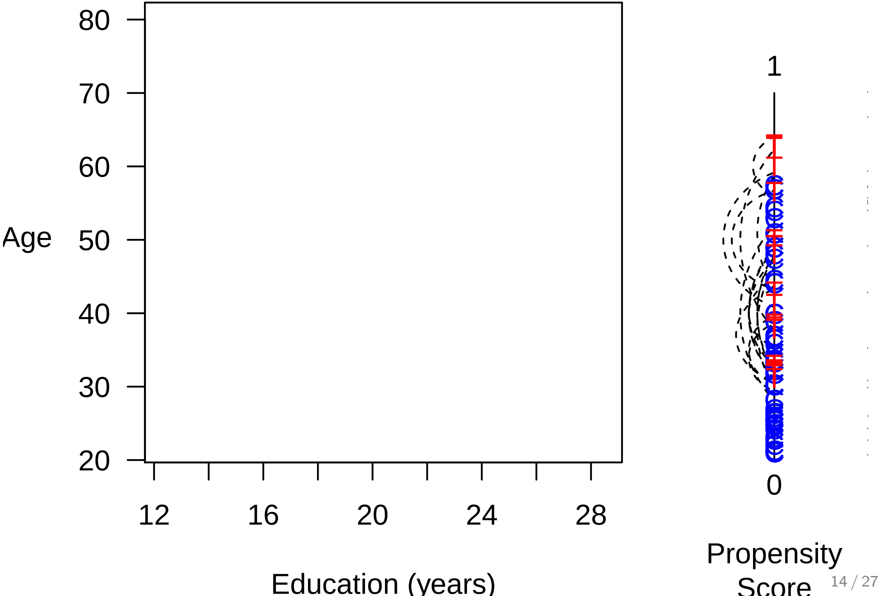

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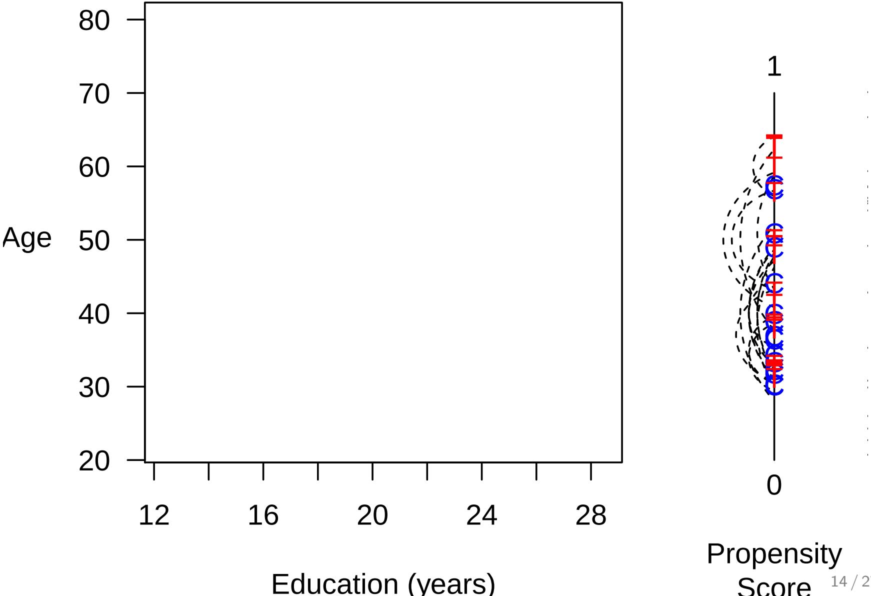

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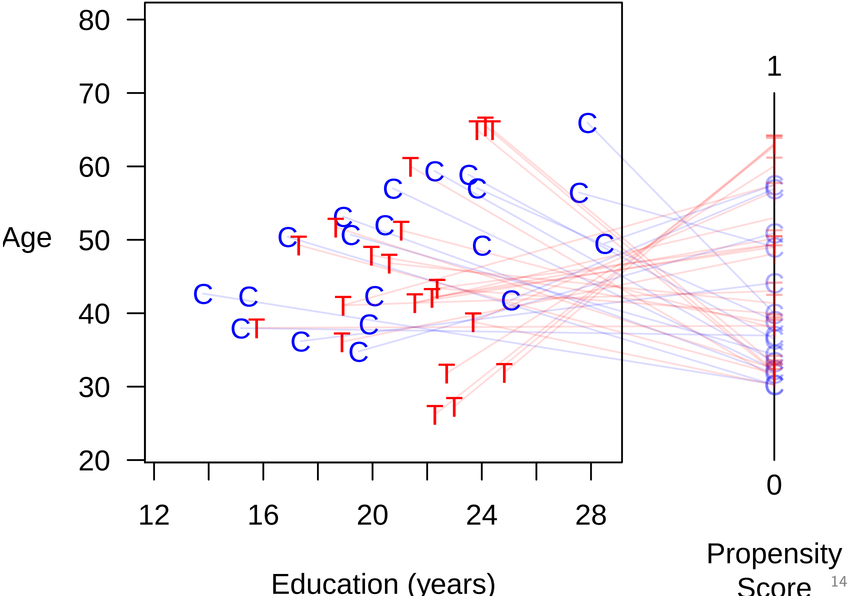

