

uniCATE: Flexible Predictive Biomarker Discovery

High-Dimensional Statistics Session, SDSS 2022

Philippe Boileau, UC Berkeley — June 2022

Collaborators

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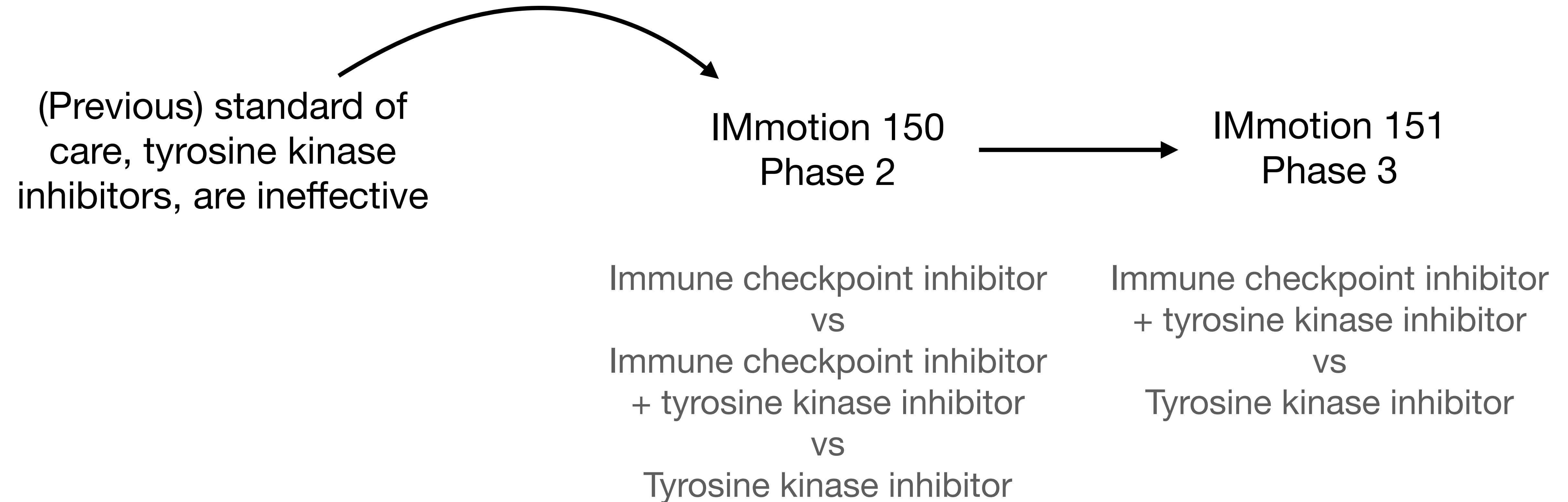
Additional support:

