Matching Methods for Observational and Experimental Causal Inference

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Readings

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- Matching, Causal Inference: bit.ly/causeI

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- Matching in Experiments, including Seguro Popular: bit.ly/ExpMex

Matching to Reduce Model Dependence

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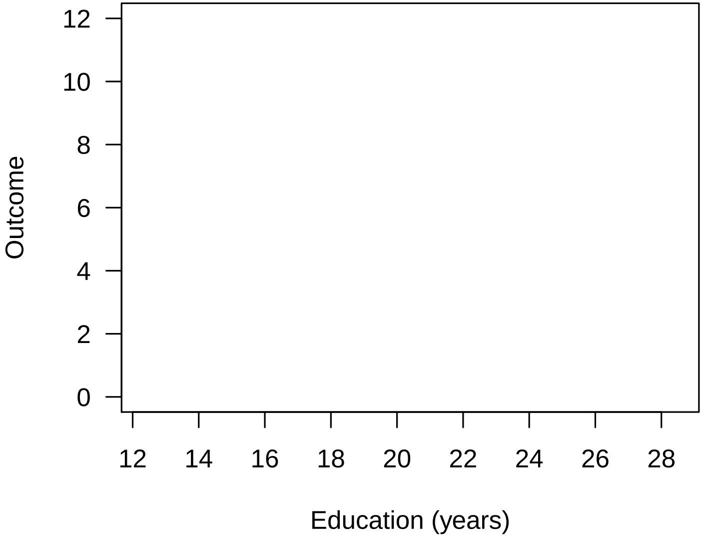

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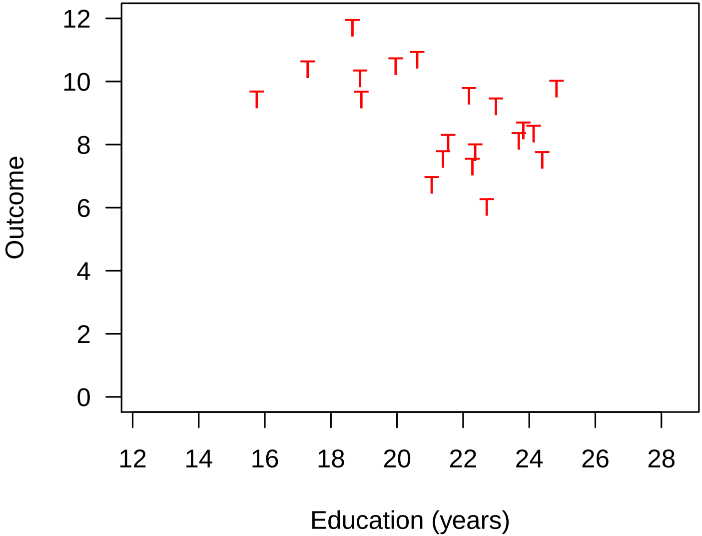

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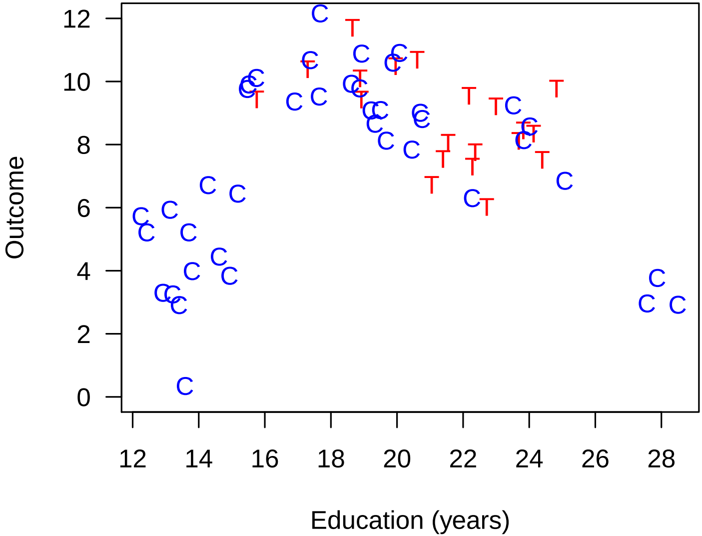

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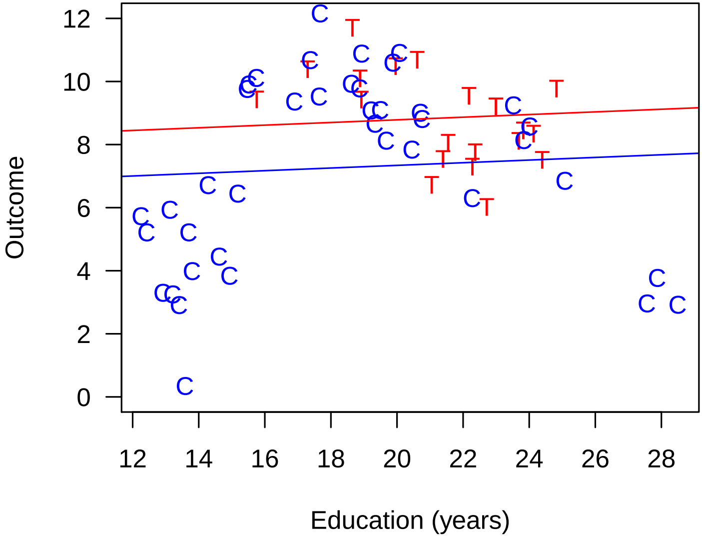

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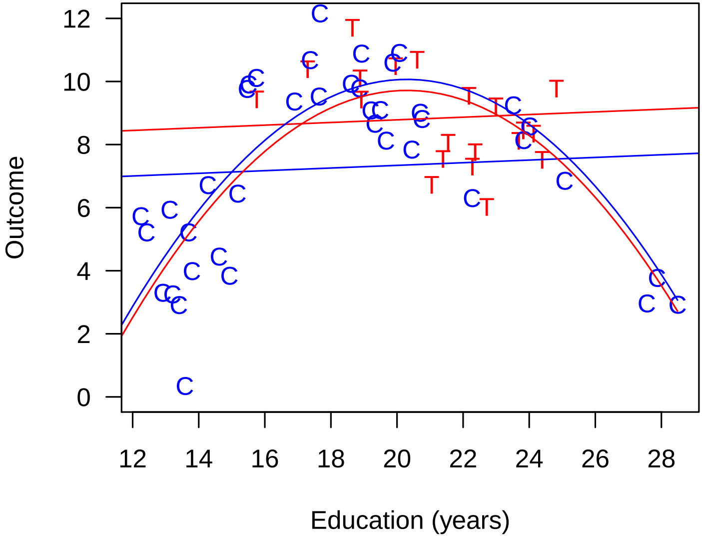

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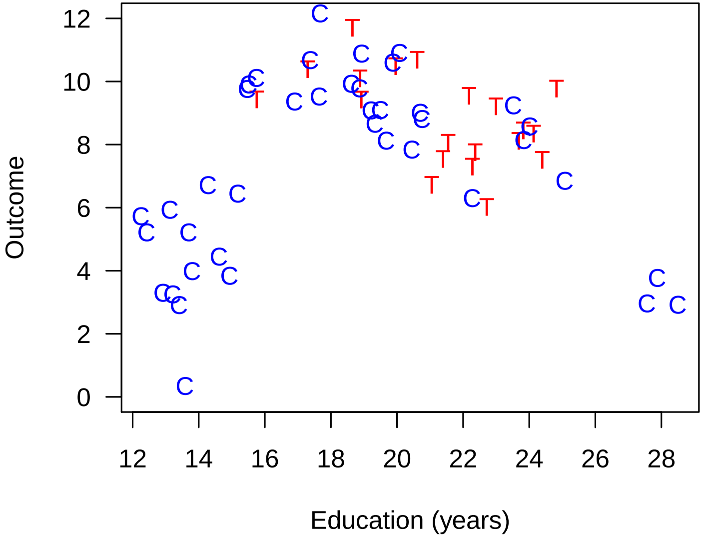

