Quantitative Social Science Methods, I, Lecture Notes: Detecting and Reducing Model Dependence in Causal Inference

Gary King[1]
Institute for Quantitative Social Science
Harvard University

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[1] GaryKing.org

Readings in Model Dependence

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- King, Gary and Langche Zeng. "The Dangers of Extreme Counterfactuals," *Political Analysis*, 14, 2, (2007): 131-159.

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`j.mp/causalinference`

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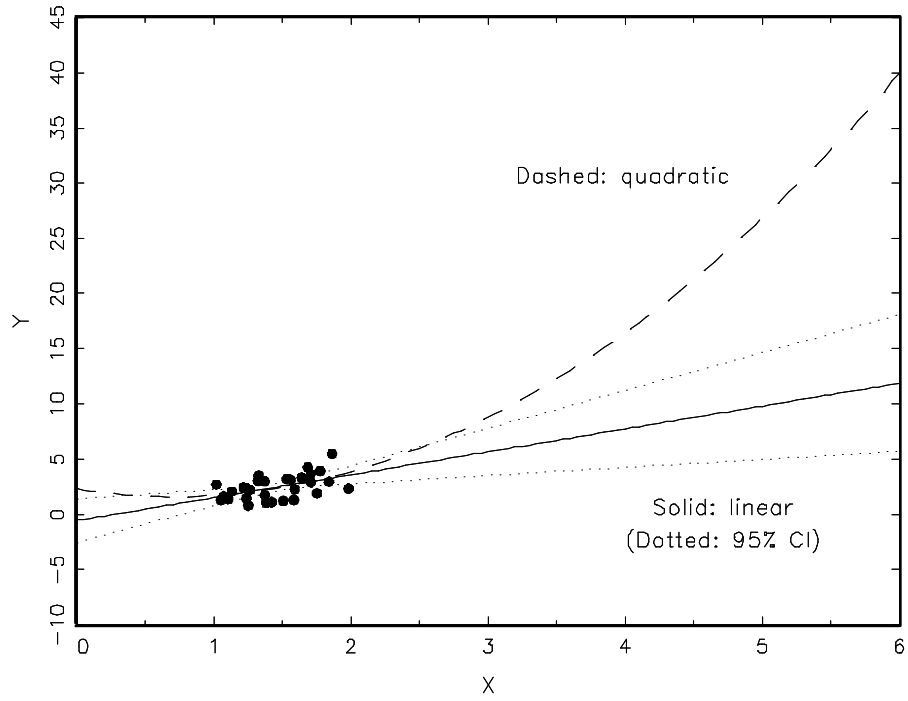
- Counterfactuals are part of most social science research

Which model would you choose? (Both fit the data well.)



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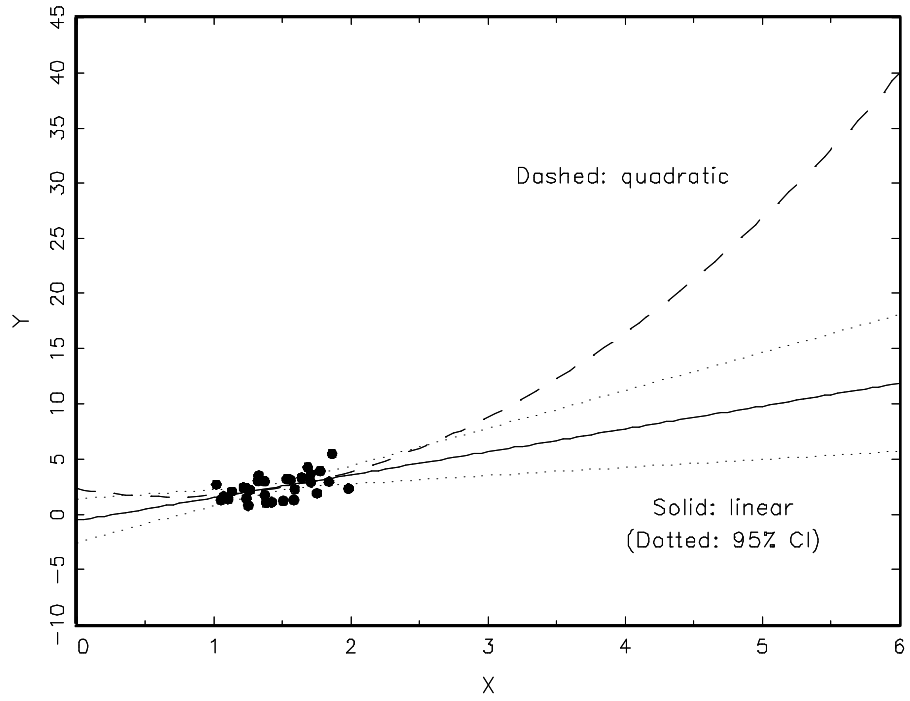

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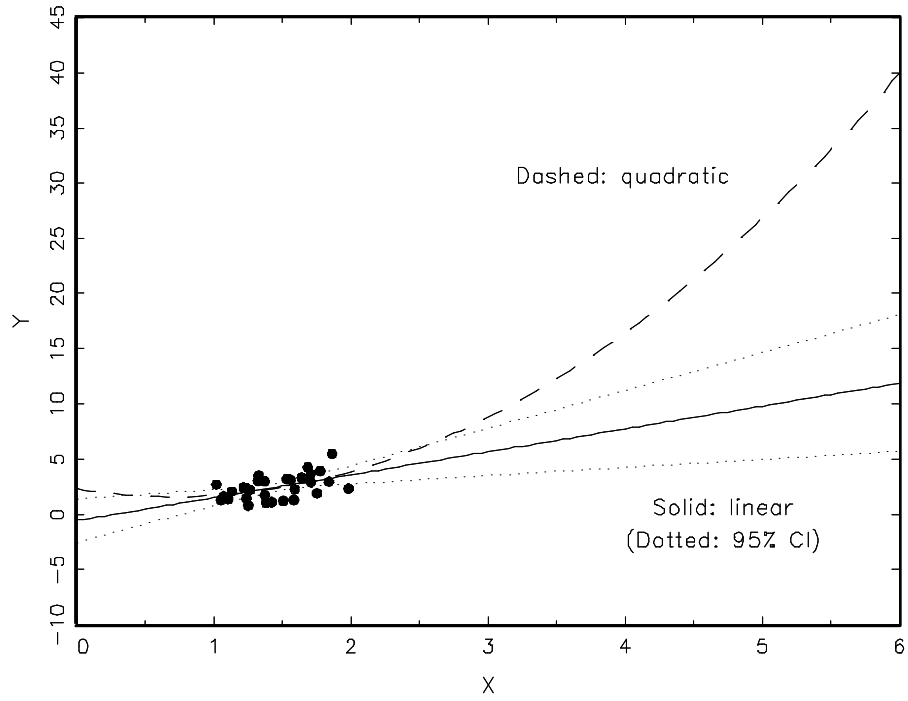

- Compare prediction at $x = 1.5$ to prediction at $x = 5$
- How do you choose a model?

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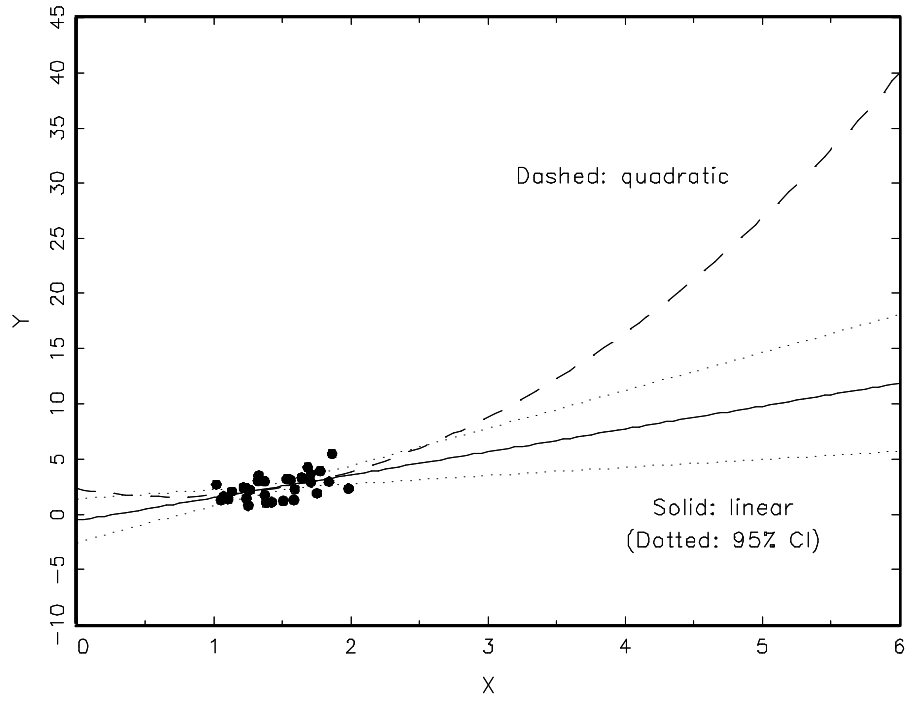

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- How do you choose a model? R^2?

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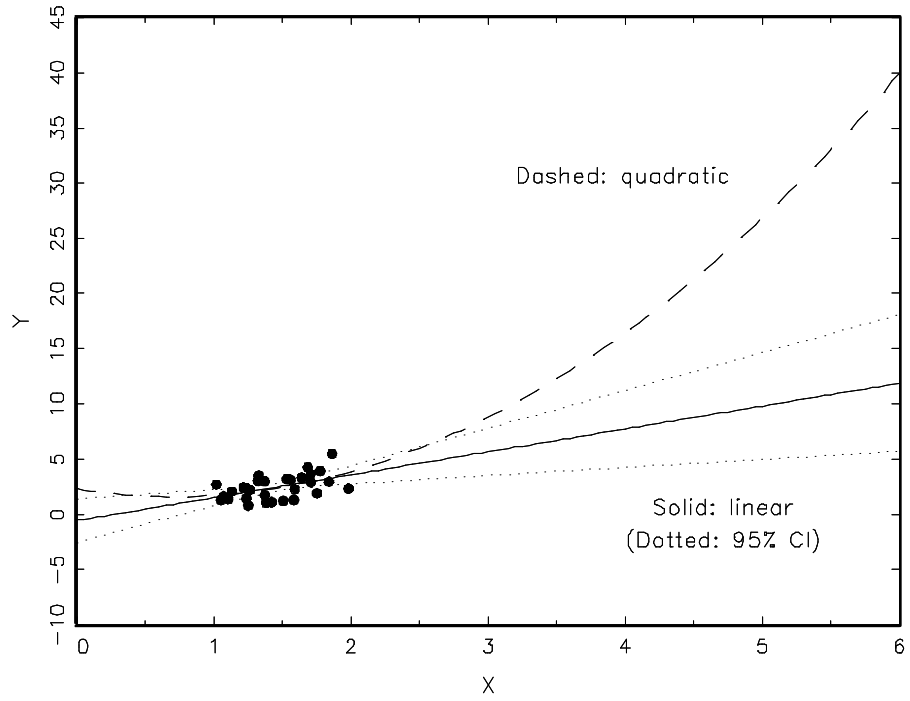

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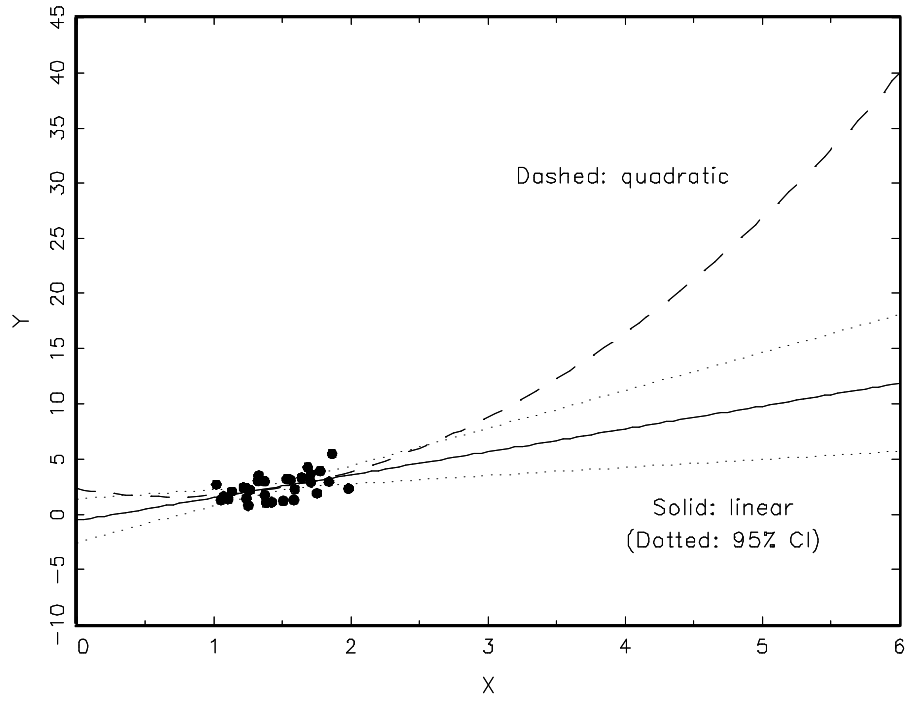

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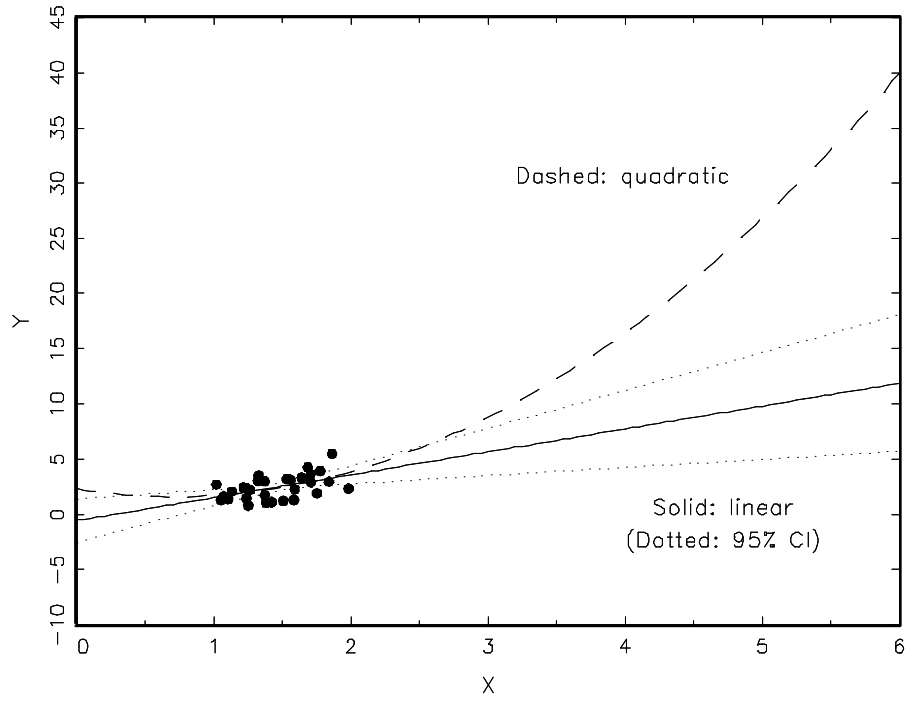

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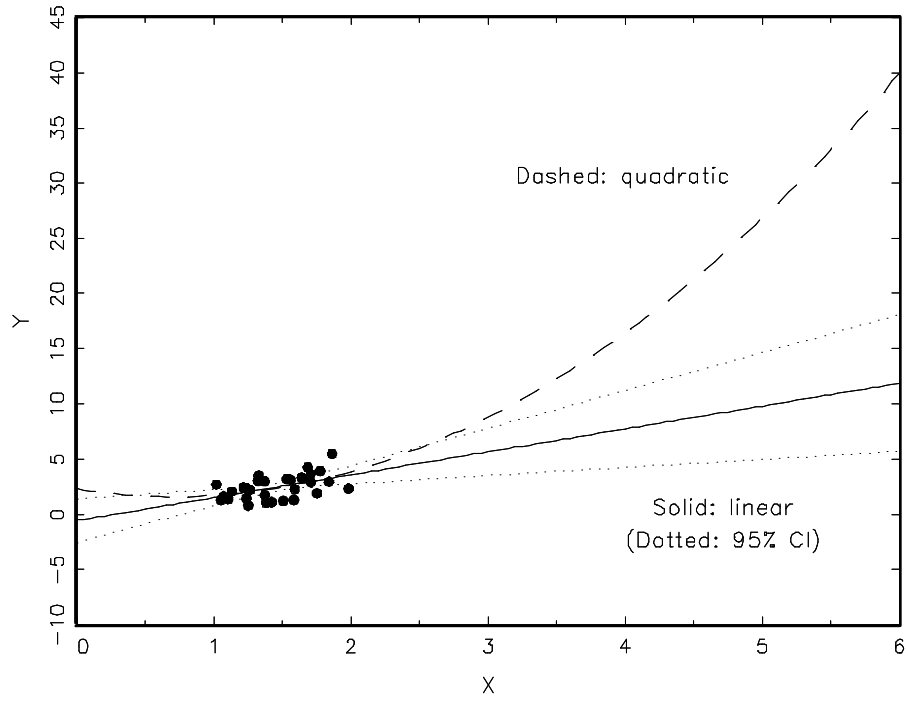

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- Same for what if questions, predictions, and causal inferences

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Model Free Inference

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Result

The maximum degree of model dependence: a function of the distance from the counterfactual to the data

A Simple Measure of Distance from The Data

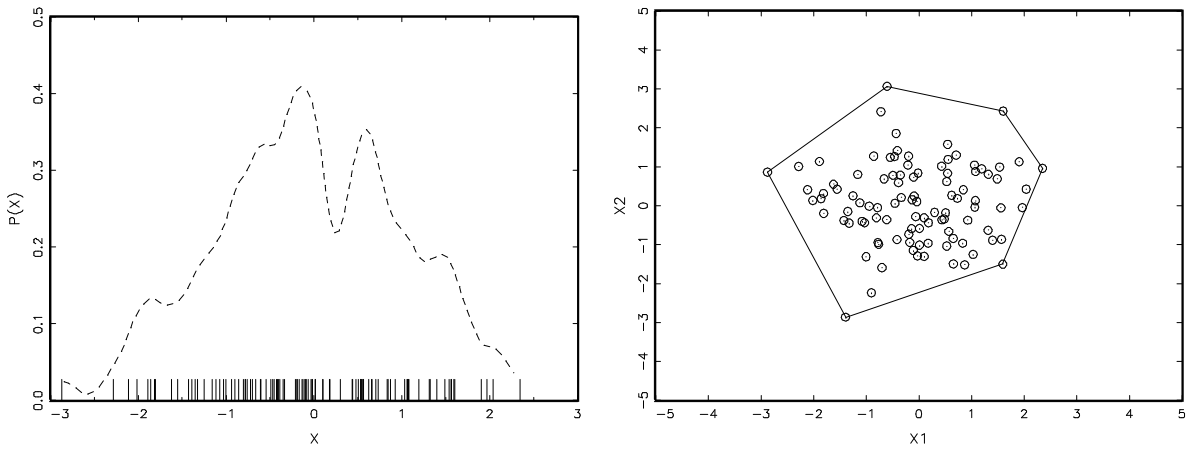

Figure: The Convex Hull

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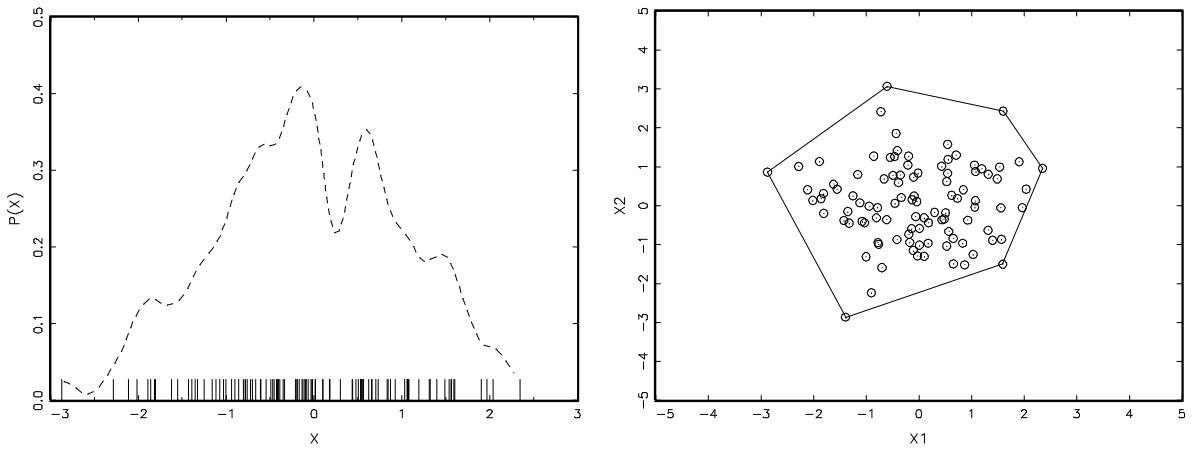

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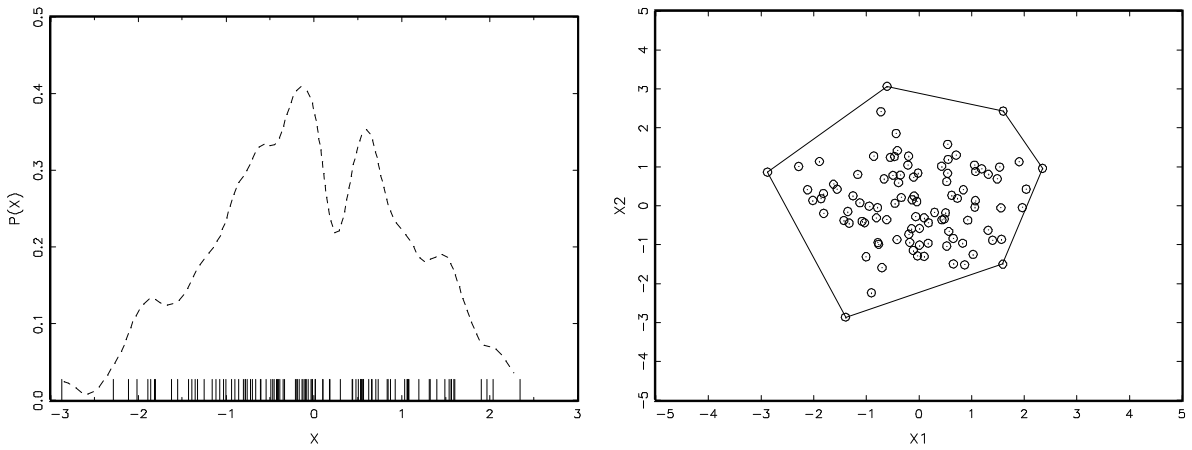

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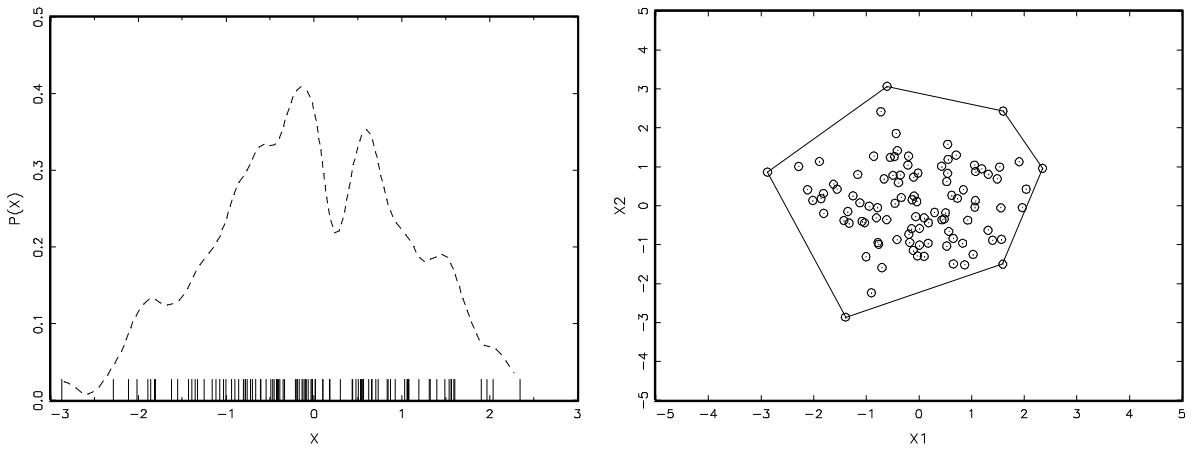

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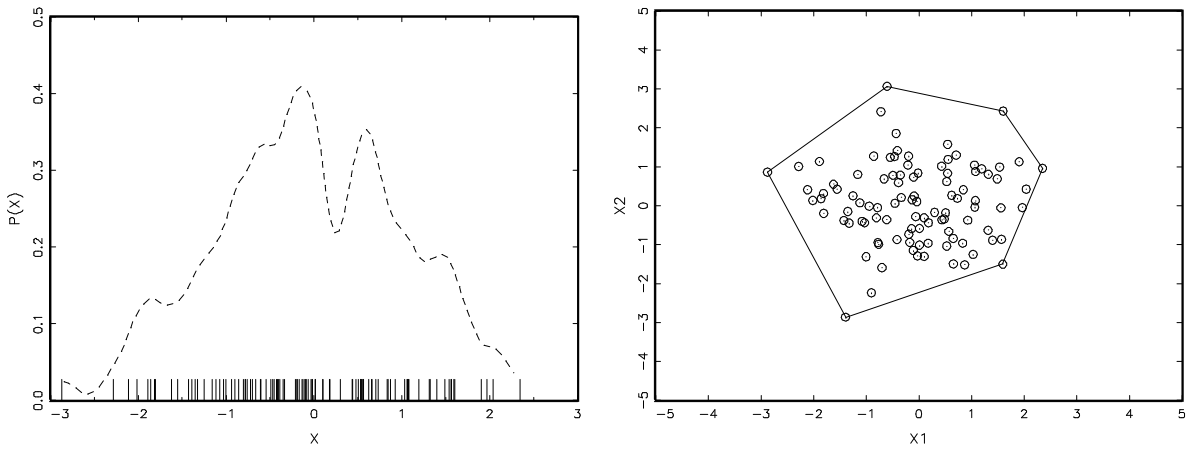

Figure: The Convex Hull

- Interpolation: Inside the convex hull
- Extrapolation: Outside the convex hull
- Works mathematically for any number of X variables
- Software to determine whether a point is in the hull (which is all we need) without calculating the hull (which would take forever), so its fast; see `GaryKing.org/whatif`

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- For illustration: let's find an example....

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Effect of Multilateral UN Intervention on Peacebuilding Success

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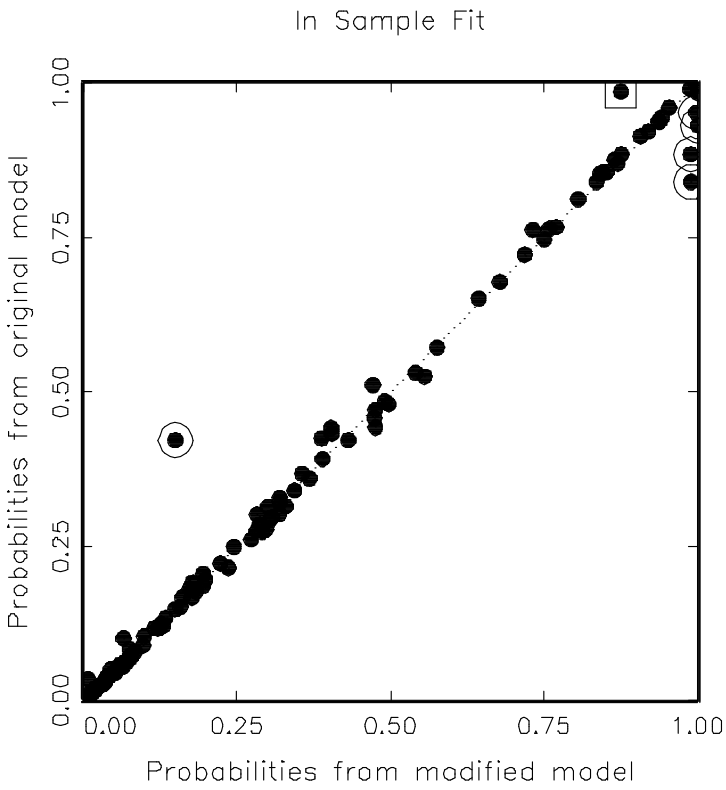
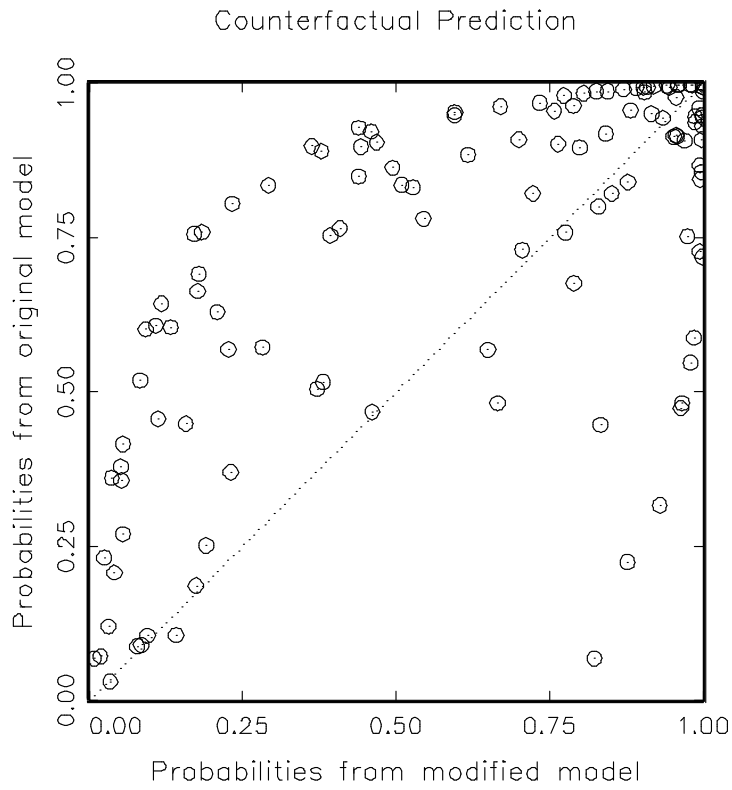
Effect of Multilateral UN Intervention on Peacebuilding Success

	Original "Interactive" Model			Modified Model		
Variables	Coeff	SE	P-val	Coeff	SE	P-val
Wartype	−1.742	.609	.004	−1.666	.606	.006
Logdead	−.445	.126	.000	−.437	.125	.000
Wardur	.006	.006	.258	.006	.006	.342
Factnum	−1.259	.703	.073	−1.045	.899	.245
Factnum2	.062	.065	.346	.032	.104	.756
Trnsfcap	.004	.002	.010	.004	.002	.017
Develop	.001	.000	.065	.001	.000	.068
Exp	−6.016	3.071	.050	−6.215	3.065	.043
Decade	−.299	.169	.077	−0.284	.169	.093
Treaty	2.124	.821	.010	2.126	.802	.008
UNOP4	3.135	1.091	.004	.262	1.392	.851
Wardur*UNOP4	—	—	—	.037	.011	.001
Constant	8.609	2.157	0.000	7.978	2.350	.000
N		122			122	
Log-likelihood		-45.649			-44.902	
Pseudo R^2		.423			.433	

Model Dependence: Same Fit, Different Predictions





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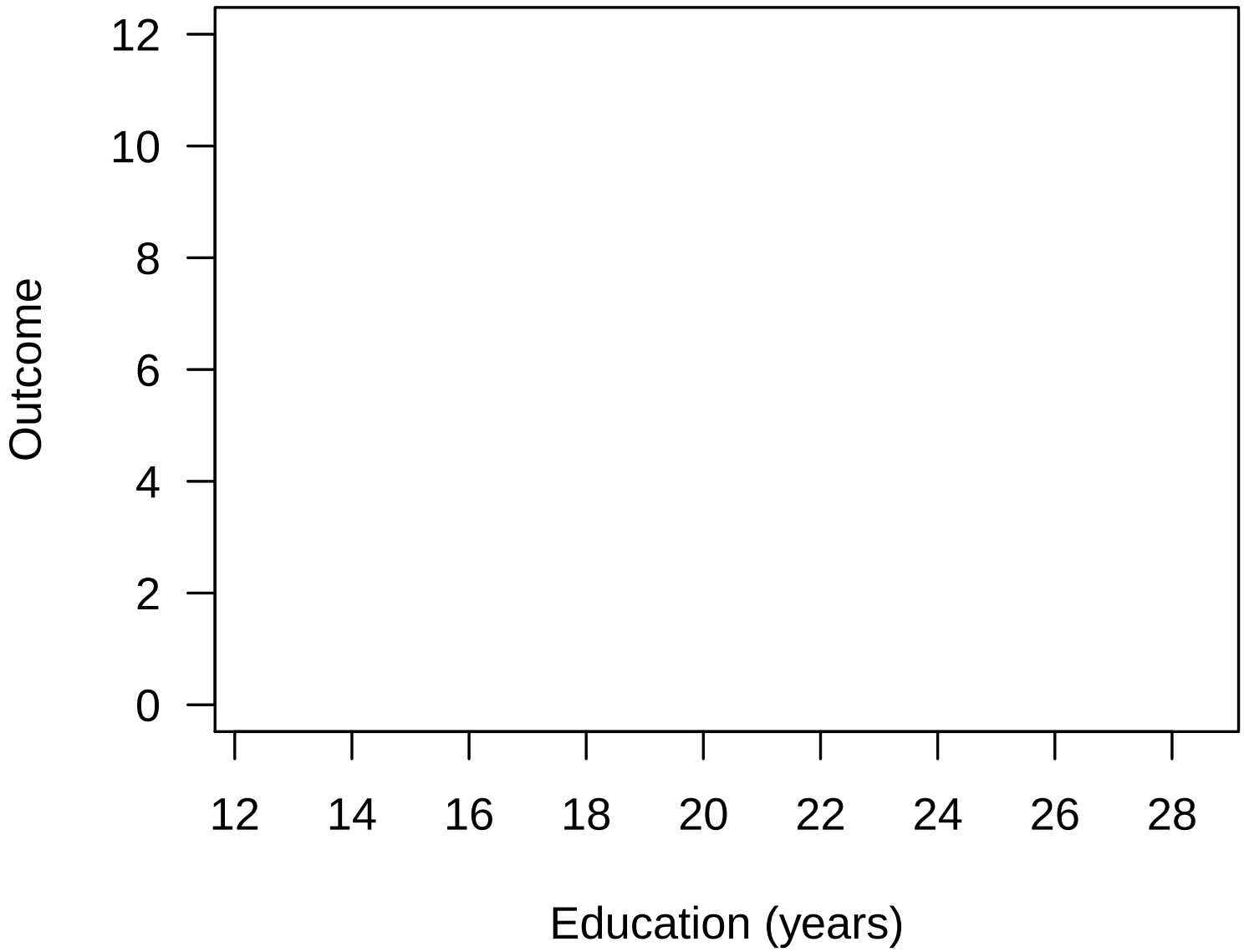

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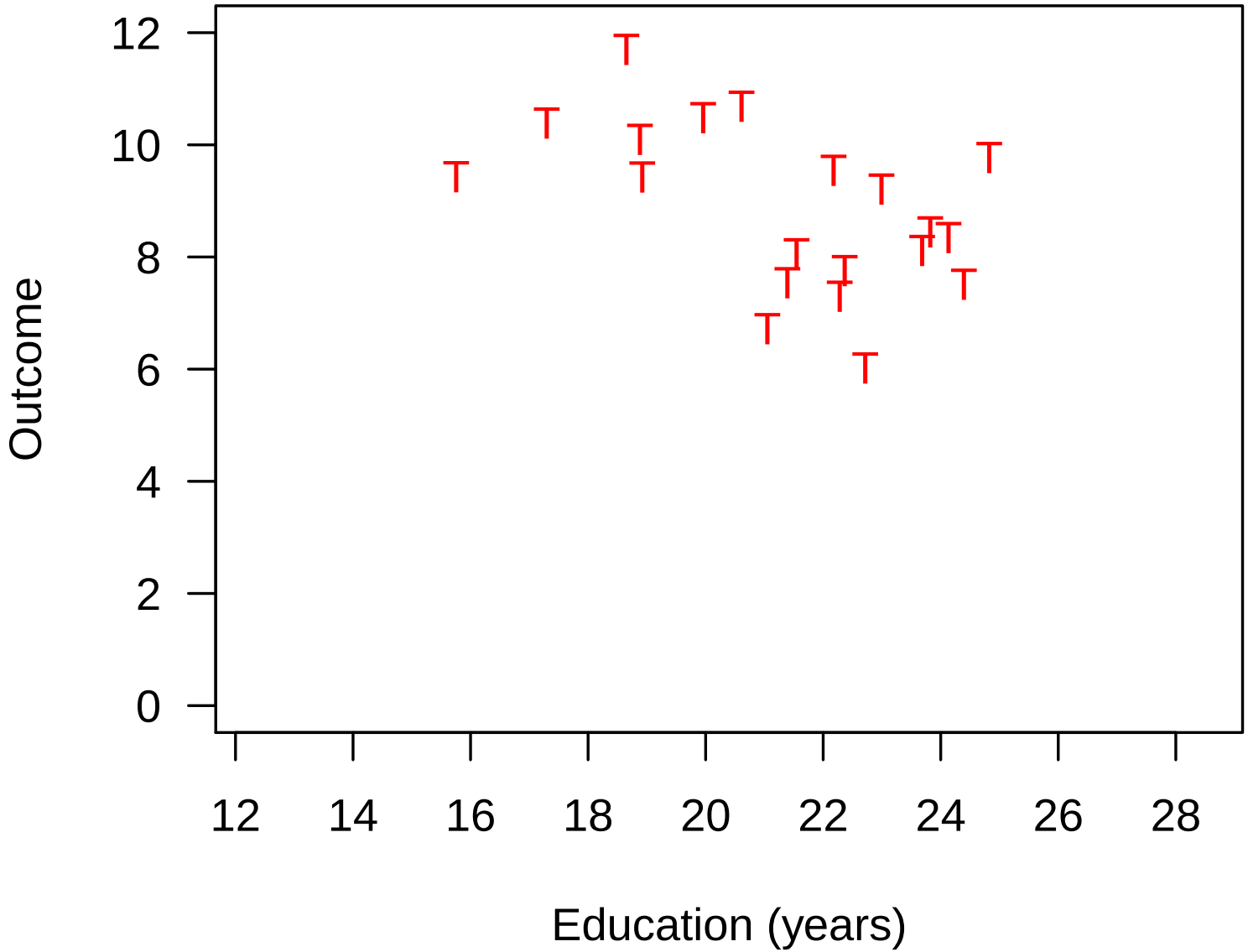

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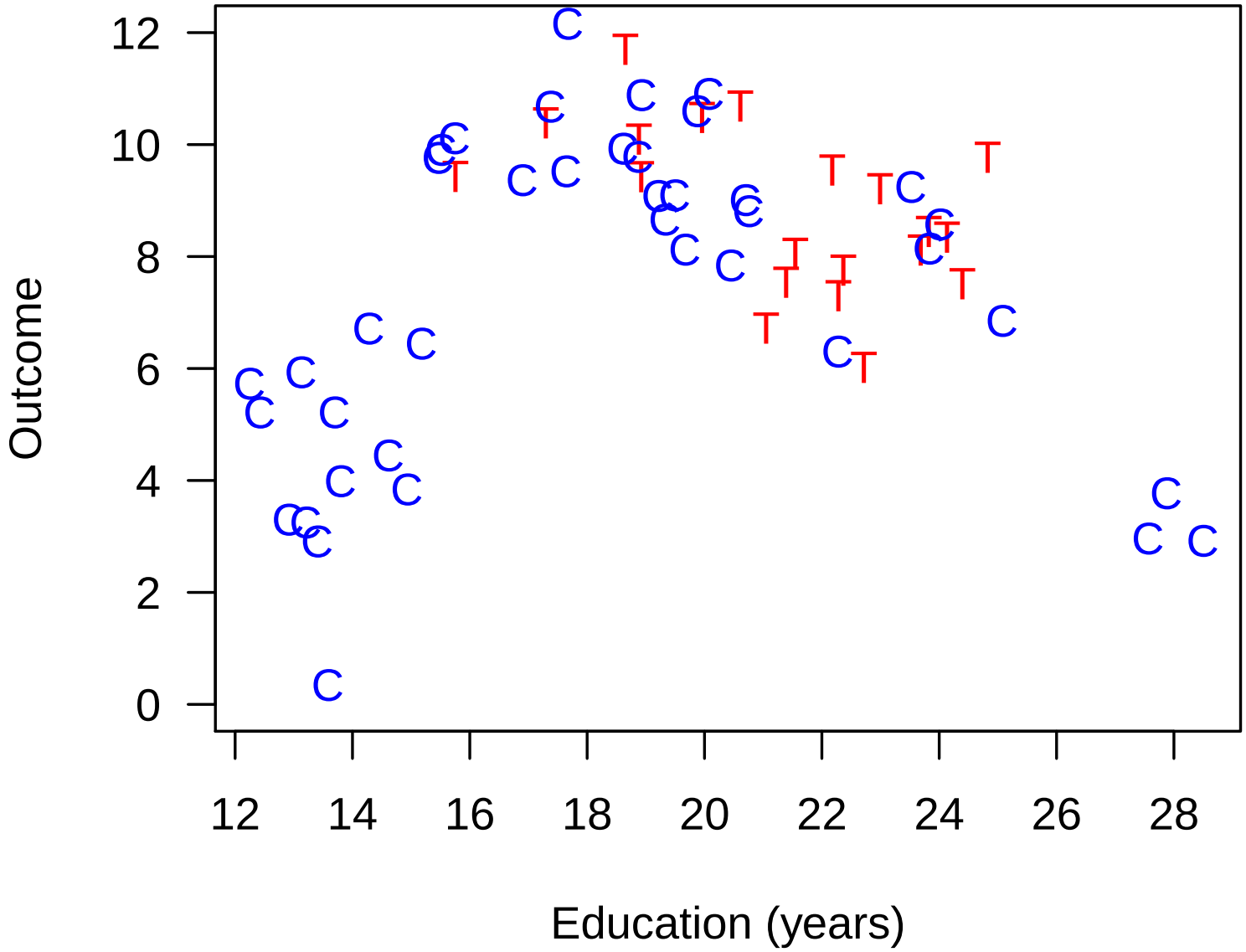

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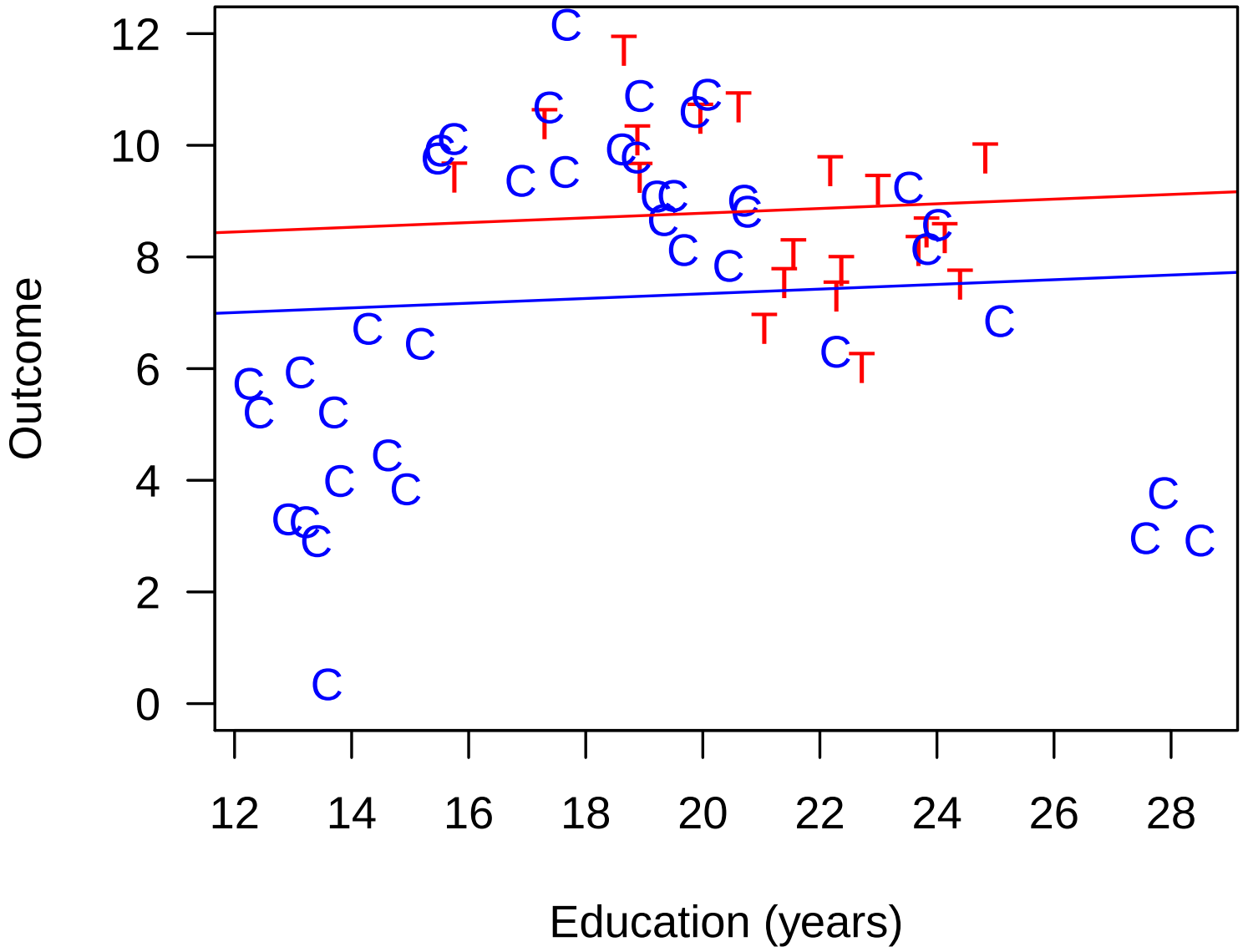

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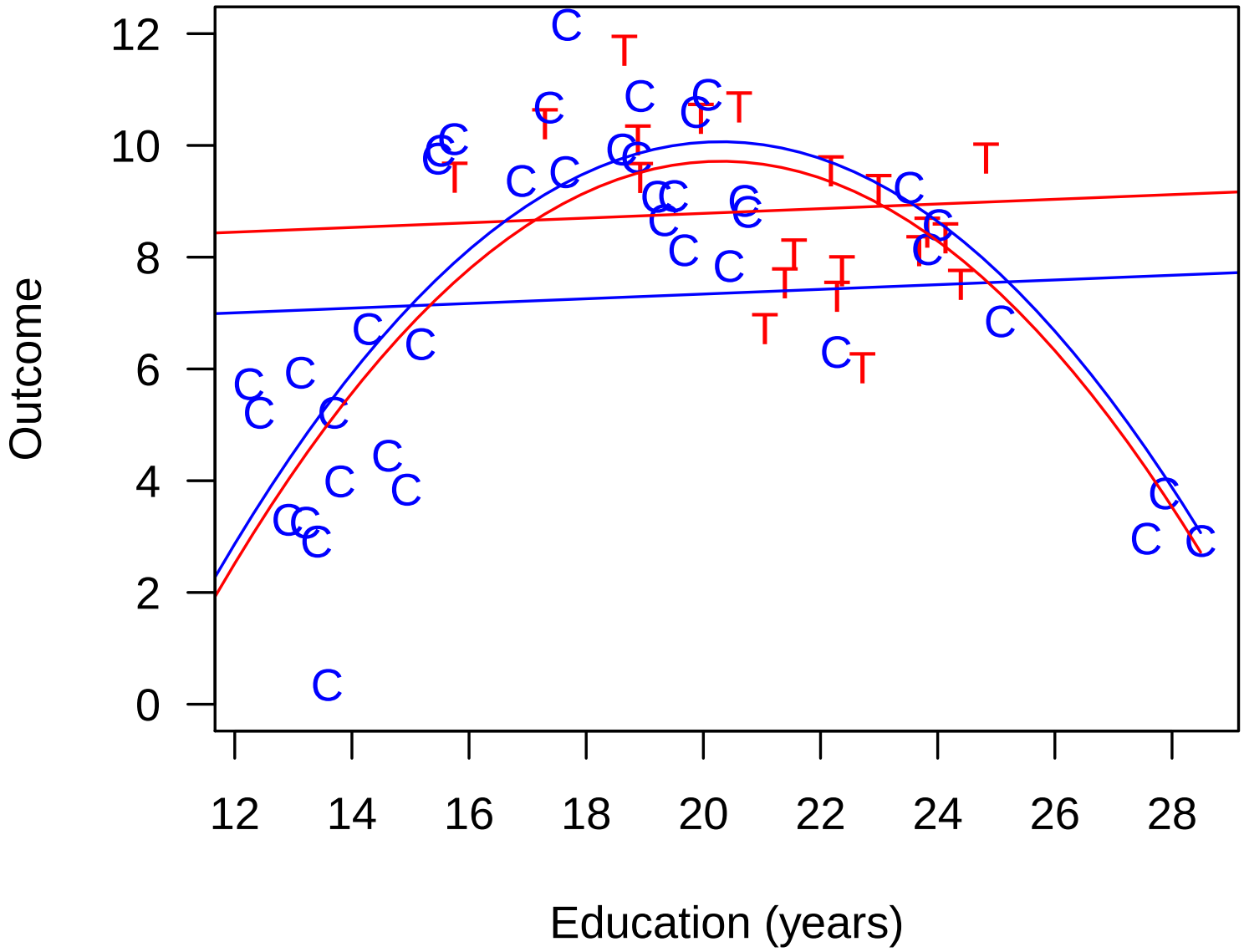

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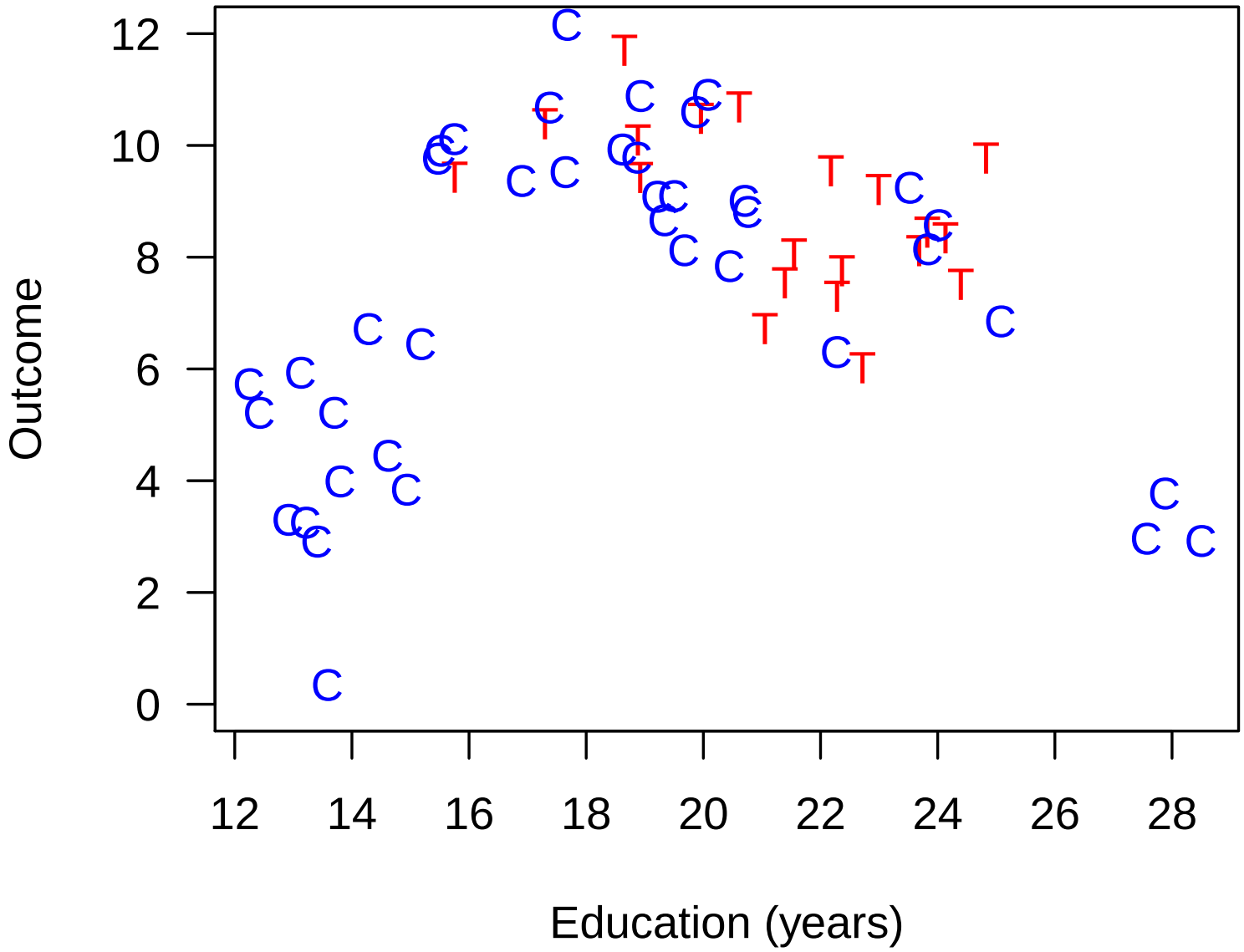

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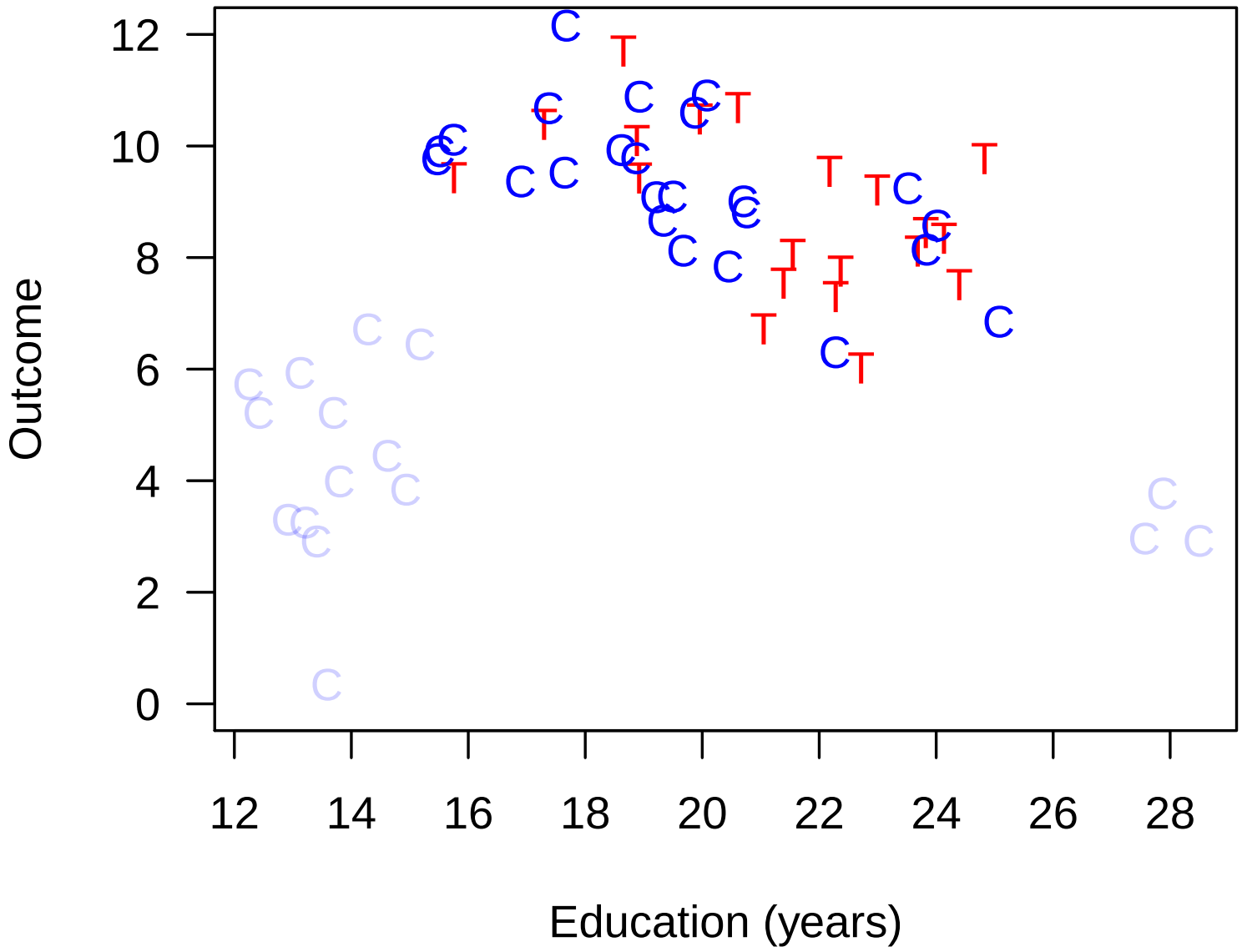