- Zoe June Assaf
- Romain Banchereau

Motivation

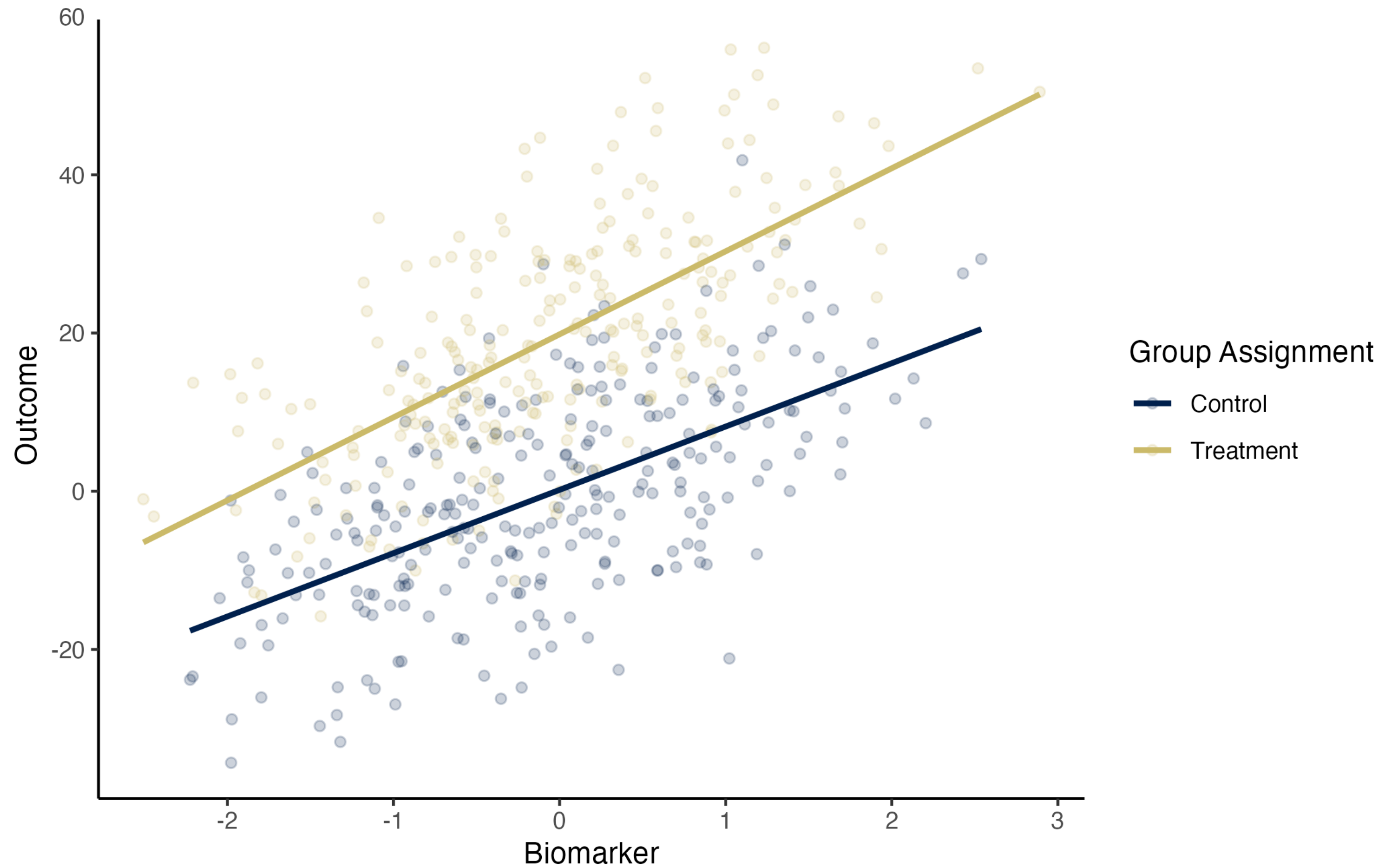
Metastatic Renal Cell Carcinoma

Finding biomarkers predictive of clinical benefit



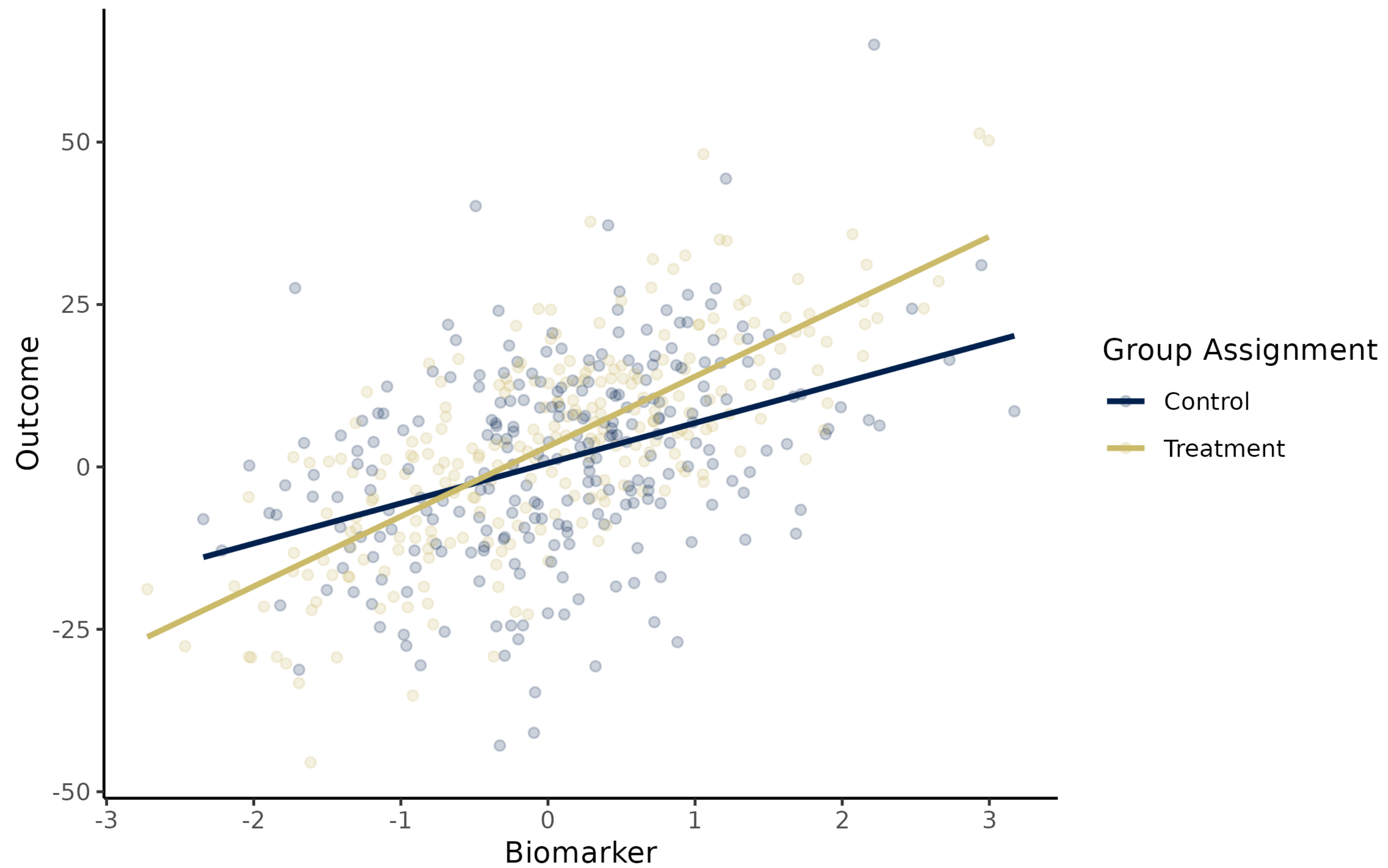
Prognostic Biomarkers

Indicators of outcome, regardless of therapy



Predictive Biomarkers

Treatment effect modifiers



Predictive Biomarker Applications

Predictive biomarkers drive personalized medicine

- **Diagnostic assay development:** Who benefits most from a therapy?
- **Targeted drug discovery:** What is the biological mechanism of a therapy?
- **Refined clinical trials:** Establish a subset of the patient population for which therapy is more efficacious?

