Simplifying Matching Methods for Causal Inference[1]

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[1]Based on joint work with Rich Nielsen, Chris Lucas, Stefano Iacus, and Giuseppe Porro

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Part 1 (of 3)

Imbalance $\rightsquigarrow$ Model Dependence $\rightsquigarrow$ Researcher Discretion $\rightsquigarrow$ Bias

Model Dependence Example

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- The question: How *model dependent* are the results?

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Effect of Multilateral UN Intervention on Peacebuilding Success

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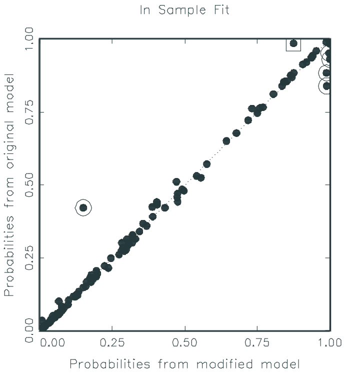
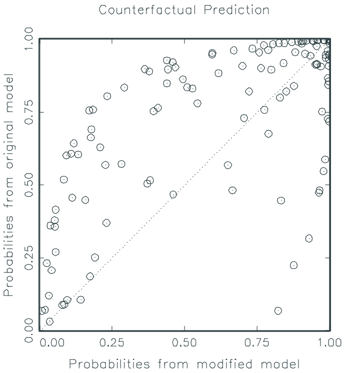
	Original "Interactive" Model			Modified Model		
Variables	Coeff	SE	P-val	Coeff	SE	P-val
Wartype	−1.742	.609	.004	−1.666	.606	.006
Logdead	−.445	.126	.000	−.437	.125	.000
Wardur	.006	.006	.258	.006	.006	.342
Factnum	−1.259	.703	.073	−1.045	.899	.245
Factnum2	.062	.065	.346	.032	.104	.756
Trnsfcap	.004	.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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- Simple to teach: coarsen, then exact match

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Monte Carlo: $\mathbf{X}_T \sim N_5(\mathbf{0}, \Sigma)$ and $\mathbf{X}_C \sim N_5(\mathbf{1}, \Sigma)$. $n = 2,000$, reps=5,000; Allow MDM & PSM to match with replacement;use automated CEM

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$\rightsquigarrow$ CEM dominates EPBR-methods in EPBR Data

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$\rightsquigarrow$ CEM works well in non-EPBR data too

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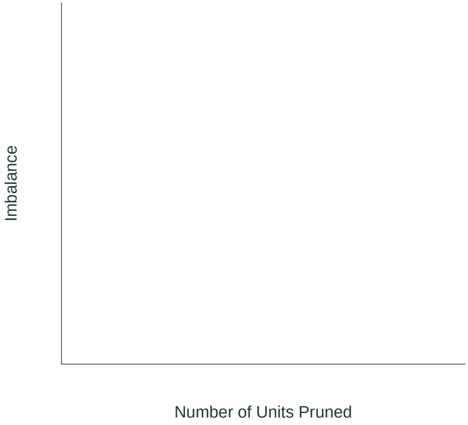
- Nonparametric Adjustments: can apply within CEM strata

Part 3 (of 3)

The Matching Frontier

The Matching Frontier

The Matching Frontier



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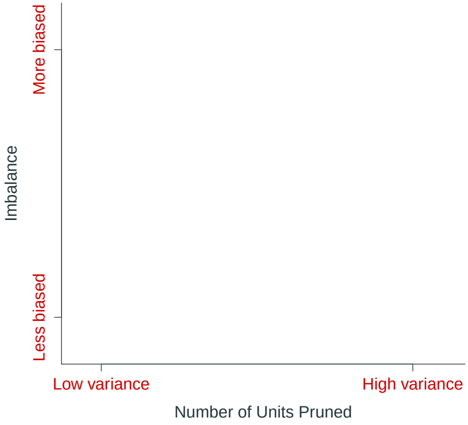

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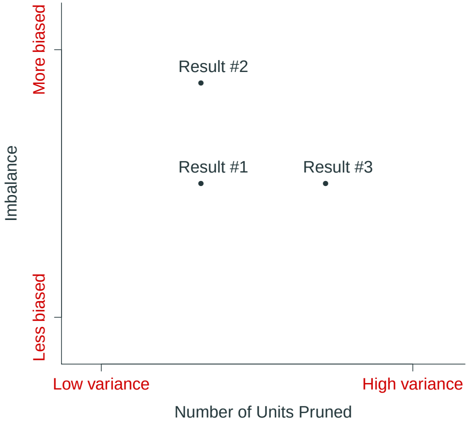

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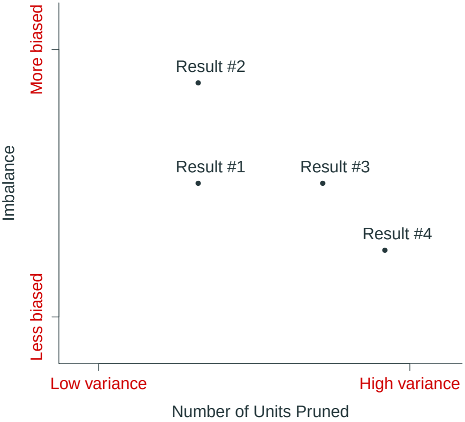

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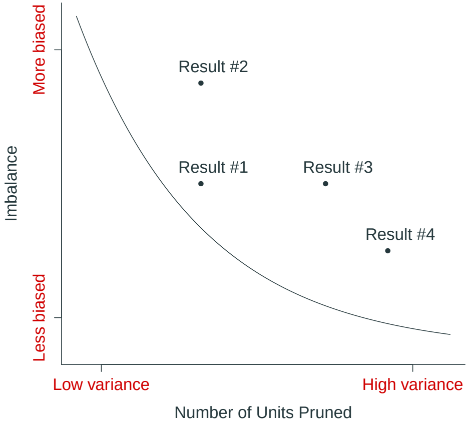

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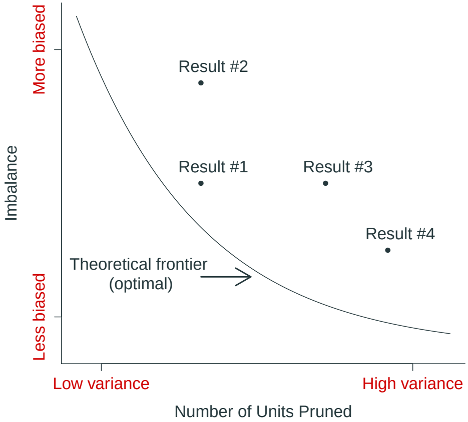

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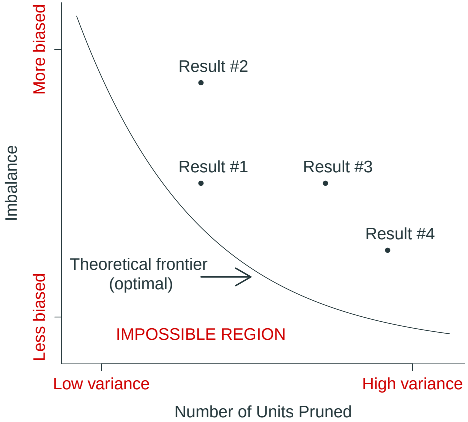

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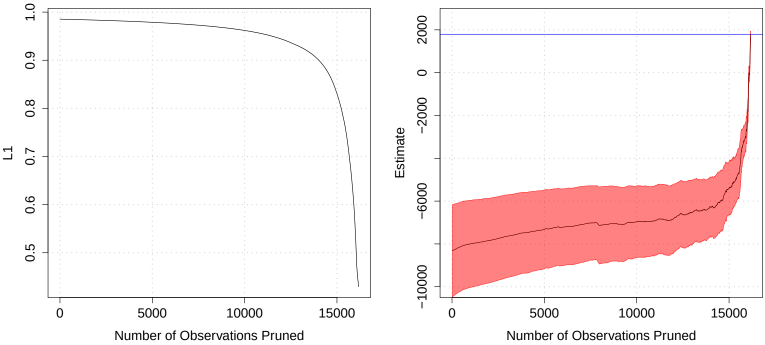
Job Training Data: Frontier and Causal Estimates



- 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

Constructing the FSATT Mahalanobis Frontier

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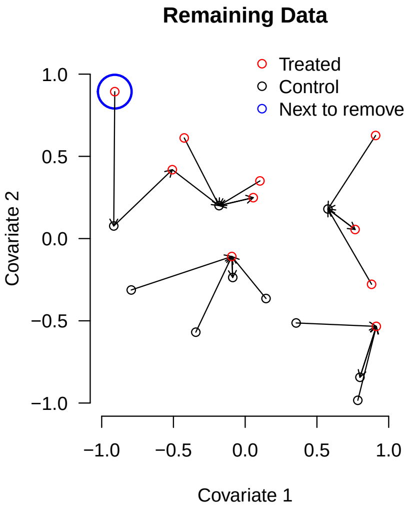

