

# Matching Methods for Causal Inference & 21 Other Topics

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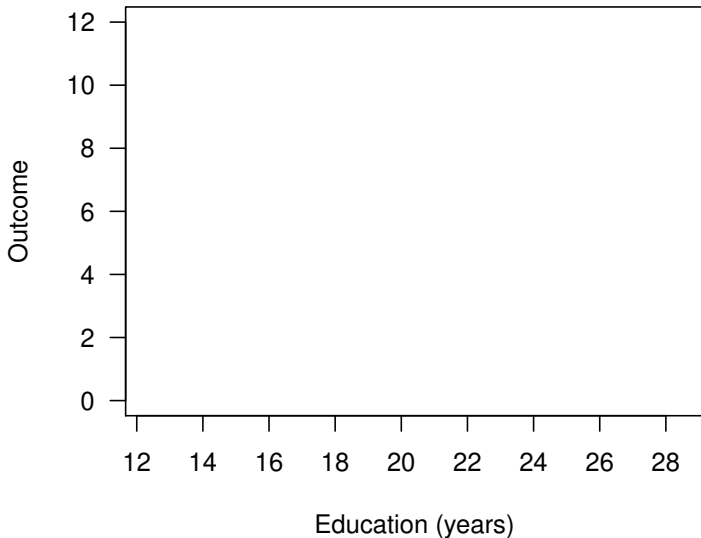
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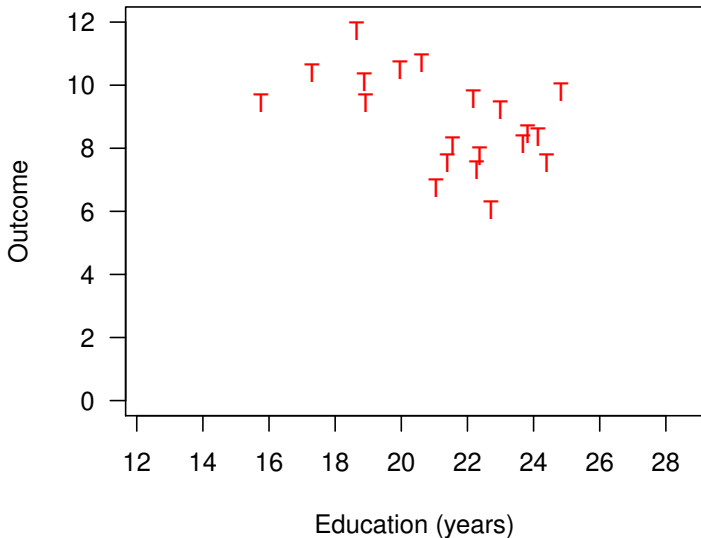
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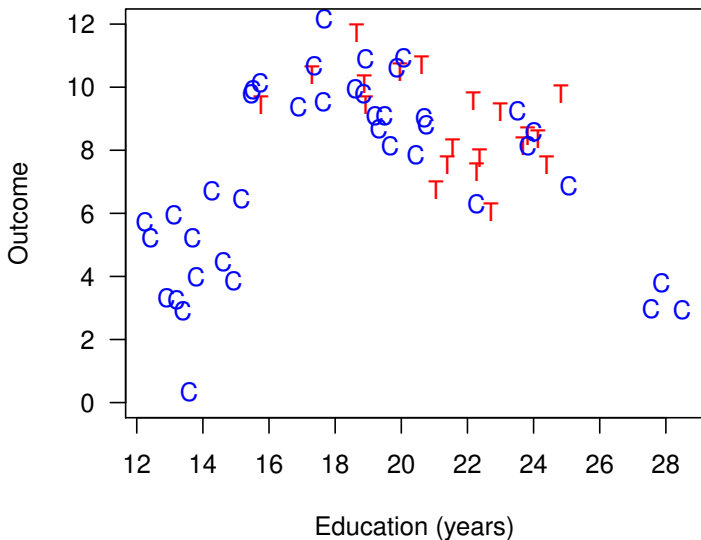
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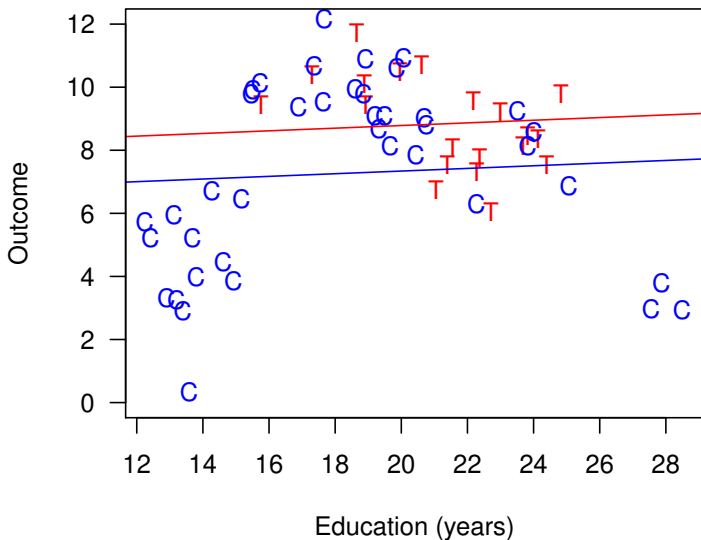
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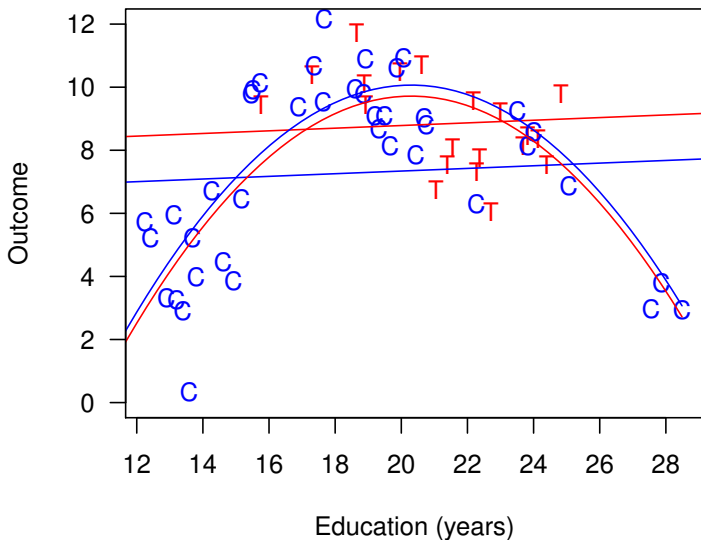
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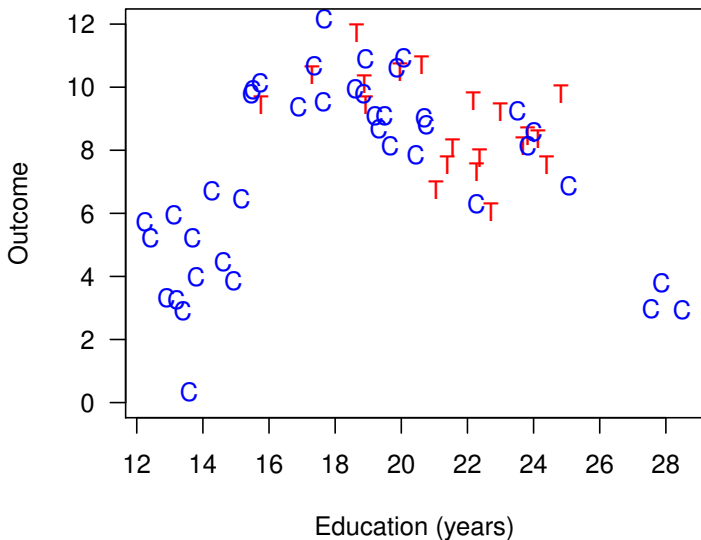
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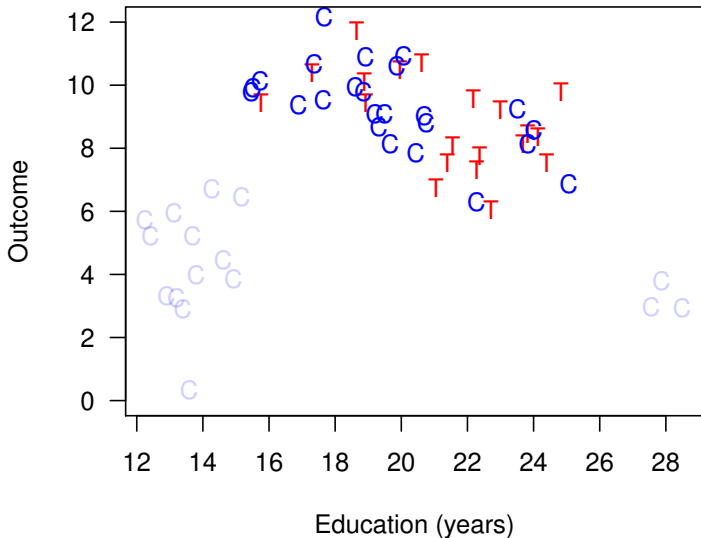
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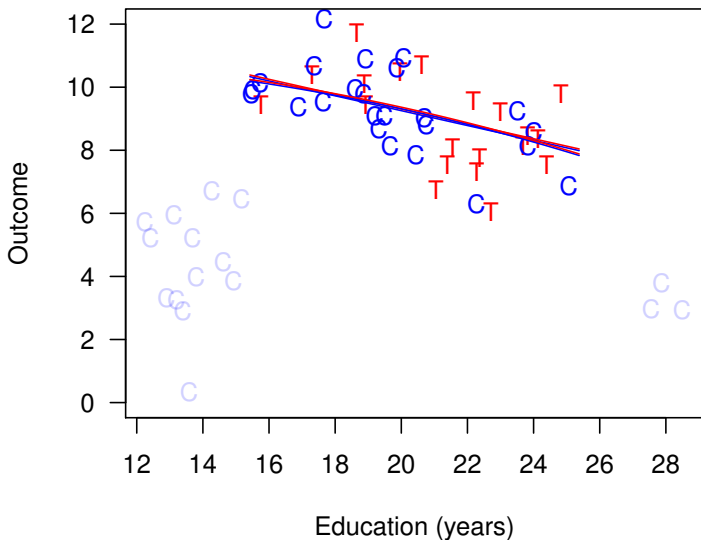
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- “Teaching psychology is mostly a waste of time” (Kahneman 2011)