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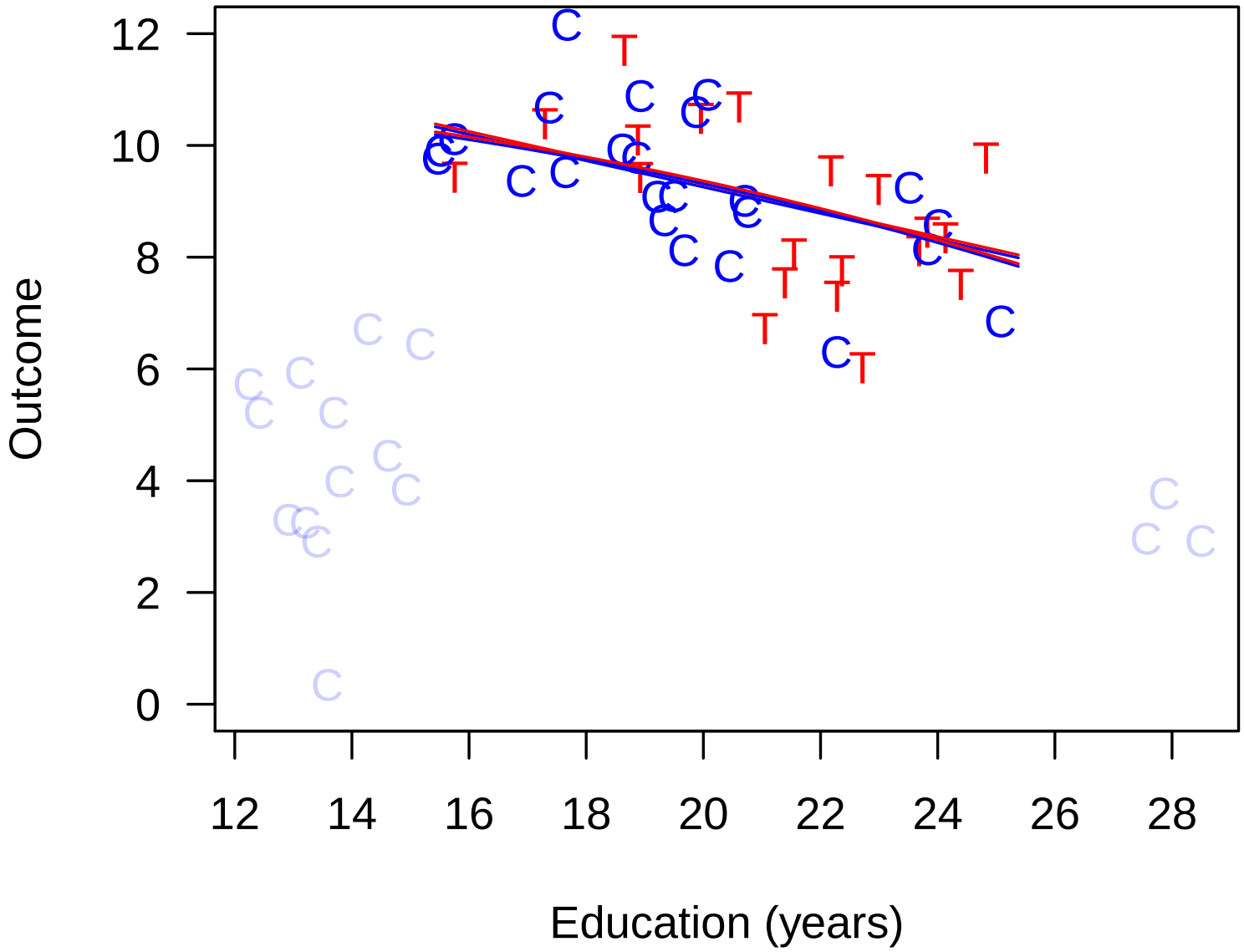

The Problems Matching Solves

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Without Matching:

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Without Matching:

Imbalance

The Problems Matching Solves

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Imbalance $\rightsquigarrow$ Model Dependence

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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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- (Normally we'd only use one or a few specifications)

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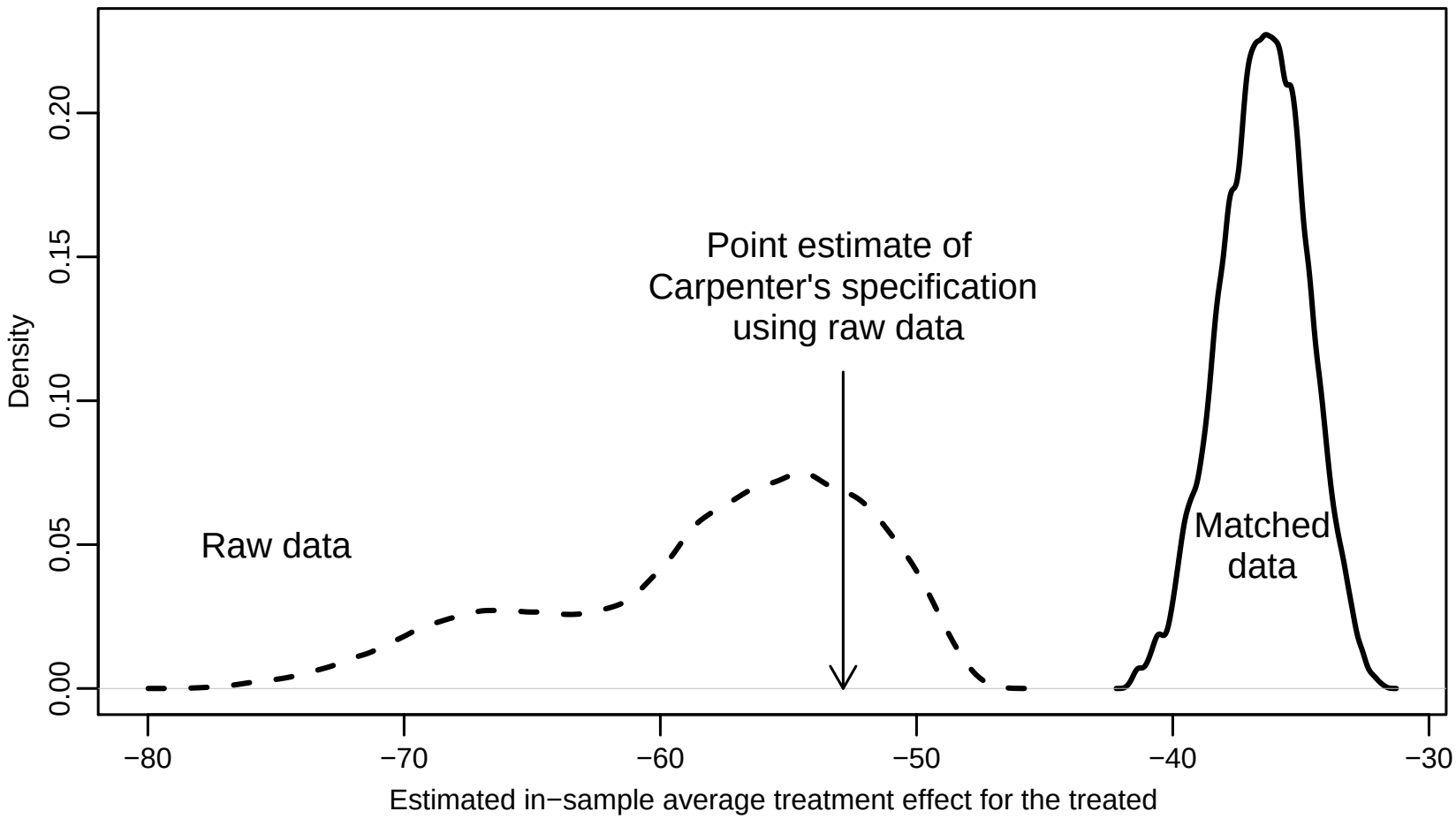

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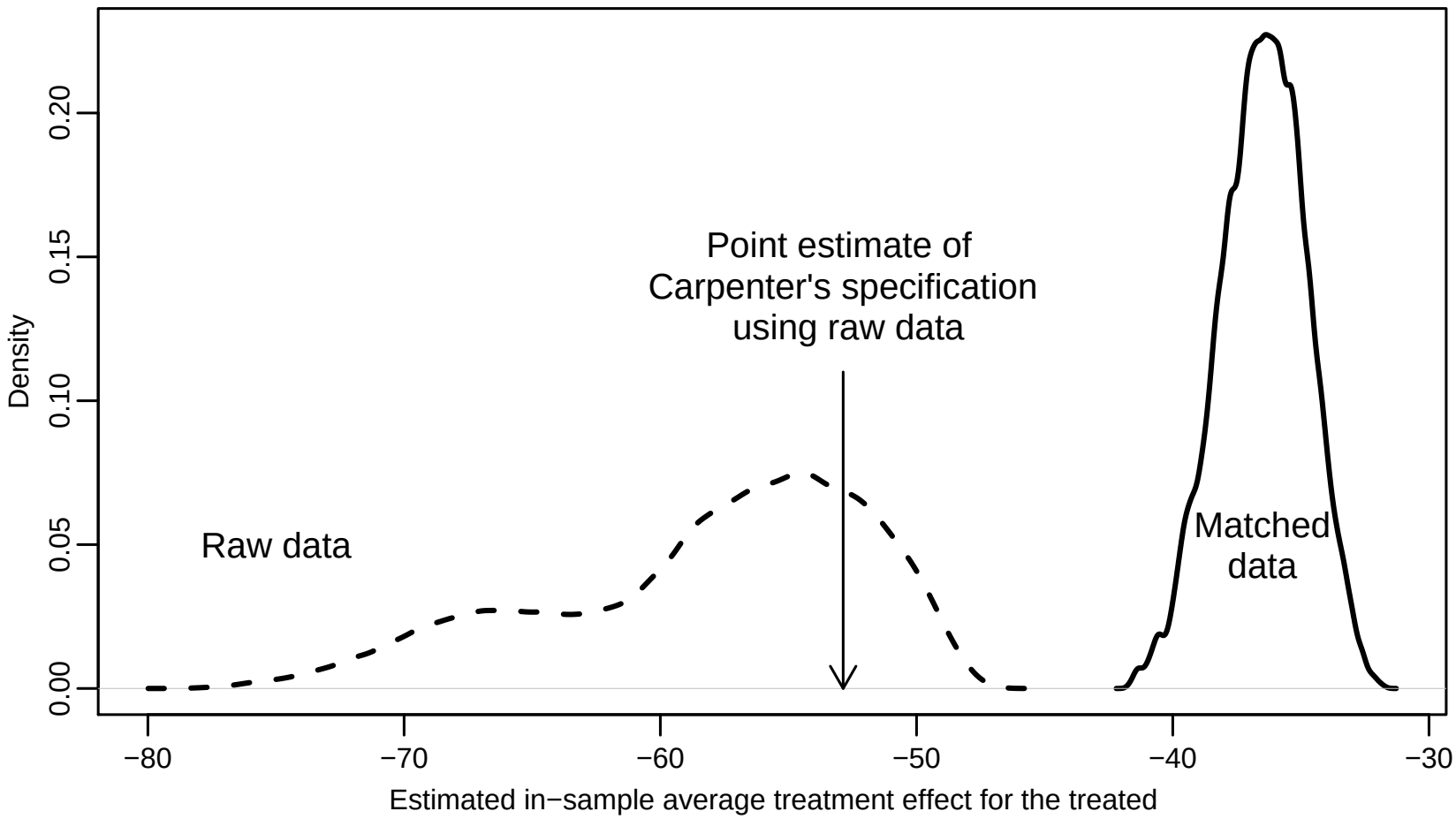
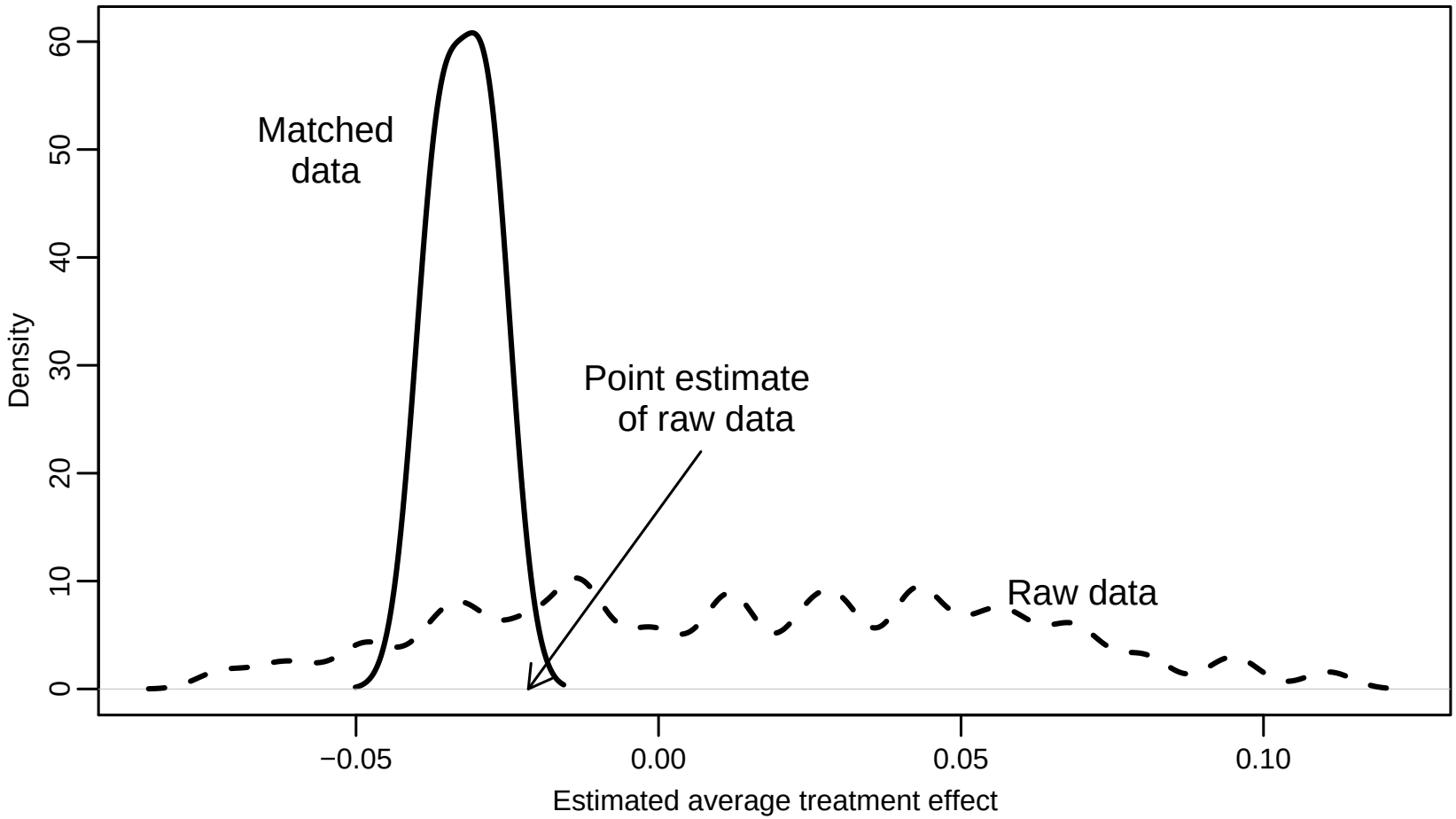


SATT Histogram: Effect of Democratic Senate majority on FDA drug approval time, across 262,143 specifications

Another Example: Jeffrey Koch, AJPS, 2002



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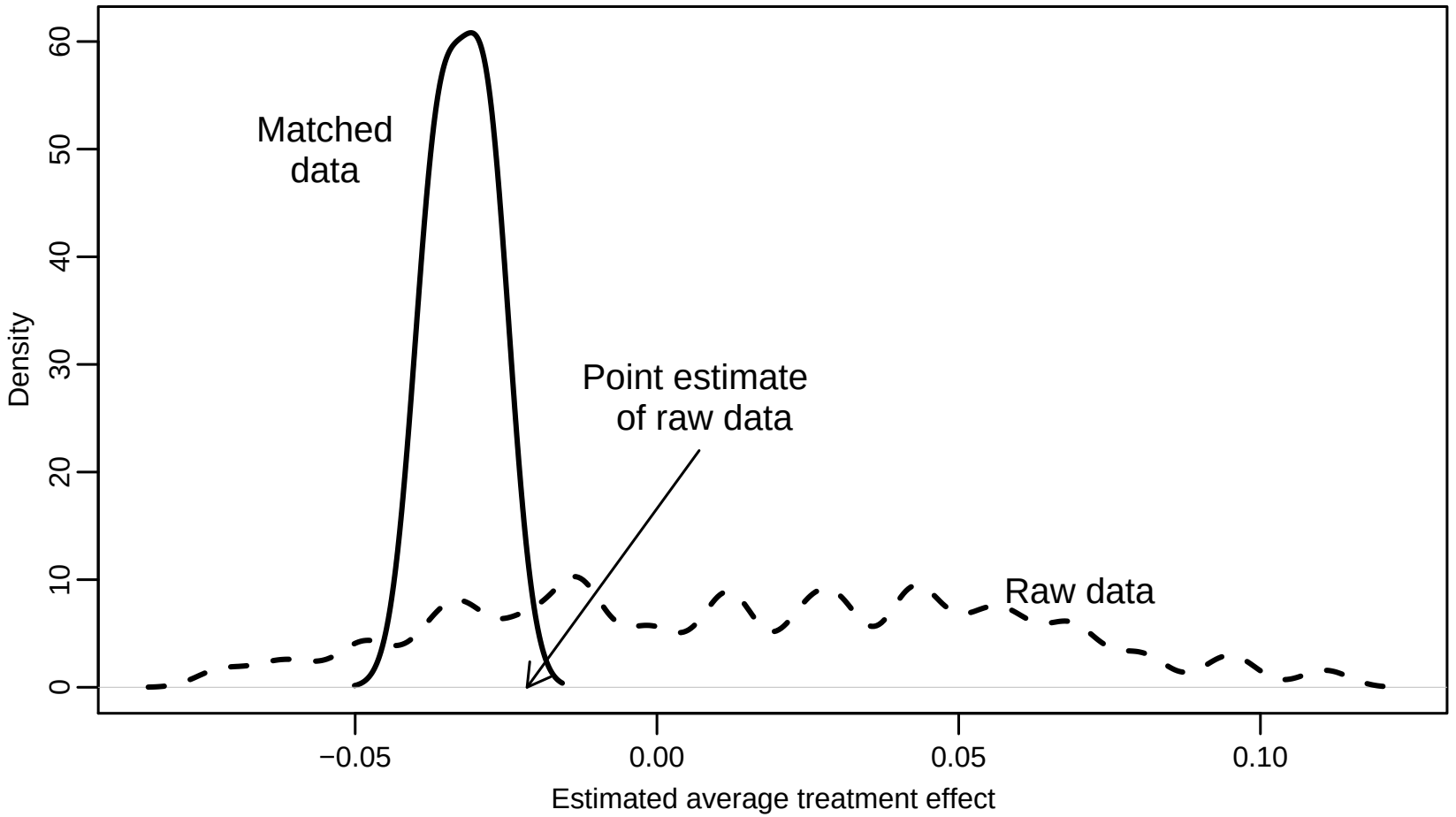

SATT Histogram: Effect of being a highly visible female Republican candidate across 63 possible specifications with the Koch data

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Types of Experiments

Matching: Finding Hidden Randomized Experiments

Types of Experiments

Complete Randomization

Matching: Finding Hidden Randomized Experiments

Types of Experiments

	Complete Randomization	*Fully Blocked*

Matching: Finding Hidden Randomized Experiments

Types of Experiments

Balance Covariates:	*Complete Randomization*	*Fully Blocked*
Observed		
Unobserved		

Matching: Finding Hidden Randomized Experiments

Types of Experiments

Balance Covariates:	*Complete Randomization*	*Fully Blocked*
Observed	On average	
Unobserved		

Matching: Finding Hidden Randomized Experiments

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Balance Covariates:	*Complete Randomization*	*Fully Blocked*
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Matching: Finding Hidden Randomized Experiments

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Balance Covariates:	*Complete Randomization*	*Fully Blocked*
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$\rightsquigarrow$ *Fully blocked* dominates *complete randomization*

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Goal of Each Matching Method (in Observational Data)

Matching: Finding Hidden Randomized Experiments

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Goal of Each Matching Method (in Observational Data)

- PSM: *complete randomization*

Matching: Finding Hidden Randomized Experiments

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Goal of Each Matching Method (in Observational Data)

- PSM: *complete randomization*
- Other methods: *fully blocked*

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Goal of Each Matching Method (in Observational Data)

- PSM: *complete randomization*
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Goal of Each Matching Method (in Observational Data)

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

Method 1: Mahalanobis Distance Matching

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(Approximates Fully Blocked Experiment)

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Procedure

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Procedure

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(Approximates Fully Blocked Experiment)

Procedure

1. Preprocess (Matching)

2. Estimation Difference in means or a model

Method 1: Mahalanobis Distance Matching

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   - Distance$(X_c, X_t) = \sqrt{(X_c - X_t)' S^{-1} (X_c - X_t)}$
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(Approximates Fully Blocked Experiment)

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- Quiz: Do you understand the distance trade offs?

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Interpretation

- Quiz: Do you understand the distance trade offs?
- Quiz: Does standardization help?

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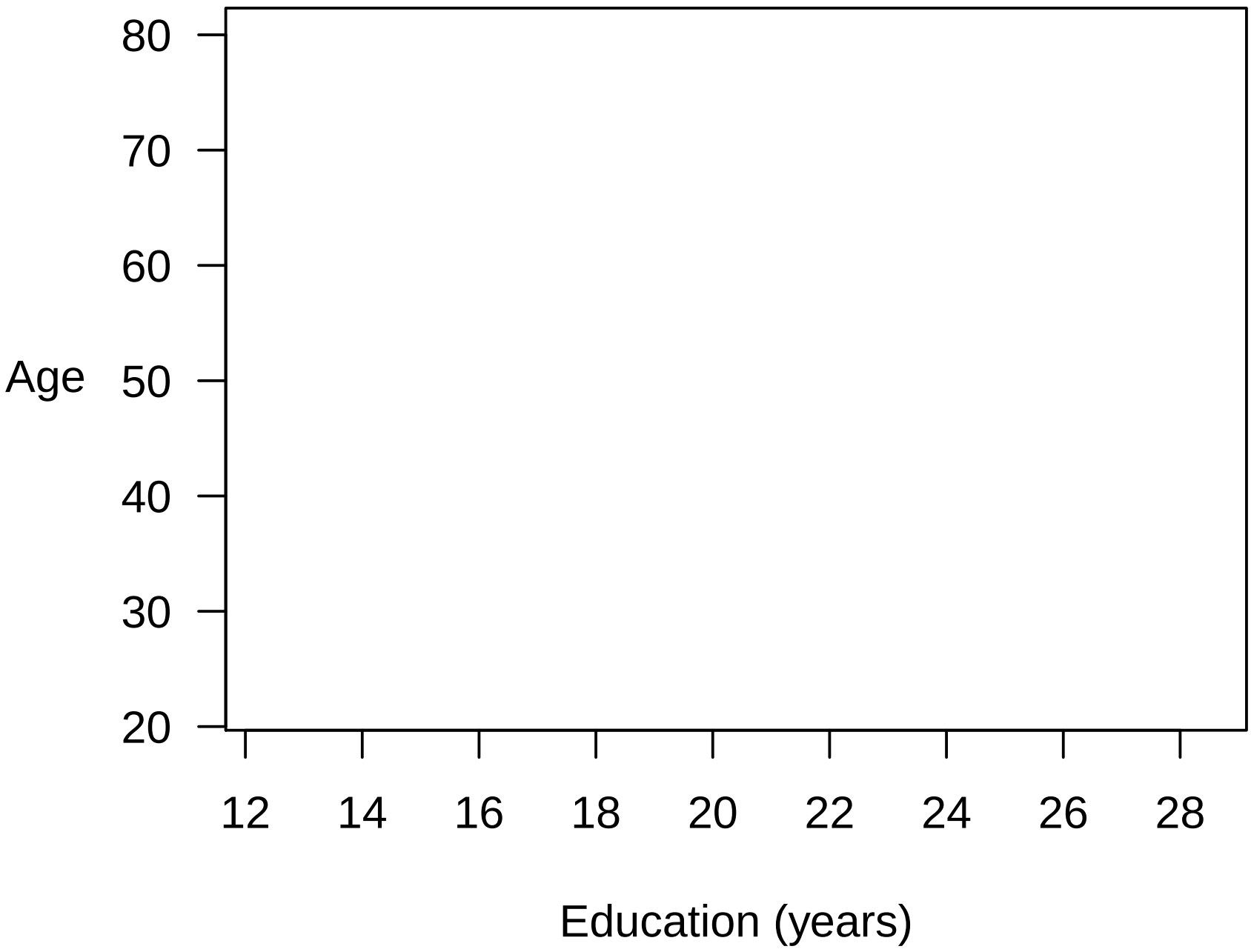
Interpretation

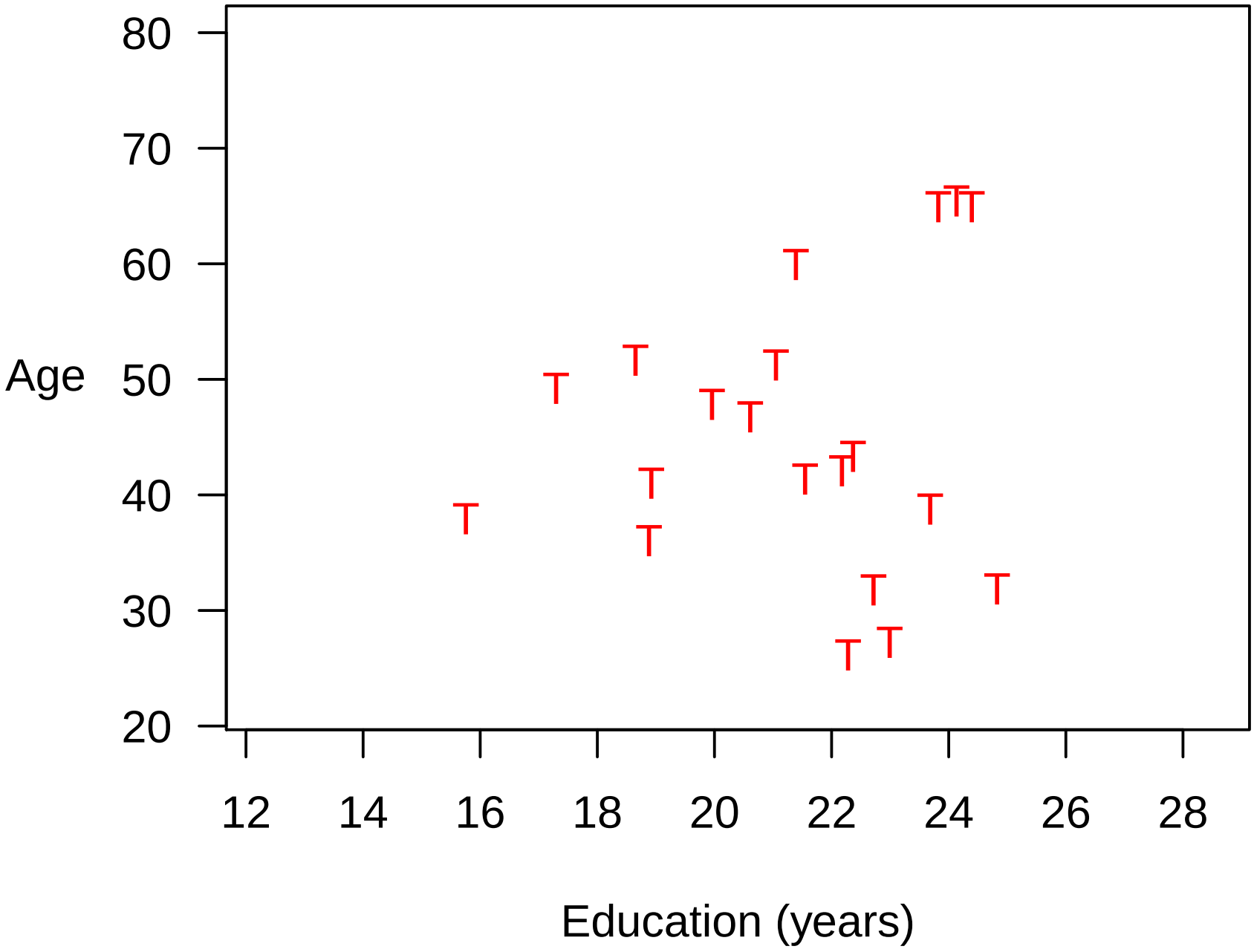
- Quiz: Do you understand the distance trade offs?
- Quiz: Does standardization help?

⇝ Mahalanobis is for methodologists; in applications, use Euclidean!

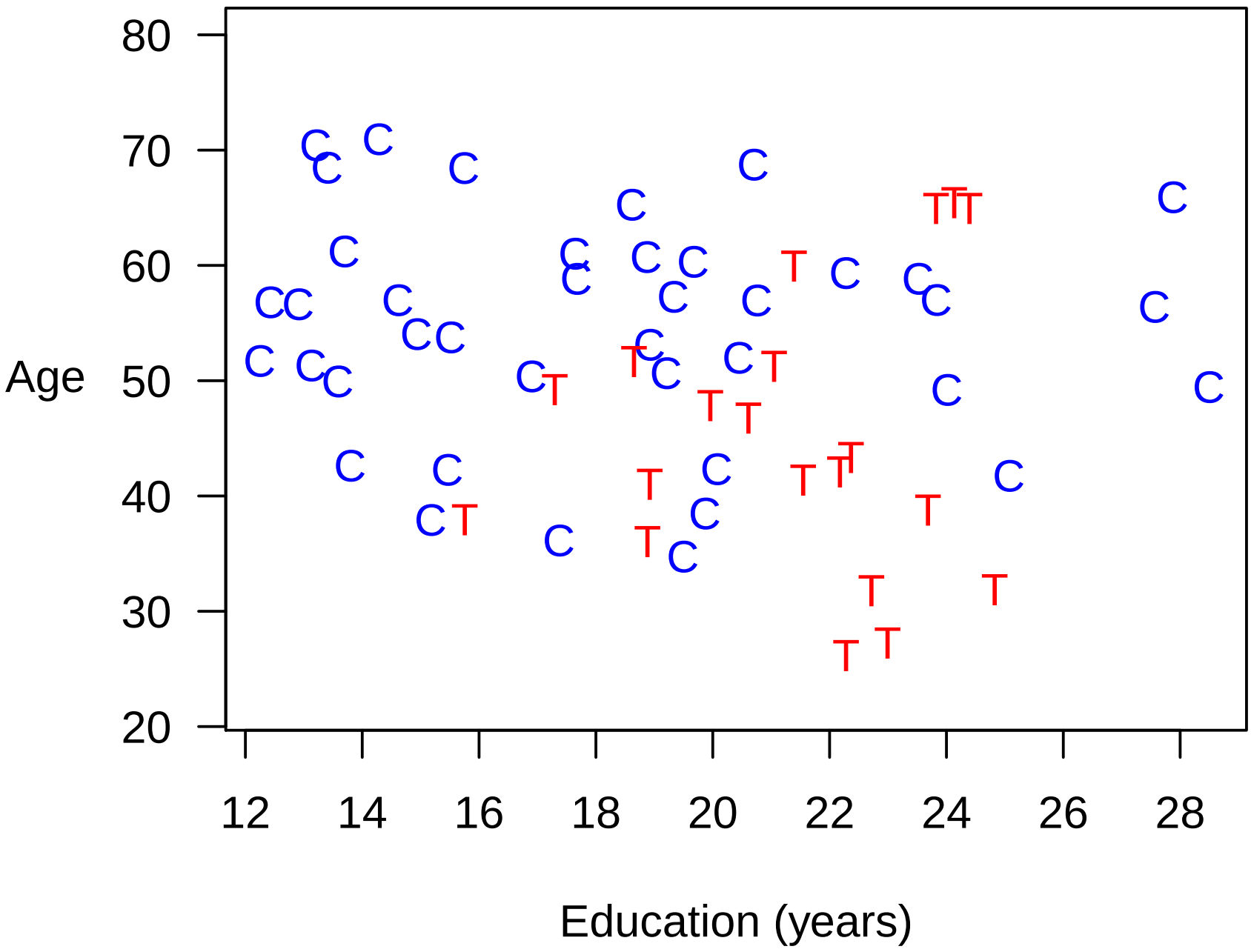
Mahalanobis Distance Matching



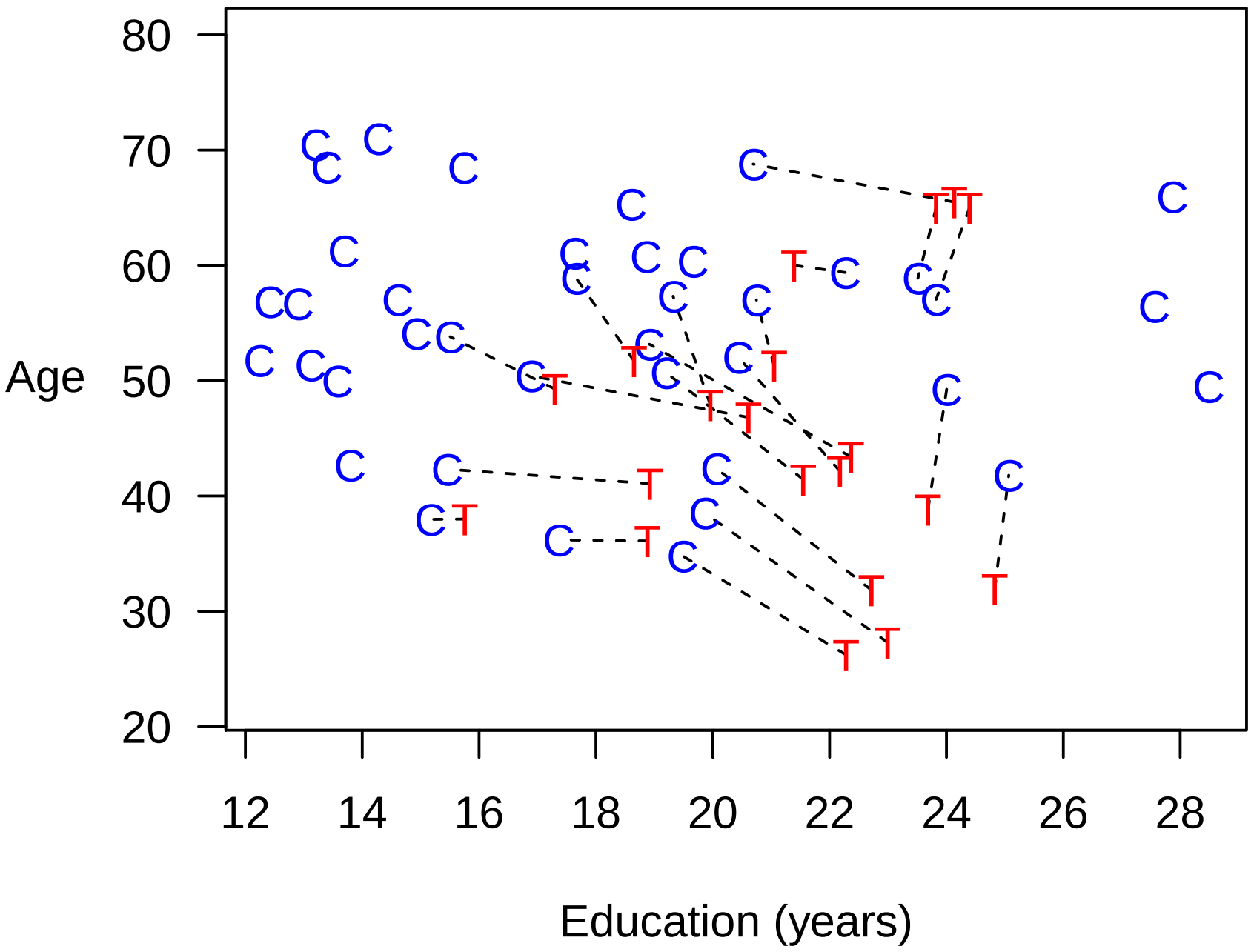
Mahalanobis Distance Matching



Mahalanobis Distance Matching



Mahalanobis Distance Matching



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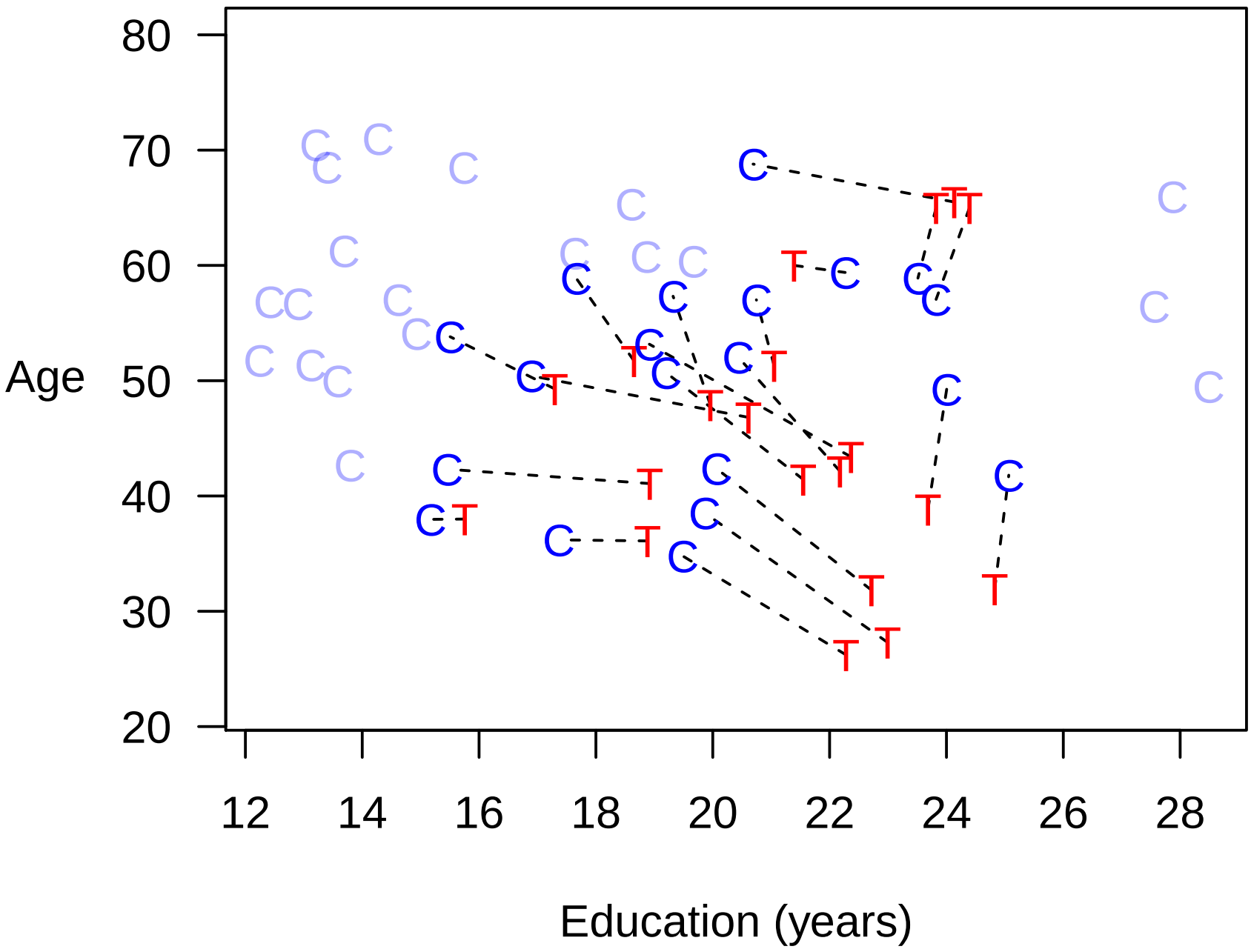

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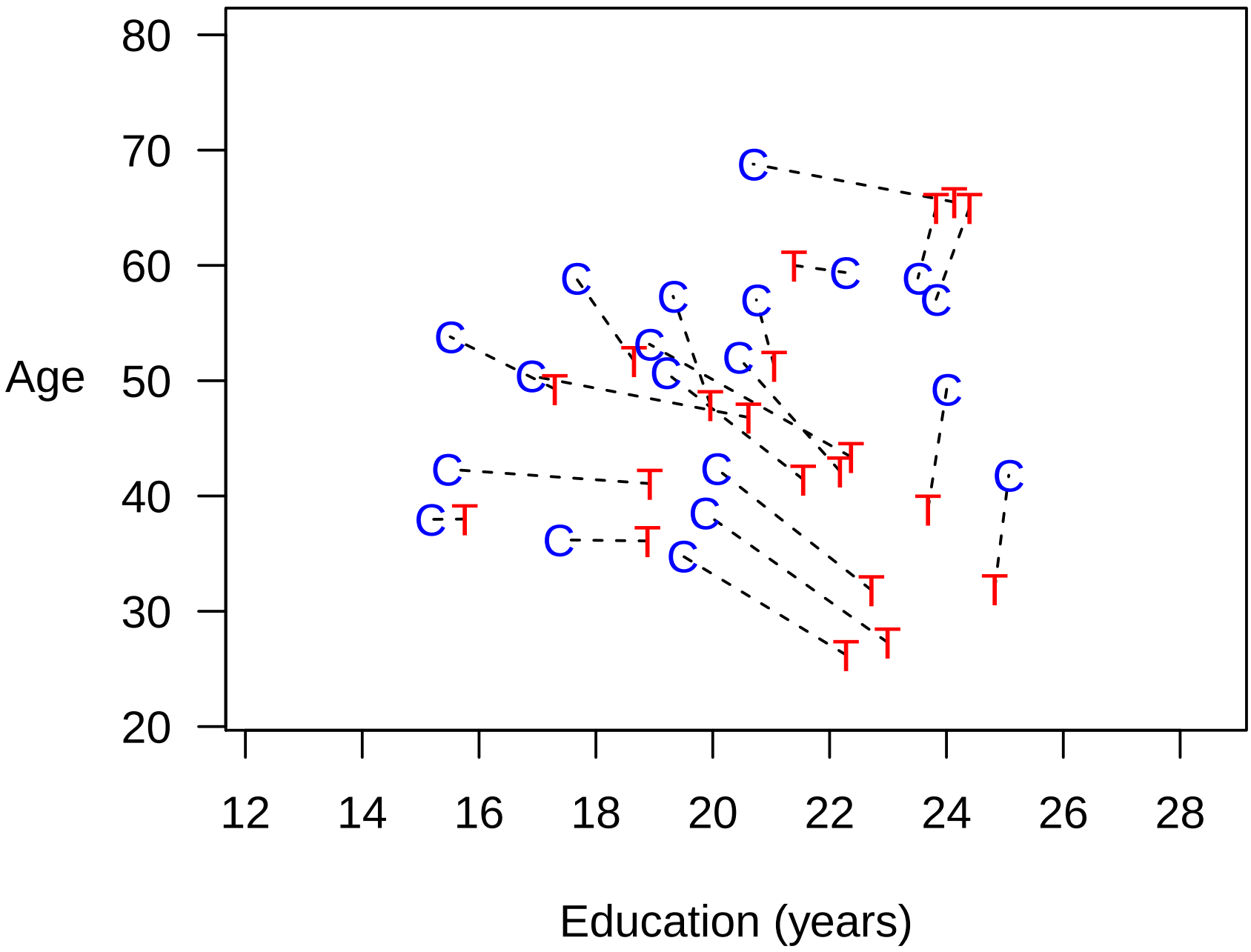

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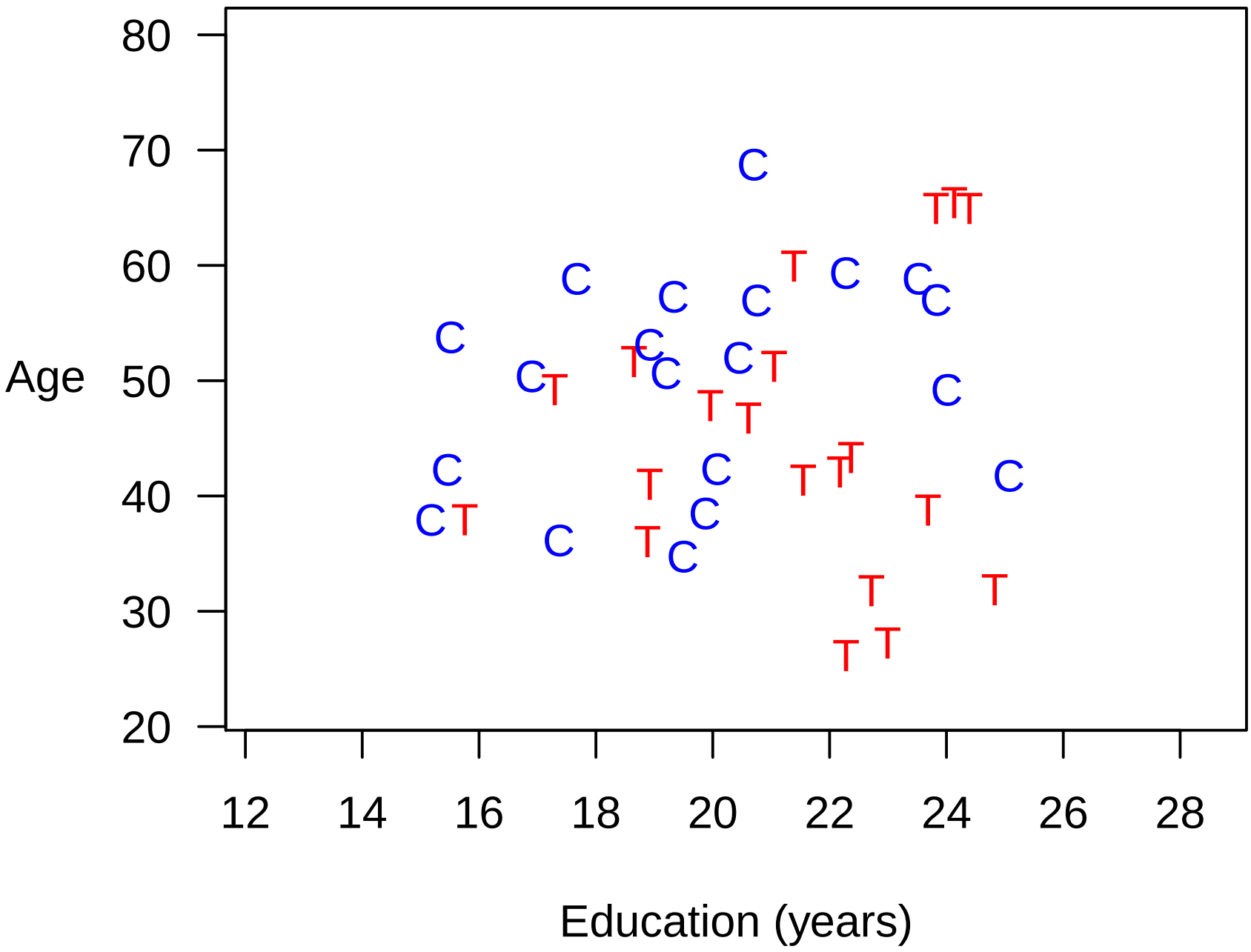

Best Case: Mahalanobis Distance Matching

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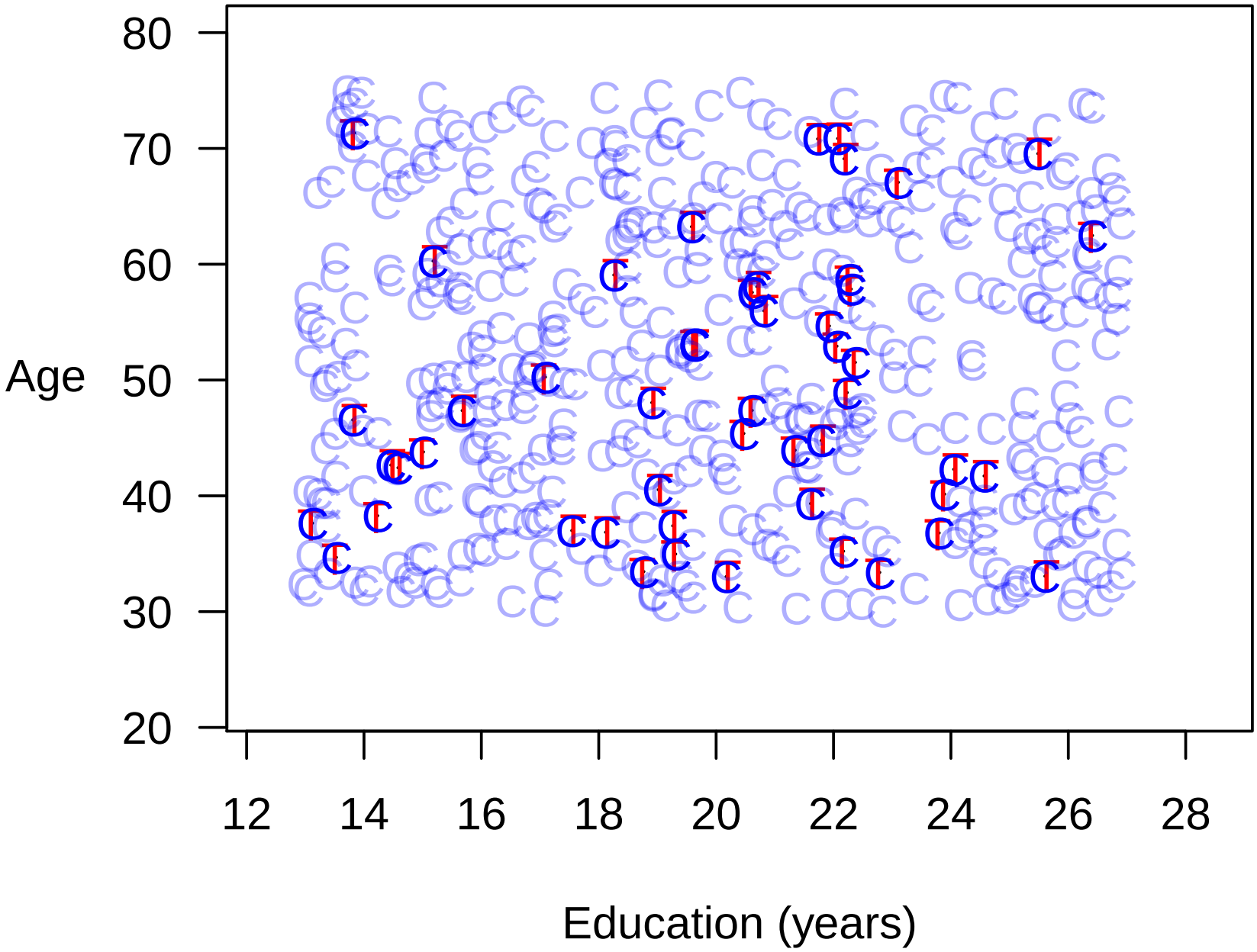

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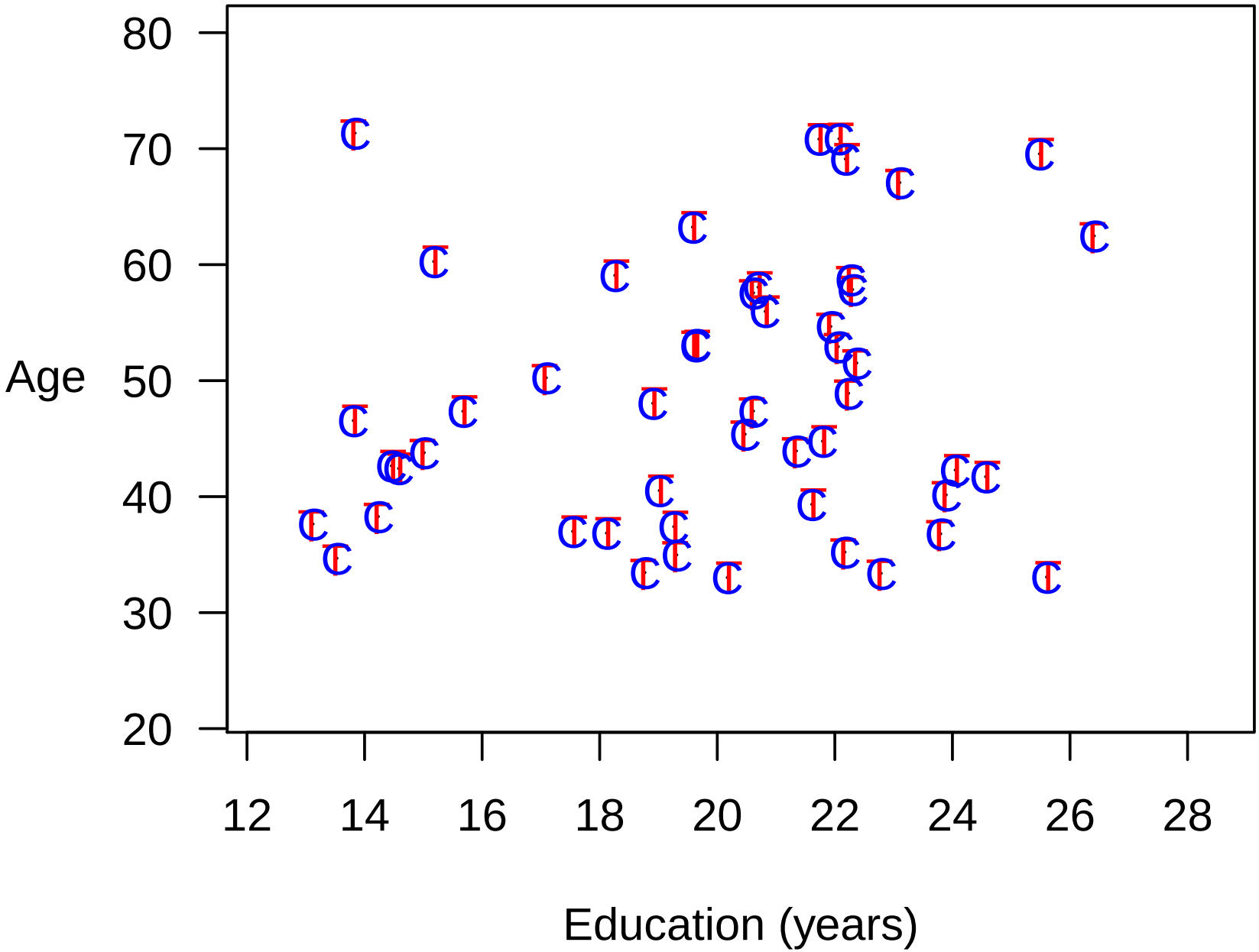

Method 2: Coarsened Exact Matching

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(Approximates Fully Blocked Experiment)

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Procedure

Method 2: Coarsened Exact Matching

(Approximates Fully Blocked Experiment)

Procedure

1. Preprocess (Matching)

Method 2: Coarsened Exact Matching

(Approximates Fully Blocked Experiment)

Procedure

1. Preprocess (Matching)

2. Estimation Difference in means or a model

Method 2: Coarsened Exact Matching

(Approximates Fully Blocked Experiment)

Procedure

1. Preprocess (Matching)
   - Temporarily coarsen X as much as you're willing
     - e.g., Education (grade school, high school, college, graduate)
2. Estimation Difference in means or a model

Method 2: Coarsened Exact Matching

(Approximates Fully Blocked Experiment)

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1. Preprocess (Matching)
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   - Apply exact matching to the coarsened X, $C(X)$
     - Sort observations into strata, each with unique values of $C(X)$
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Interpretation

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Interpretation

- Quiz: Do you understand distance trade offs?

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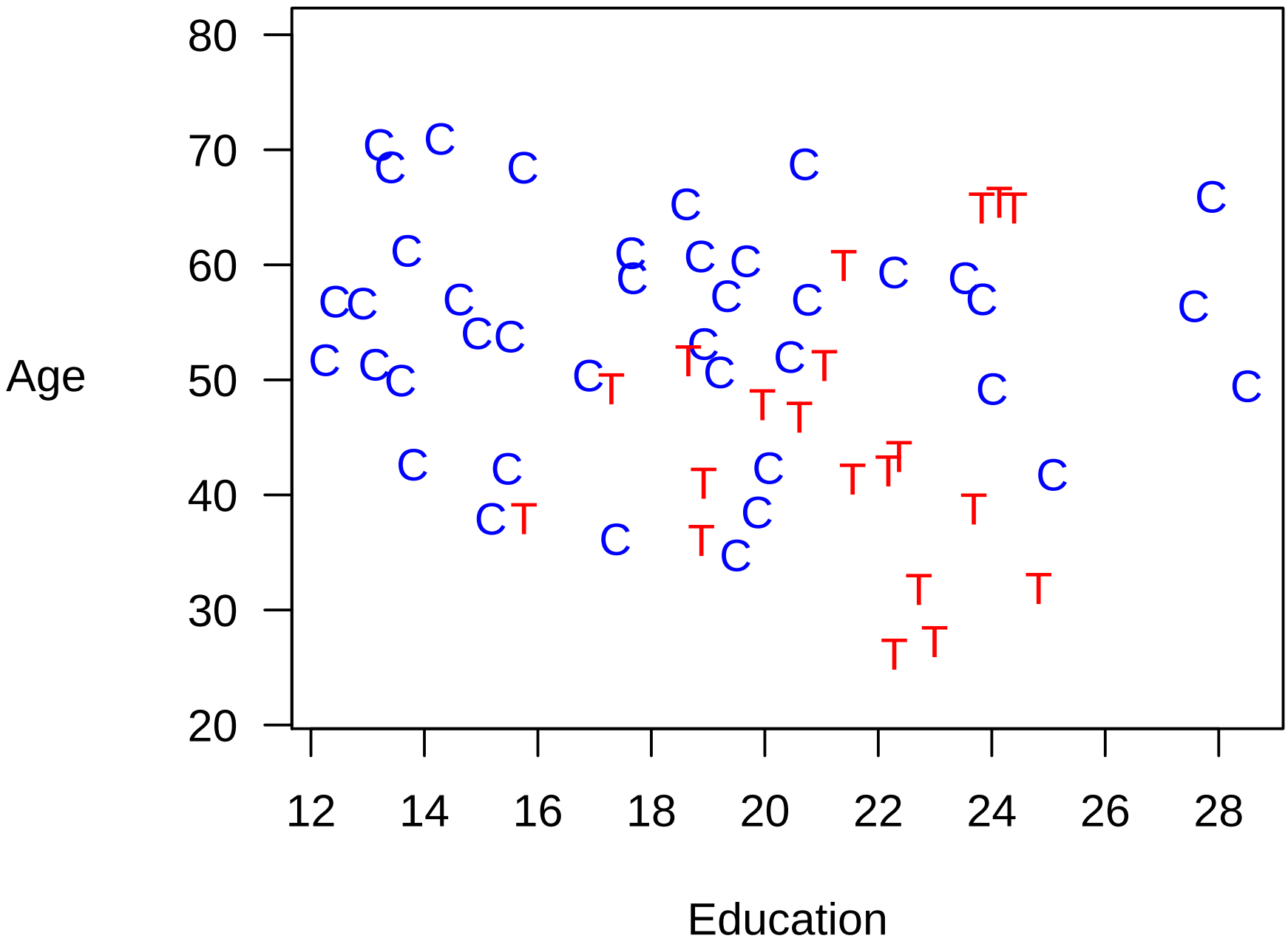
Interpretation

- Quiz: Do you understand distance trade offs?
- Quiz: What do you do if you have too few observations?

