Simplifying Matching Methods for Causal Inference

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Boston College, 9/24/2019

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3 Problems, 3 Solutions

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Matching to Reduce Model Dependence

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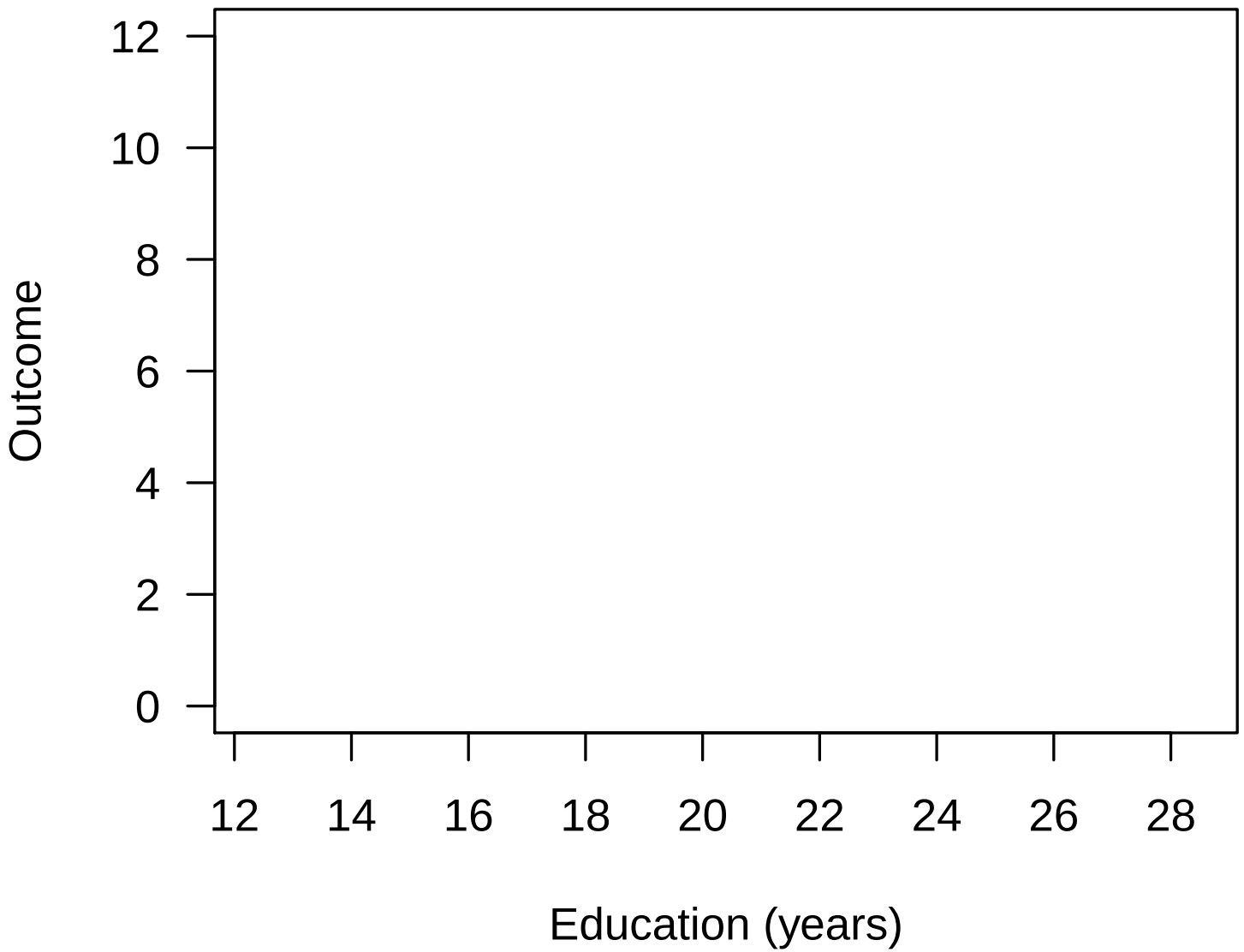

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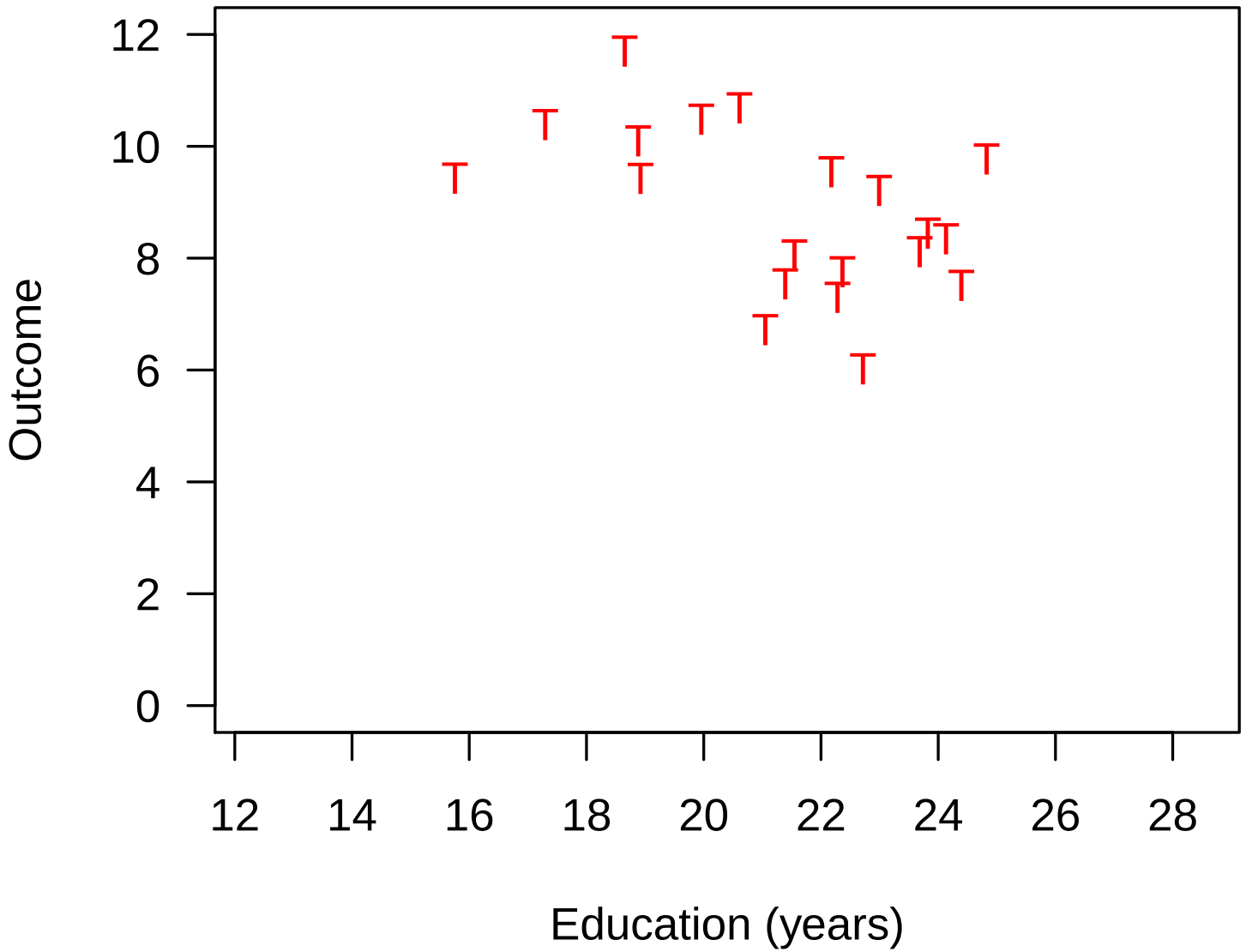

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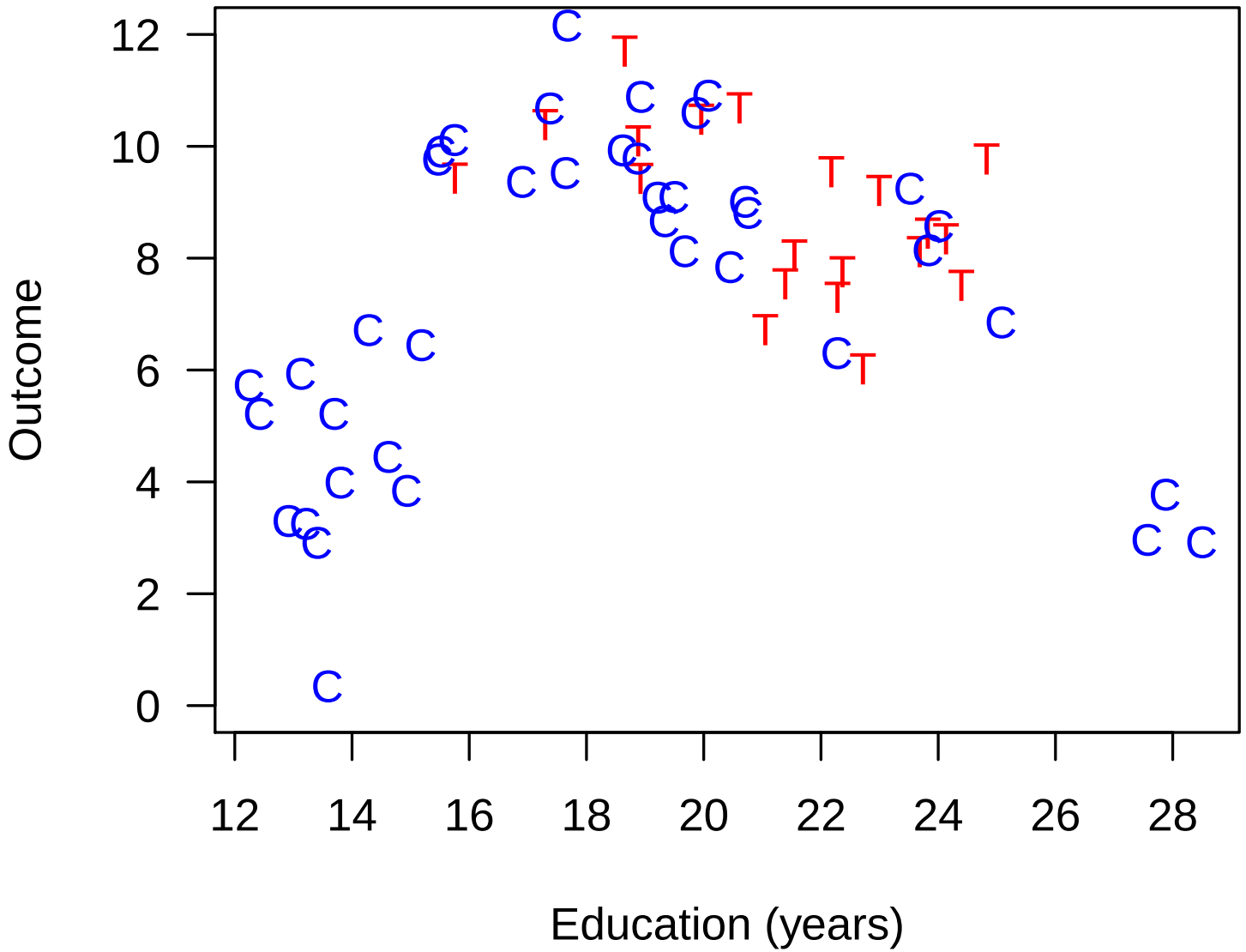

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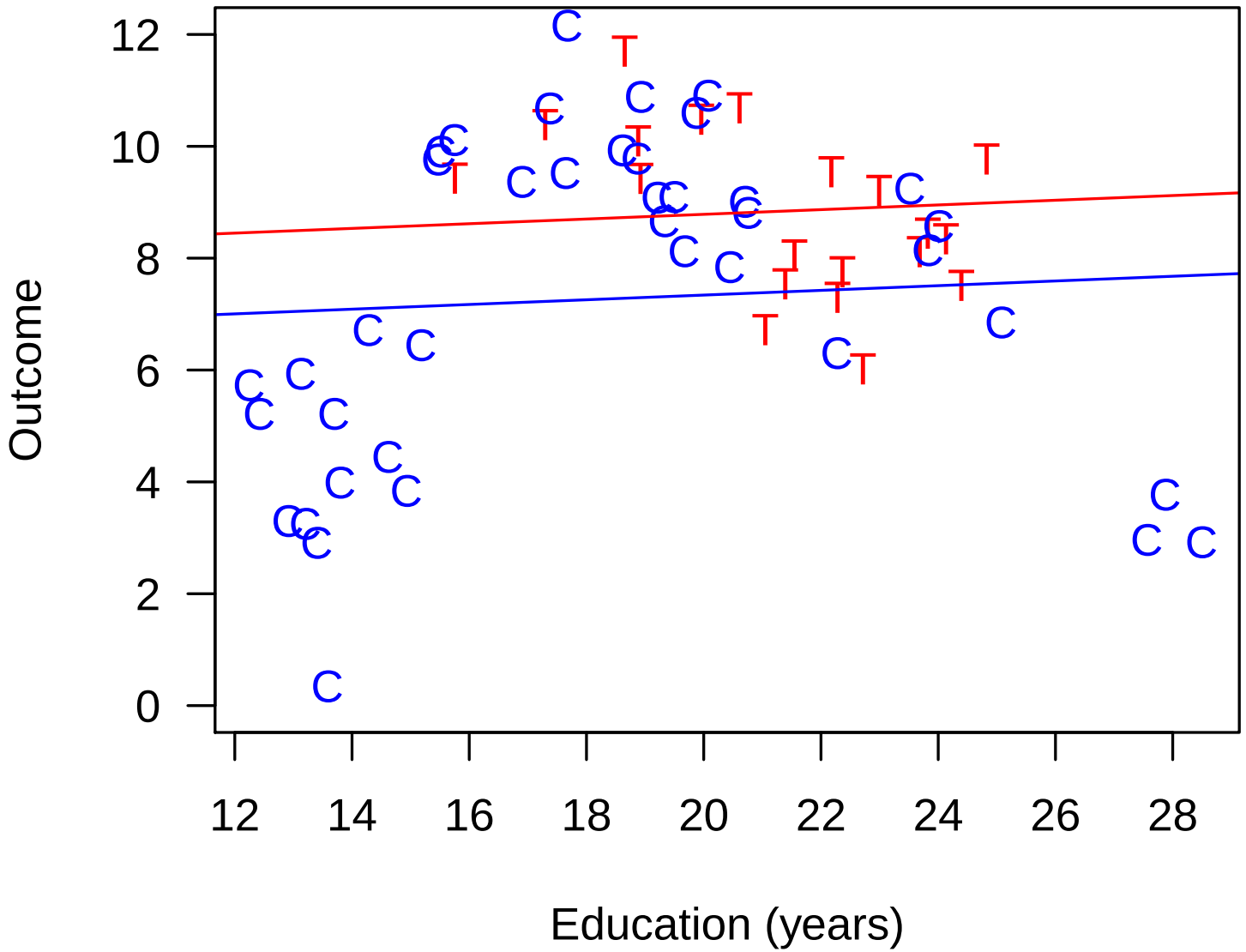

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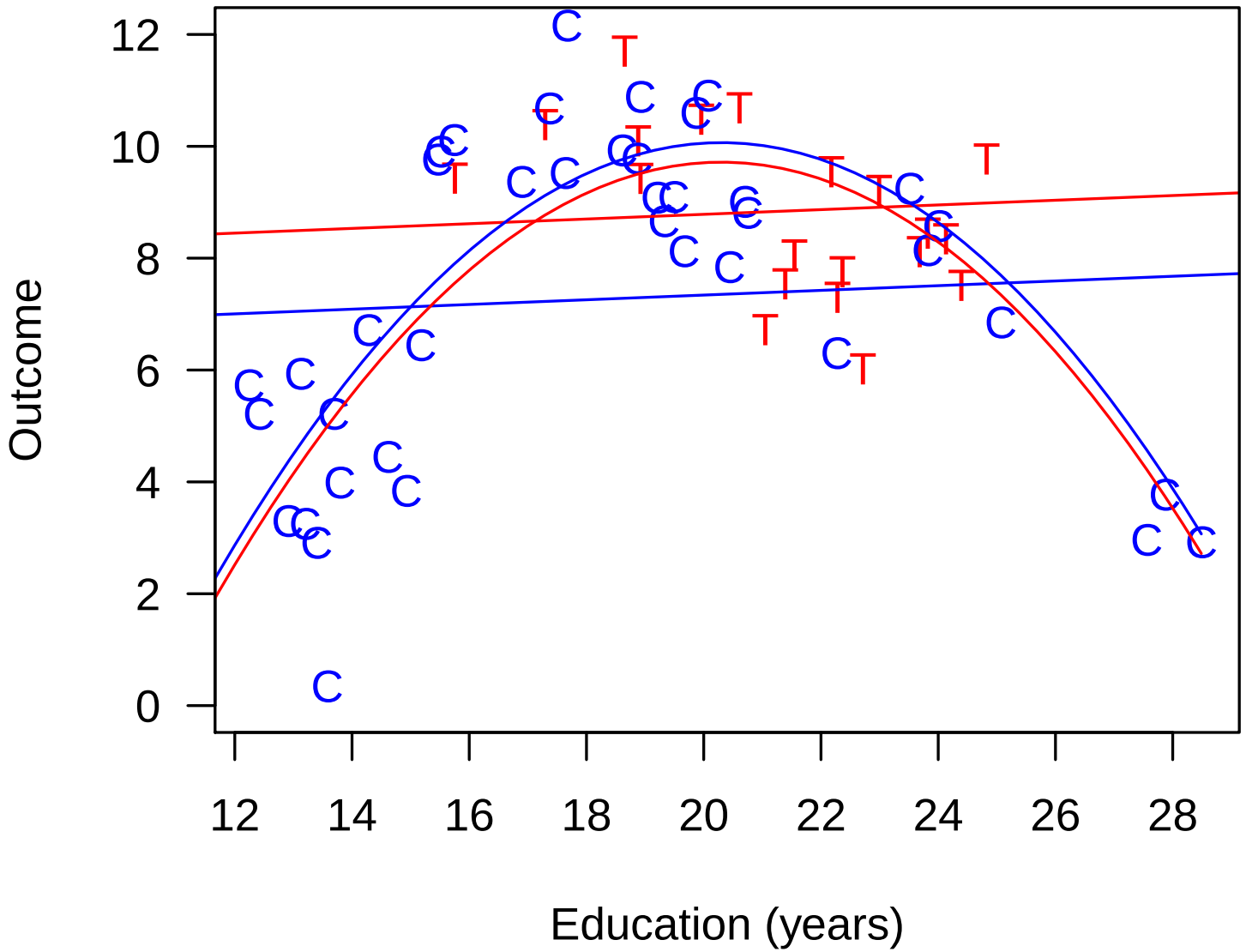

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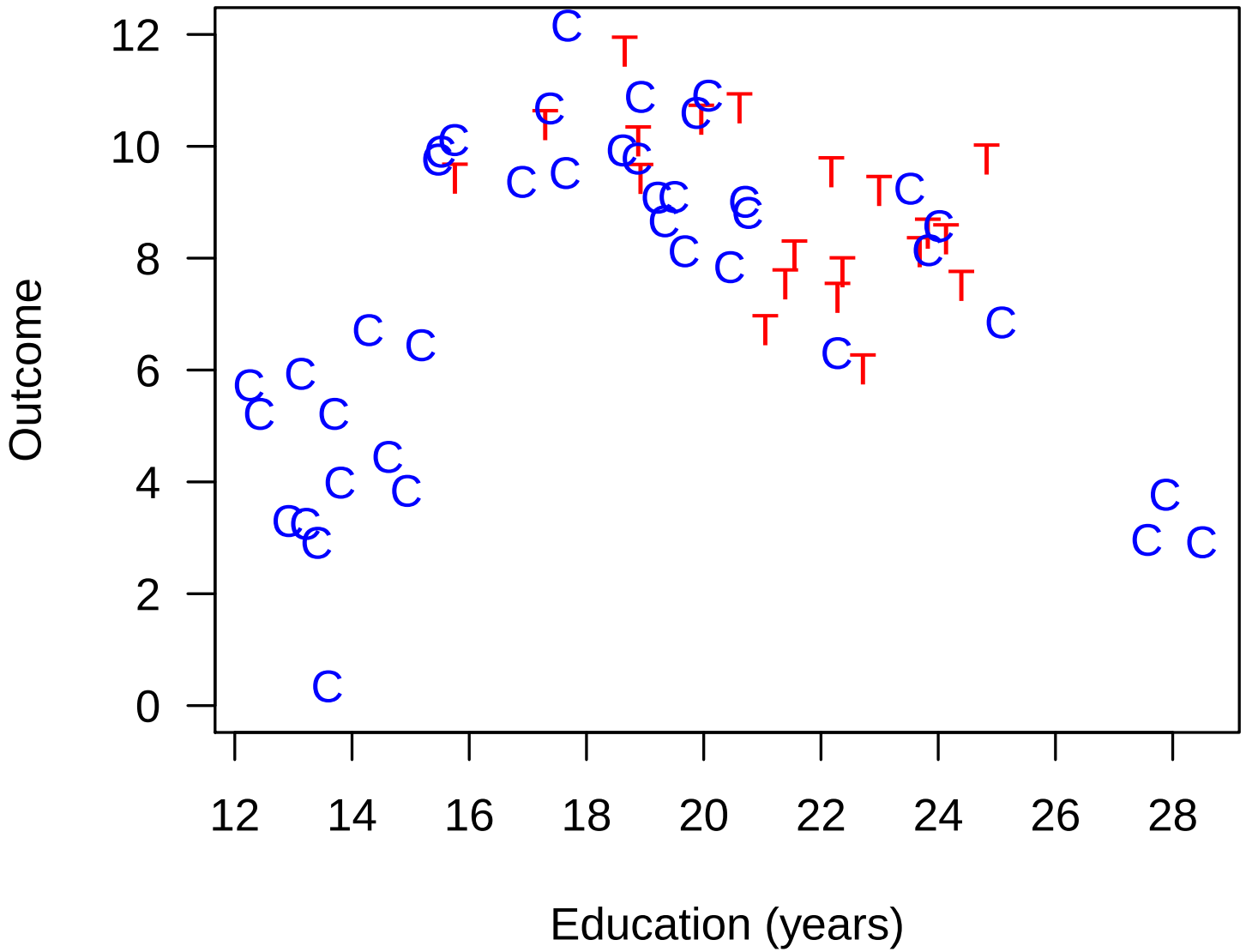