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A central project of statistics: Automating away human discretion

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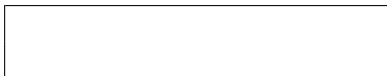
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  - **Pruning nonmatches makes control vars matter less:** reduces imbalance, model dependence, researcher discretion, & bias

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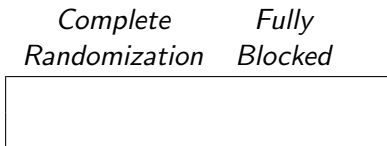
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- Other methods: *fully blocked*
- **Other matching methods dominate PSM** (wait, it gets worse)

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- Match each treated unit to the nearest control unit

## 2. Estimation Difference in means or a model

# Method 1: Mahalanobis Distance Matching

(Approximates Fully Blocked Experiment)

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- $\text{Distance}(X_c, X_t) = \sqrt{(X_c - X_t)'S^{-1}(X_c - X_t)}$
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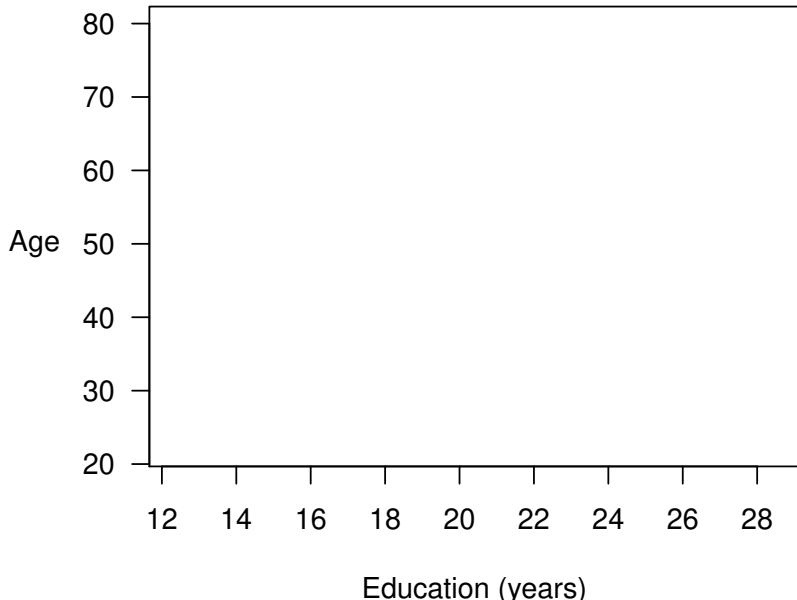
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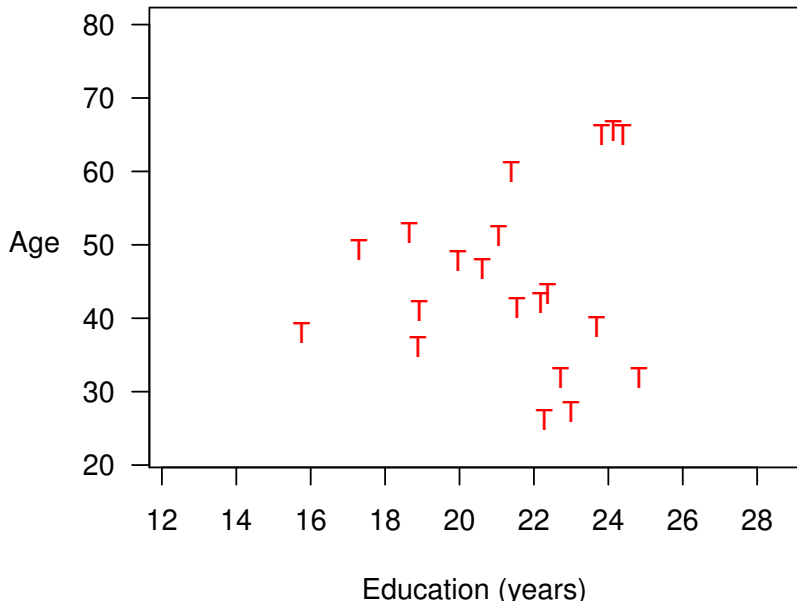
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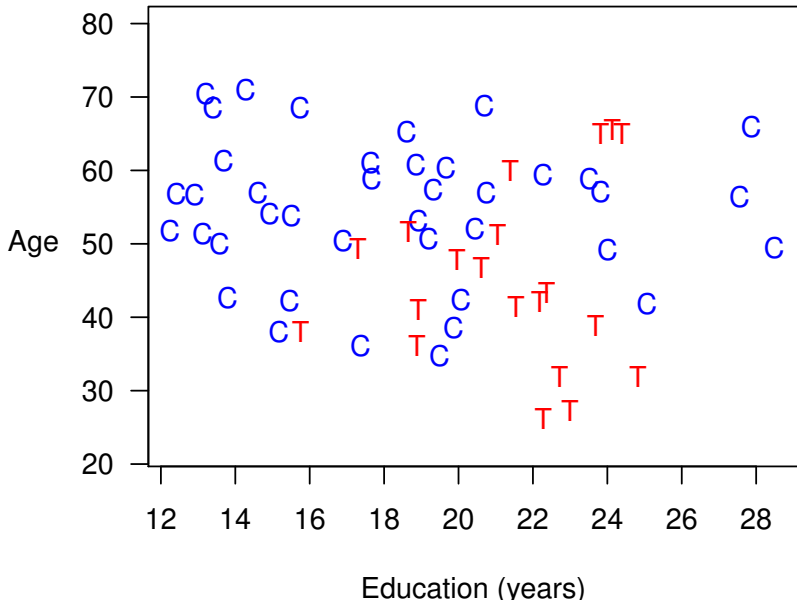
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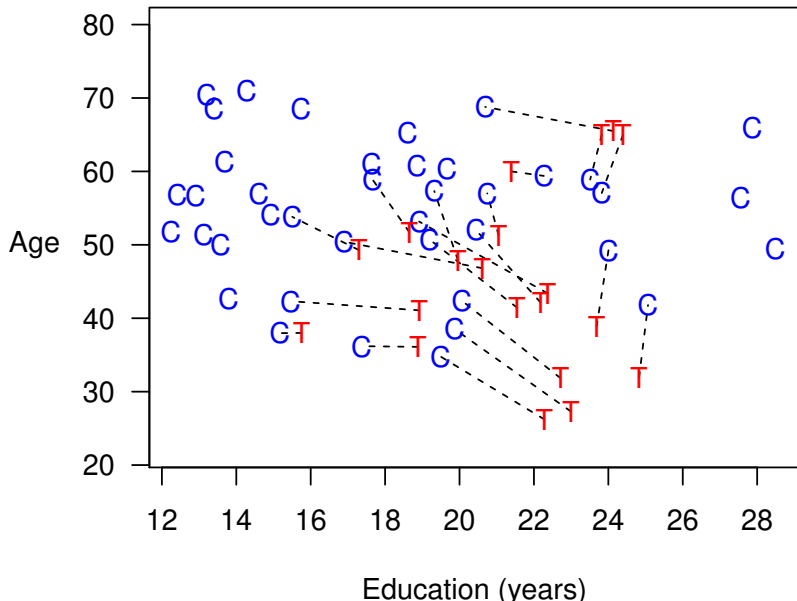
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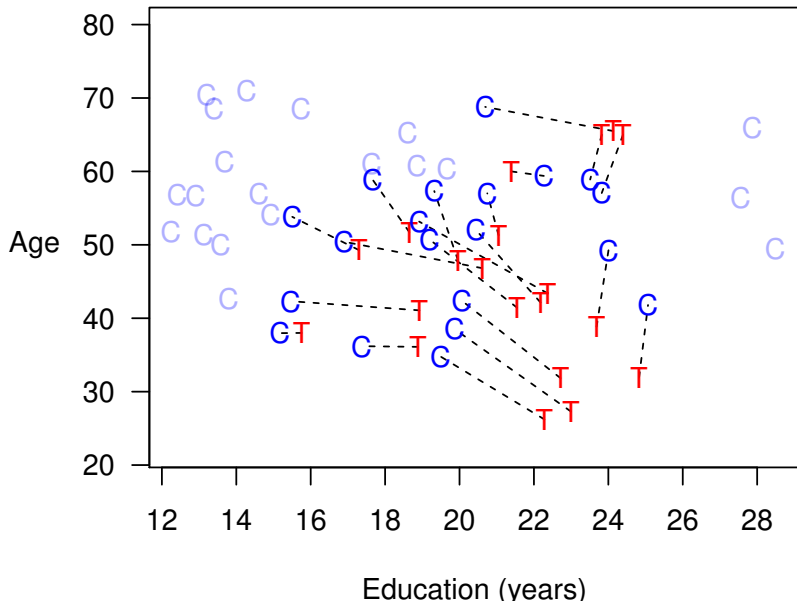
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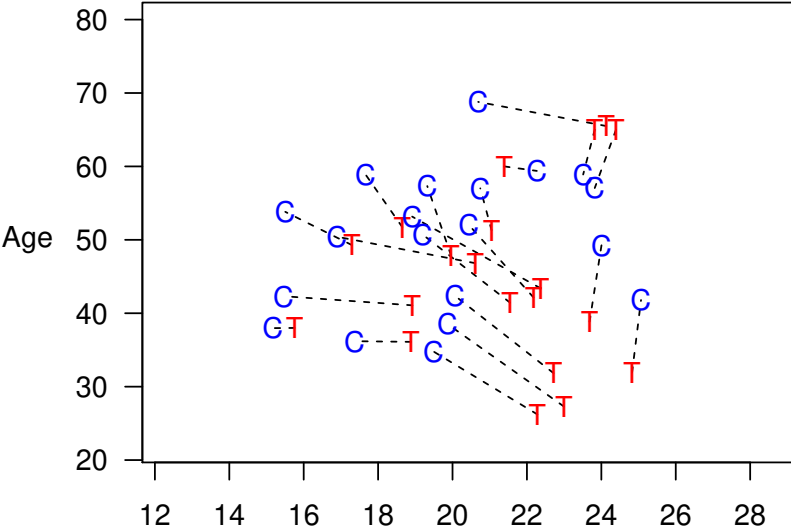
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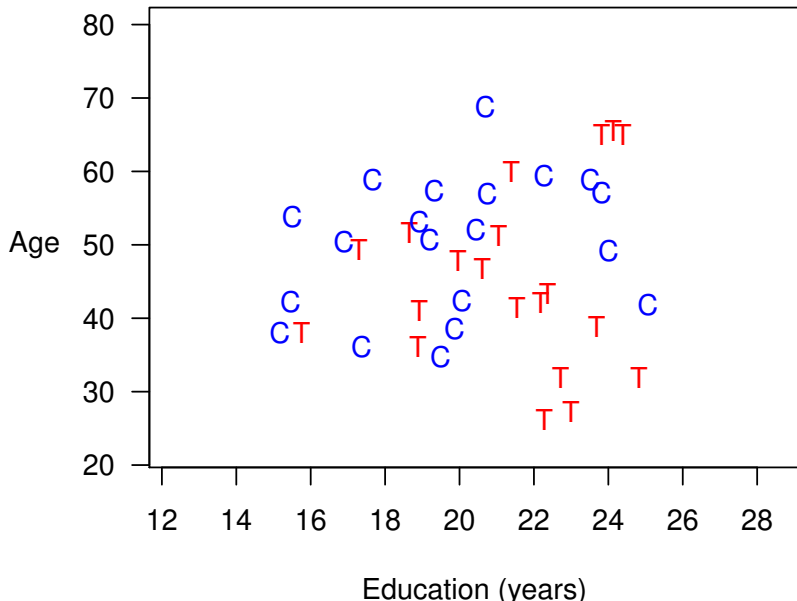
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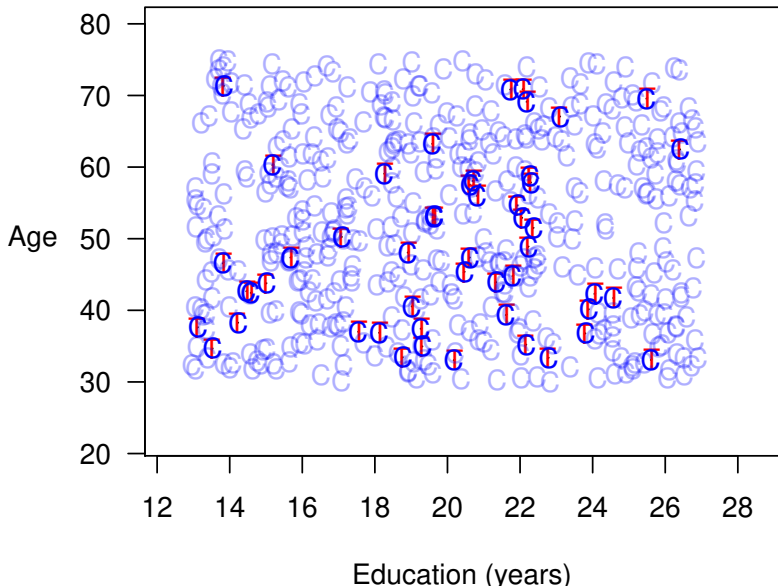