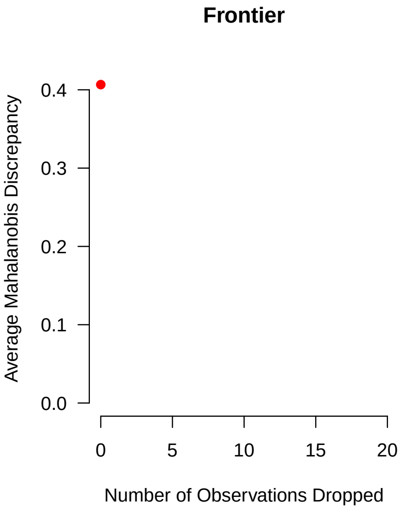

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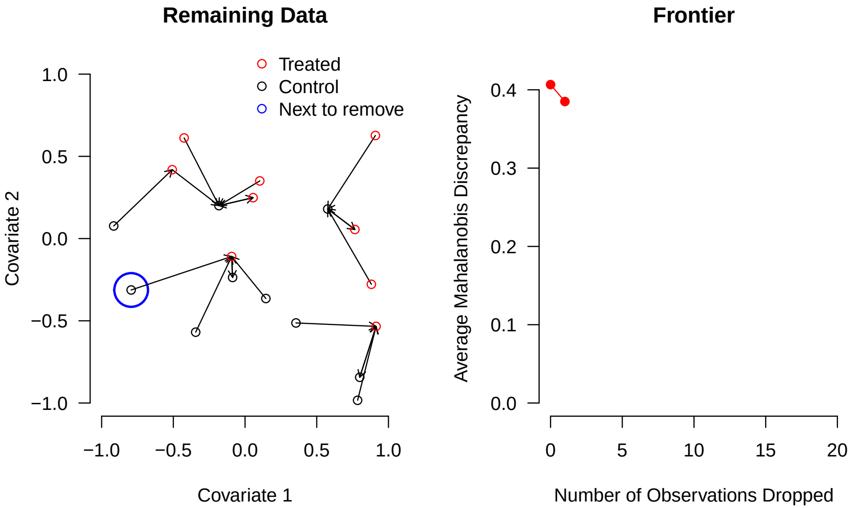

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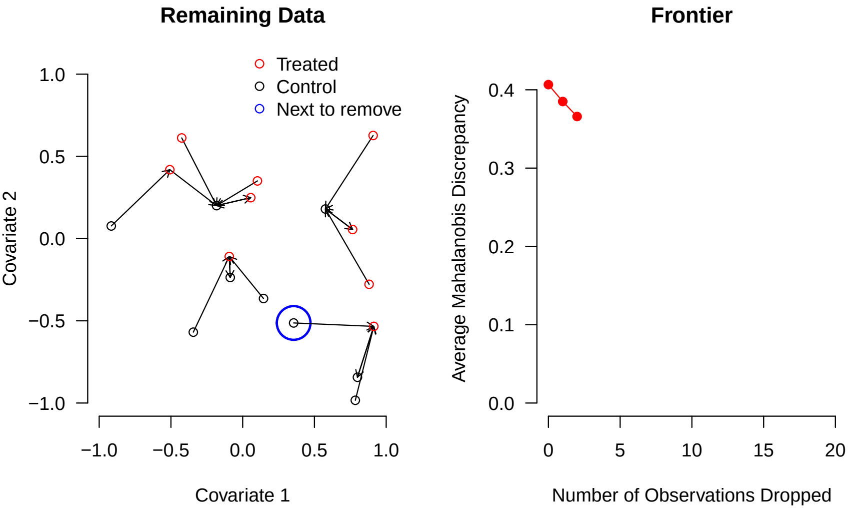

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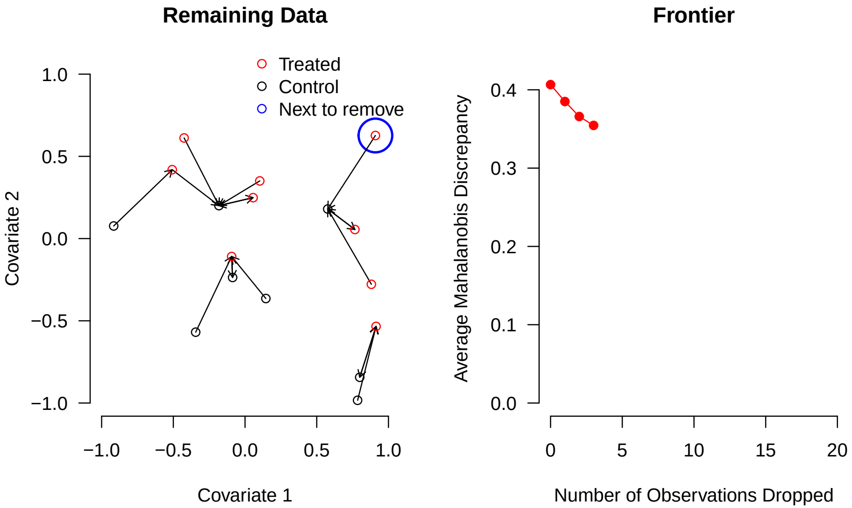

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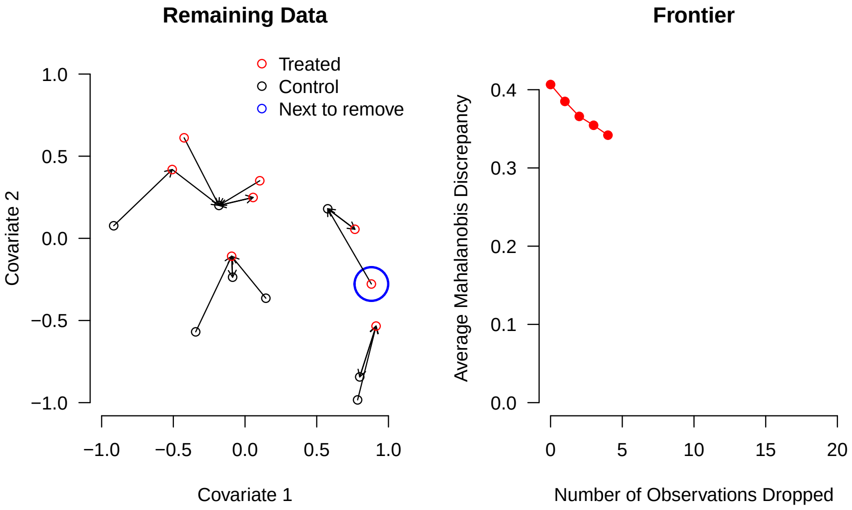

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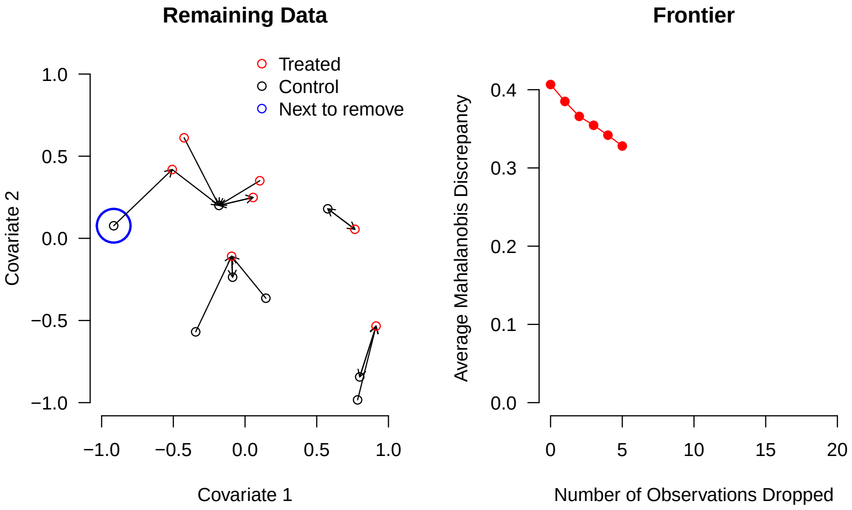