Coarsened Exact Matching

Coarsened Exact Matching



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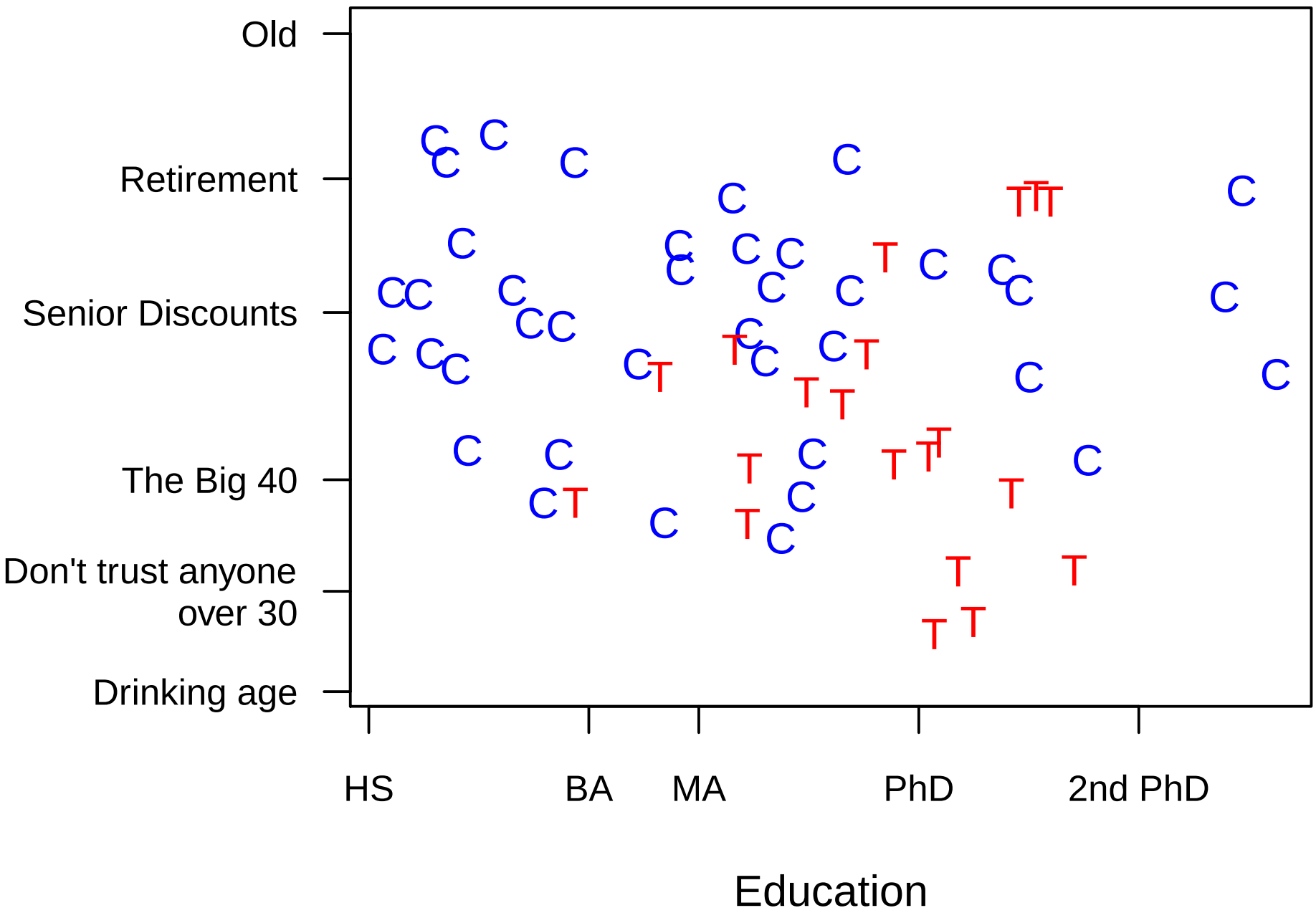

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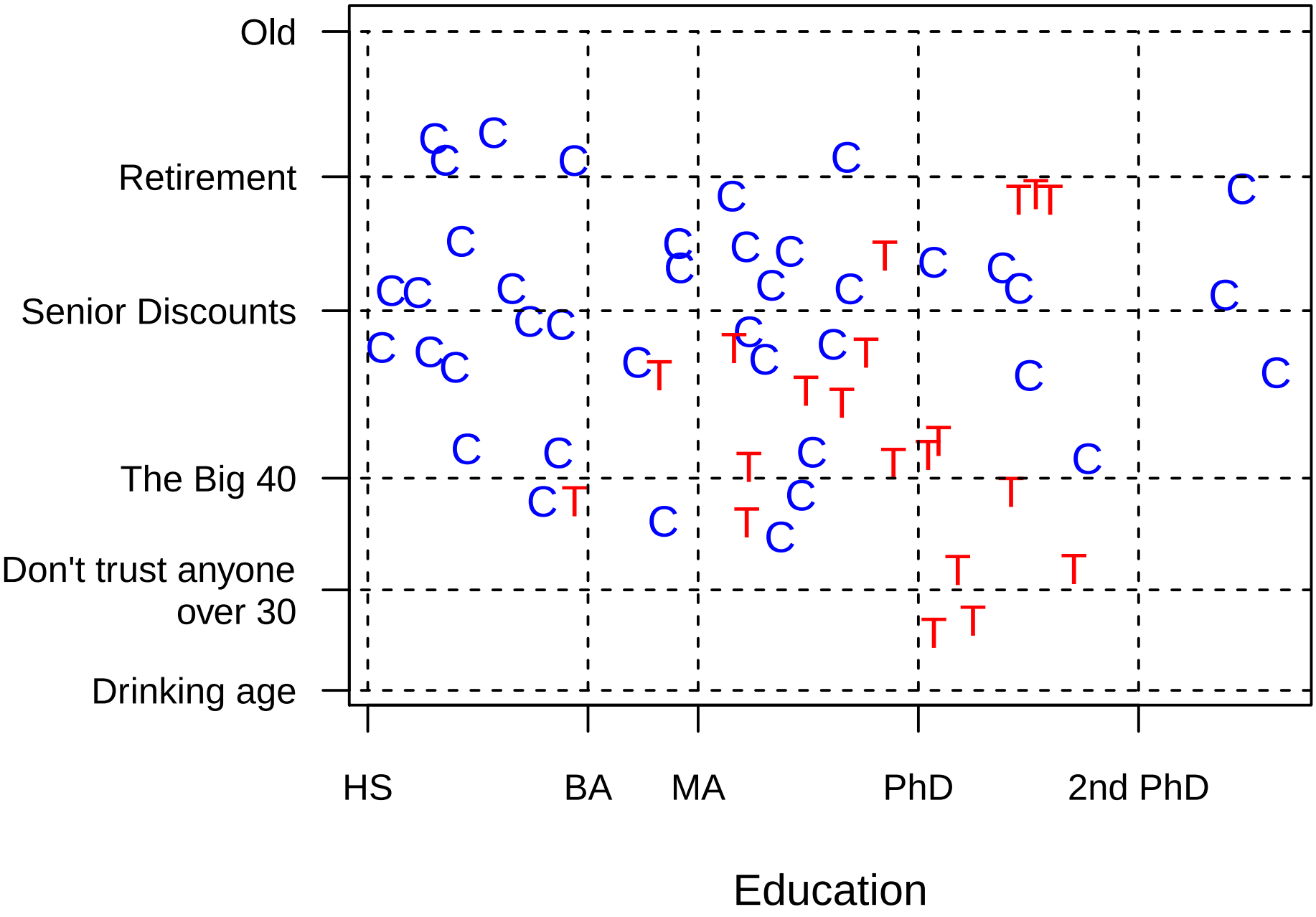

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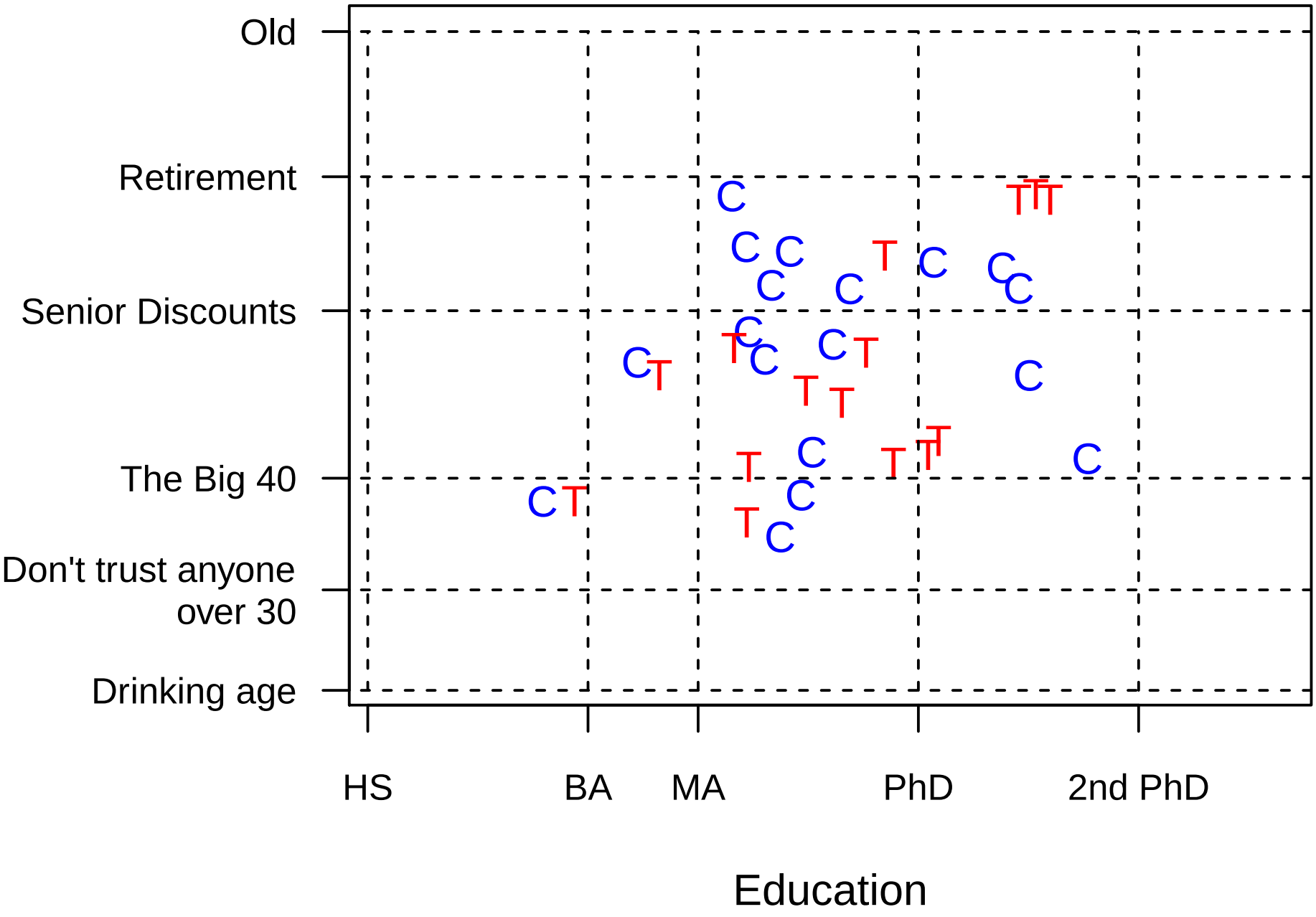

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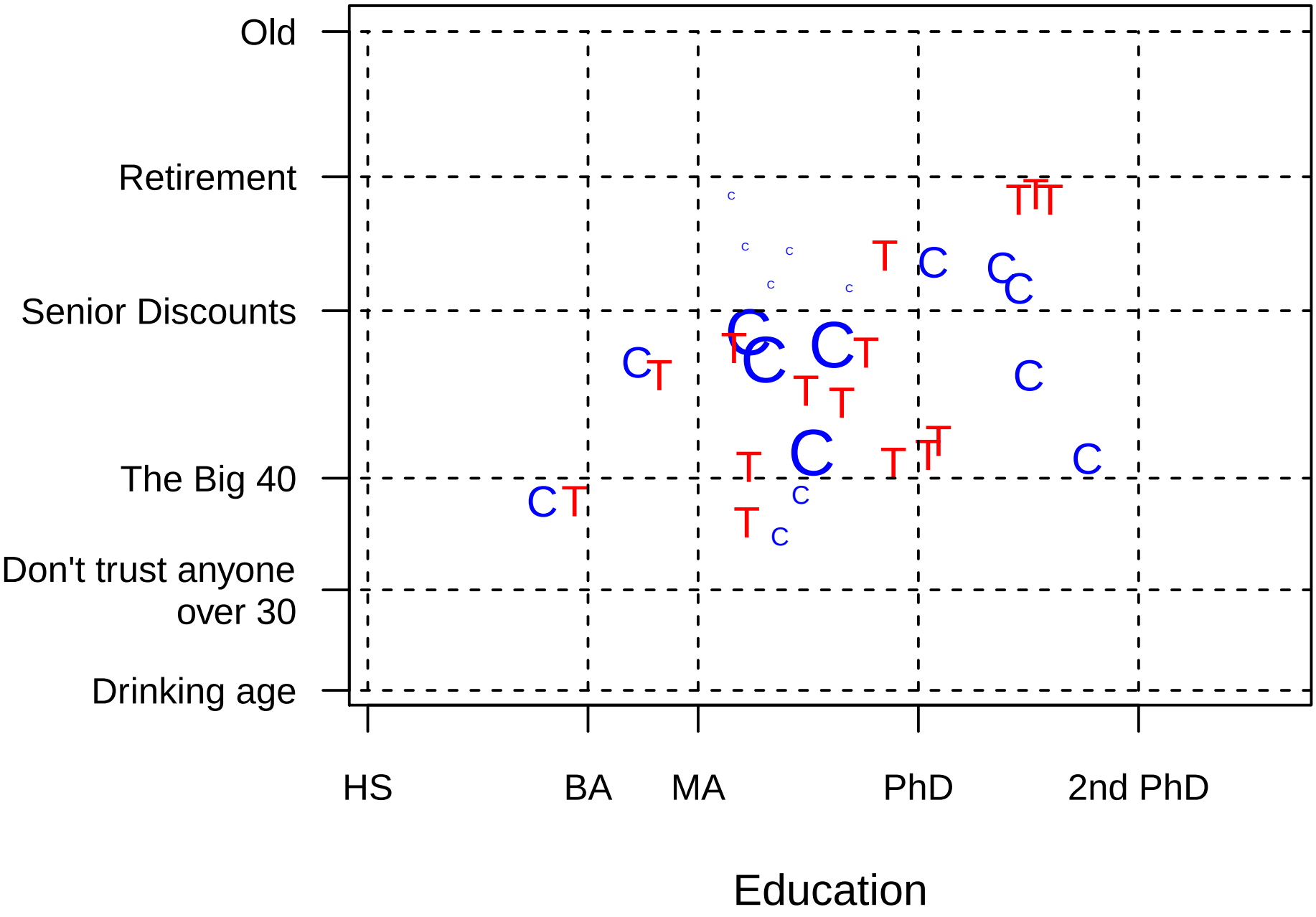

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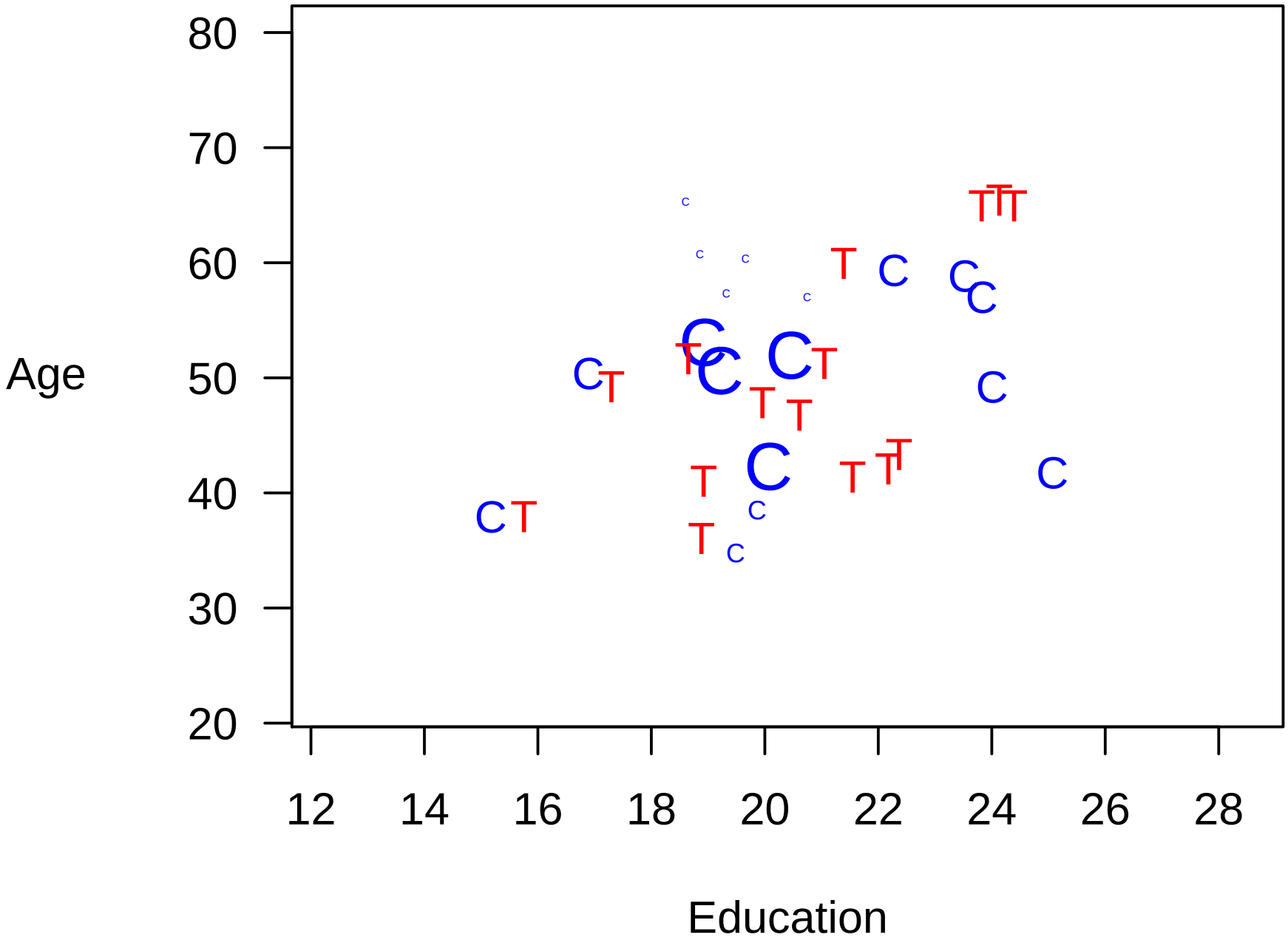

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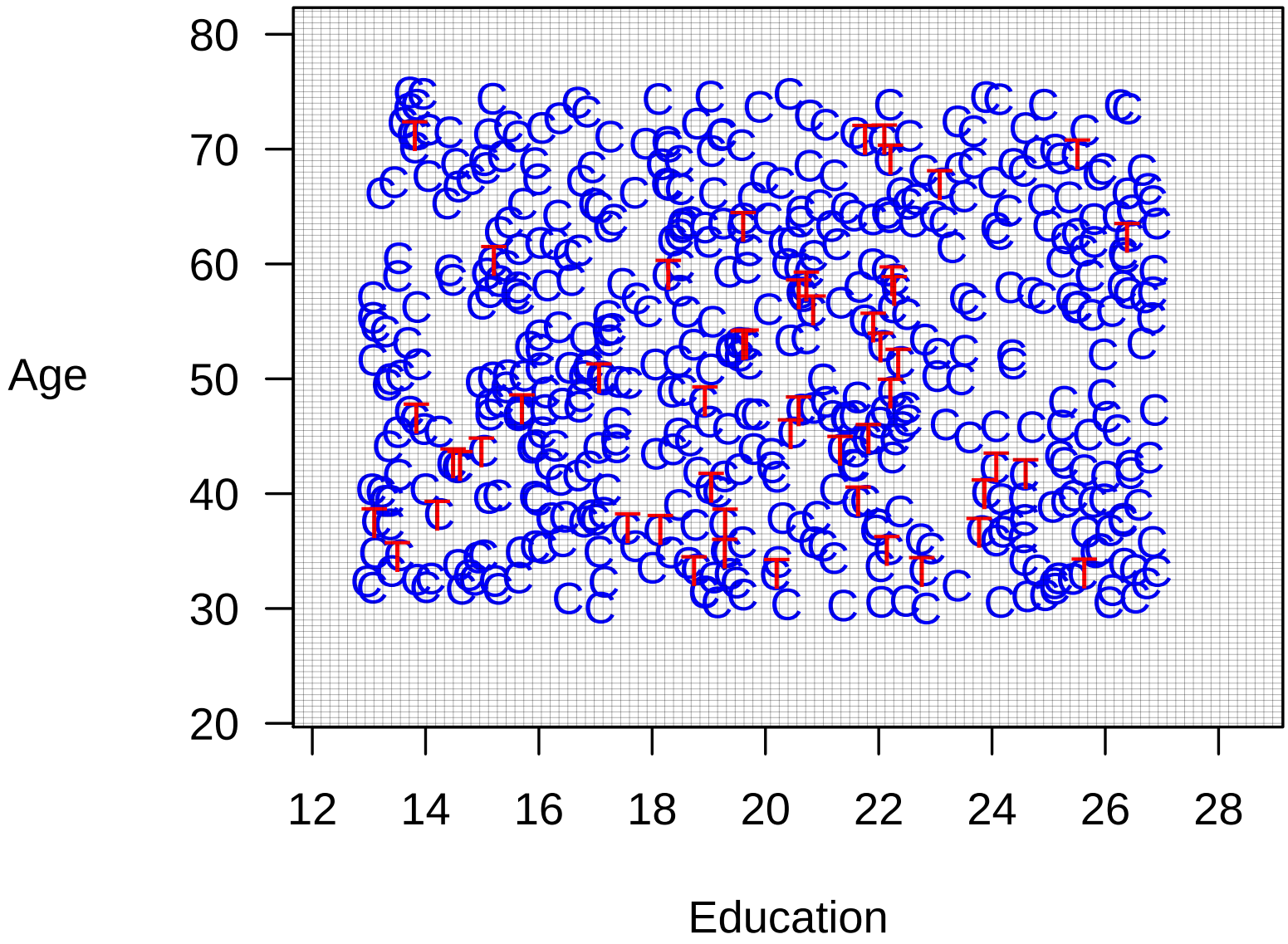

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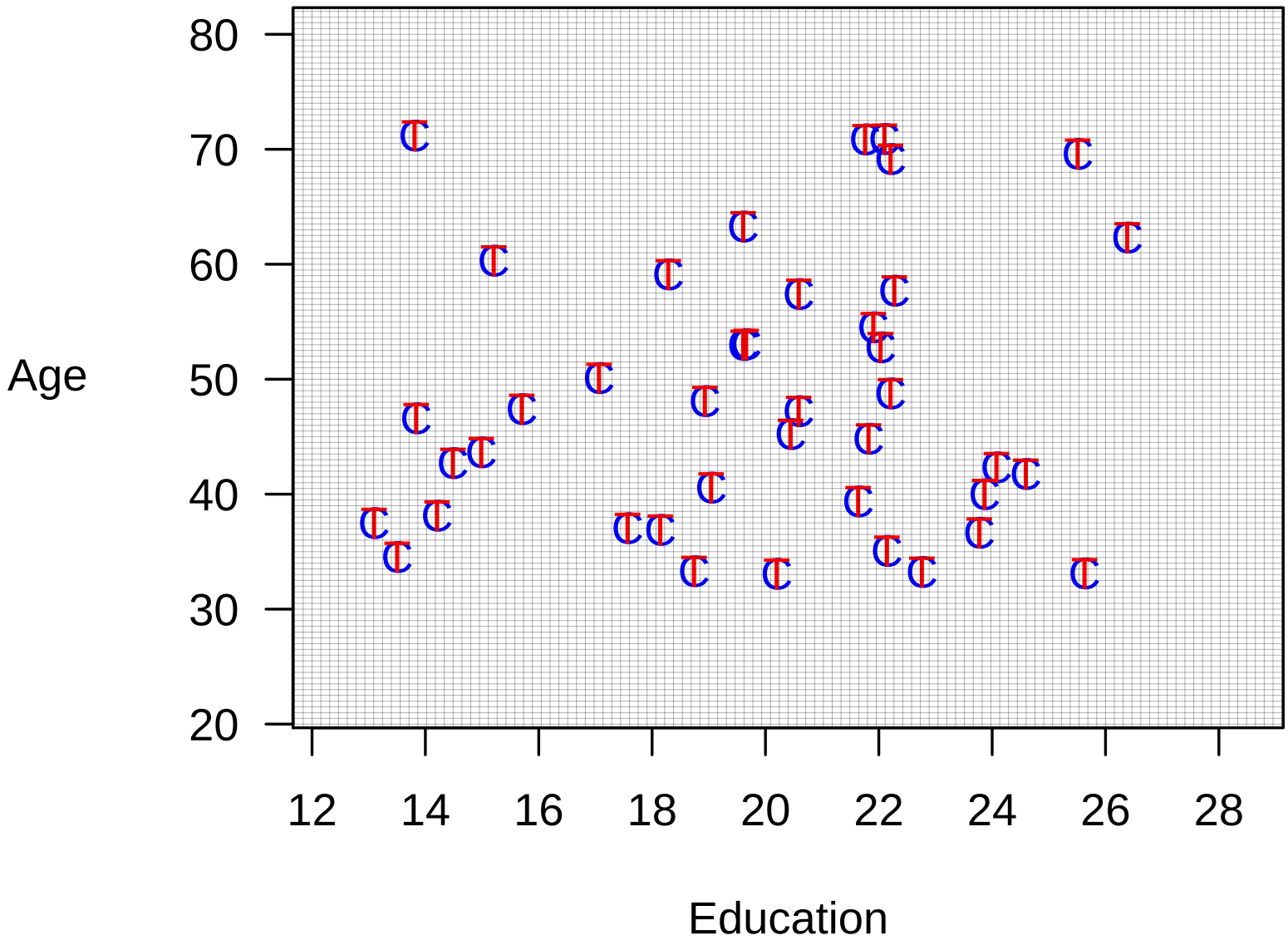

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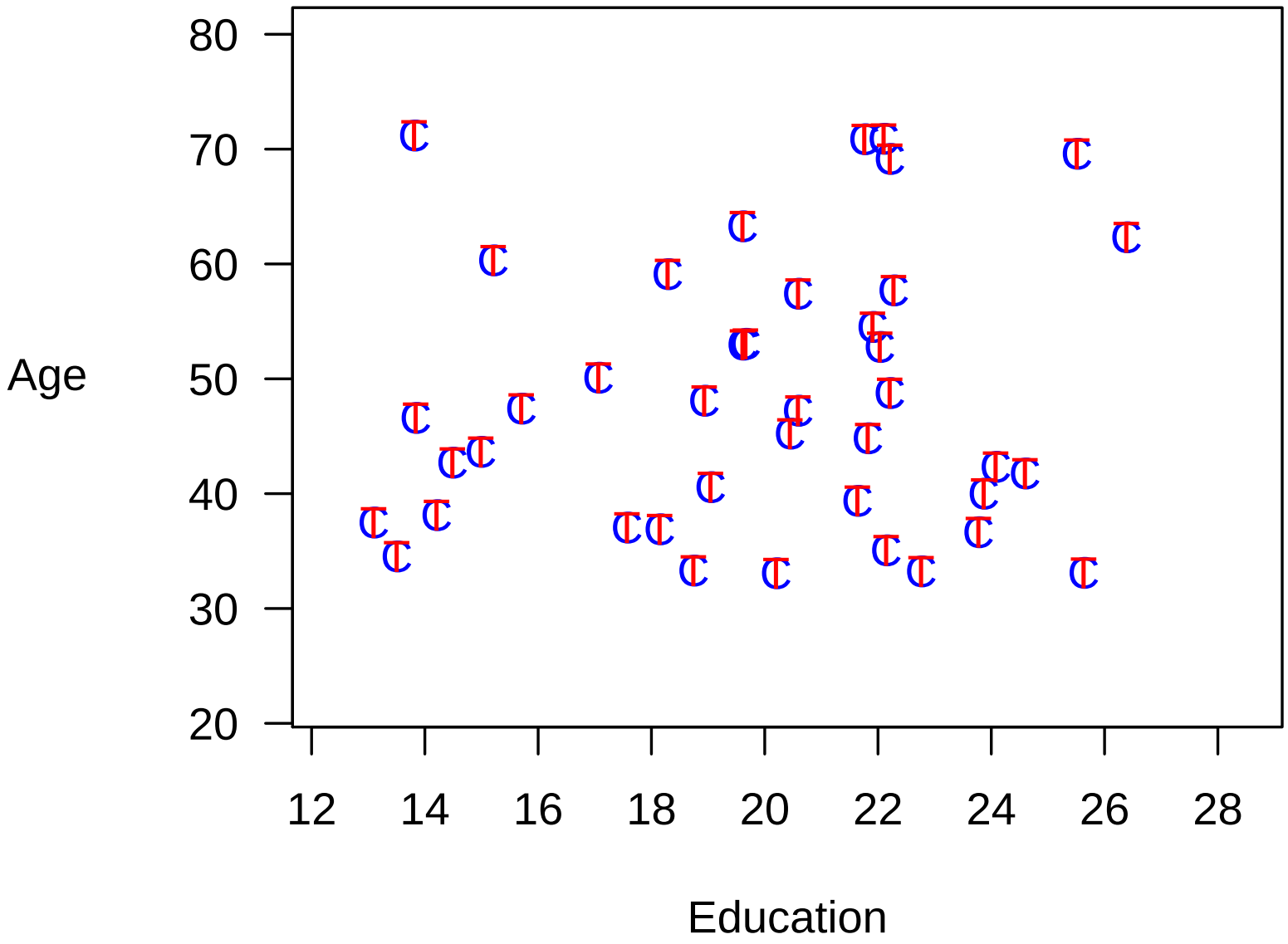

Method 3: Propensity Score Matching

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(Approximates Completely Randomized Experiment)

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Procedure

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Procedure

1. Preprocess (Matching)

Method 3: Propensity Score Matching

(Approximates Completely Randomized Experiment)

Procedure

1. Preprocess (Matching)

2. Estimation Difference in means or a model

Method 3: Propensity Score Matching

(Approximates Completely Randomized Experiment)

Procedure

1. Preprocess (Matching)
   - 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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Method 3: Propensity Score Matching

(Approximates Completely Randomized Experiment)

Procedure

1. Preprocess (Matching)
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   - Distance$(X_c, X_t) = |\pi_c - \pi_t|$
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(Approximates Completely Randomized Experiment)

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- Quiz: Do you understand distance trade offs?
- Quiz: What do you do when one variable is very important?

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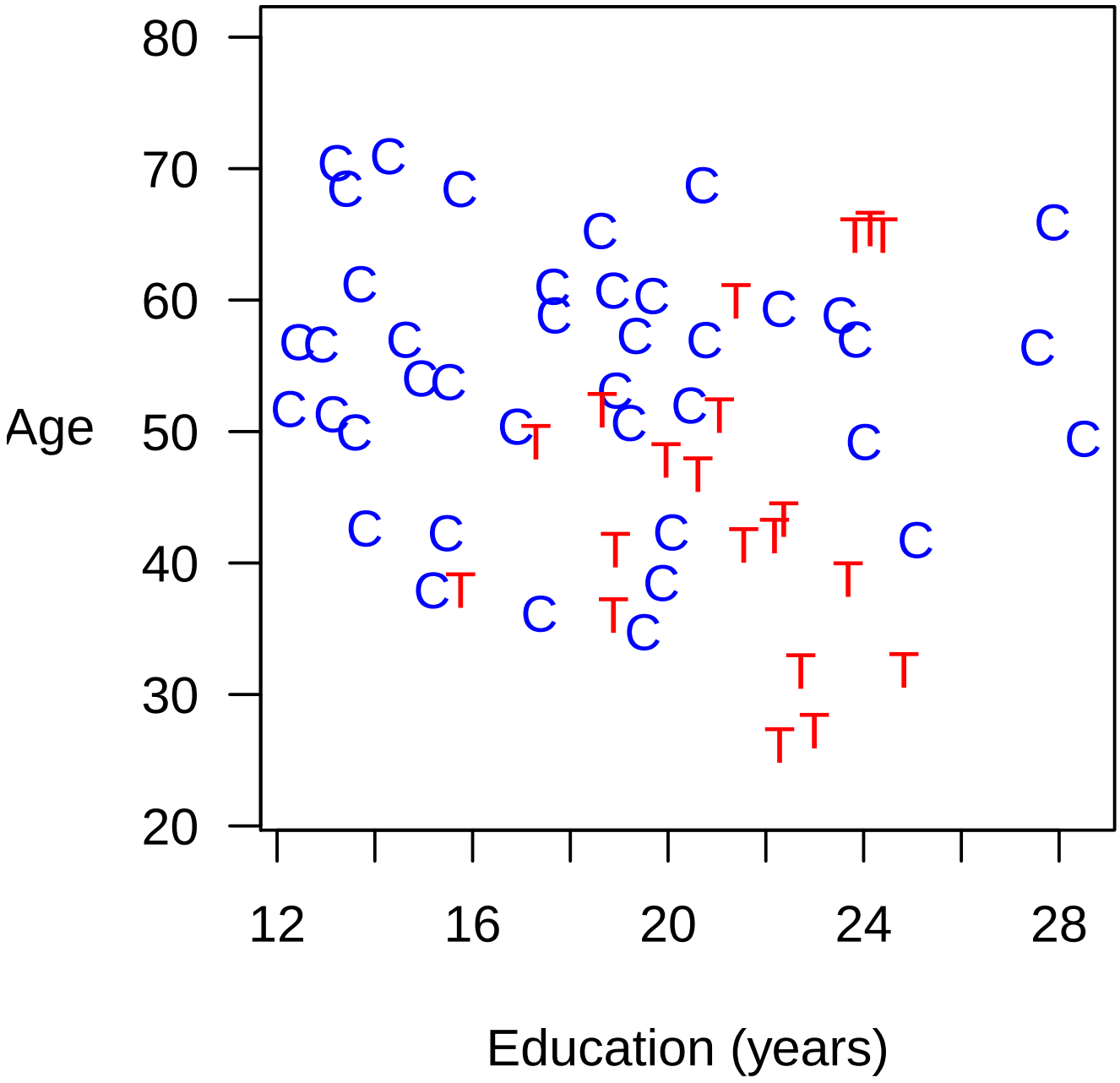

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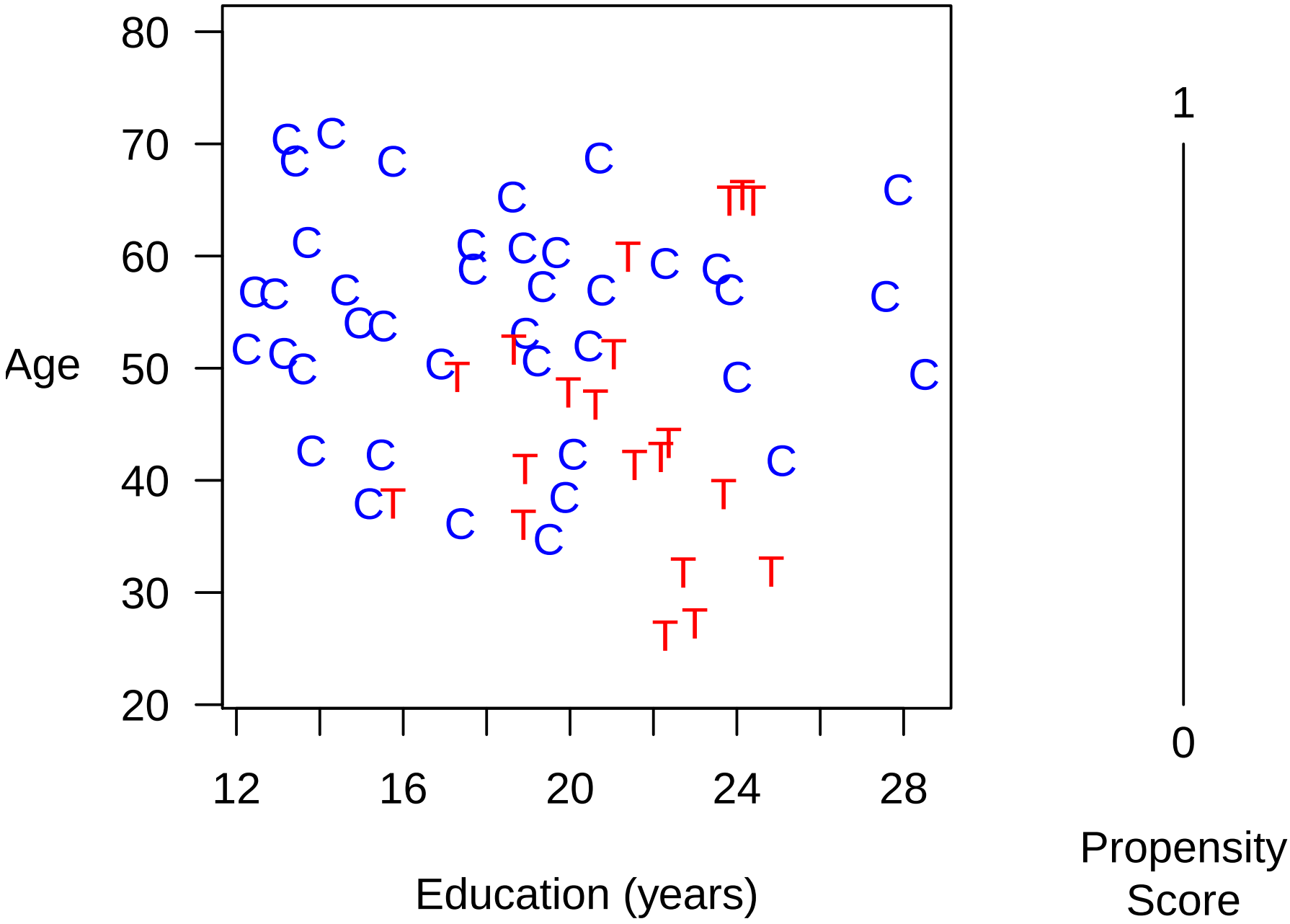

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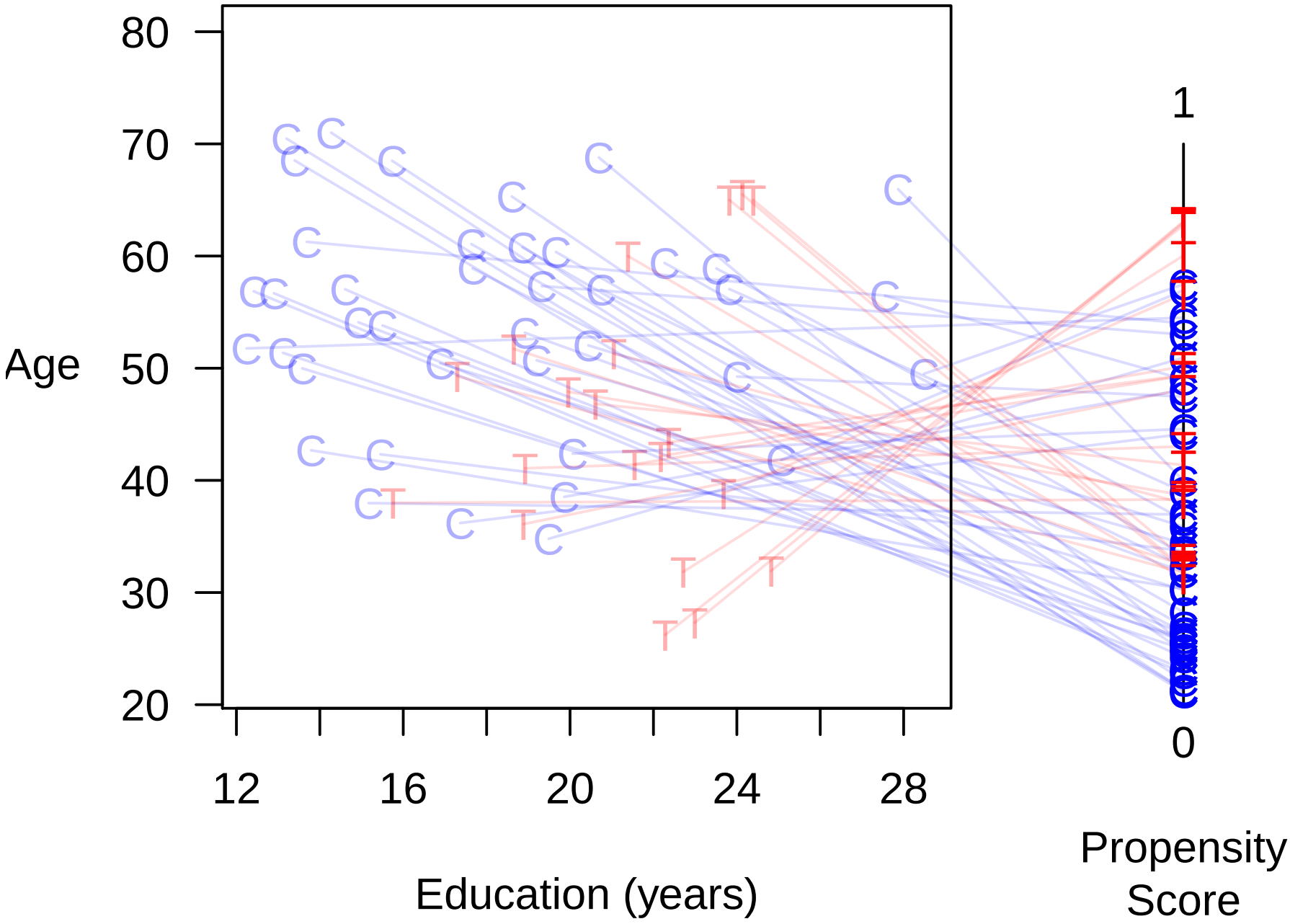

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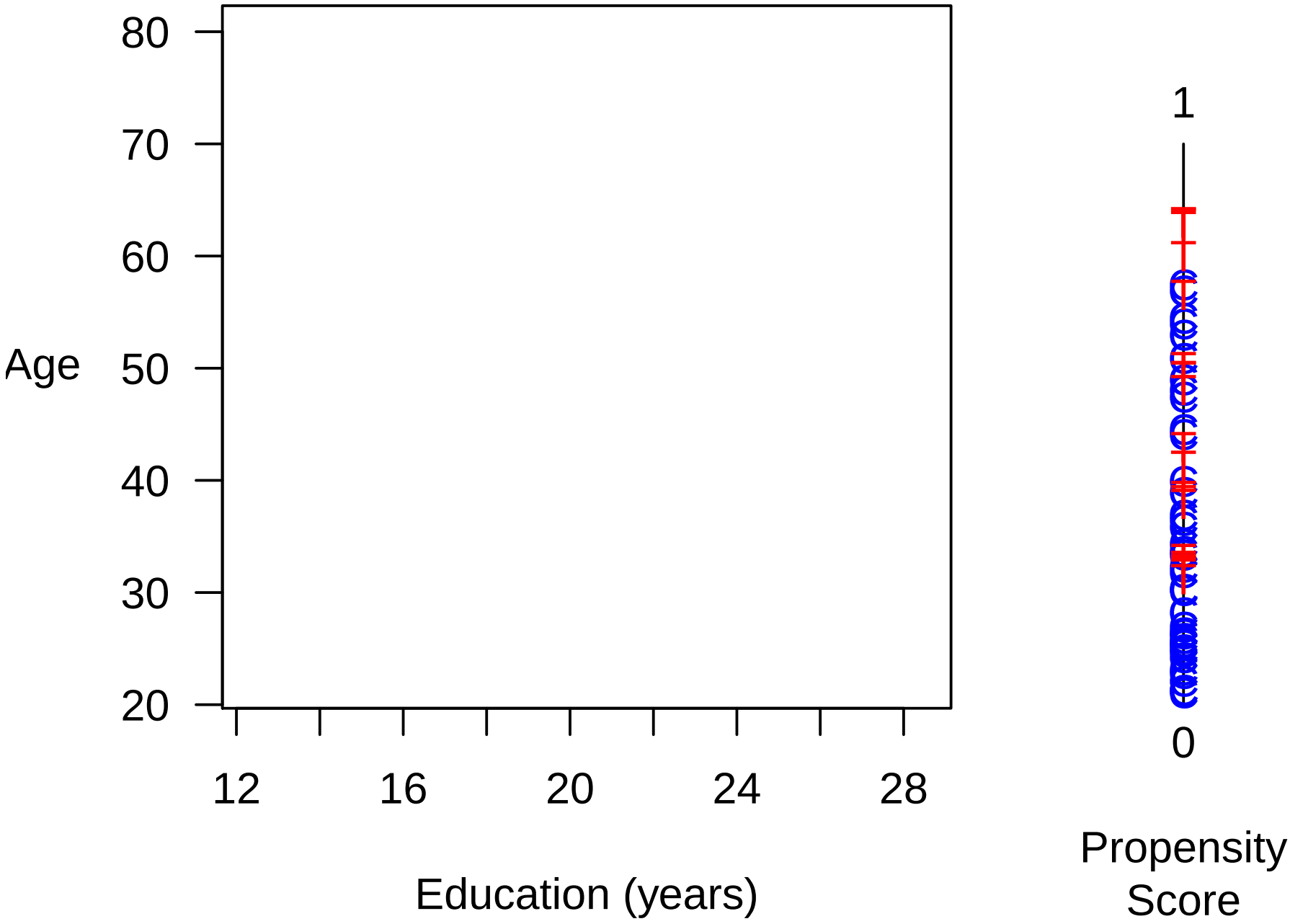

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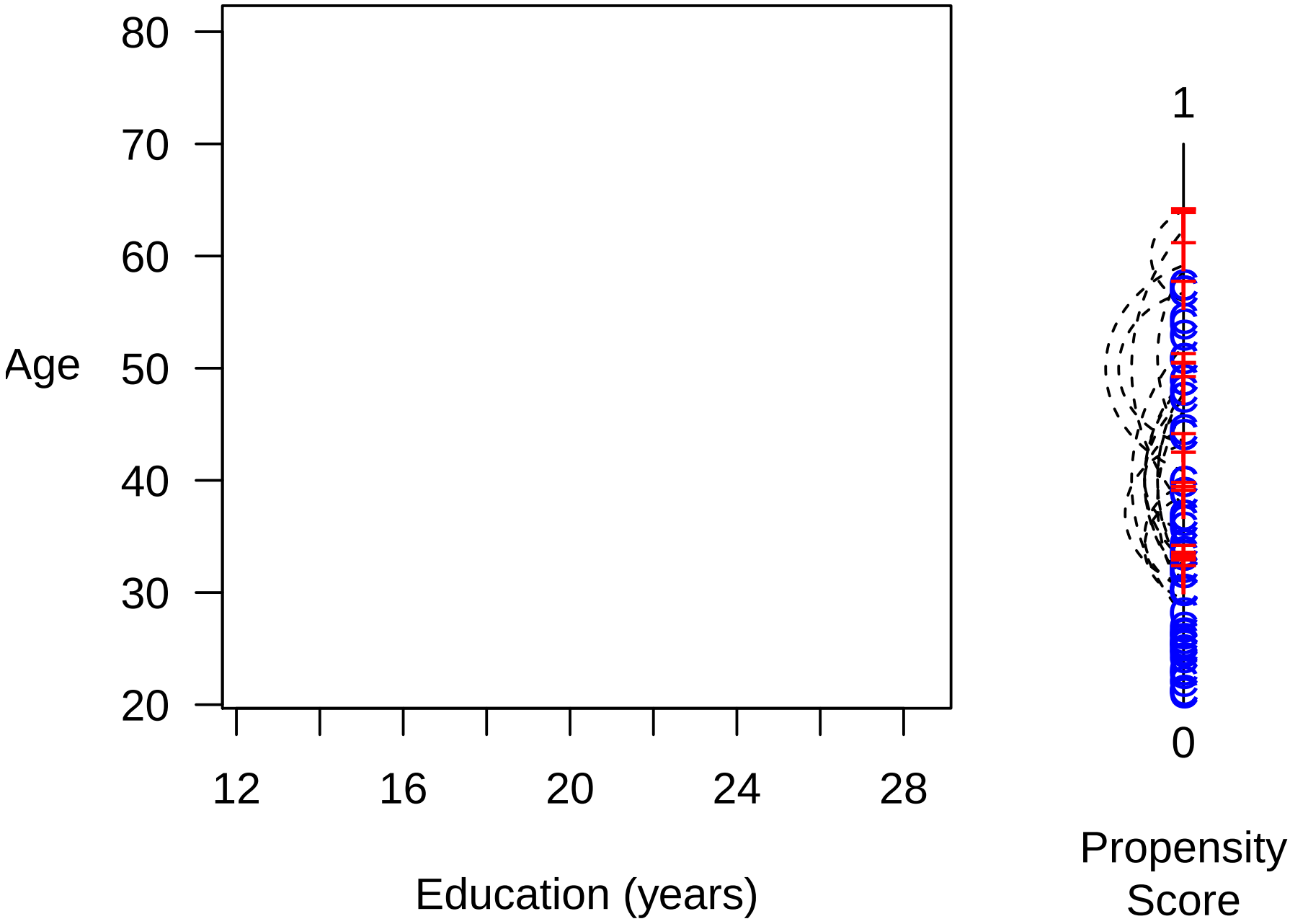

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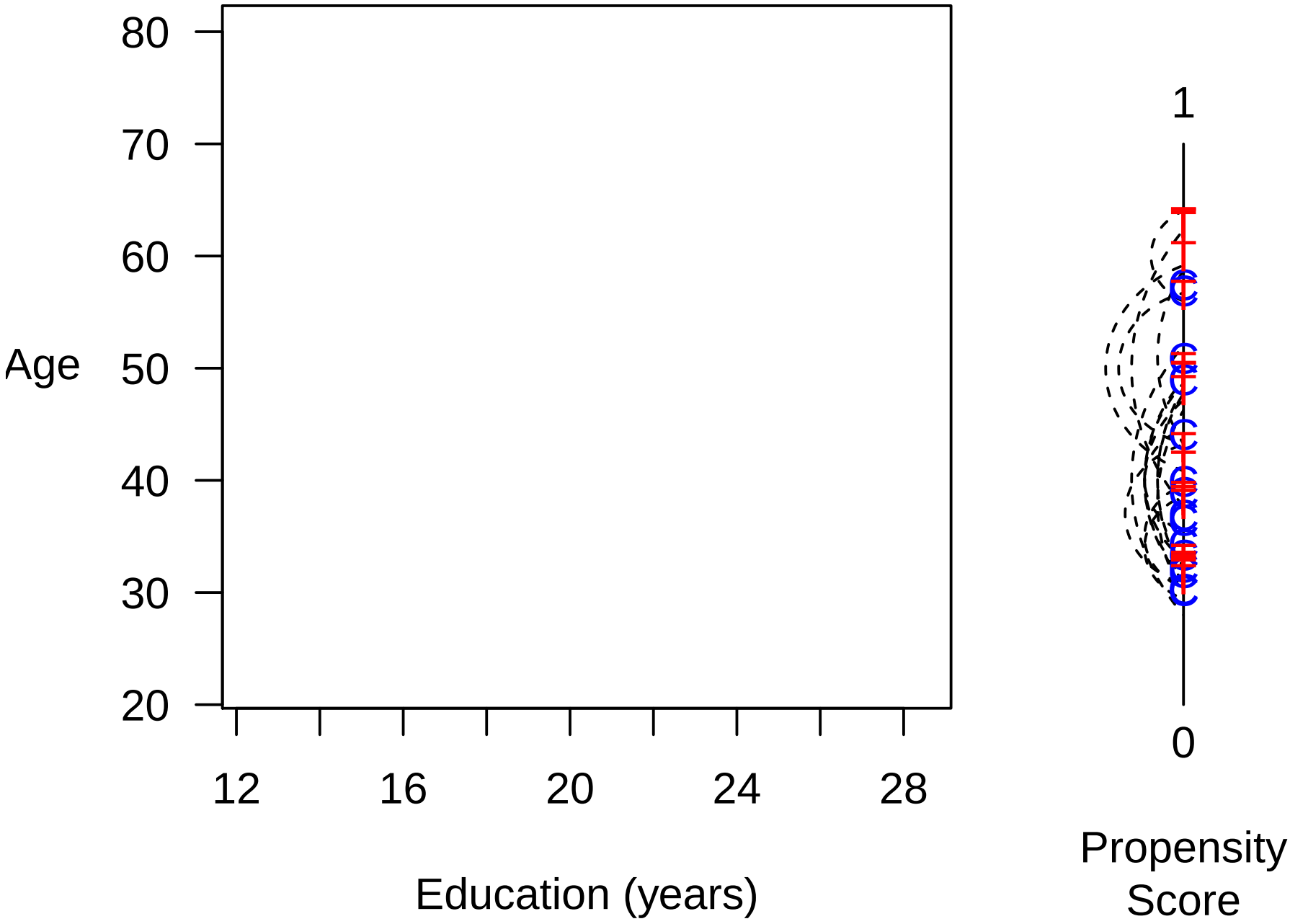

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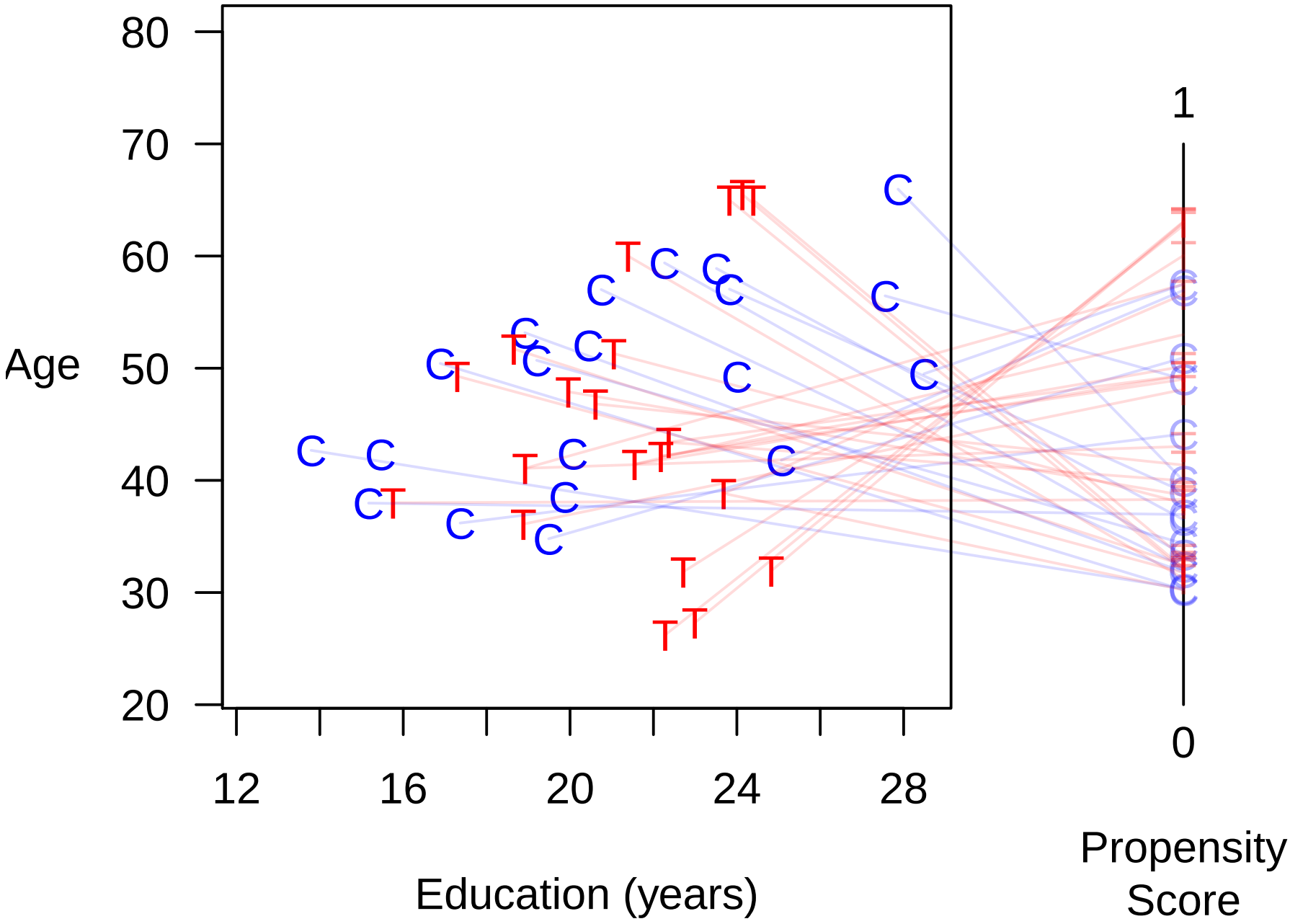