Discovering Predictive Biomarkers

Uncovering Predictive Biomarkers

A variable selection problem

- Easy when there are few biomarkers to consider:
 - Linear models with treatment-biomarker interaction terms
 - Conditional average treatment effect (CATE) estimation
- Harder when there are a large number of biomarkers: Penalized versions of the above methods are used.
- **Bottom line:** Discovery of predictive biomarkers is the byproduct of another inference procedure.

Example: Modified Covariates Approach

A method for modeling treatment-biomarker interactions directly

- Tian et al (2014) demonstrated that the treatment-biomarker interactions can be modeled directly through a minor transformation of the outcome.
- In high-dimensions, the interaction coefficients of a linear model are estimated using penalized regression methods, like the LASSO.
- An “augmented” version of the methodology was developed, accounting for prognostic effects. Equivalent to LASSO regression with treatment-biomarker interactions.

Issues with Penalized Regression Methods

Unreliable biomarker selection

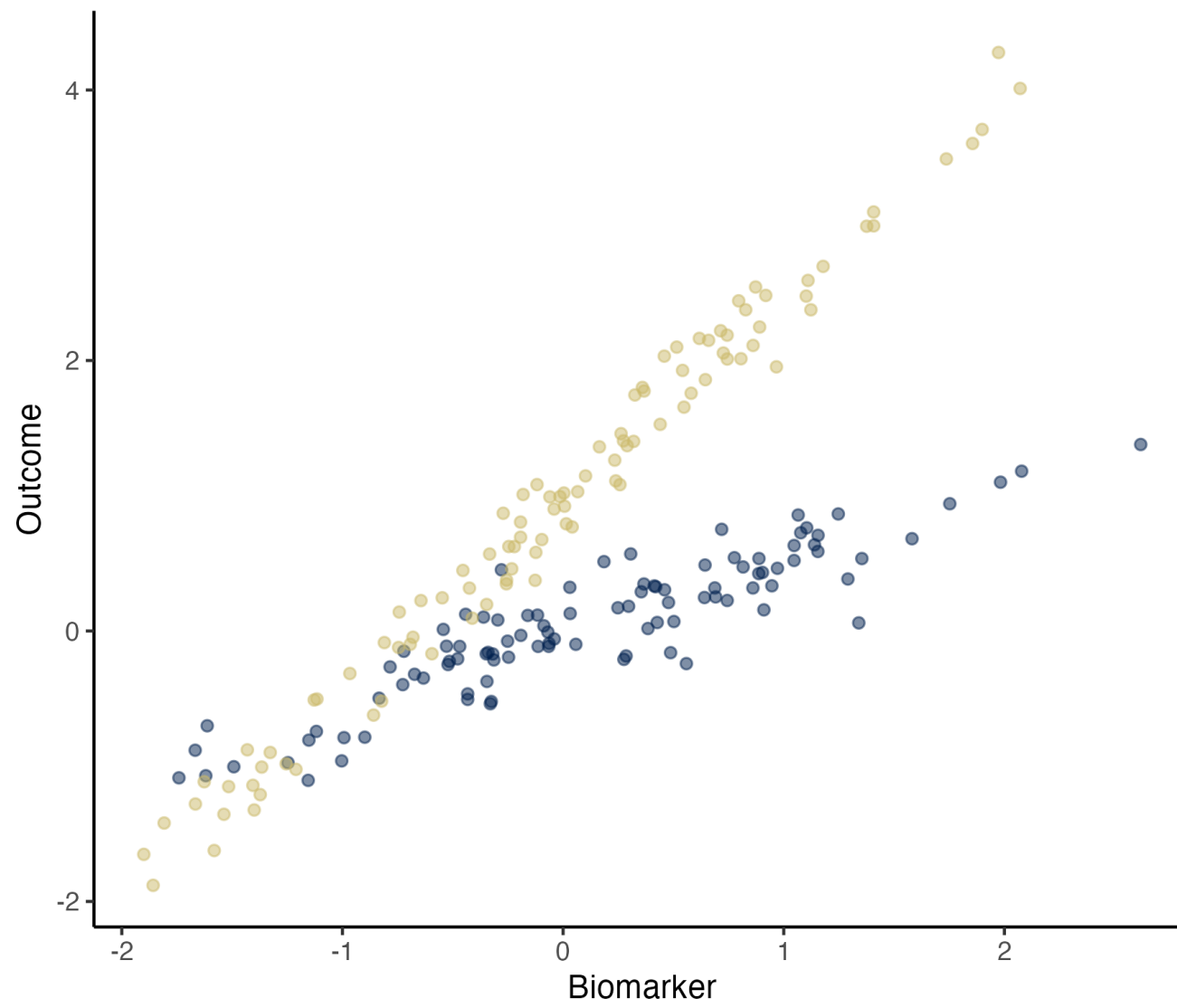
Strong assumptions: sparsity and correlation structure.