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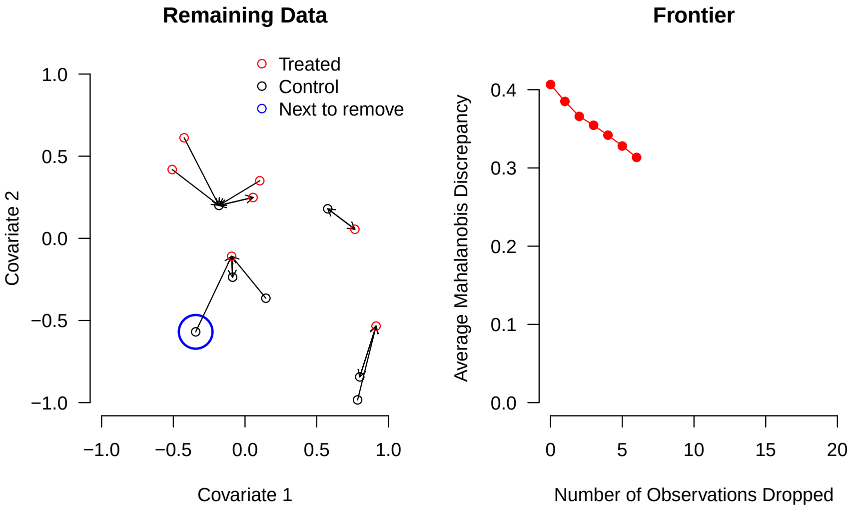

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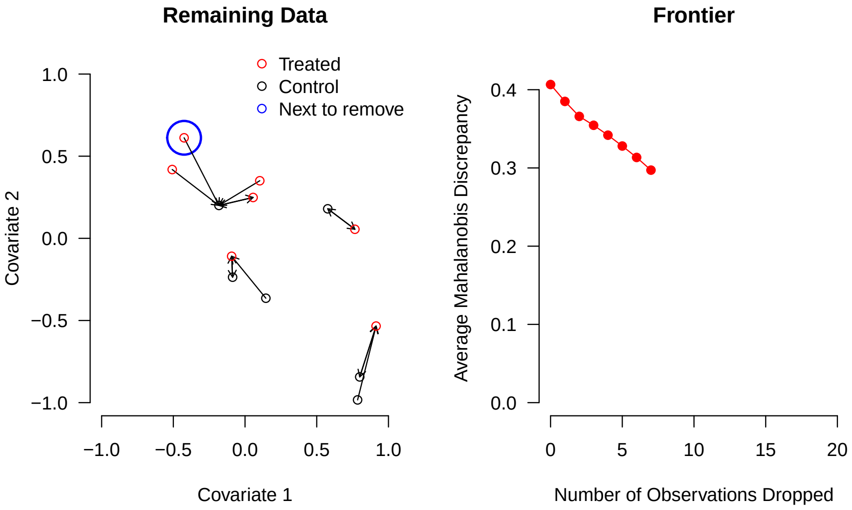

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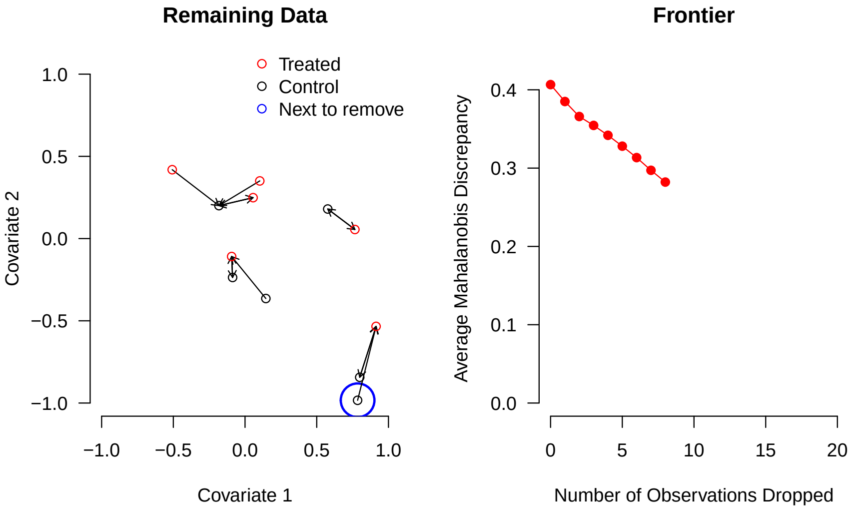

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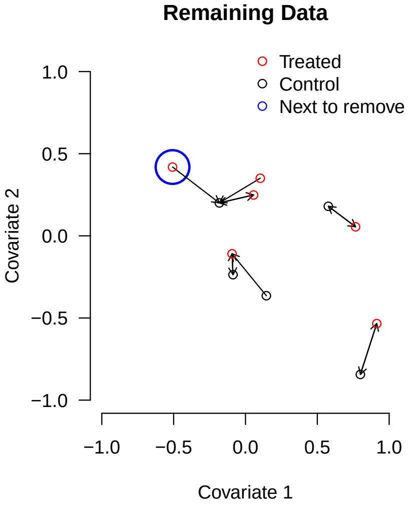

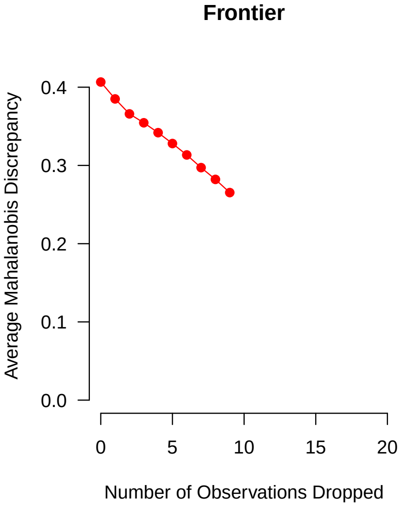

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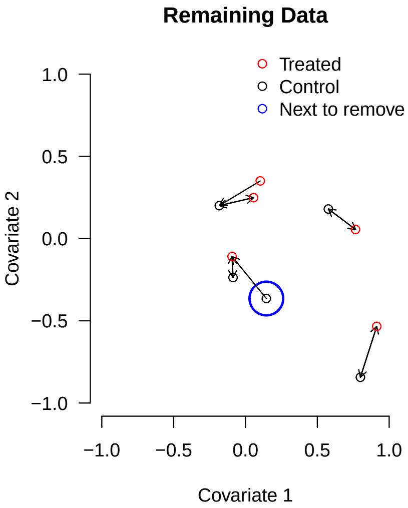

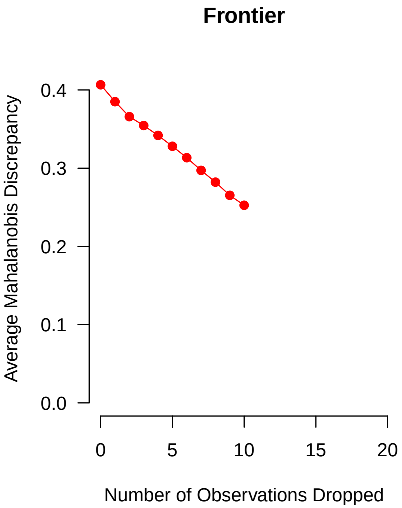

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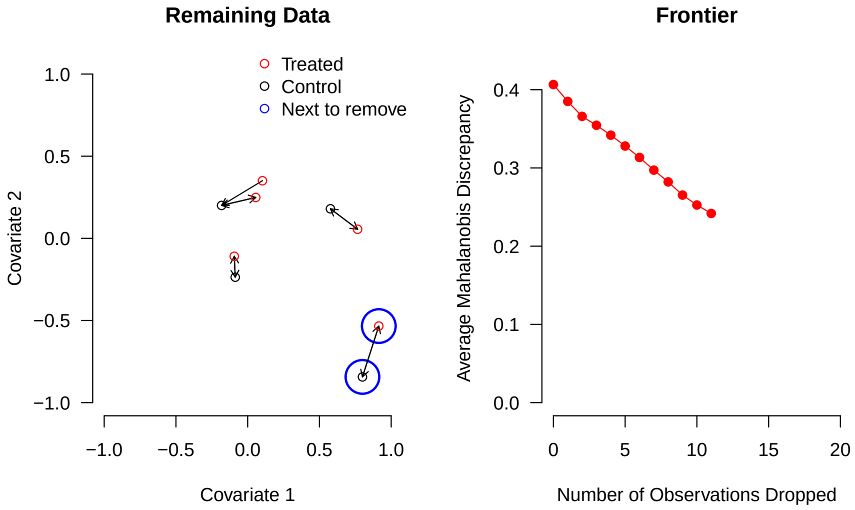