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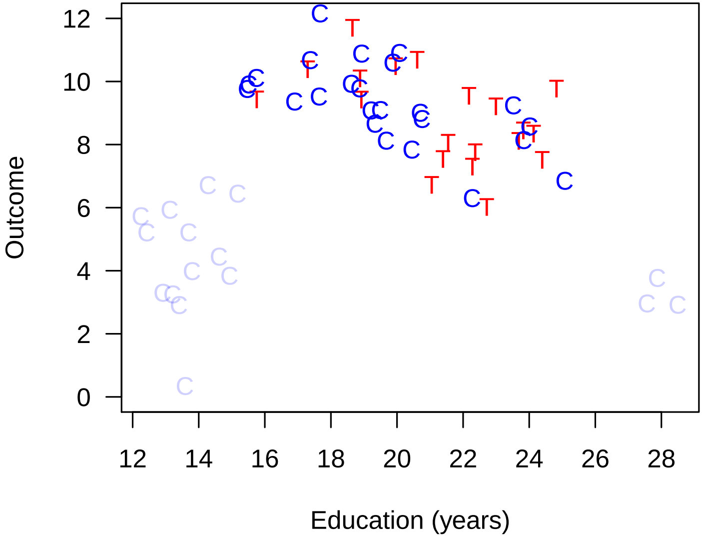

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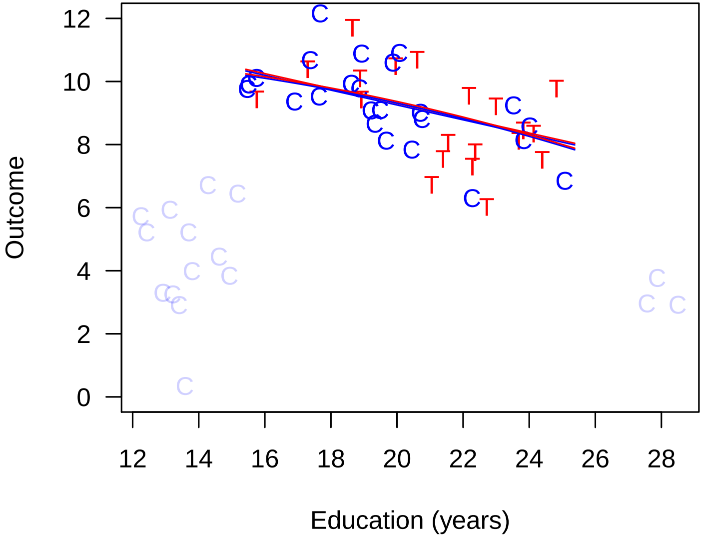

The Problems Matching Solves

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Imbalance

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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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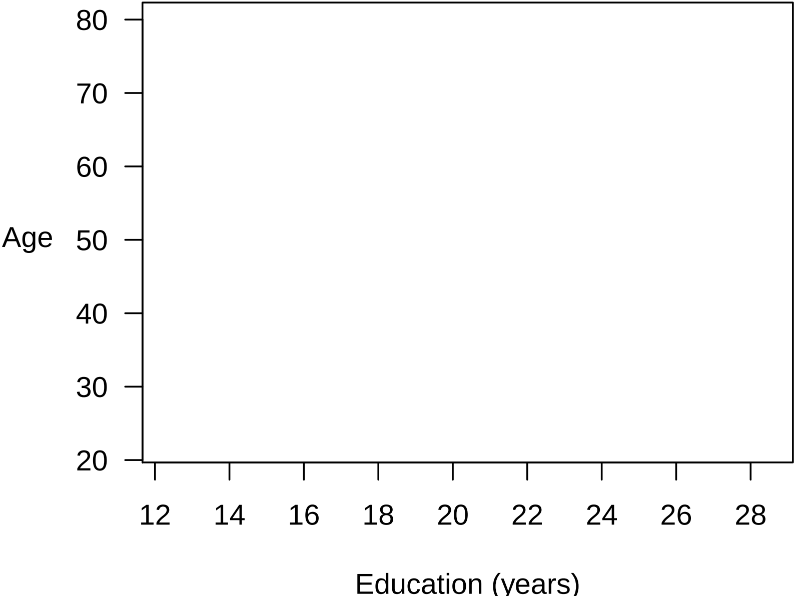

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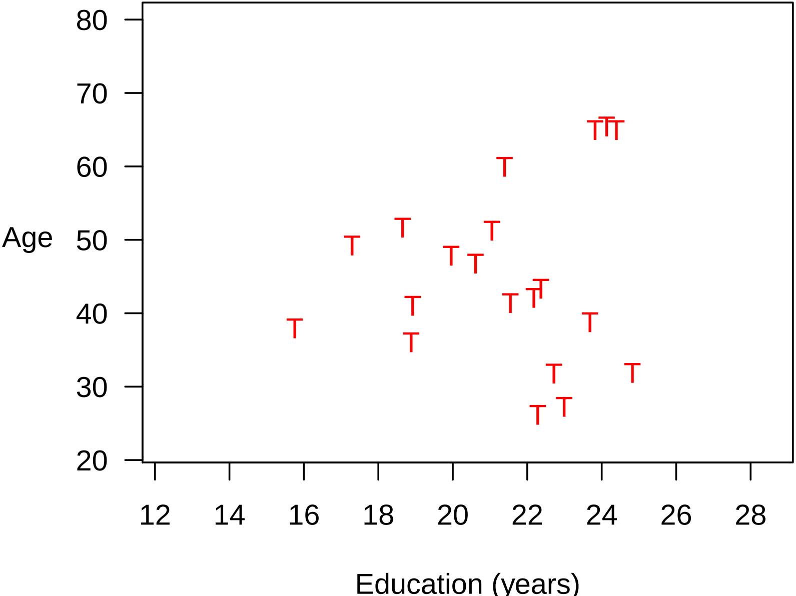

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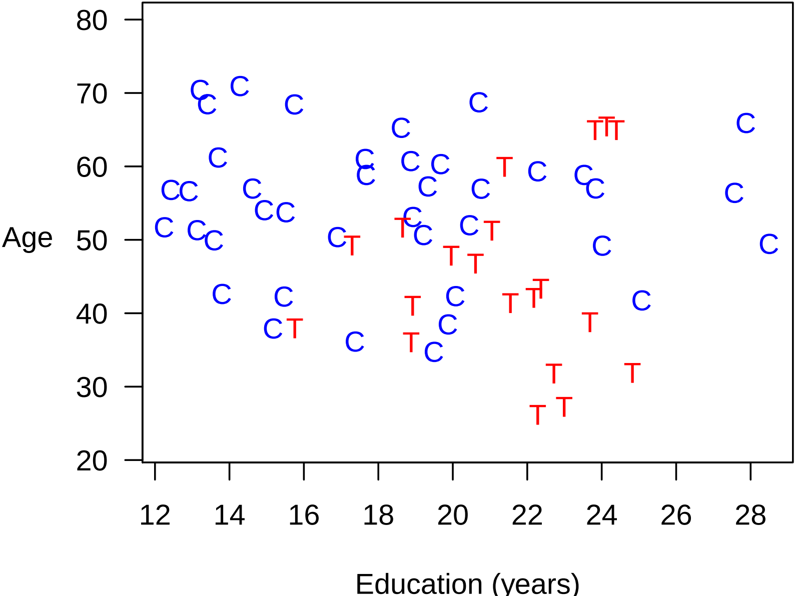