Violations produce to high false positive rates, leading to:

- Resources wasted on follow-up experiments and trials
- Decreased signal to noise ratio in diagnostic assays

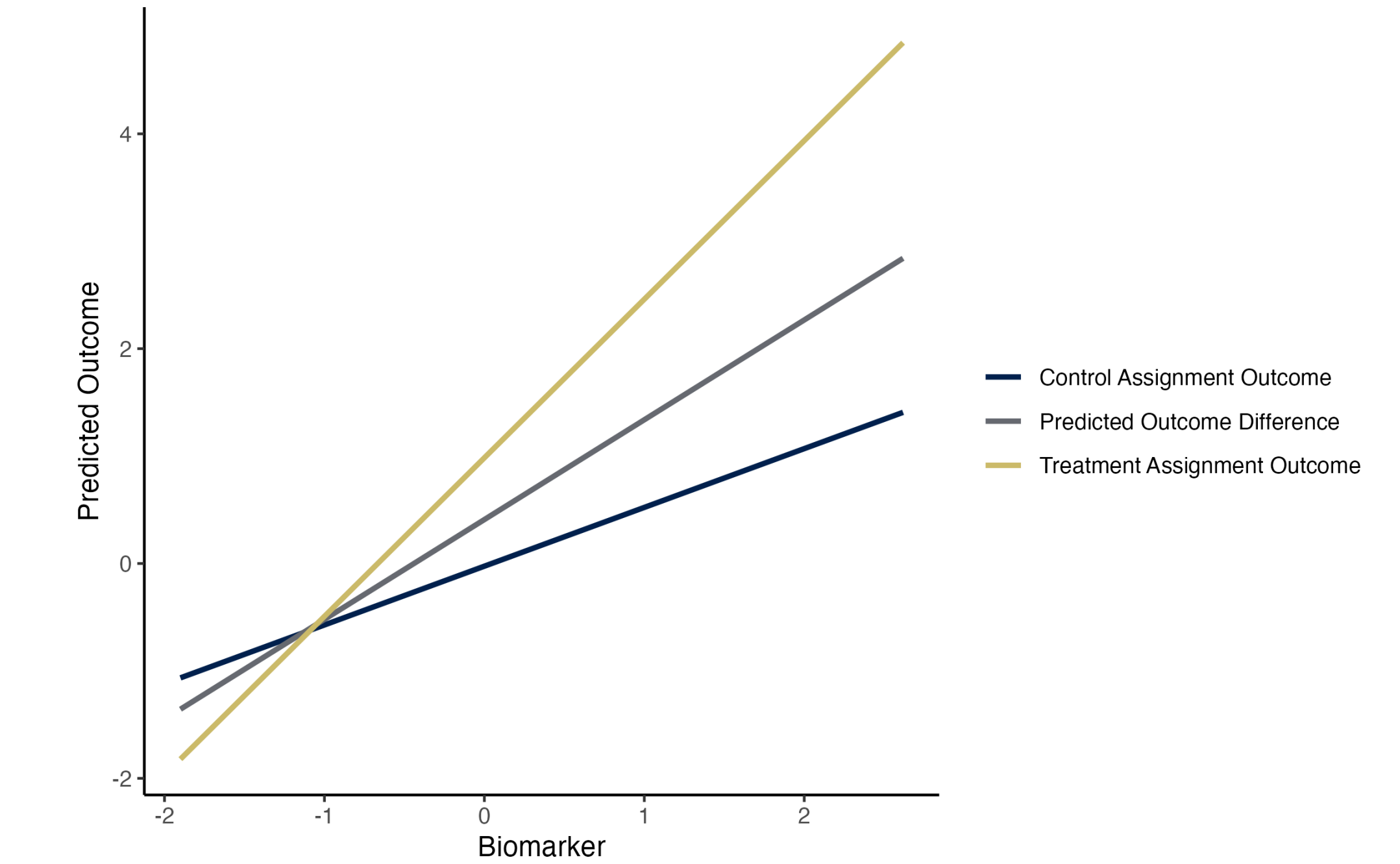
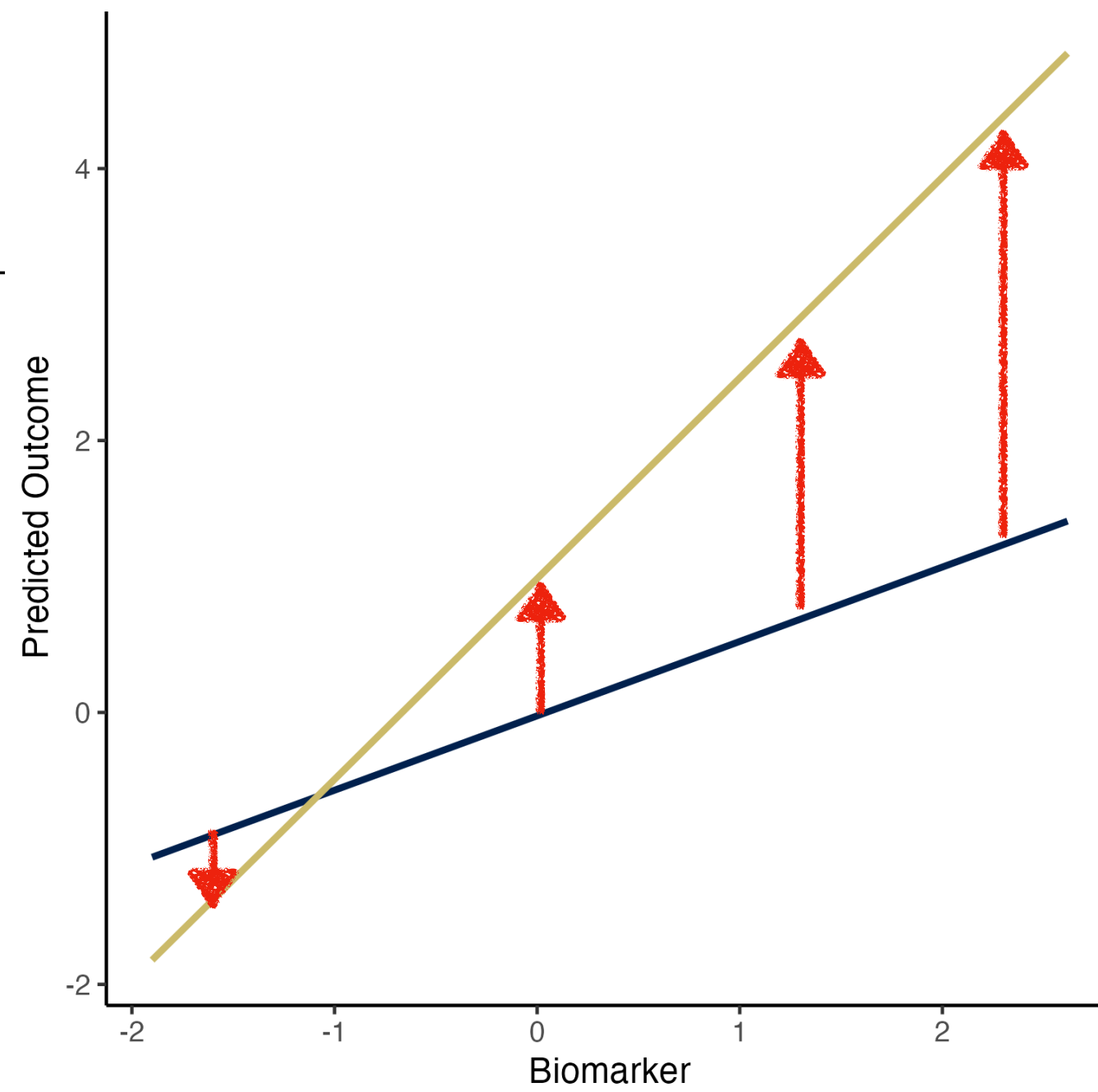
We need to consider alternative problem formulations.