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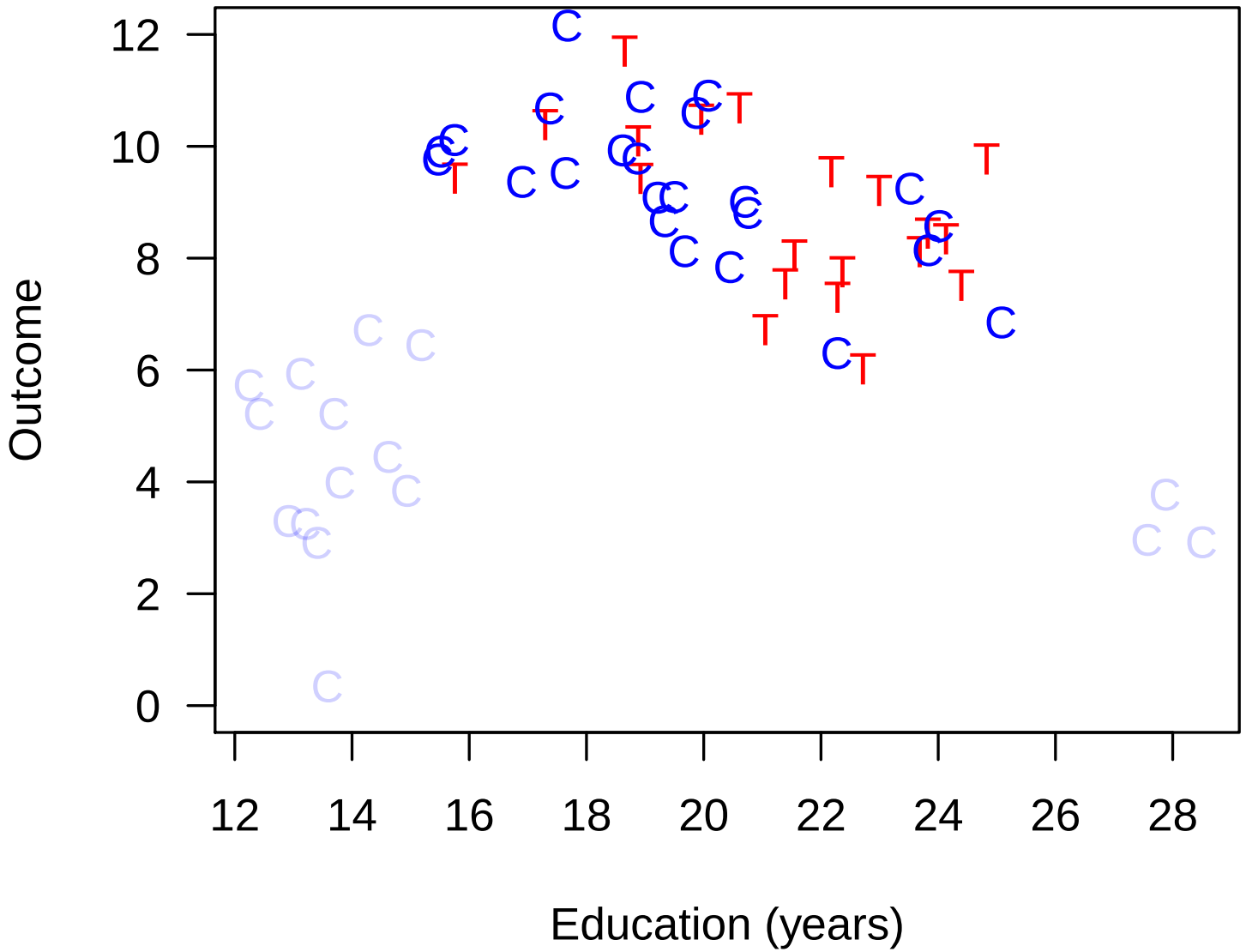

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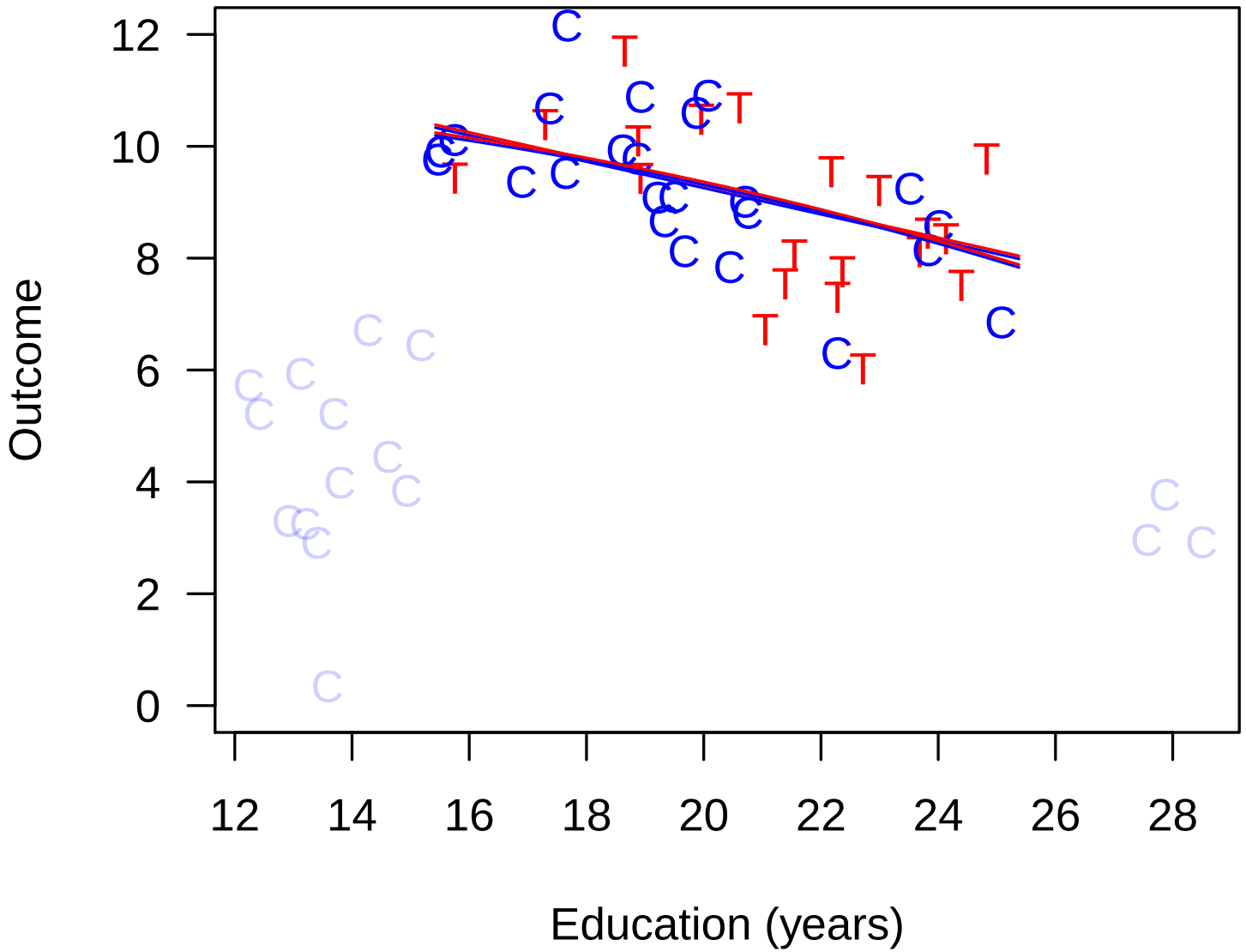

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- "Teaching psychology is mostly a waste of time" (Kahneman 2011)

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

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   - (Many adjustments available to this basic method)
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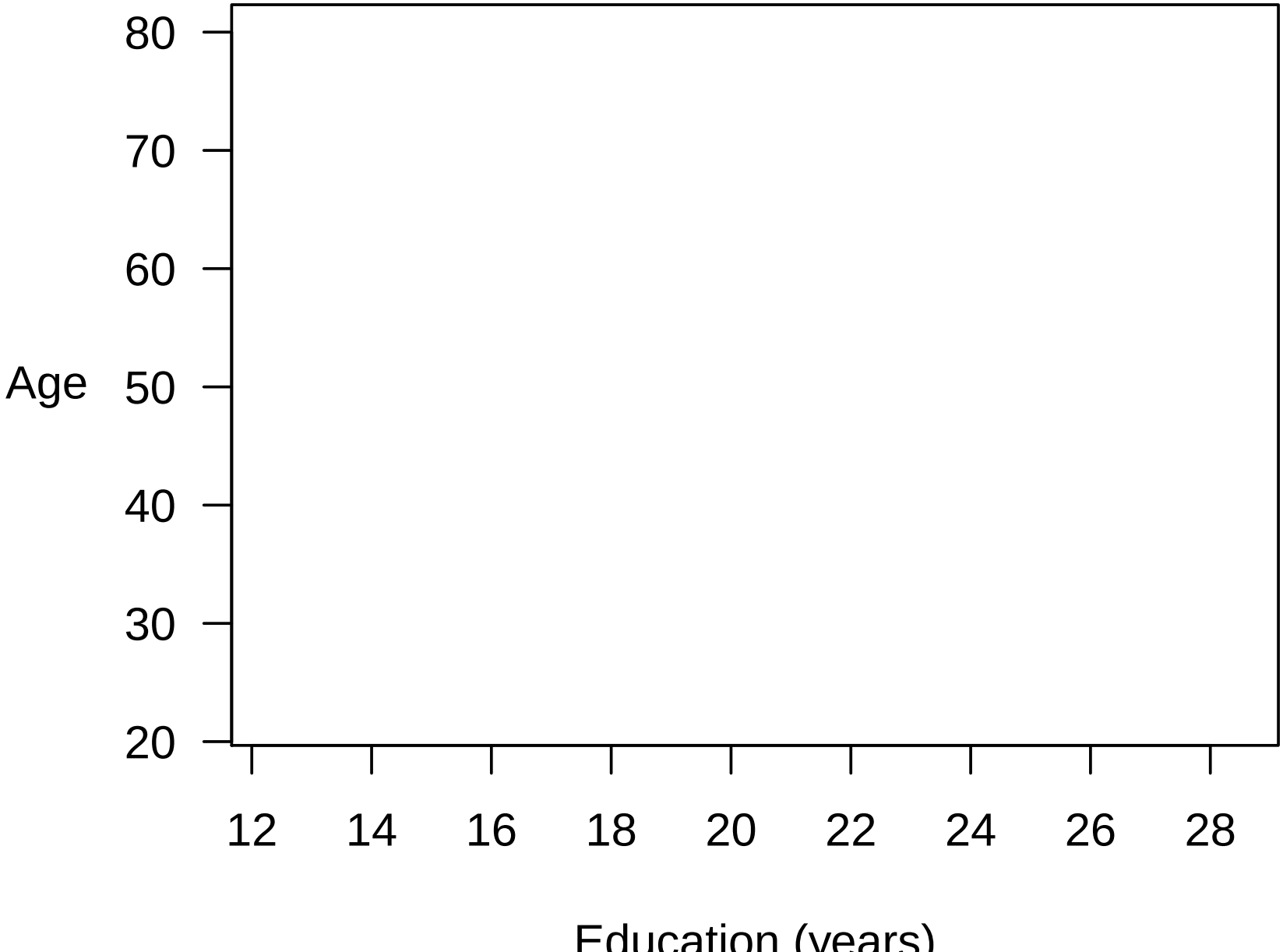

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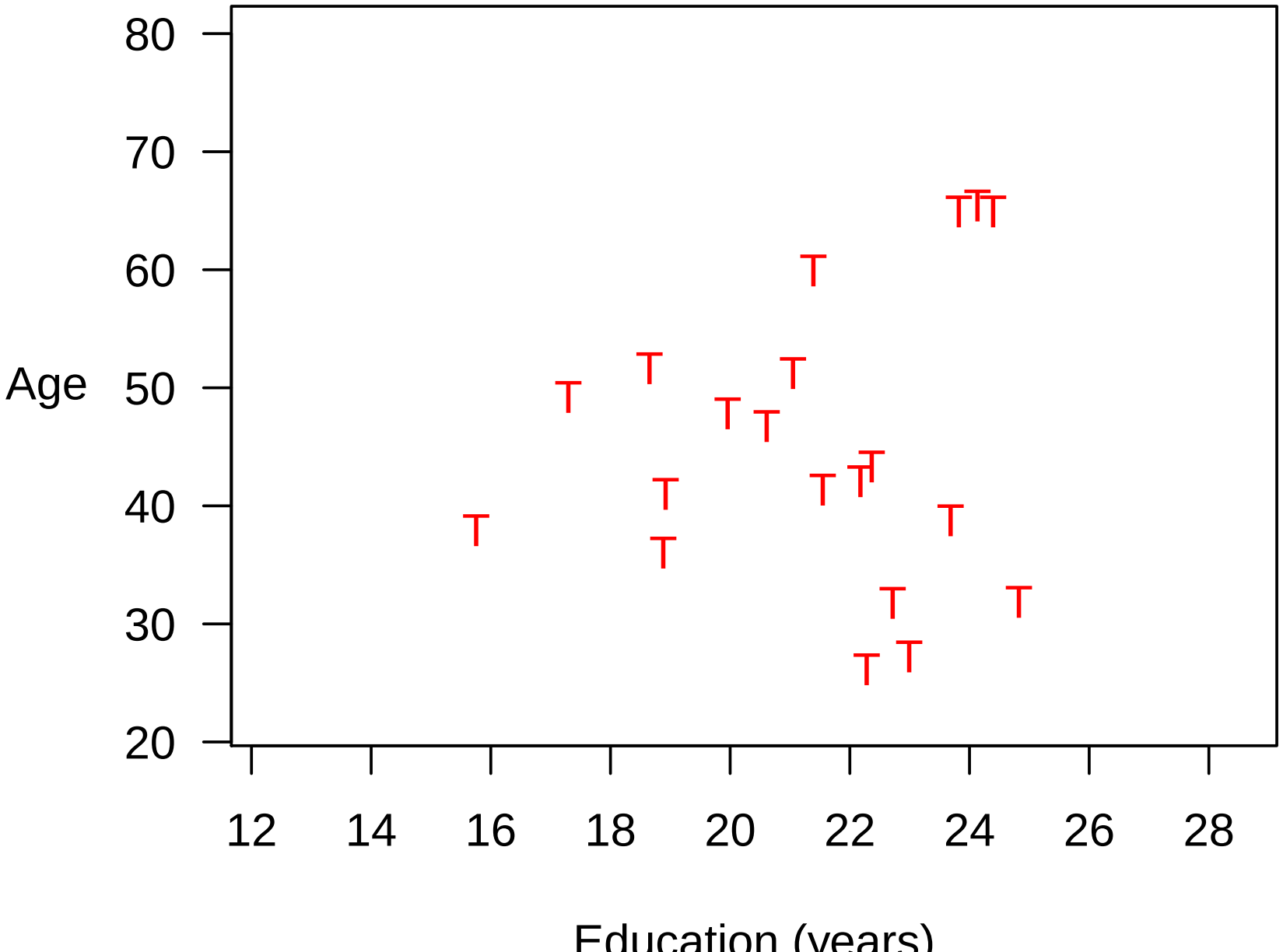

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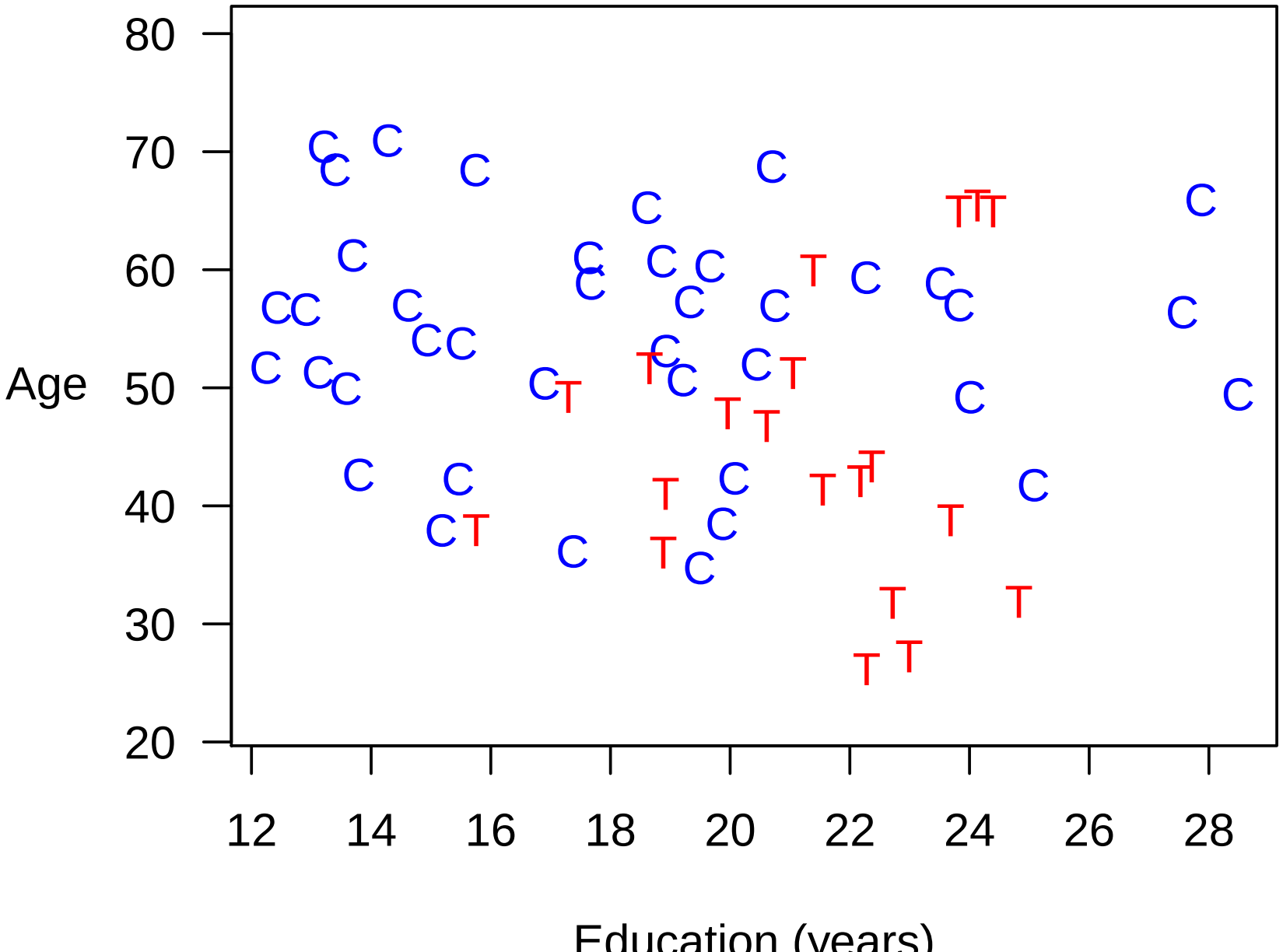