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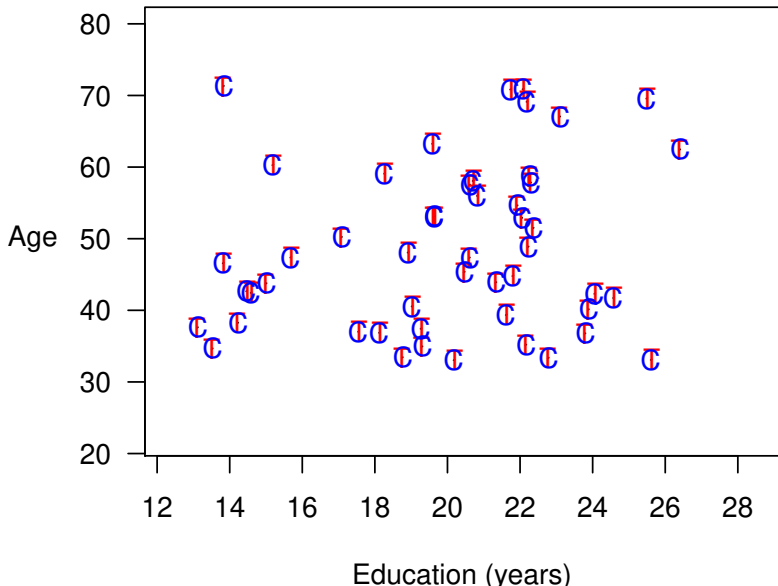


## Best Case: Mahalanobis Distance Matching

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## Method 2: Coarsened Exact Matching

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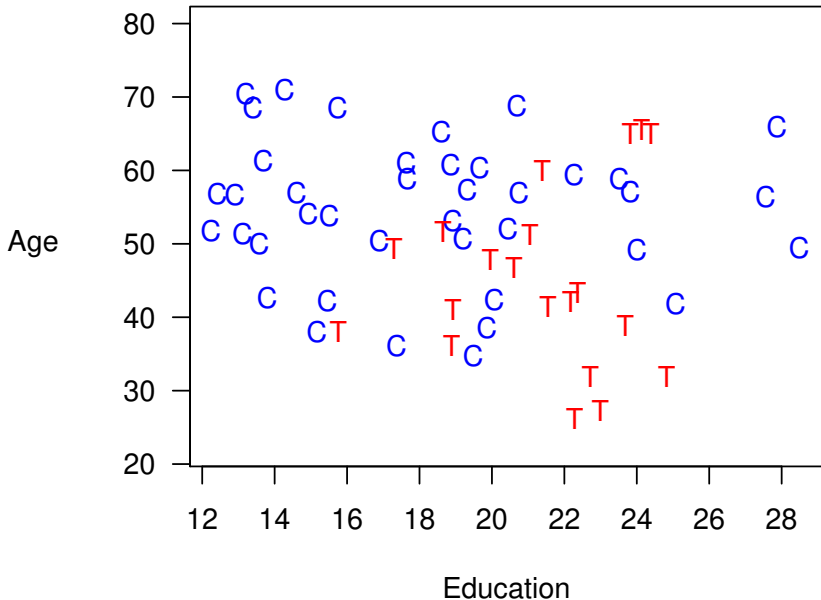
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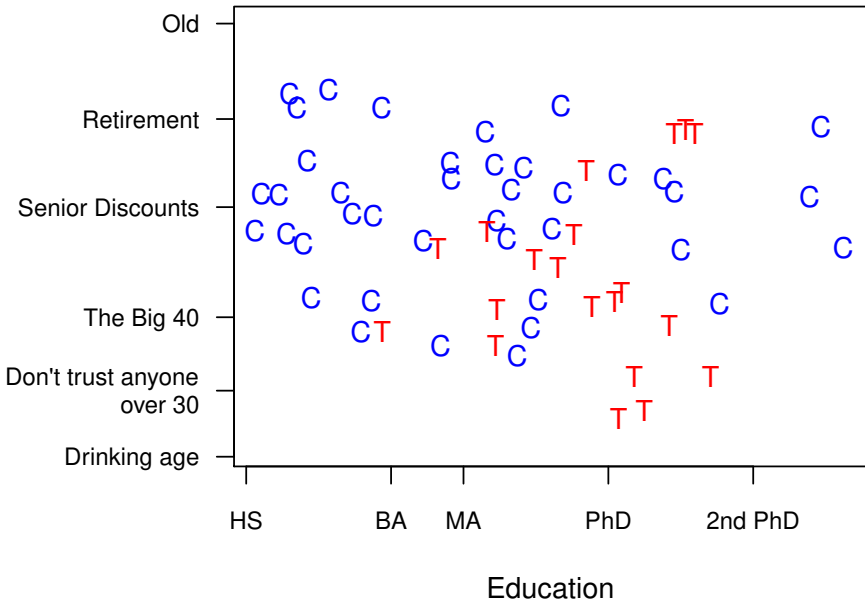
- Weight controls in each stratum to equal treated