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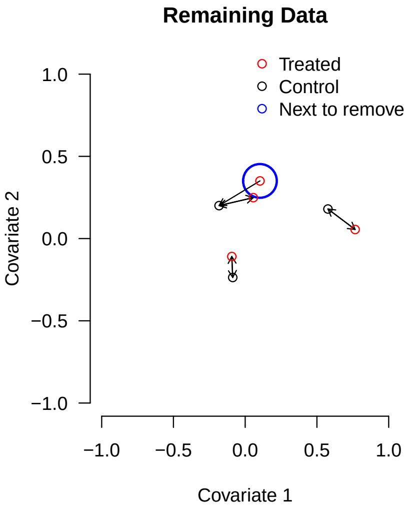

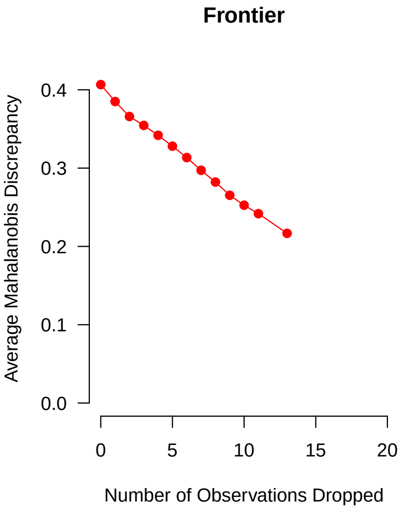

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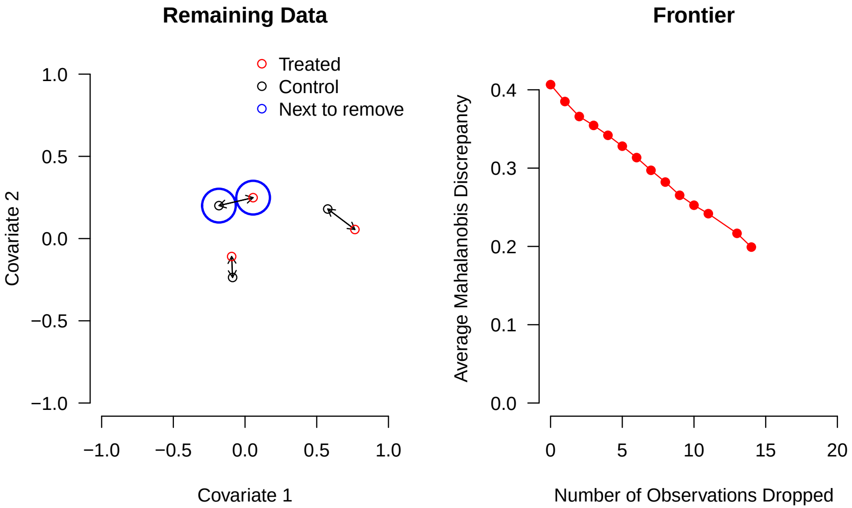

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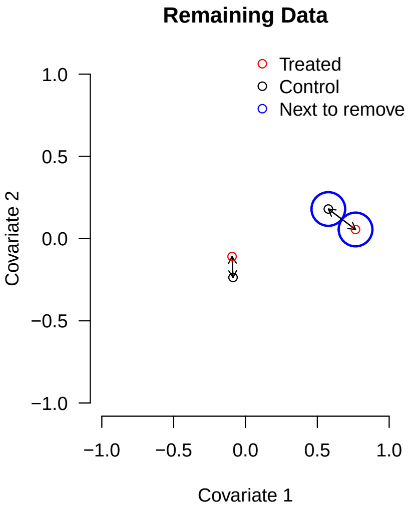

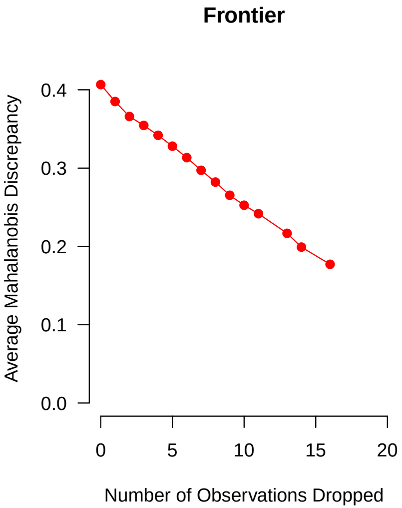

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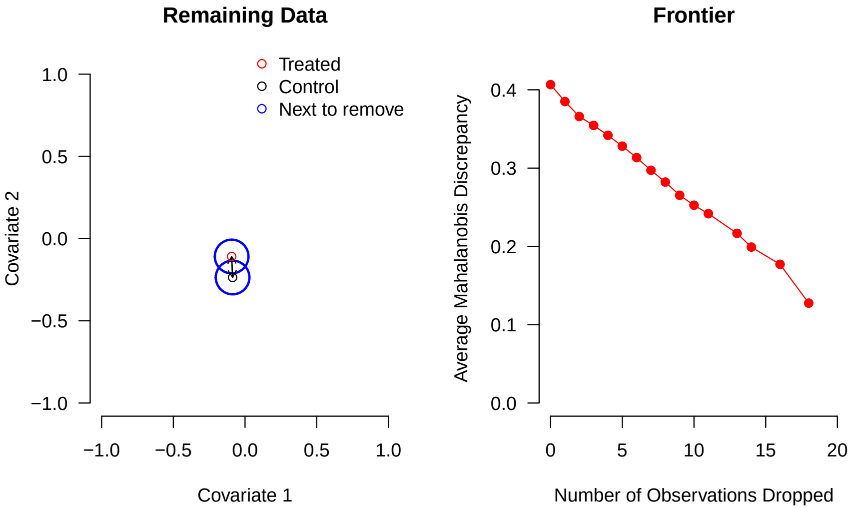

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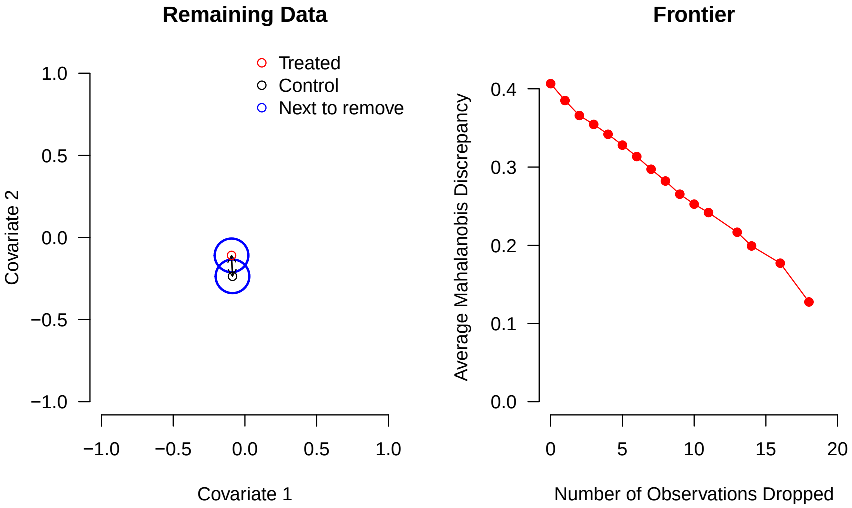

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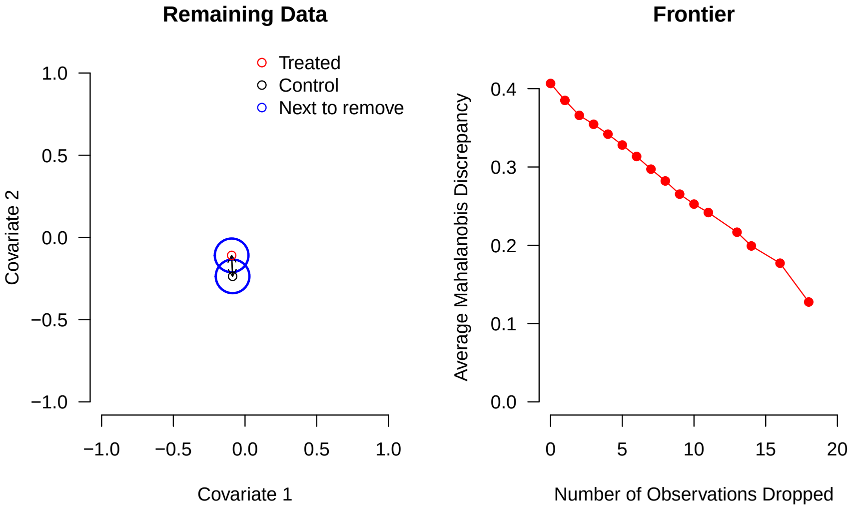

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- Very fast; works with any continuous imbalance metric

