

# Interpretable Statistical Learning Methods

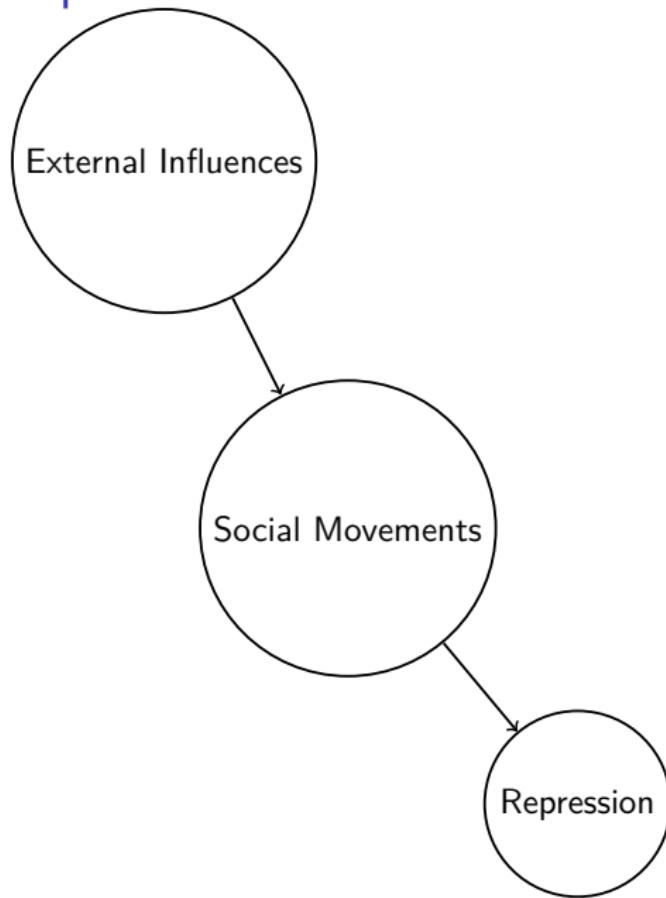
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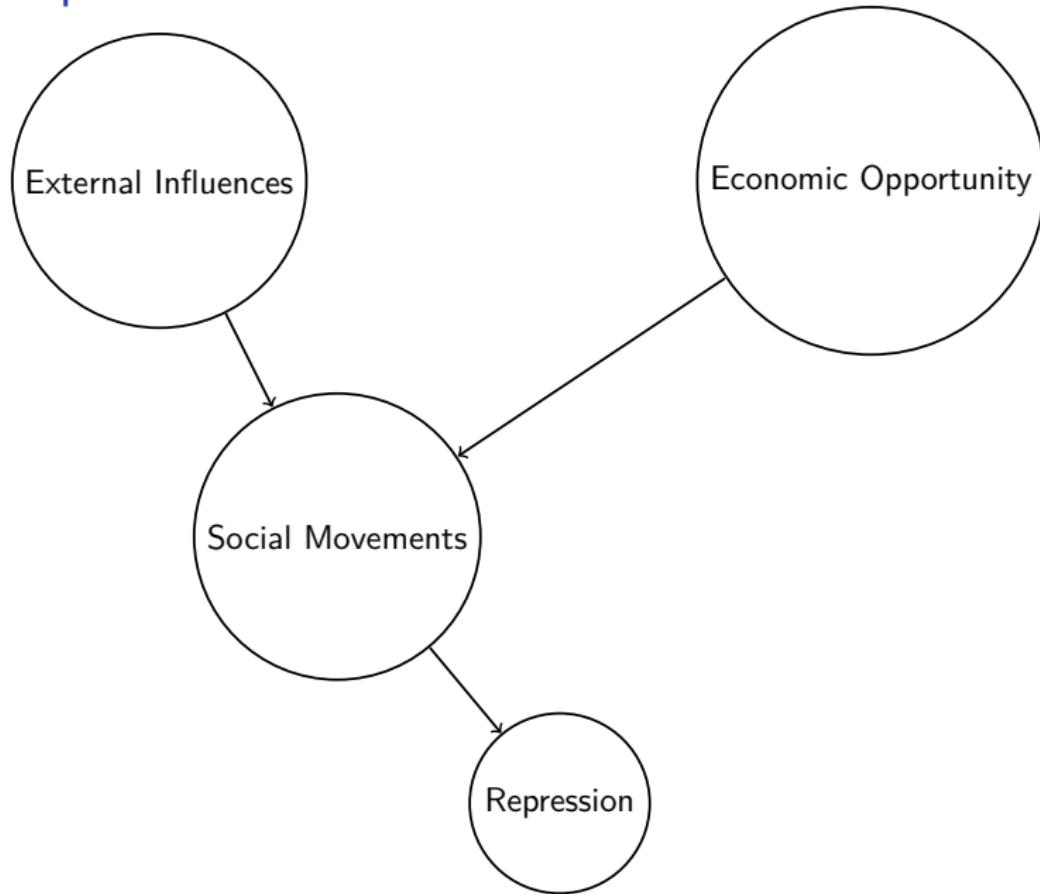
# Introduction

- statistical learning  $\approx$  flexible generalization of regression
  - ▶ learns interactions, nonlinearities, without prespecification
  - ▶ not generally interpretable
- my contribution: methods for making statistical learning methods usable in political science
  - ▶ implemented in easy-to-use software
  - ▶ empirical applications