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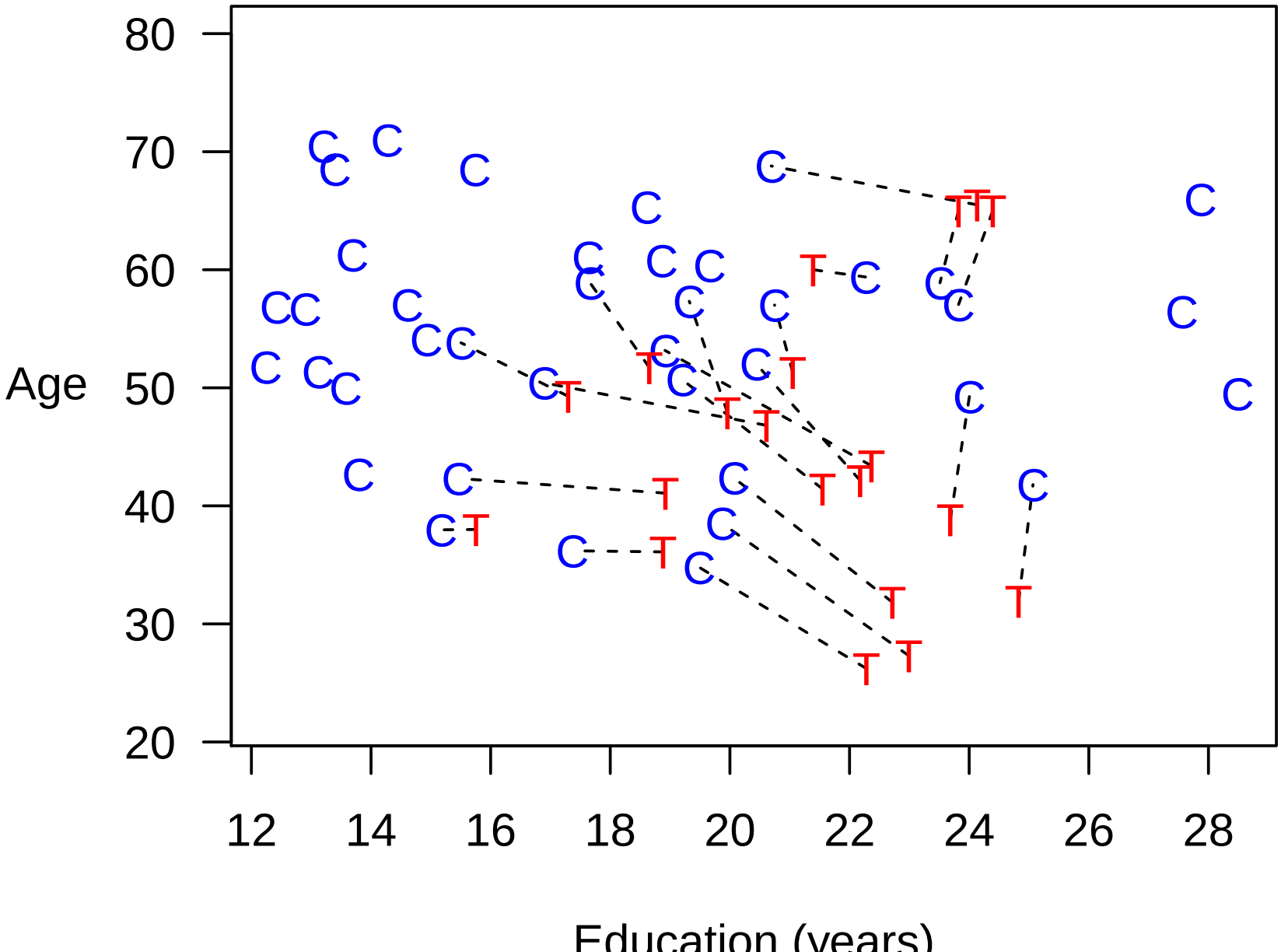

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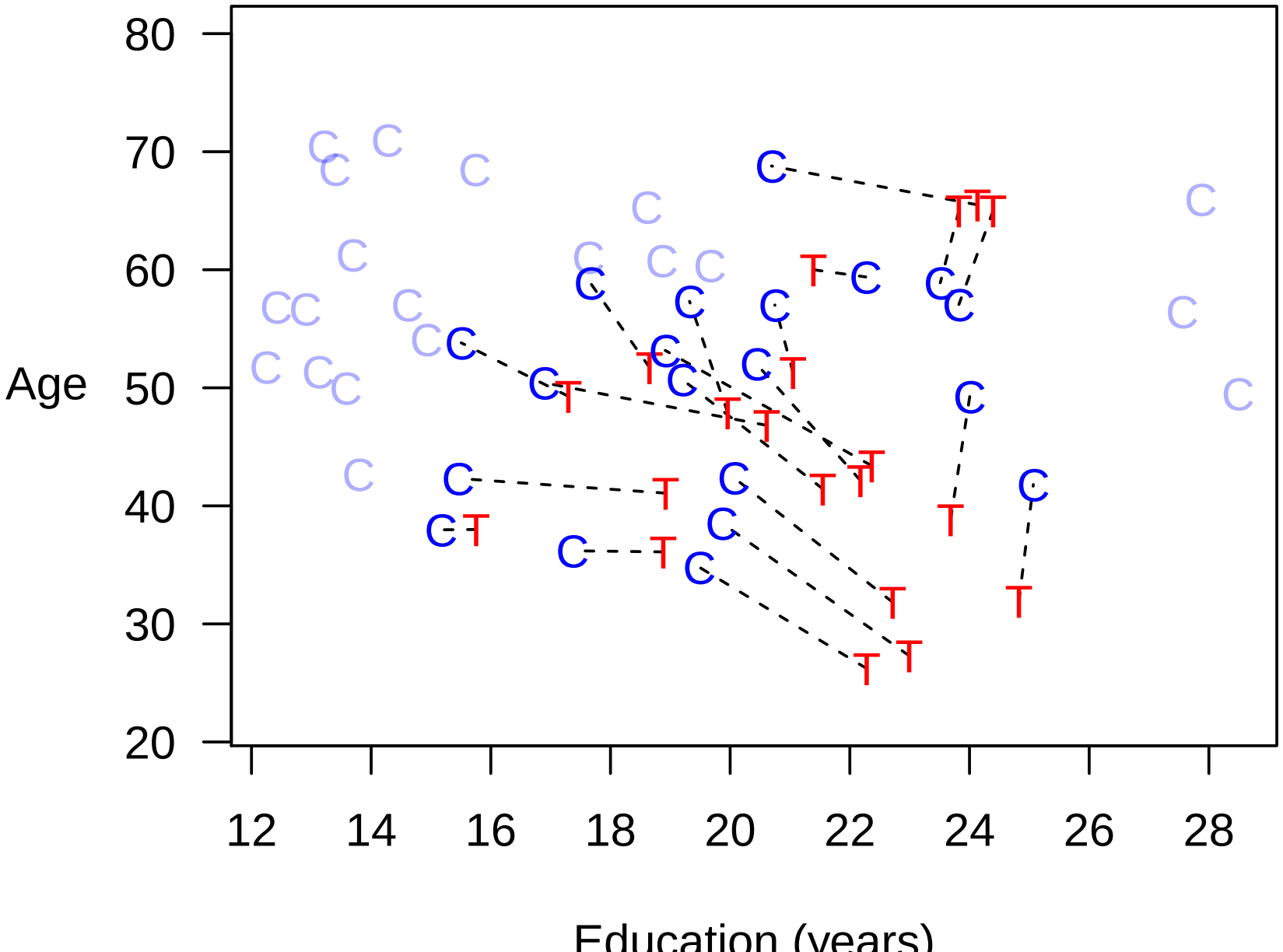

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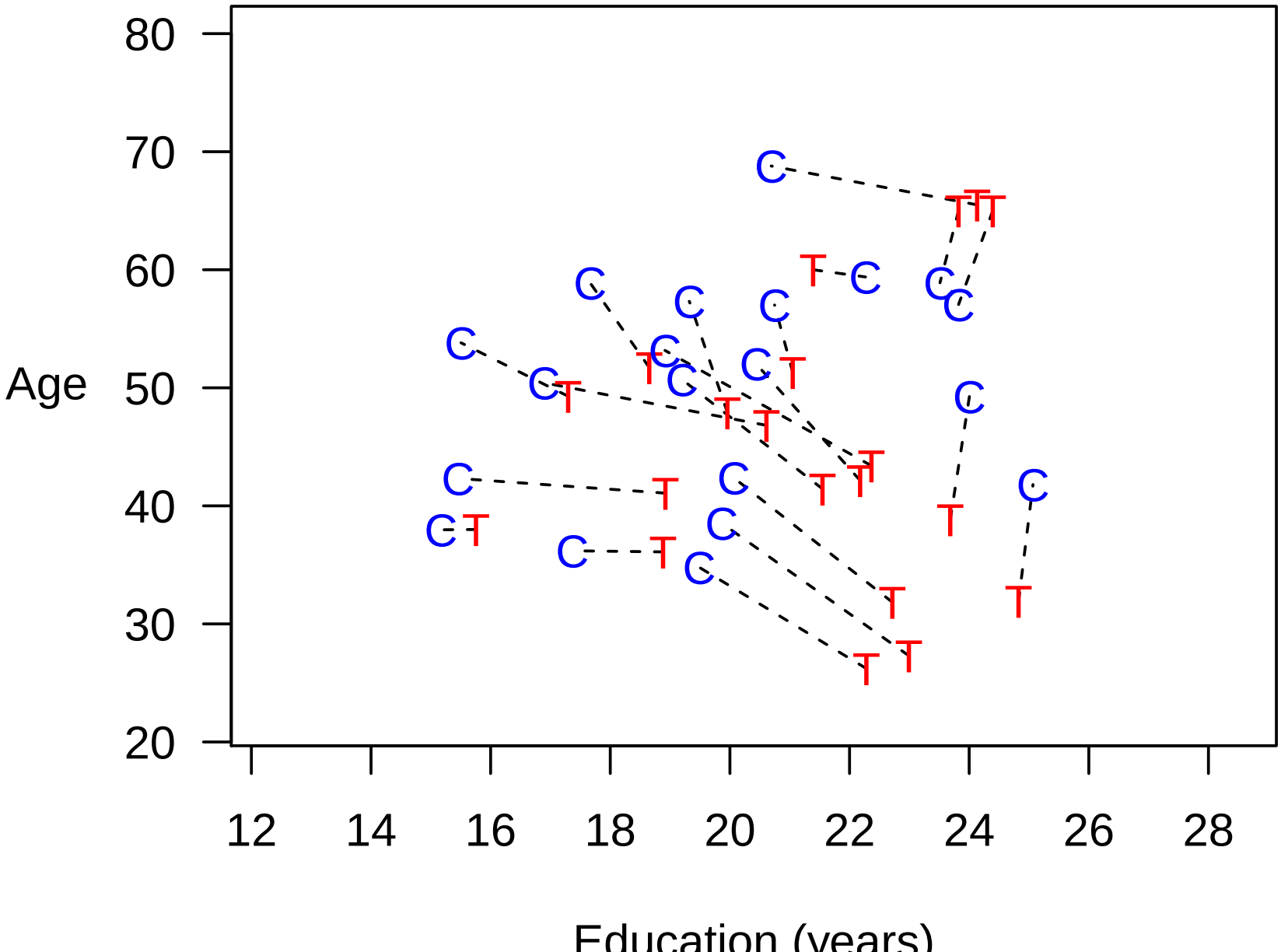

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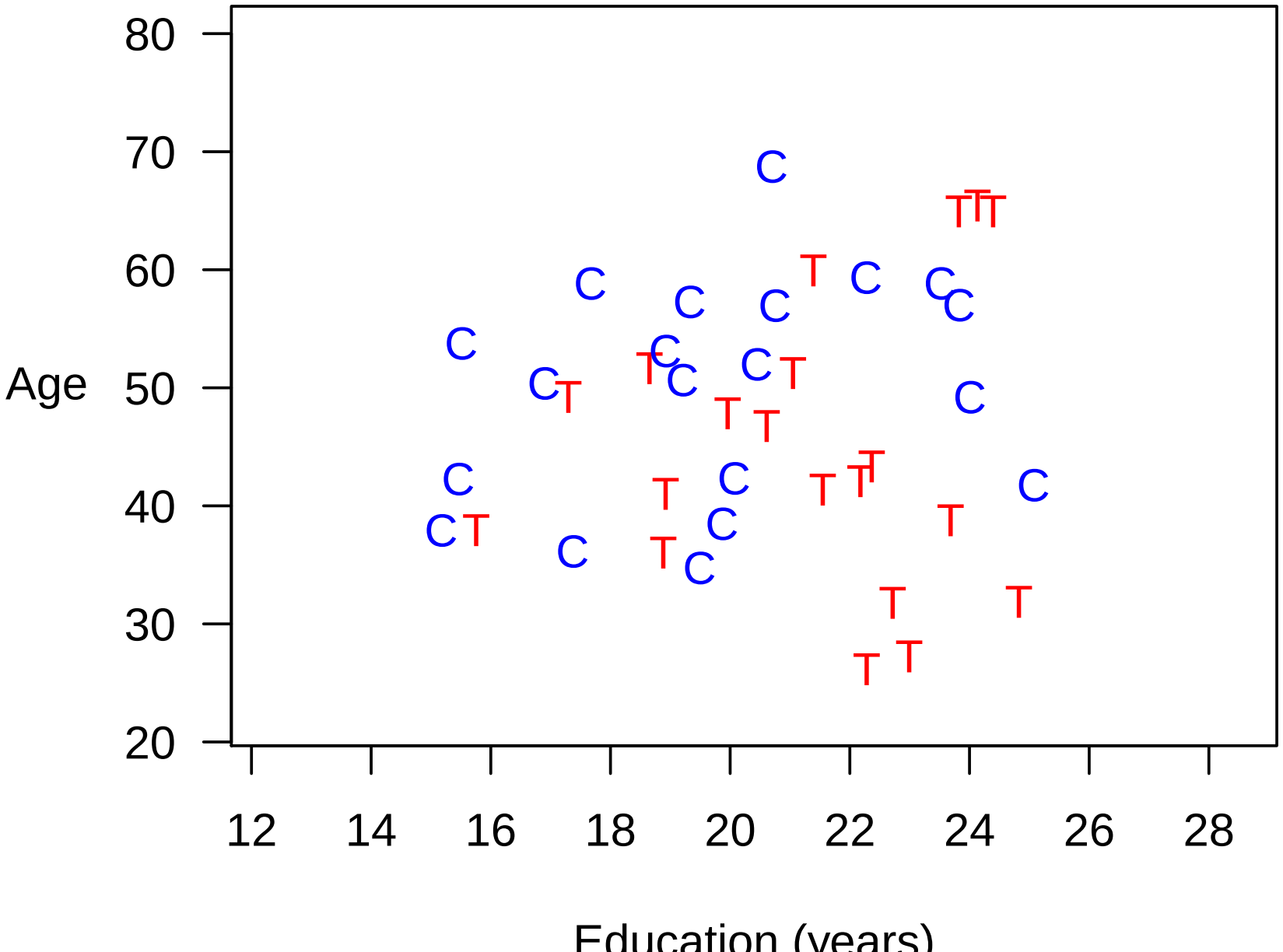

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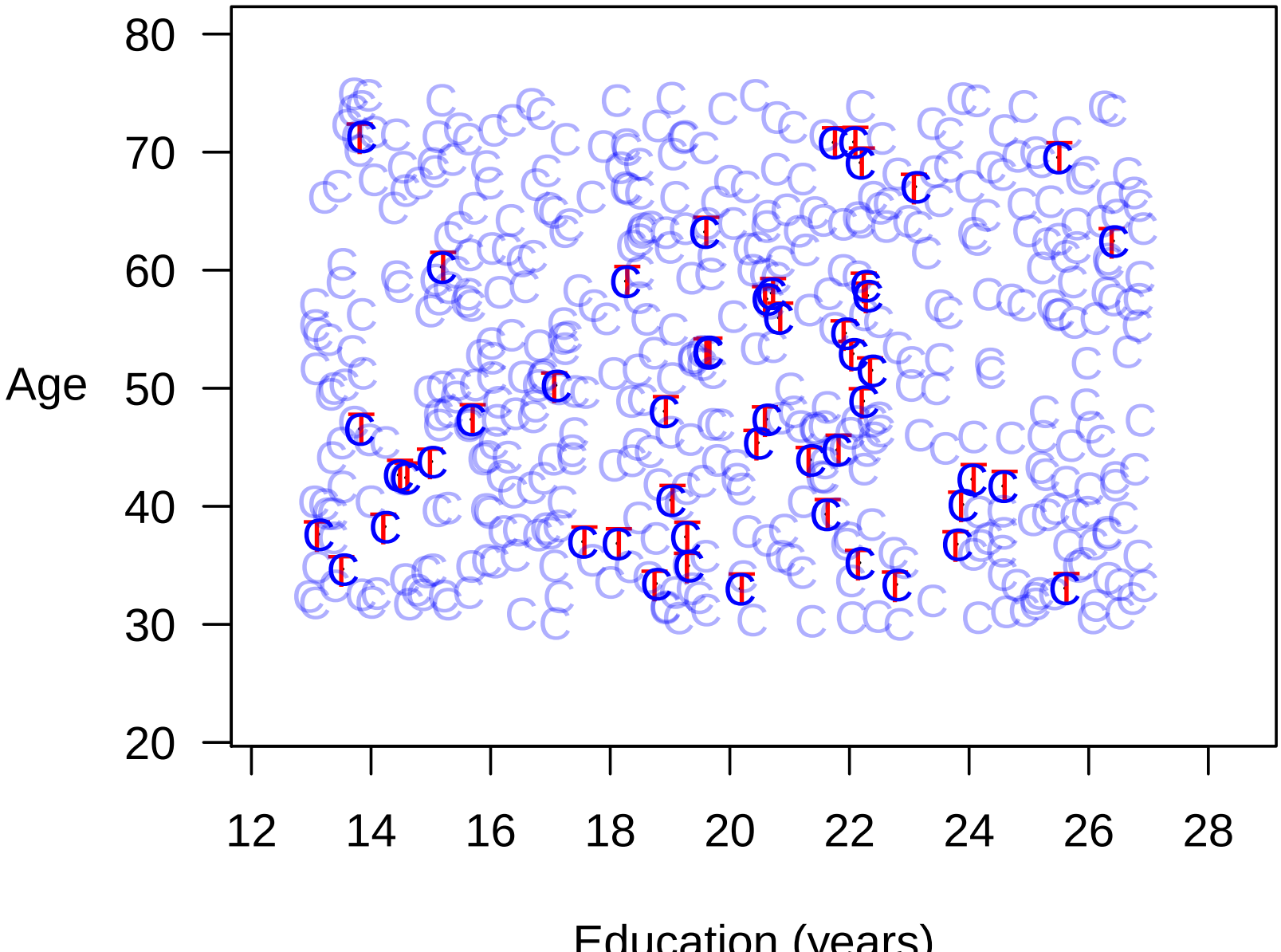

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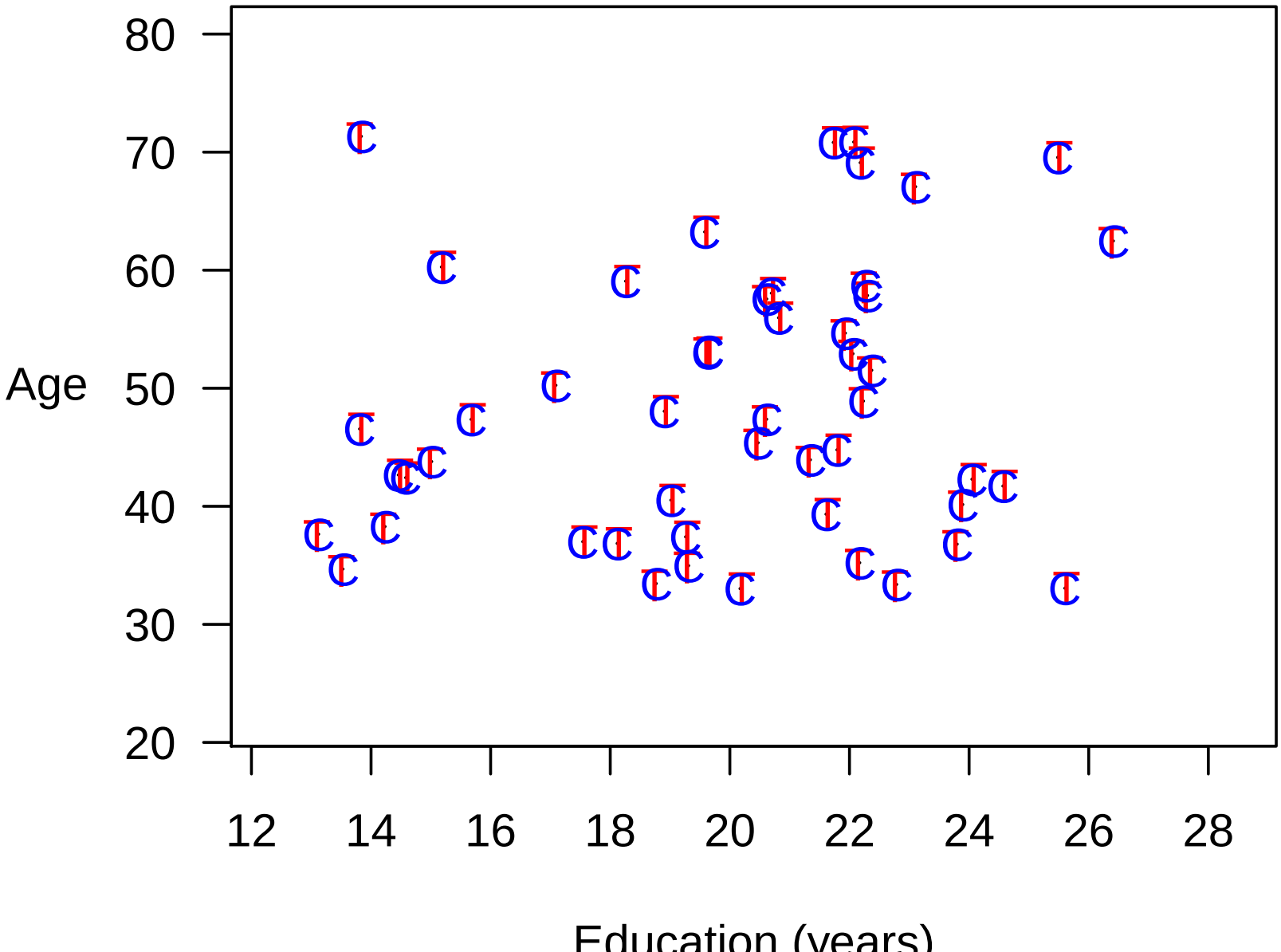