Constructing the L1/L2 SATT Frontier

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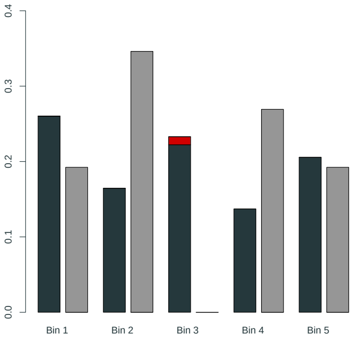

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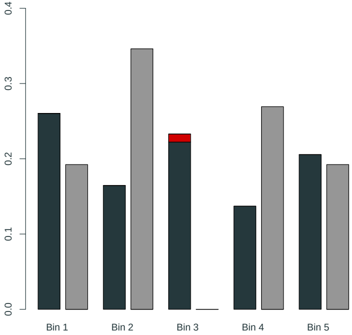

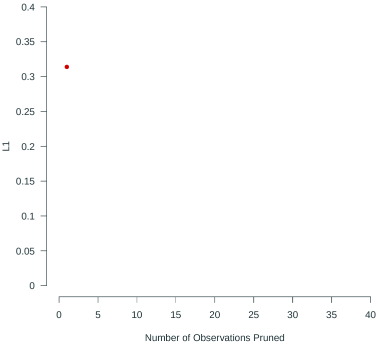

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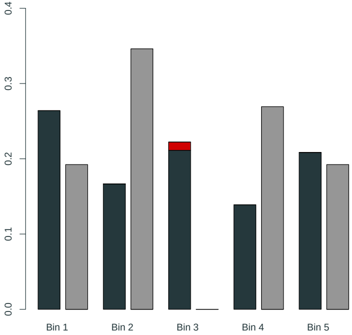

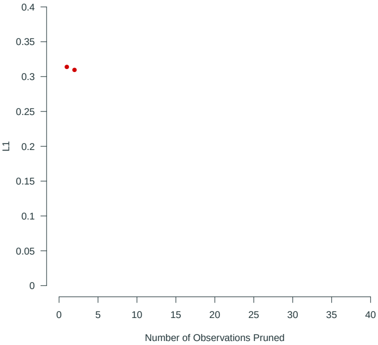

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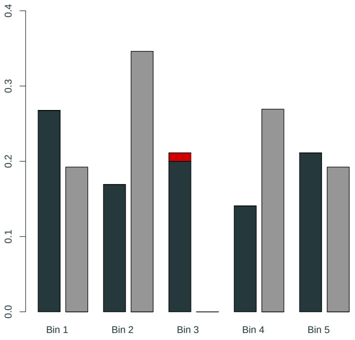

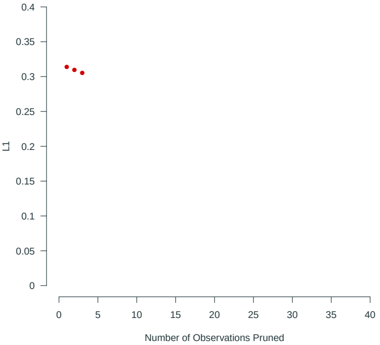

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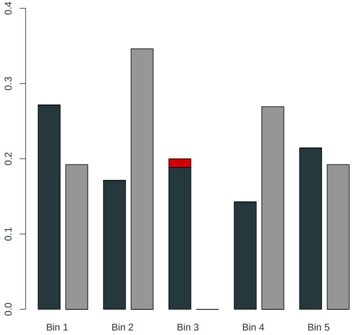

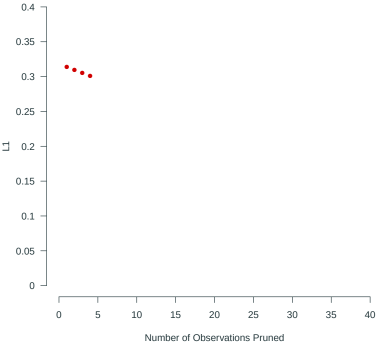

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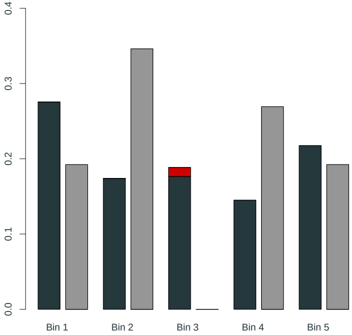

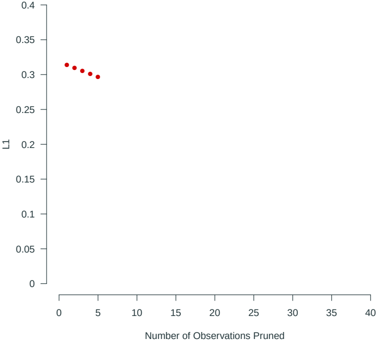

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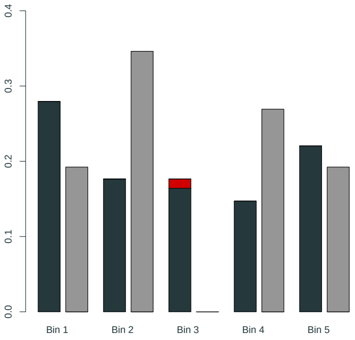

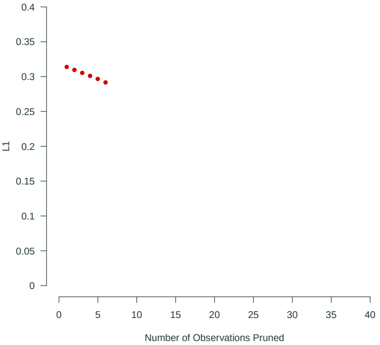

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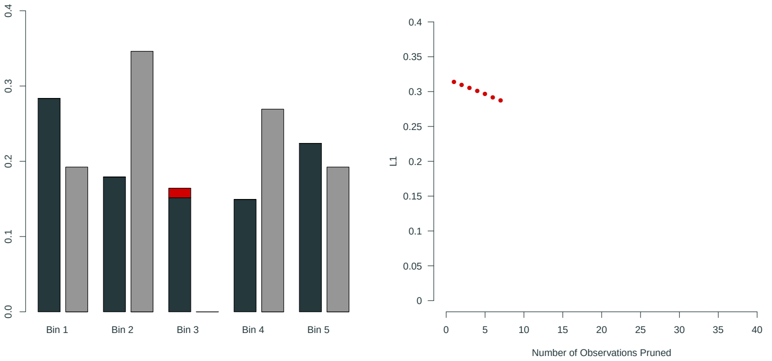

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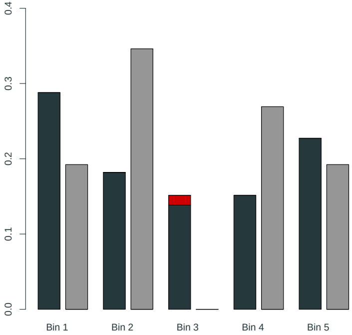

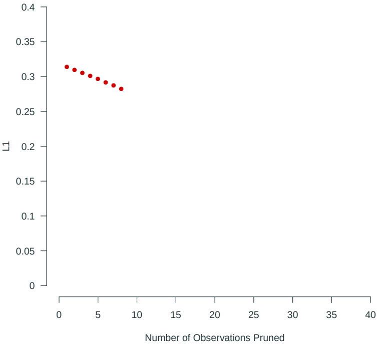

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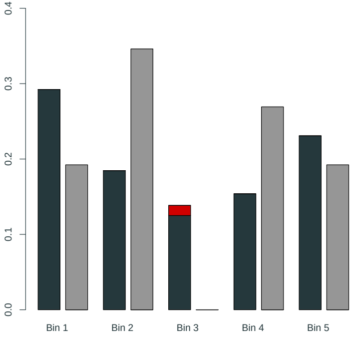

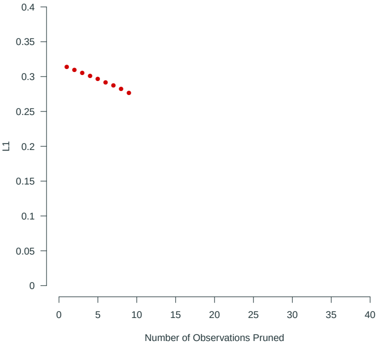

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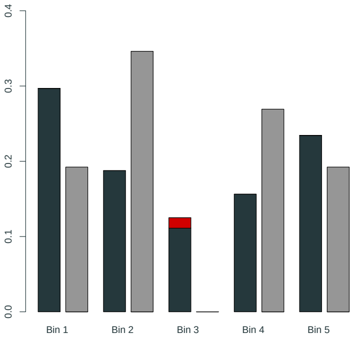