A Dedicated Variable Importance Parameter



Group Assignment

- Control
- Treatment



Control Assignment Outcome

Treatment Assignment Outcome

uniCATE

Assumption-lean estimator of biomarker predictiveness

Estimating this parameter for a **centered** biomarker is easy in a nonparametric model!

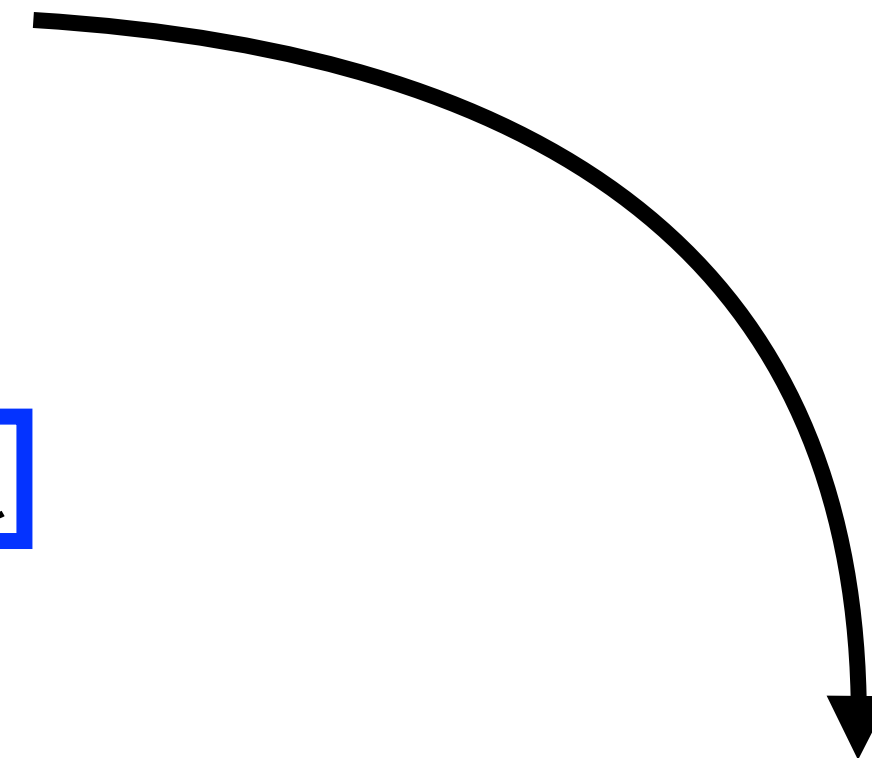
$$\frac{\frac{1}{n} \sum_{i=1}^n (\text{predicted outcome difference}^*)_i (\text{biomarker})_i}{\frac{1}{n} \sum_{i=1}^n (\text{biomarker})_i^2}$$

This estimator is **asymptotically linear**. The only assumption in an RCT: the biomarker has non-zero variance.