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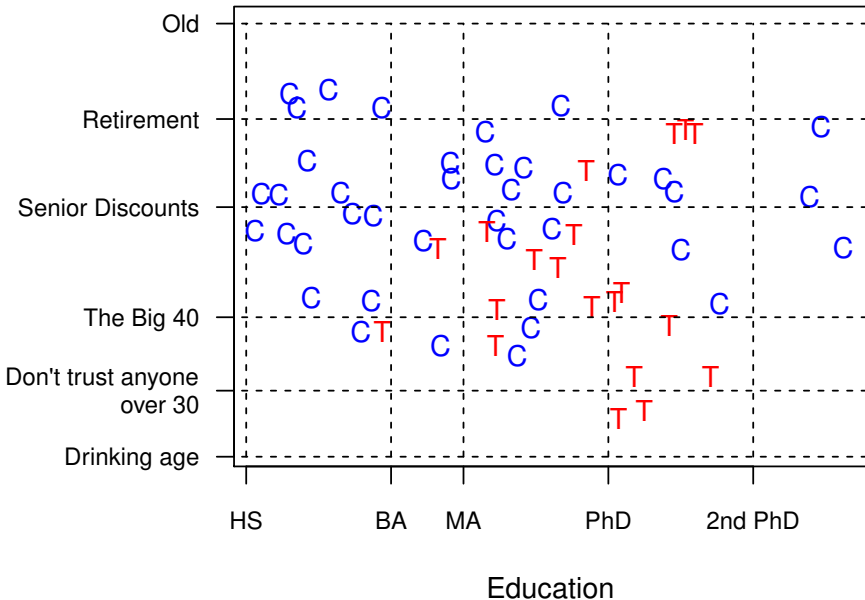
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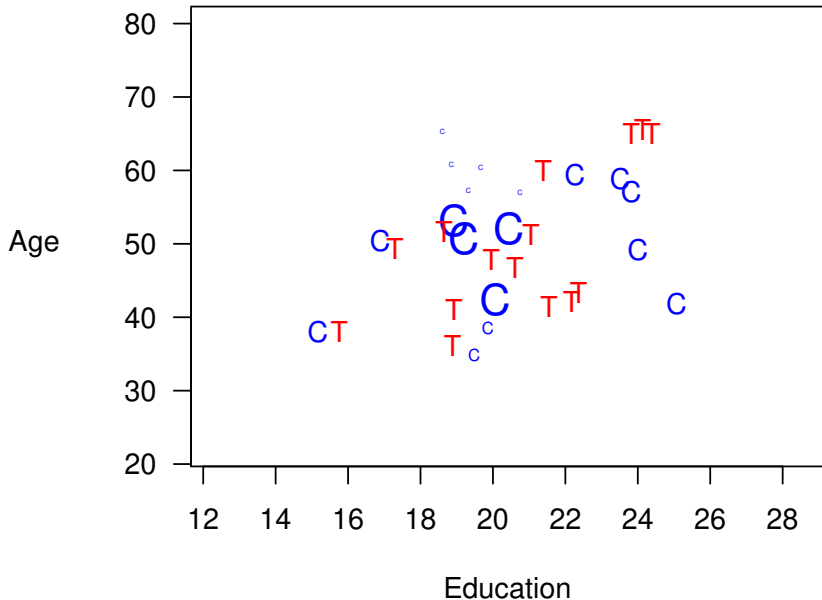
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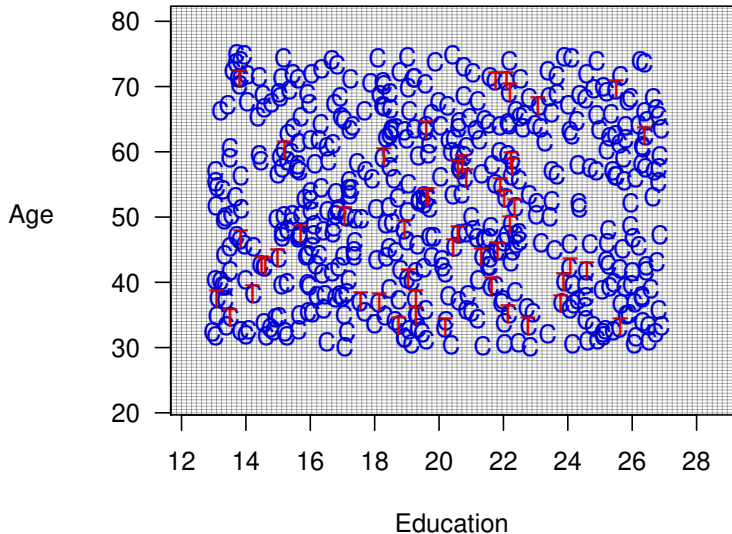


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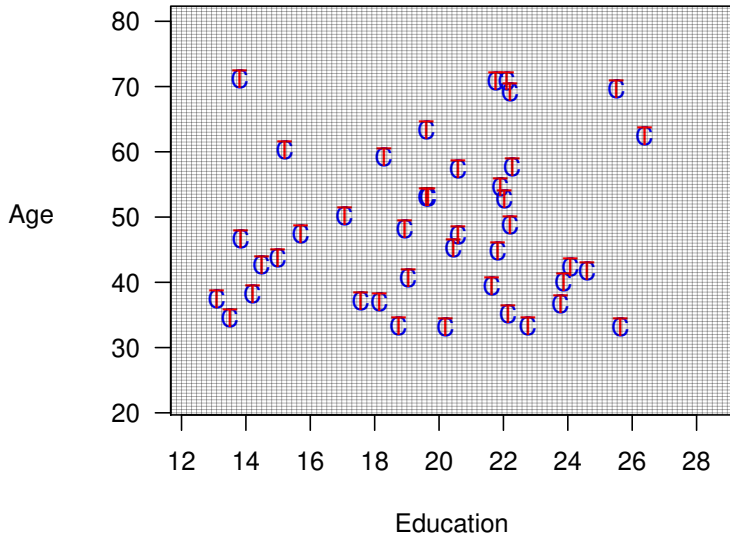