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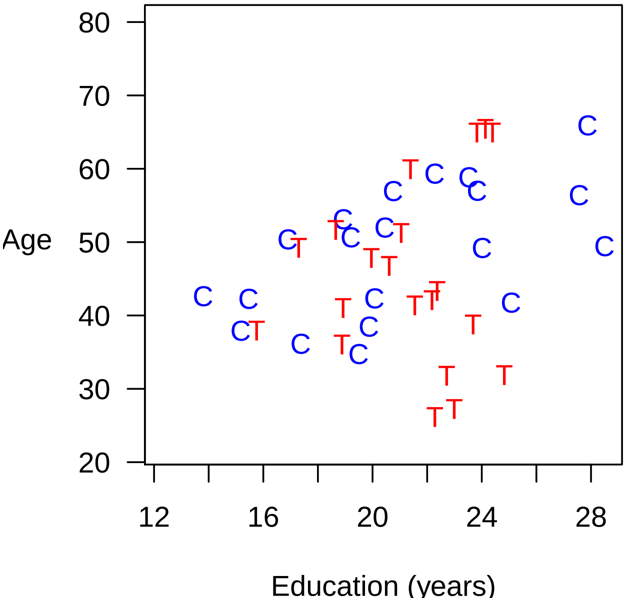

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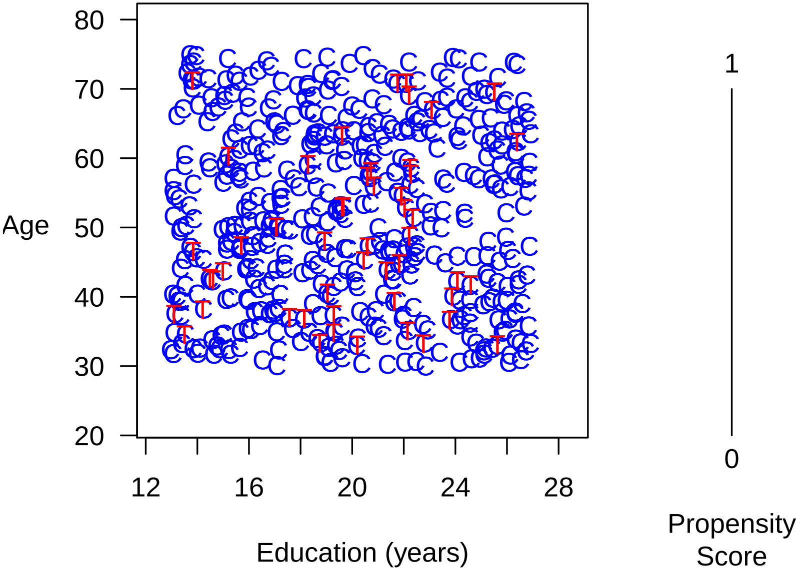

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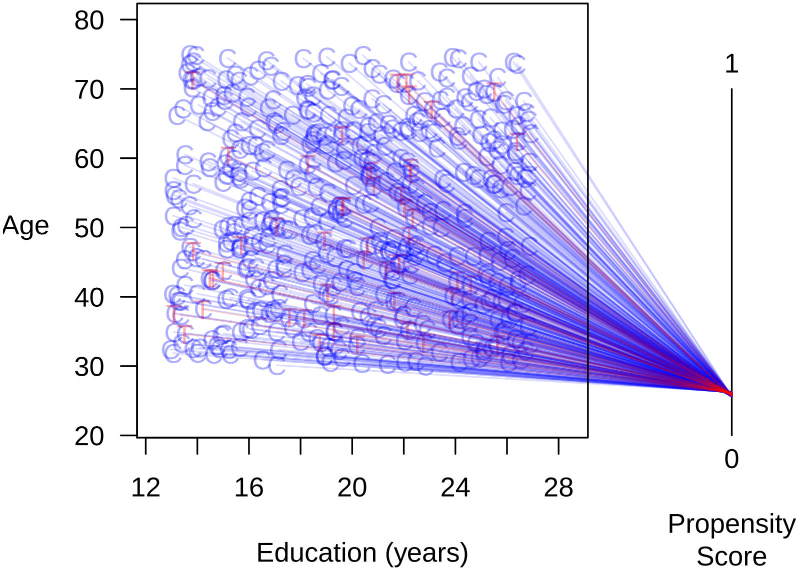