uniCATE in Action

uniCATE ranks biomarkers based on predictiveness

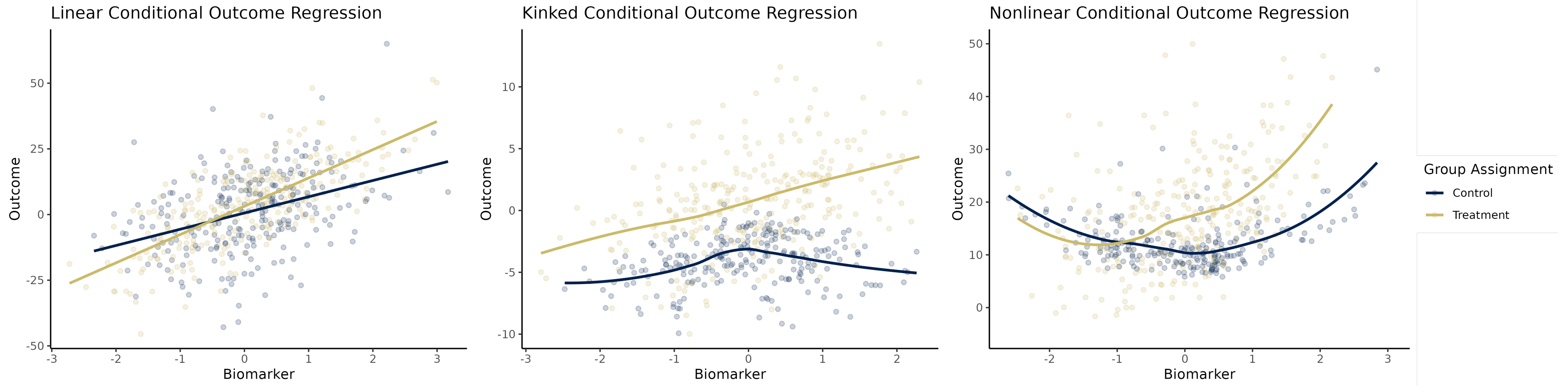
```
n ← 200  
biomarker_1 ← rnorm(n, mean = 0, sd = 1)  
biomarker_2 ← rnorm(n, mean = 0, sd = 1)  
biomarker_3 ← rnorm(n, mean = 0, sd = 1)  
biomarker_4 ← rnorm(n, mean = 0, sd = 1)  
covariate ← rbinom(n, 1, 0.4)  
treatment ← rbinom(n, 1, 0.5)  
response ← covar + 1 * biomarker_1 * treatment  
+ 2 * biomarker_2 * treatment
```



| | Est. | SE | Z-score | P | P (BH) |
|-------------|-------------|-----------|----------------|----------|---------------|
| biomarker_2 | 1.90 | 0.0768 | 24.7 | 3.58E-13 | 1.43E-13 |
| biomarker_1 | 0.820 | 0.129 | 6.38 | 1.75E-10 | 3.51E-10 |
| biomarker_3 | 0.0482 | 0.145 | 0.333 | 7.39E-01 | 9.03E-01 |
| biomarker_4 | -0.0202 | 0.166 | -0.122 | 9.03E-01 | 9.03E-01 |