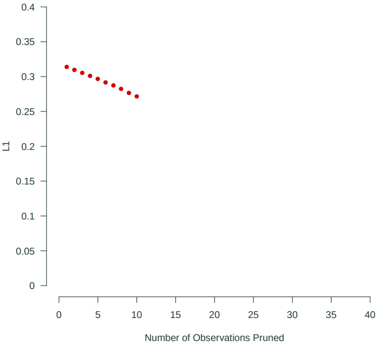

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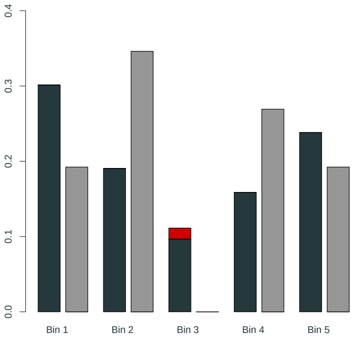

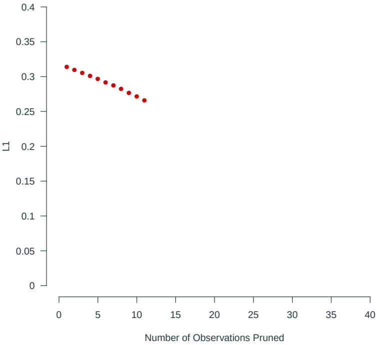

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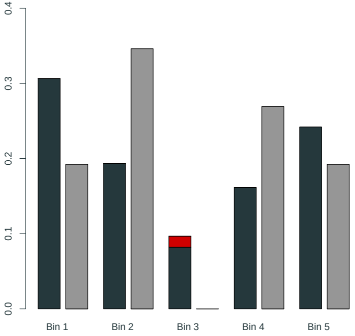

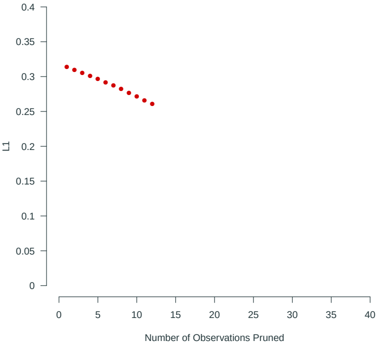

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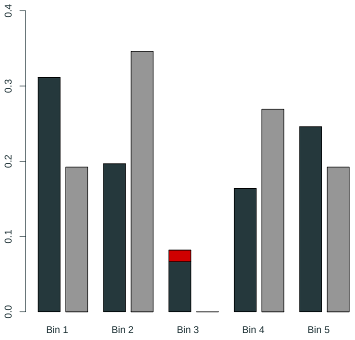

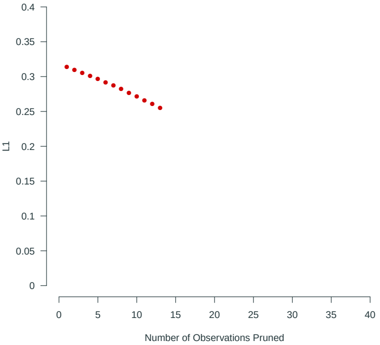

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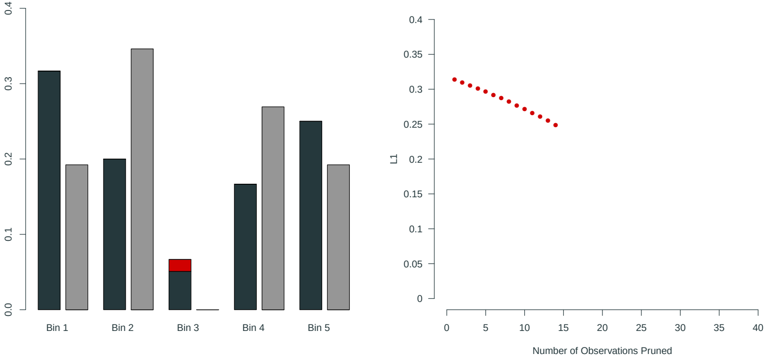

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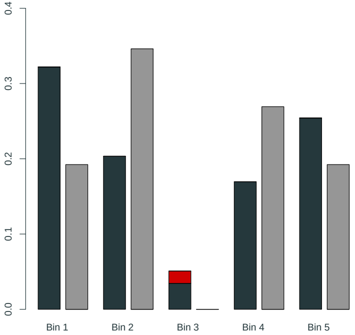

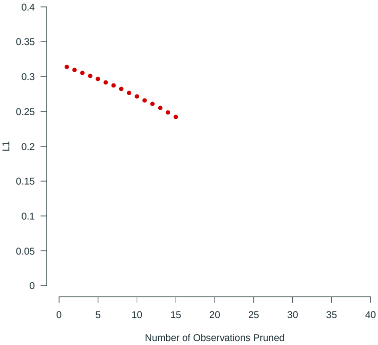

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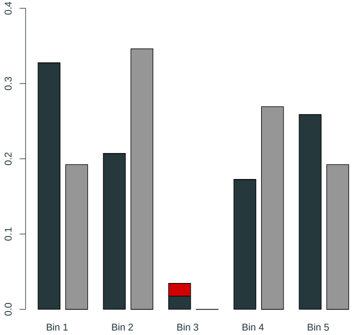

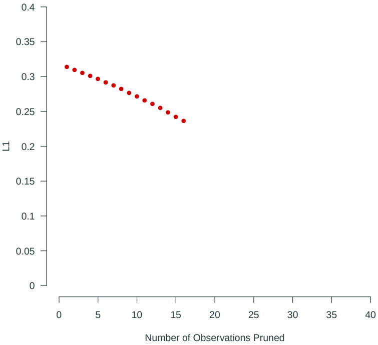

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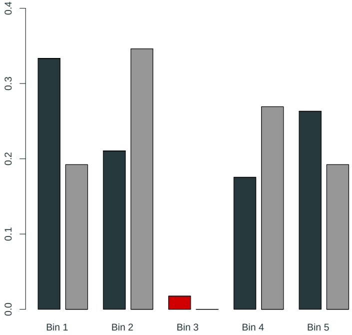

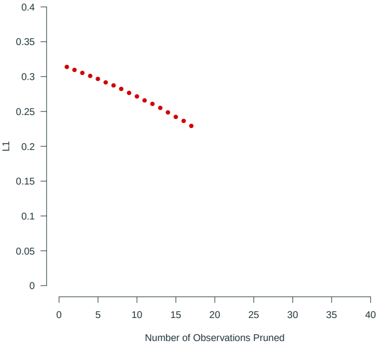

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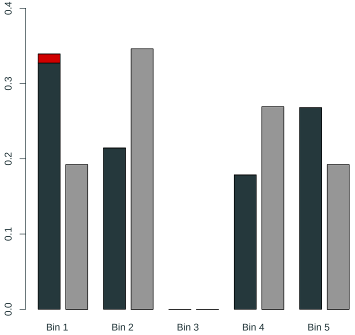

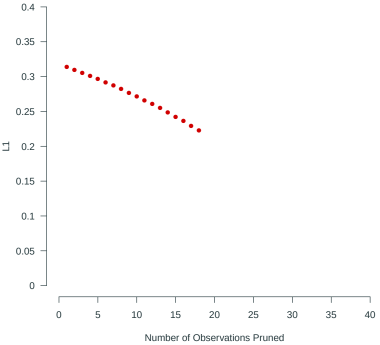

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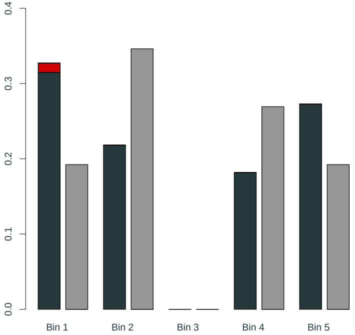

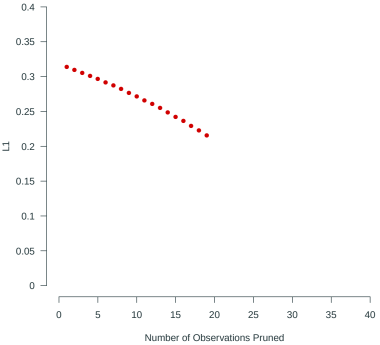

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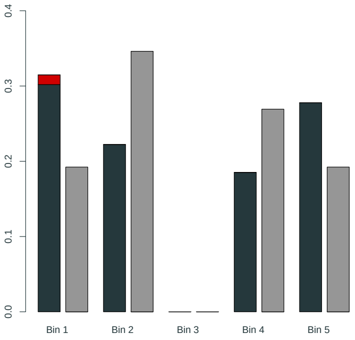