Method 2: Coarsened Exact Matching (Most powerful easy-to-use approach)

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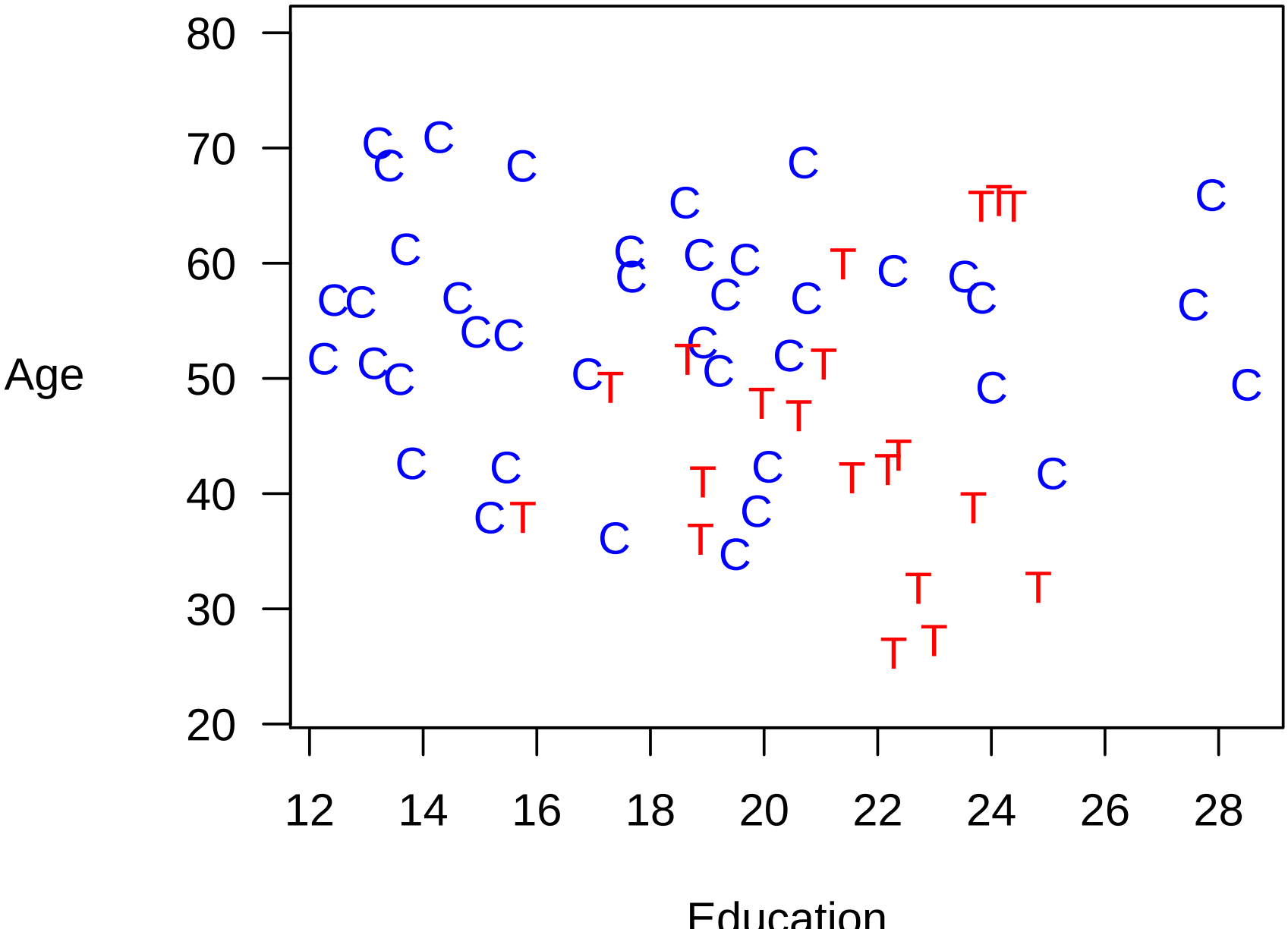

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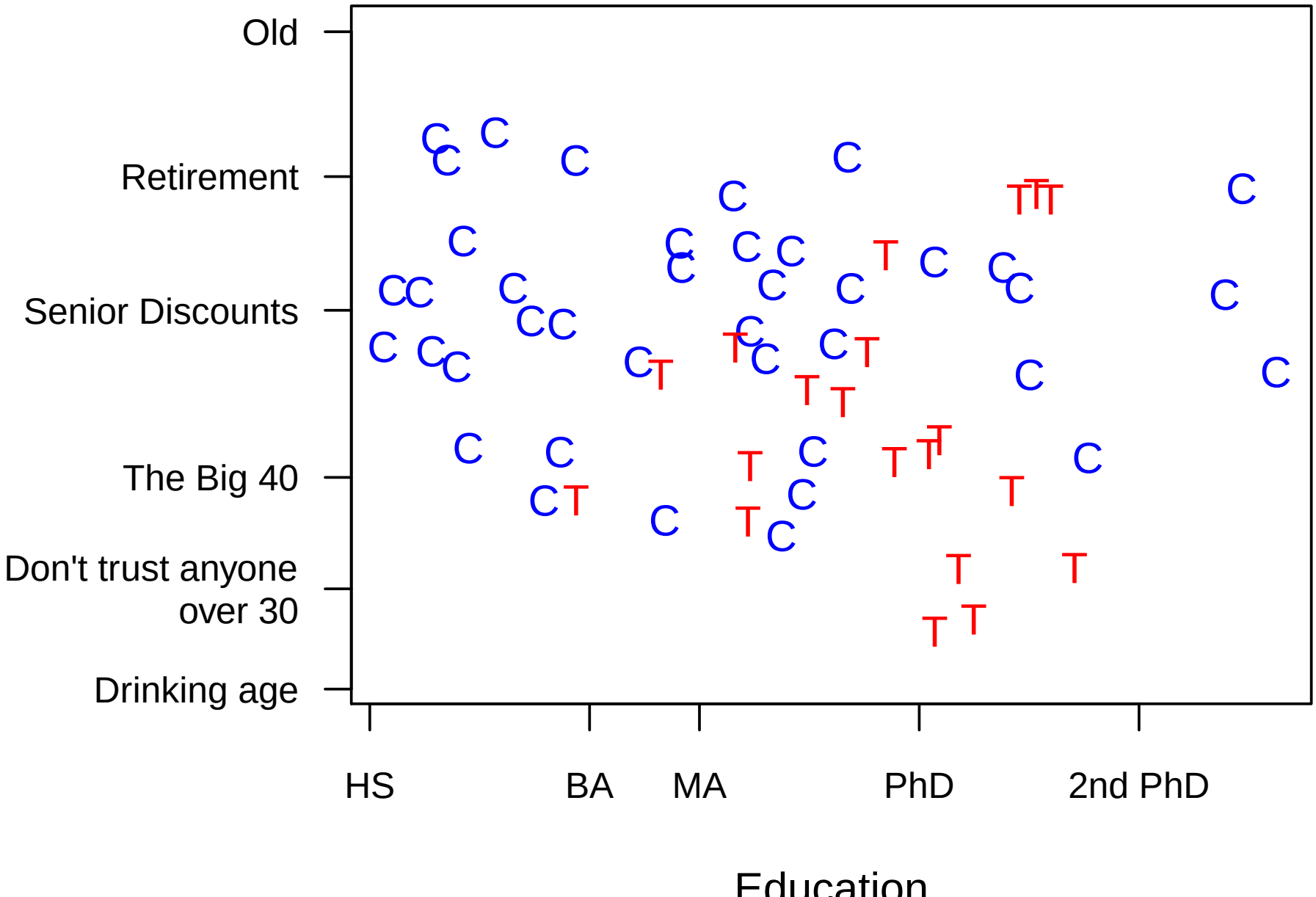

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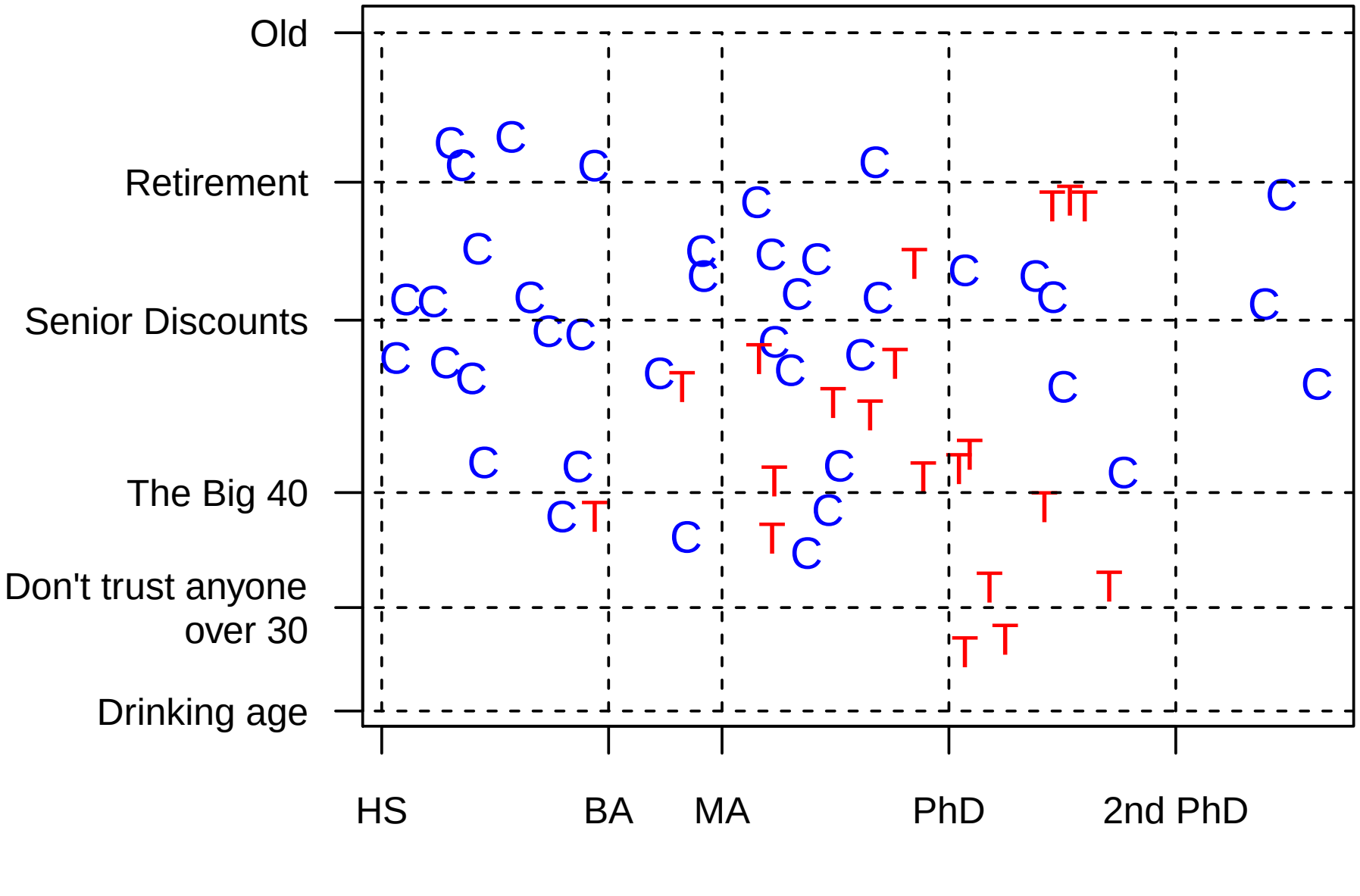

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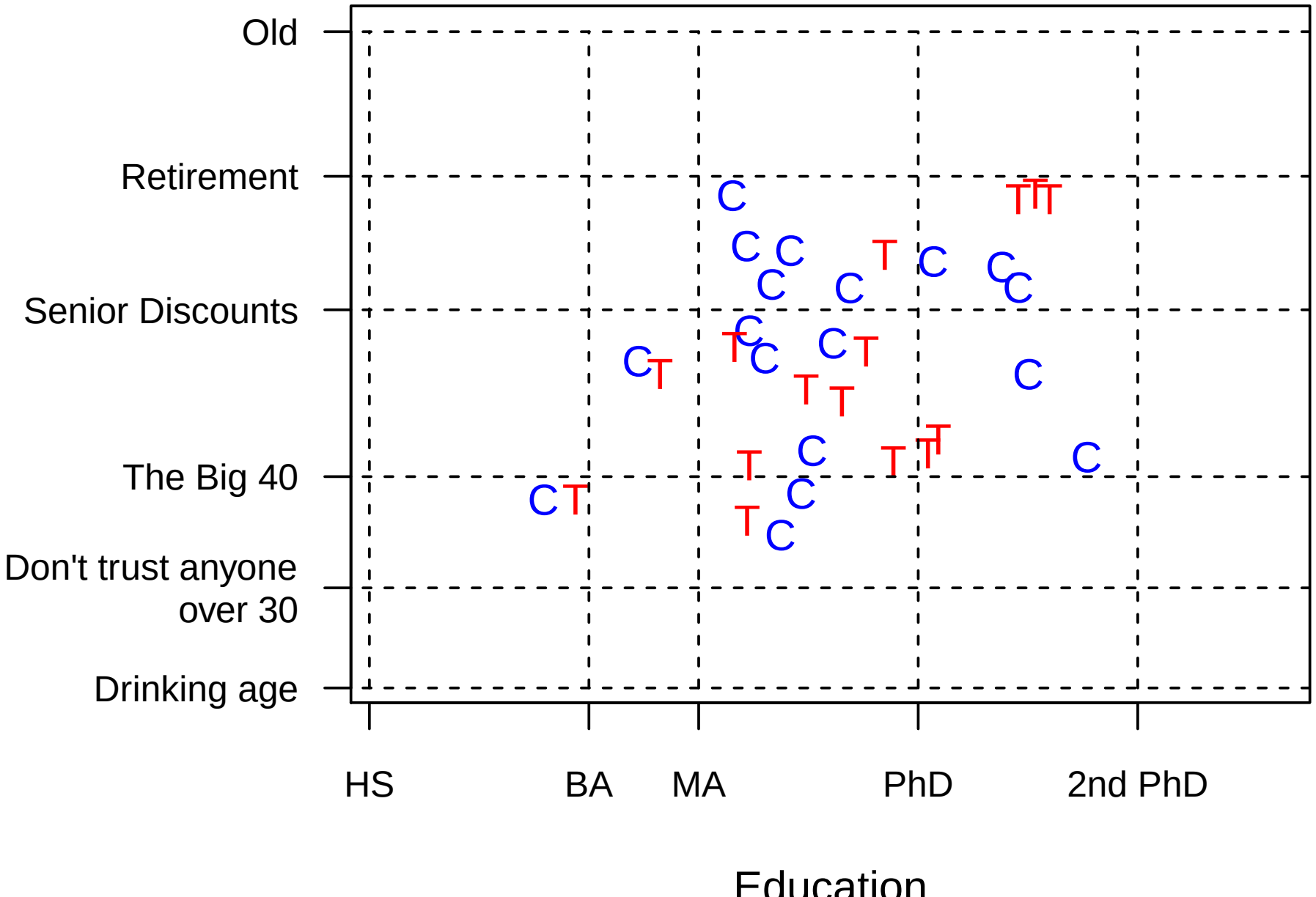

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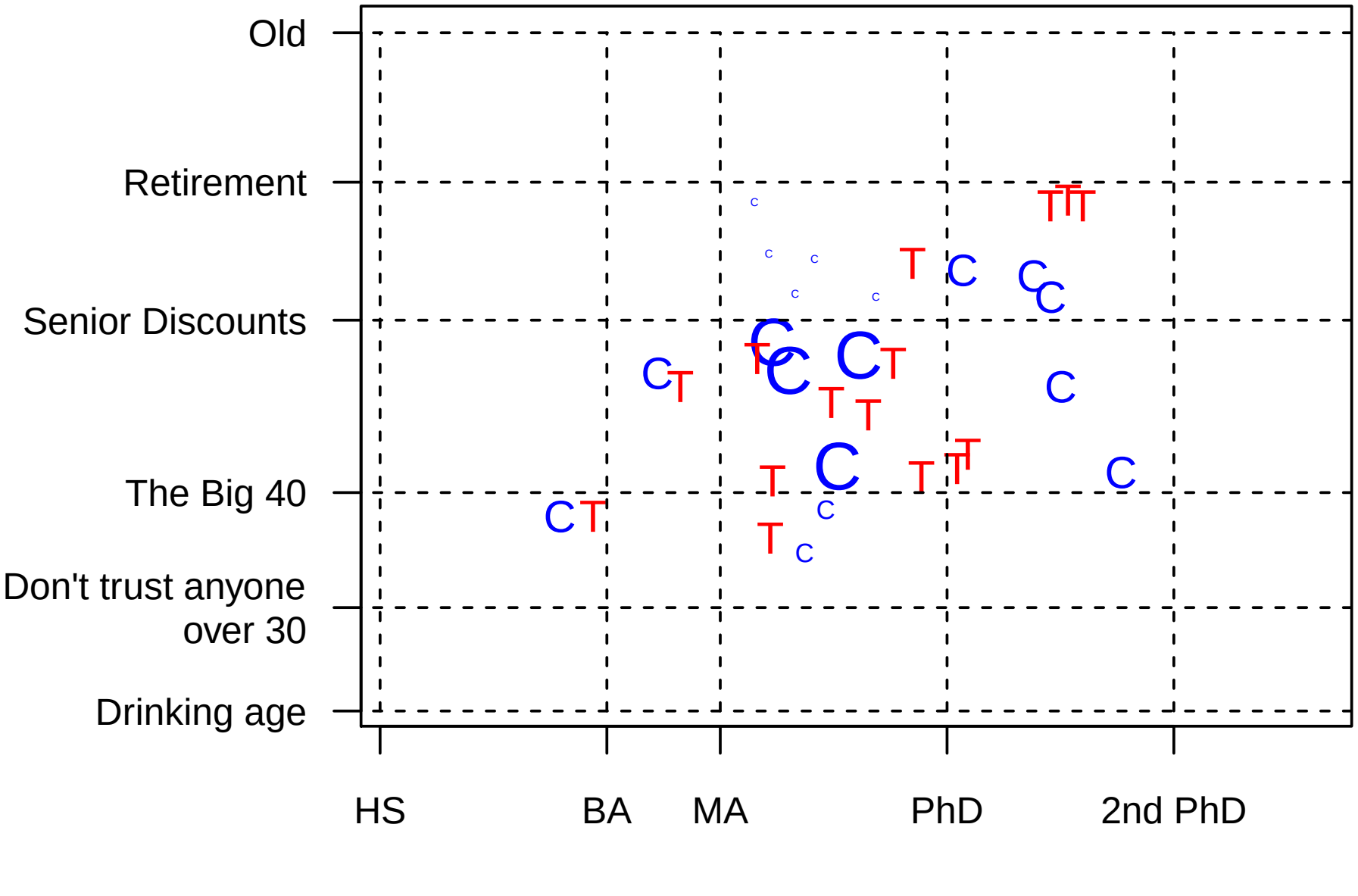