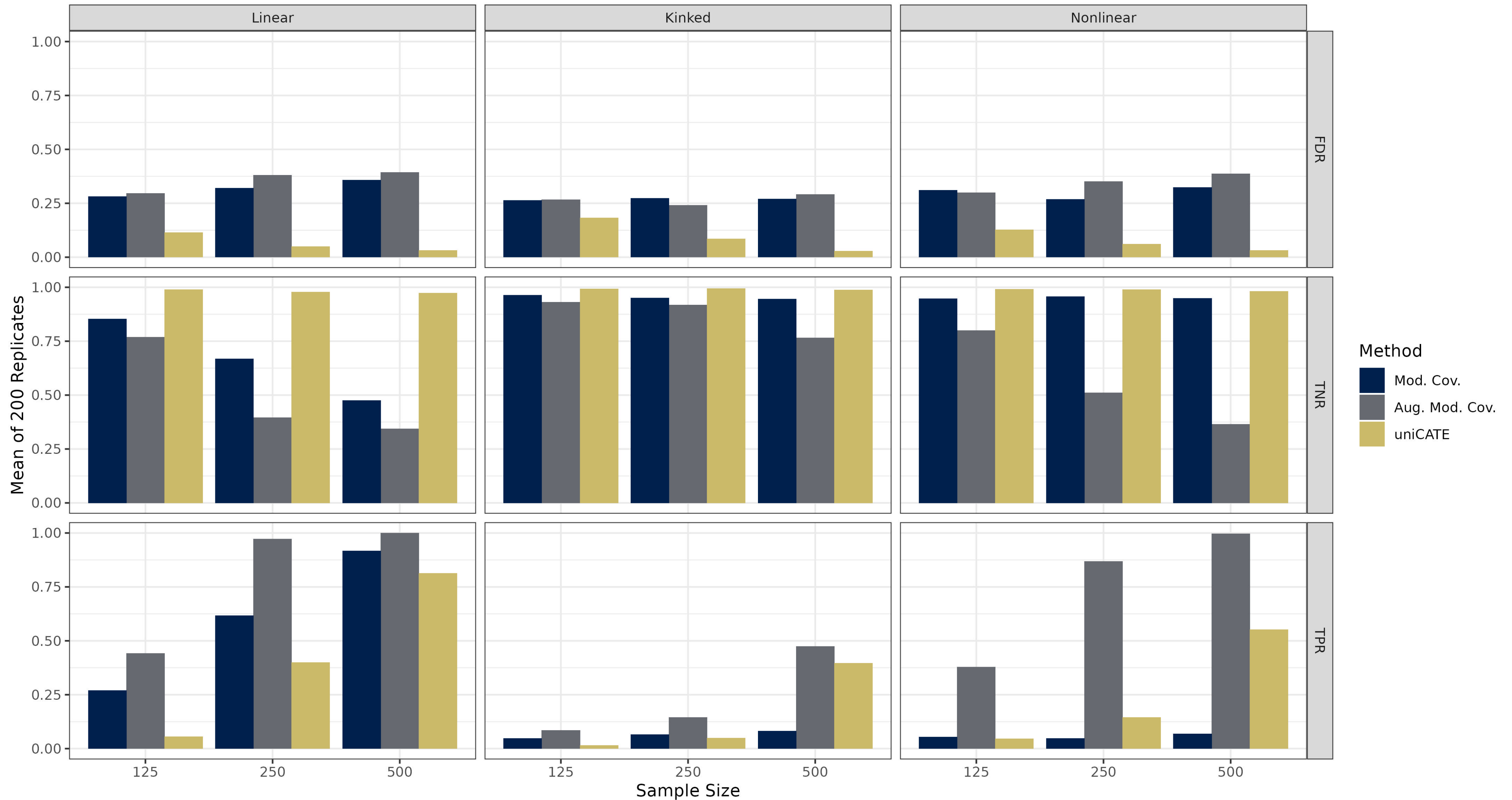
Simulation Studies

Considered Biomarker-Outcome Relationships



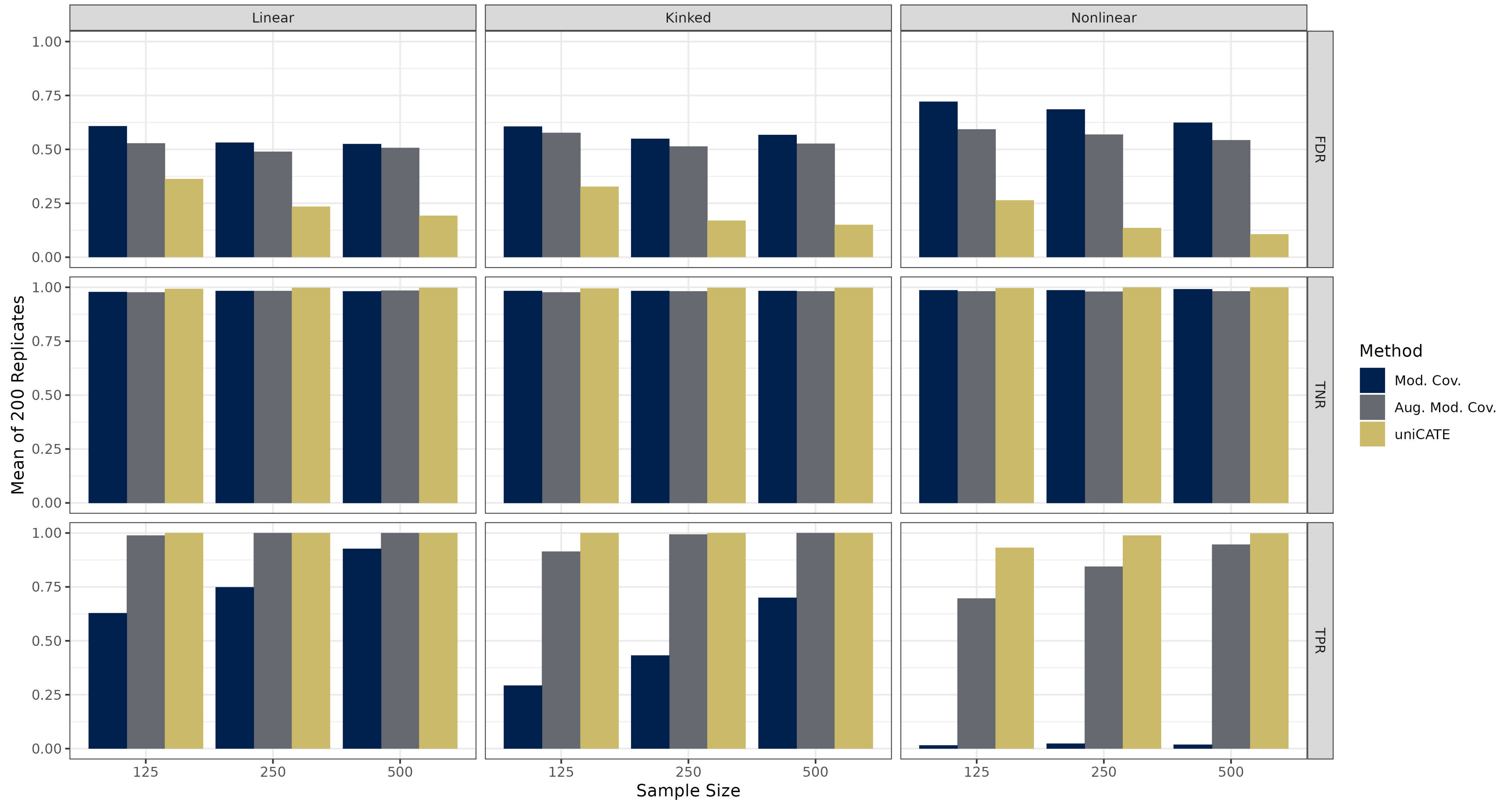
uniCATE Controls False Positive Rates

Classification of Non-Sparse, Moderate-Dimensional, and Uncorrelated Predictive Biomarkers