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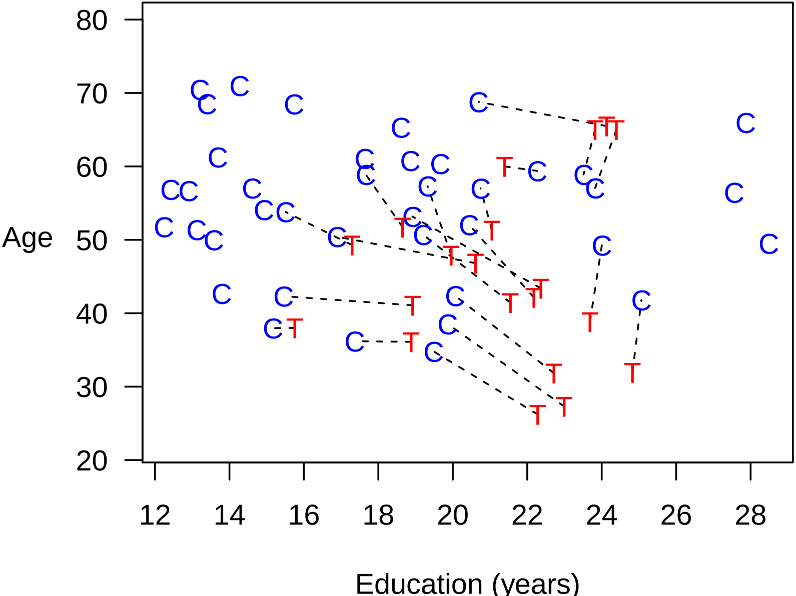

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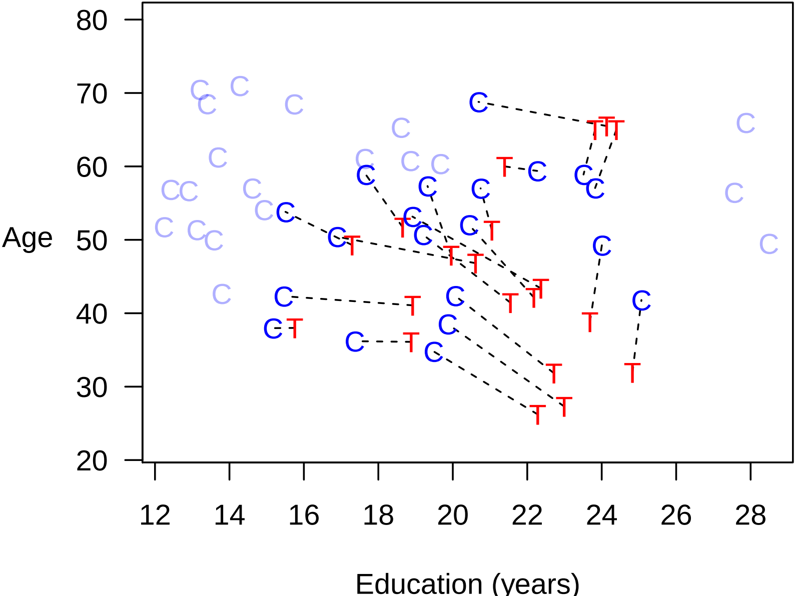

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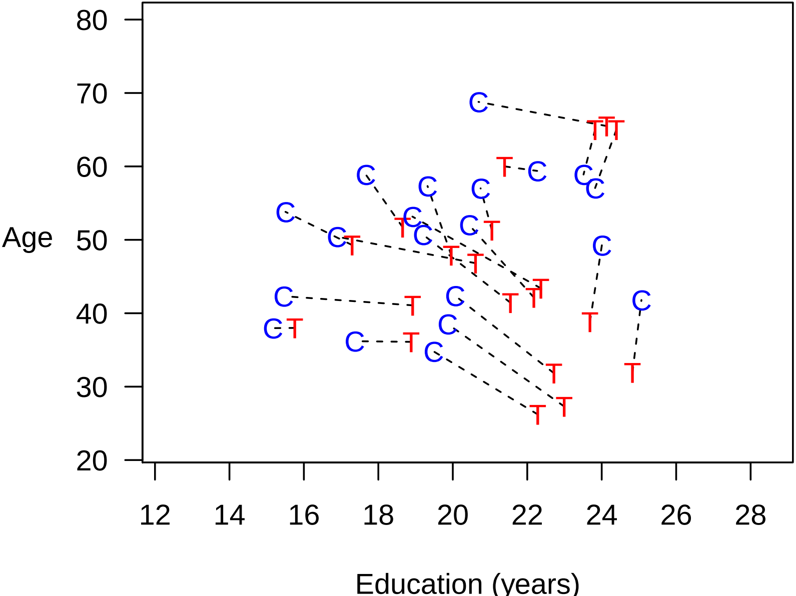

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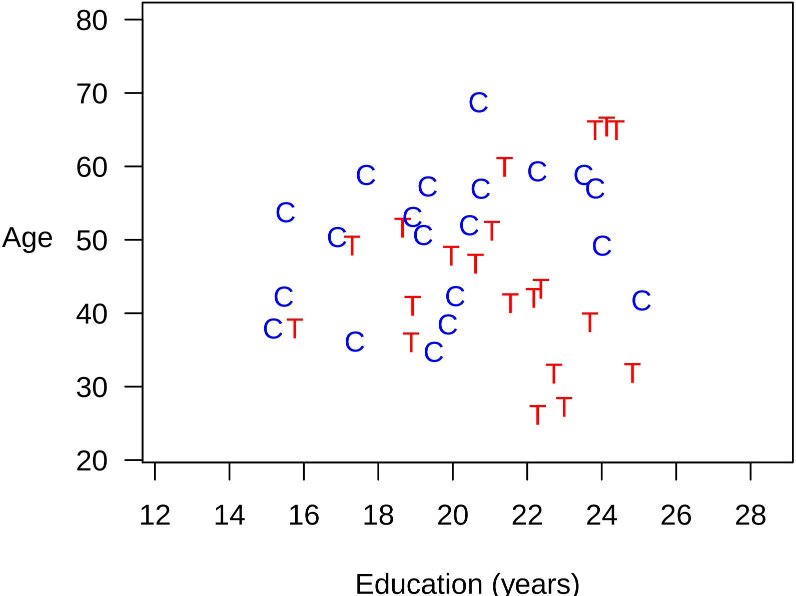

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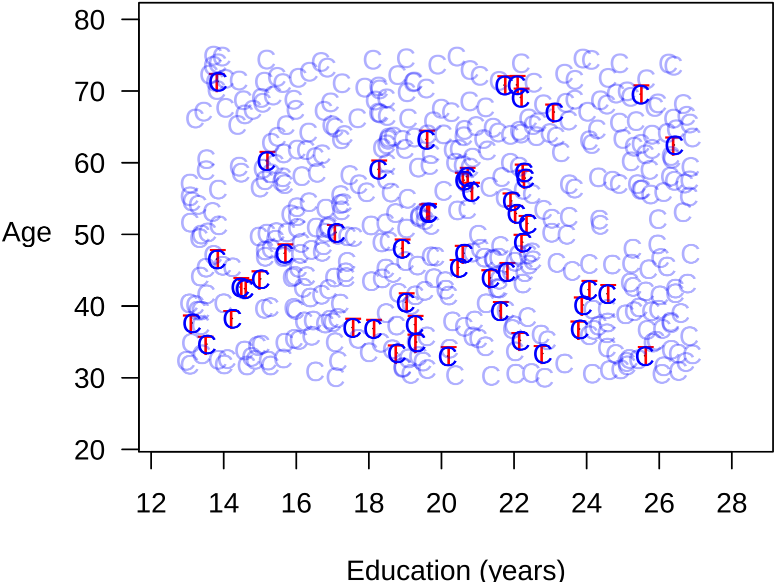

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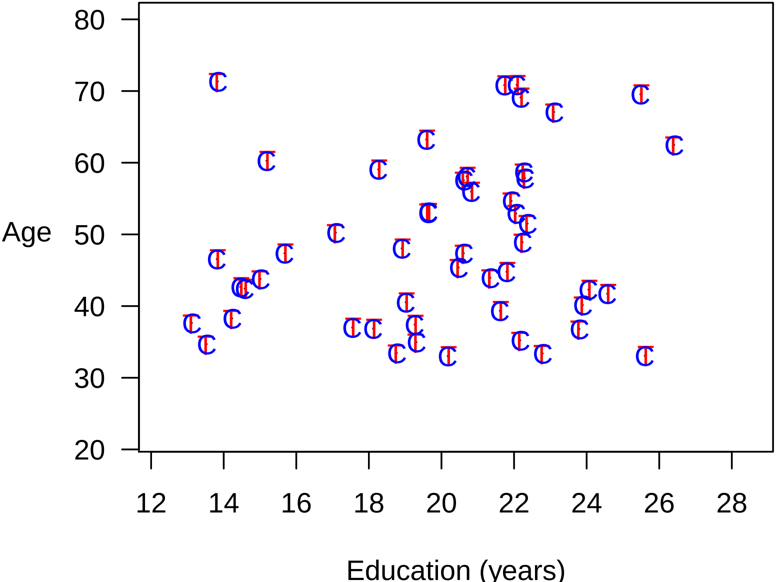