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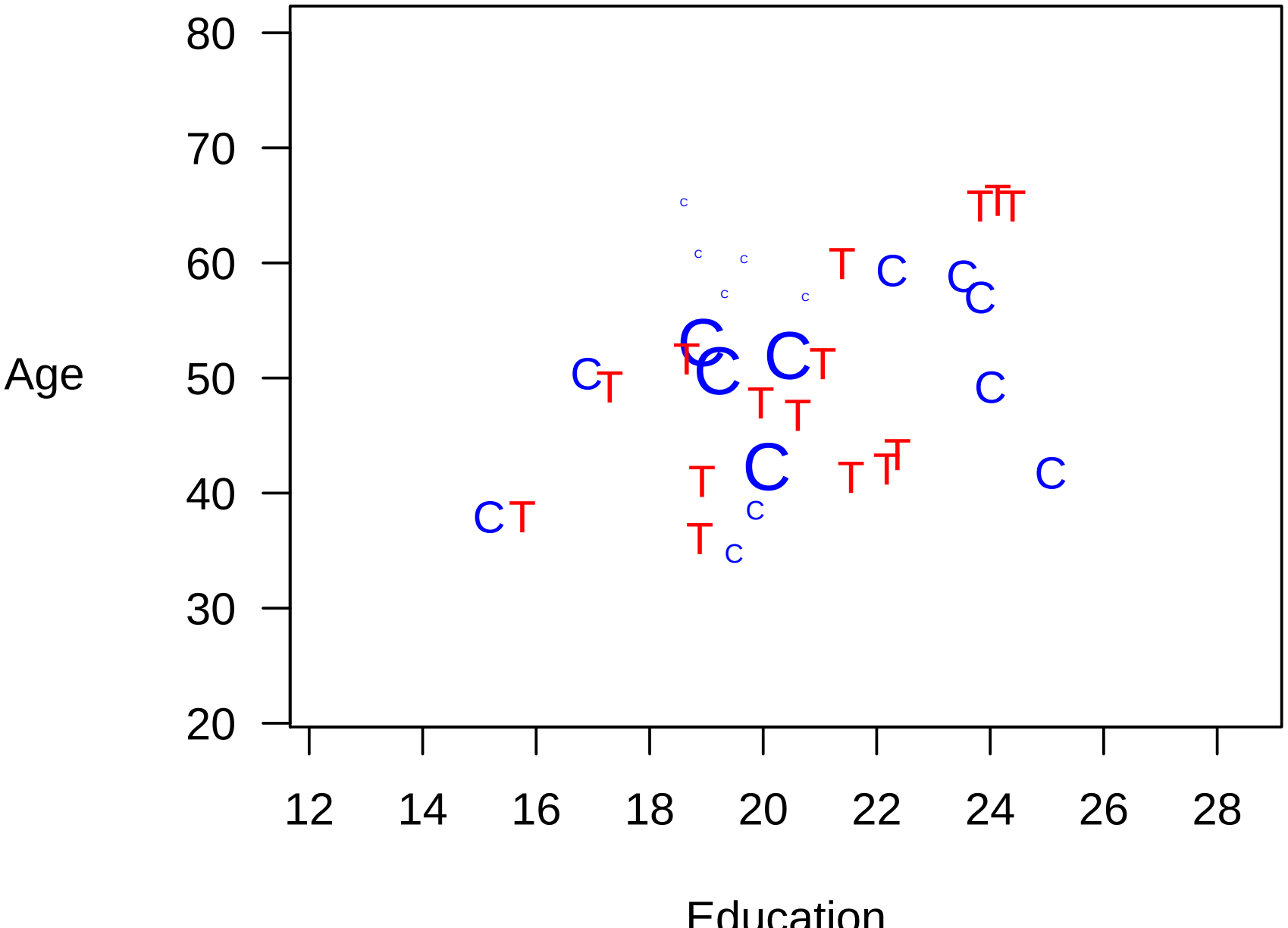

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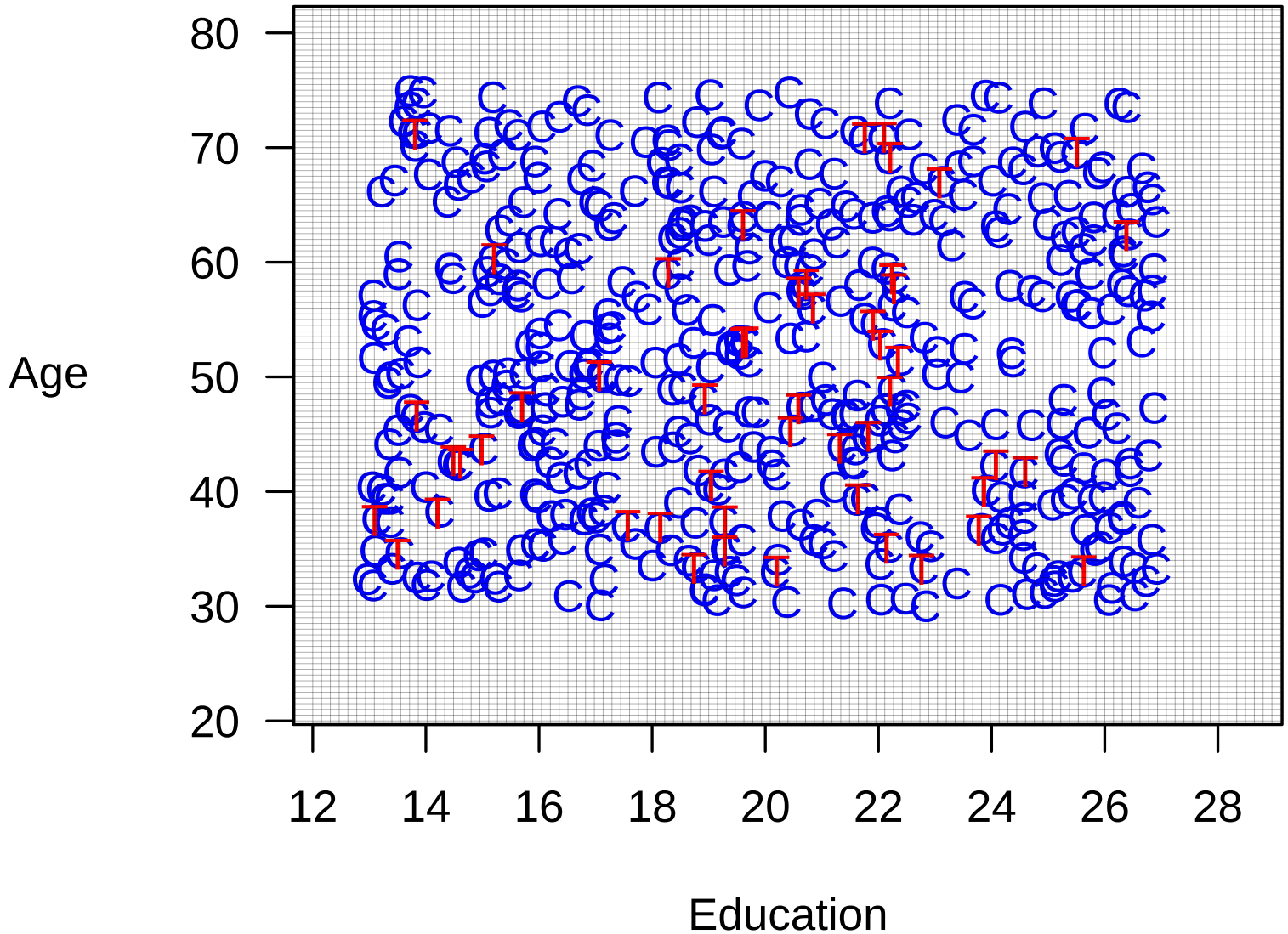

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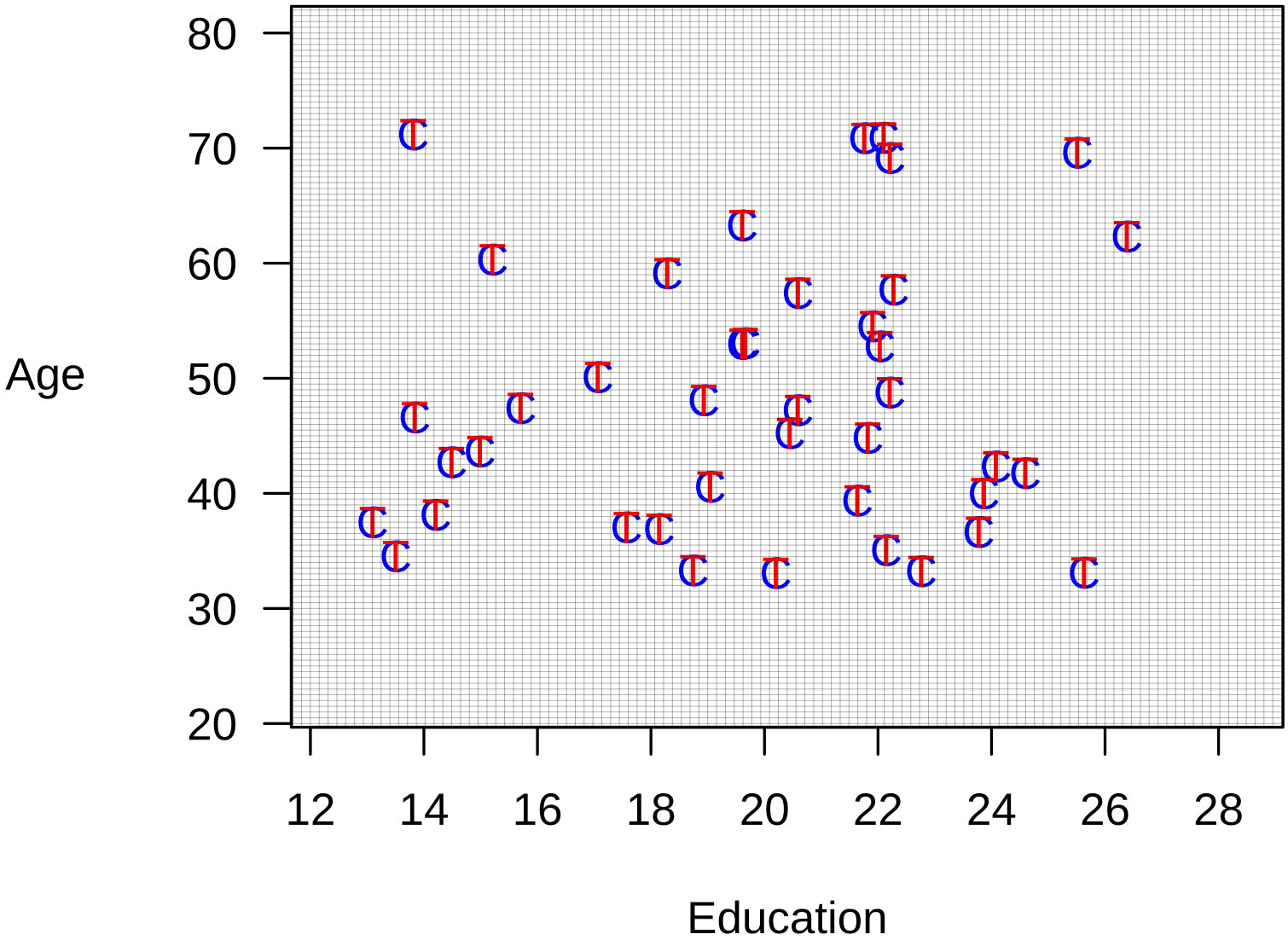

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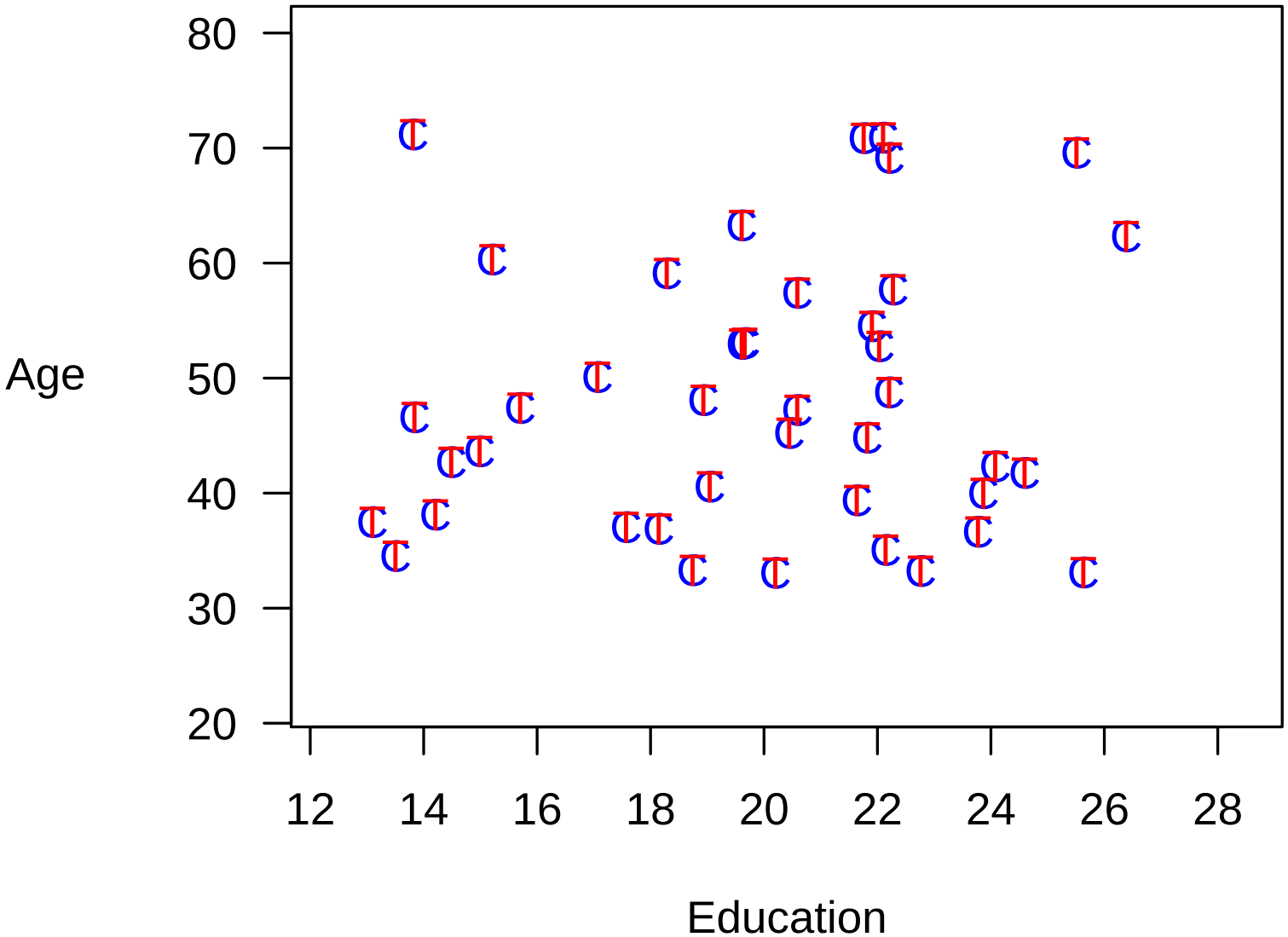

Method 3: Propensity Score Matching

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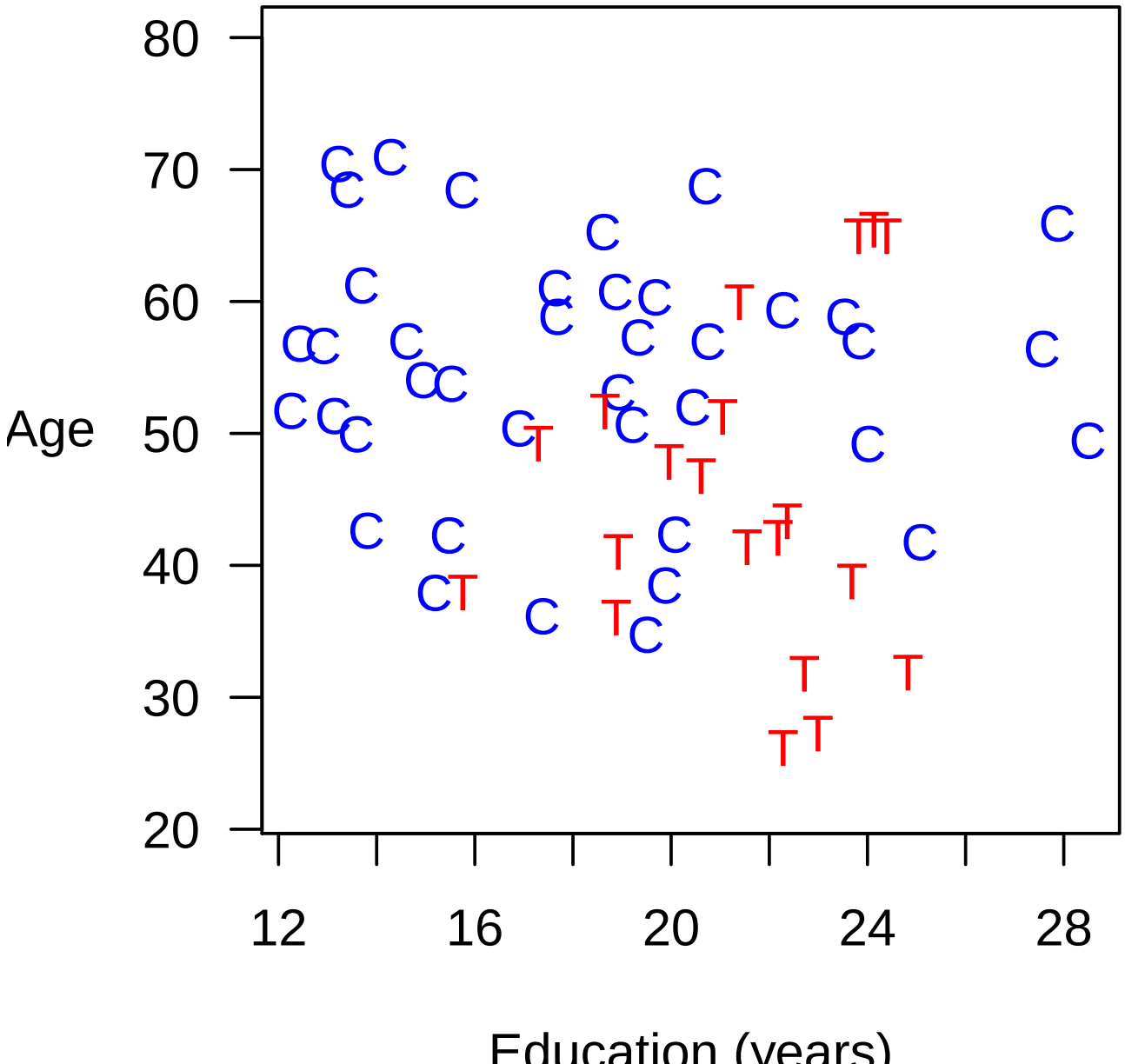
Propensity Score Matching



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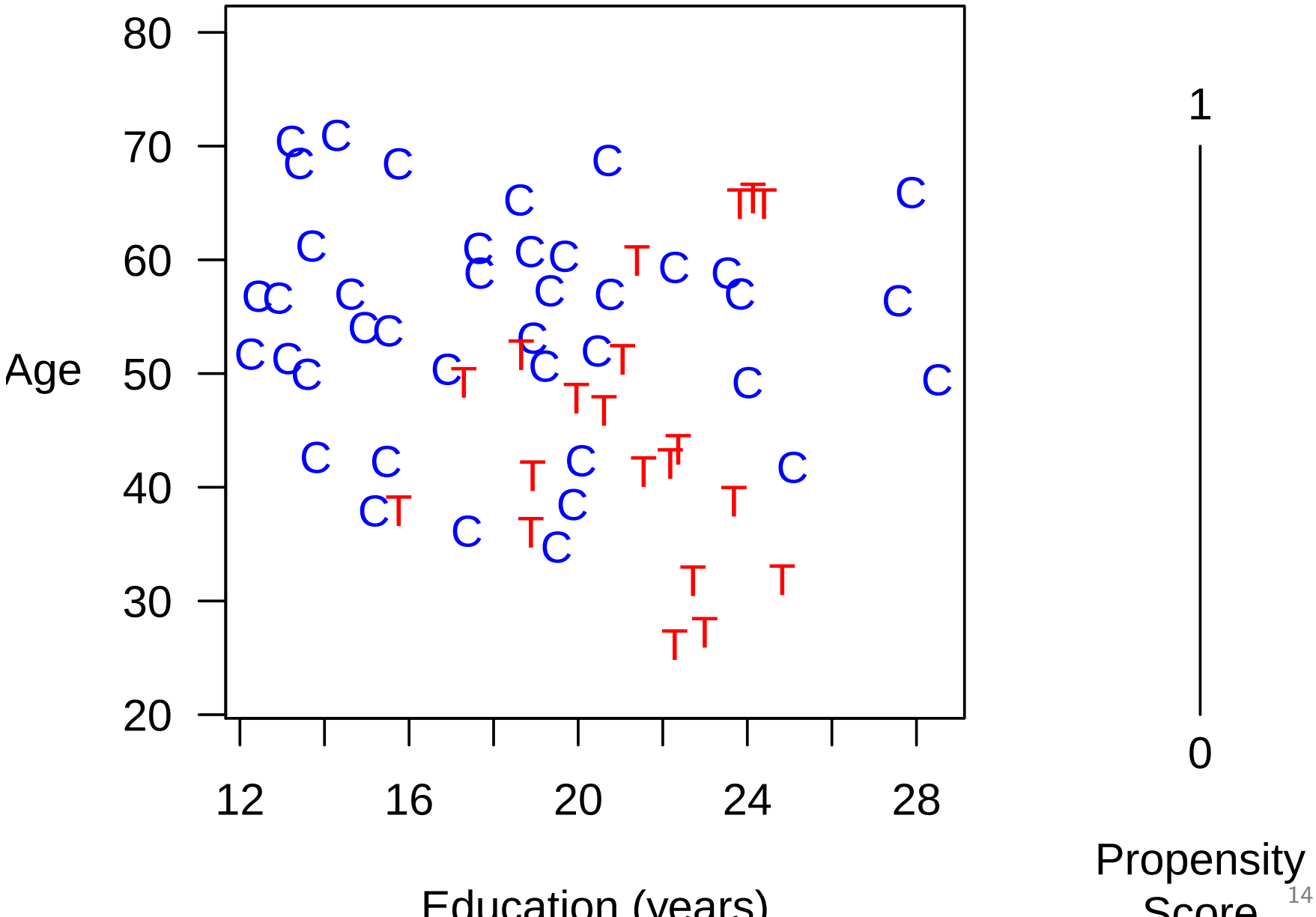