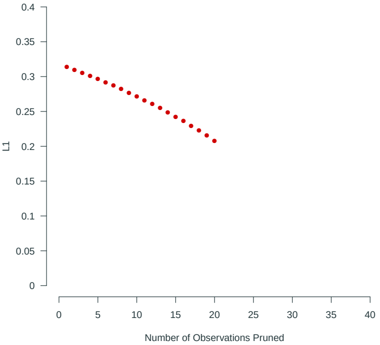

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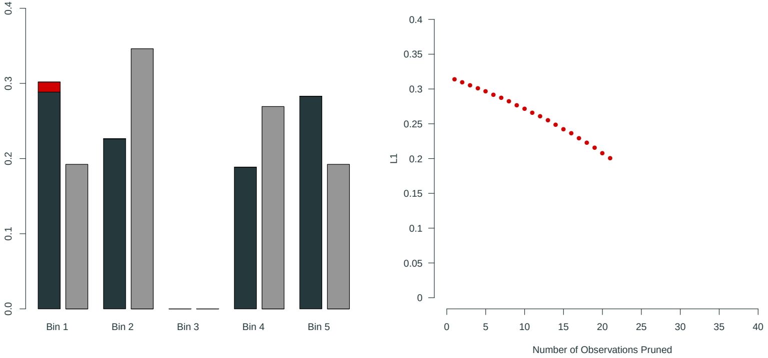

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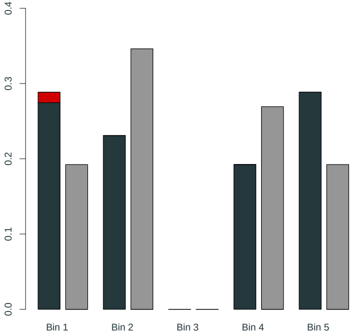

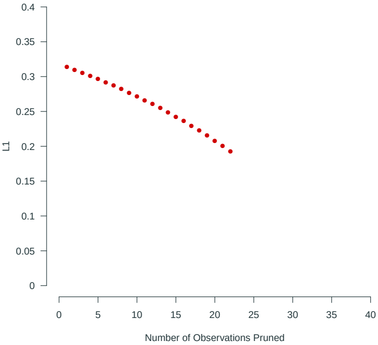

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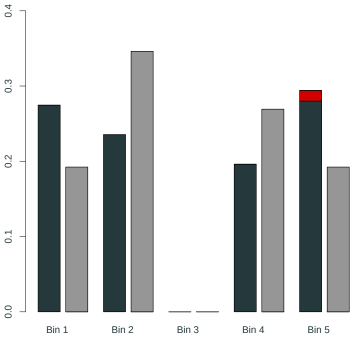

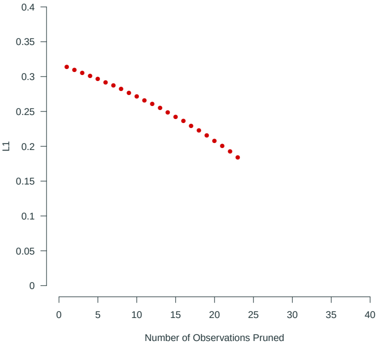

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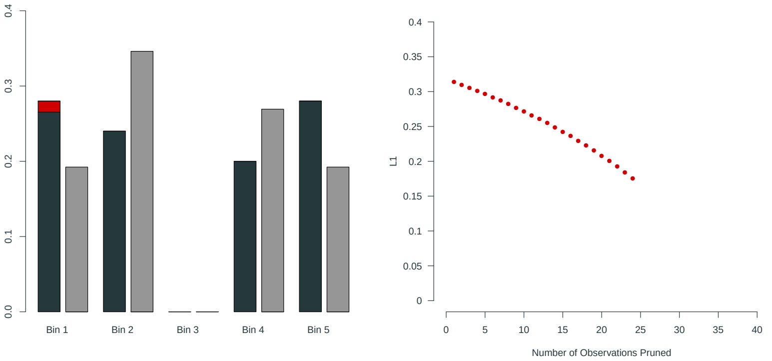

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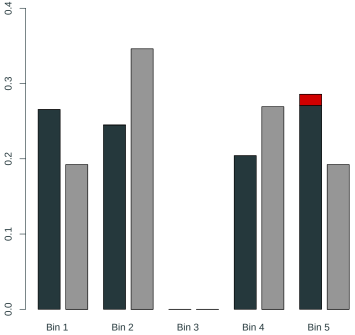

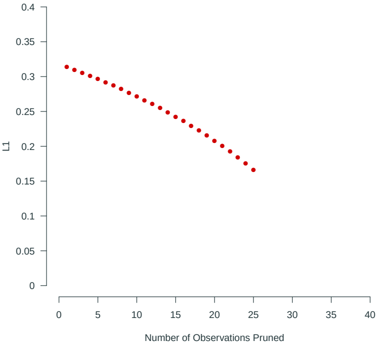

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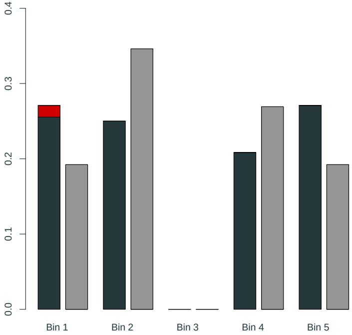

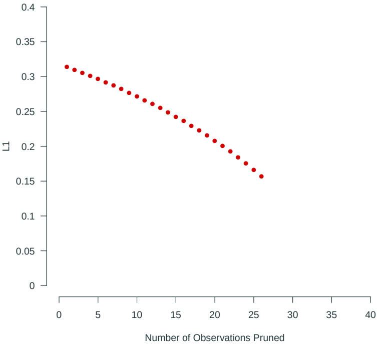

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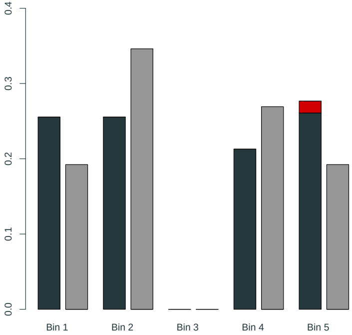

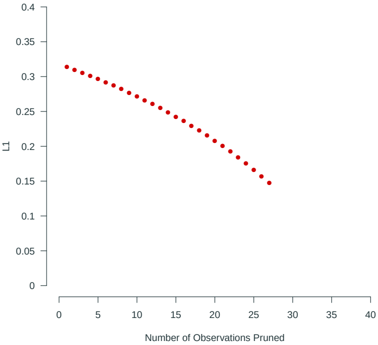

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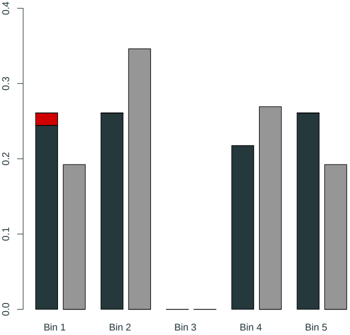

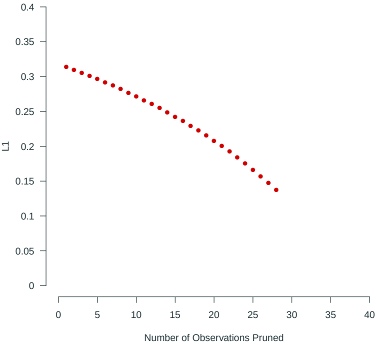

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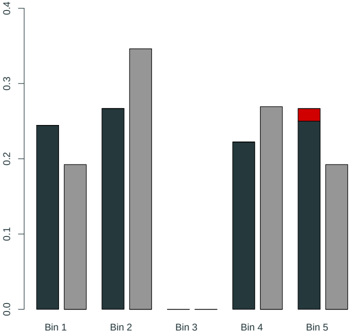

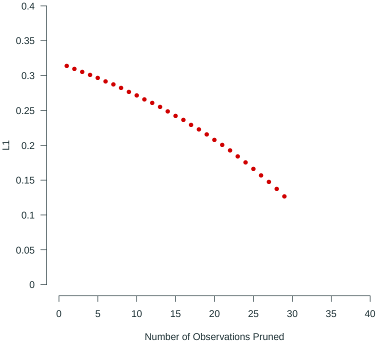

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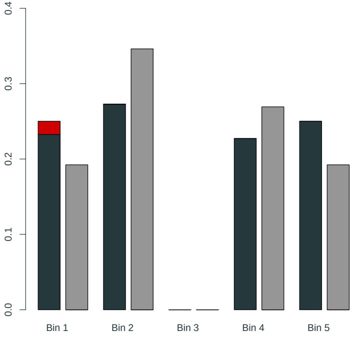