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2. Estimation Difference in means or a model

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   - Weight controls in each stratum to equal treateds

Coarsened Exact Matching

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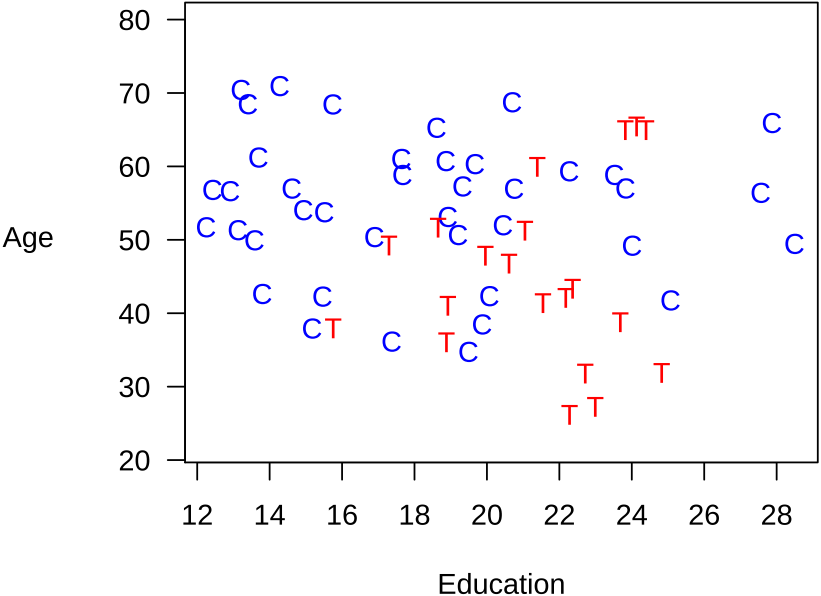

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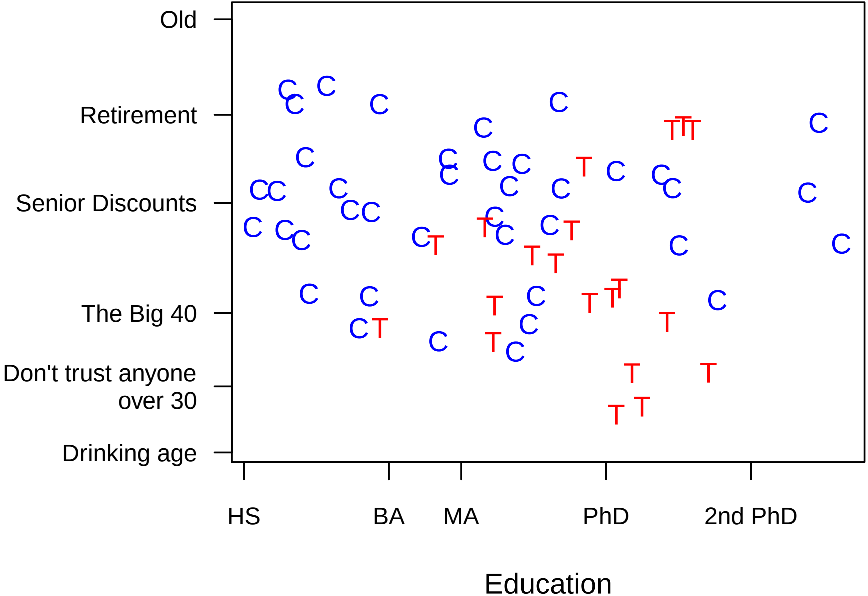

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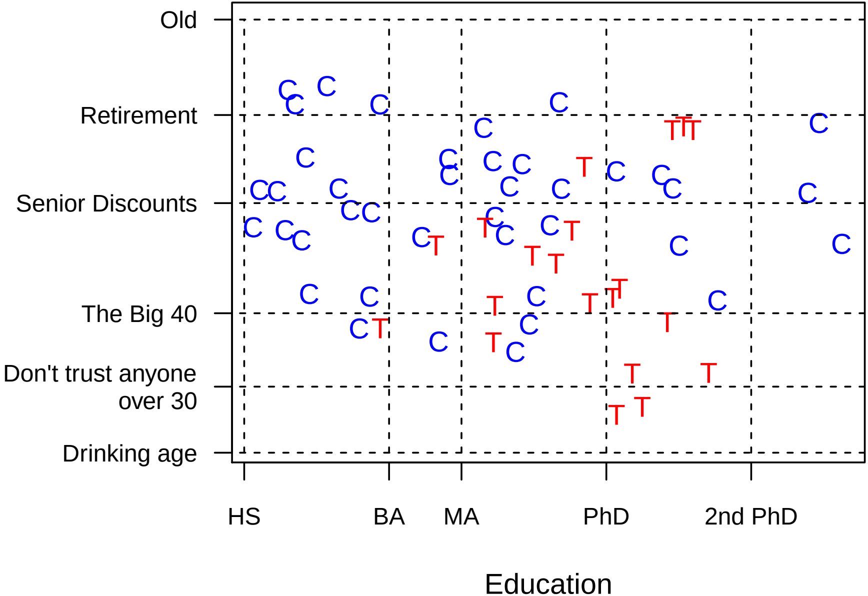

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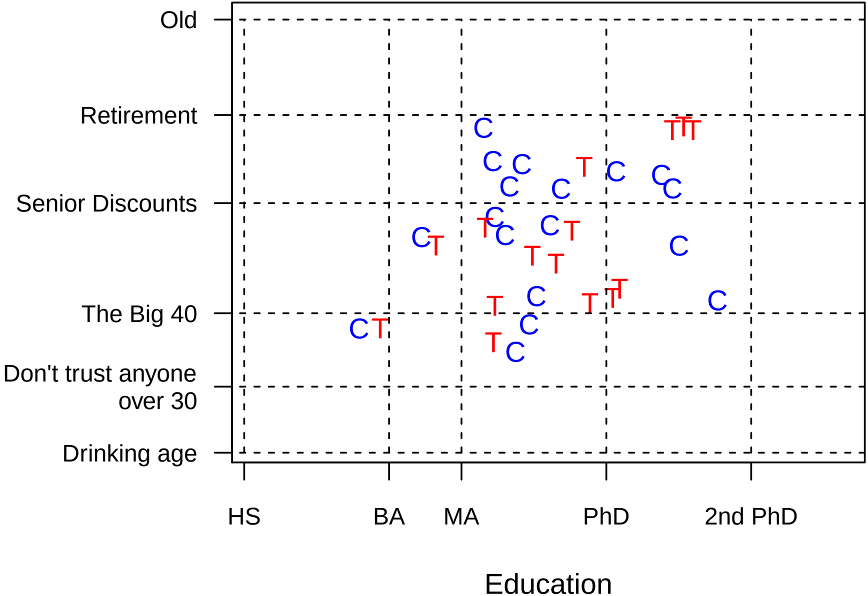