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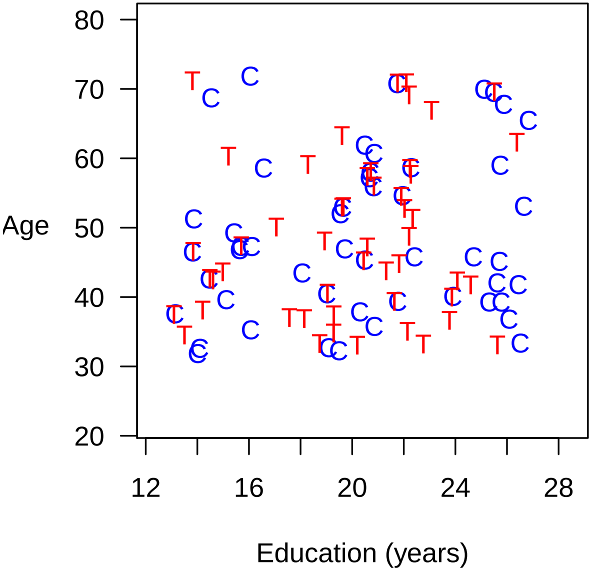
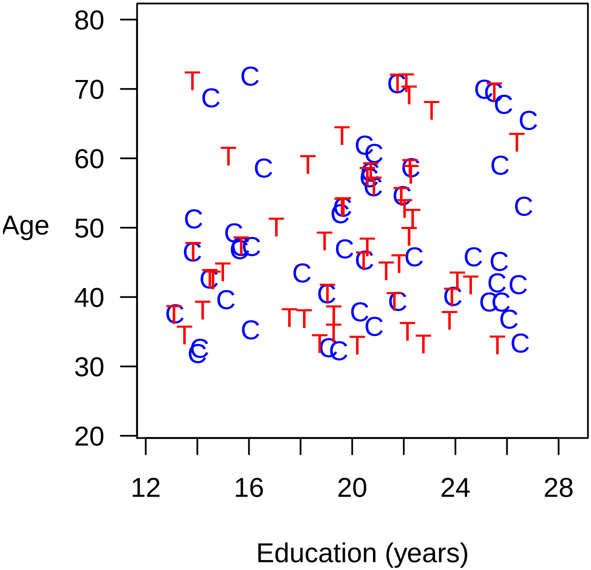


Best Case: Propensity Score Matching is Suboptimal



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   - Doesn't PSM solve the curse of dimensionality problem? Nope. The PSM Paradox gets worse with more covariates

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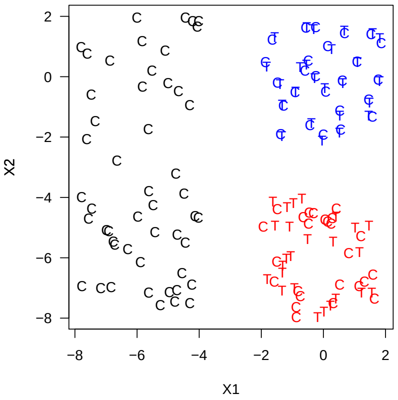

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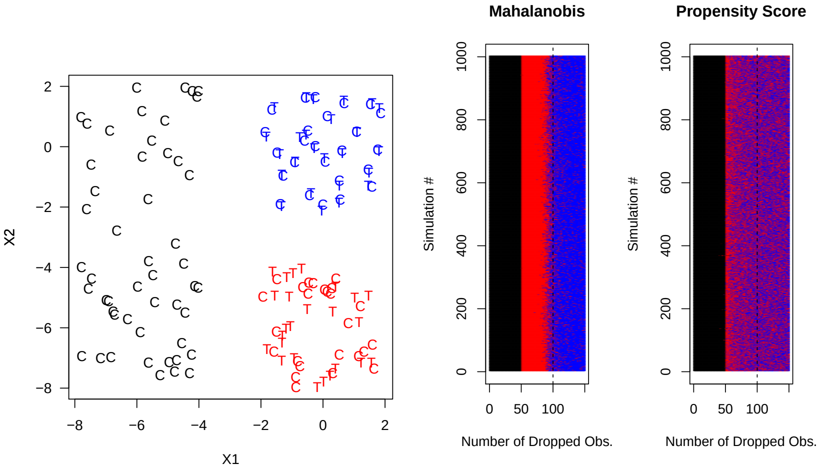
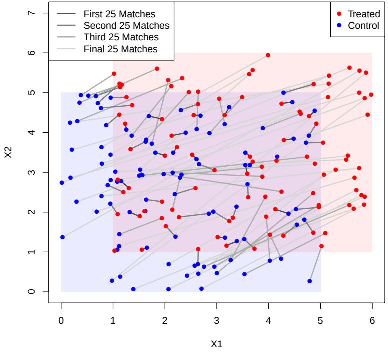


What Does PSM Match?