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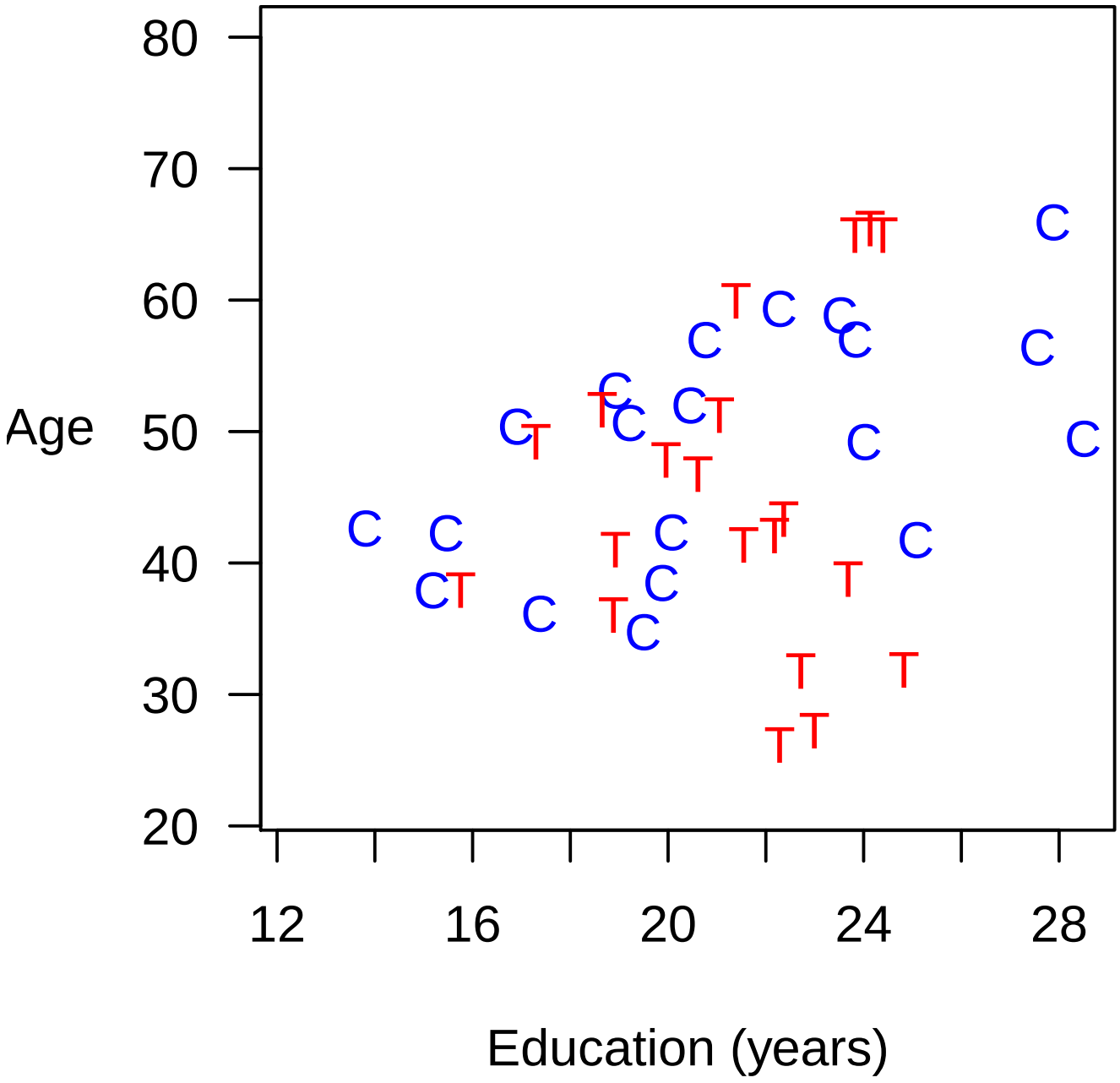

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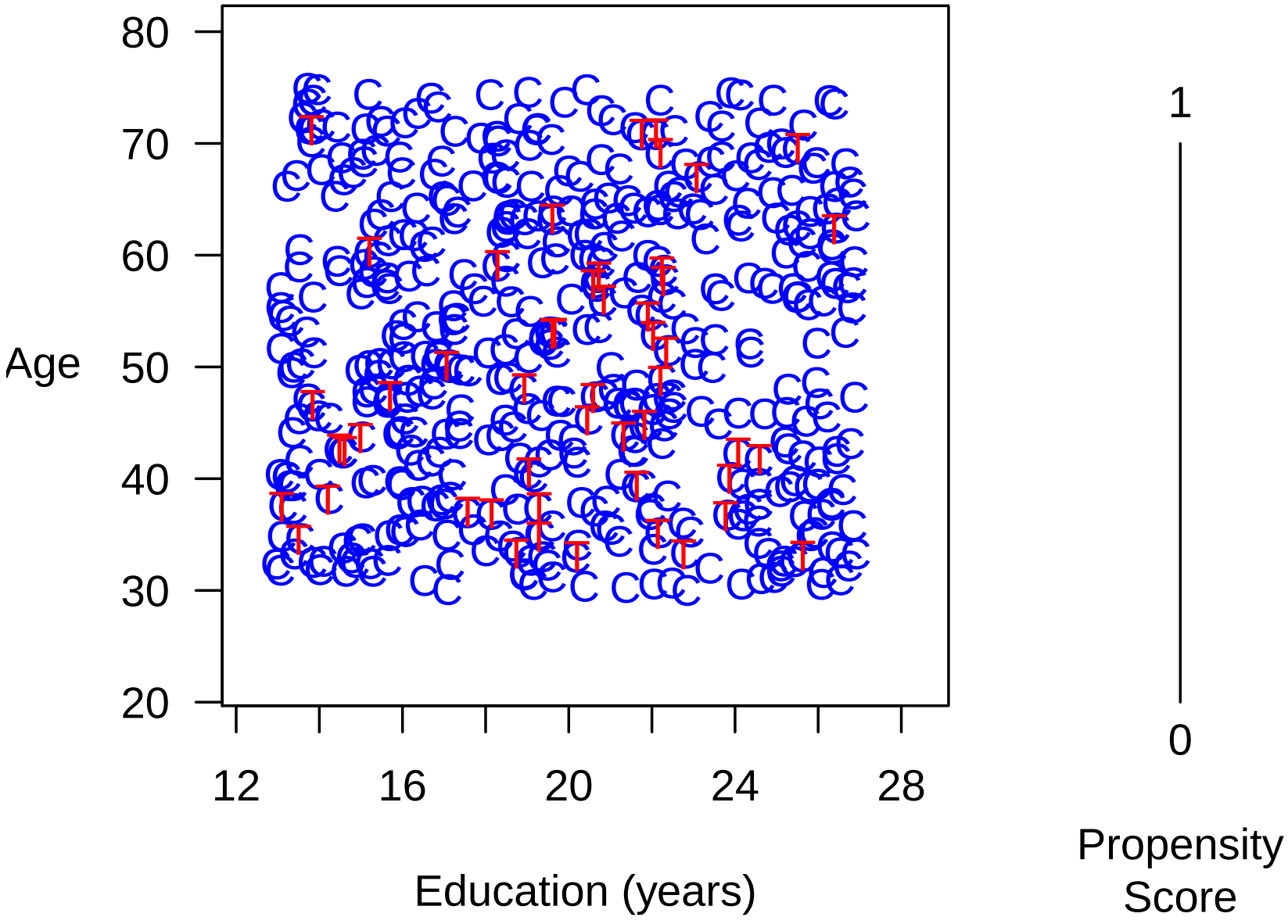

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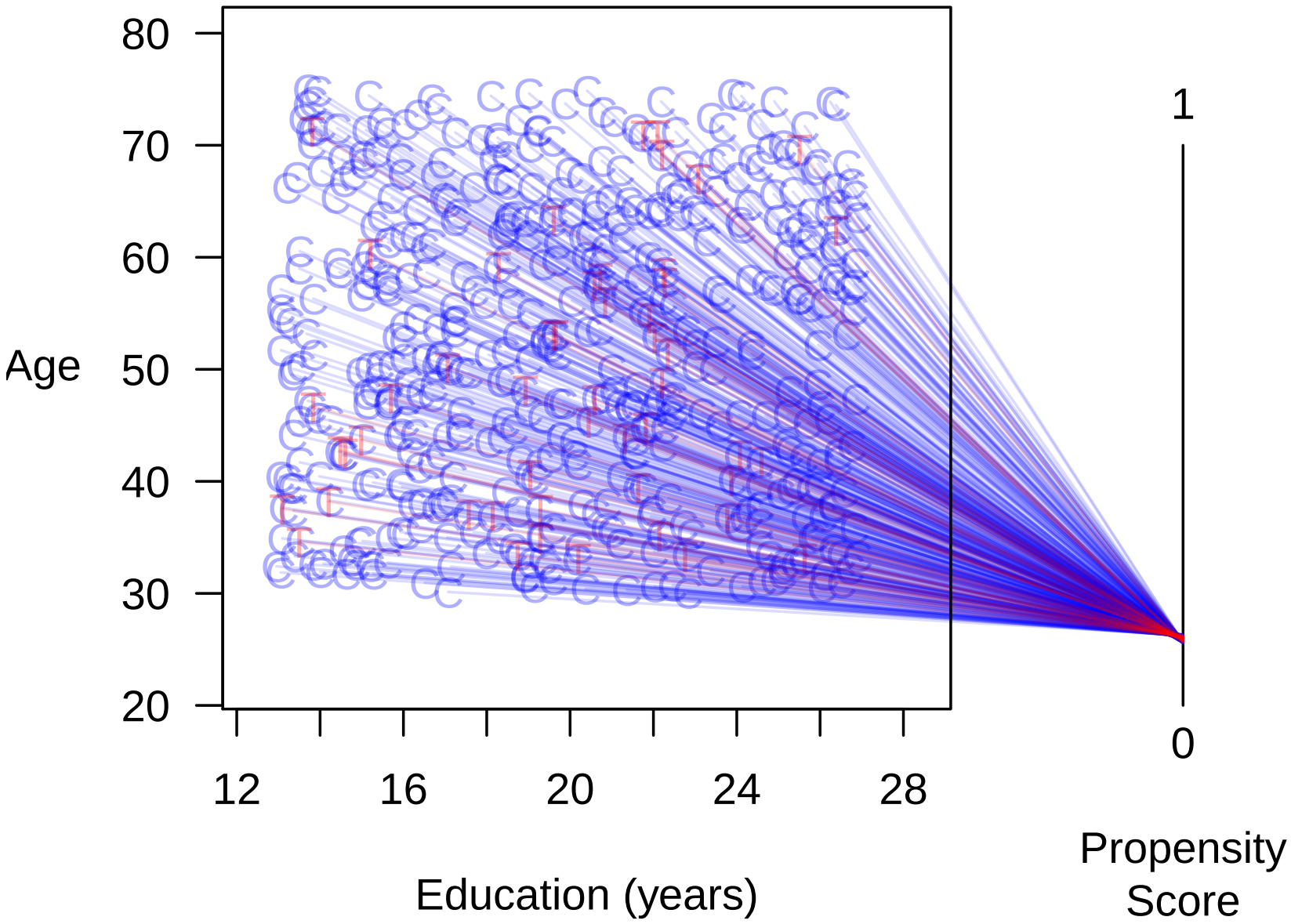

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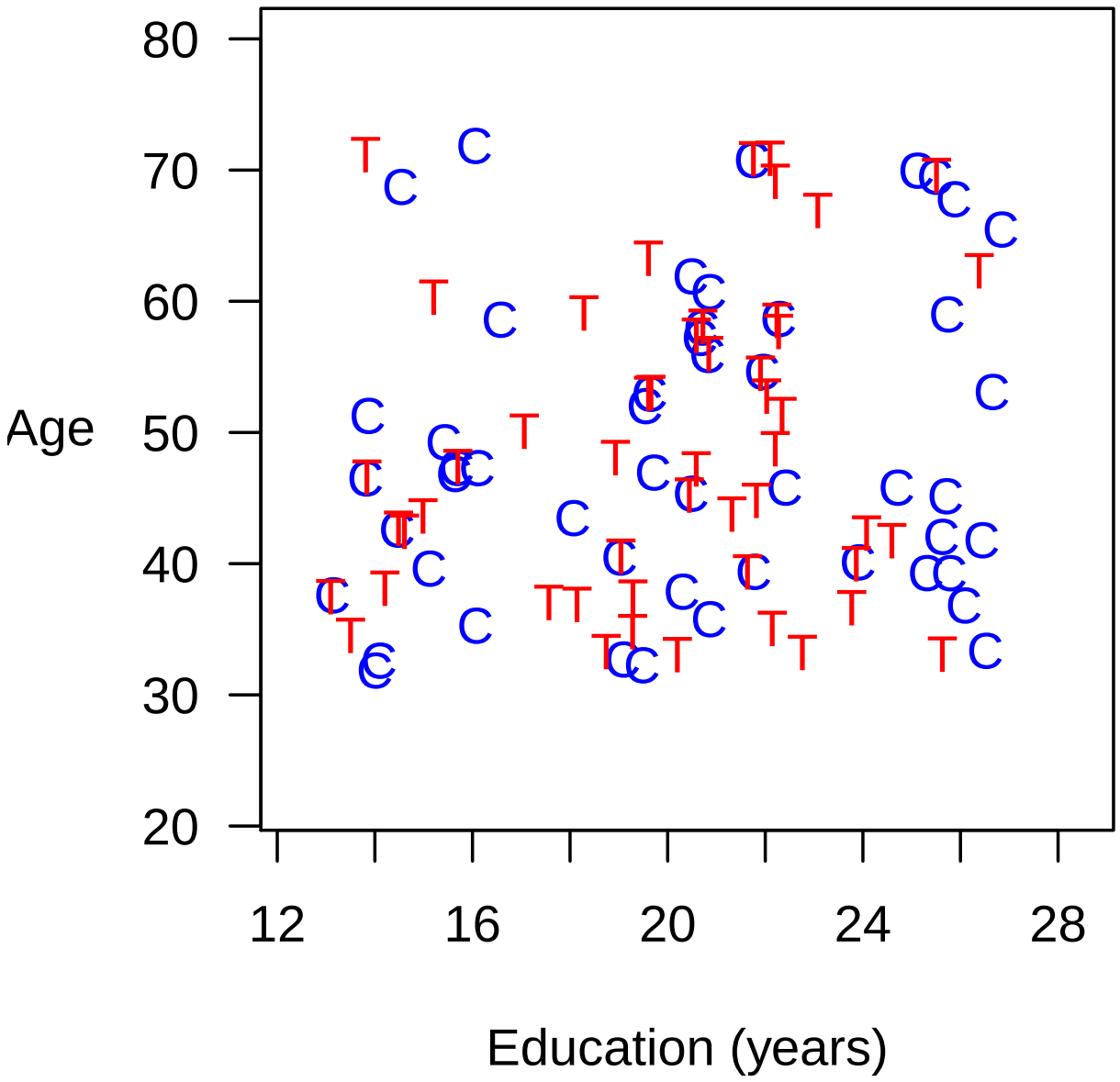
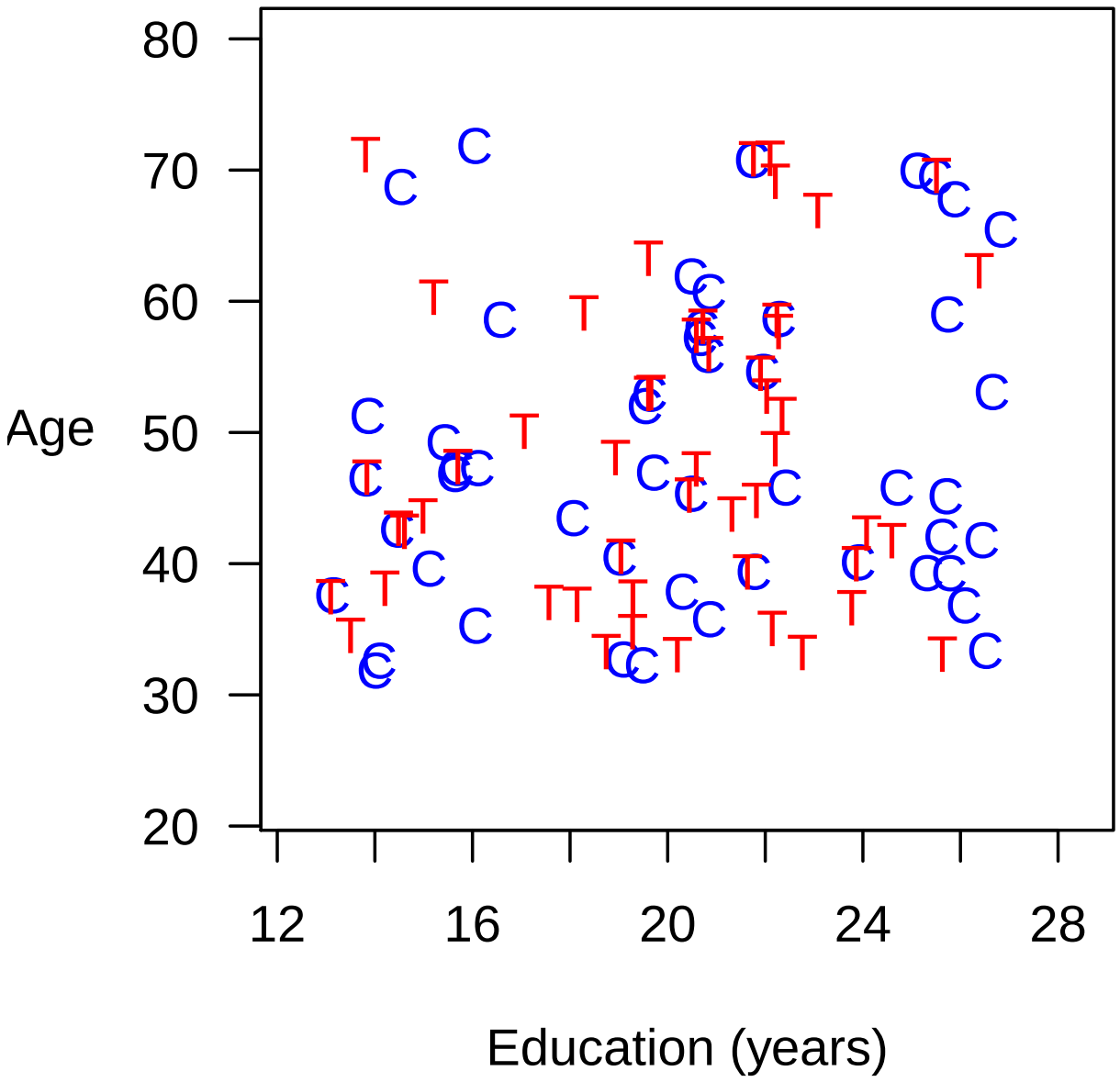


Best Case: Propensity Score Matching is Suboptimal



Detecting Model Dependence

Matching to Reduce Model Dependence

Three Matching Methods

Problems with Propensity Score Matching

The Matching Frontier

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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.

PSM's Statistical Properties

1. Low Standards: Sometimes helps, never optimizes
   - *Efficient* relative to complete randomization, but
   - *Inefficient* relative to (the more powerful) full blocking
   - Other methods dominate:
     $X_c = X_t \implies \pi_c = \pi_t$ but
     $\pi_c = \pi_t \not\Rightarrow X_c = X_t$
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   - 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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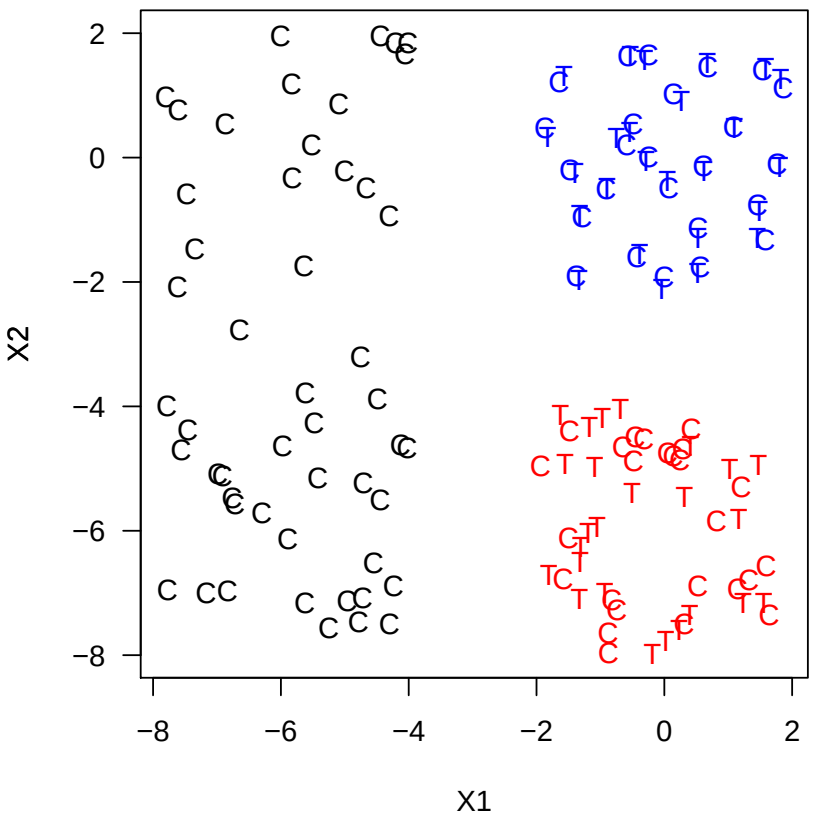

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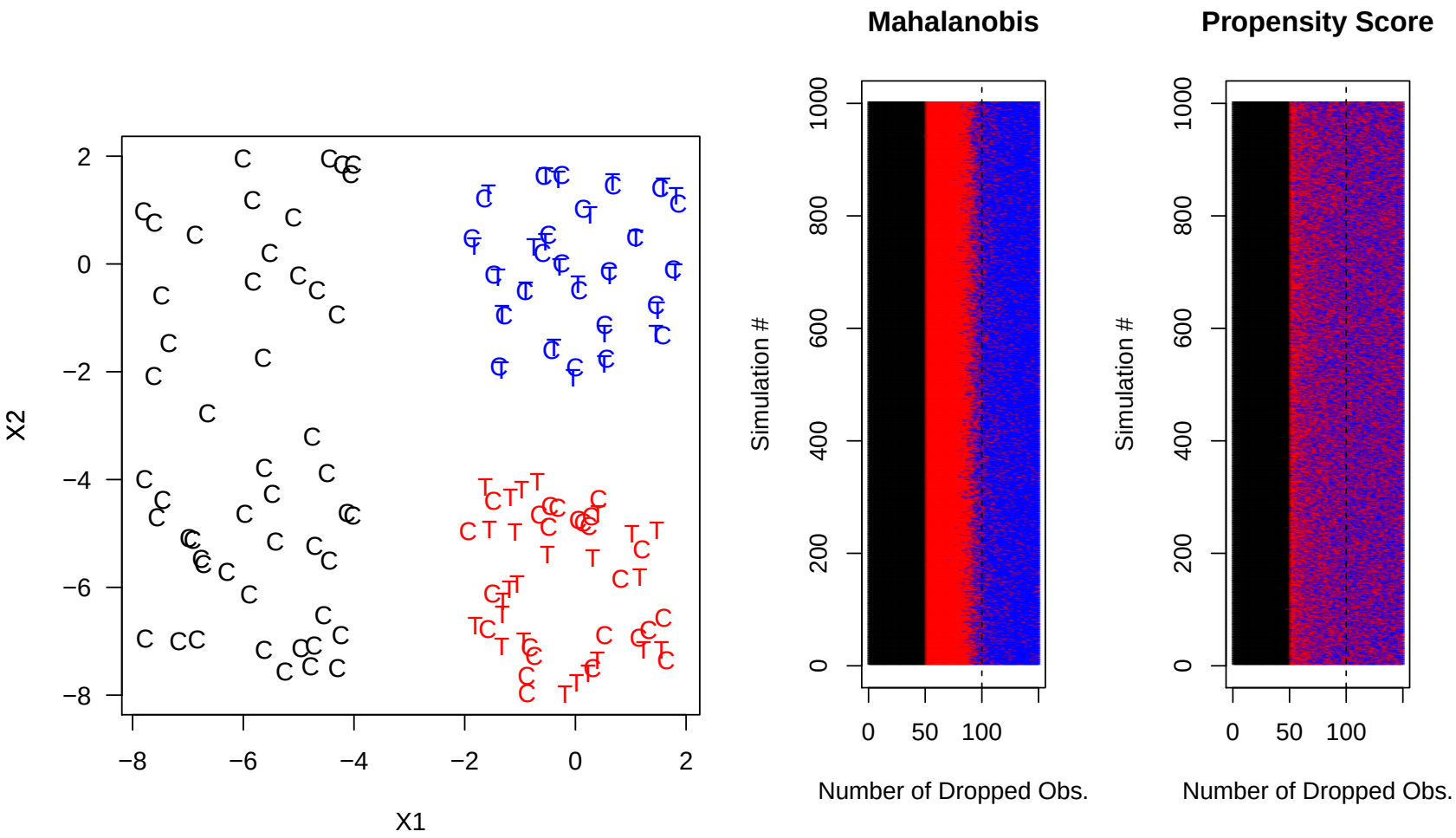
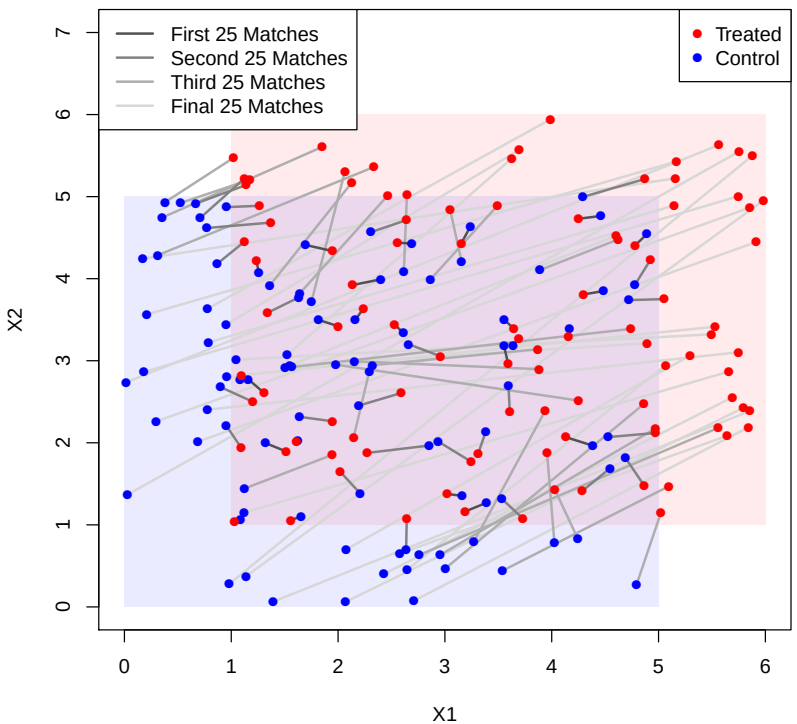


What Does PSM Match?

MDM Matches



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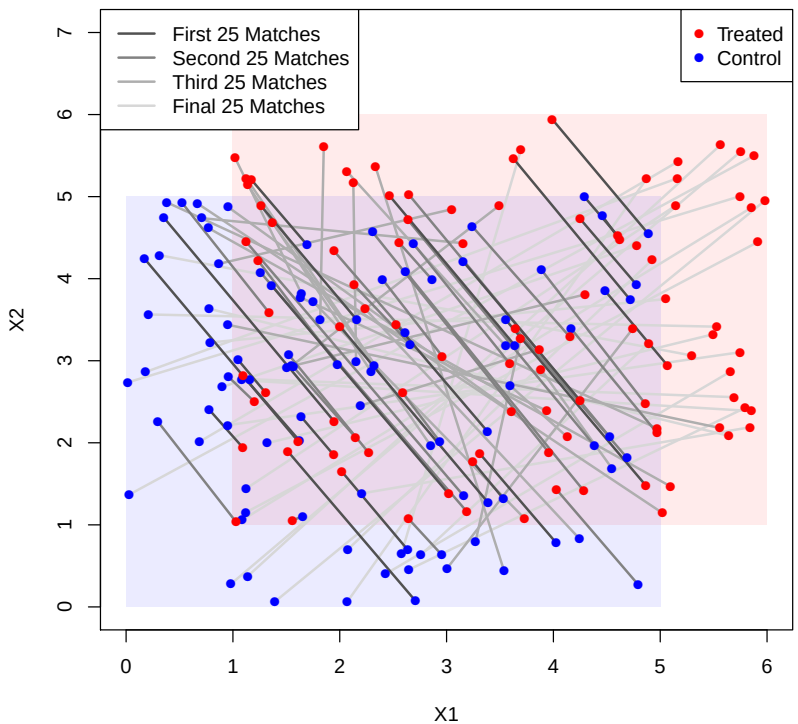
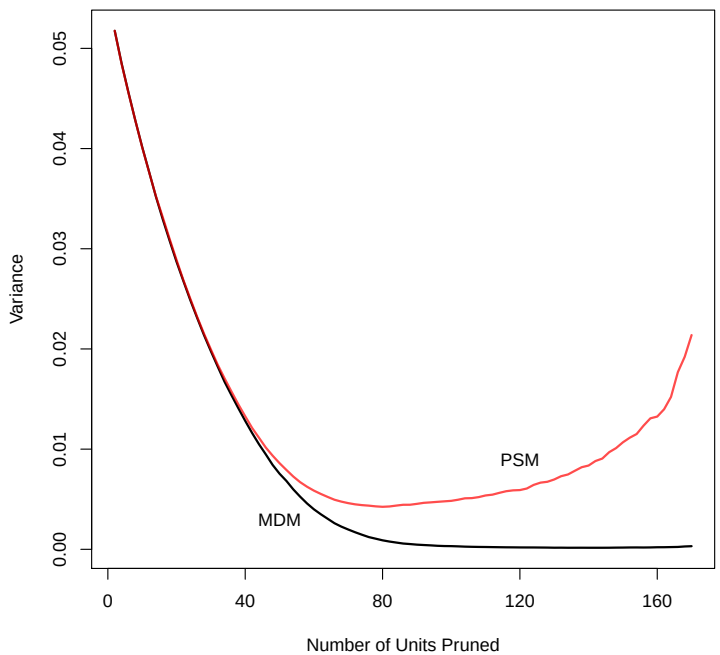


Controls: $X_1, X_2 \sim$ Uniform(0,5)

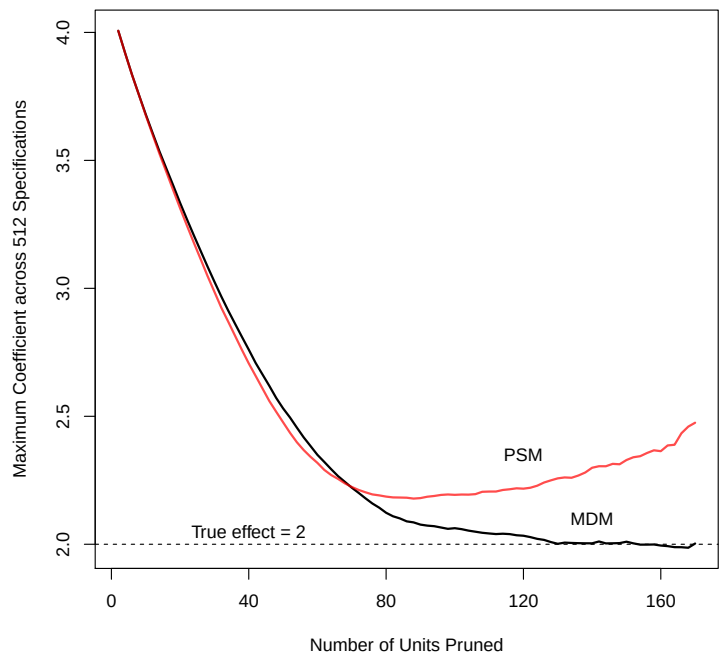
Treateds: $X_1, X_2 \sim$ Uniform(1,6)

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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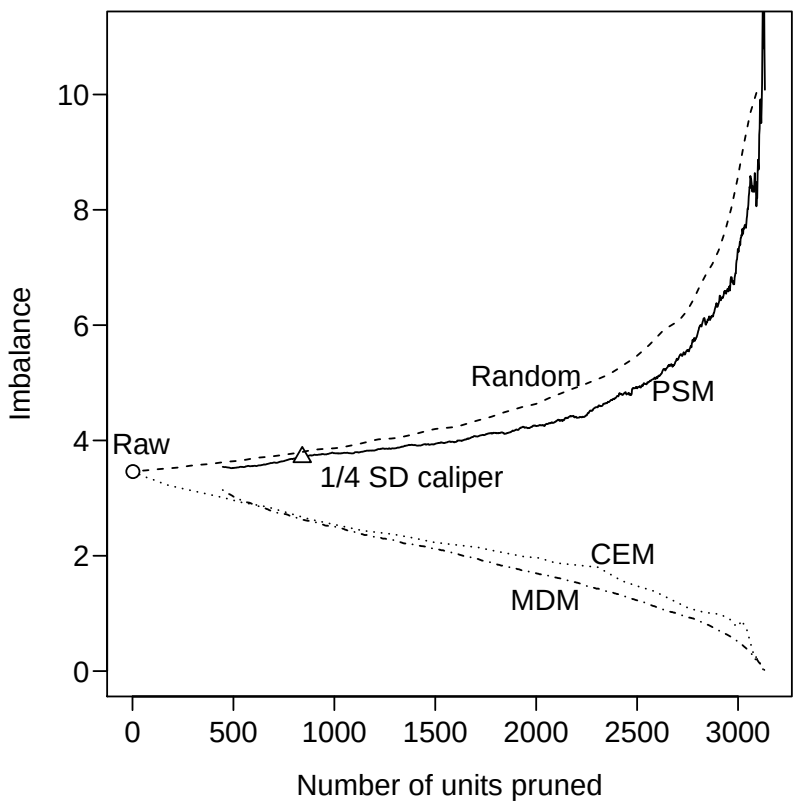
Finkel et al. (JOP, 2012)



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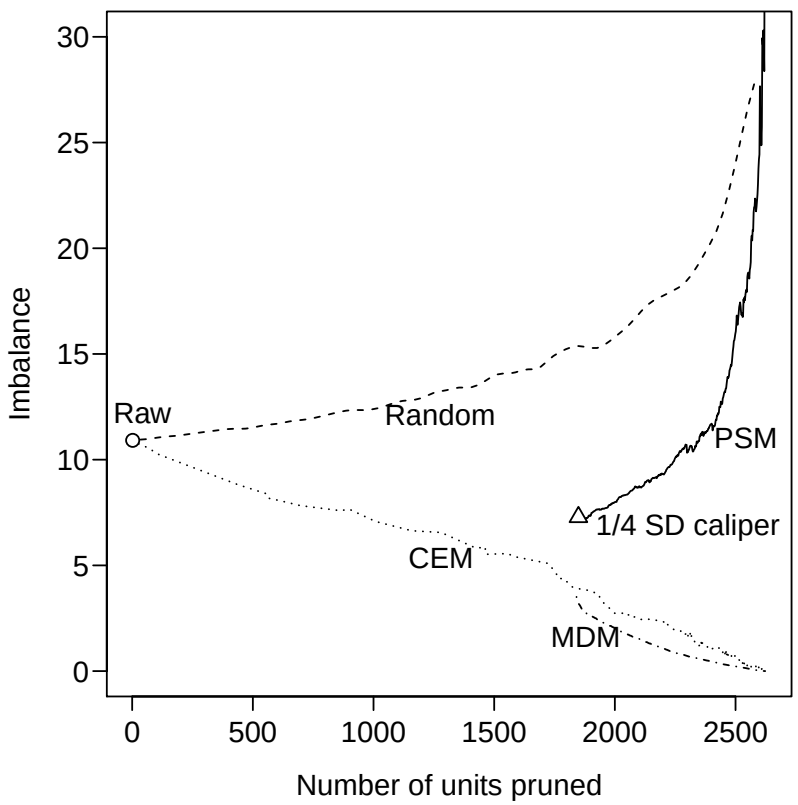

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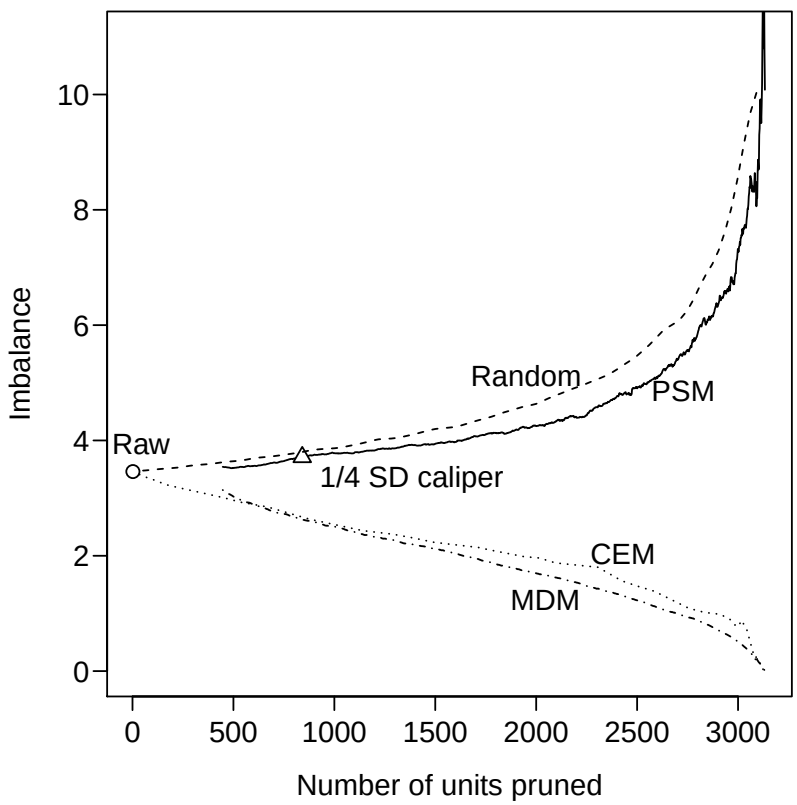

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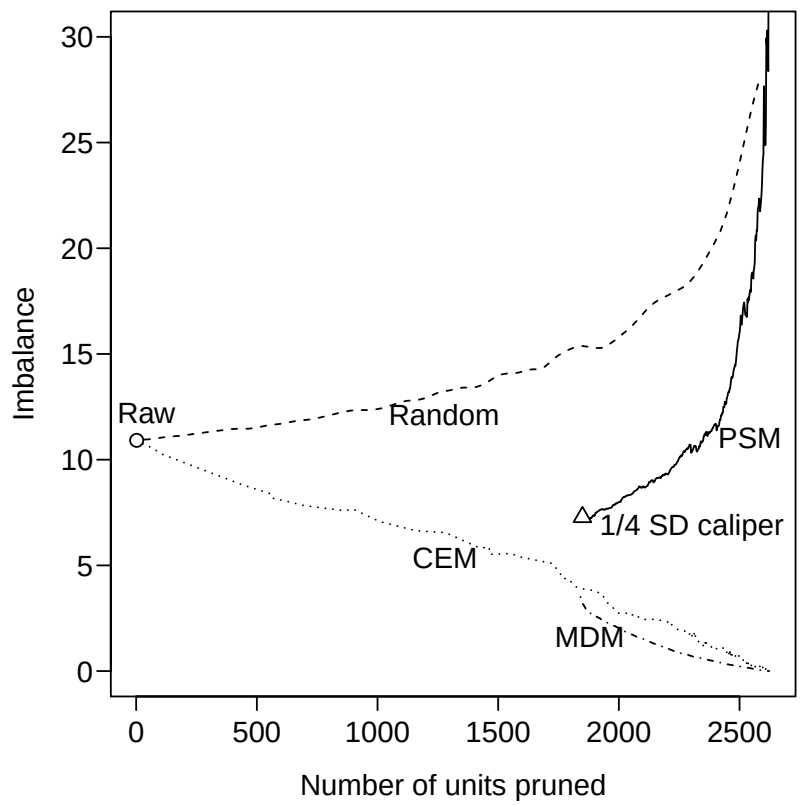

Similar pattern for > 20 other real data sets we checked

Detecting Model Dependence

Matching to Reduce Model Dependence

Three Matching Methods

Problems with Propensity Score Matching

The Matching Frontier

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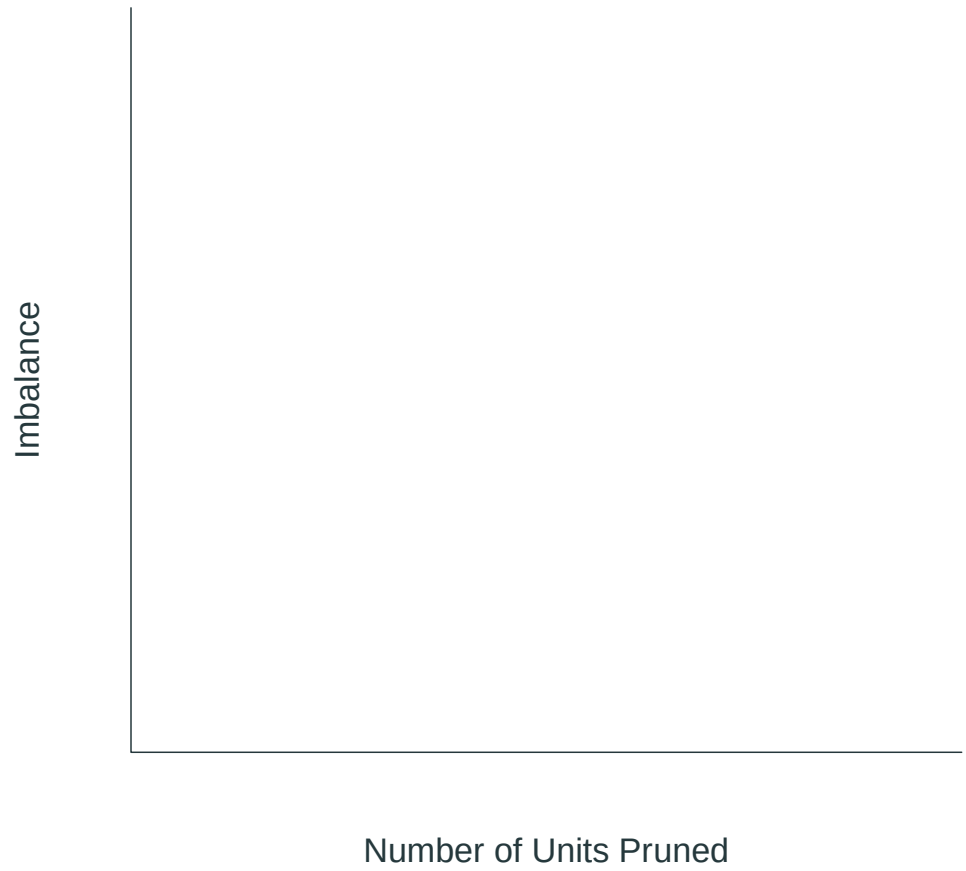
- Choose imbalance; check n after: exact matching, CEM

A Solution: The Matching Frontier



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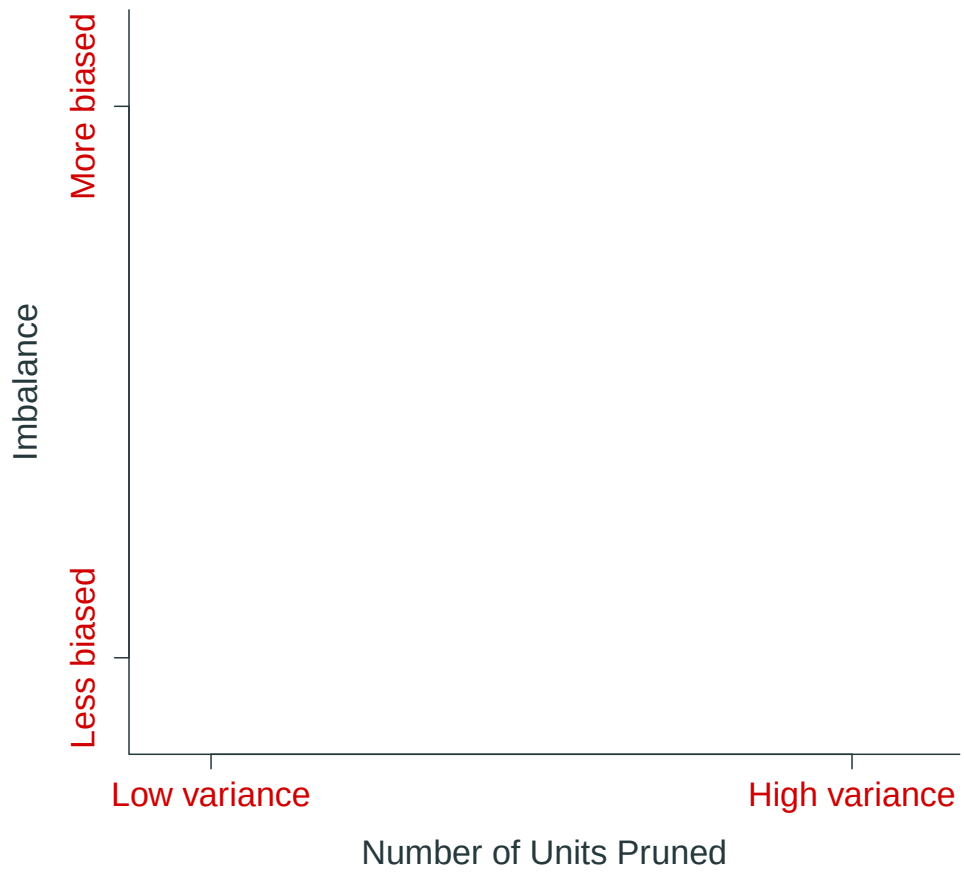

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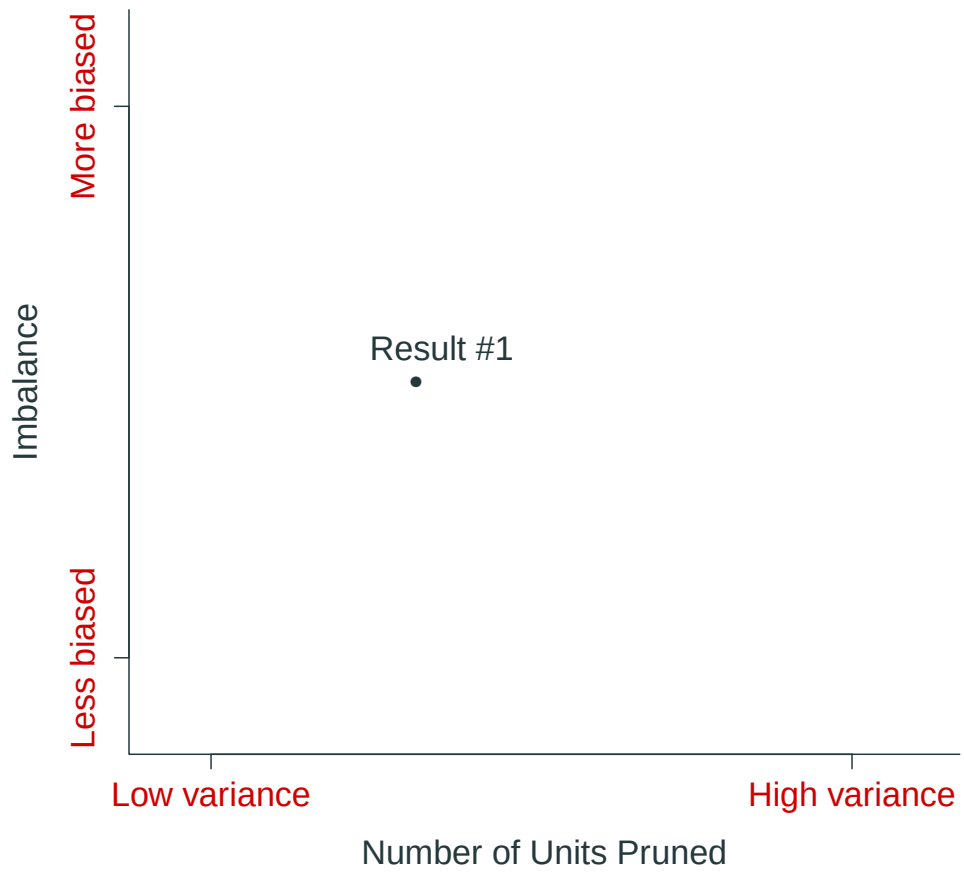

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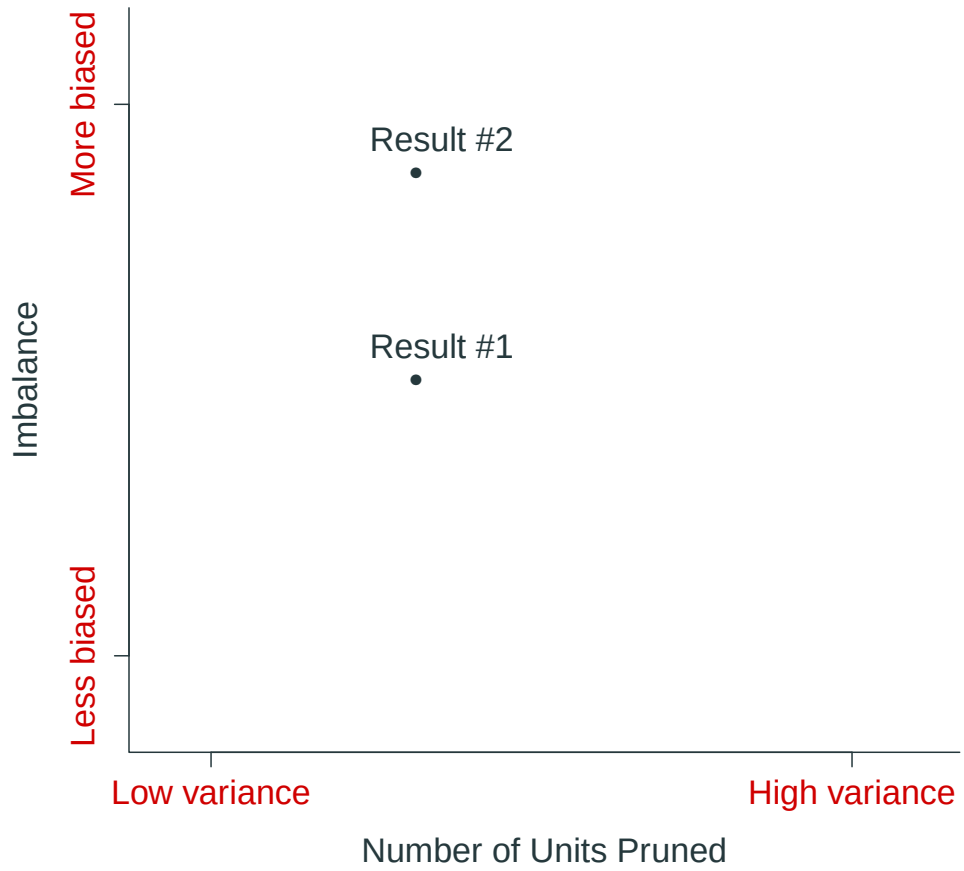

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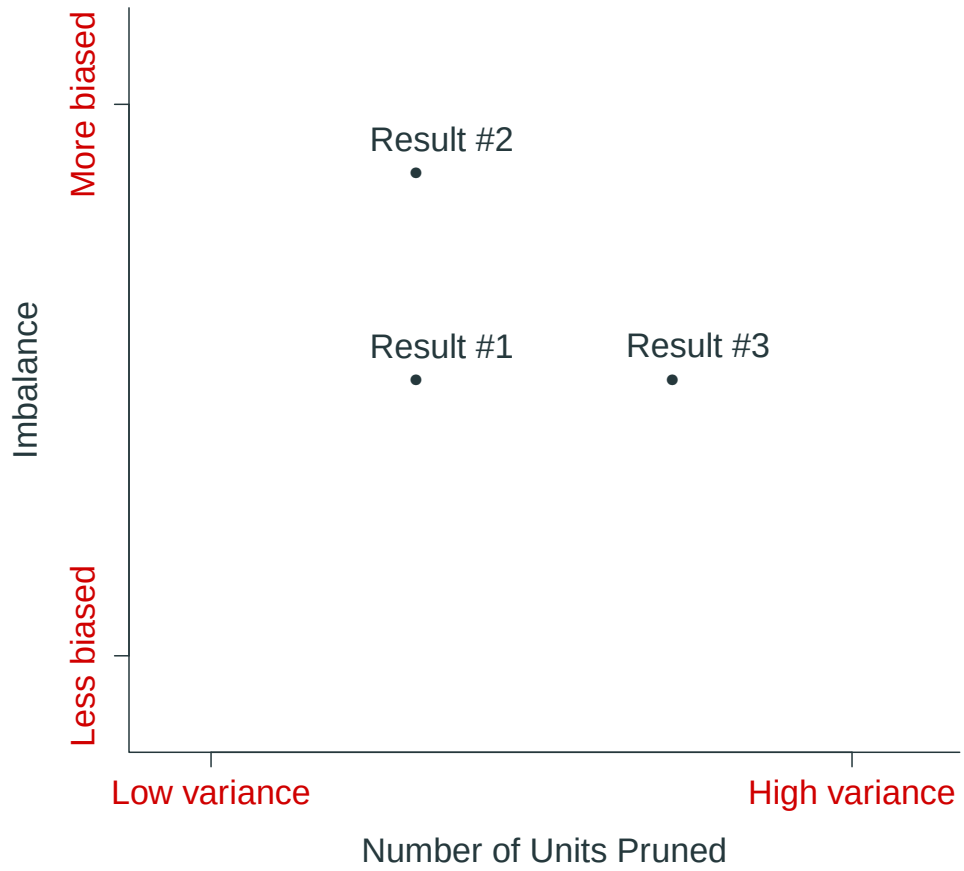

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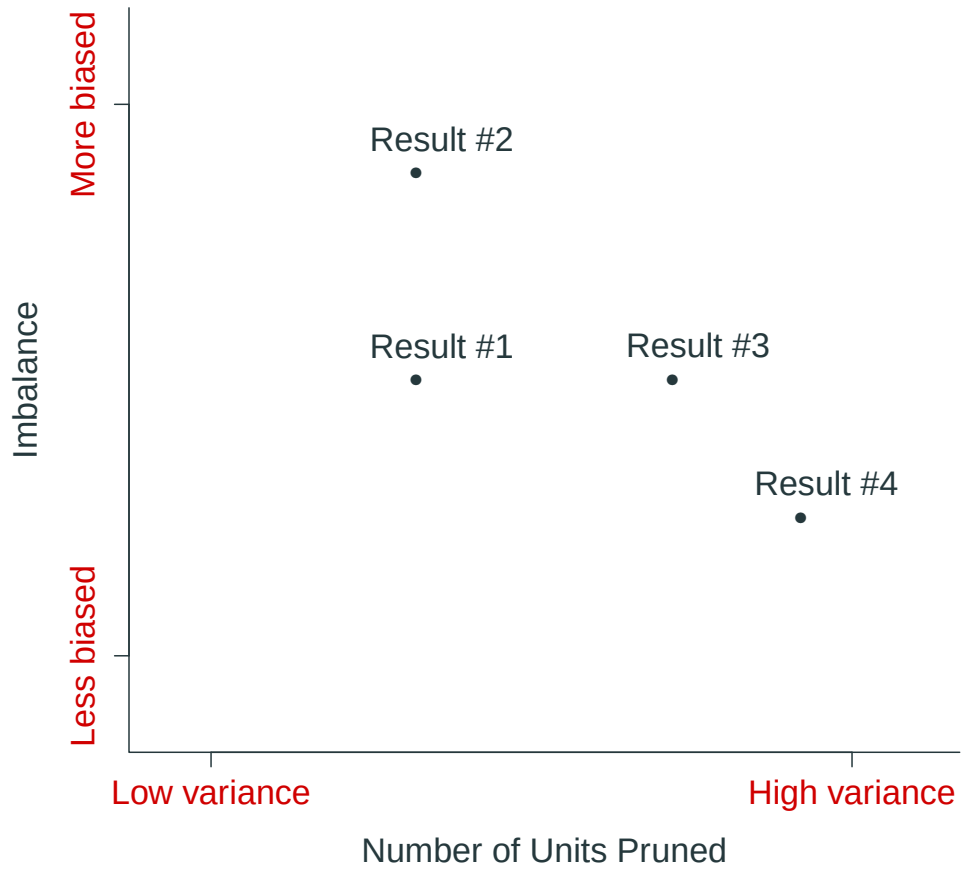

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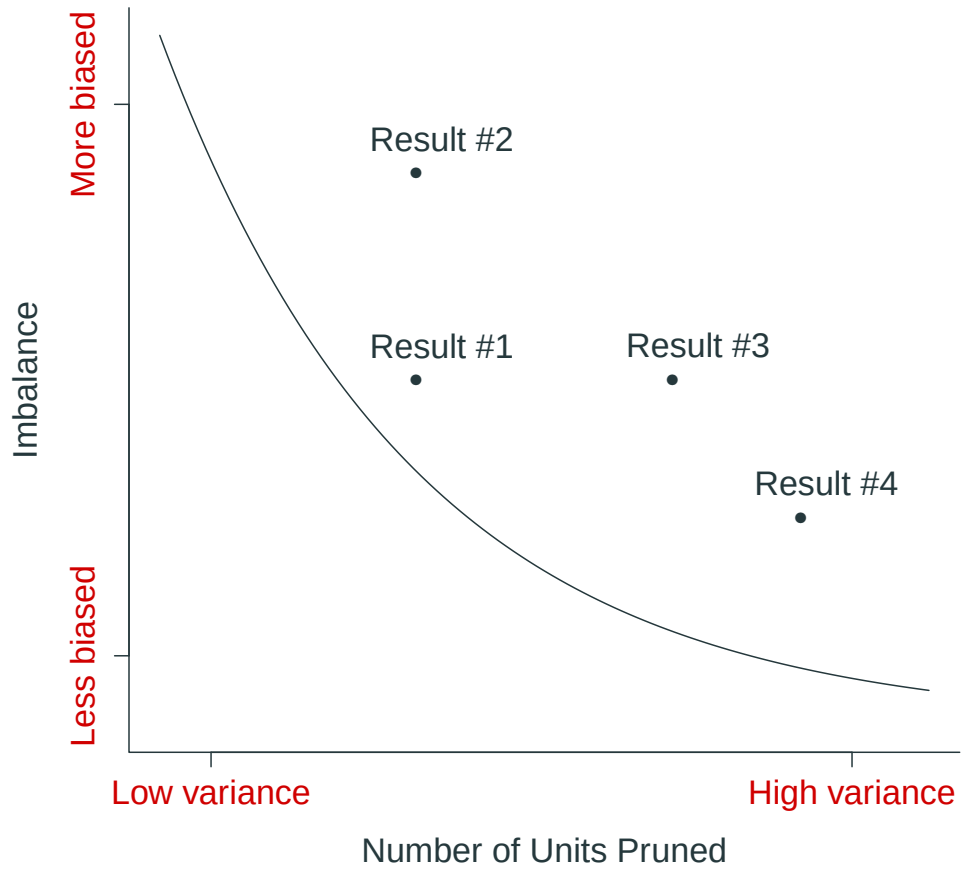