uniCATE *Still* Controls False Positive Rates

Classification of Sparse, High-Dimensional, and Correlated Predictive Biomarkers



Application to IMmotion 150/151

Application to IMmotion 150

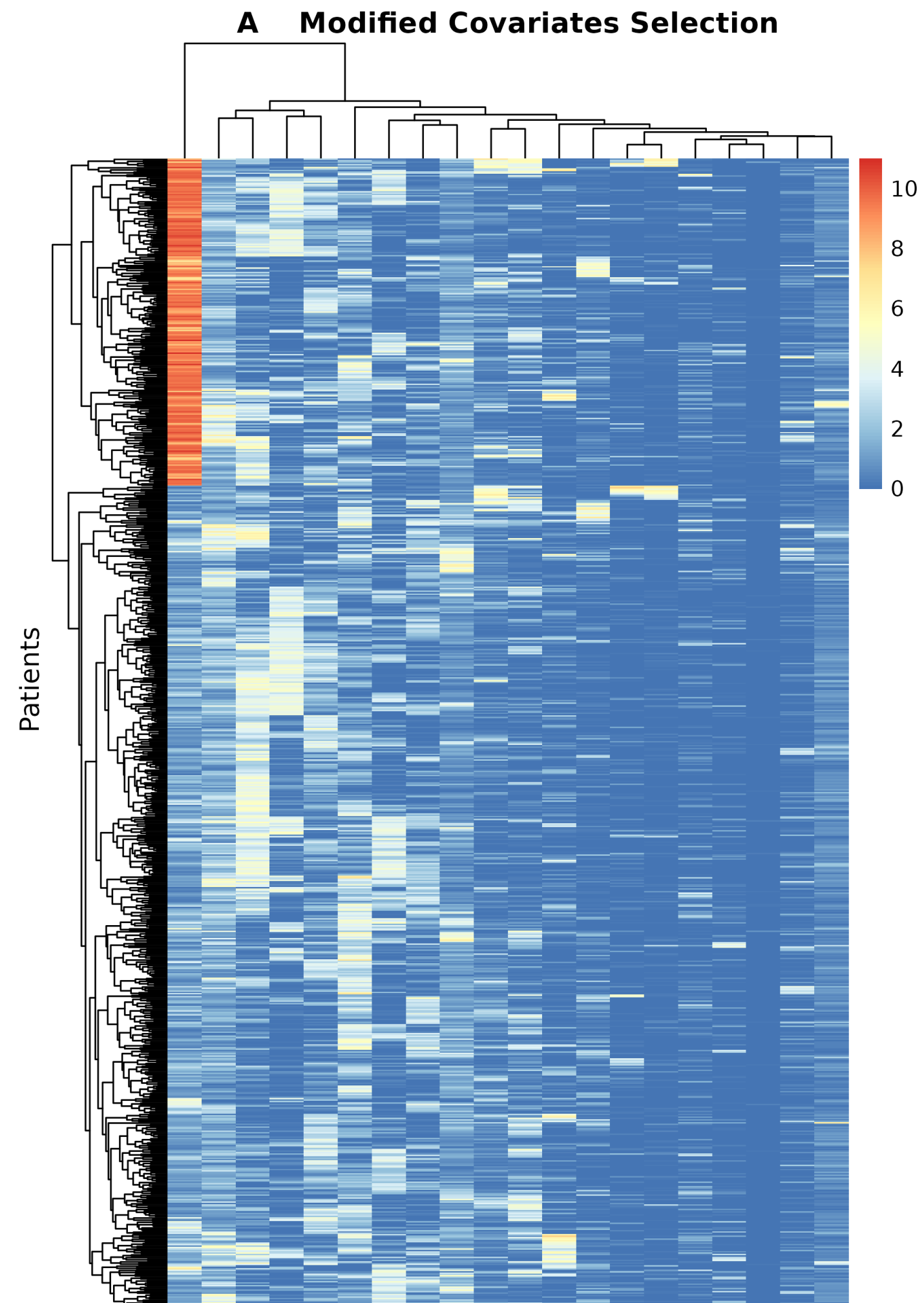
uniCATE's results align with recent findings in nivolumab

1. Only patients with tumor RNA-seq data in the sunitinib (n=71) and atezolizumab + bevacizumab (n=77) arms were considered.
2. Selected the 500 most variable, log-transformed genes as biomarkers.
3. Objective response was used as the response variable.

92 genes were identified as predictive using a 5% FDR cutoff. They are associated with immune responses, including those mediated by B cells and lymphocytes.

Validation on IMmotion 151

uniCATE identifies meaningful predictive biomarkers



Conclusion

- uniCATE is an assumption-lean inference procedure that controls the rate of false positive predictive biomarkers in high dimensional RCTs.
- Check out uniCATE's implementation in the uniCATE R package, available at github.com/insightengineering/uniCATE

Questions?

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