MDM Matches



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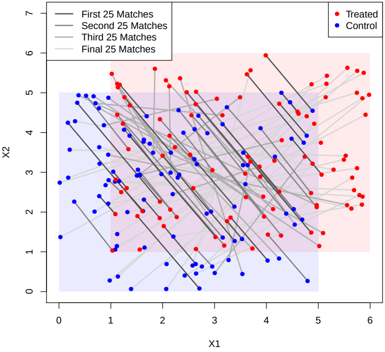
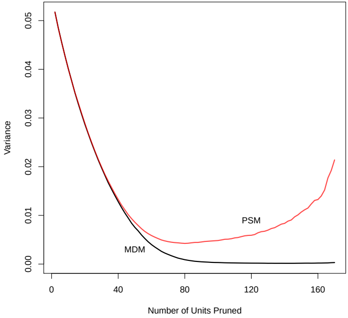


Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$

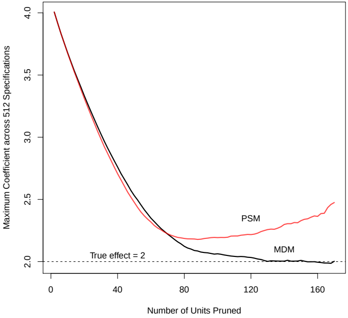
Treateds: $X_1, X_2 \sim \text{Uniform}(1,6)$

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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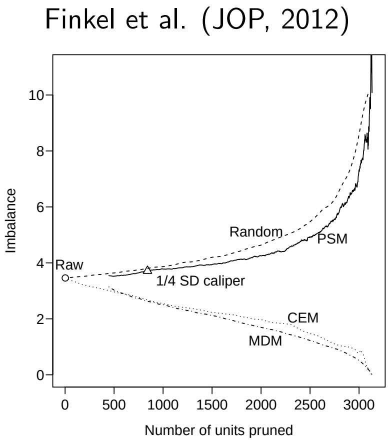

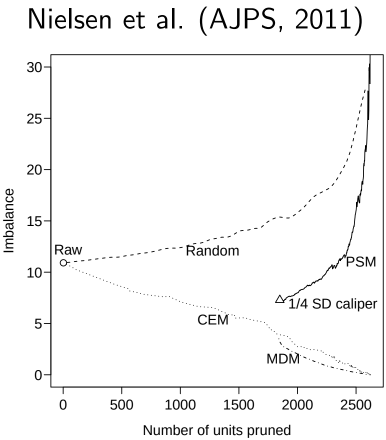

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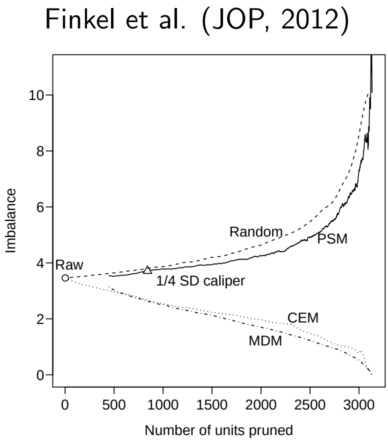

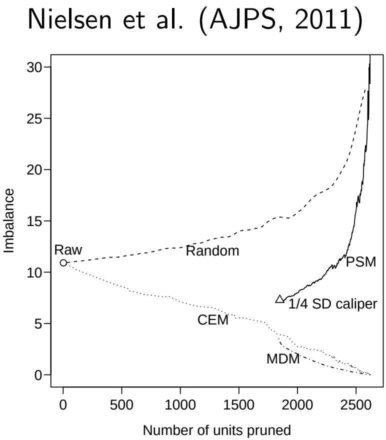

Similar pattern for > 20 other real data sets we checked

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- Choose an imbalance metric, then run.

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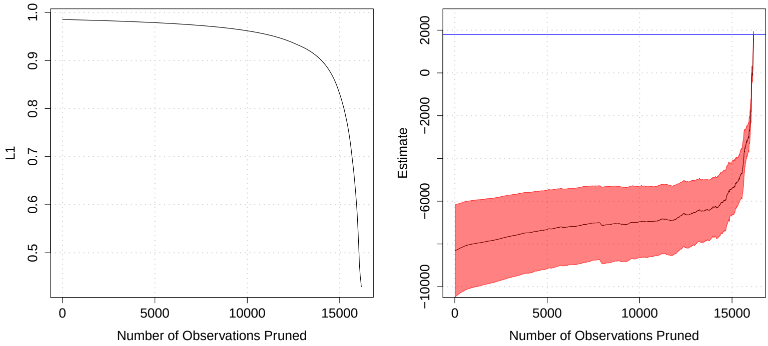
Job Training Data: Frontier and Causal Estimates



- 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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