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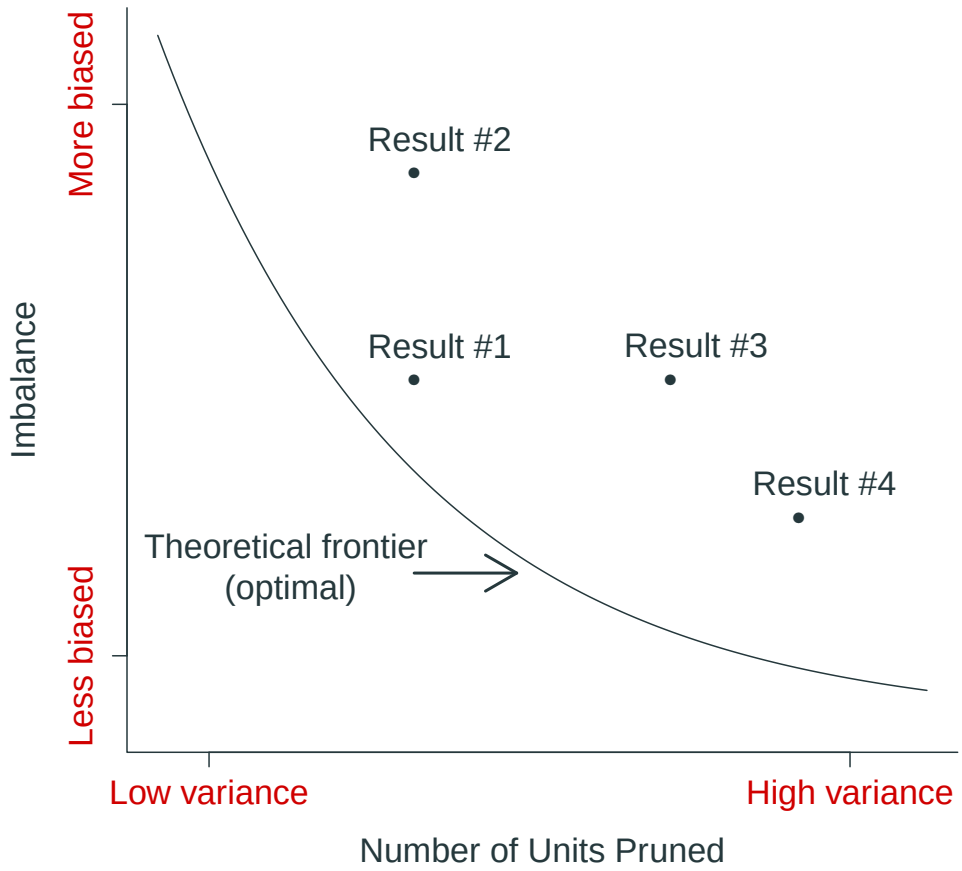

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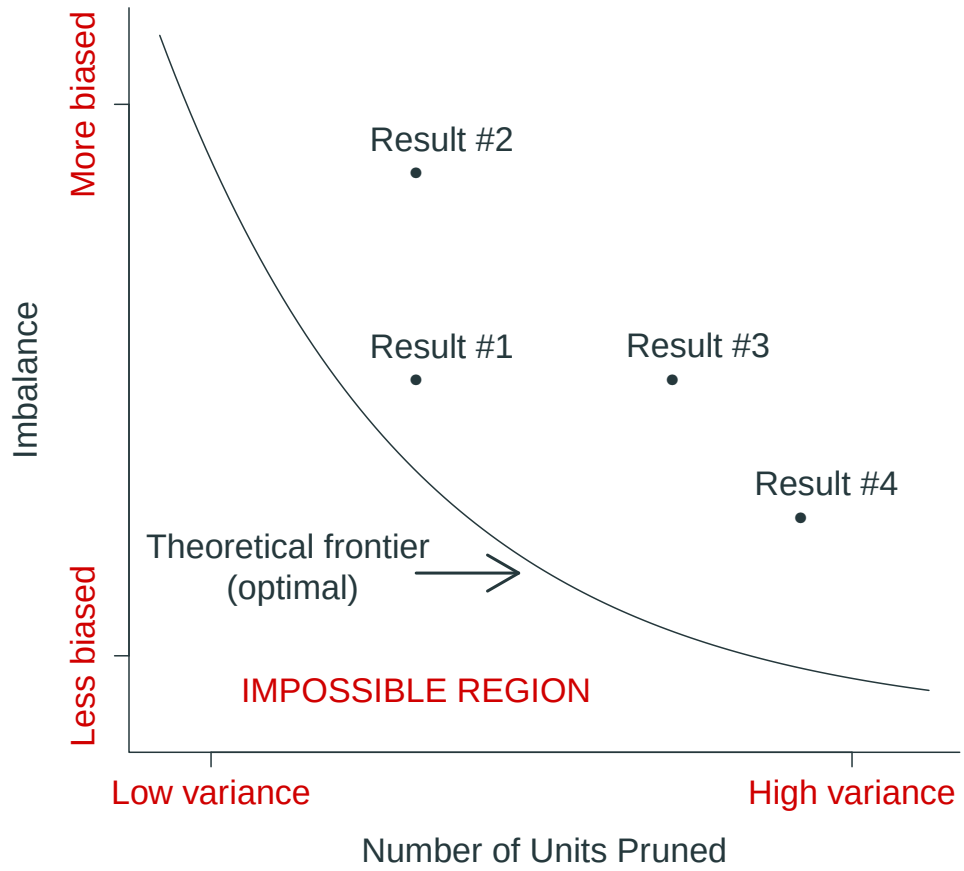

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Constructing the FSATT Mahalanobis Frontier

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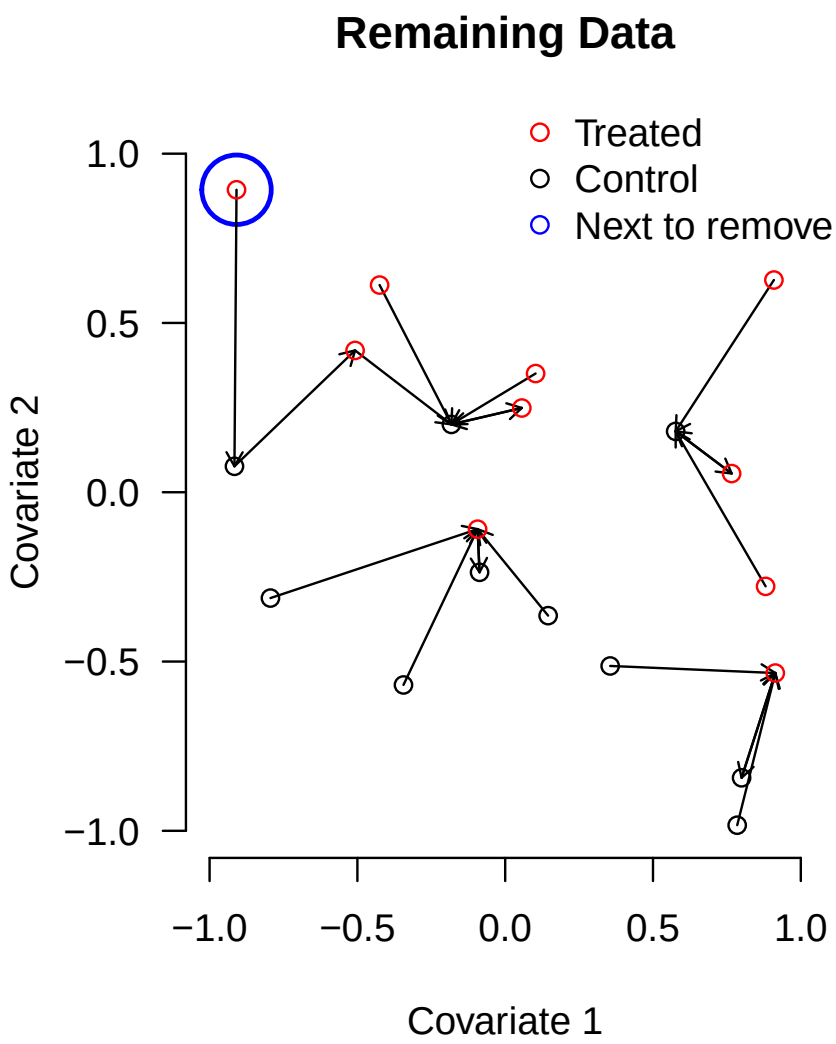

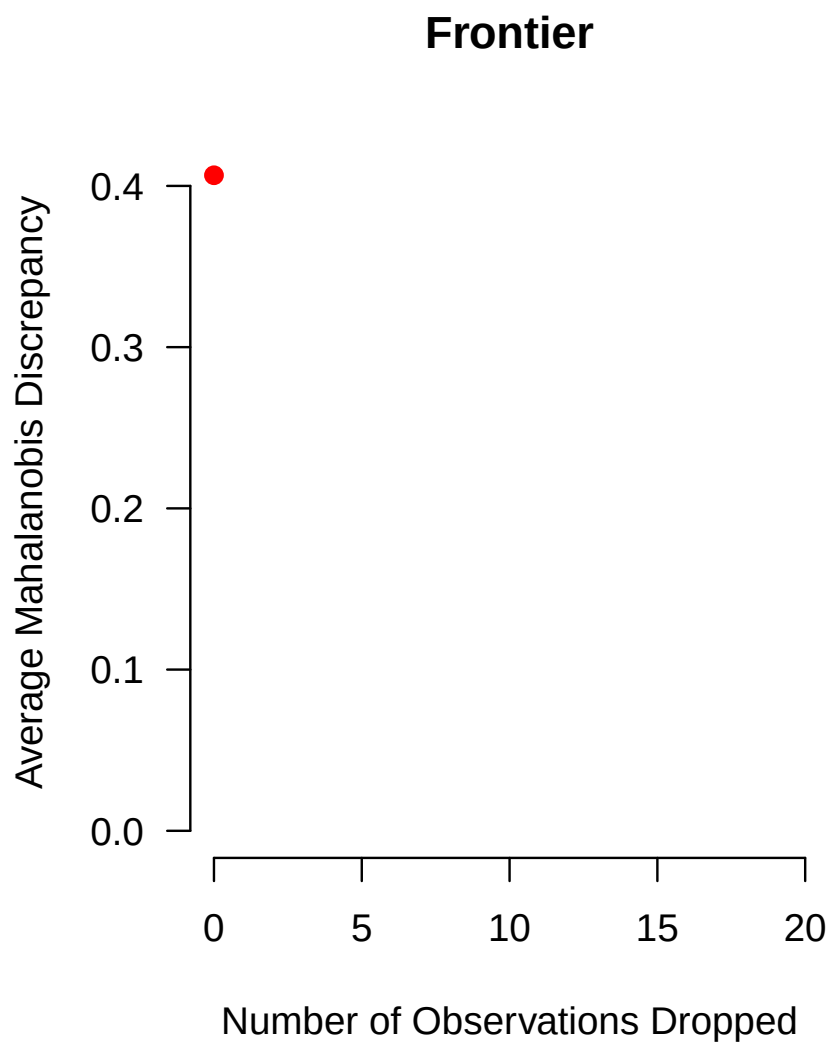

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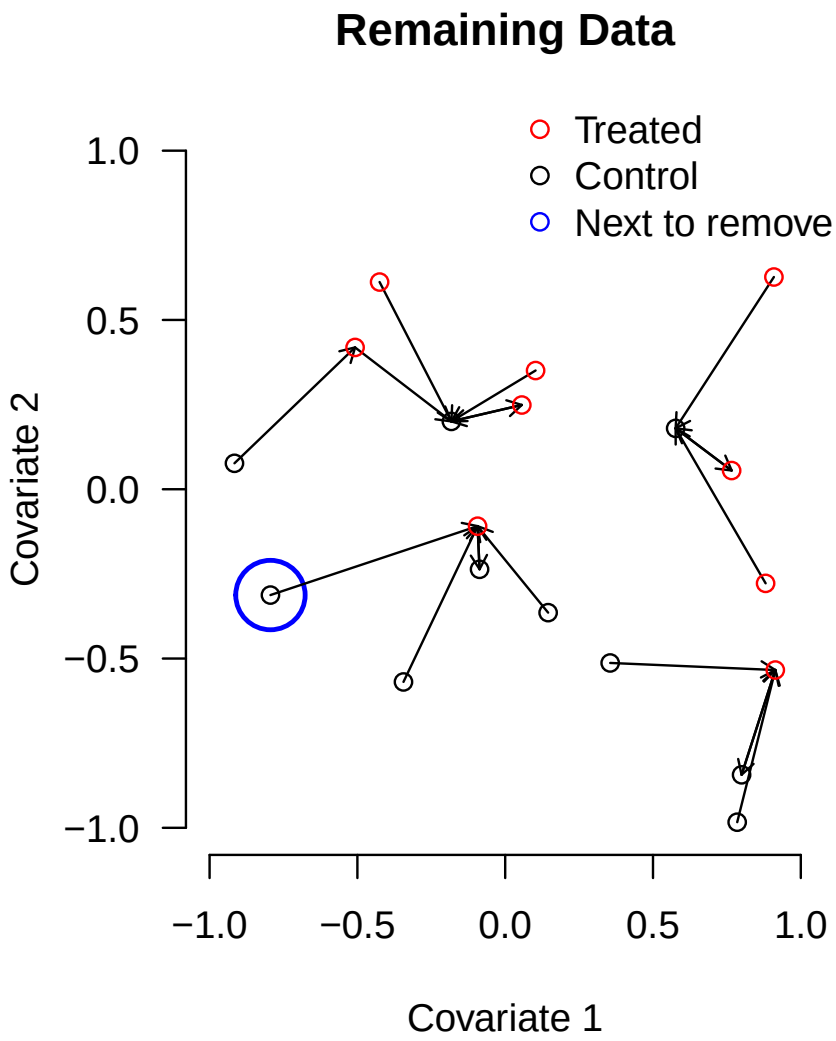

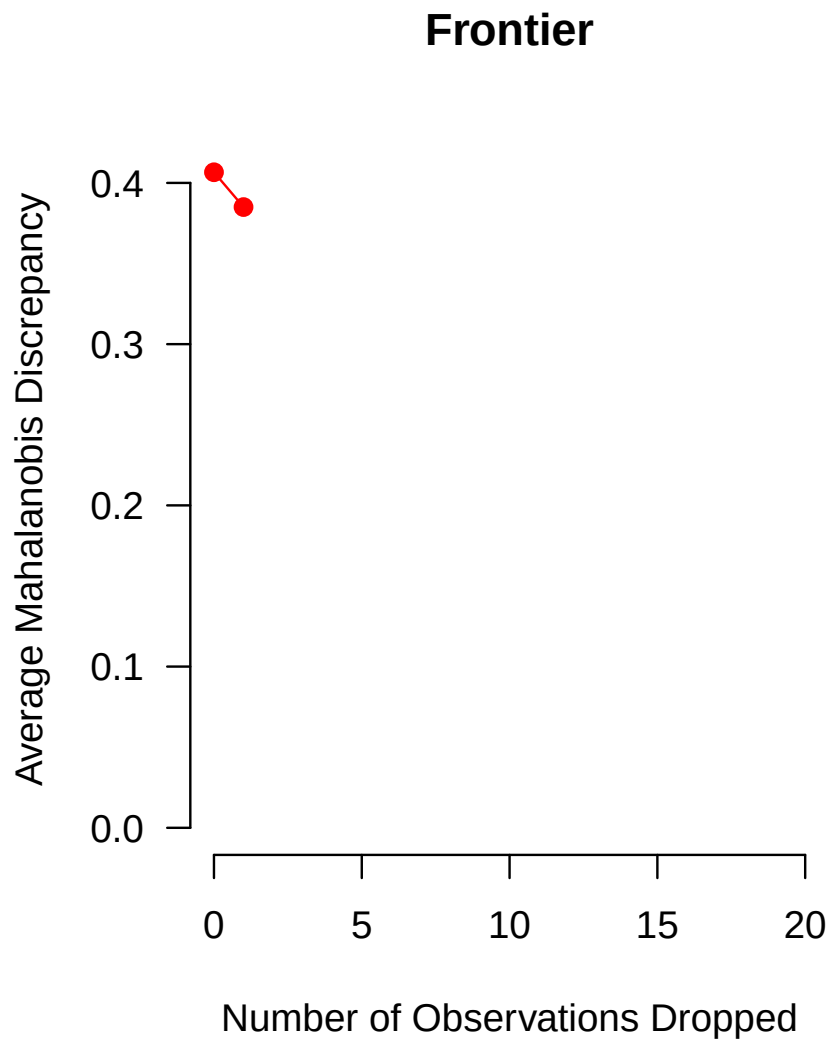

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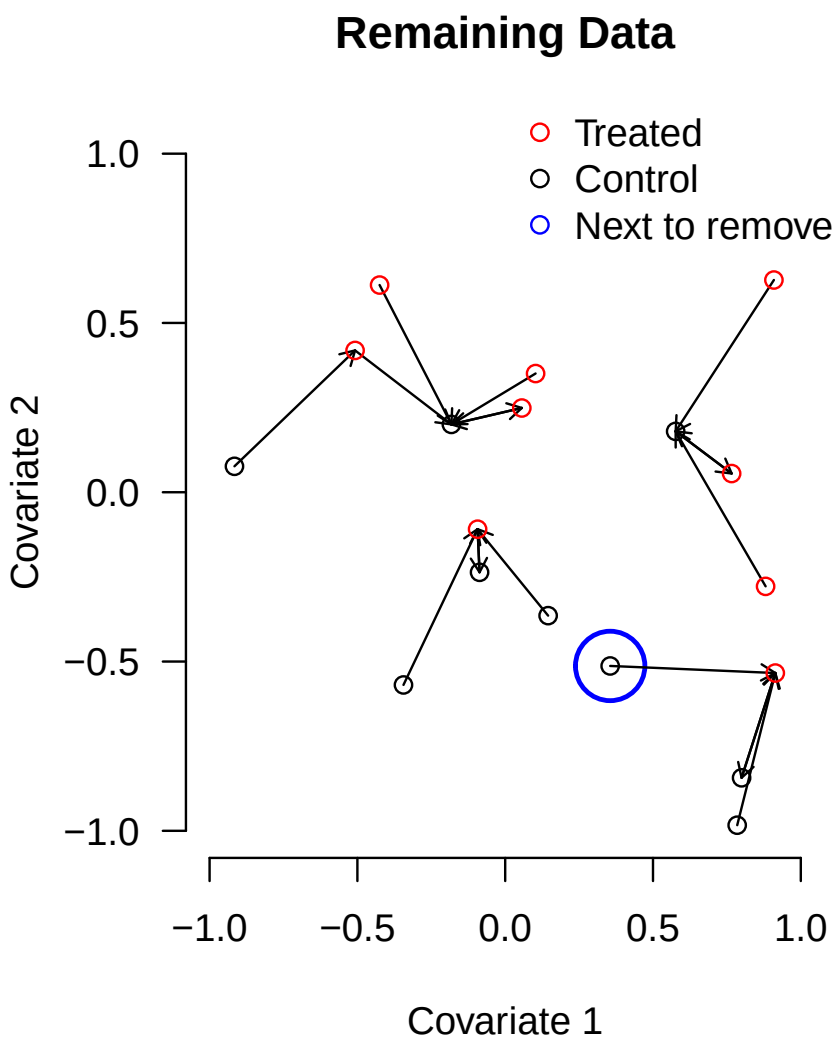

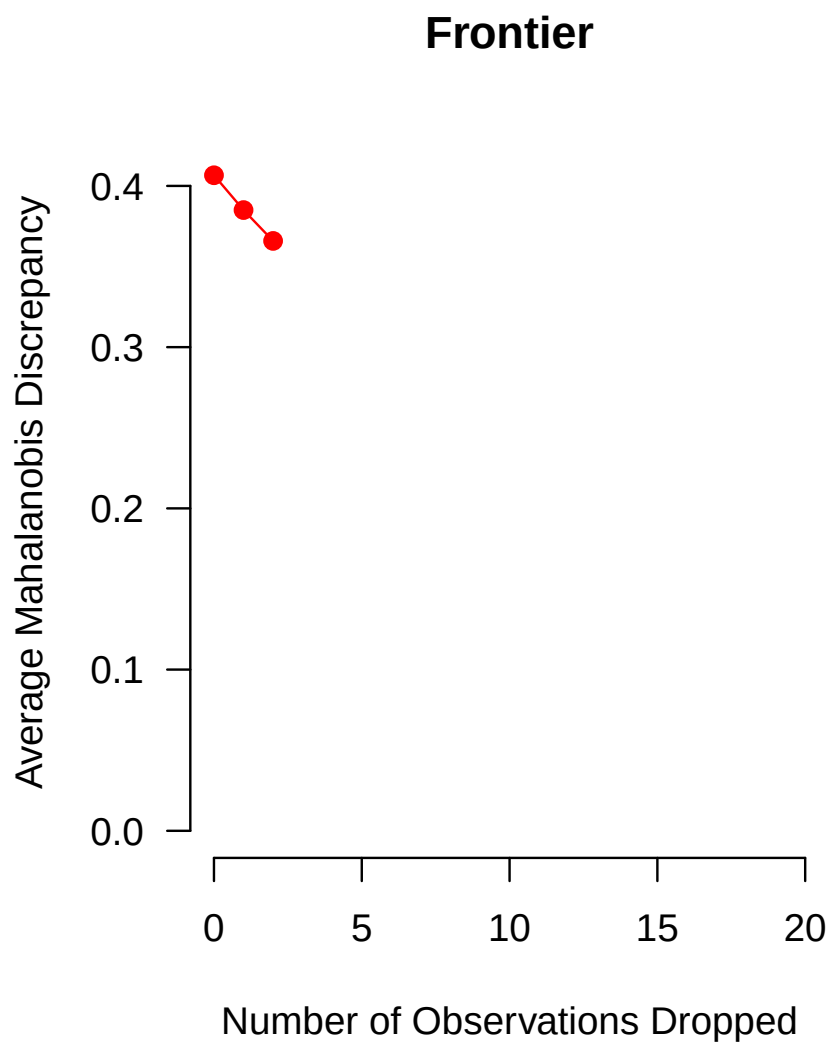

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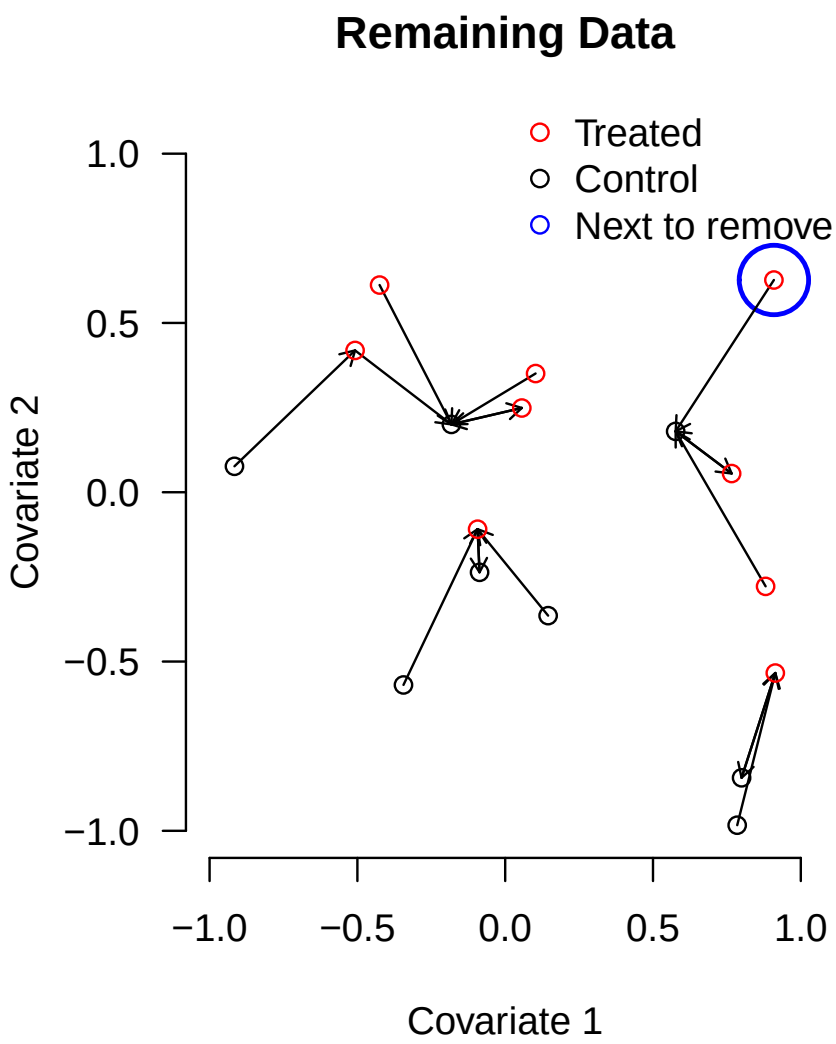

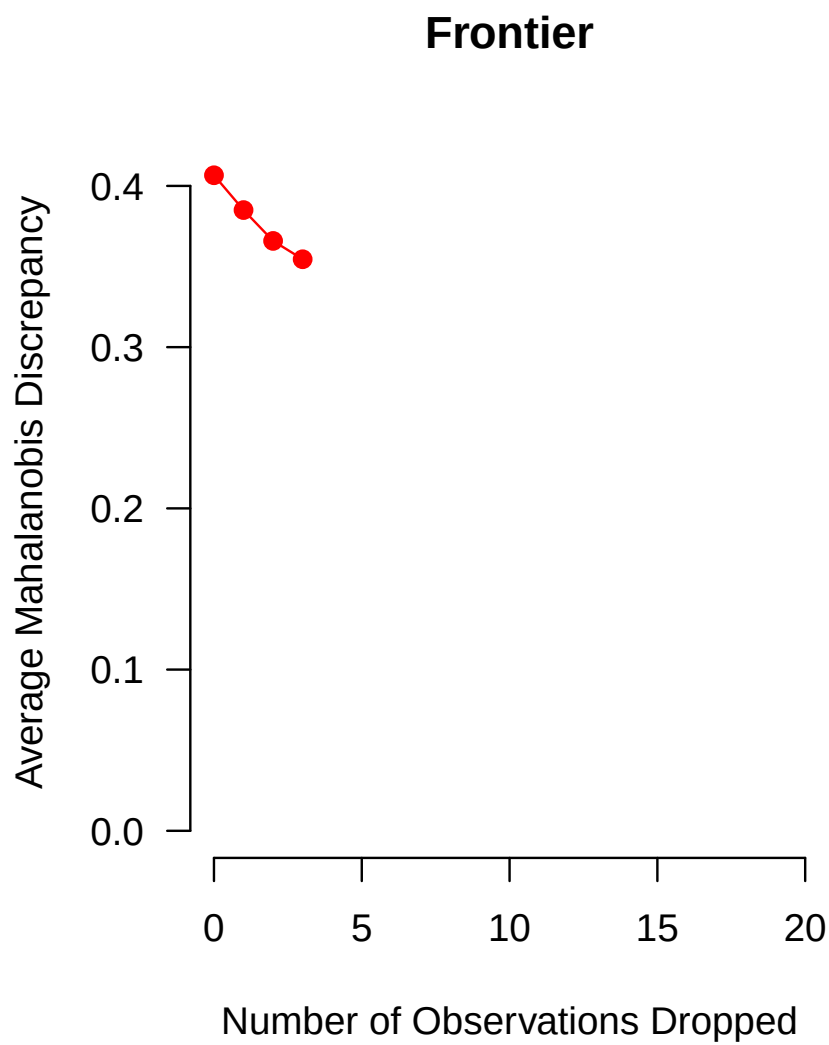

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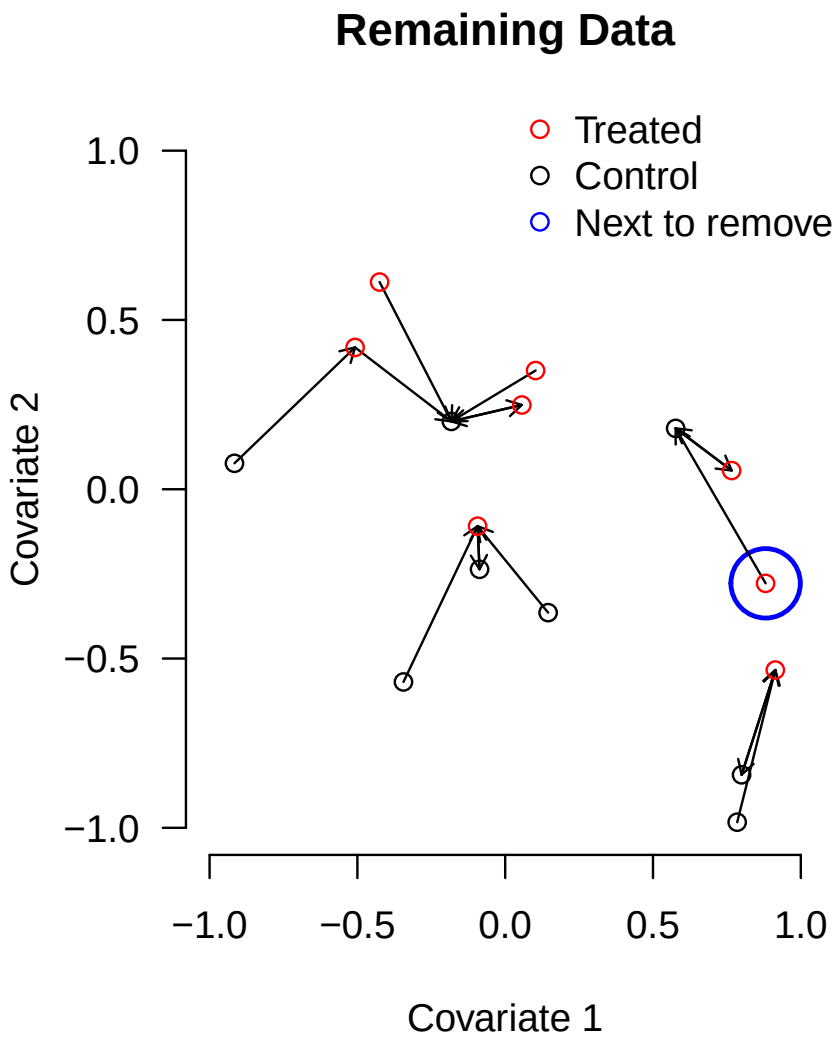

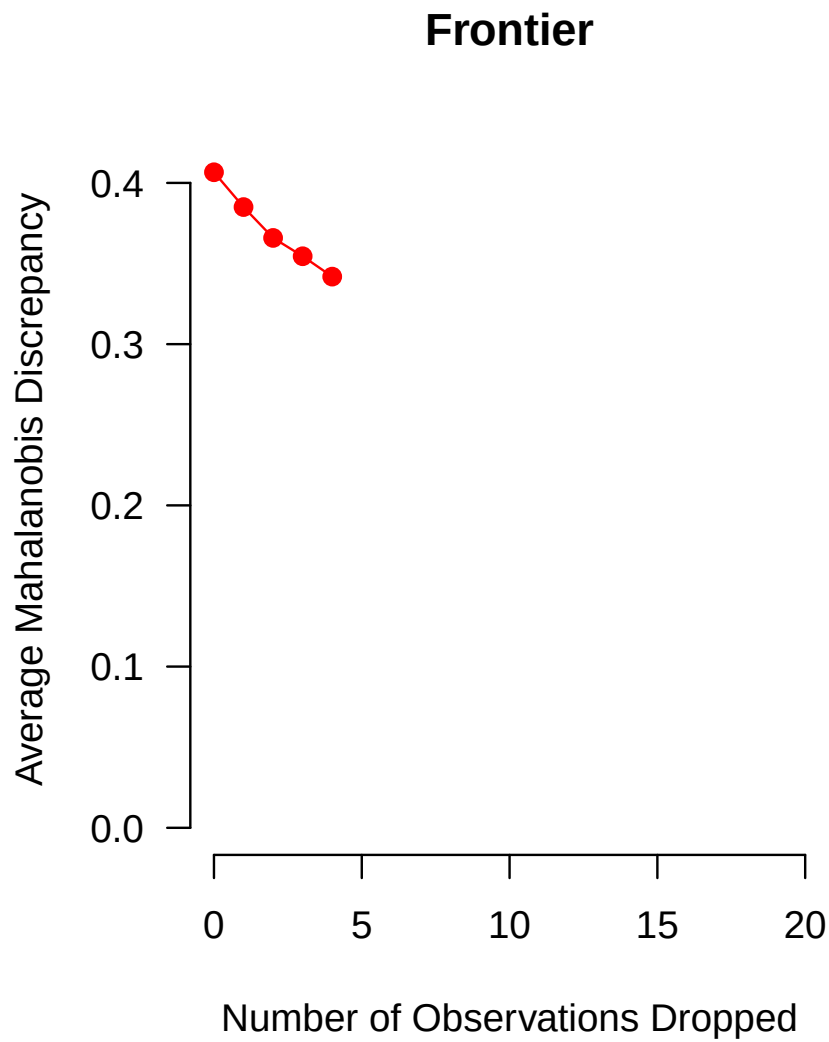

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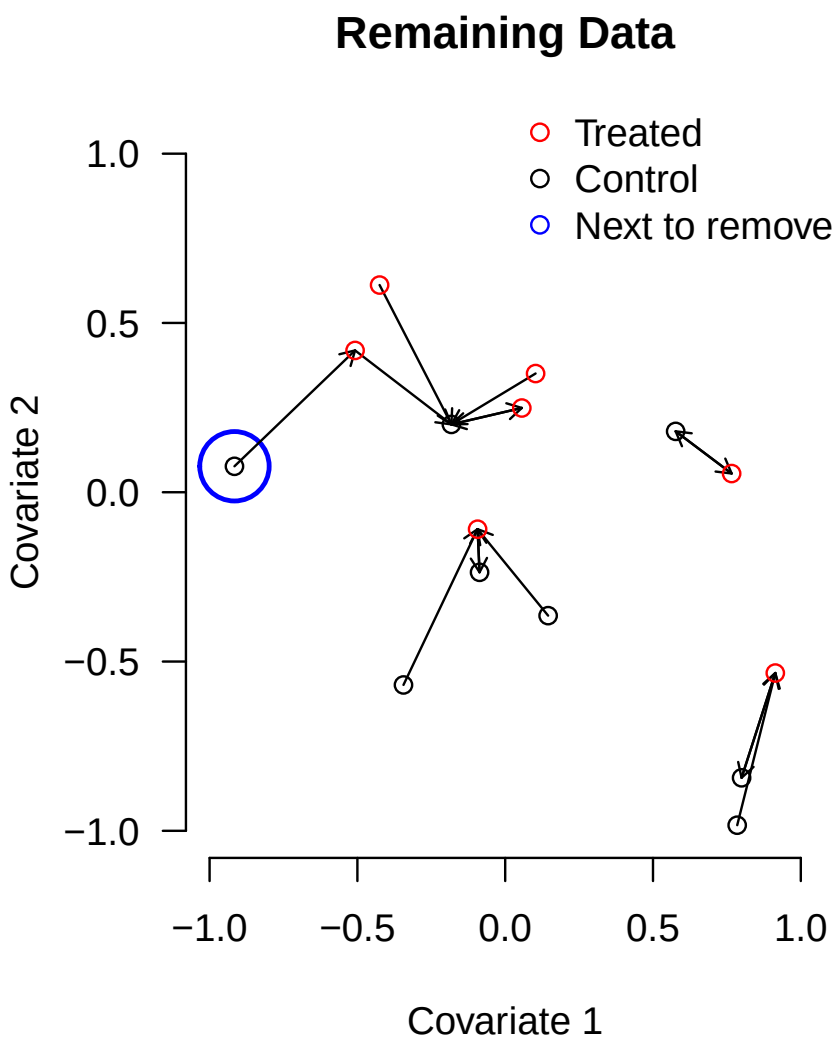

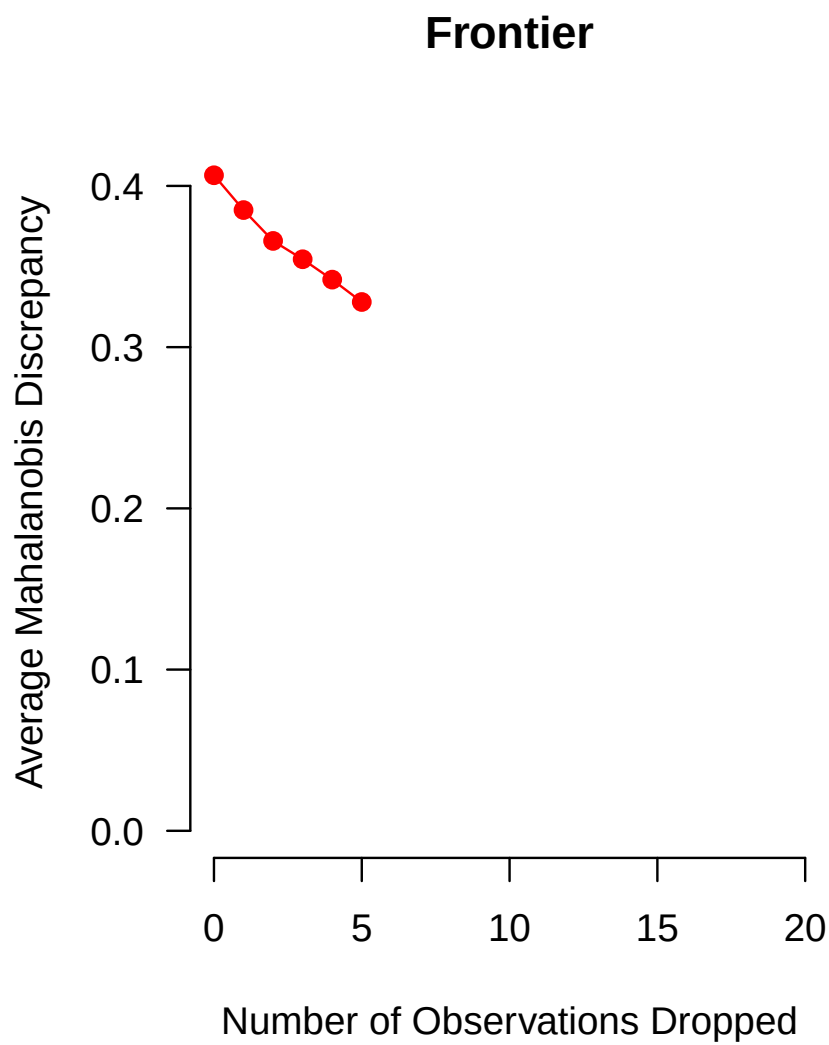

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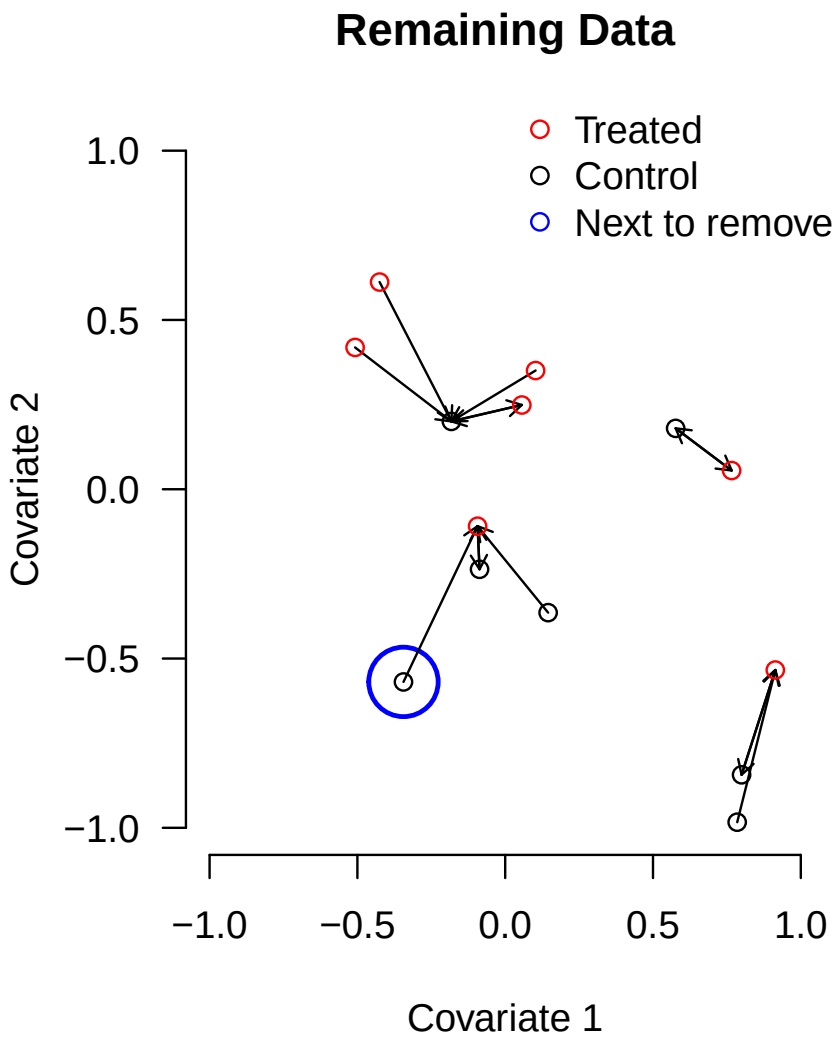

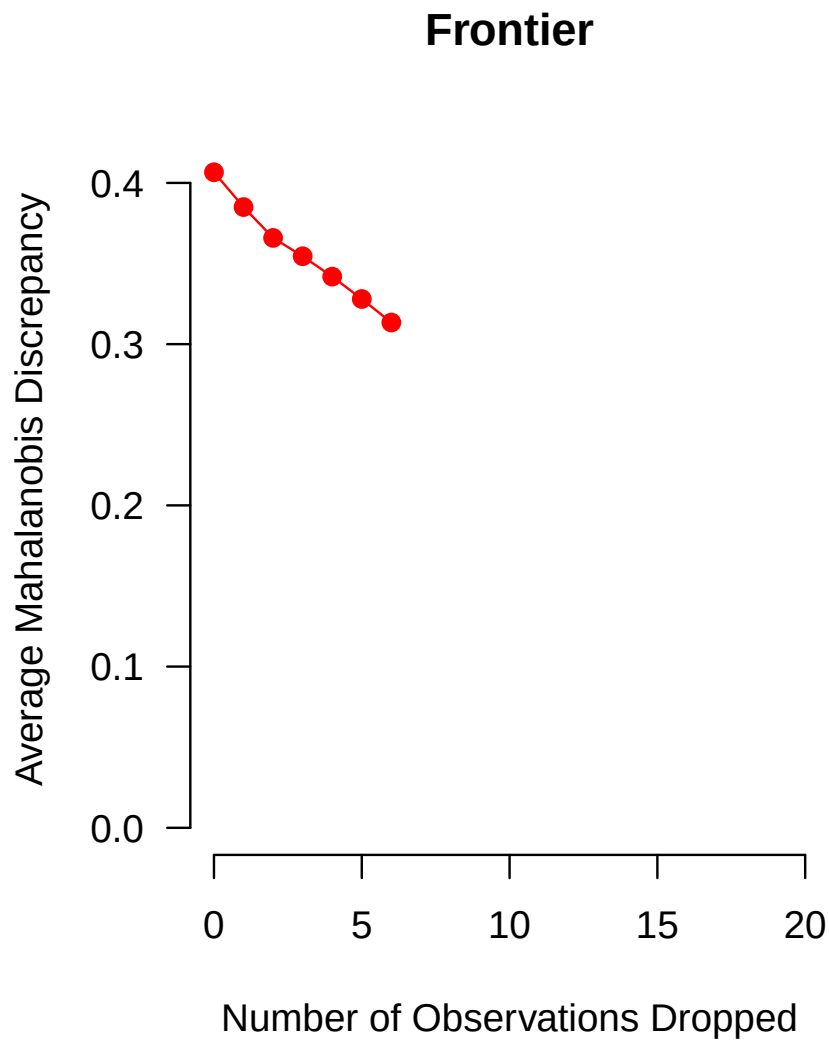

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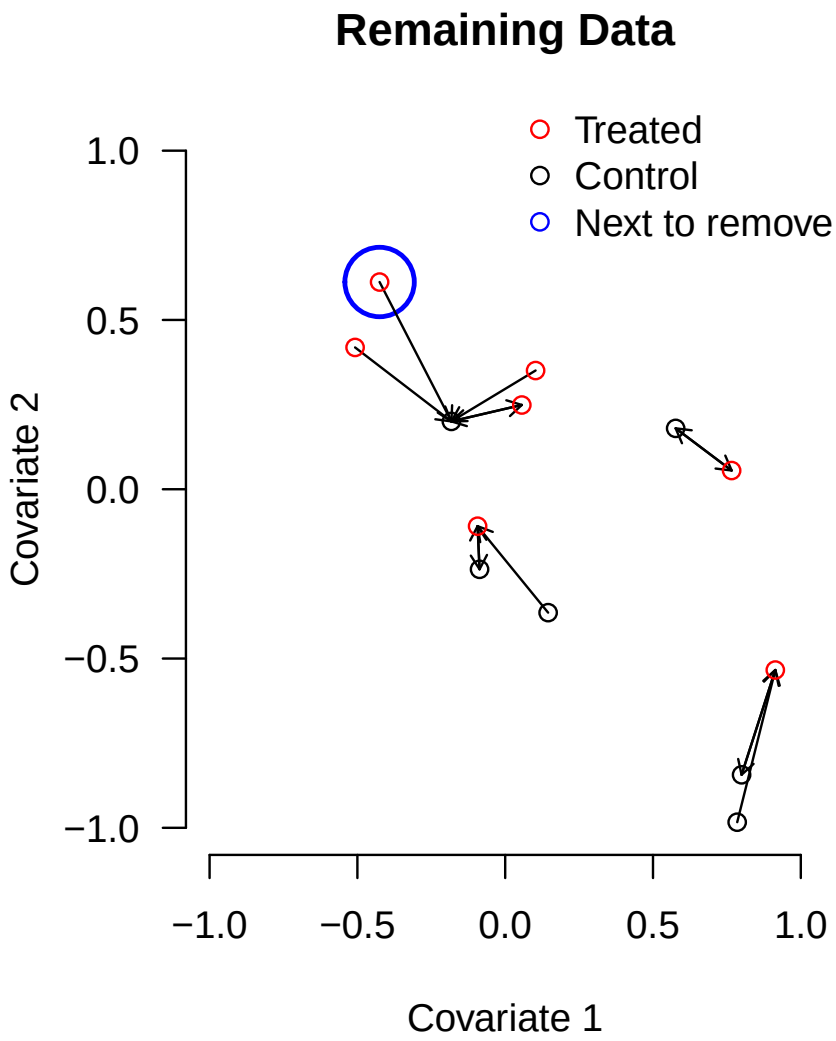

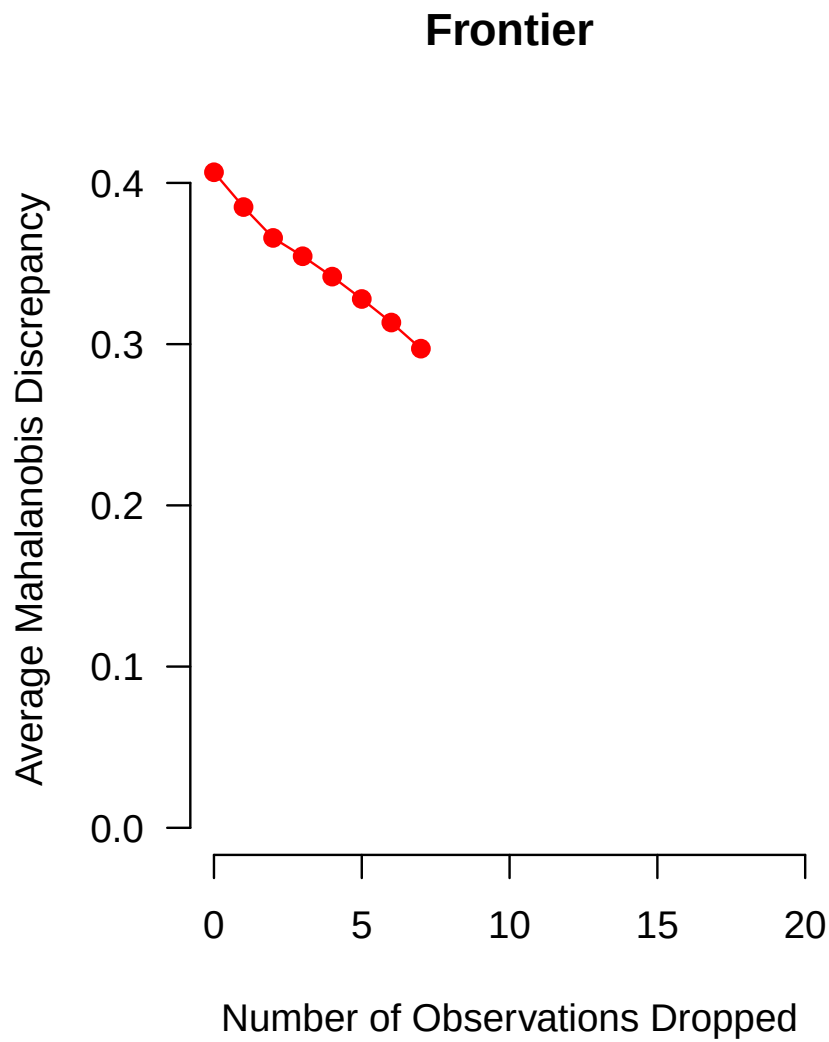

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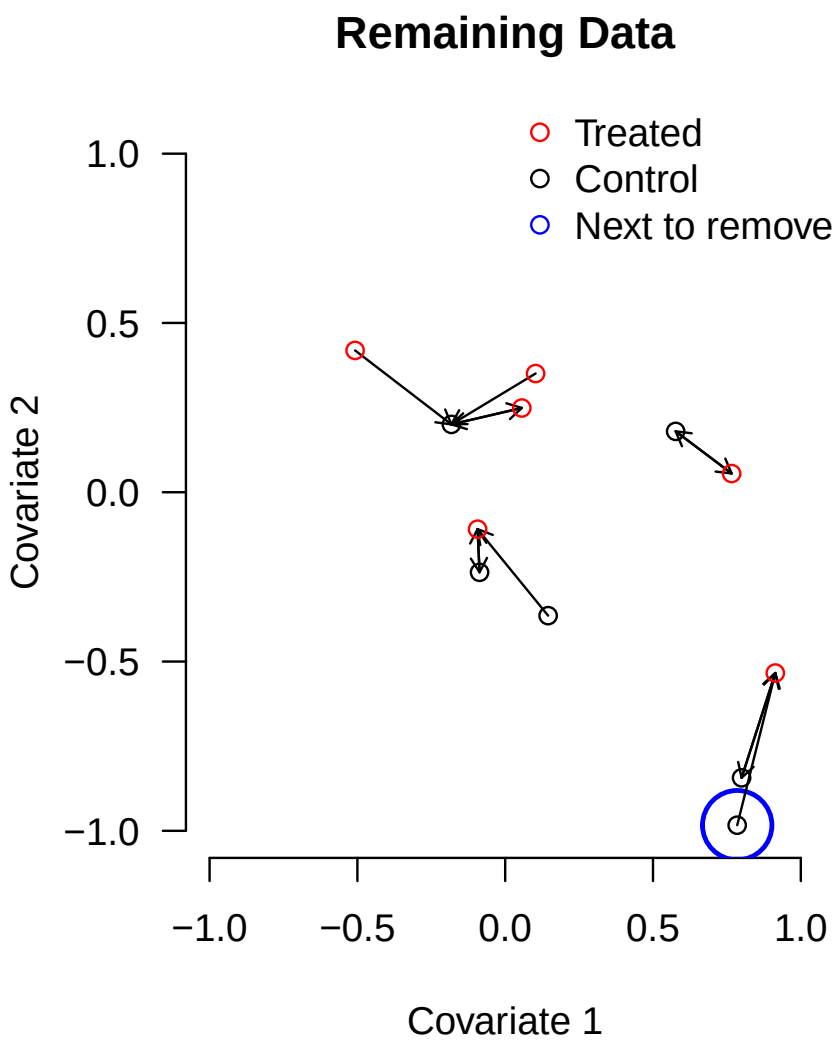

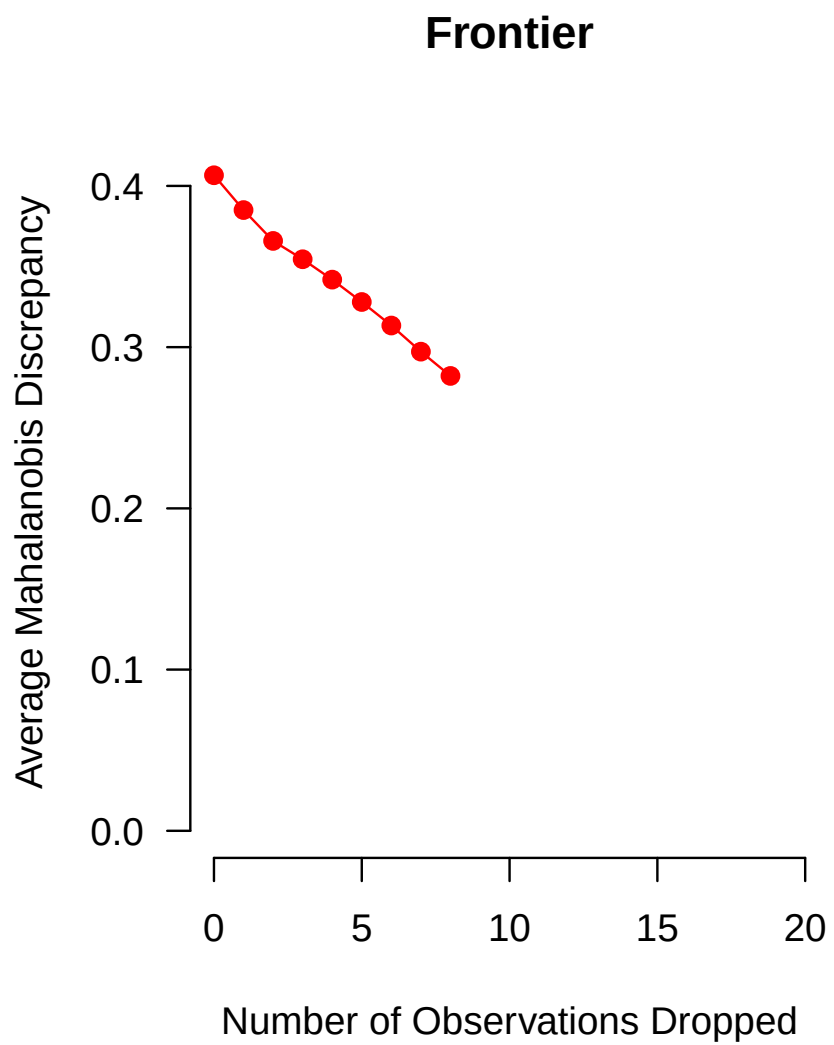

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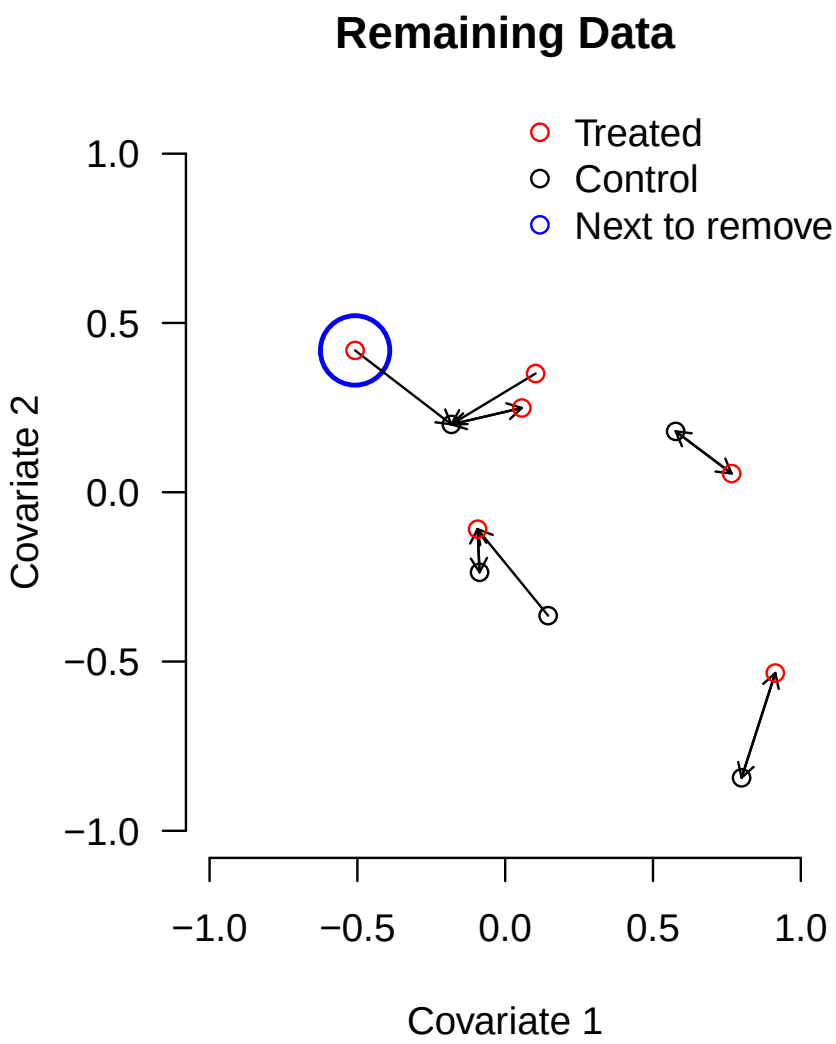