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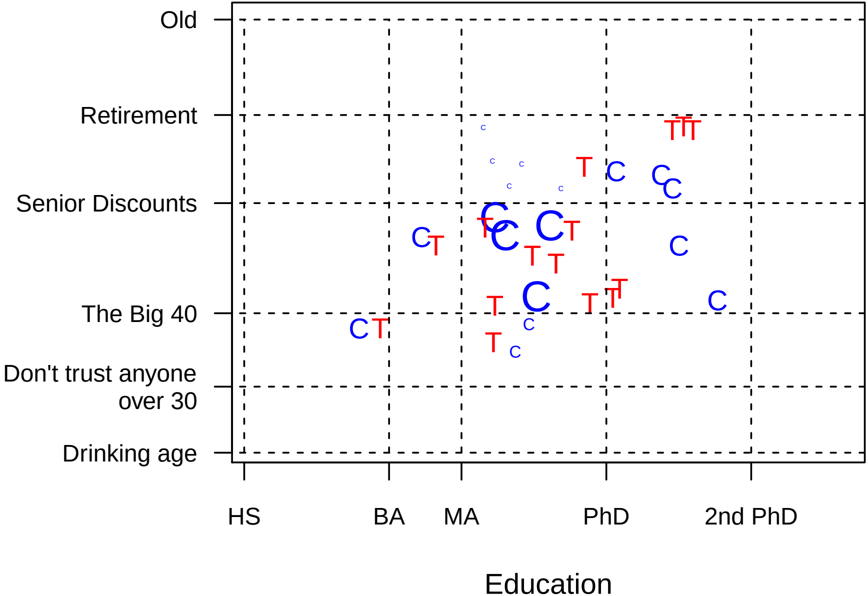

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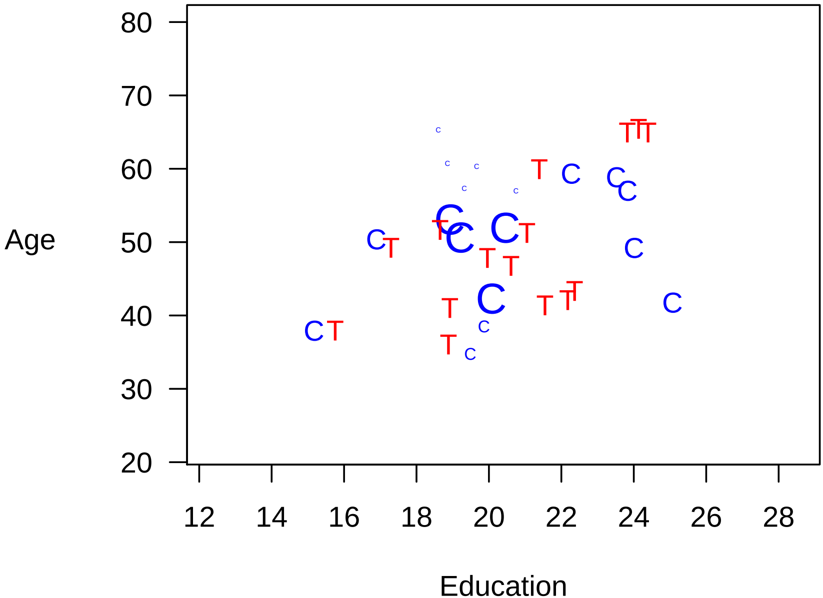

Best Case: Coarsened Exact Matching

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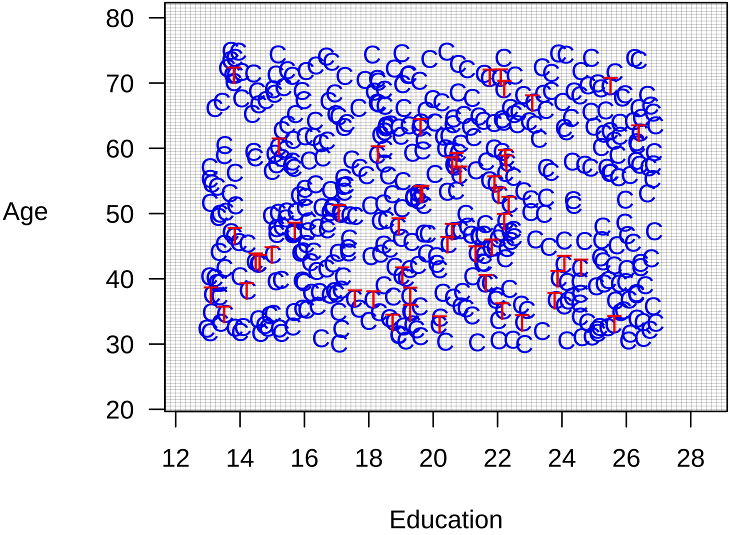

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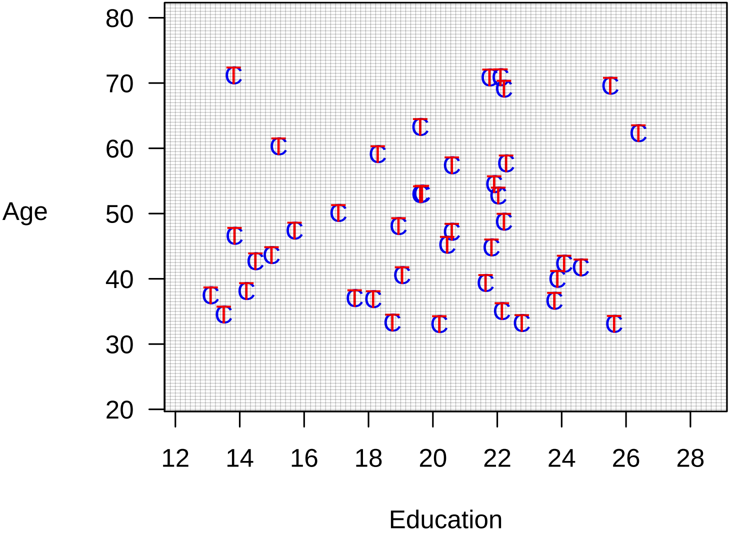

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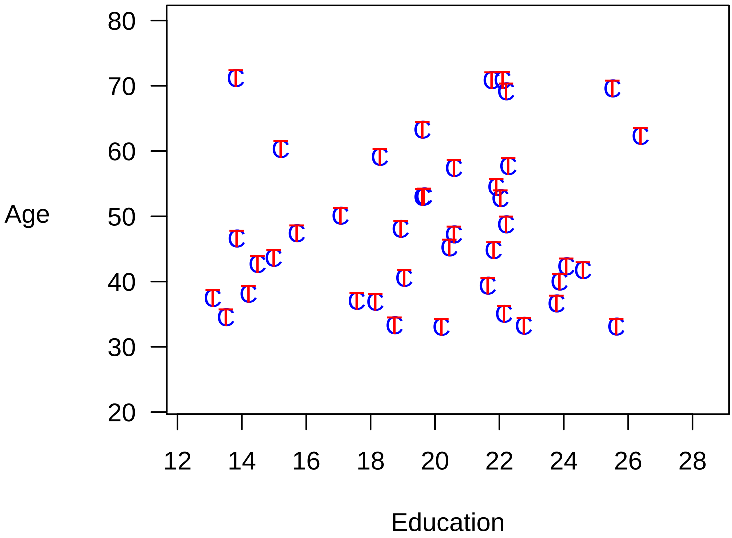

Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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1. Preprocess (Matching)

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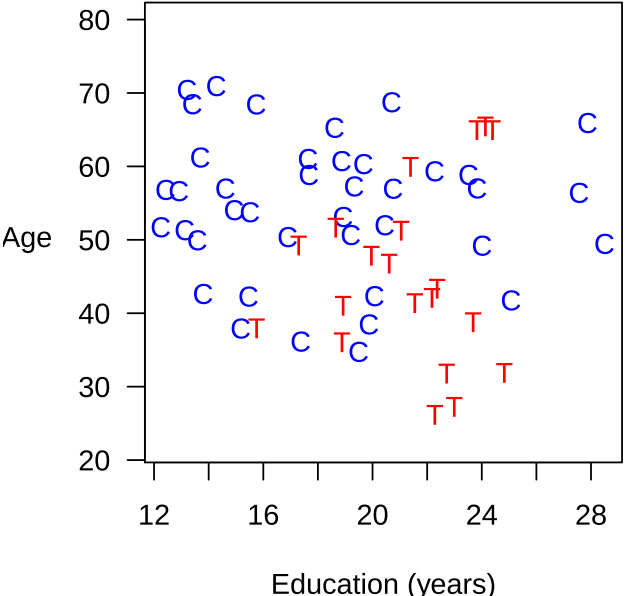
    - (Many adjustments available to this basic method)
2. Estimation Difference in means or a model