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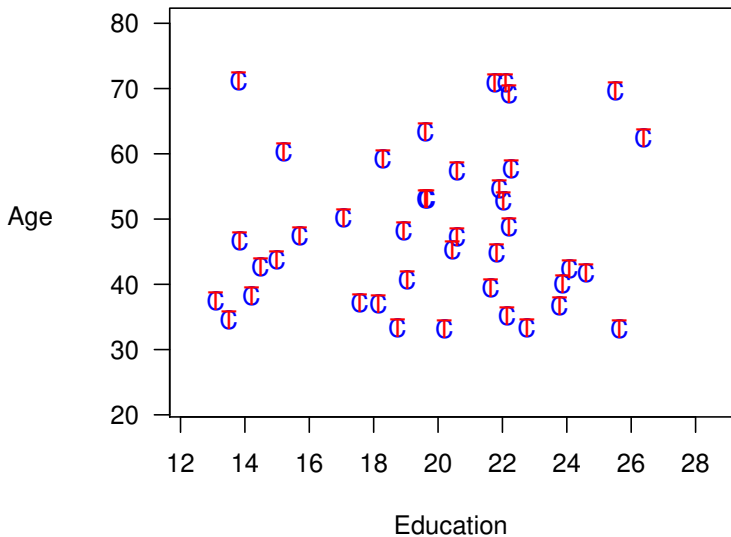
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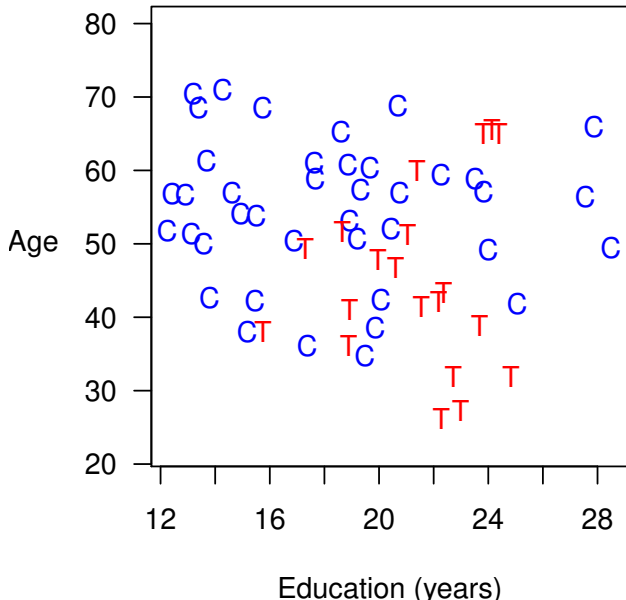
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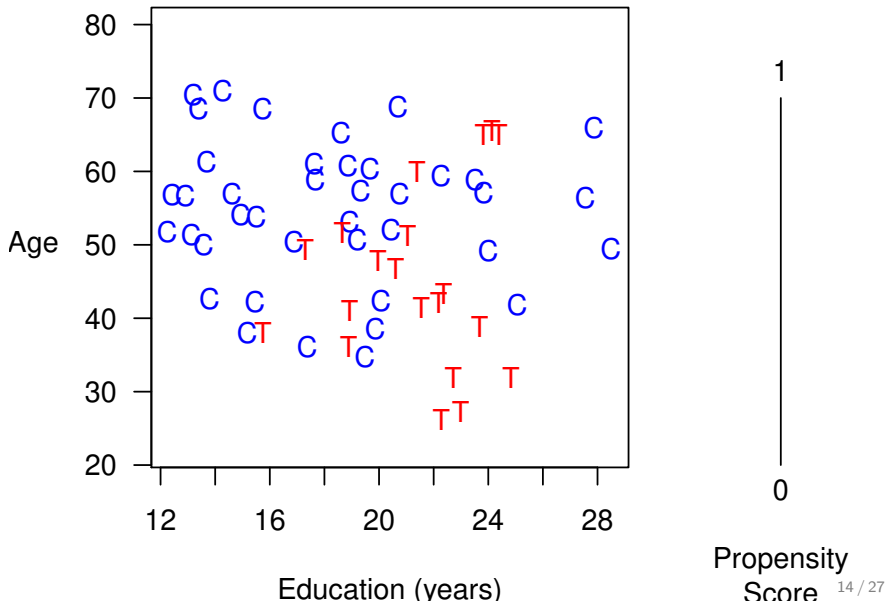
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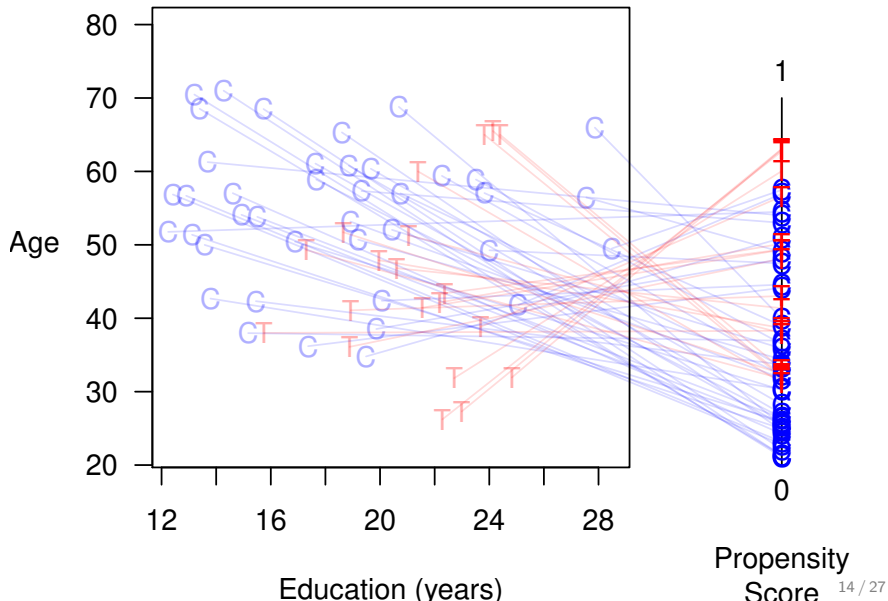
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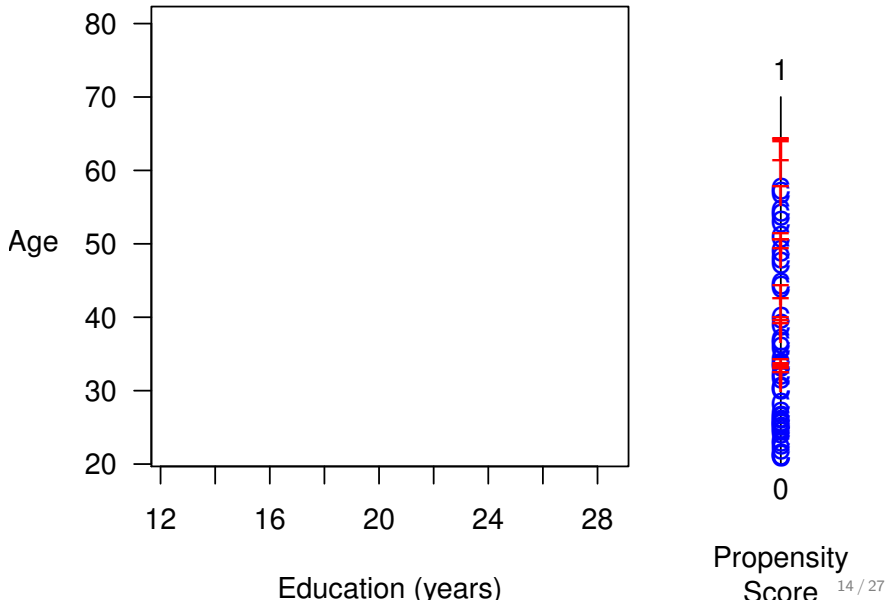