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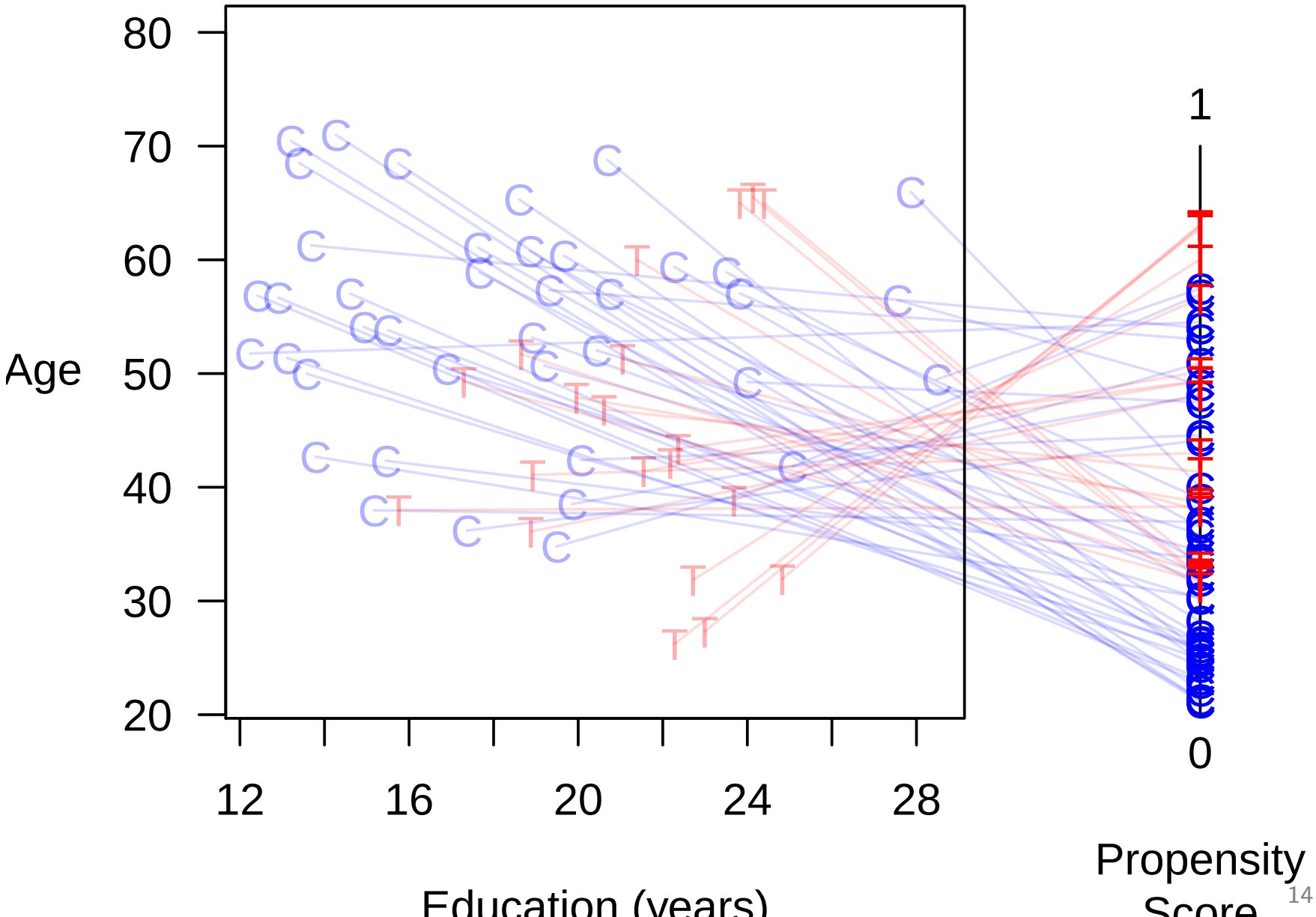

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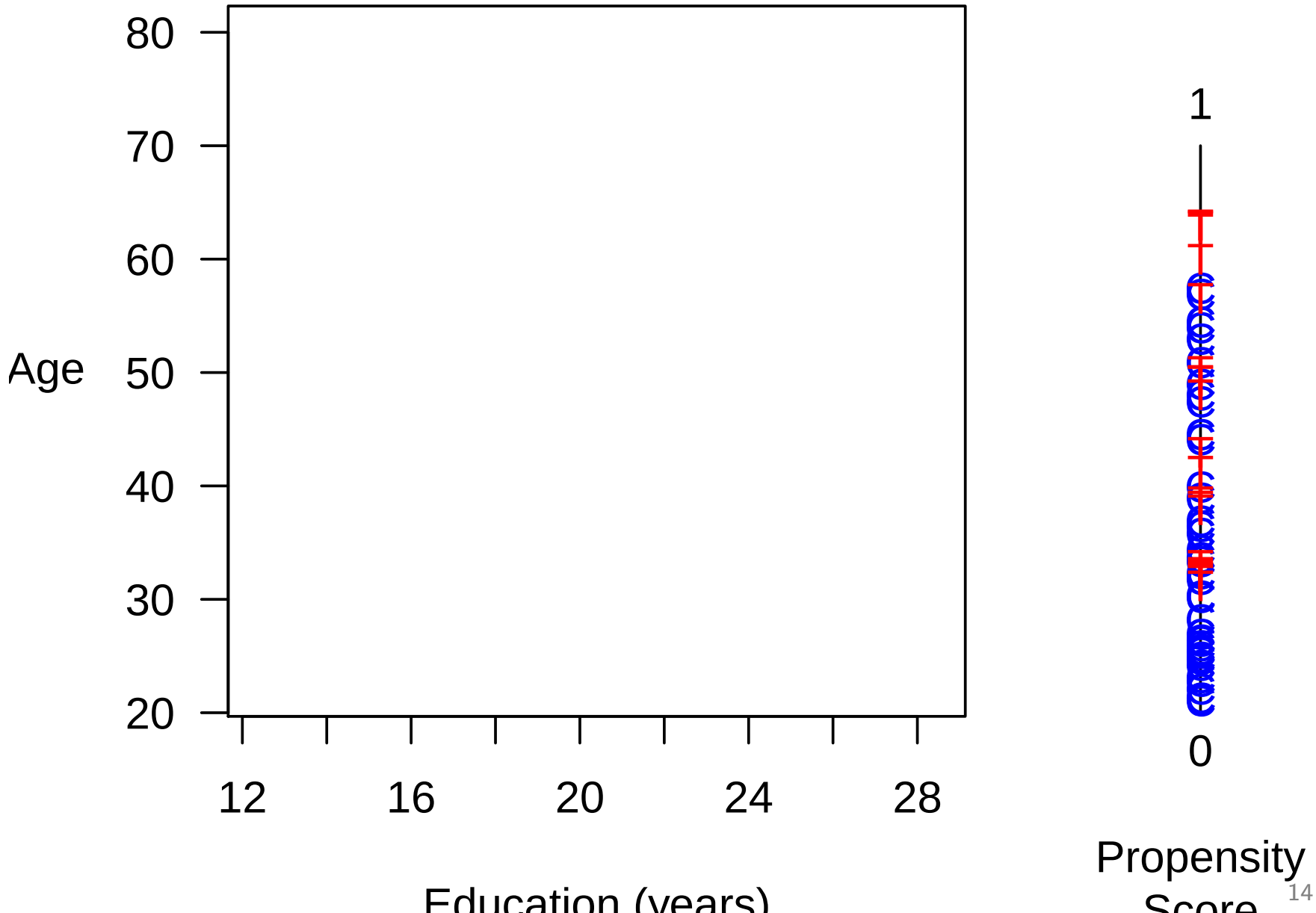

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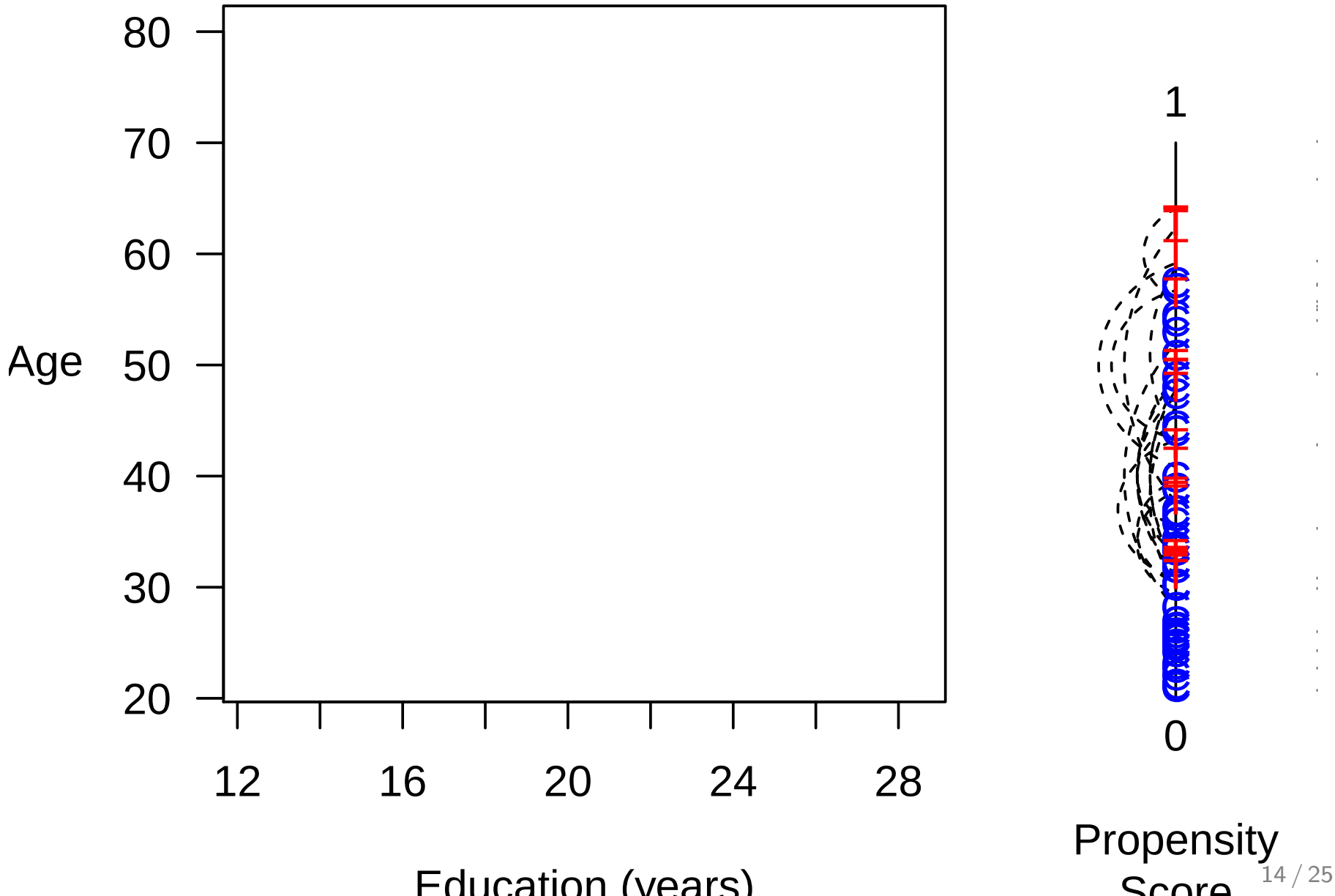

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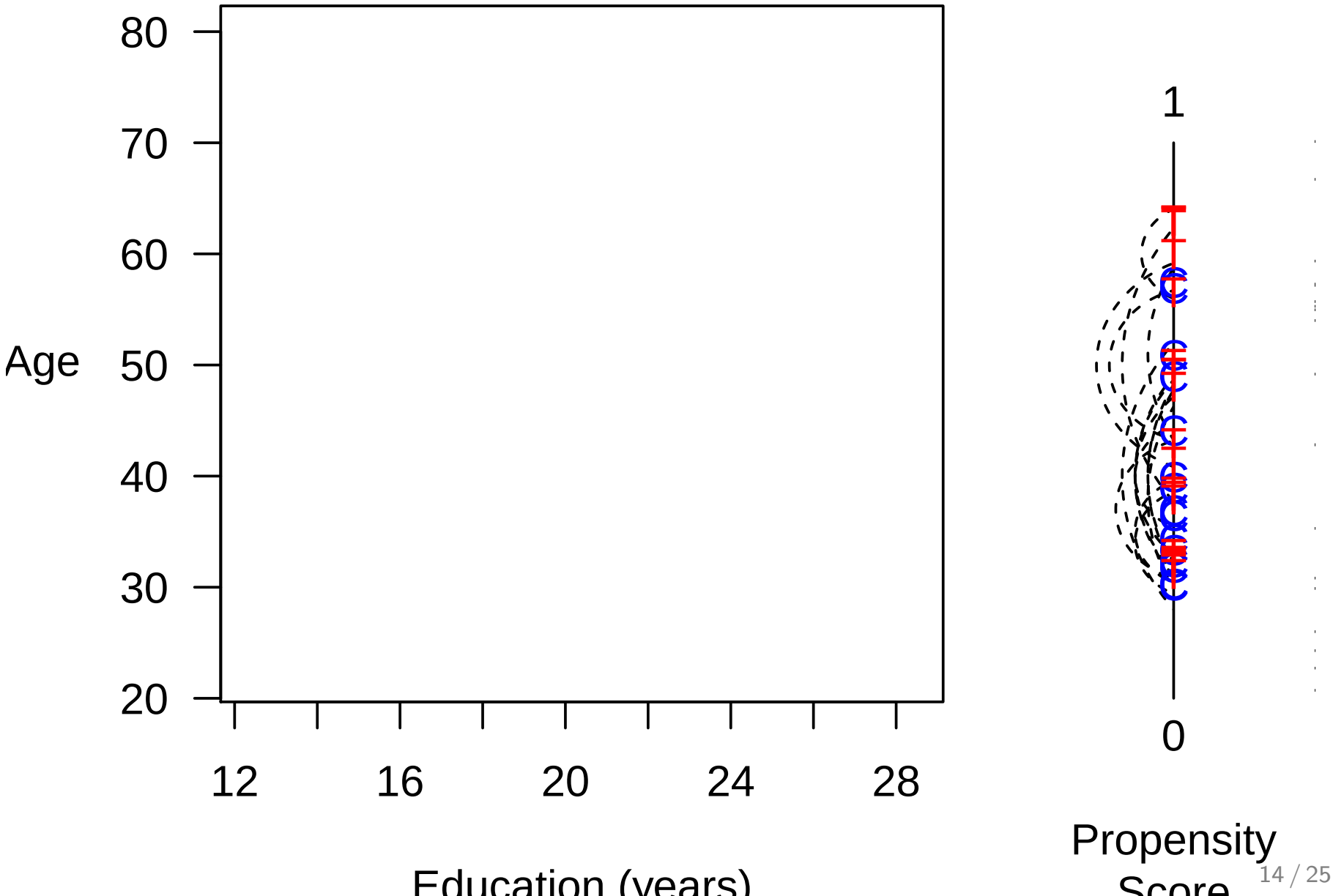

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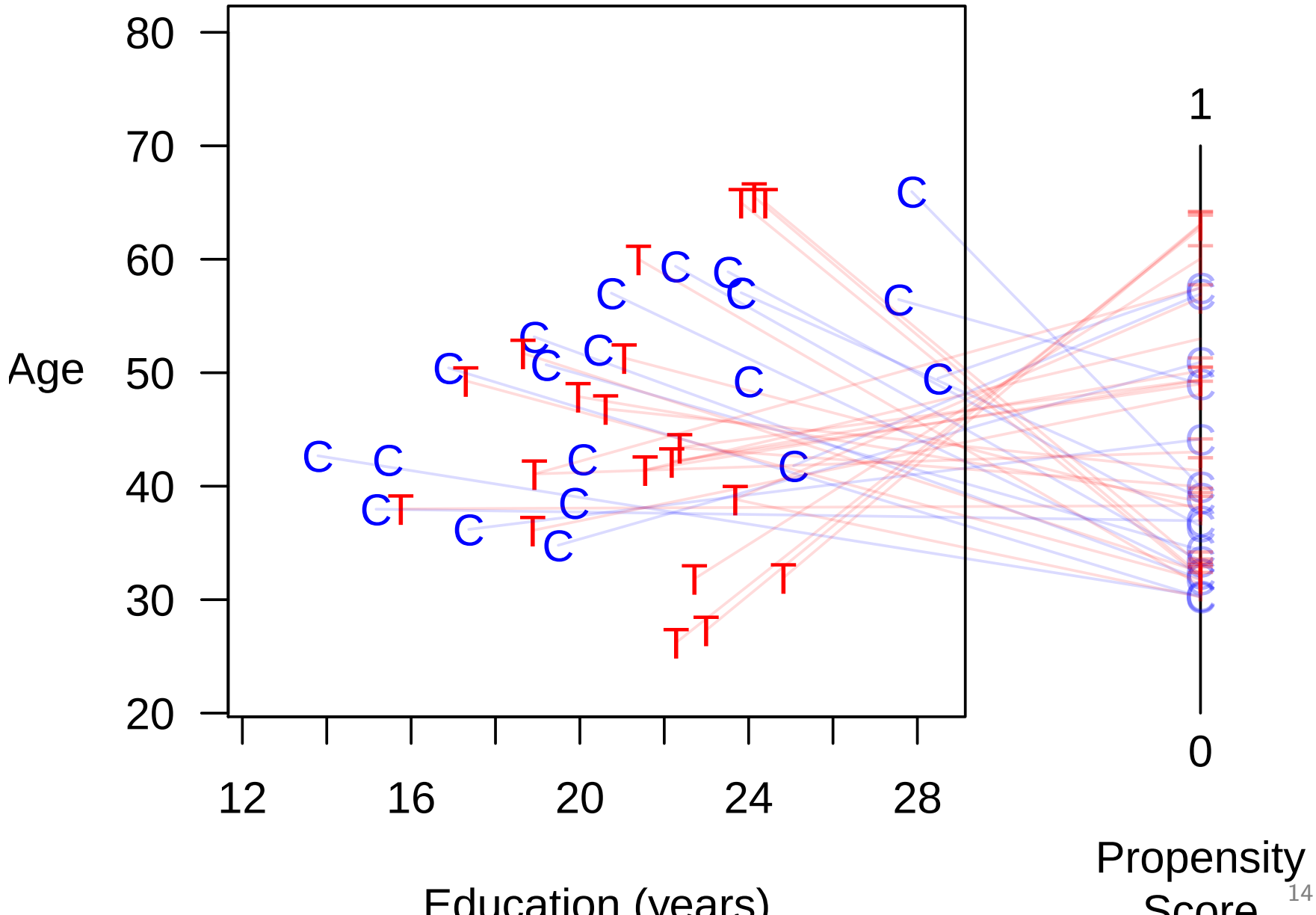

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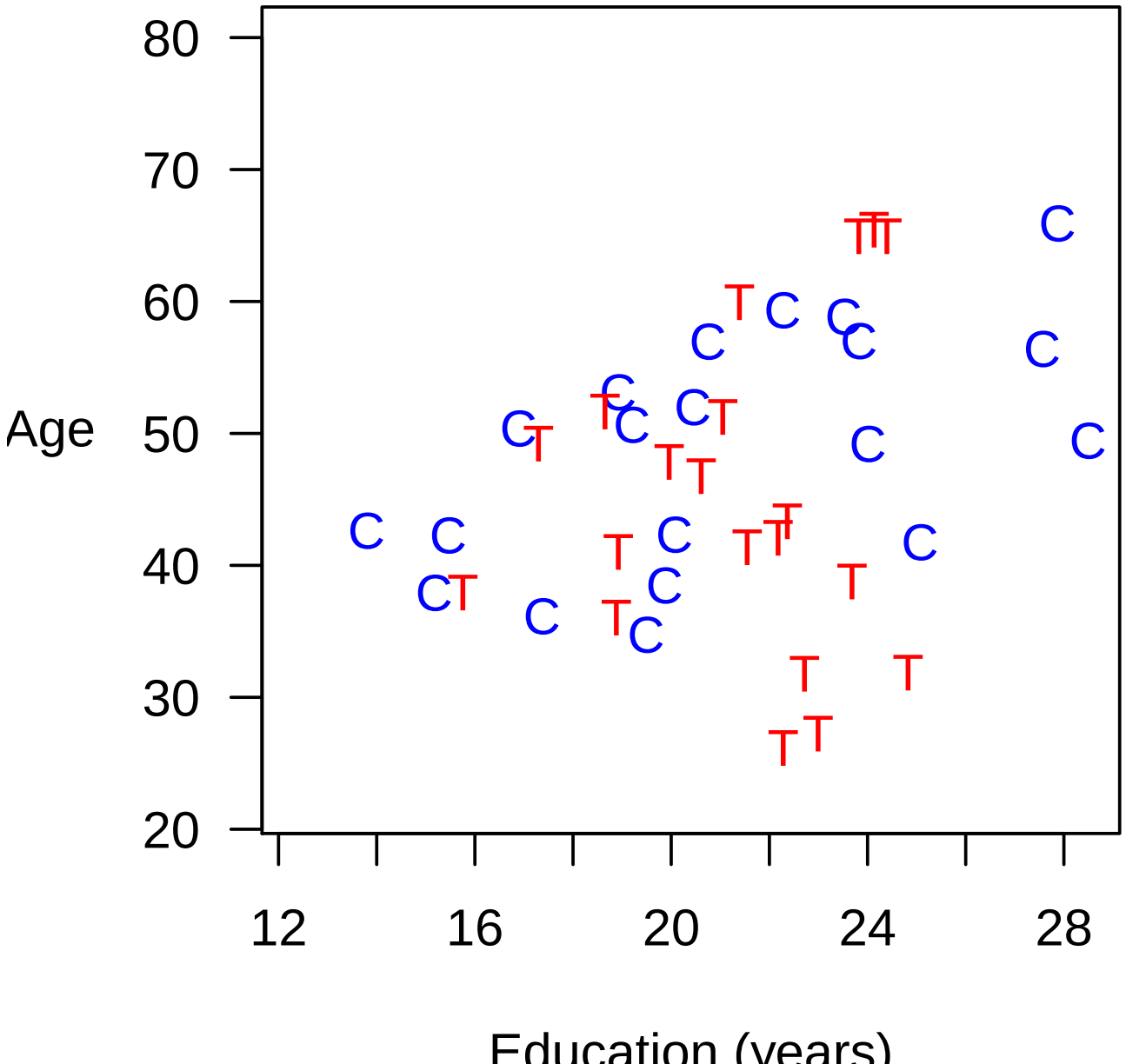