Propensity Score Matching



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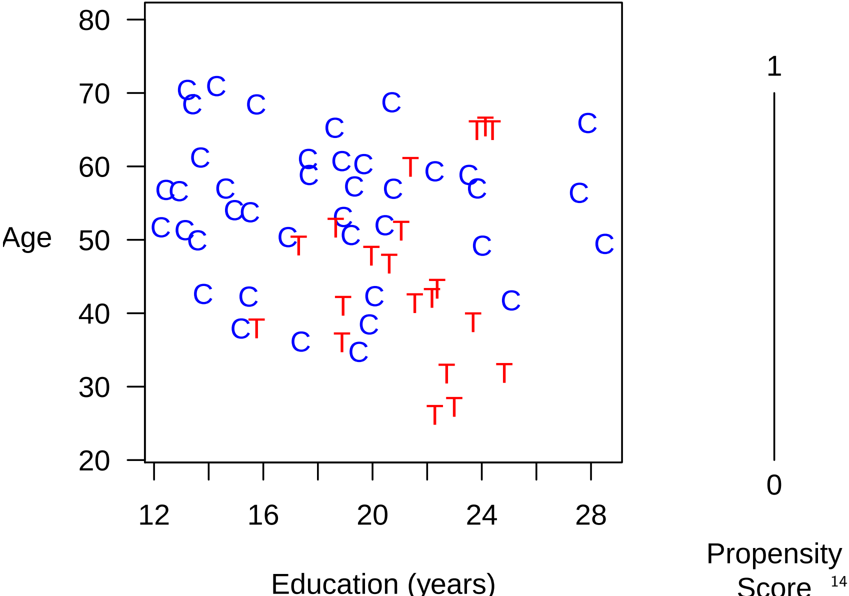

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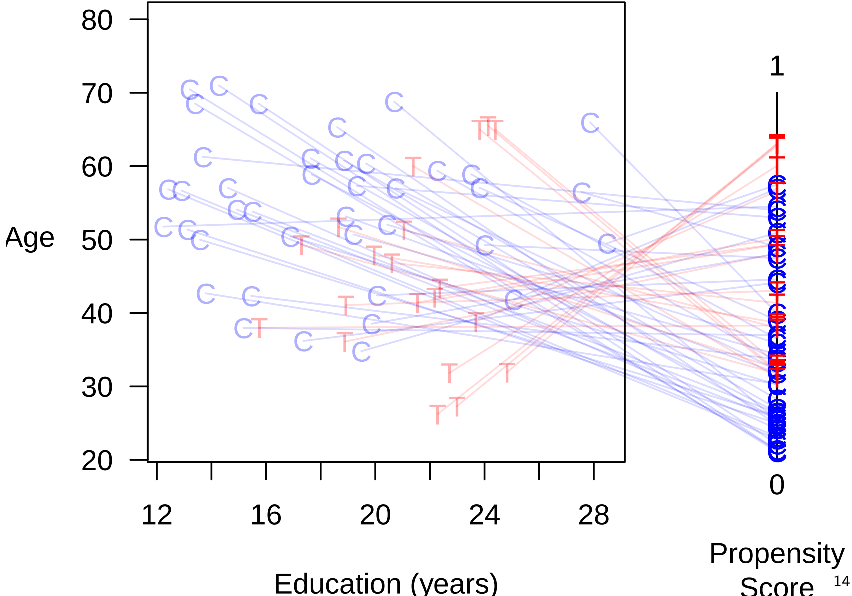

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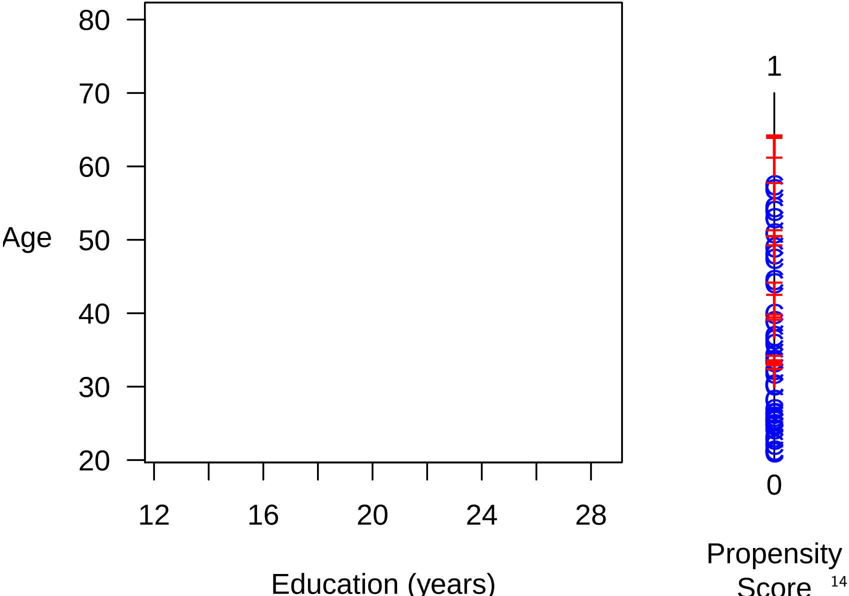

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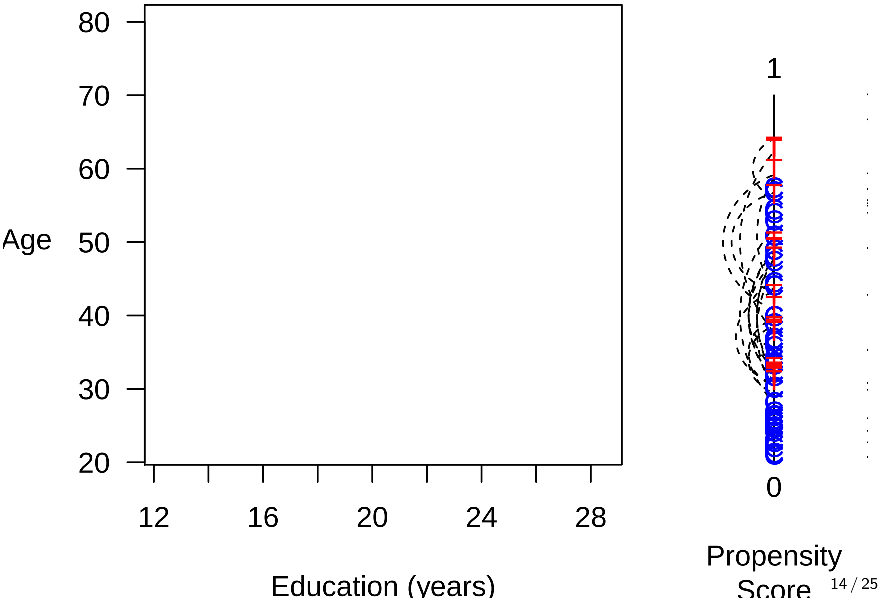