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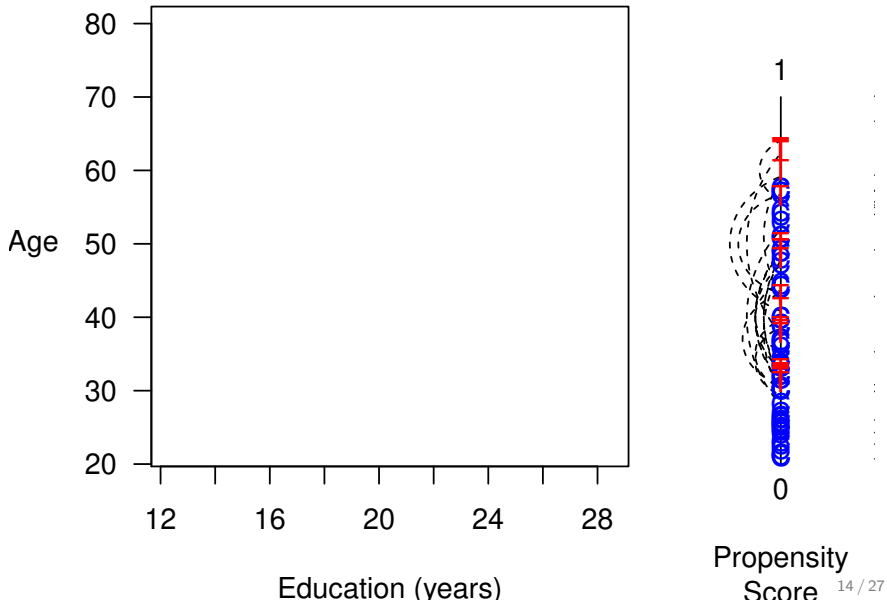
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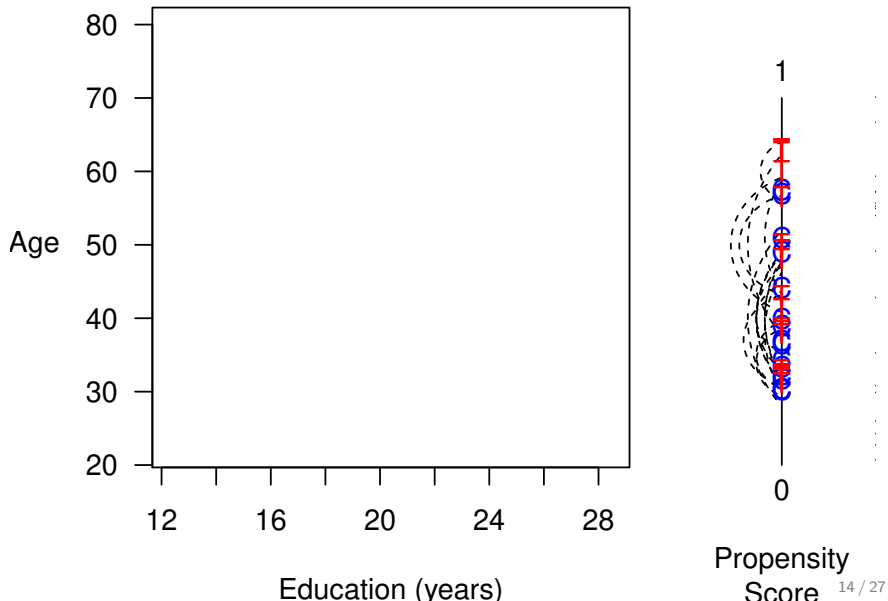
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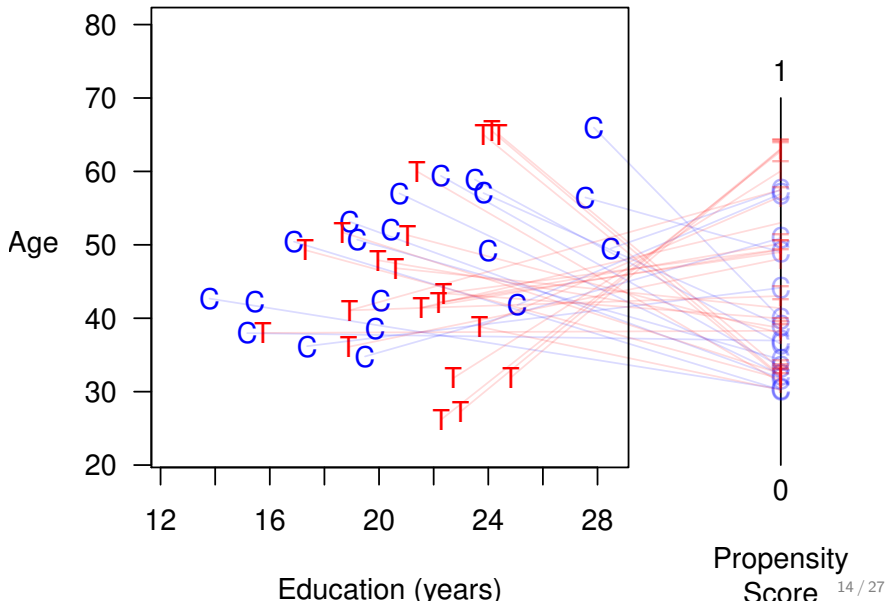
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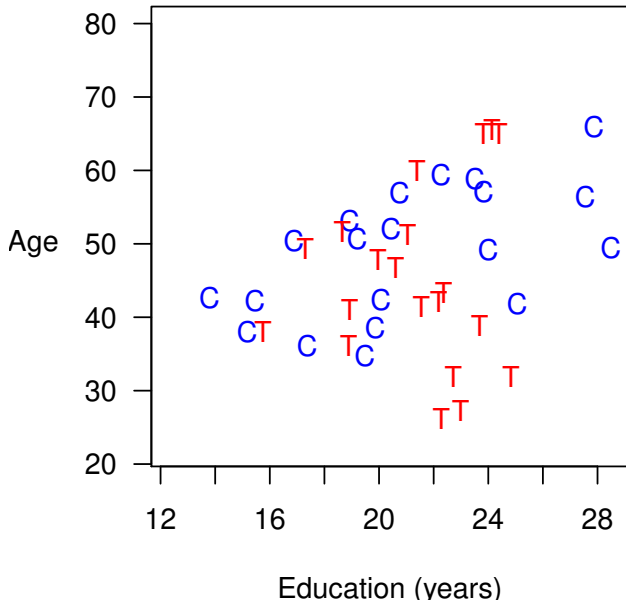
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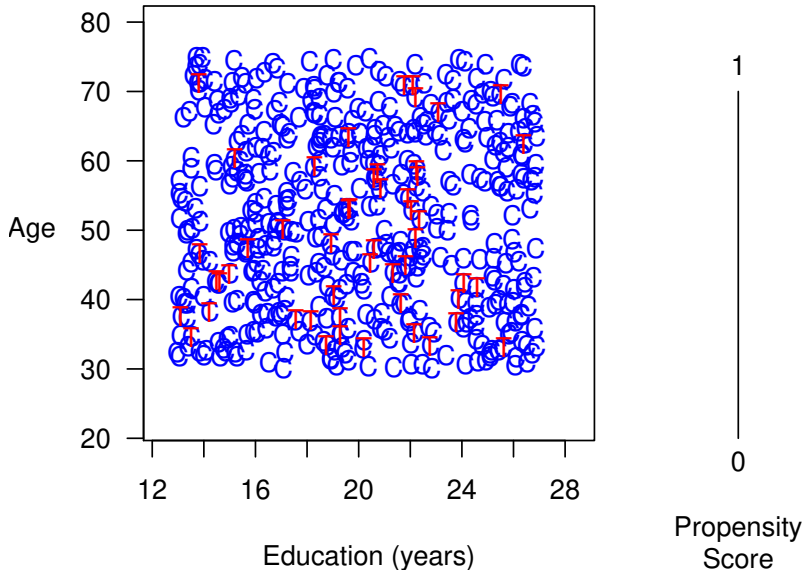