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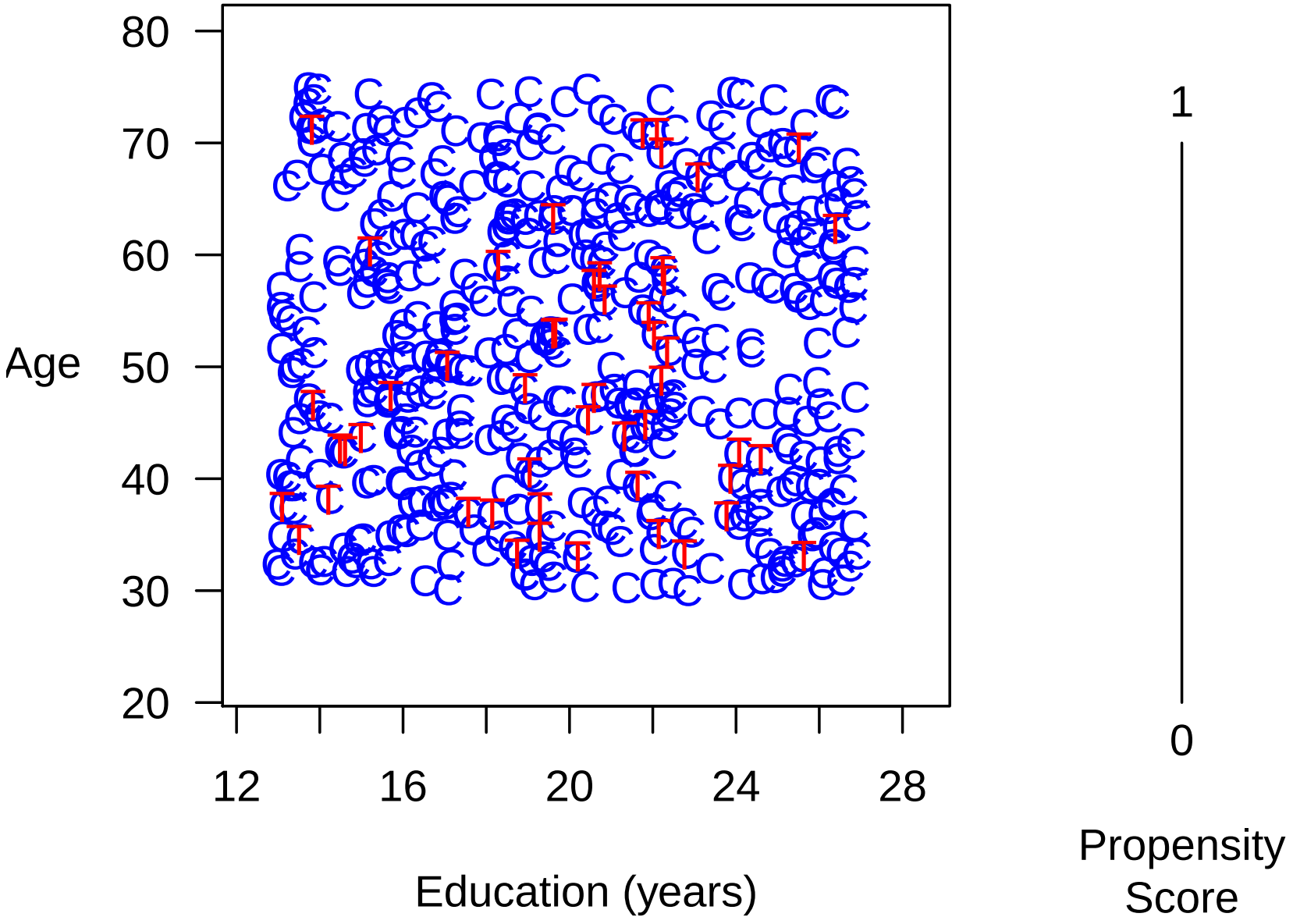

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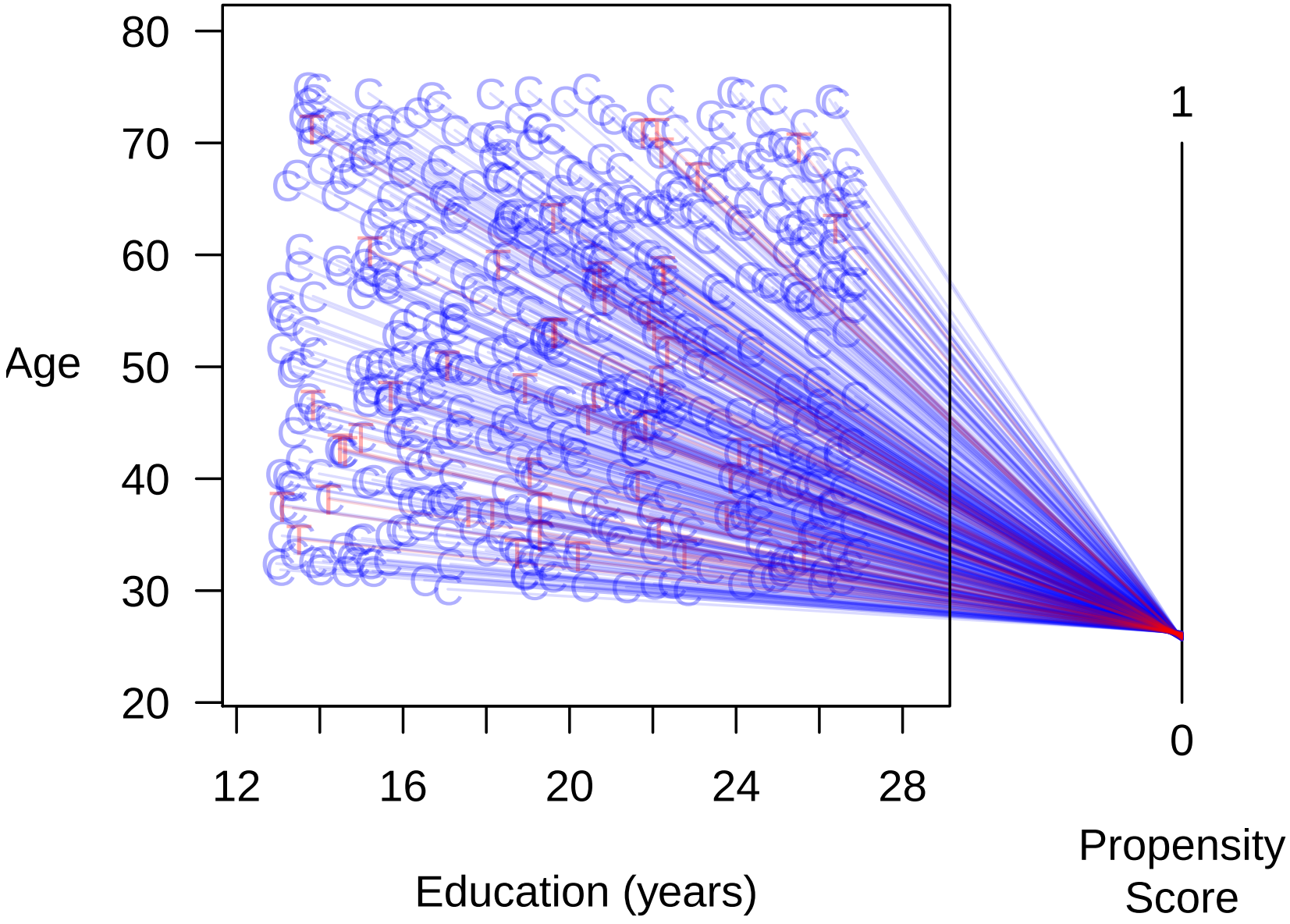

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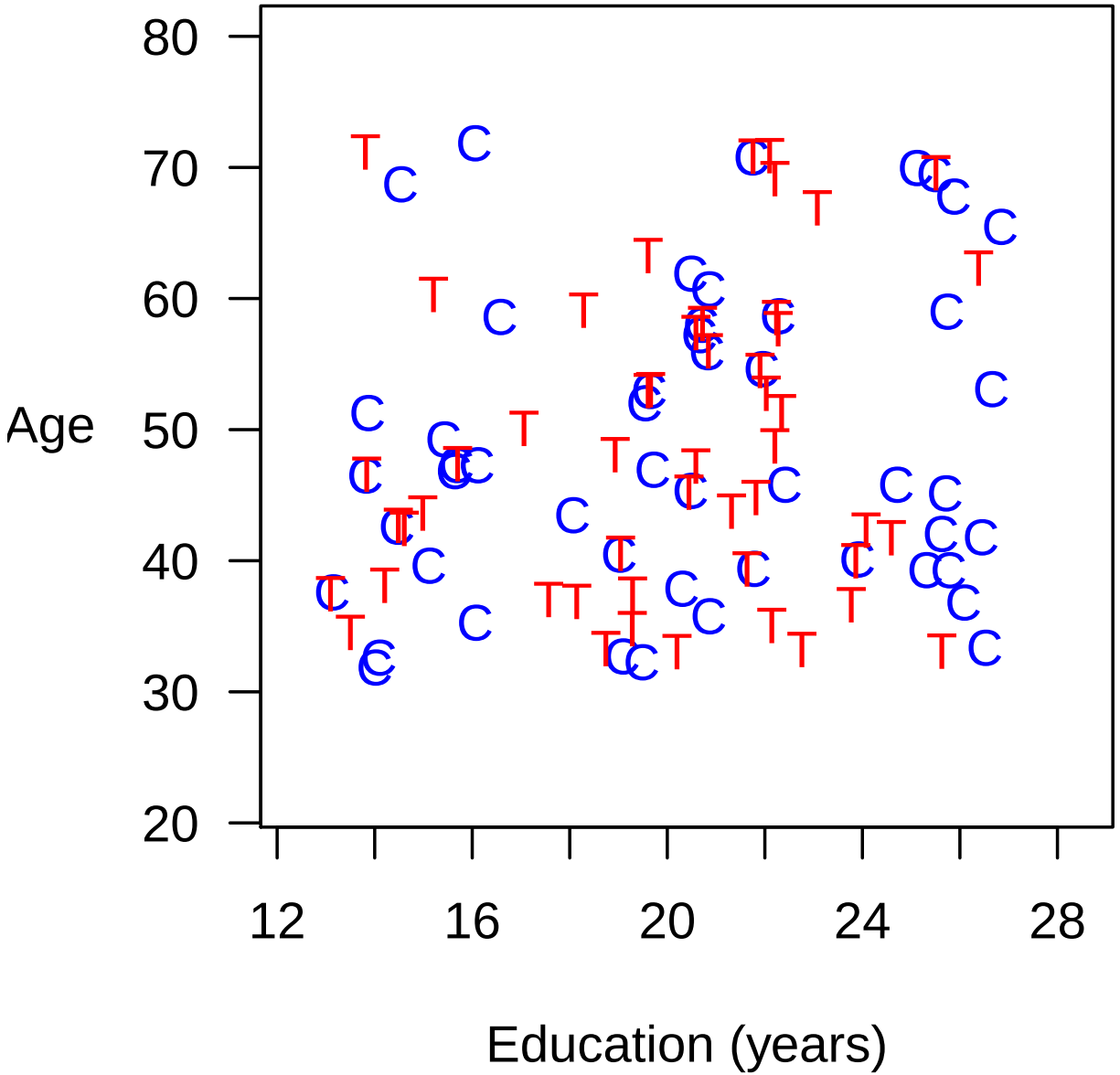

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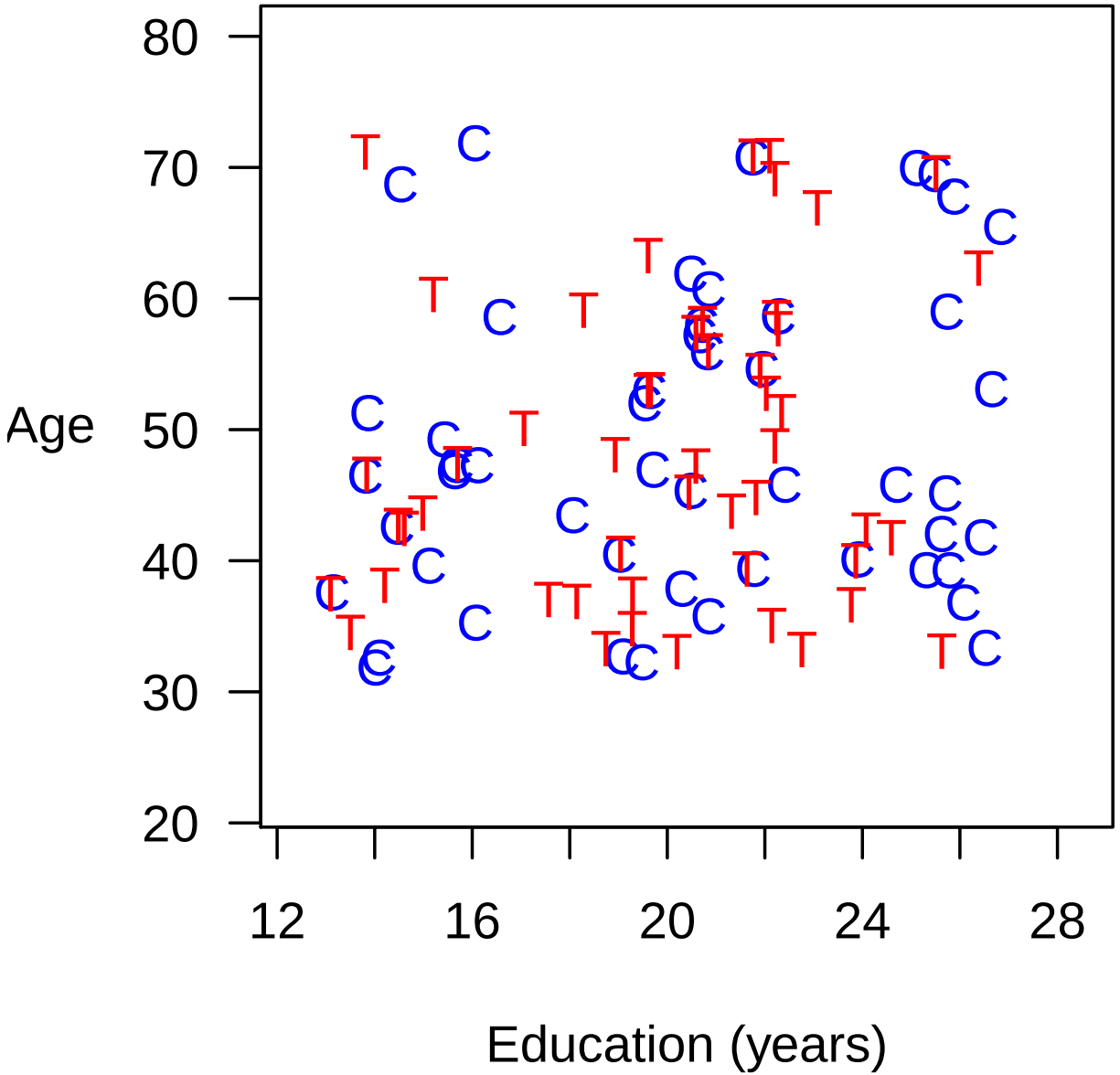

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PSM is Blind Where Other Methods Can See

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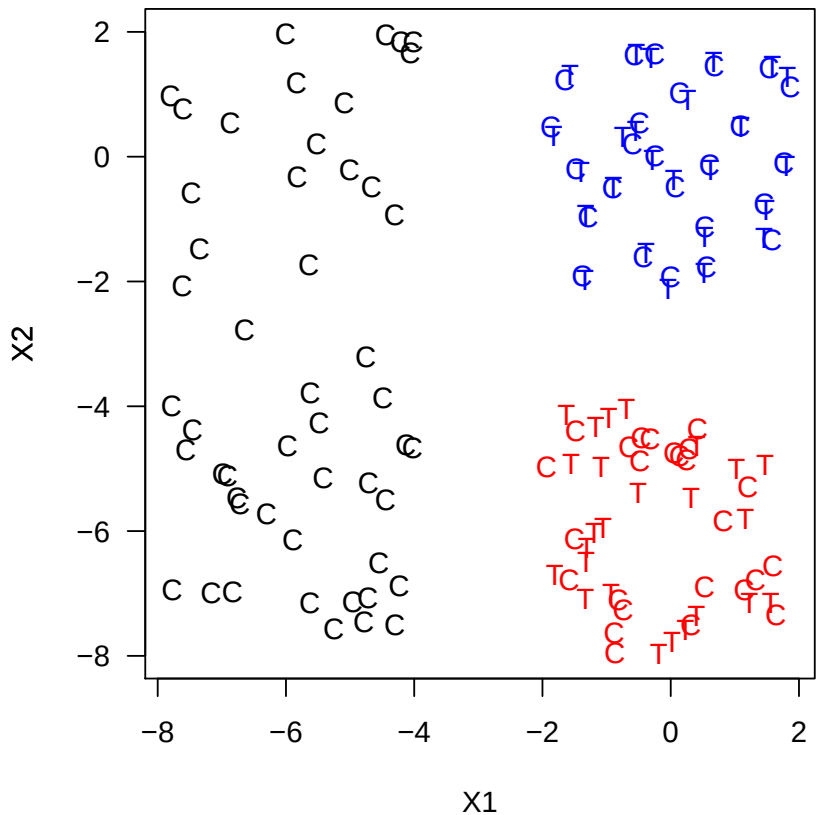