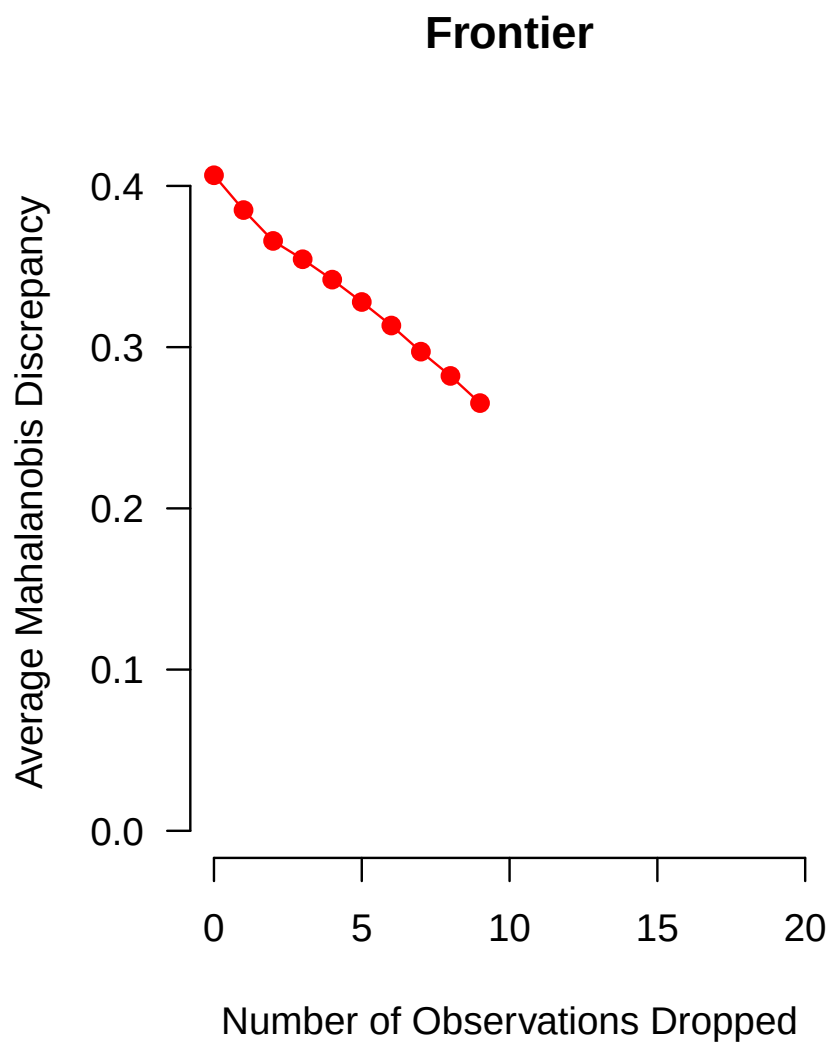

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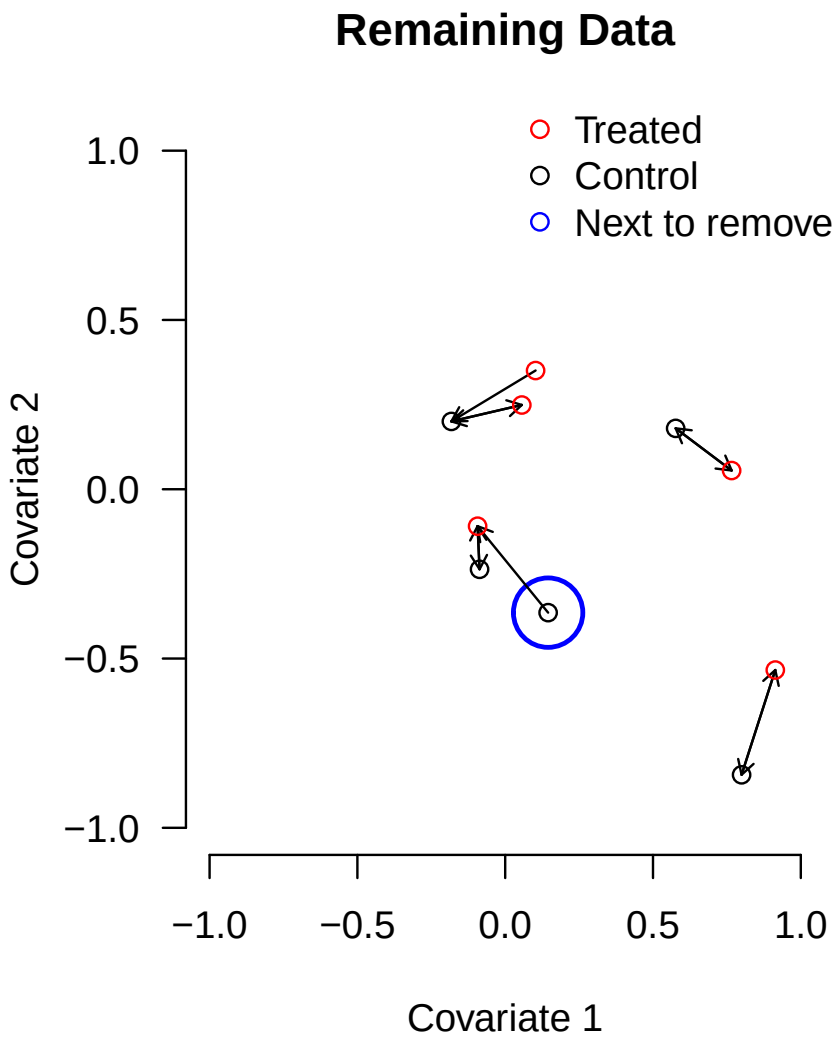

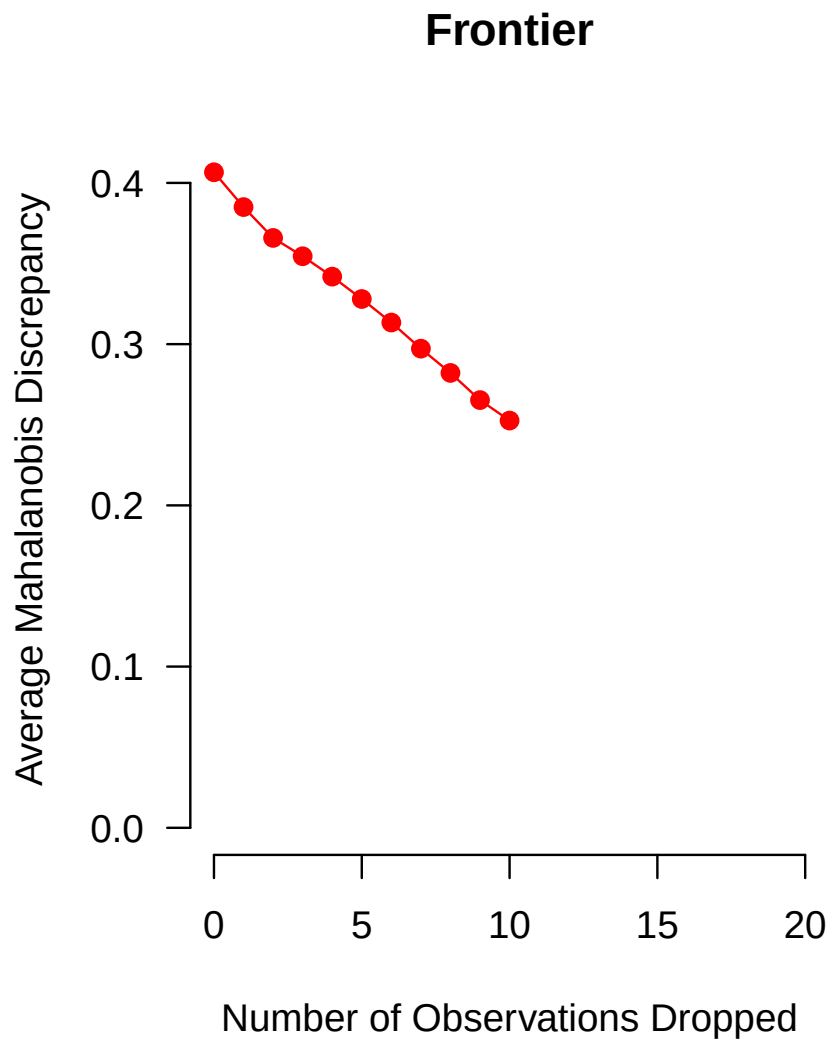

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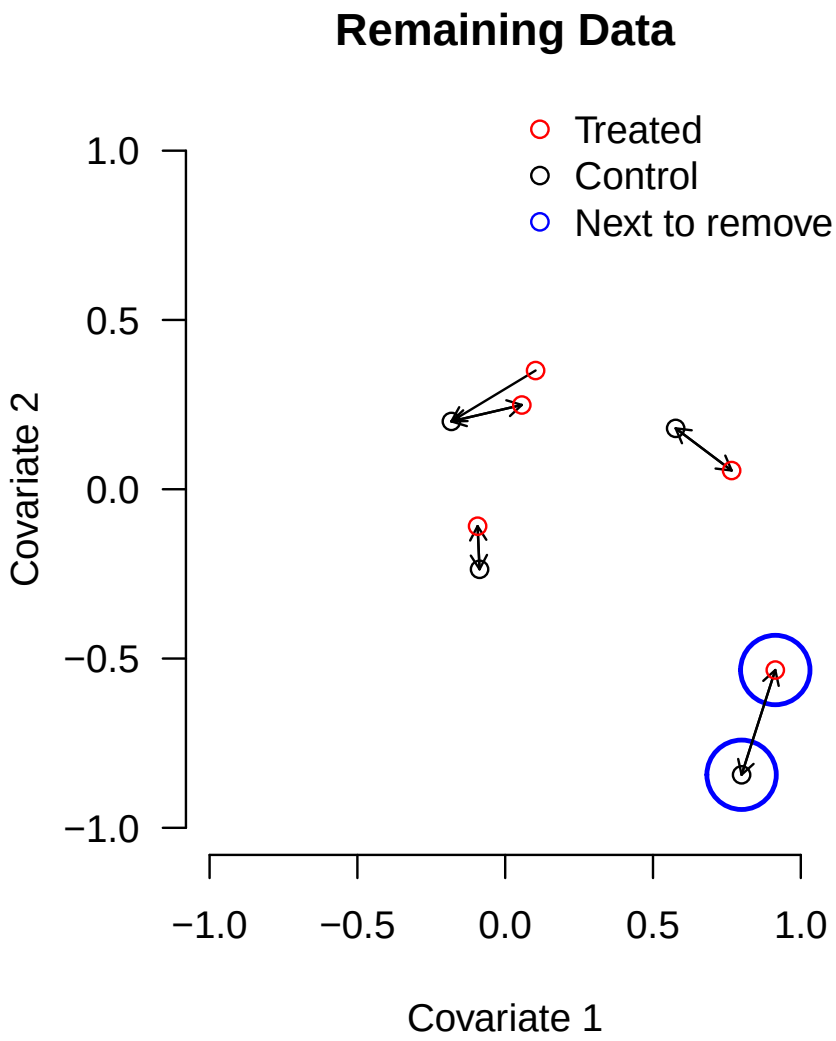

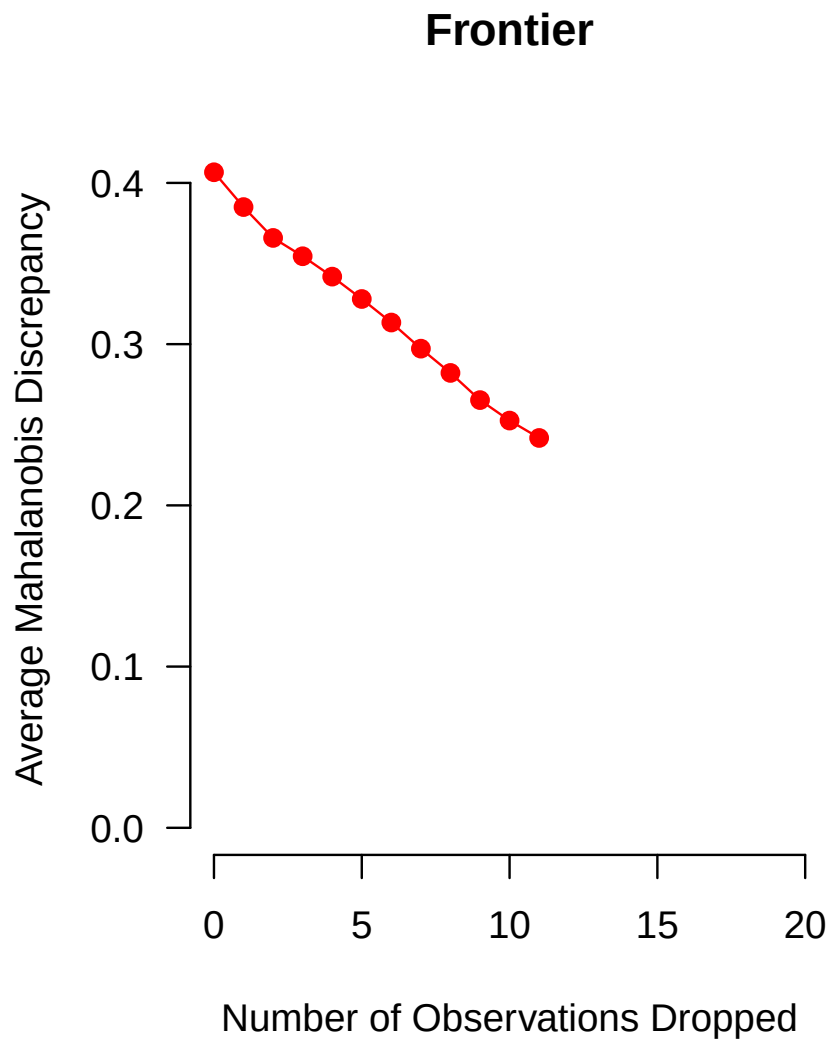

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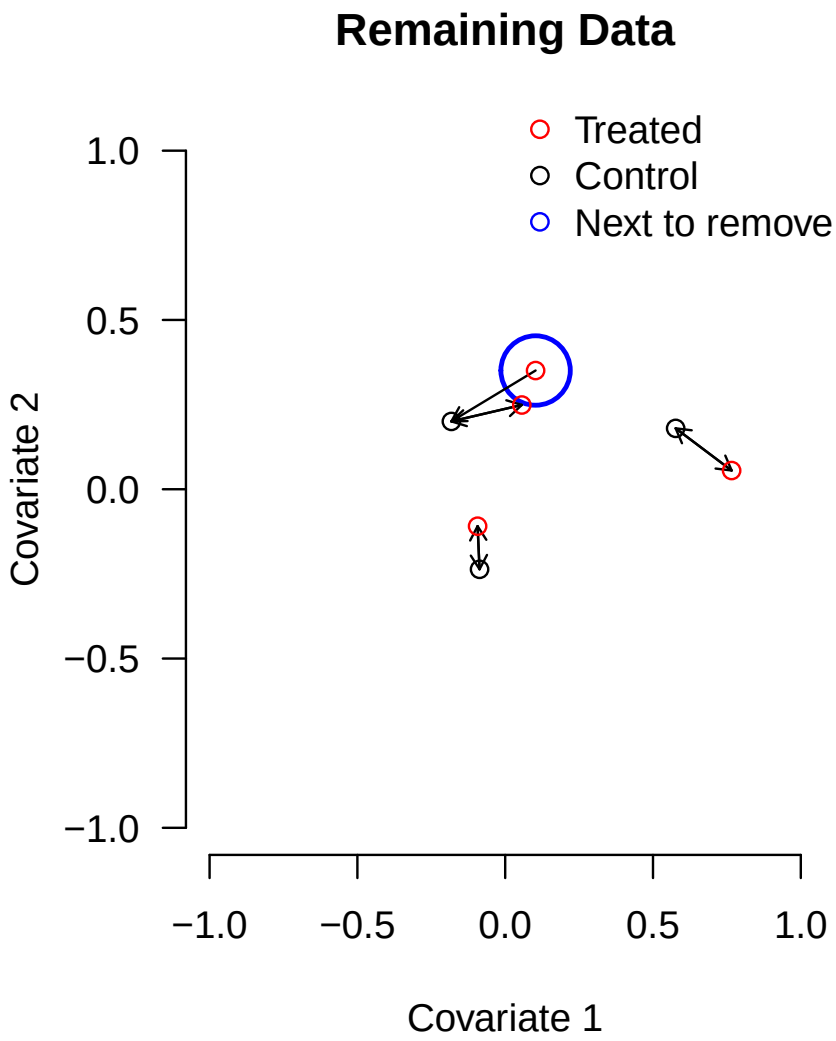

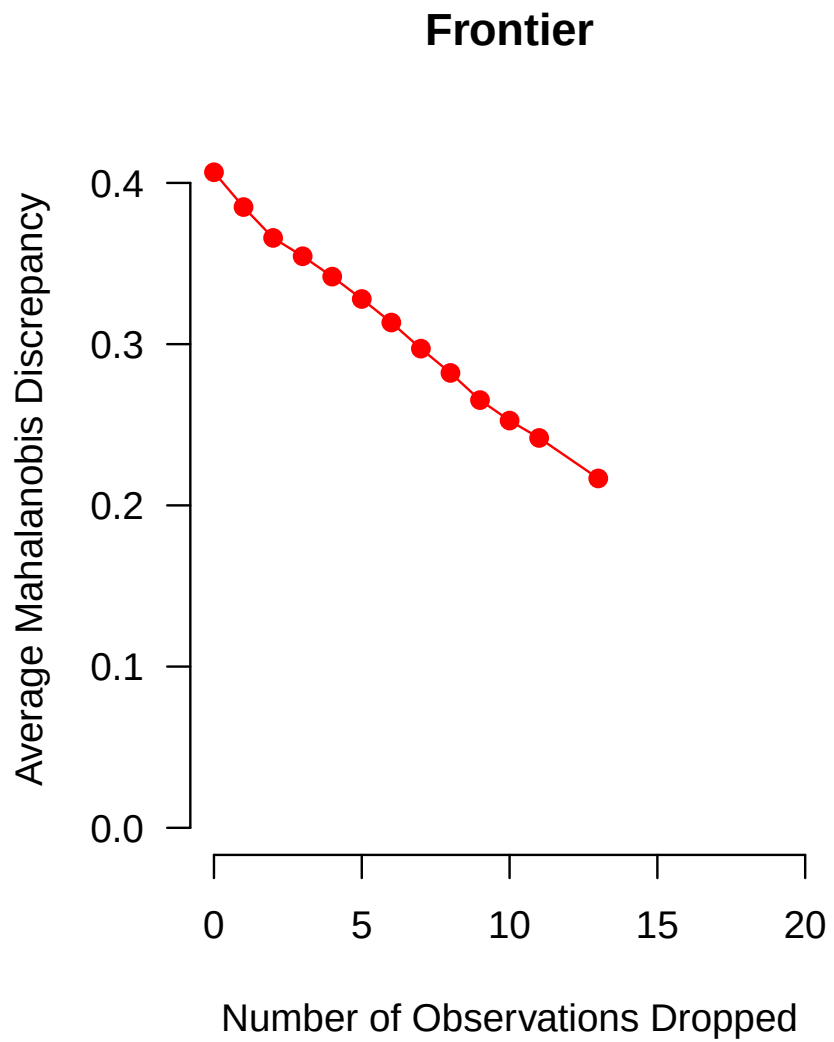

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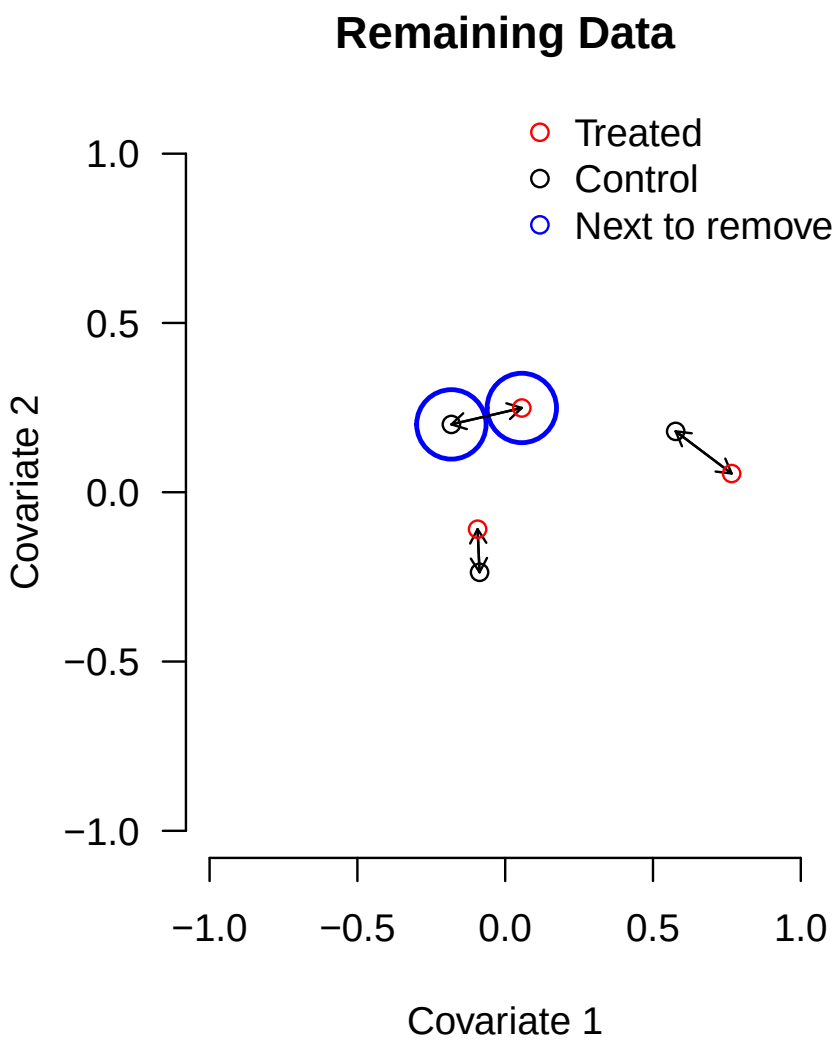

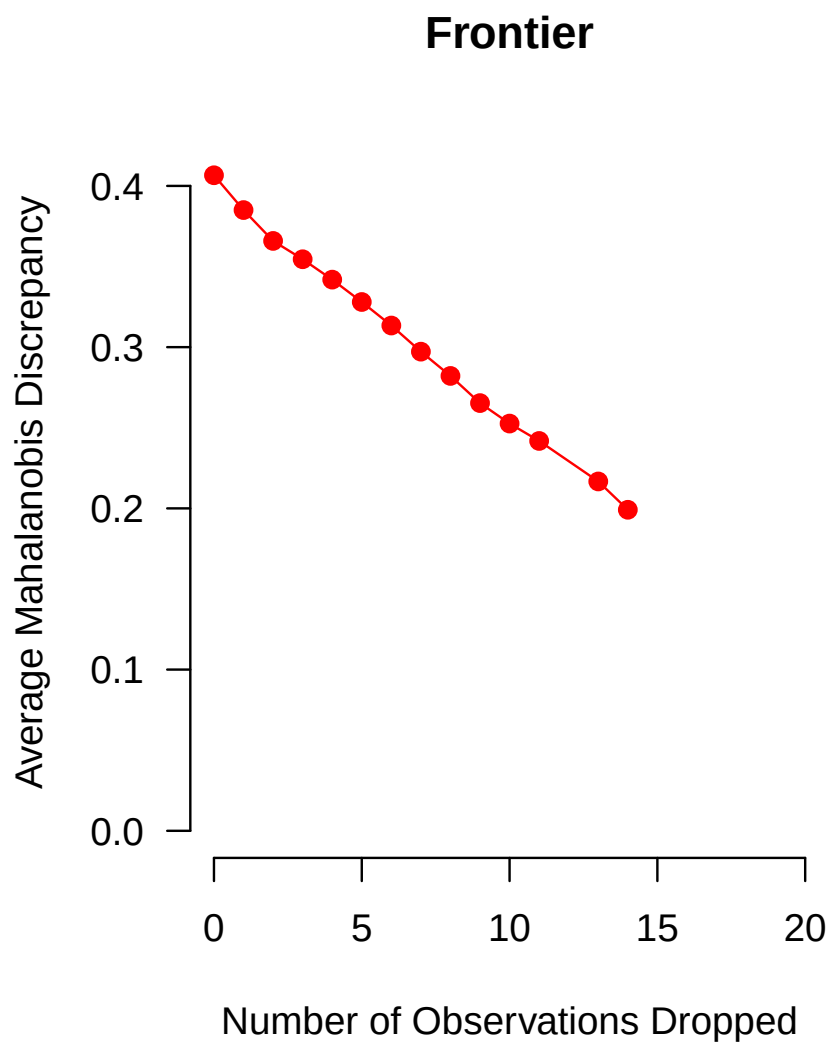

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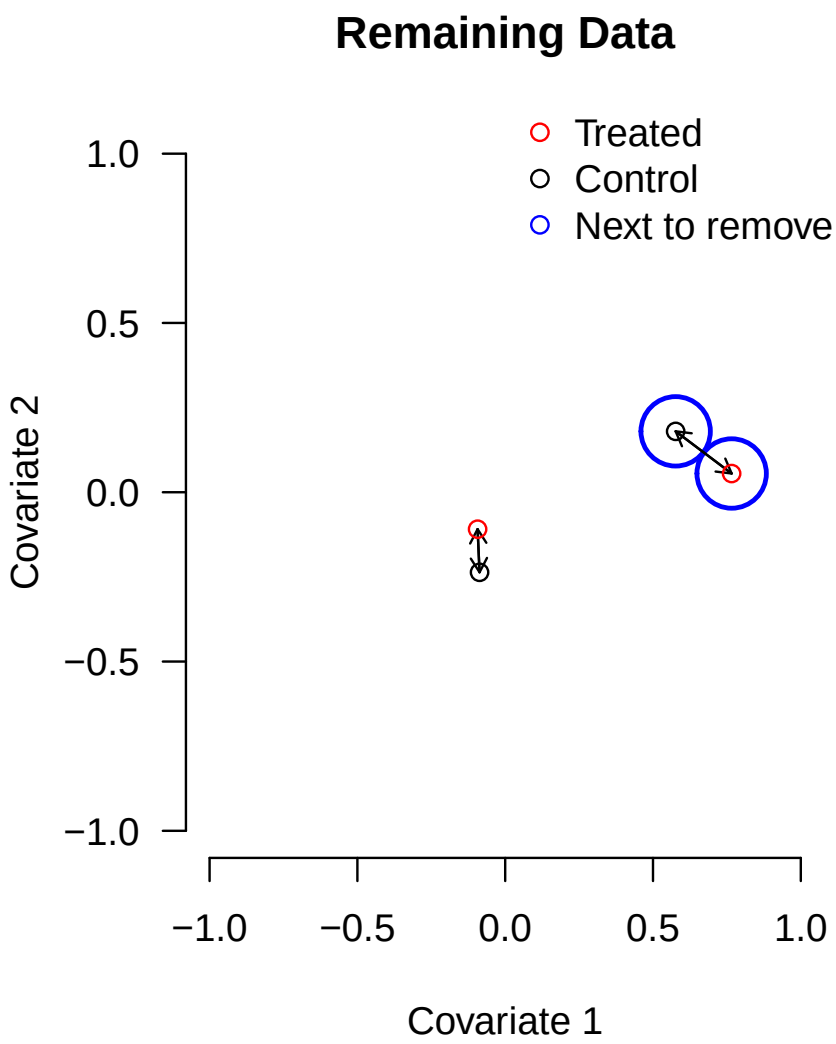

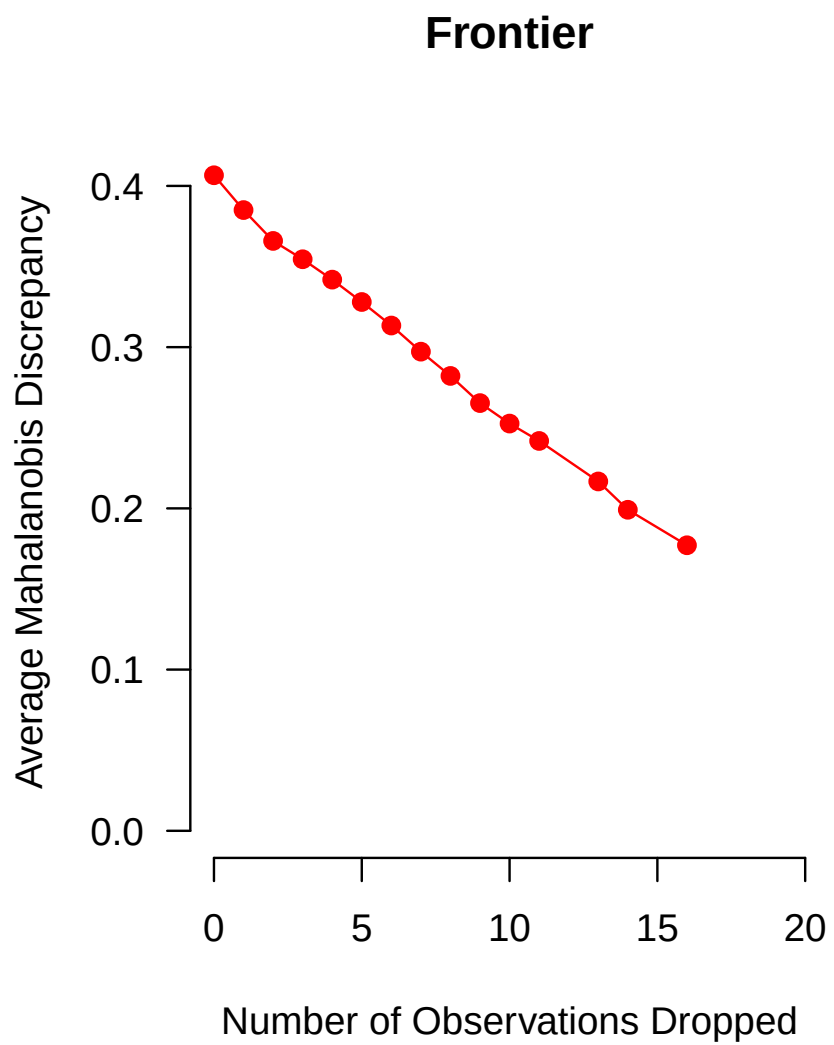

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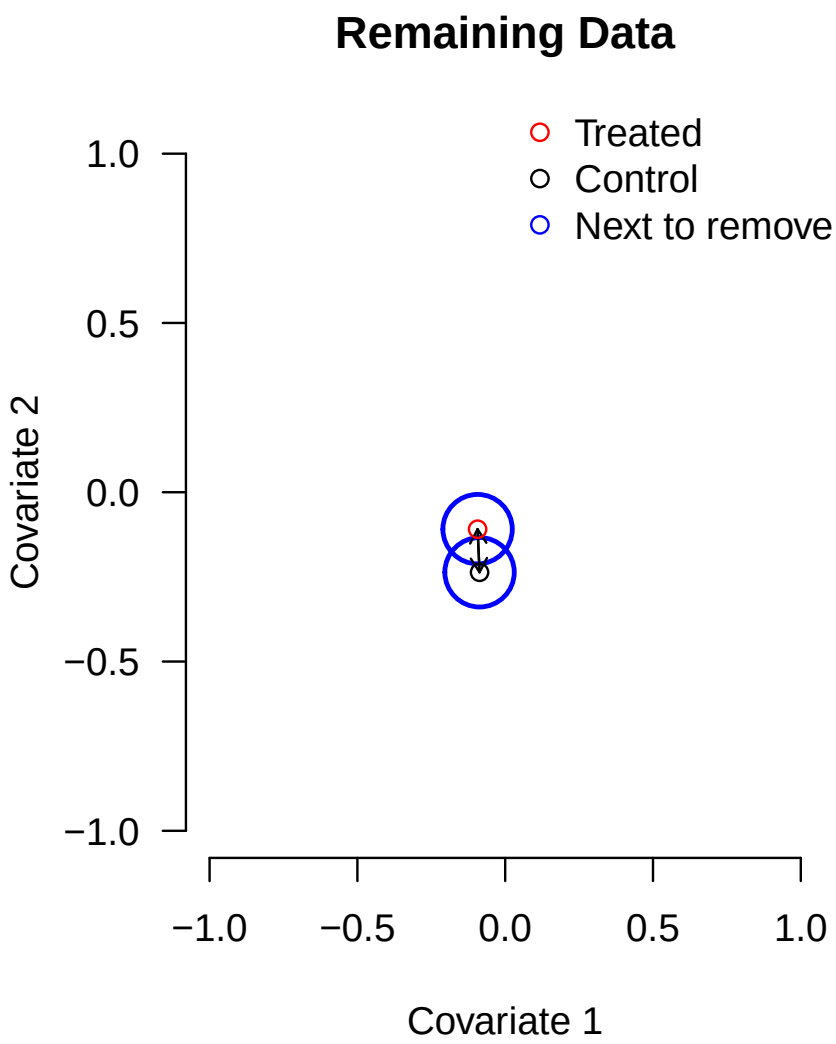

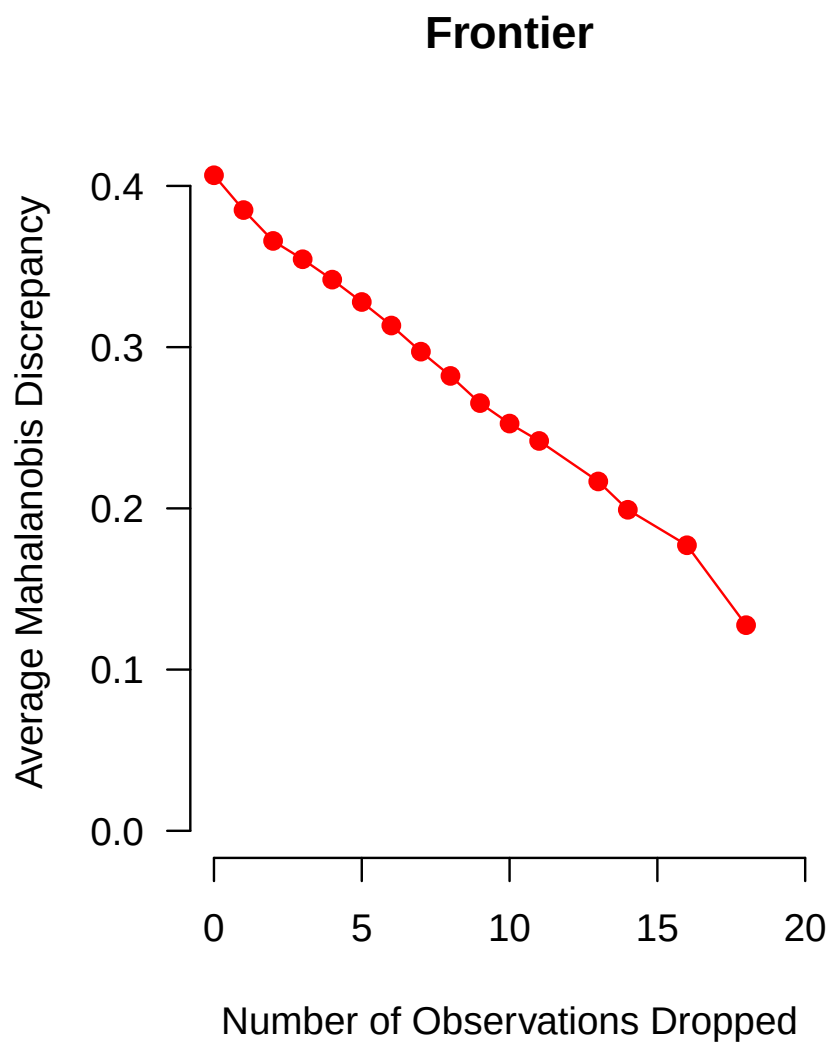

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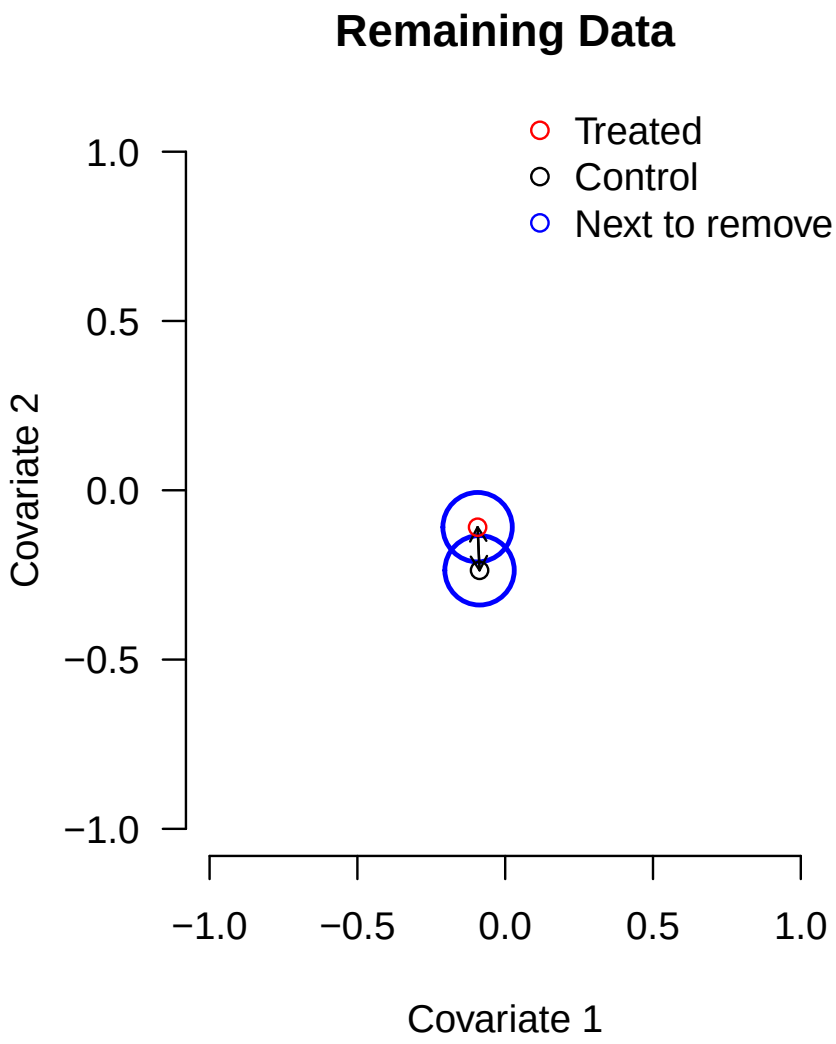

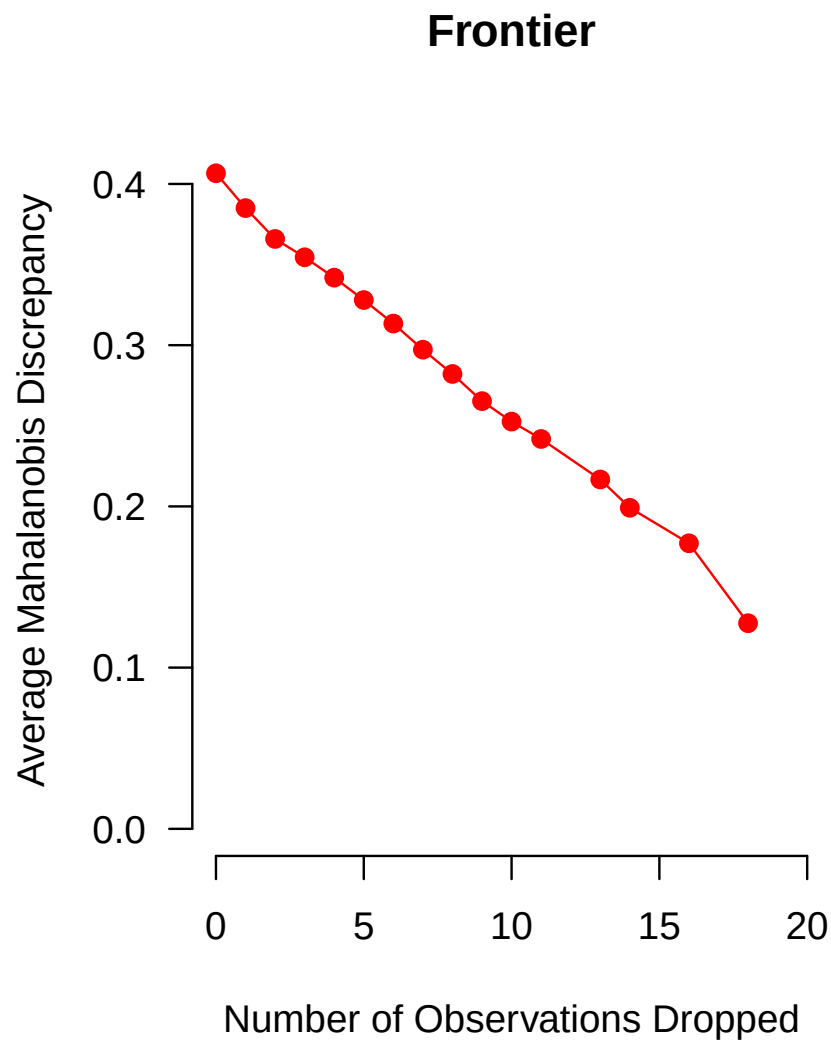

- Warning: figure omits details and proof!

Discrete algorithm

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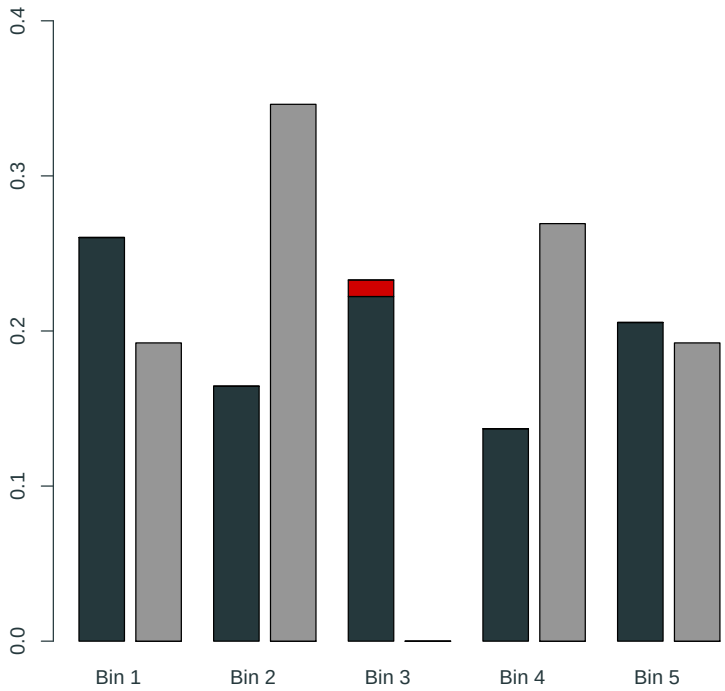

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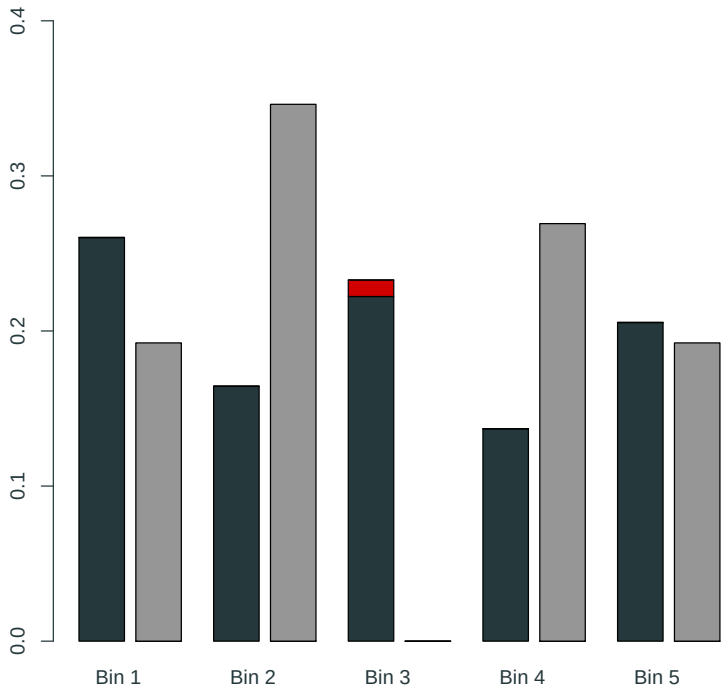

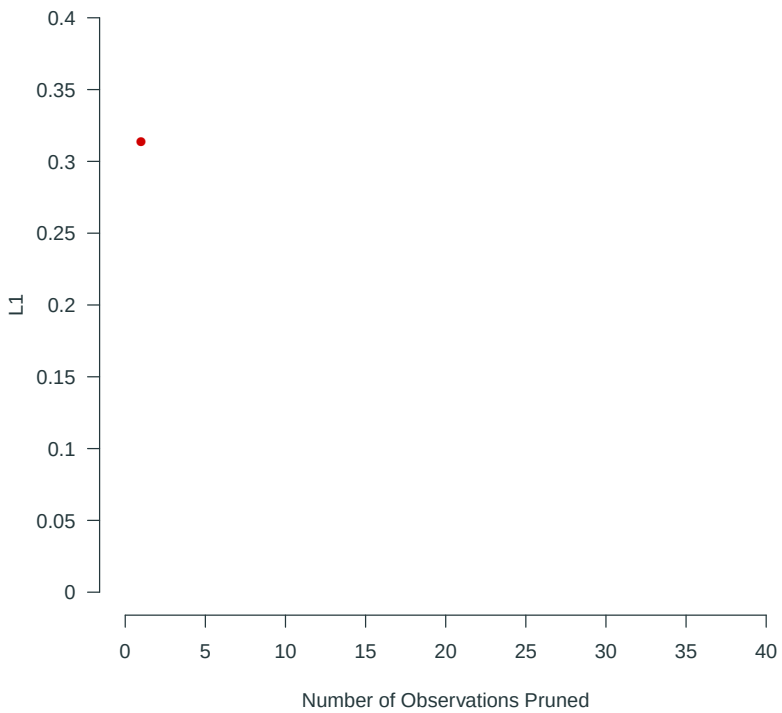

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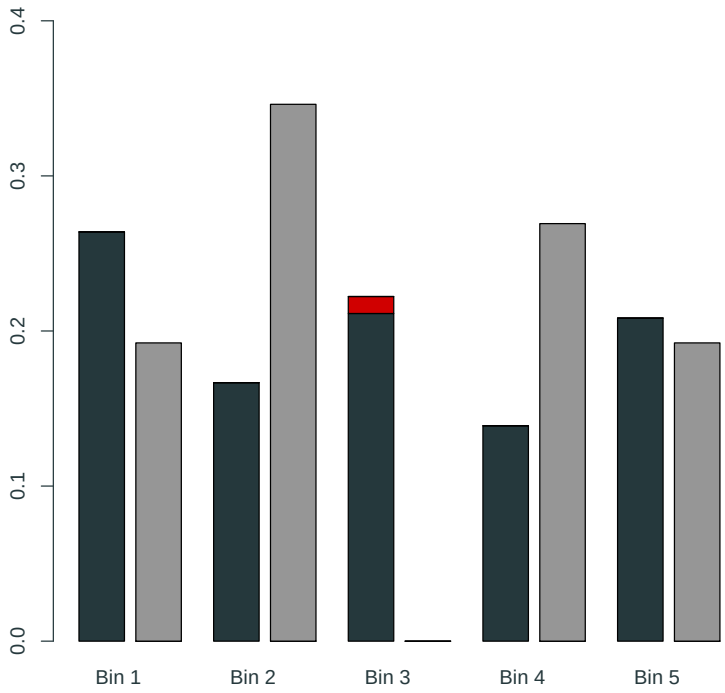

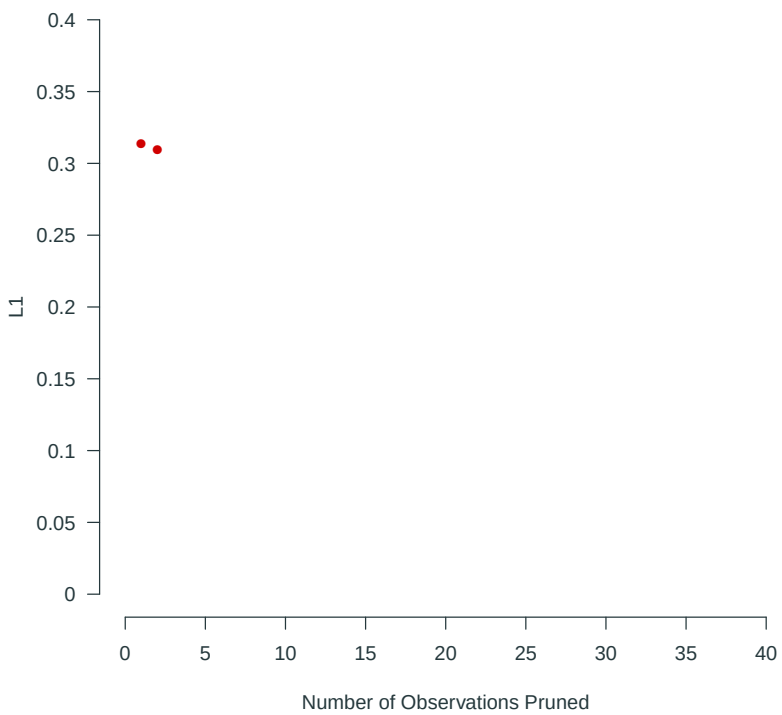

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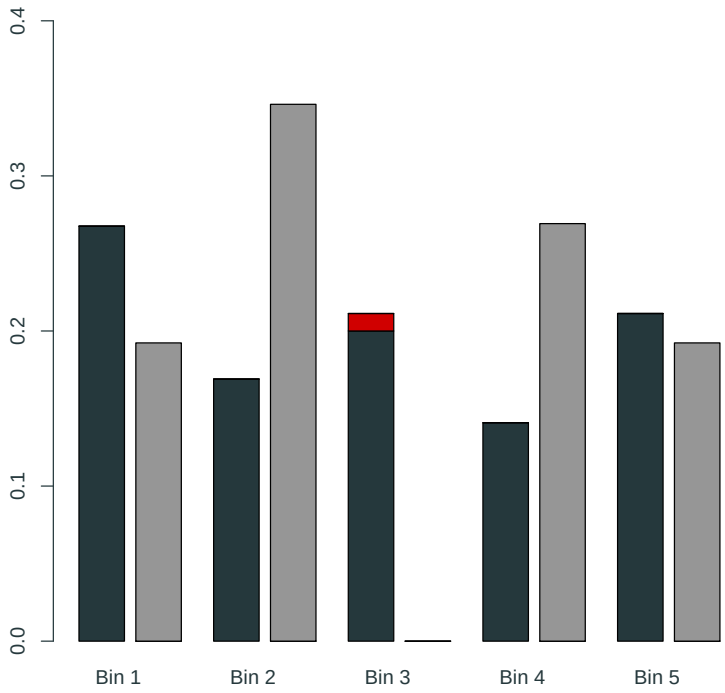

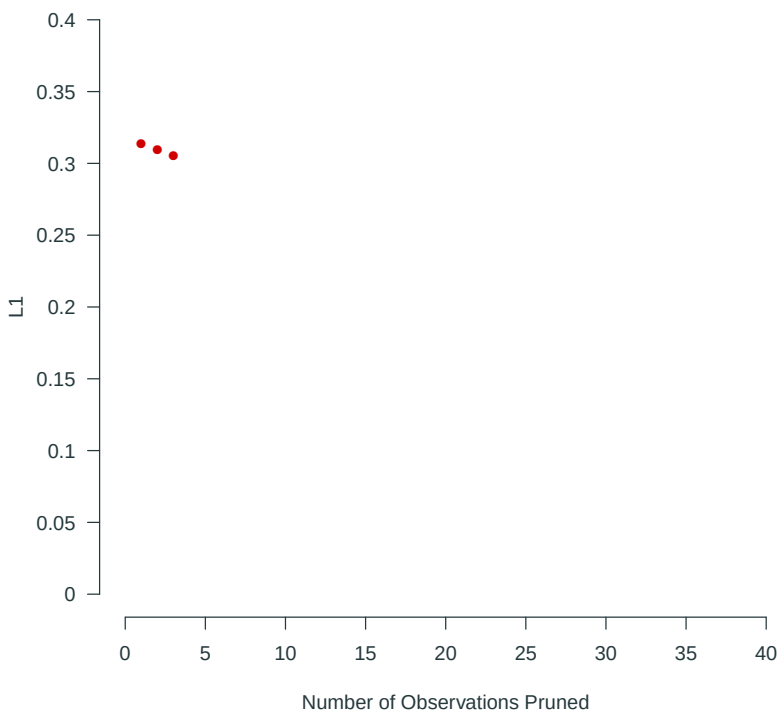

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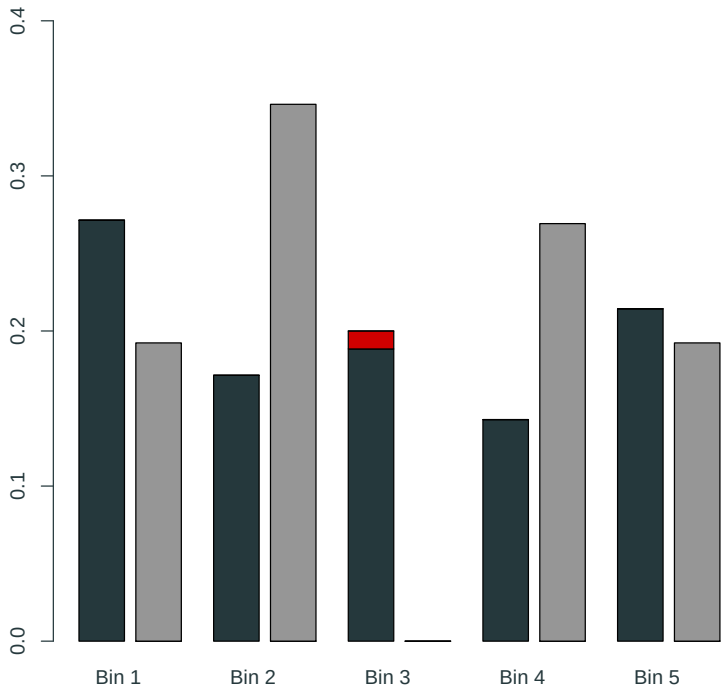

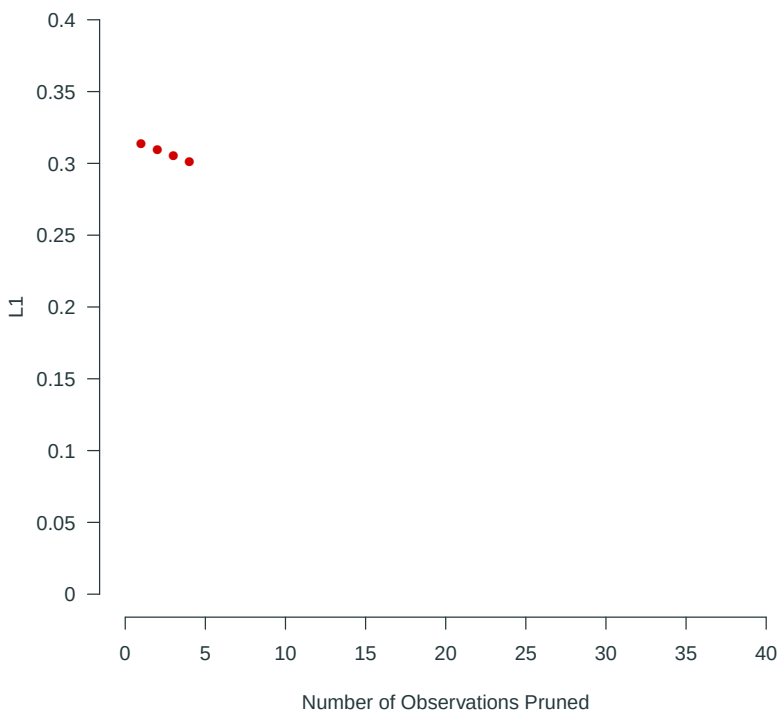

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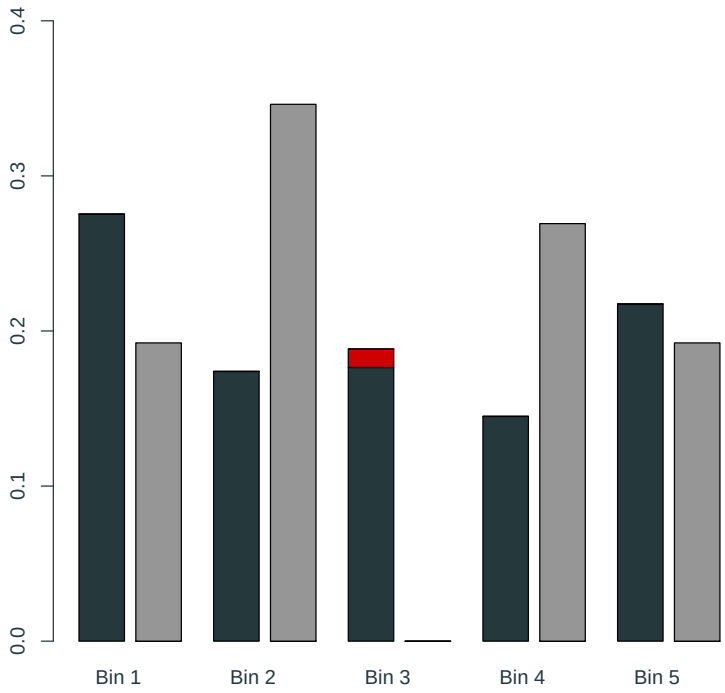