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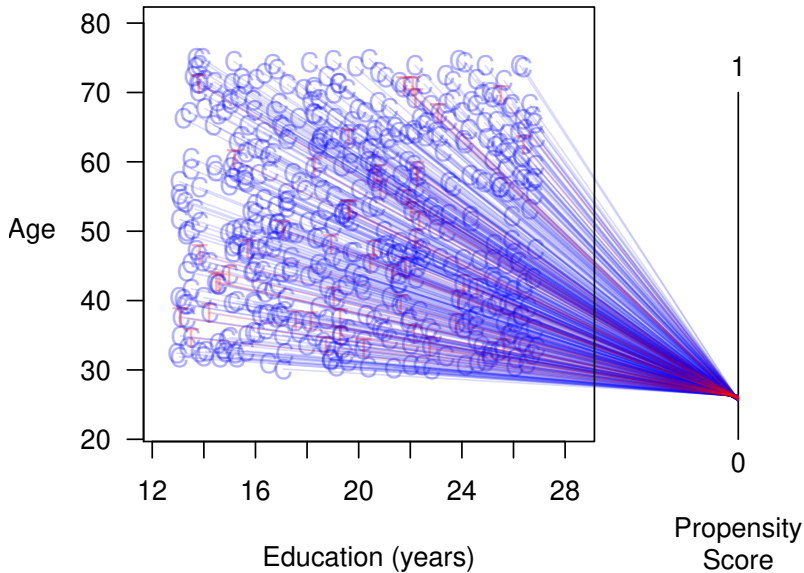


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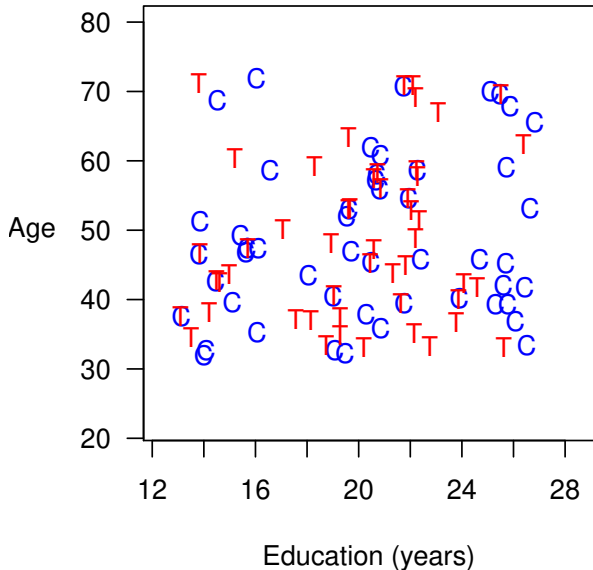
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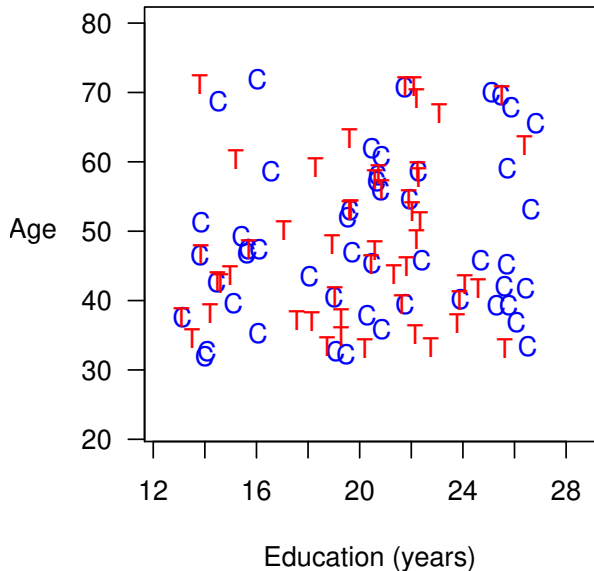
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## Best Case: Propensity Score Matching is Suboptimal