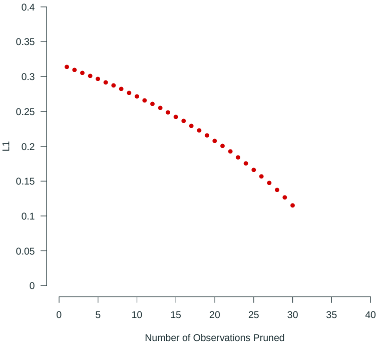

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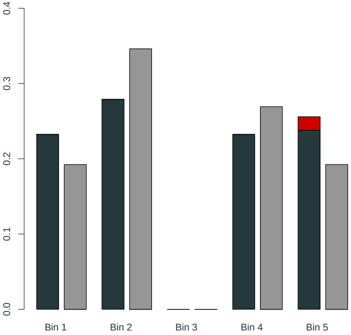

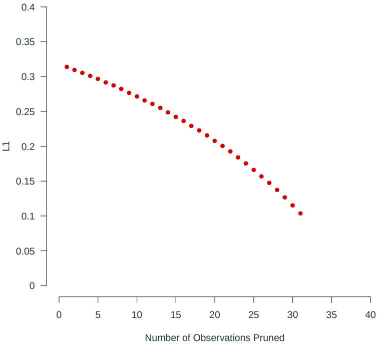

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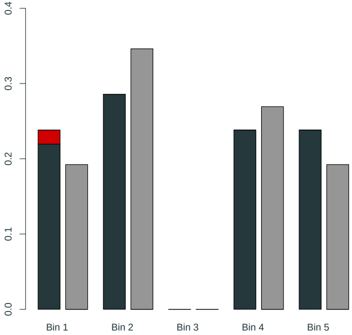

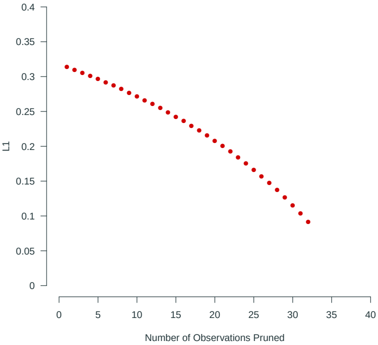

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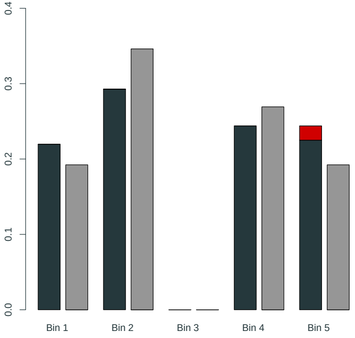

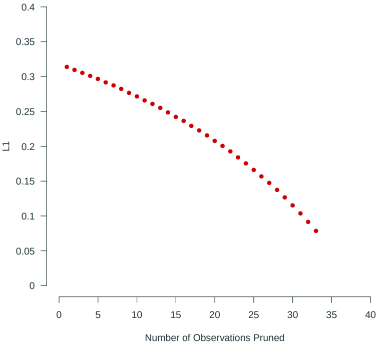

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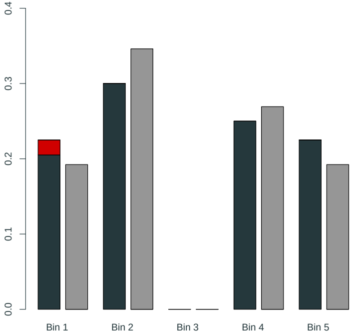

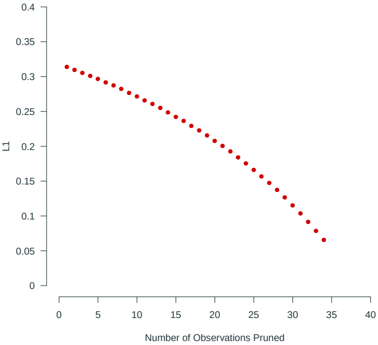

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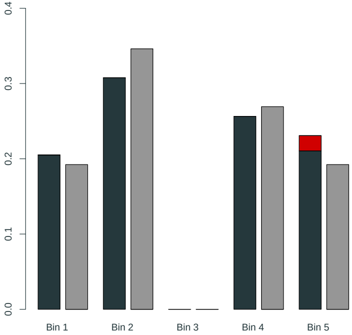

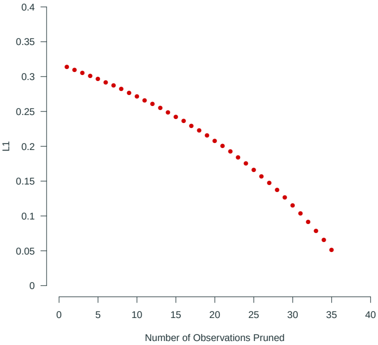

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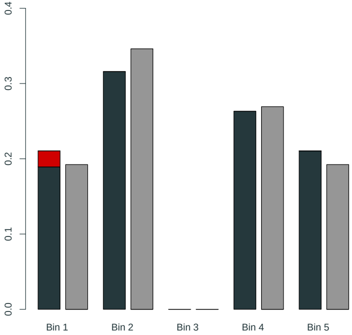

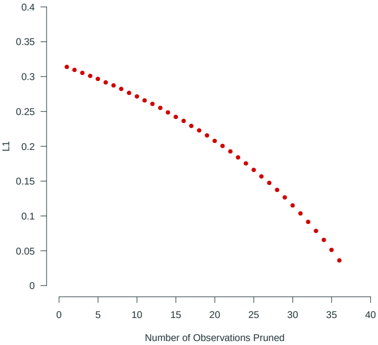

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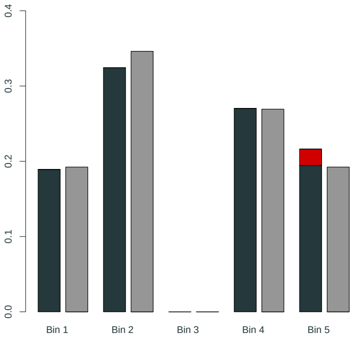

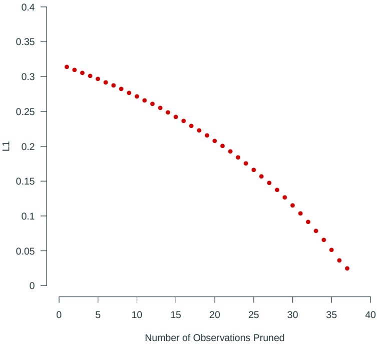

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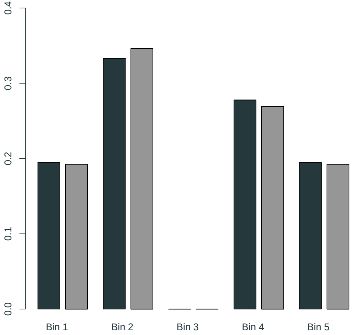

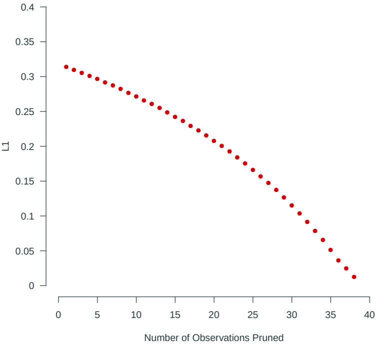

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  - Trying to be invariant to the substance: be wary of methods claiming to be invariant to what you know!

For more information, papers, & software

GaryKing.org

Part 4 (of 3), :-)

Matching Theories of Inference (in one slide)

Assumptions to Justify Current Practice

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Existing Theory of Inference: Stop What You're Doing!

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Alternative Theory of Inference: It's Gonna be OK!

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- Framework: simple random sampling from a population
- Exact matching: Rarely possible; but would make estimation easy
- Assumptions:
  - *Unconfoundedness*: $T \perp Y(0) \mid X$ (Healthy & unhealthy get meds)
  - *Common support*: $\Pr(T = 1|X) < 1$ ($T = 0, 1$ are both possible)
- Approximate matching (bias correction, new variance estimation): common, but all current practices would have to change

Alternative Theory of Inference: It's Gonna be OK!

- Framework: stratified random sampling from a population
- Define A: a stratum in a partition of the product space of X ("continuous" variables have natural breakpoints)
- We already know and use these procedures: Group strong and weak partisans; Don't match college dropout with 1st year grad student
- Assumptions:
  - *Set-wide Unconfoundedness*: $T \perp Y(0) \mid A$
  - *Set-wide Common support*: $\Pr(T = 1|A) < 1$
- Fits all common matching methods & practices; no asymptotics

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- Easy extensions for: multi-level, continuous, & mismeasured treatments; A too wide, n too small