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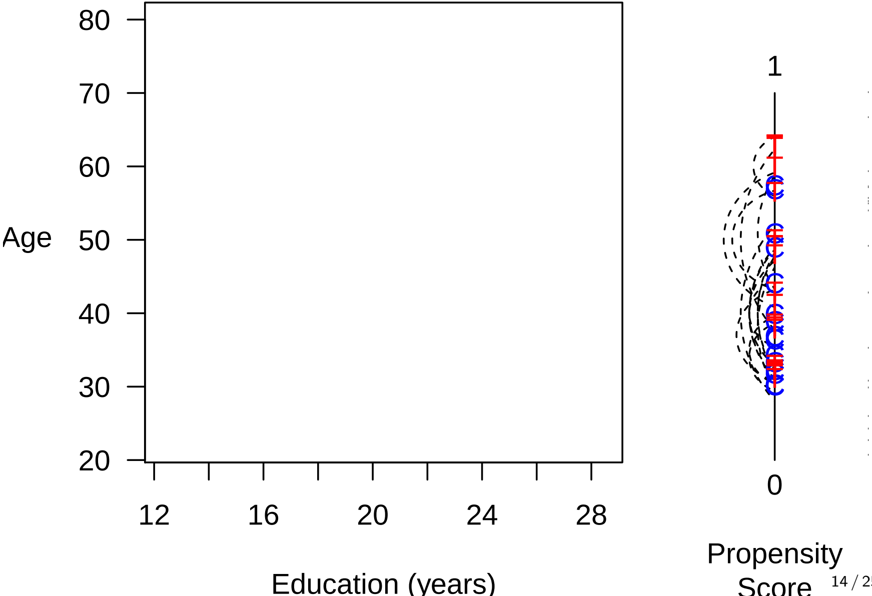

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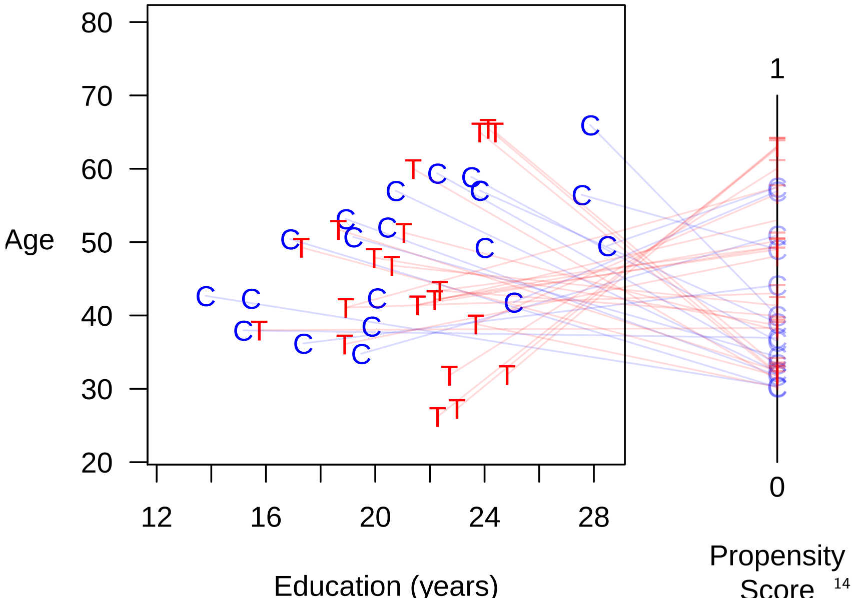

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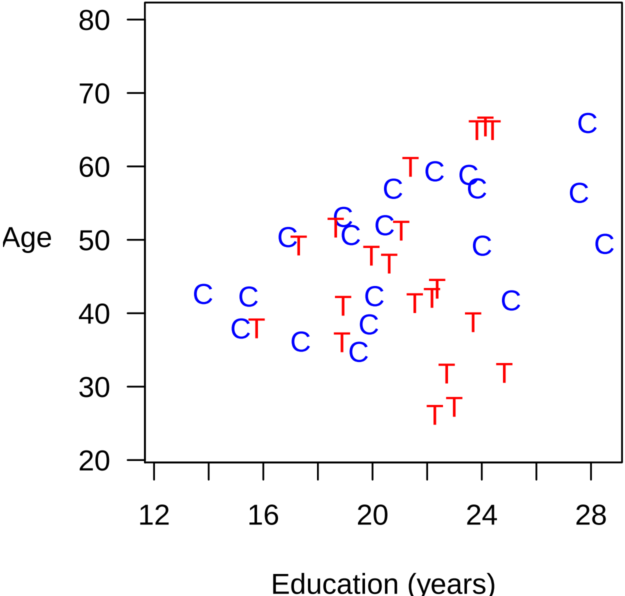

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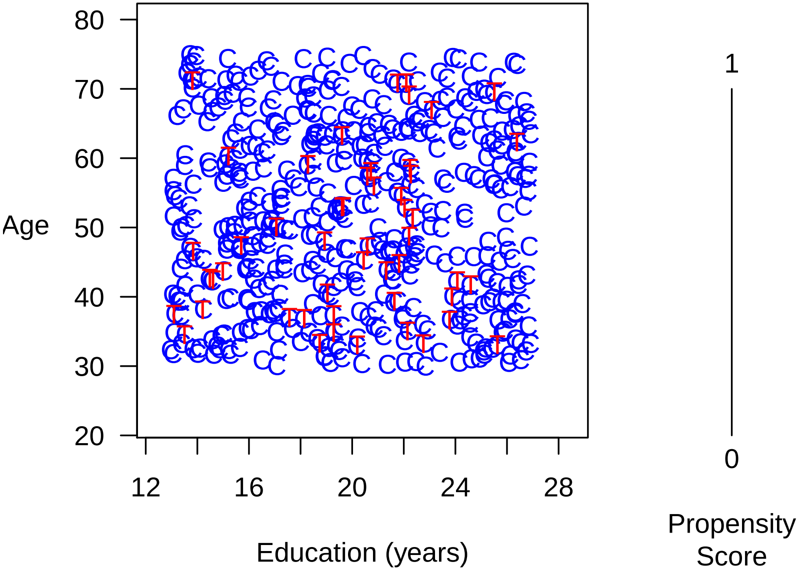

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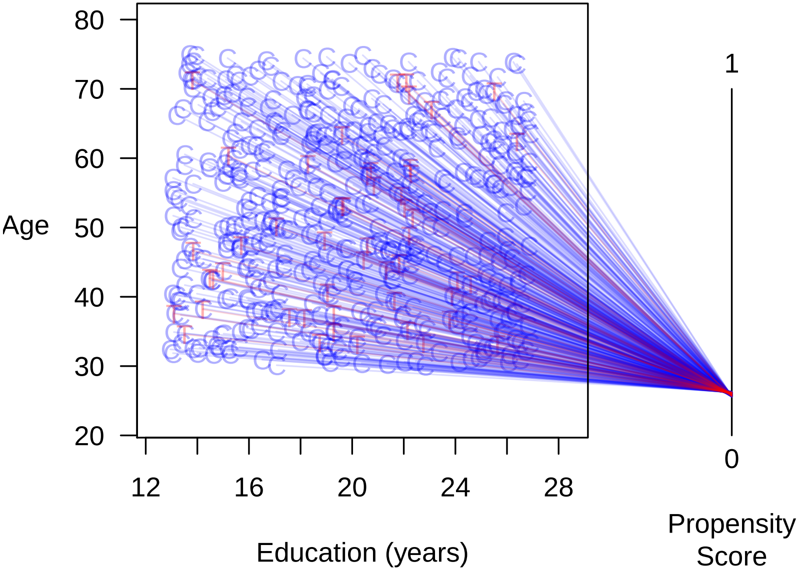