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

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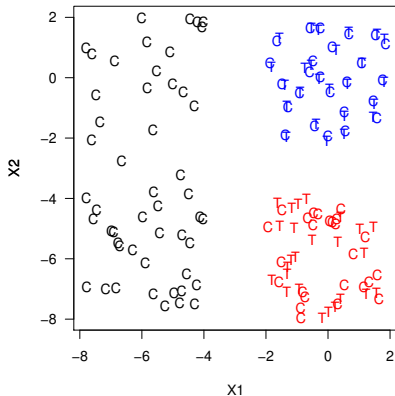
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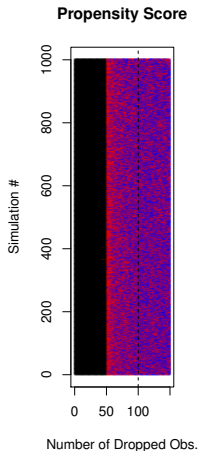
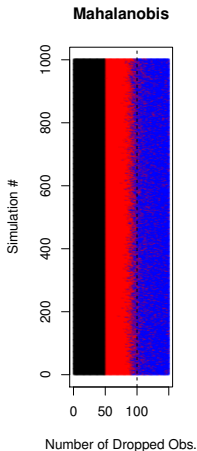
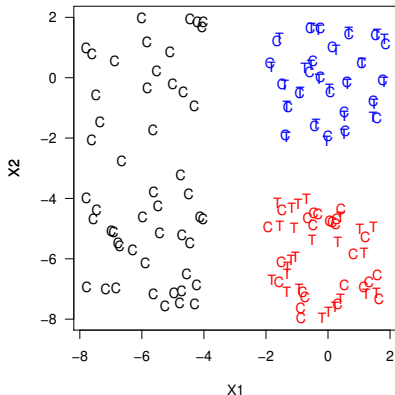
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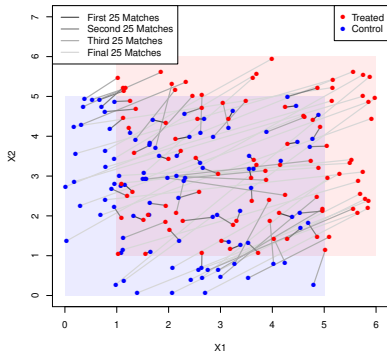


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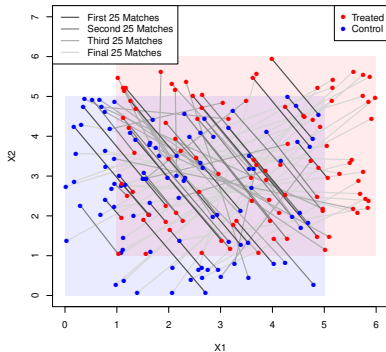


# What Does PSM Match?

## MDM Matches



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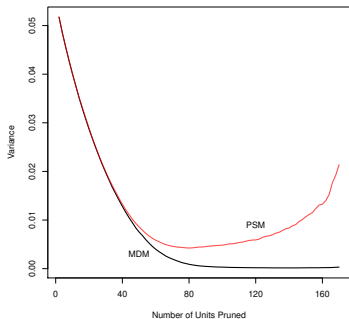


Controls:  $X_1, X_2 \sim \text{Uniform}(0,5)$

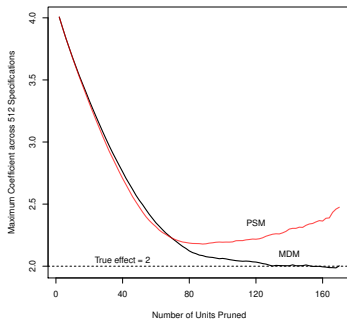
Treateds:  $X_1, X_2 \sim \text{Uniform}(1,6)$

# PSM Increases Model Dependence & Bias

## Model Dependence



## Bias

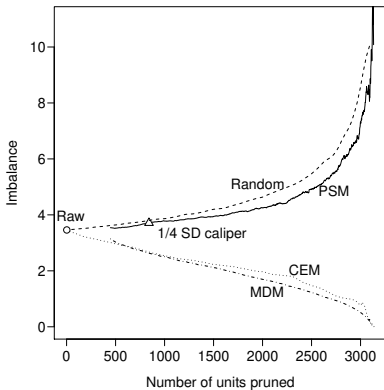


$$Y_i = 2T_i + X_{1i} + X_{2i} + \epsilon_i$$
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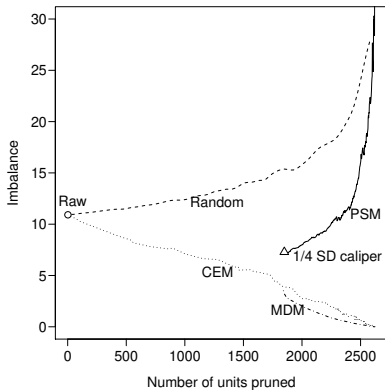
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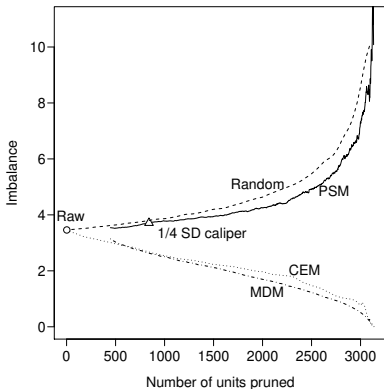


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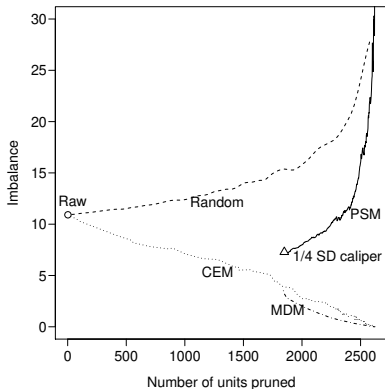


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Similar pattern for > 20 other real data sets we checked

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- Choose an imbalance metric, then run.

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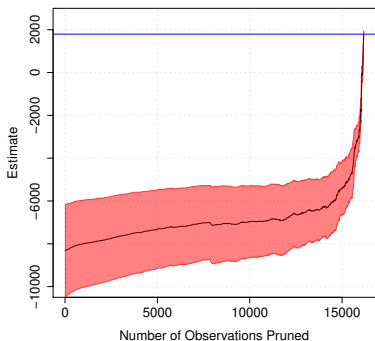
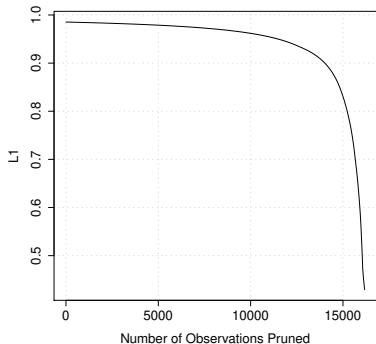
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## Job Training Data: Frontier and Causal Estimates



- 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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