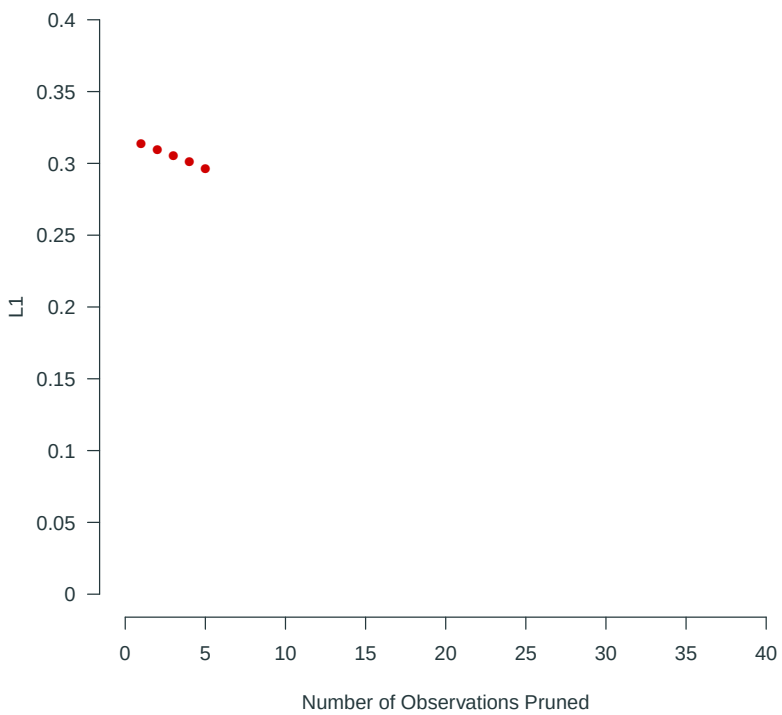

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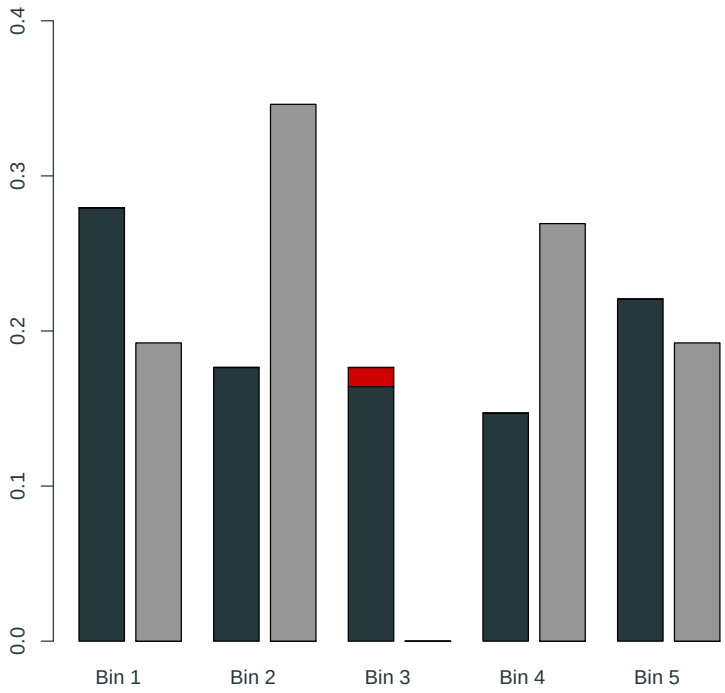

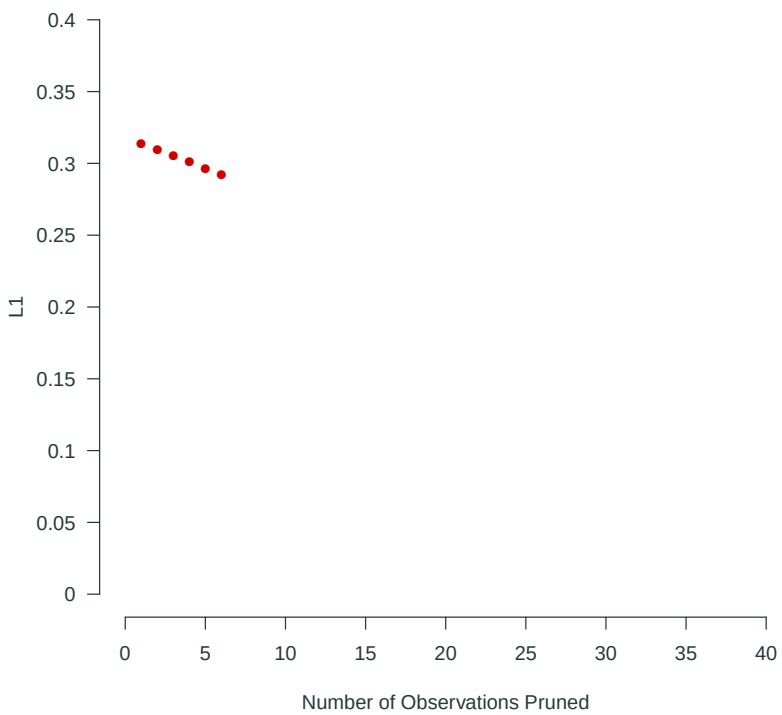

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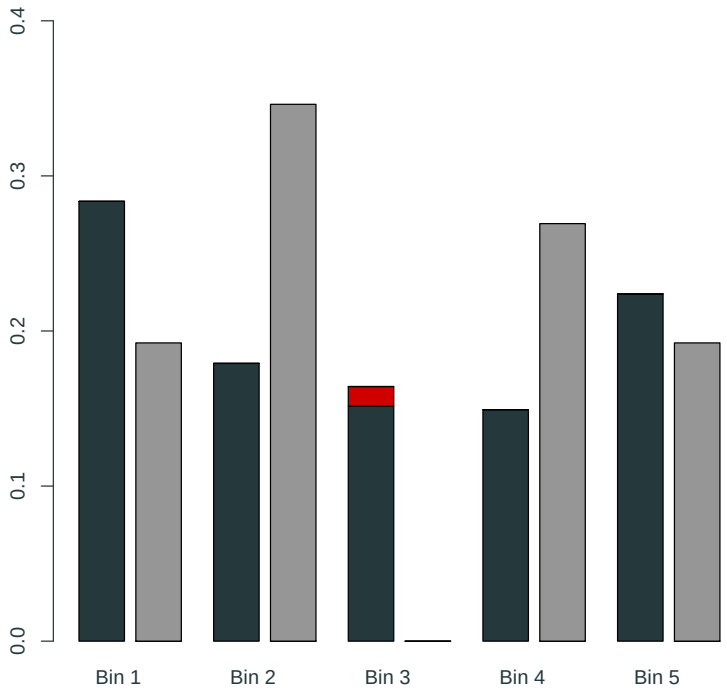

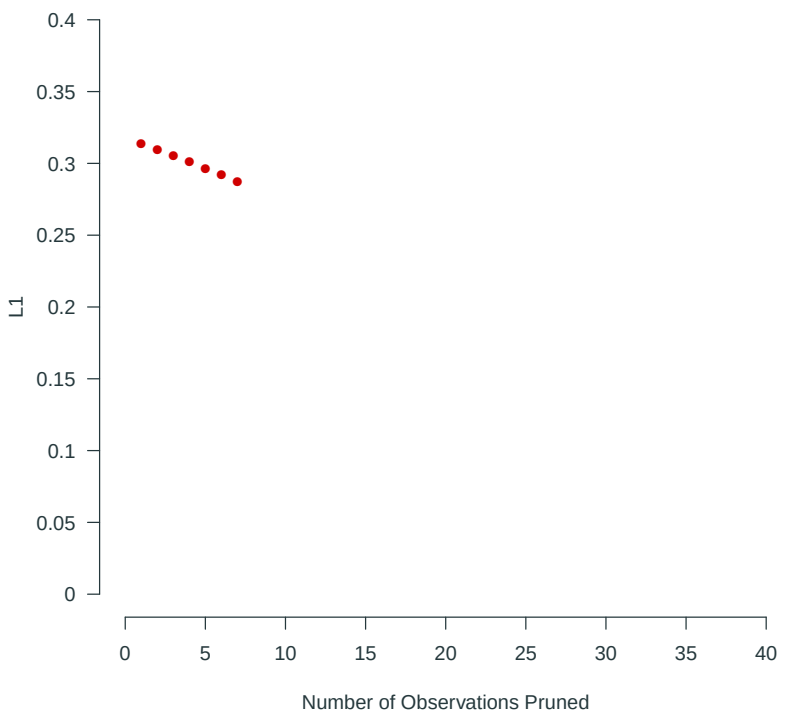

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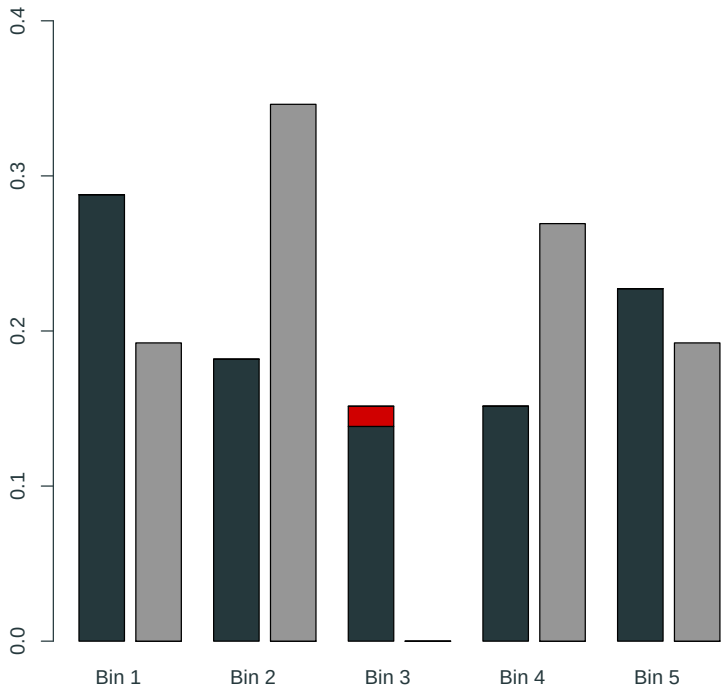

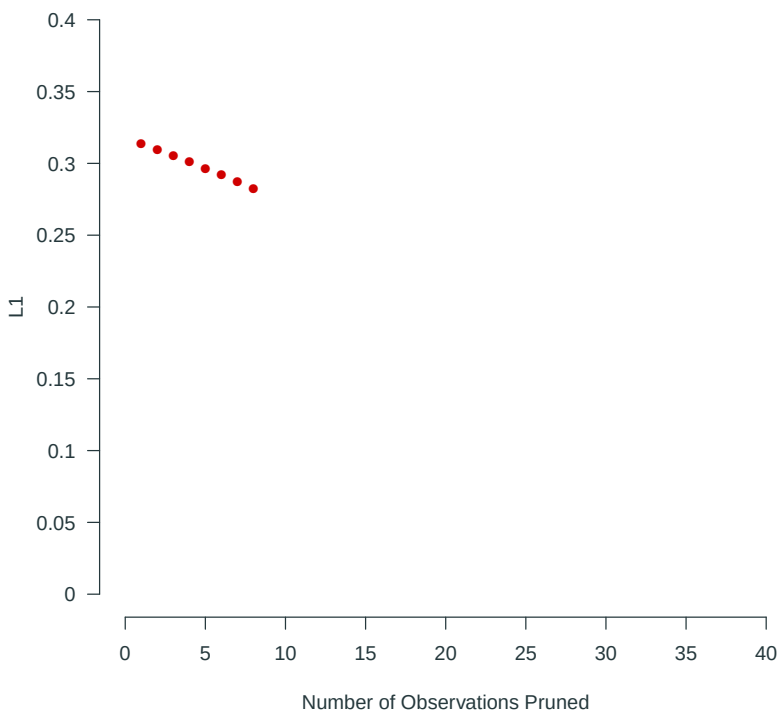

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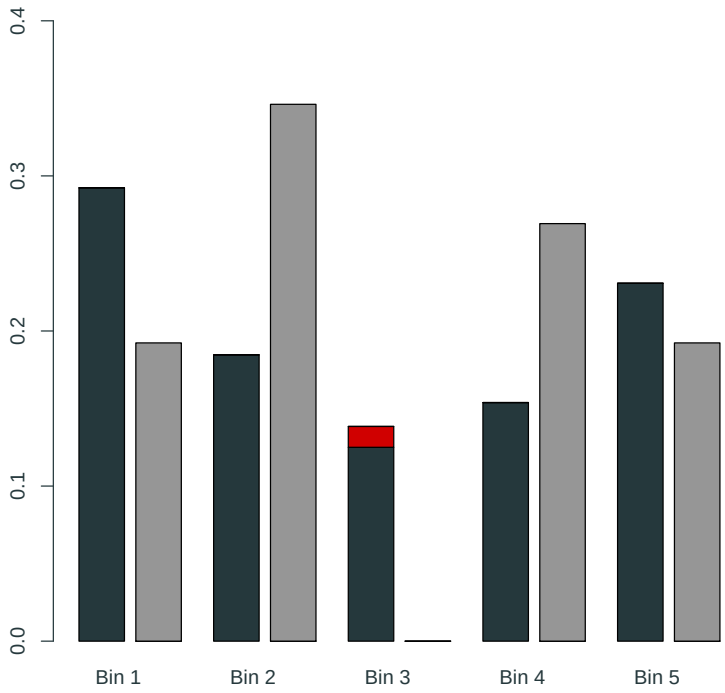

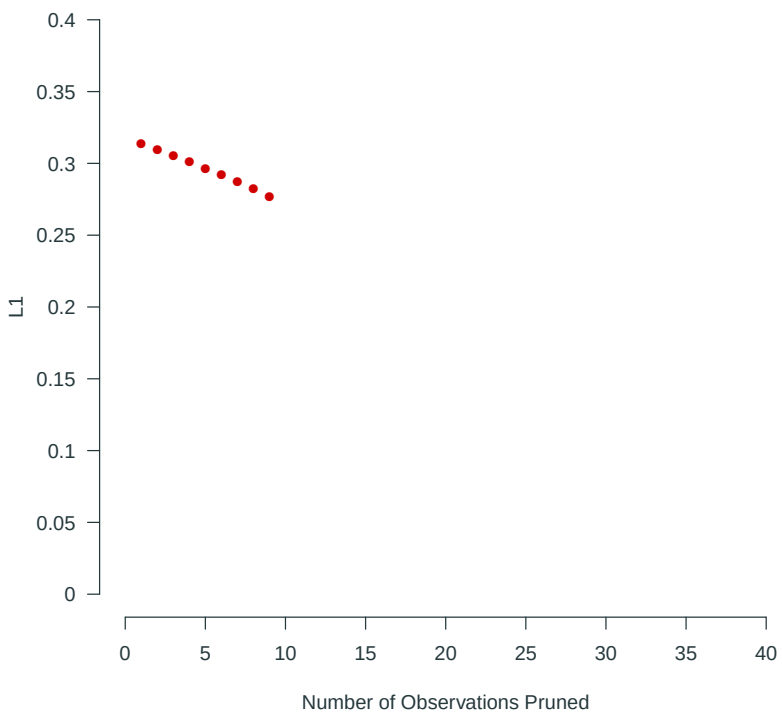

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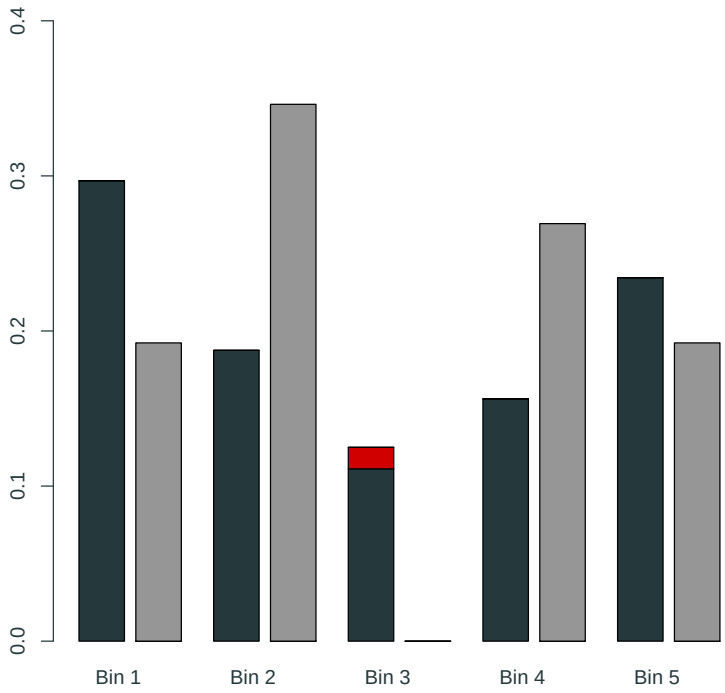

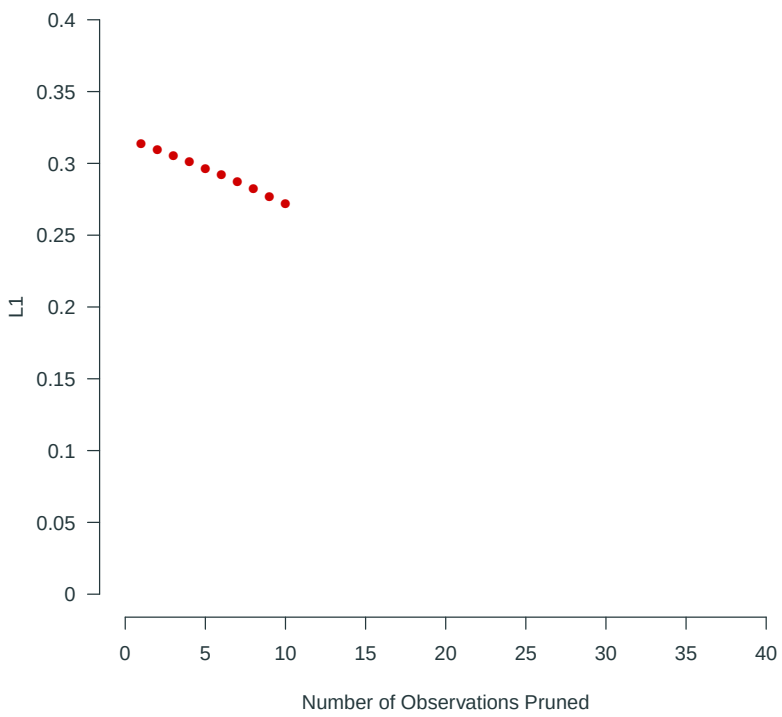

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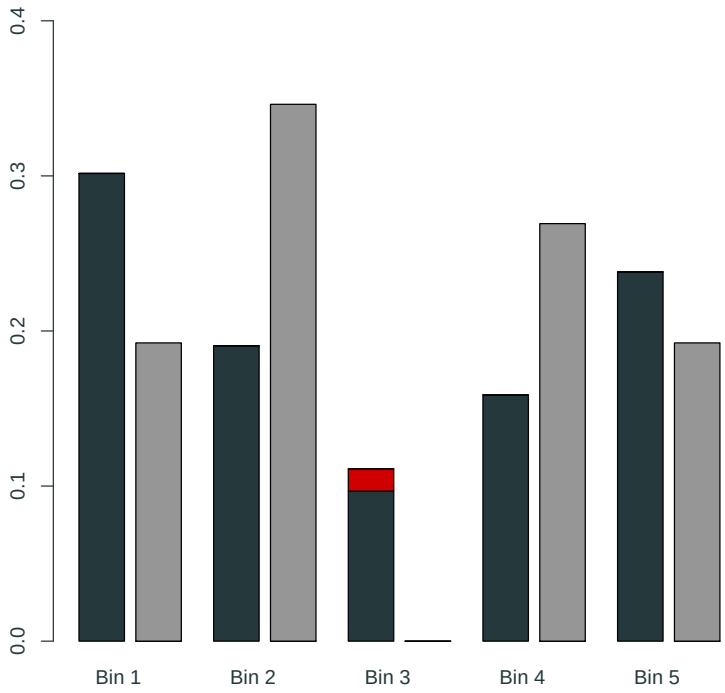

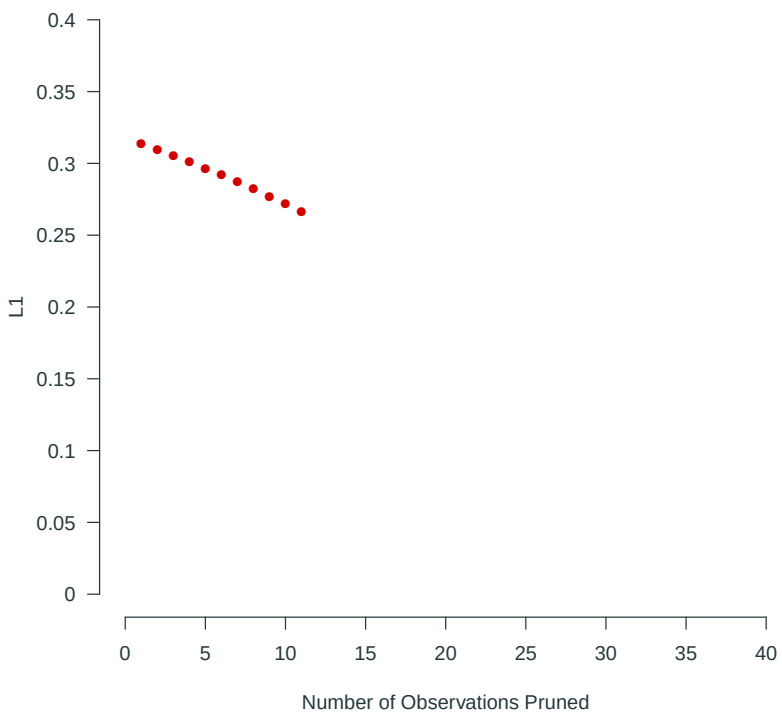

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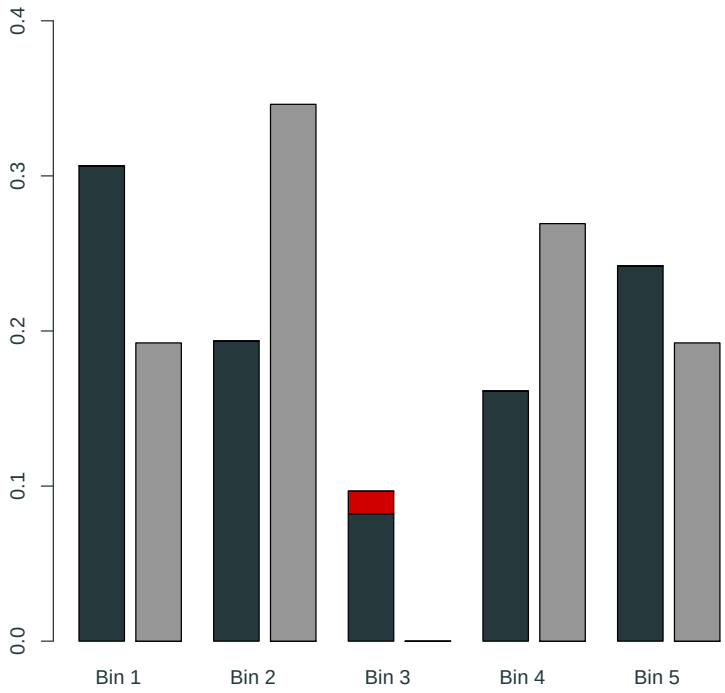

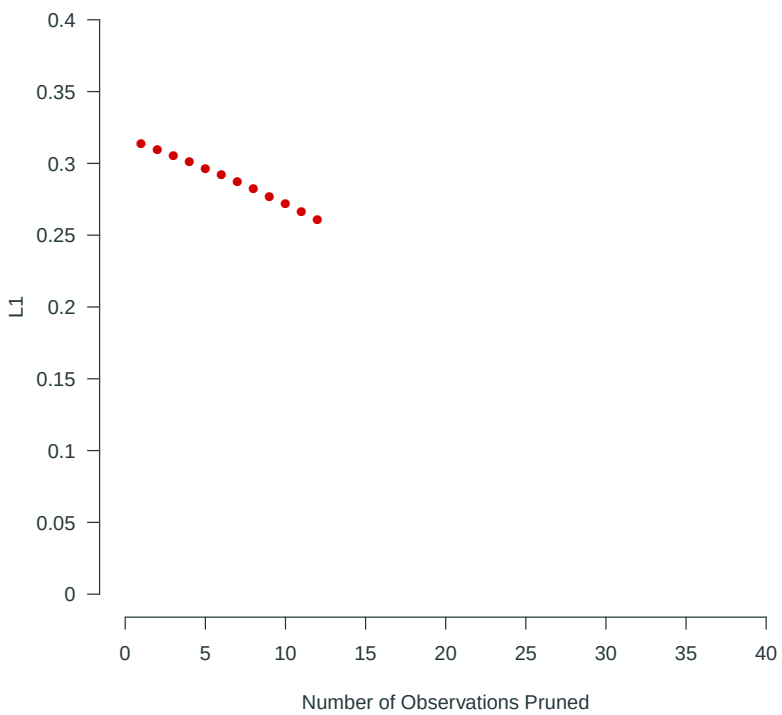

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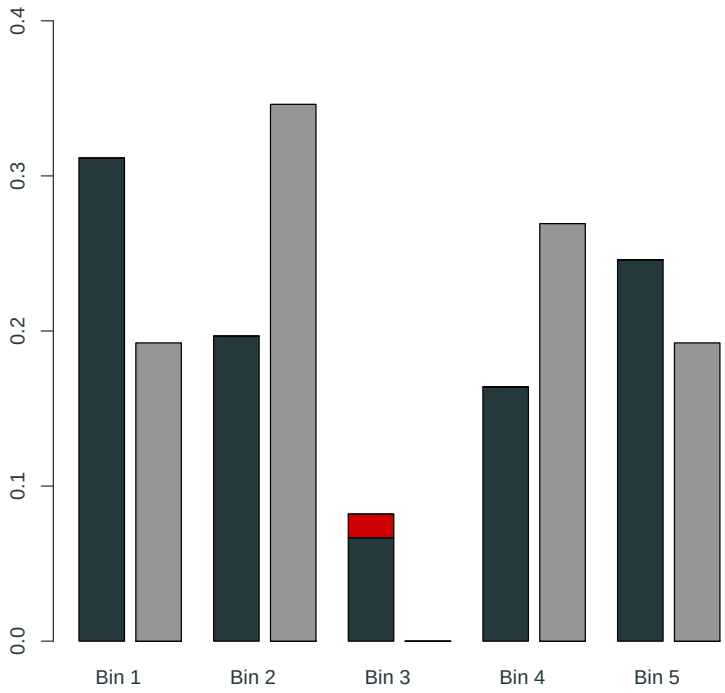

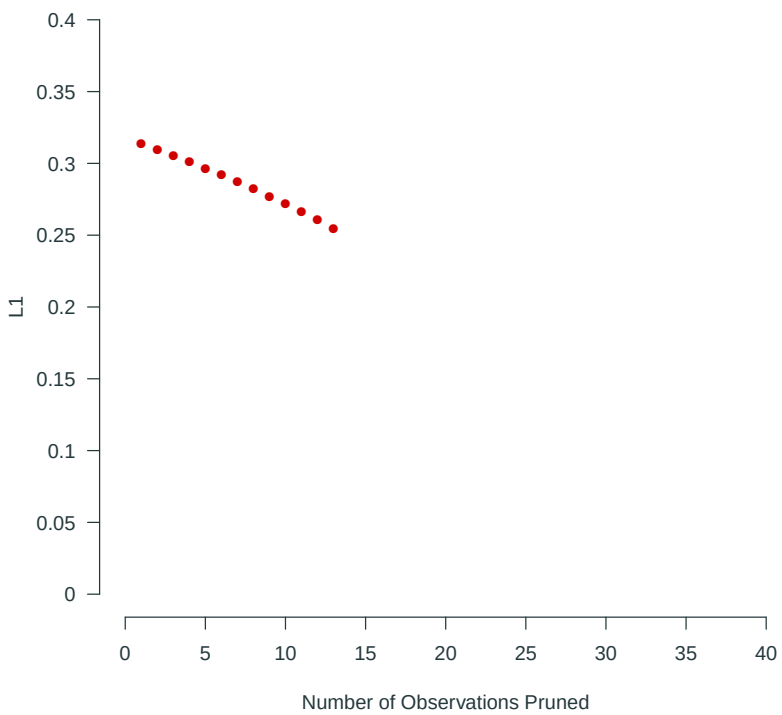

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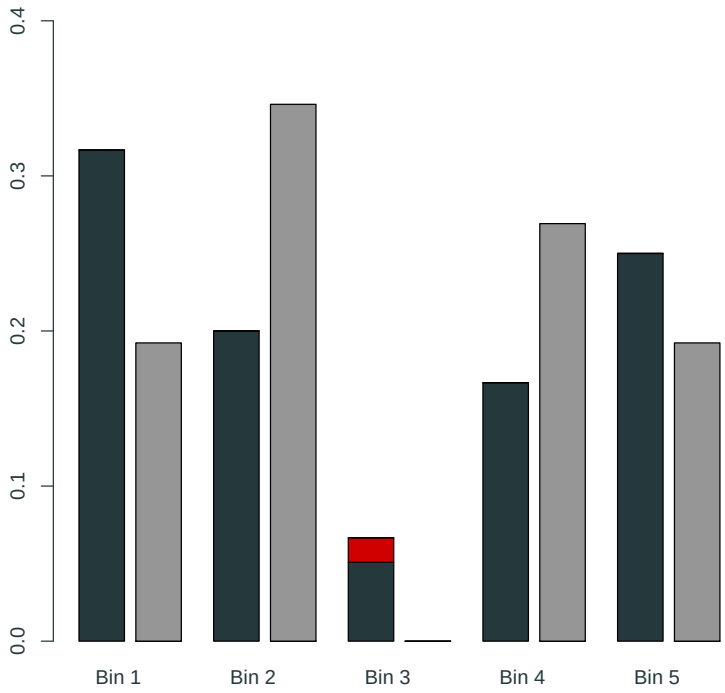

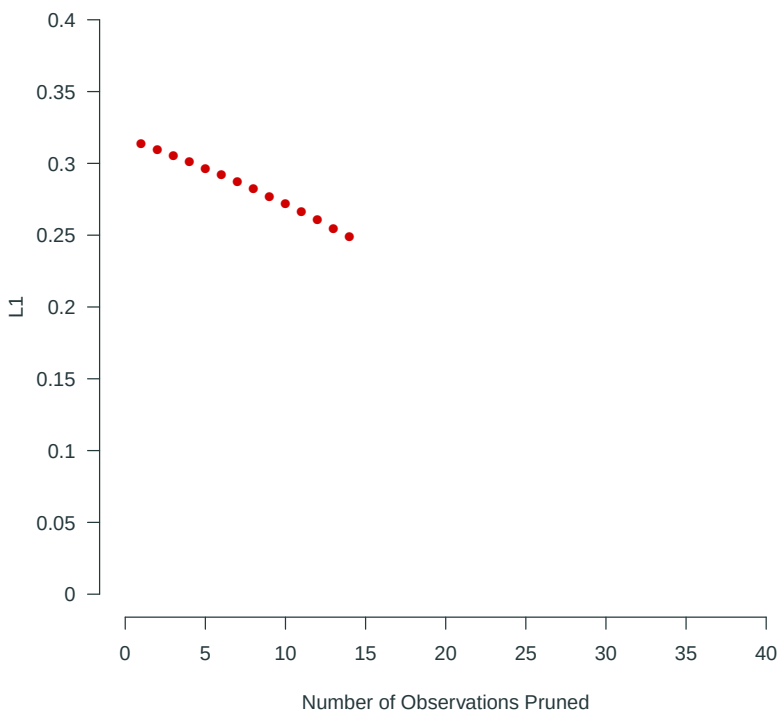

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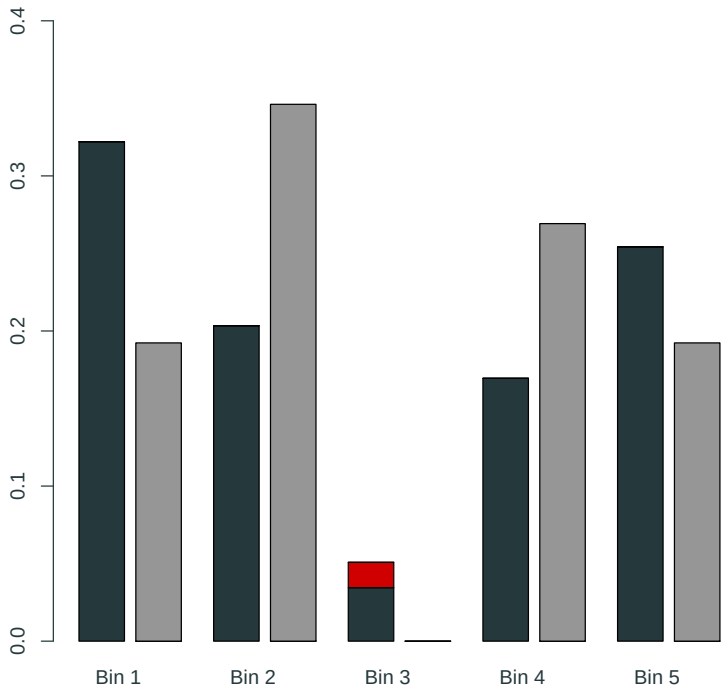

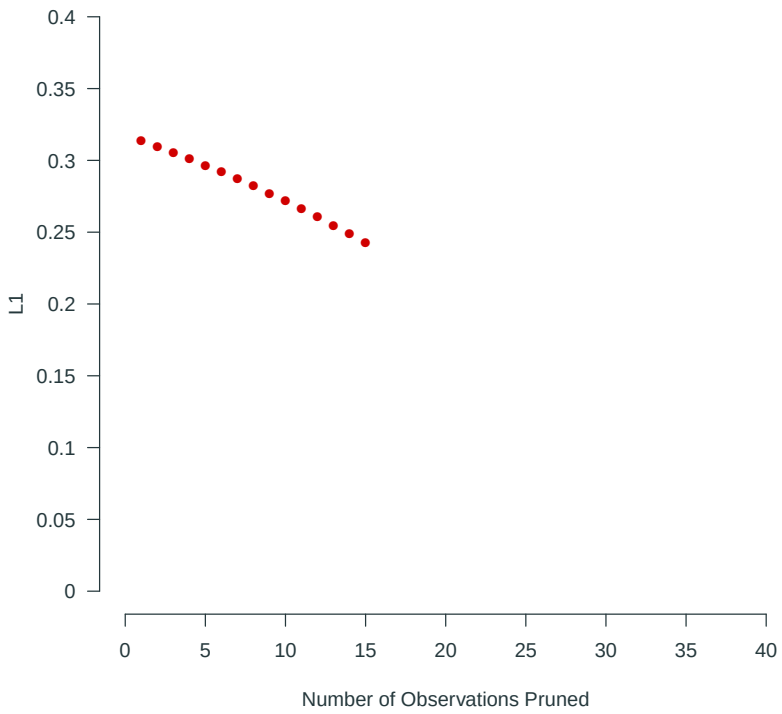

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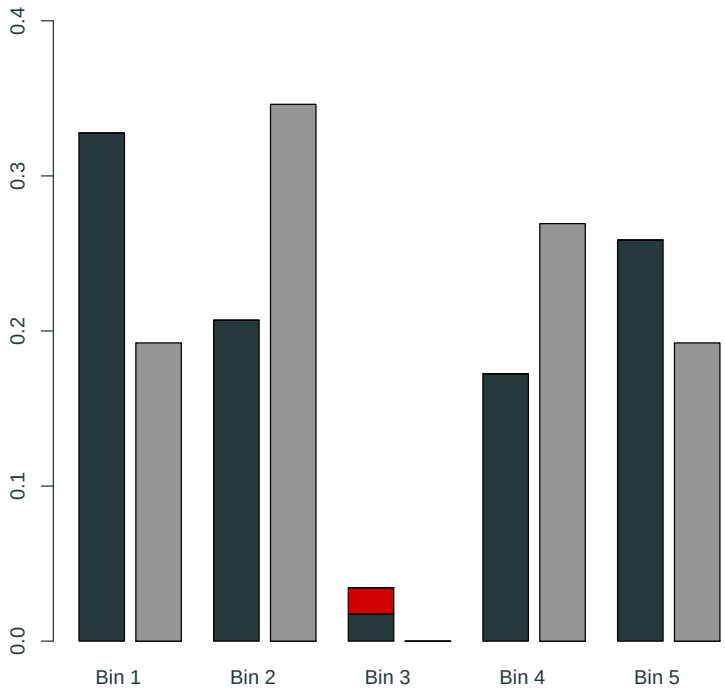

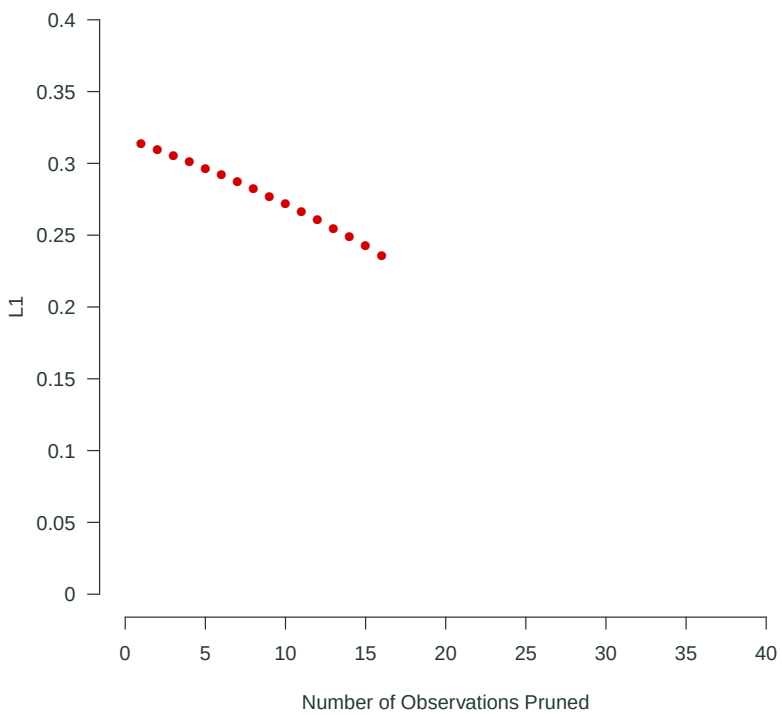

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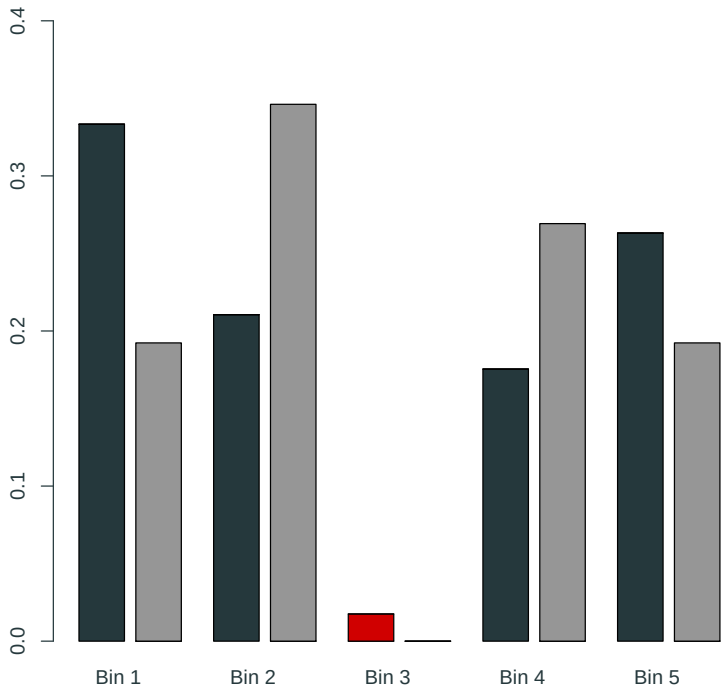

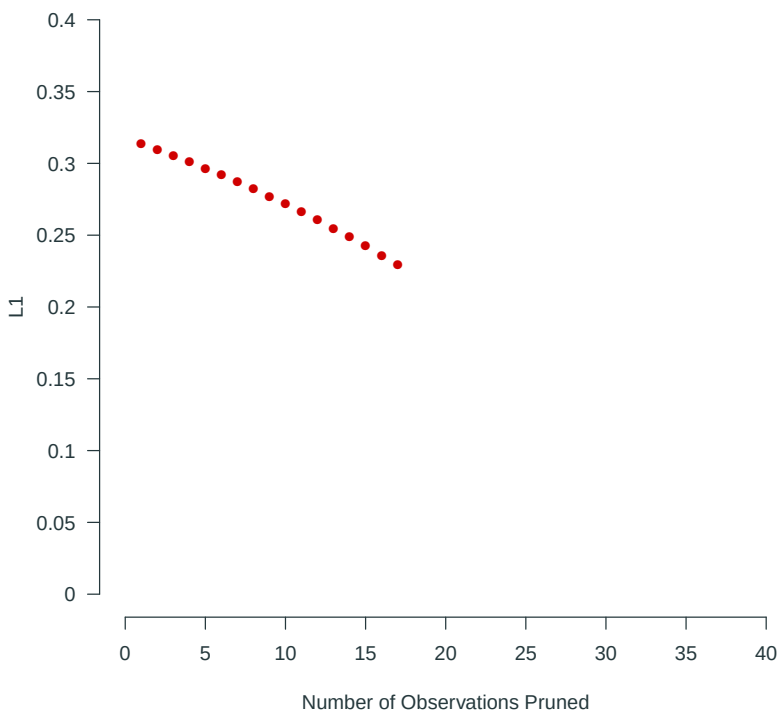

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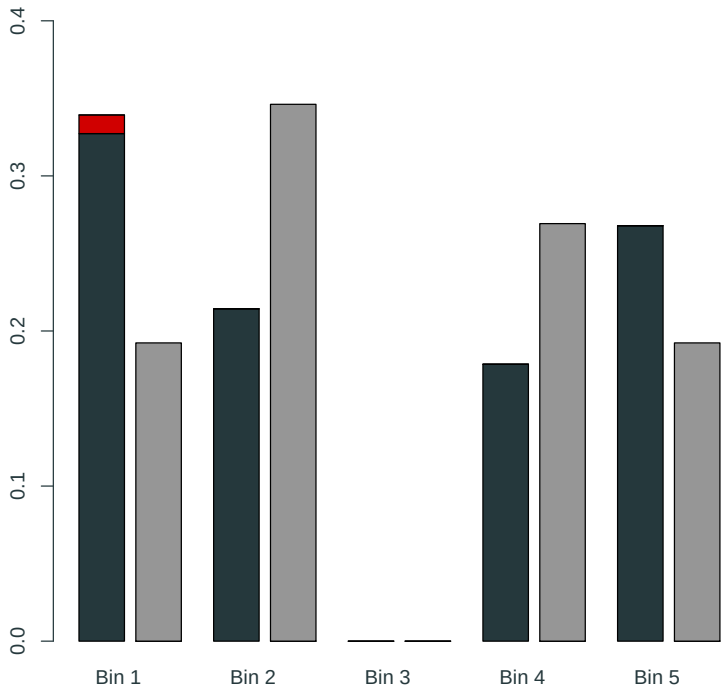

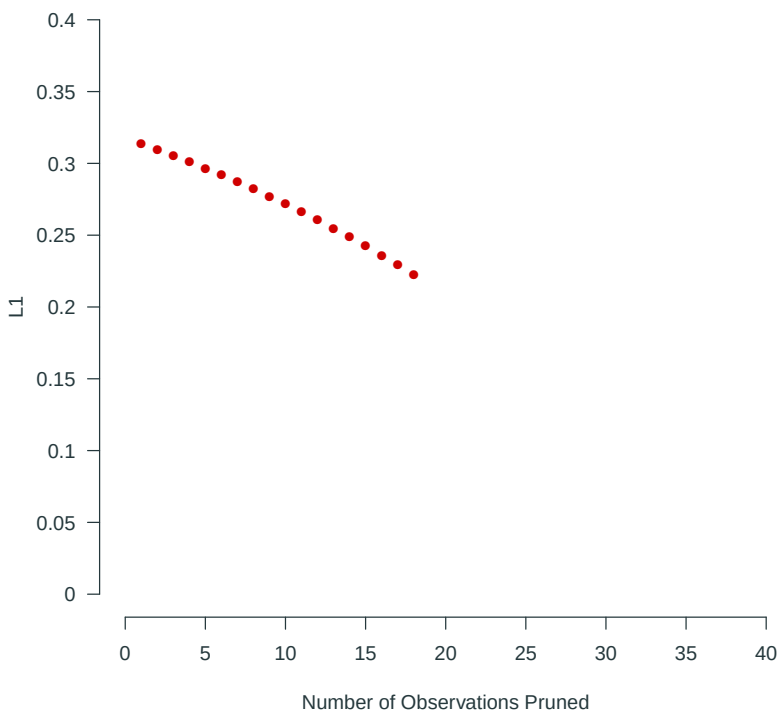

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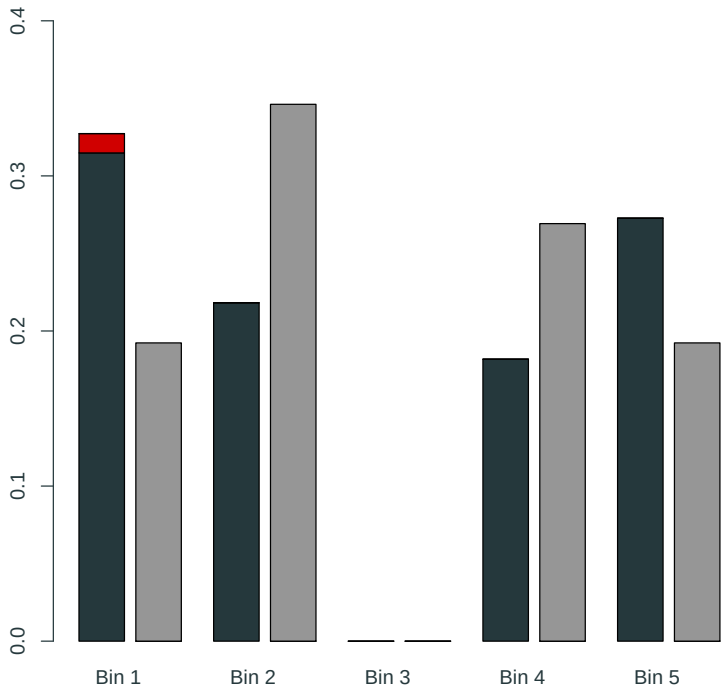

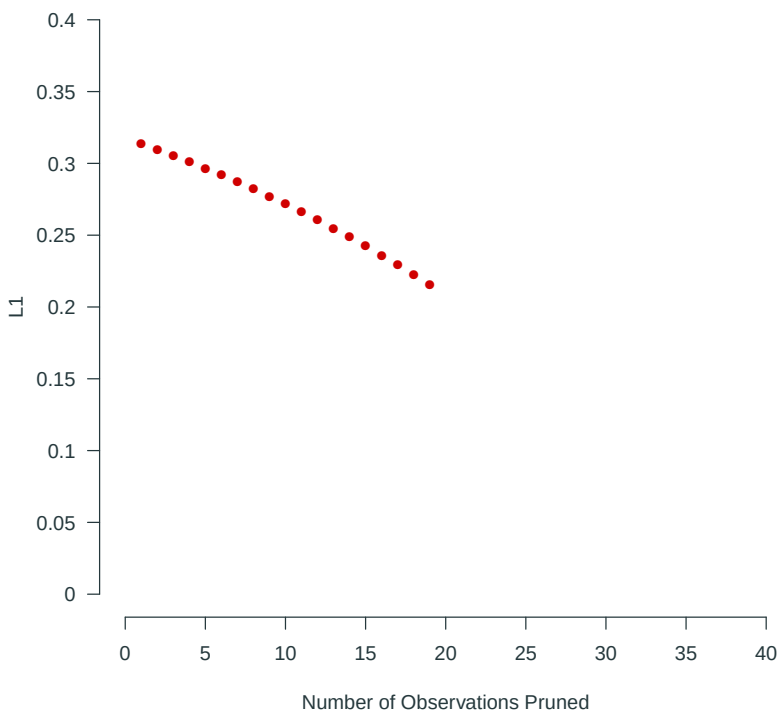

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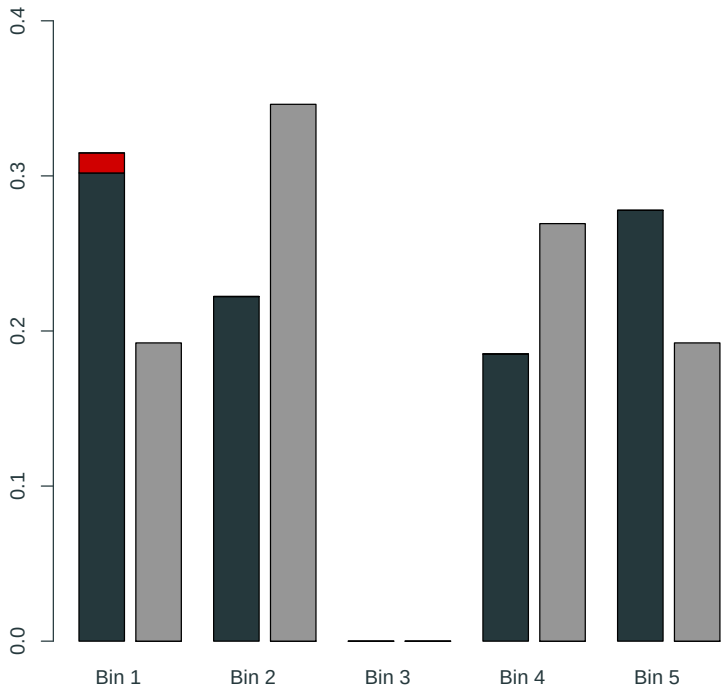

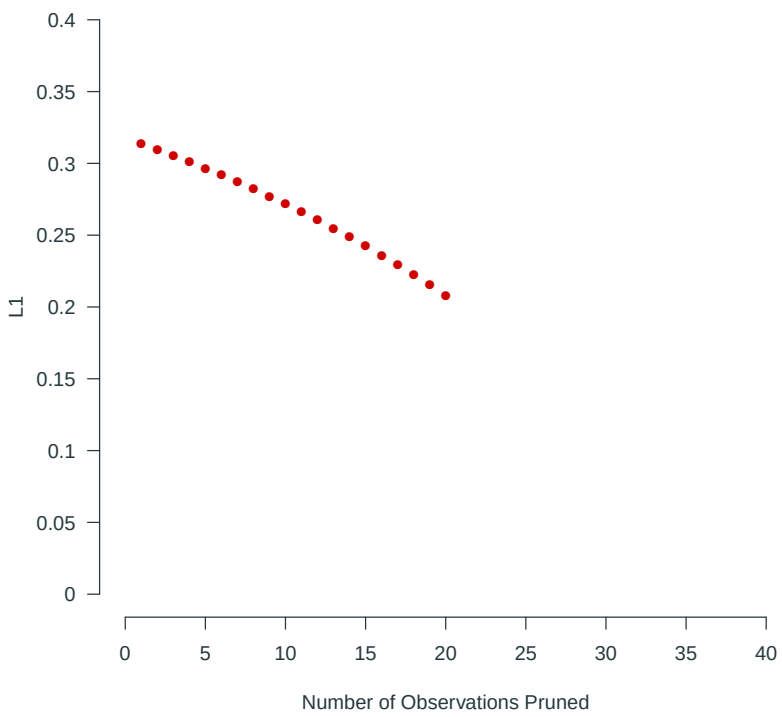

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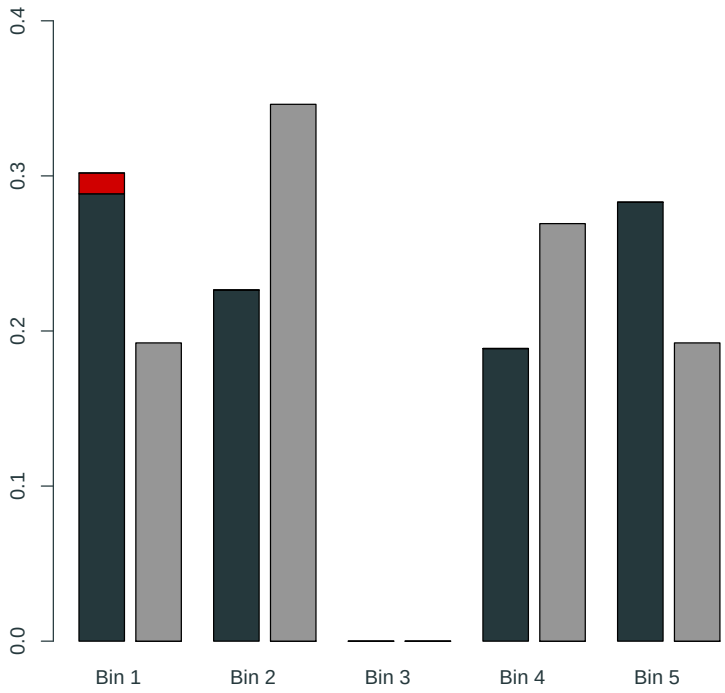

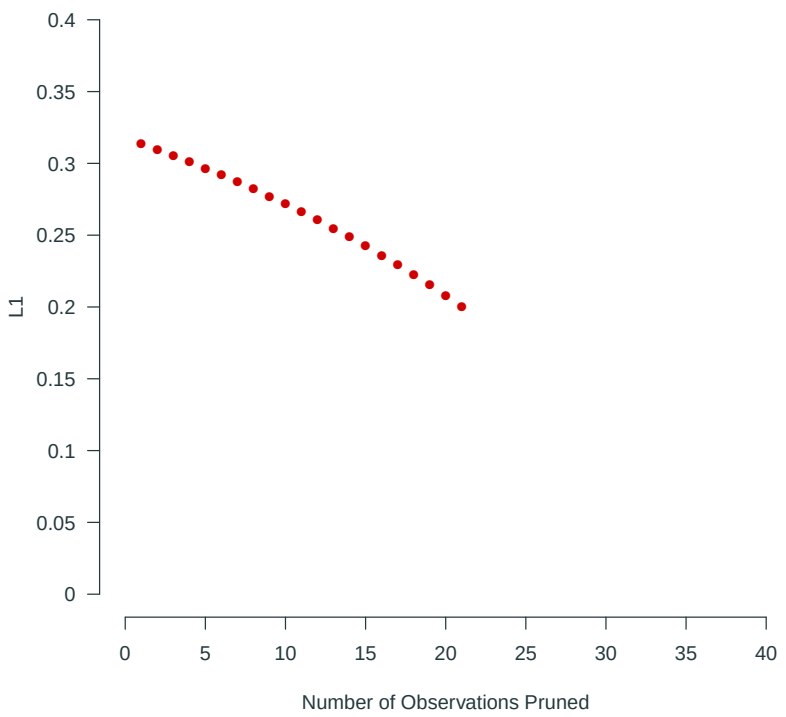

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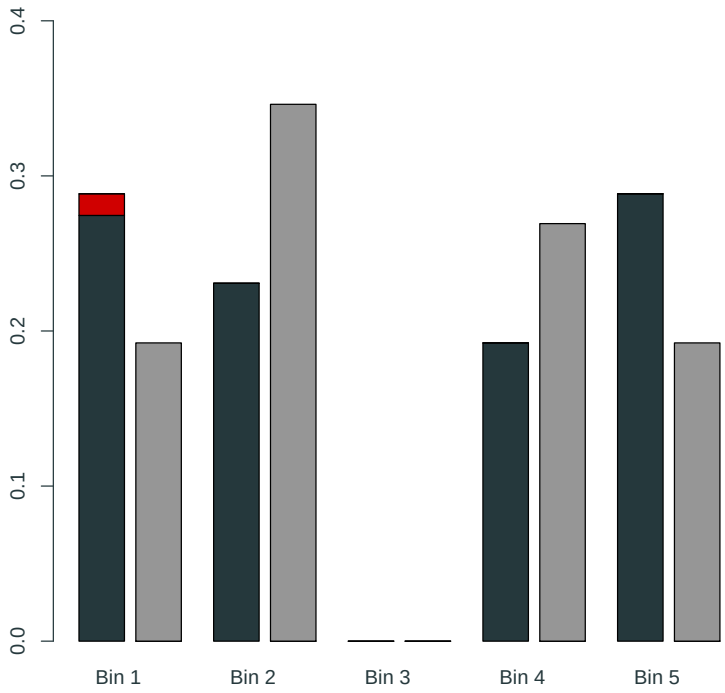