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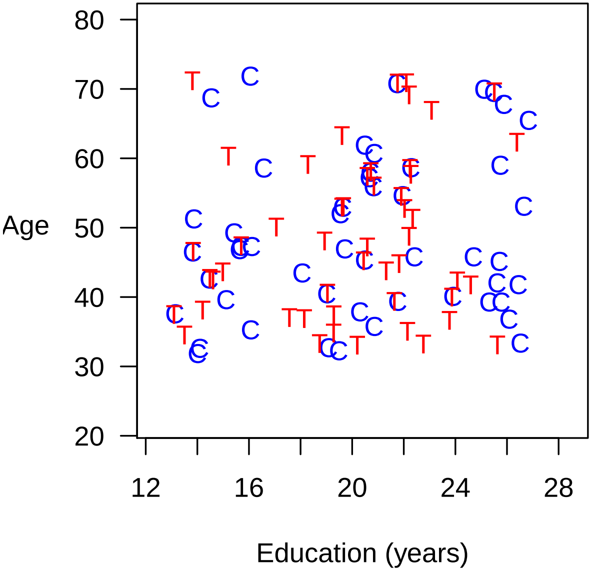
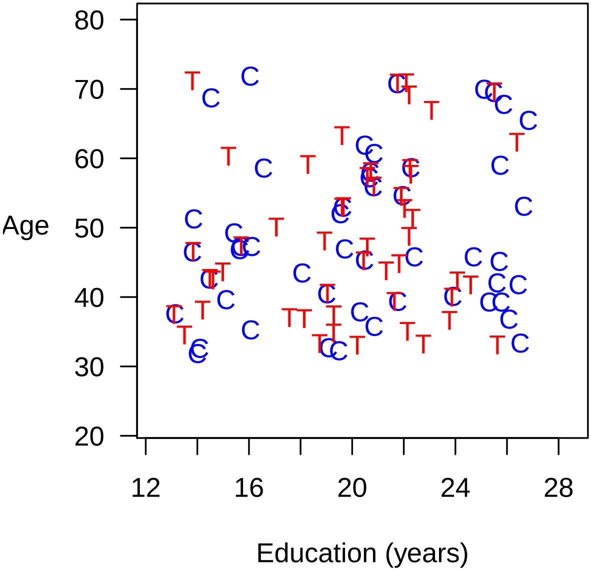


Best Case: Propensity Score Matching is Suboptimal



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   - If the data have no good matches, the paradox won't be a problem but you're cooked anyway.
   - Doesn't PSM solve the curse of dimensionality problem? Nope. The PSM Paradox gets worse with more covariates

PSM is Blind Where Other Methods Can See

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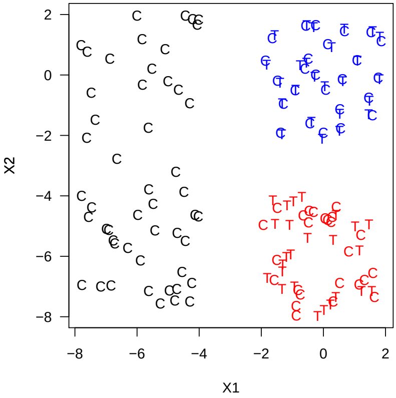

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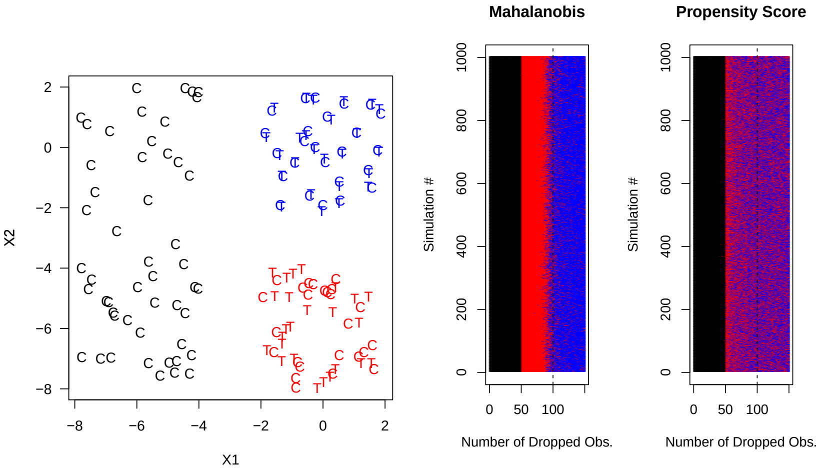
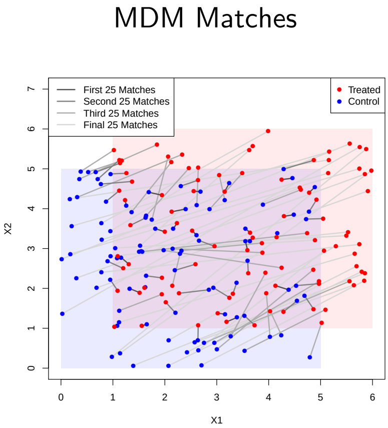
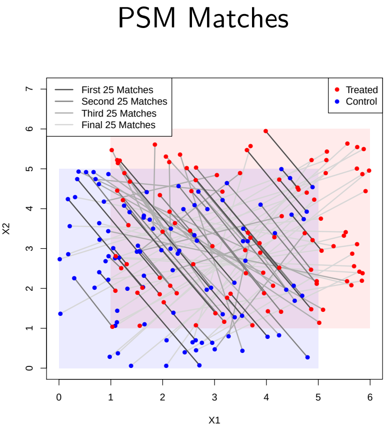


What Does PSM Match?

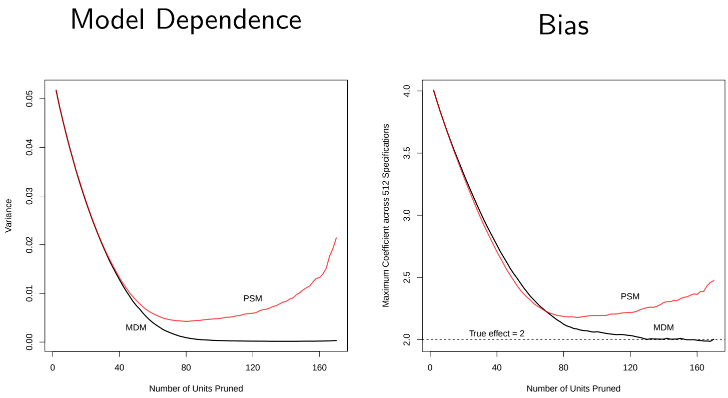




Controls: $X_1, X_2 \sim \text{Uniform}(0{,}5)$

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

PSM Increases Model Dependence & Bias



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

The Propensity Score Paradox in Real Data

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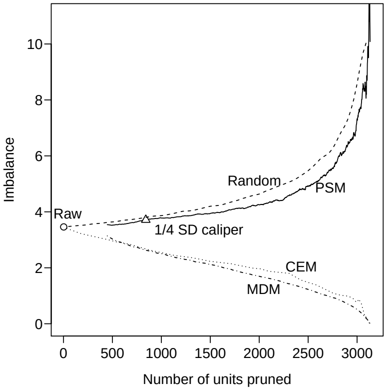
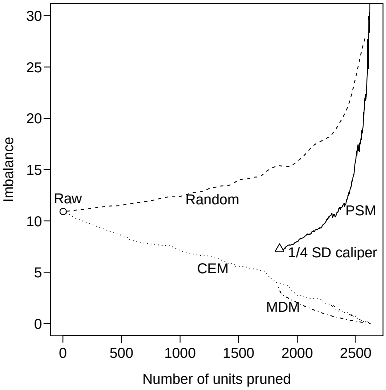
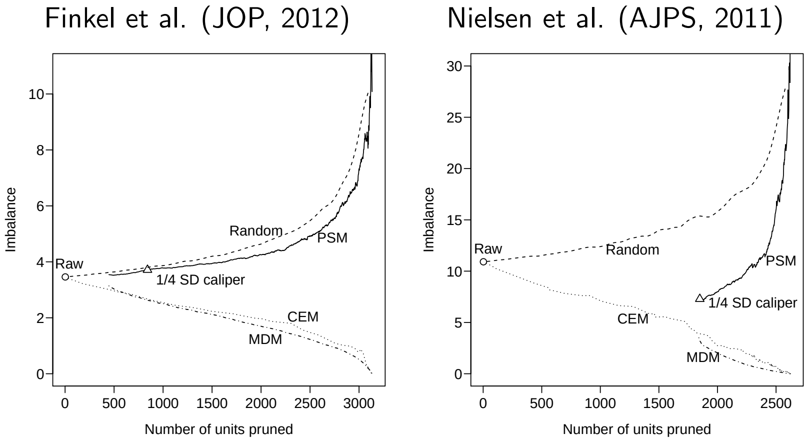
Finkel et al. (JOP, 2012)



Nielsen et al. (AJPS, 2011)



The Propensity Score Paradox in Real Data



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

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2. If we lose pairs, we check for selection bias by rerunning this check

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For more information, articles, & software

GaryKing.org