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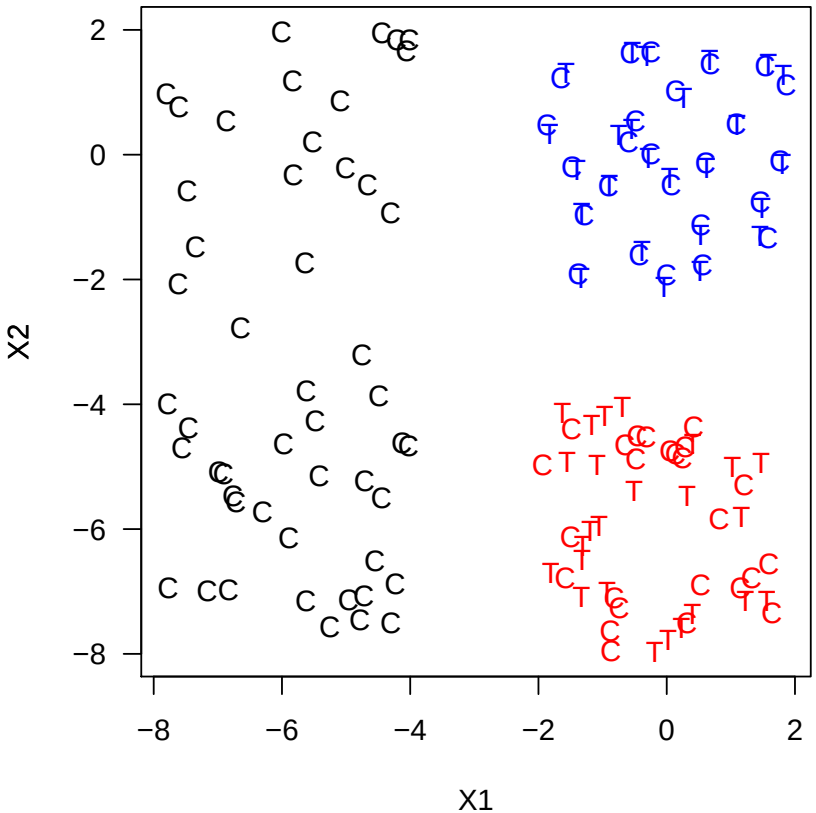
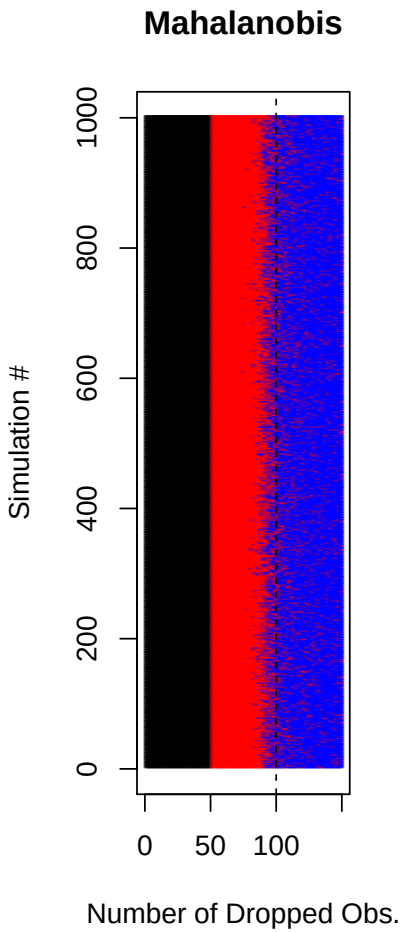
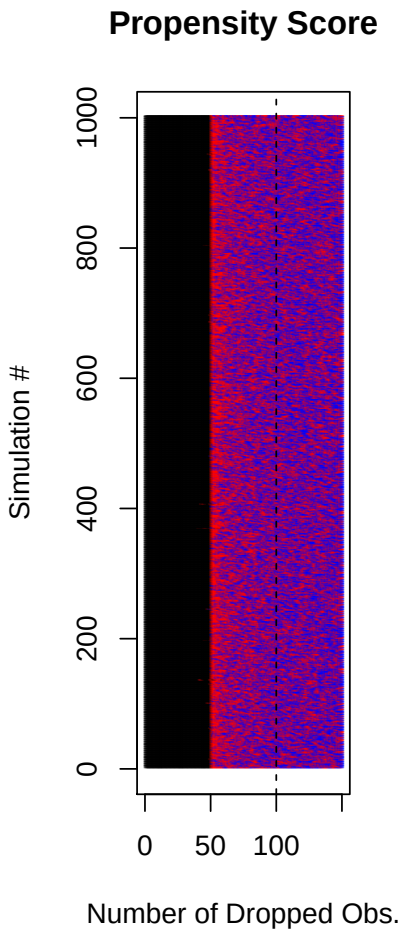
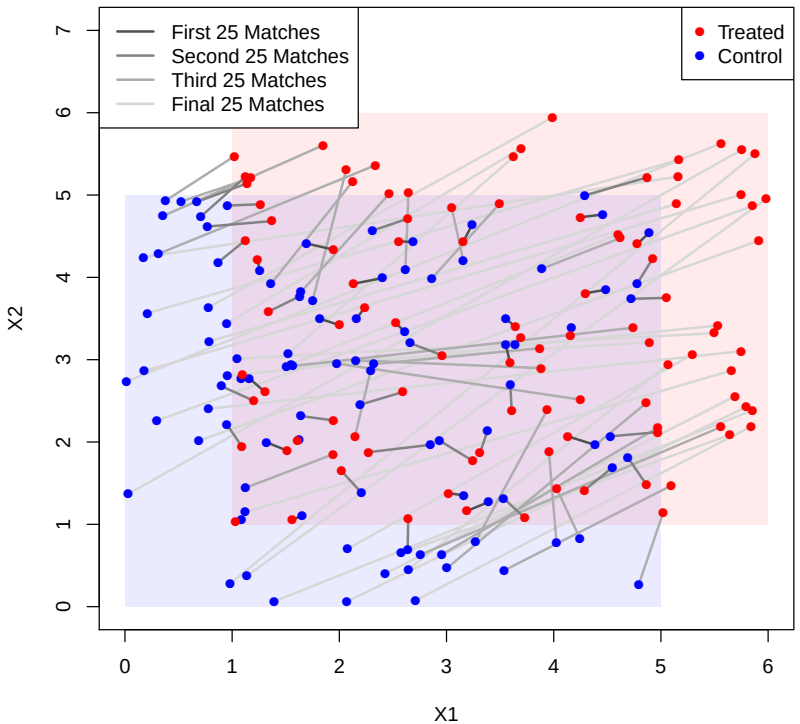






What Does PSM Match?

MDM Matches



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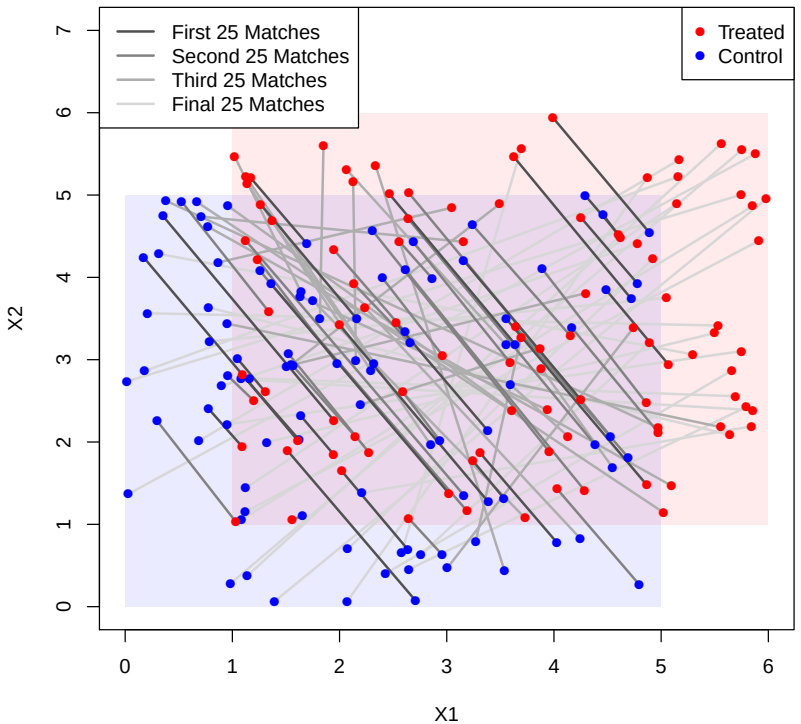
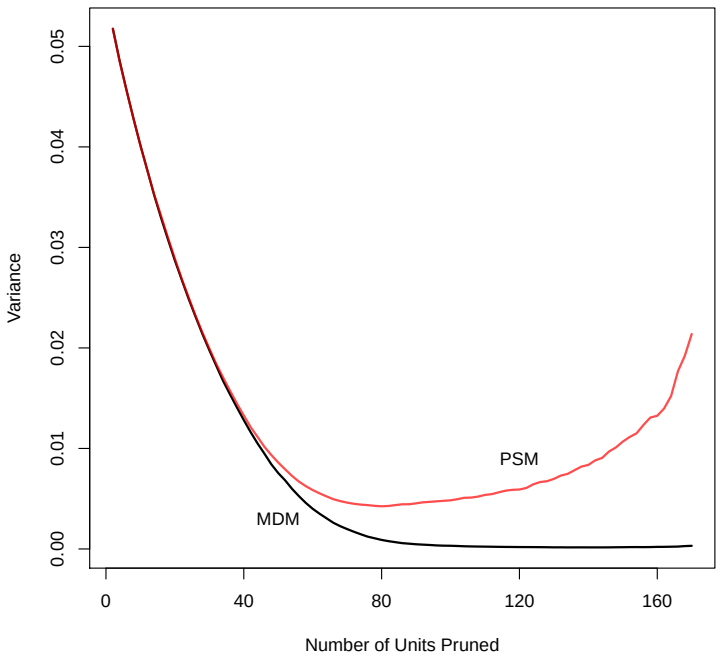


Controls: $X_1, X_2 \sim \text{Uniform}(0,5)$

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

PSM Increases Model Dependence & Bias

Model Dependence



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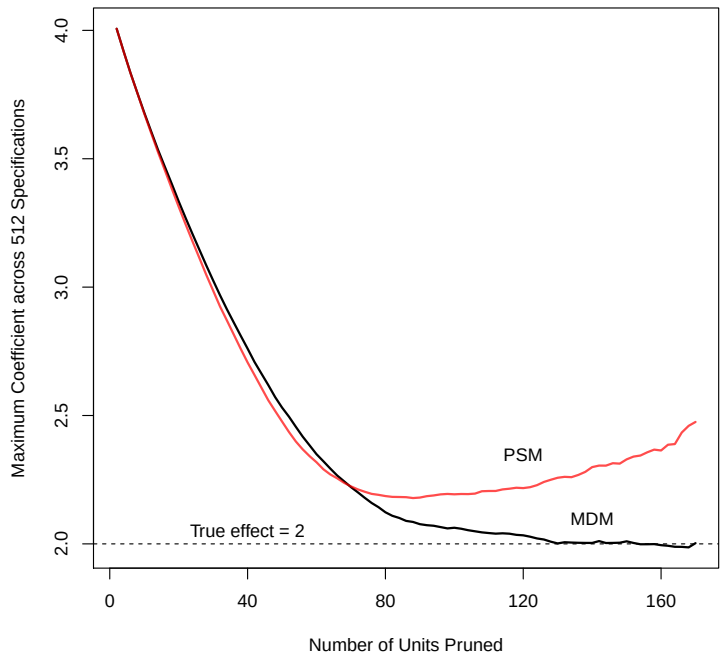

$$Y_i = 2T_i + X_{1i} + X_{2i} + \epsilon_i$$
$$\epsilon_i \sim N(0, 1)$$

The Propensity Score Paradox in Real Data

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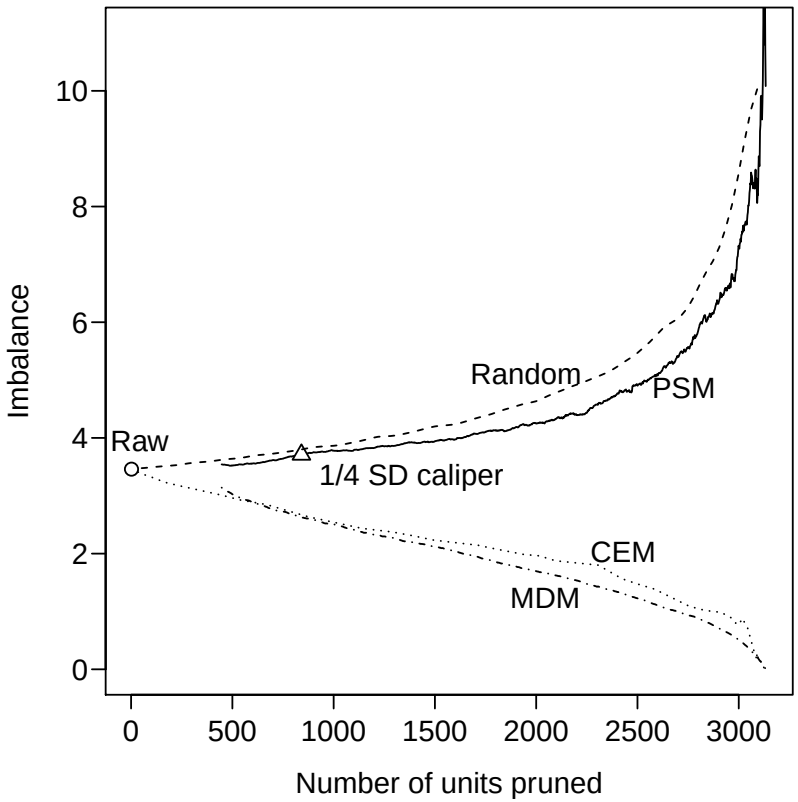

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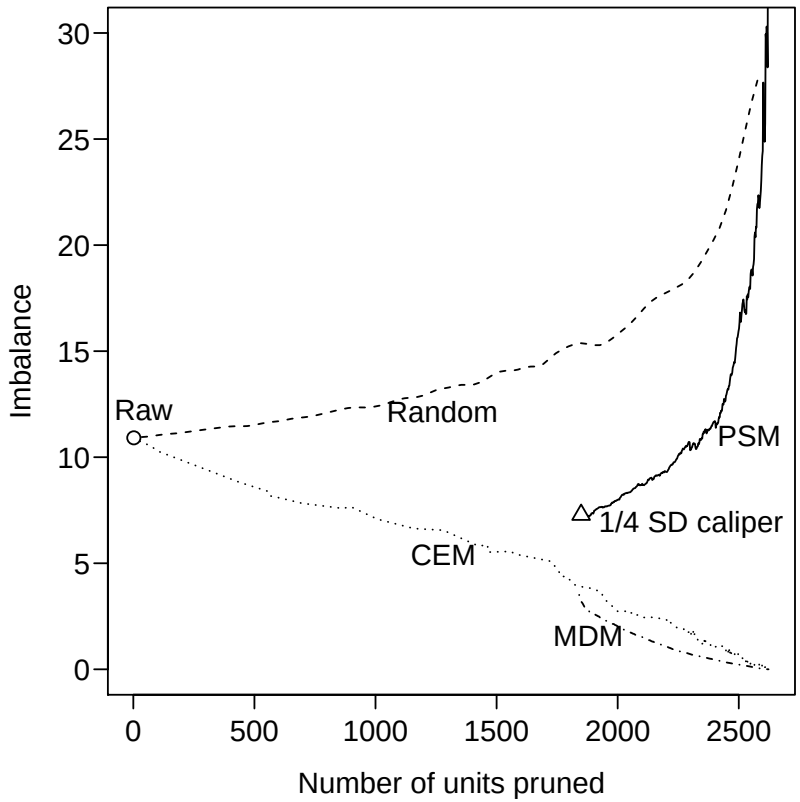

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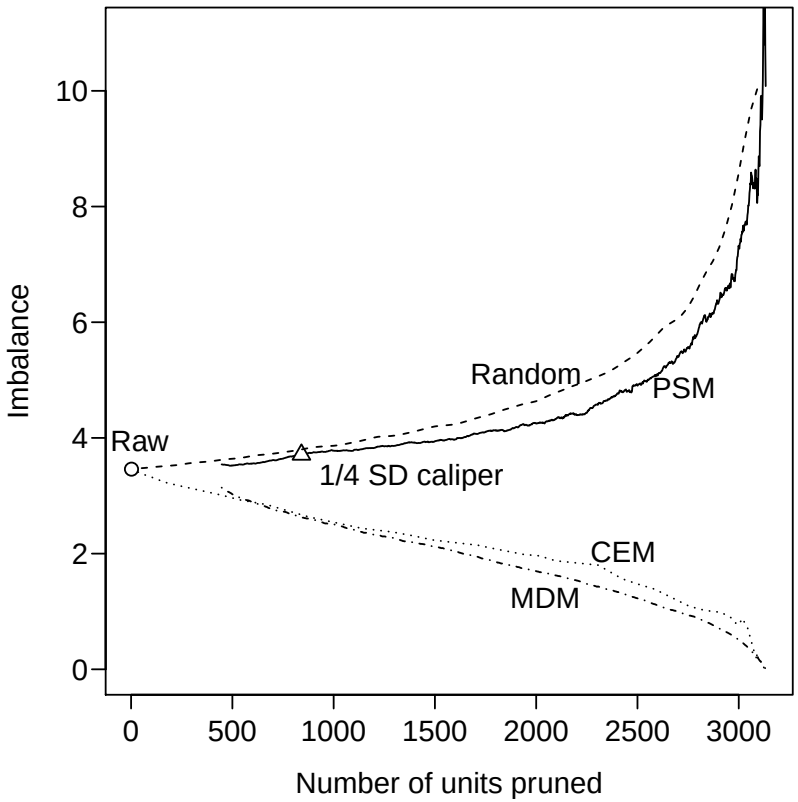

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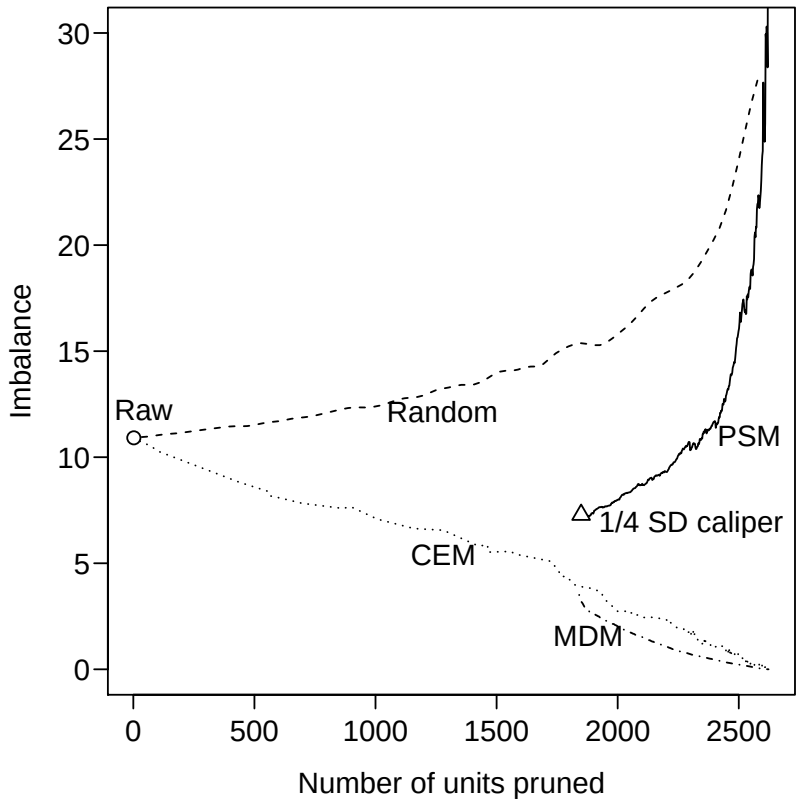

Similar pattern for $>$ 20 other real data sets we checked

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- Choose an imbalance metric, then run.

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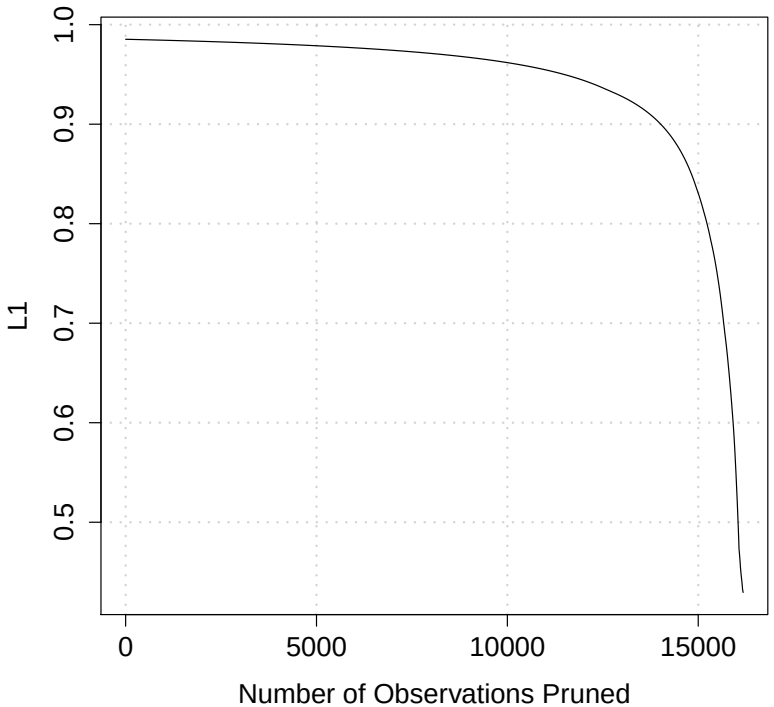
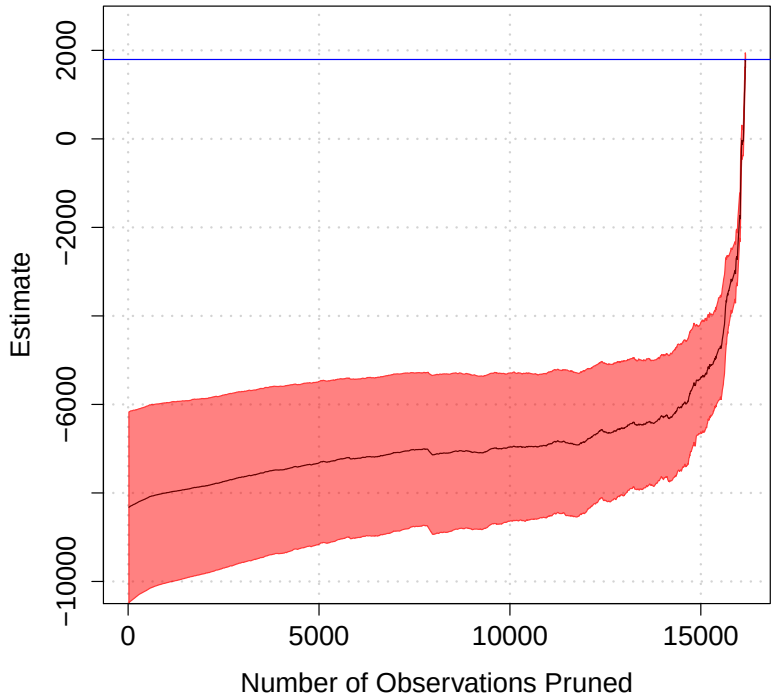
Job Training Data: Frontier and Causal Estimates





- 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