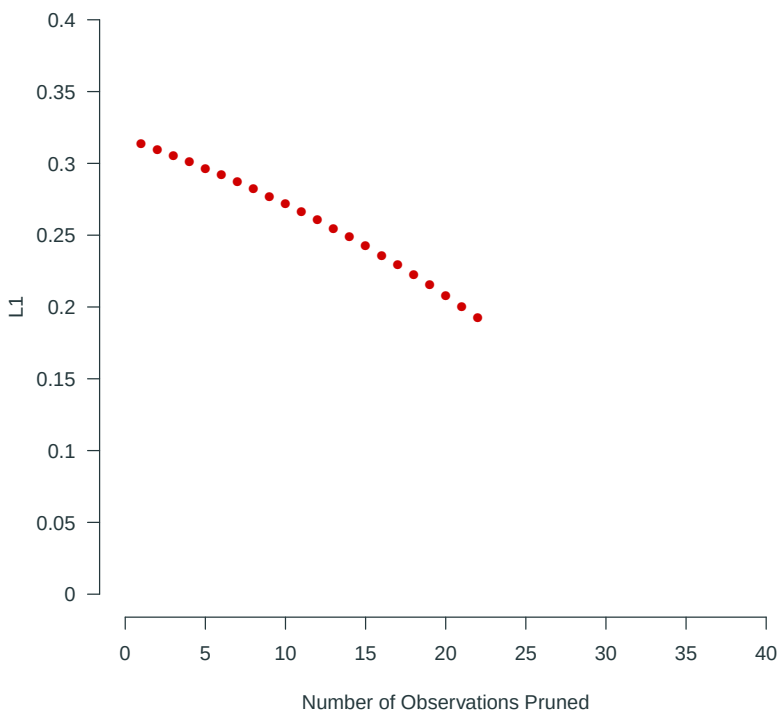

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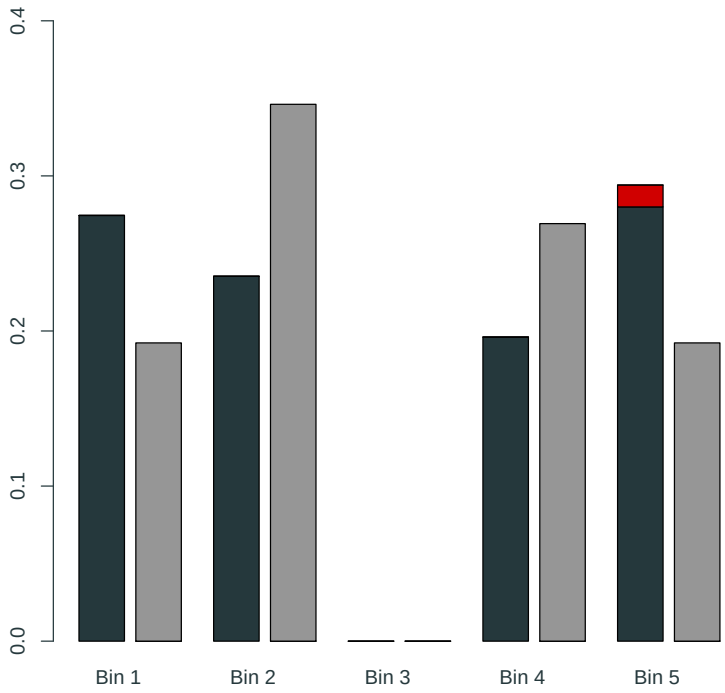

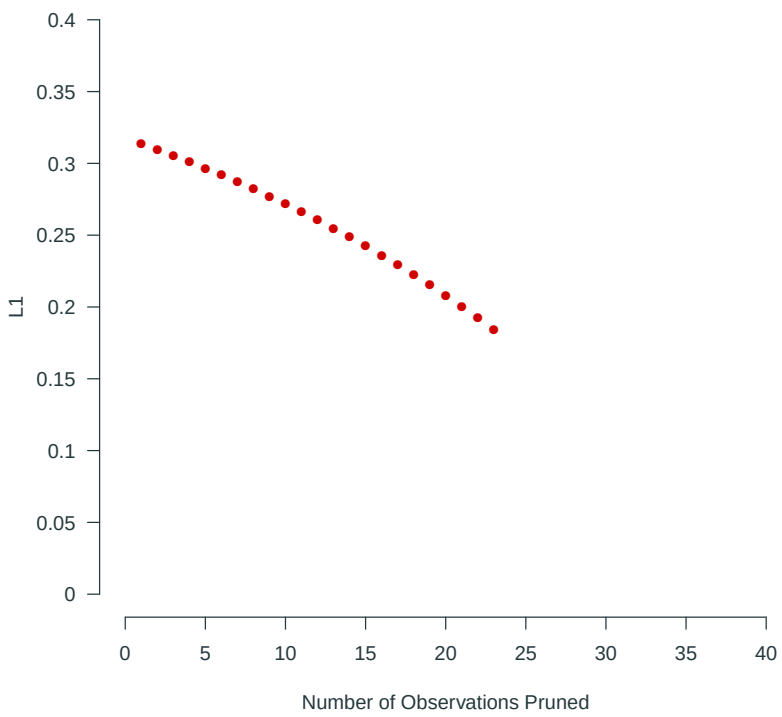

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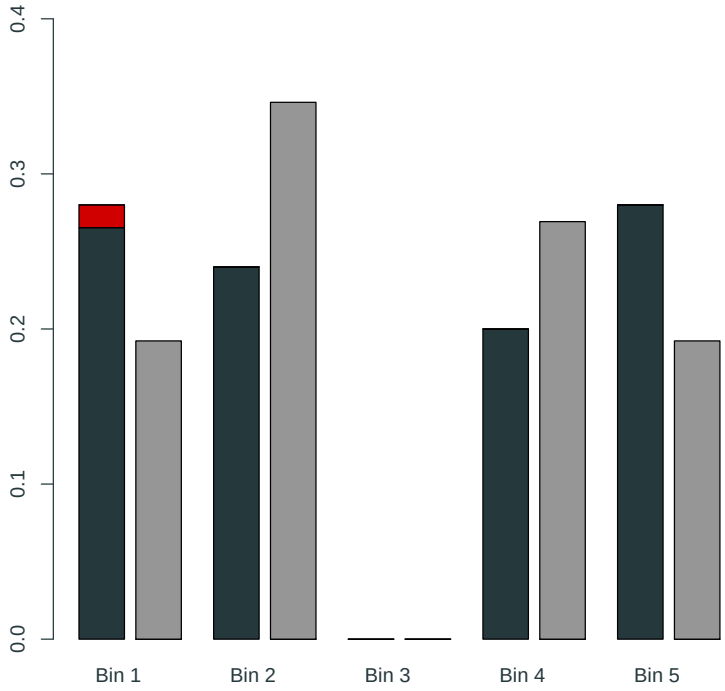

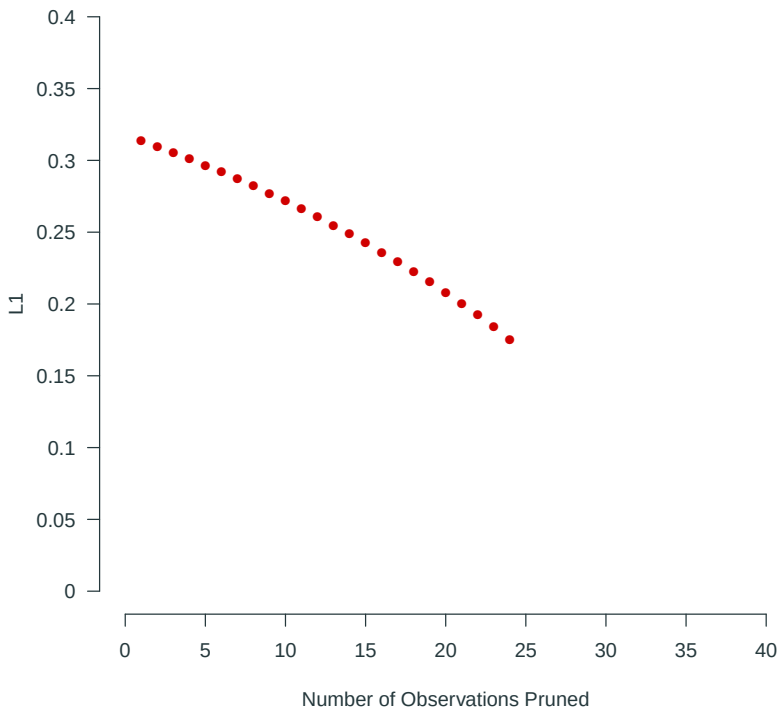

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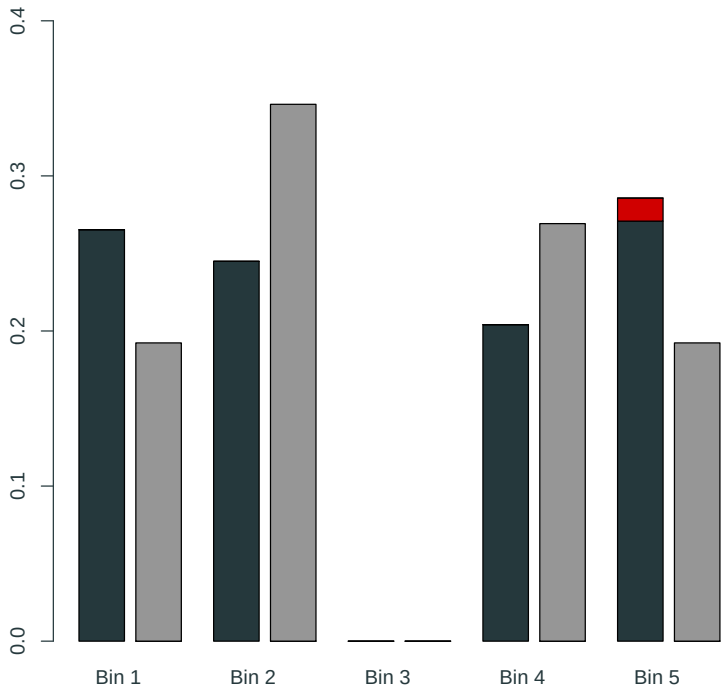

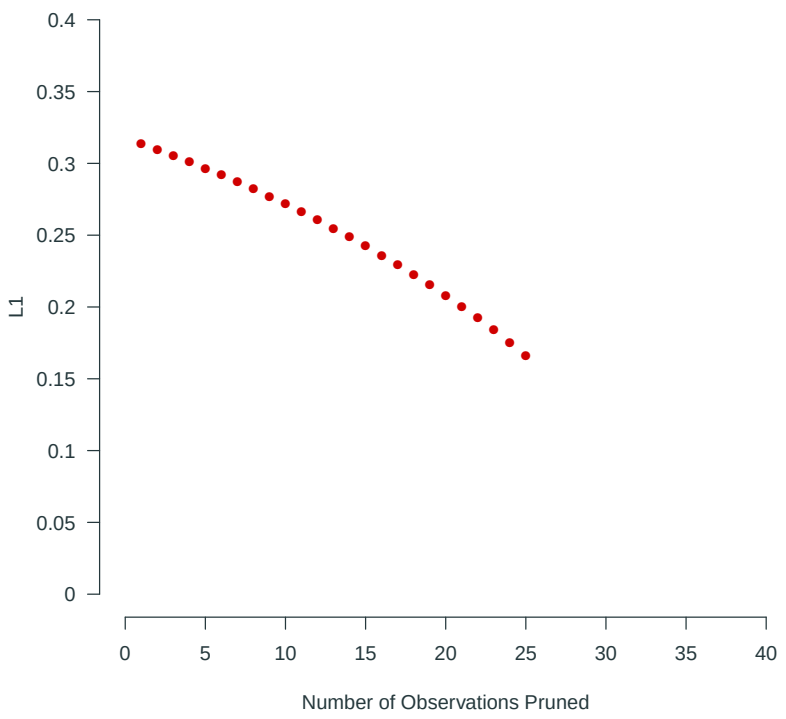

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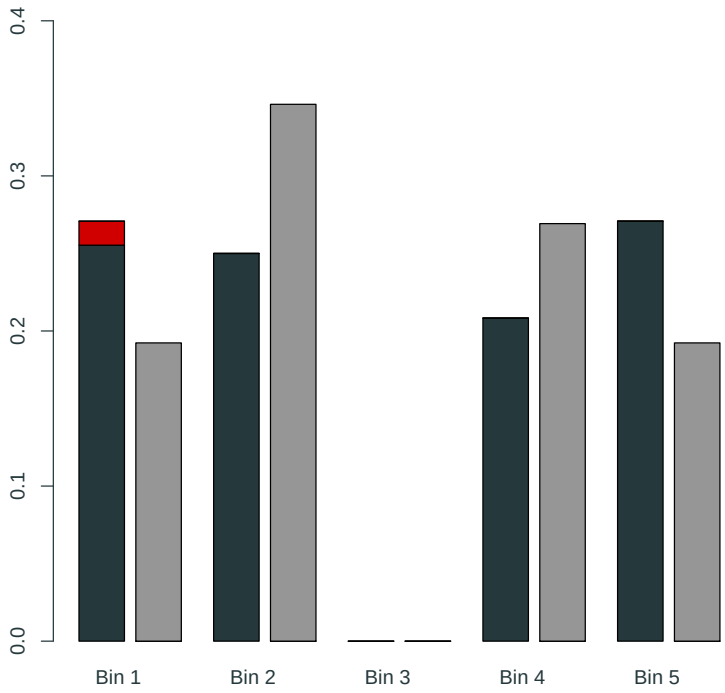

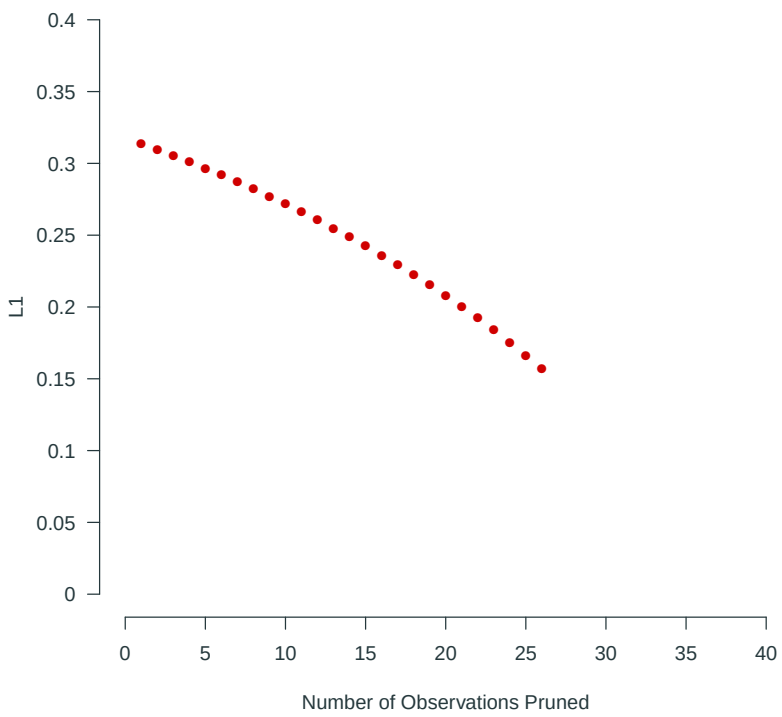

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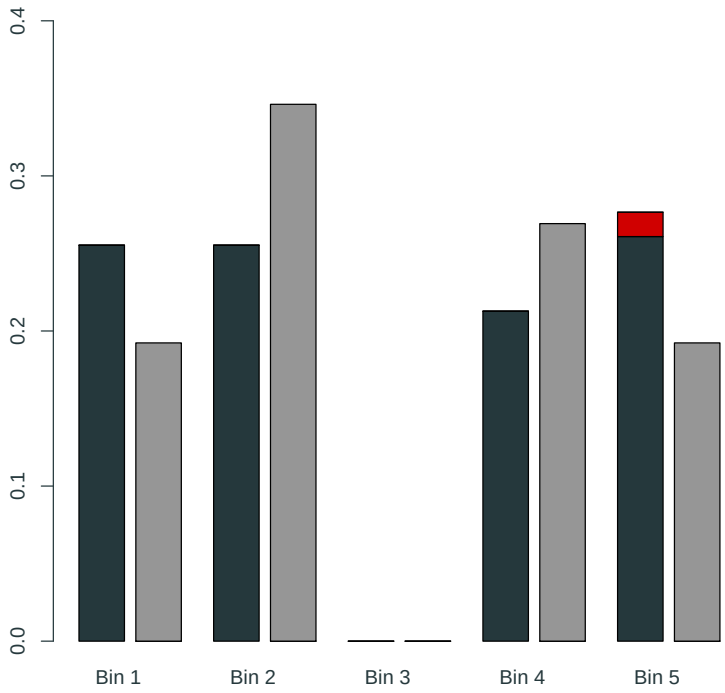

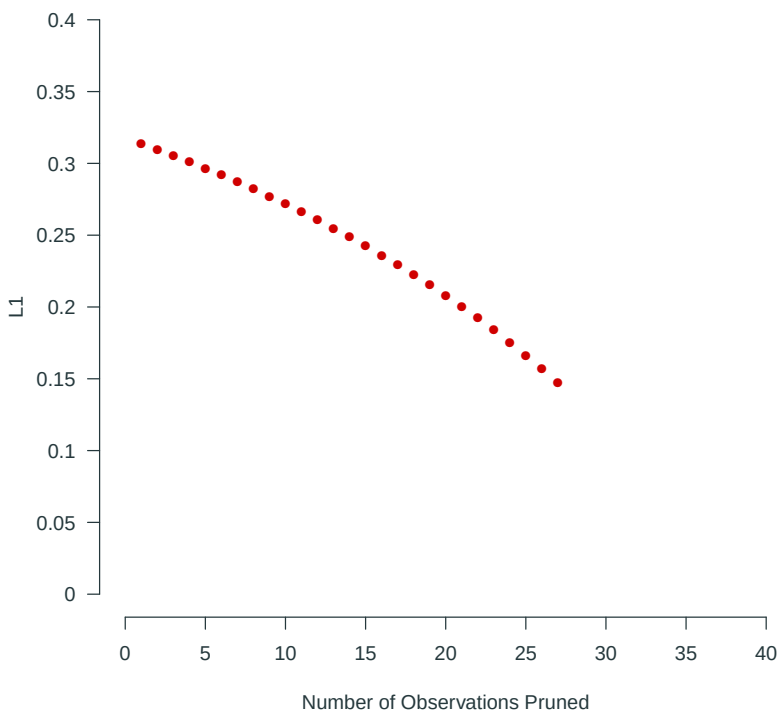

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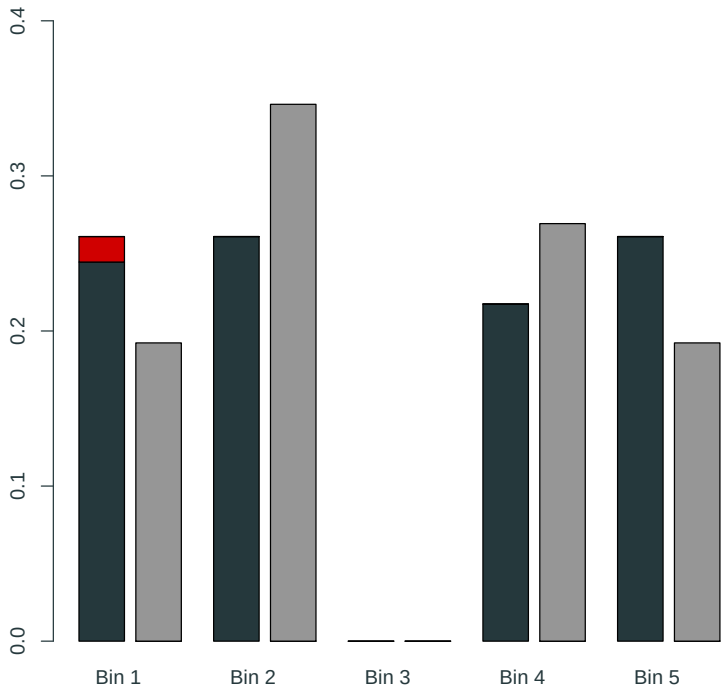

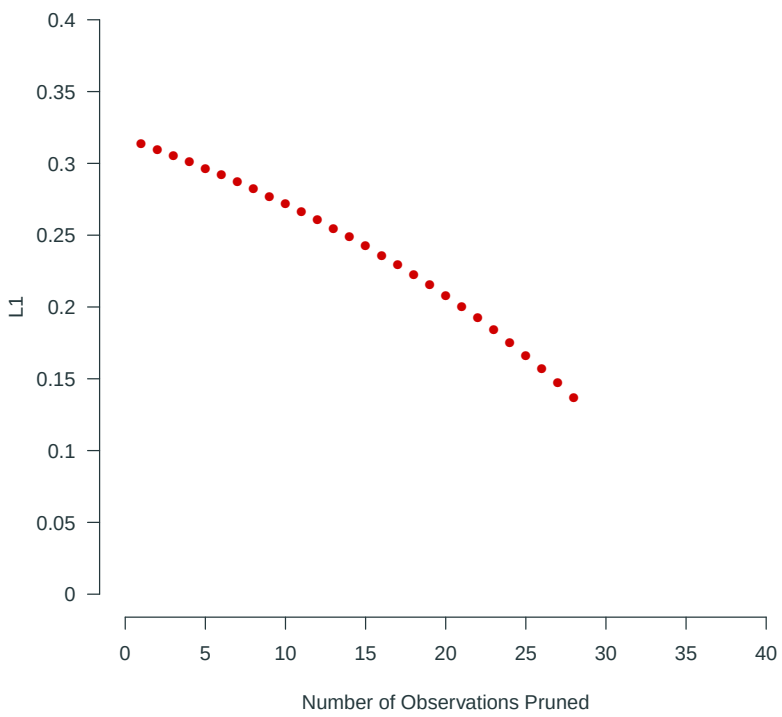

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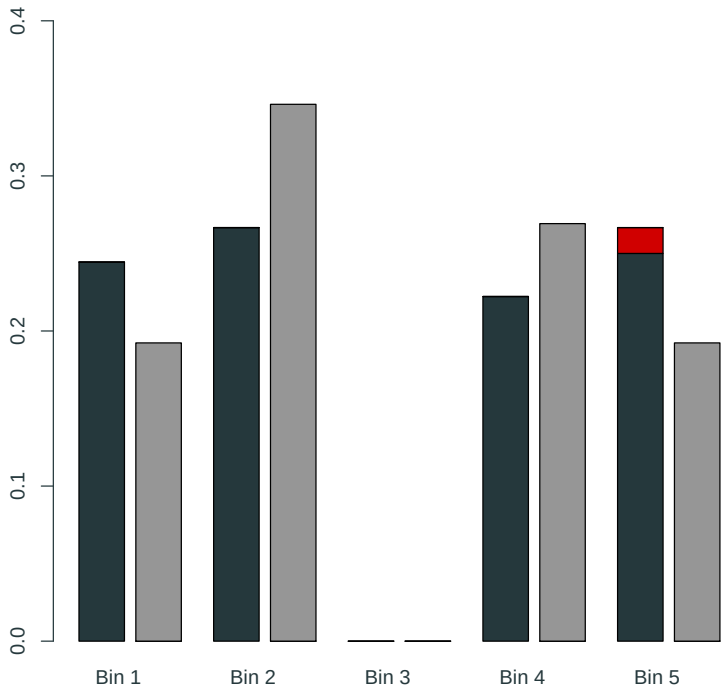

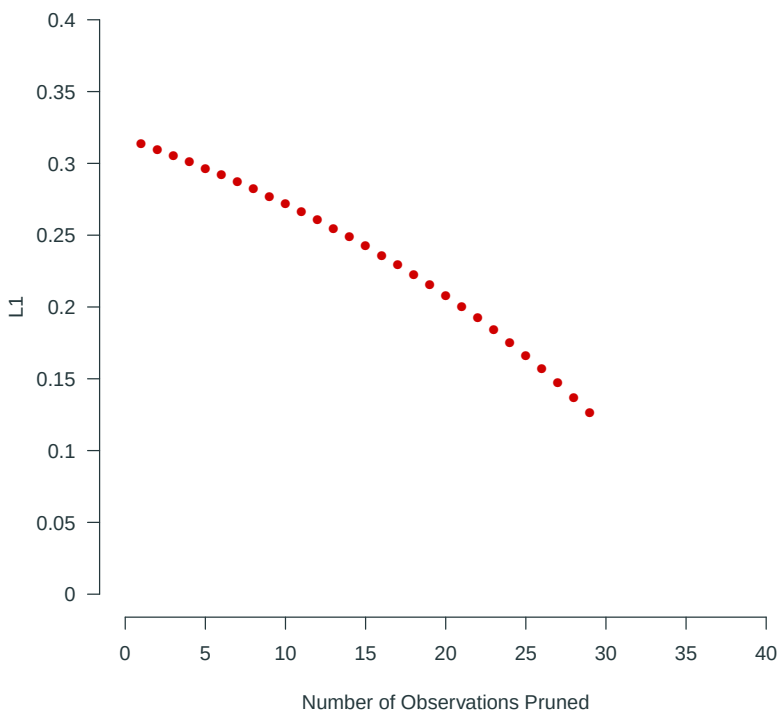

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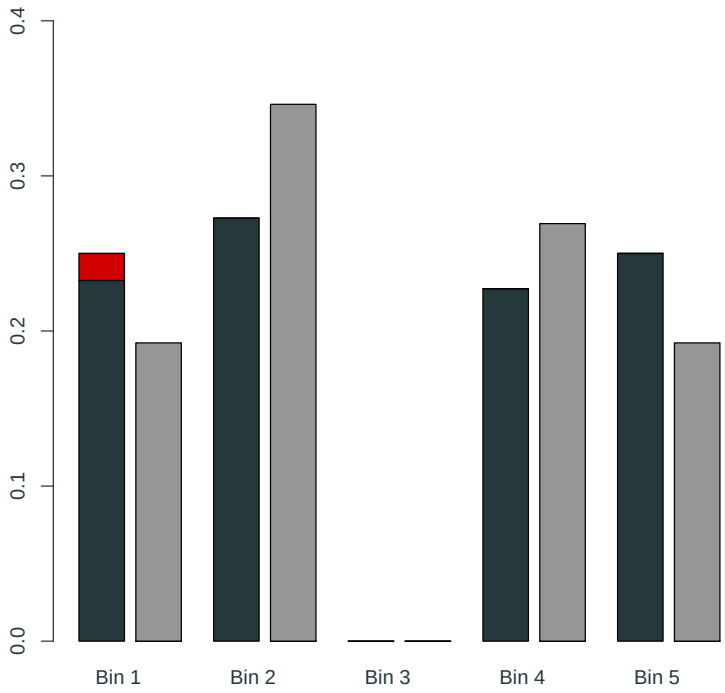

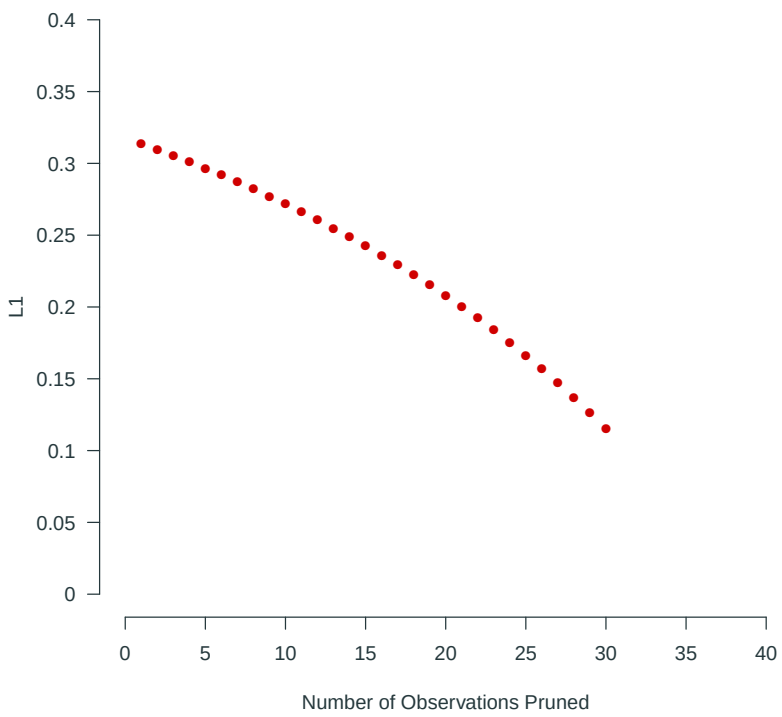

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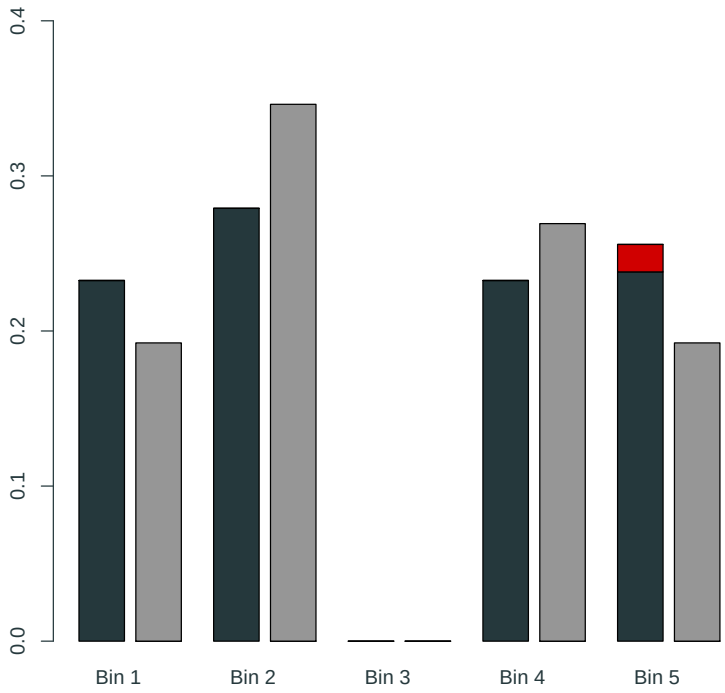

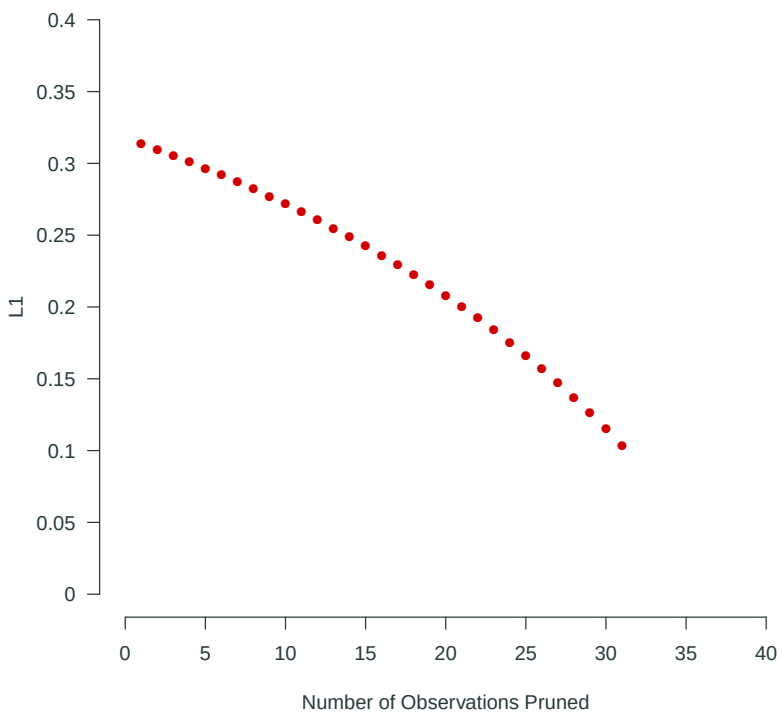

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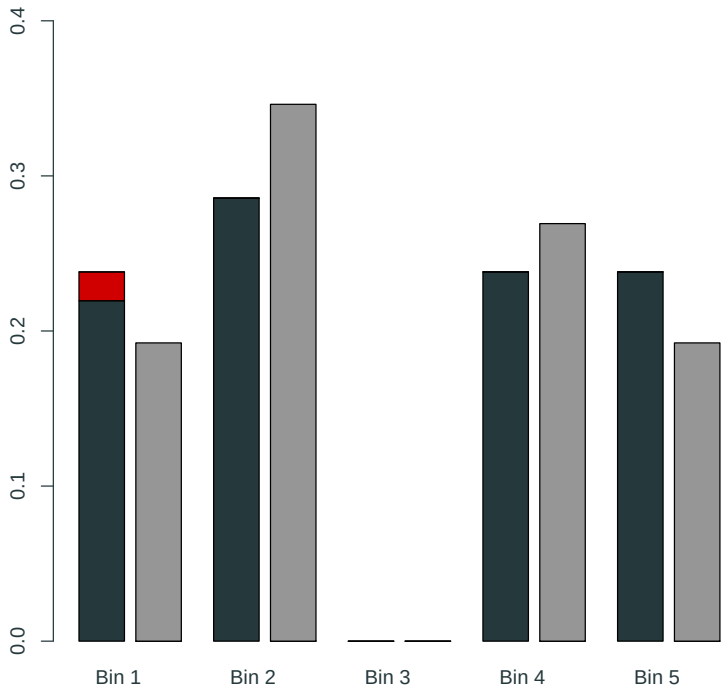

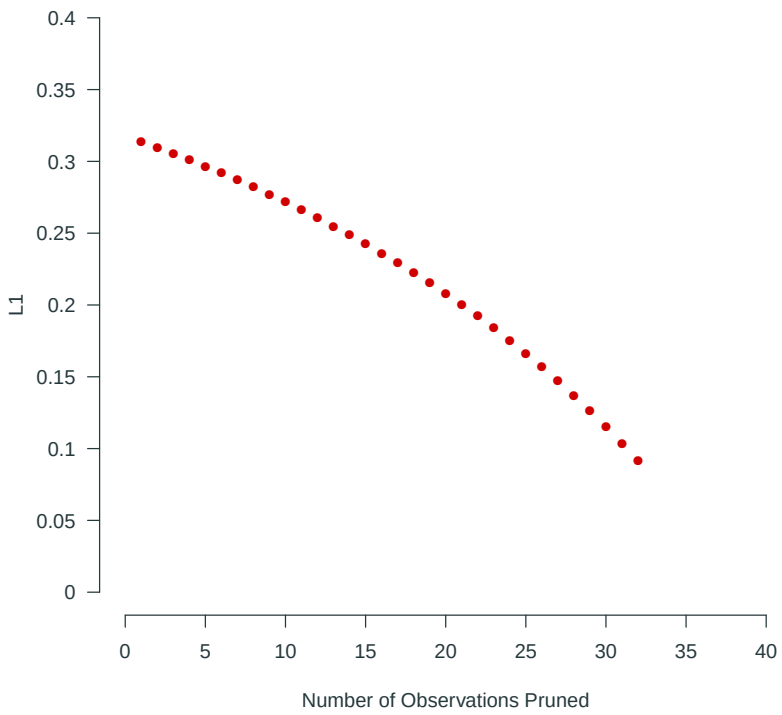

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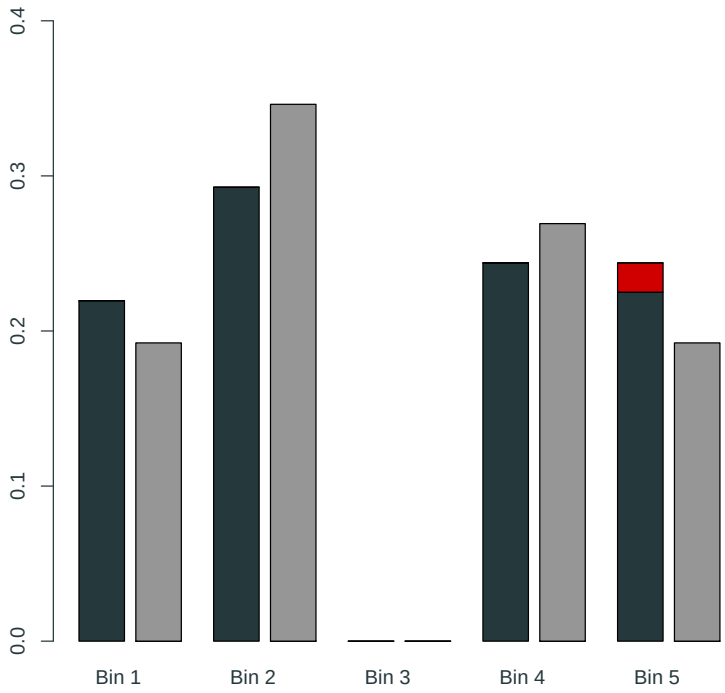

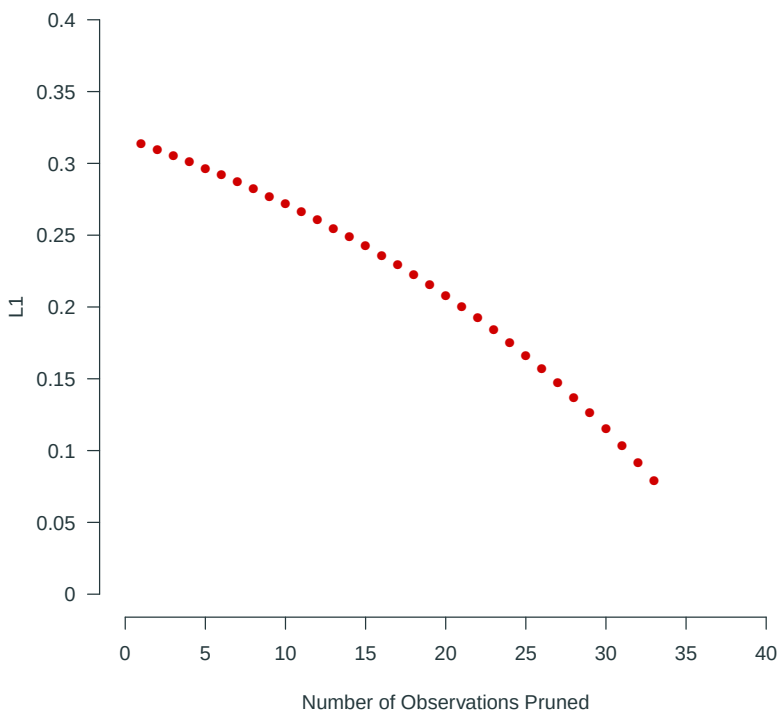

Discrete algorithm

Short version:

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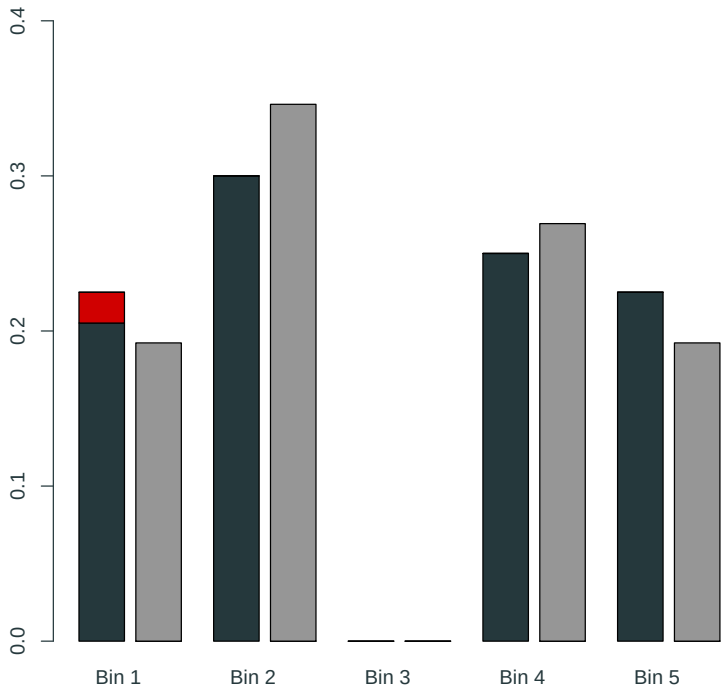

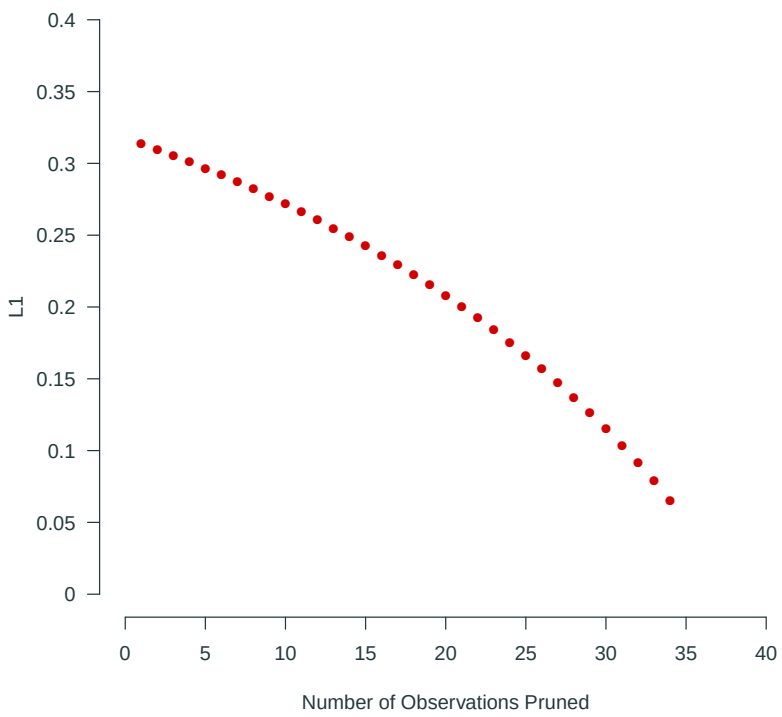

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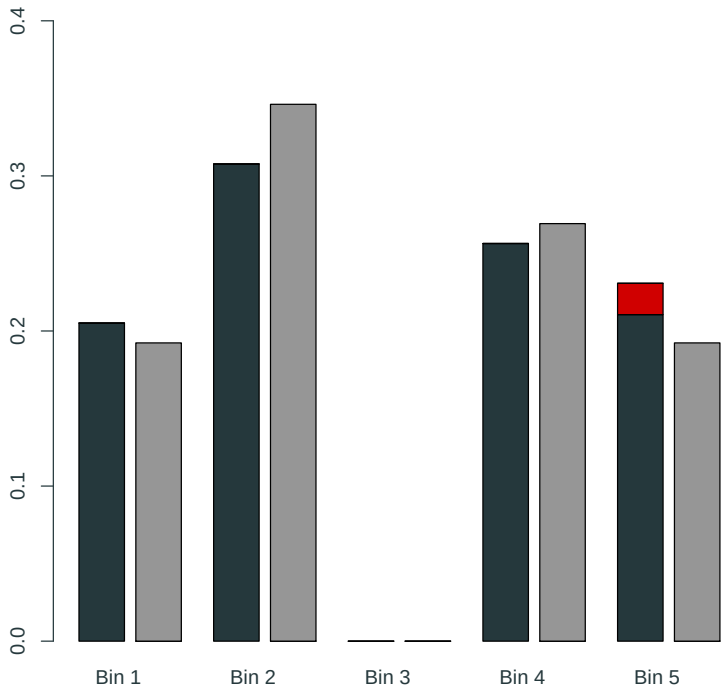

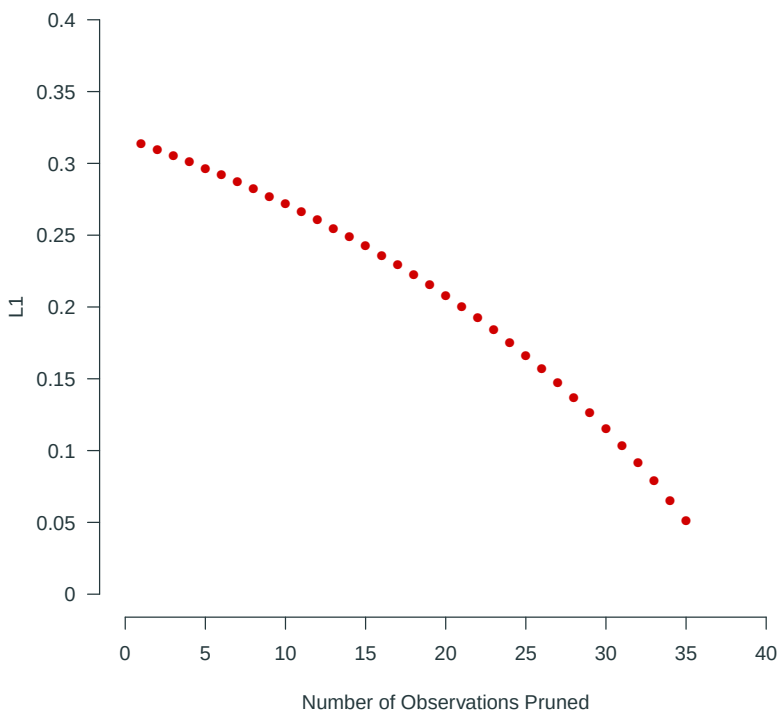

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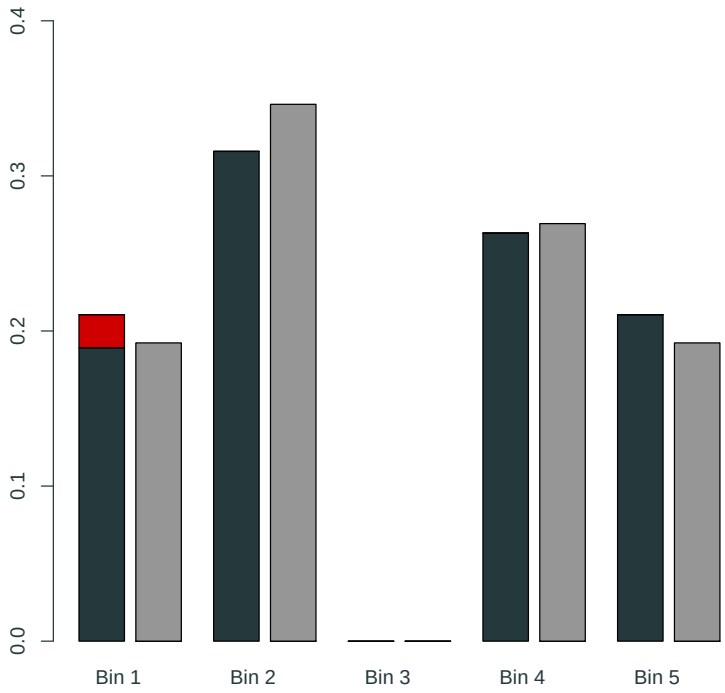

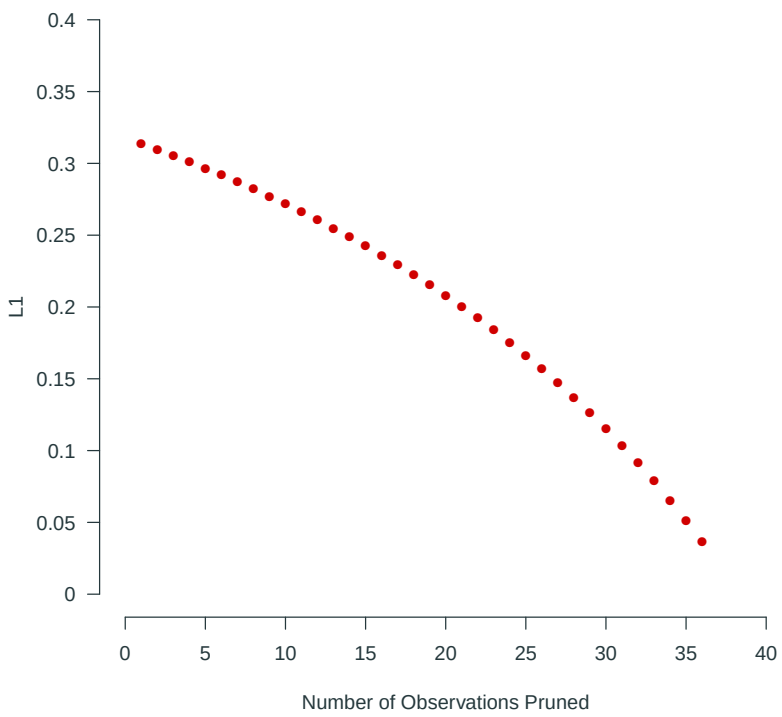

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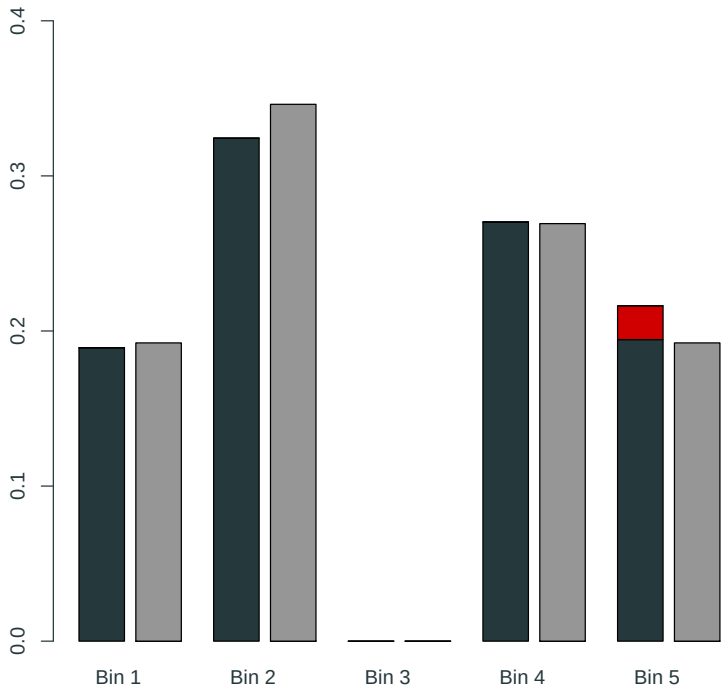

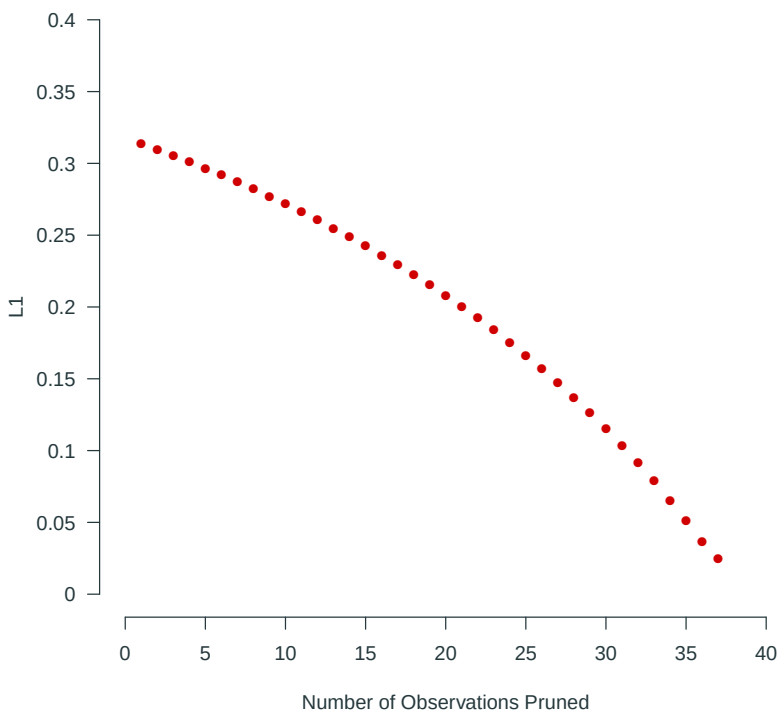

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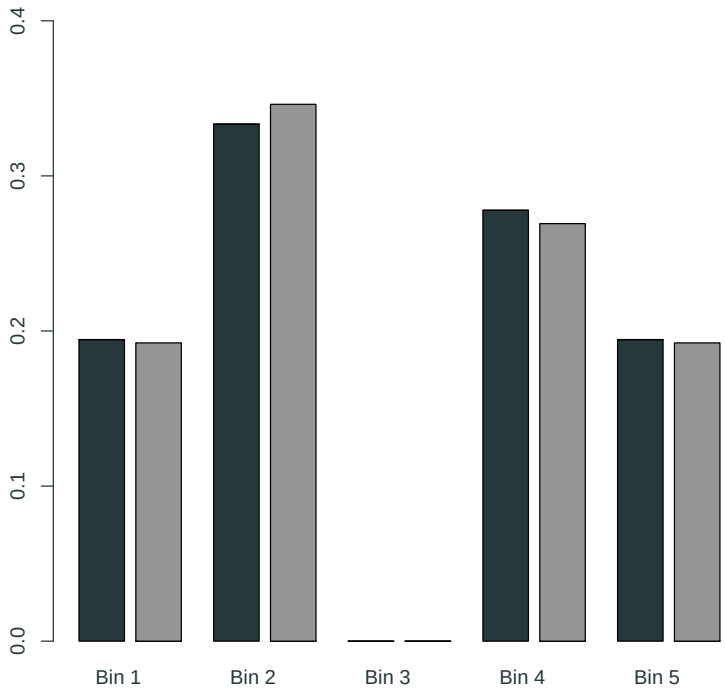
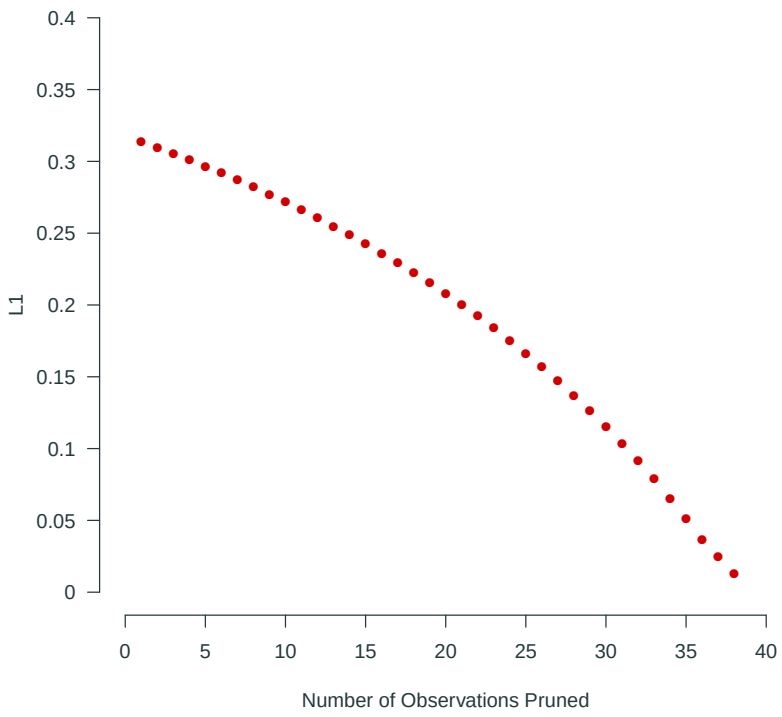
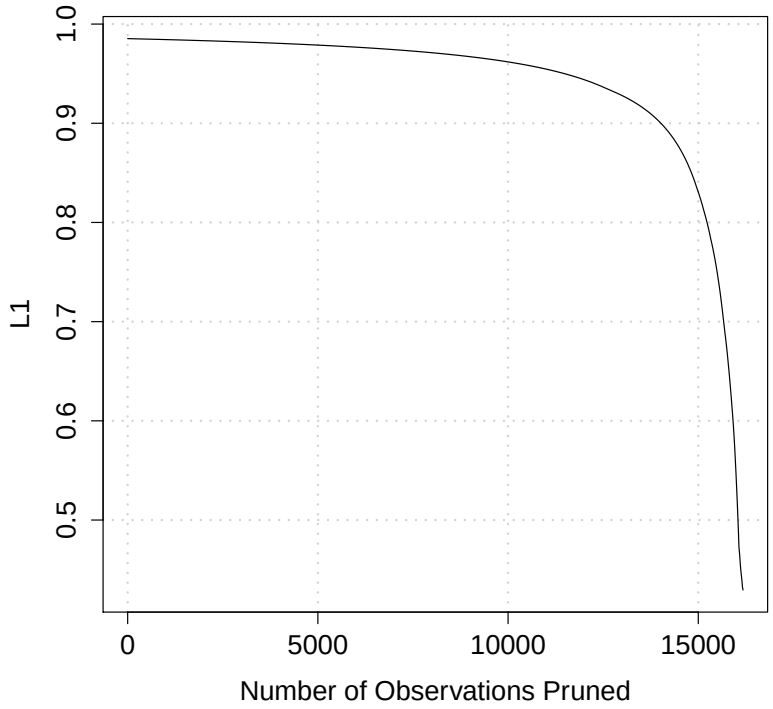
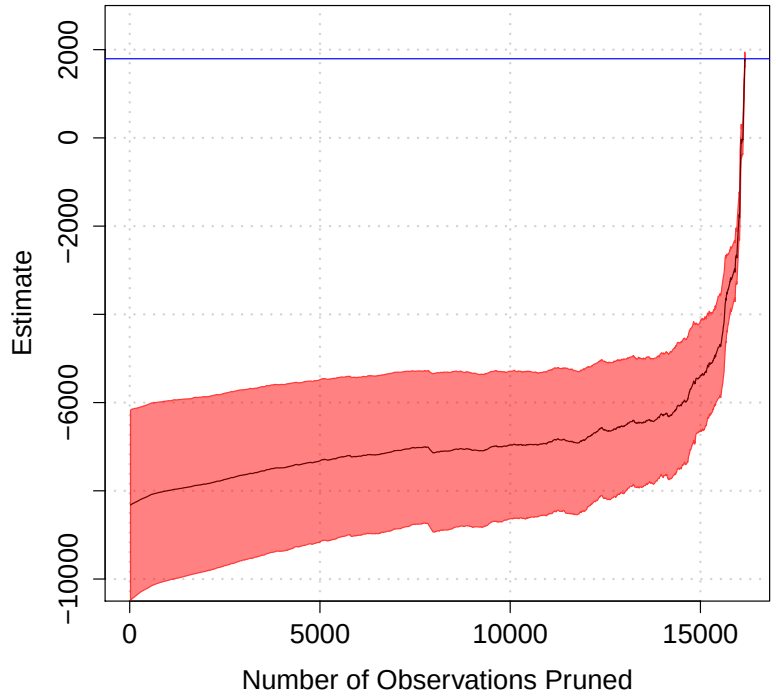




Job Training Data: Frontier and Causal Estimates





- 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