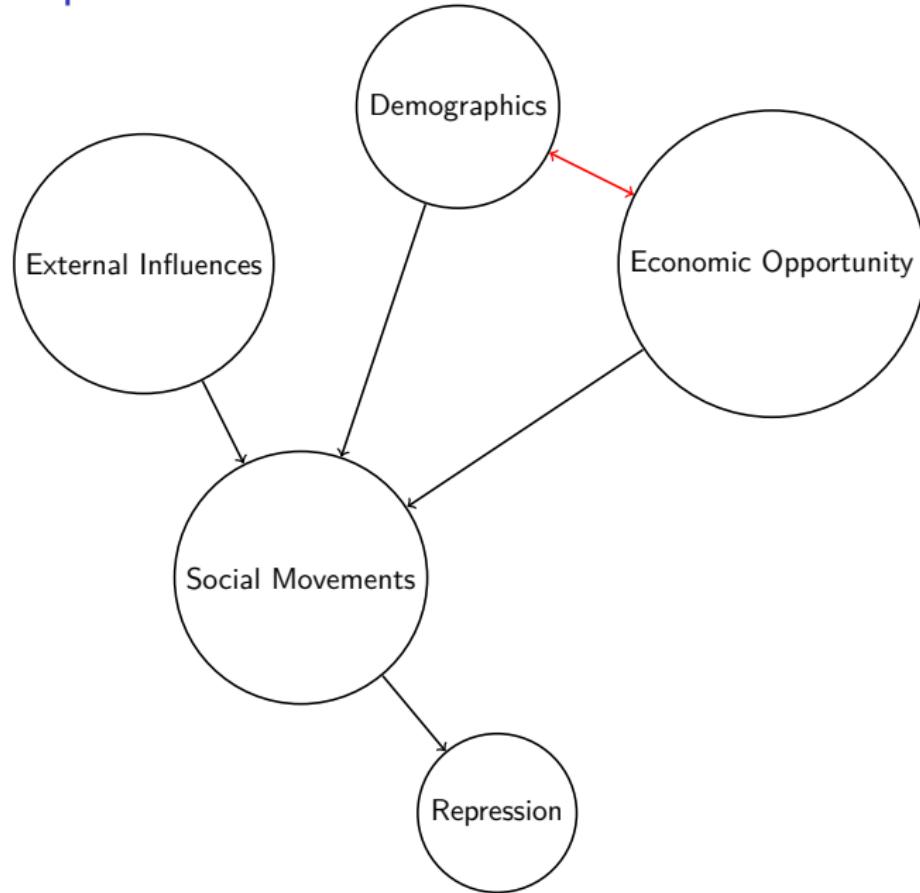
# Repression



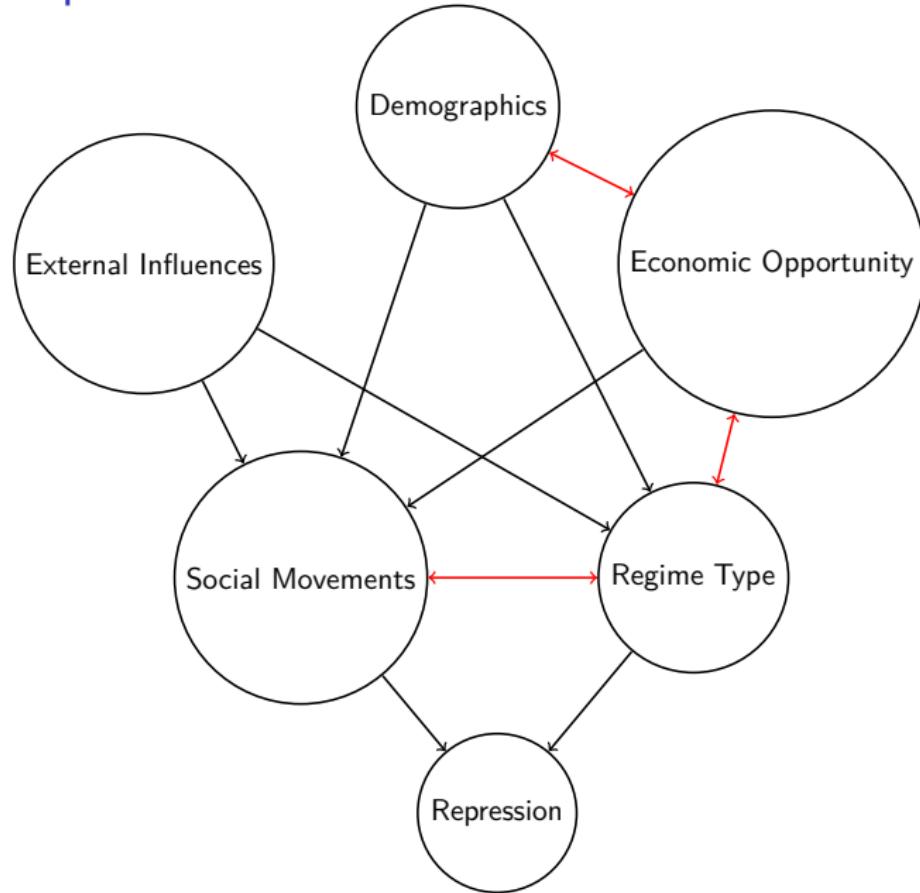
# Repression



# Repression



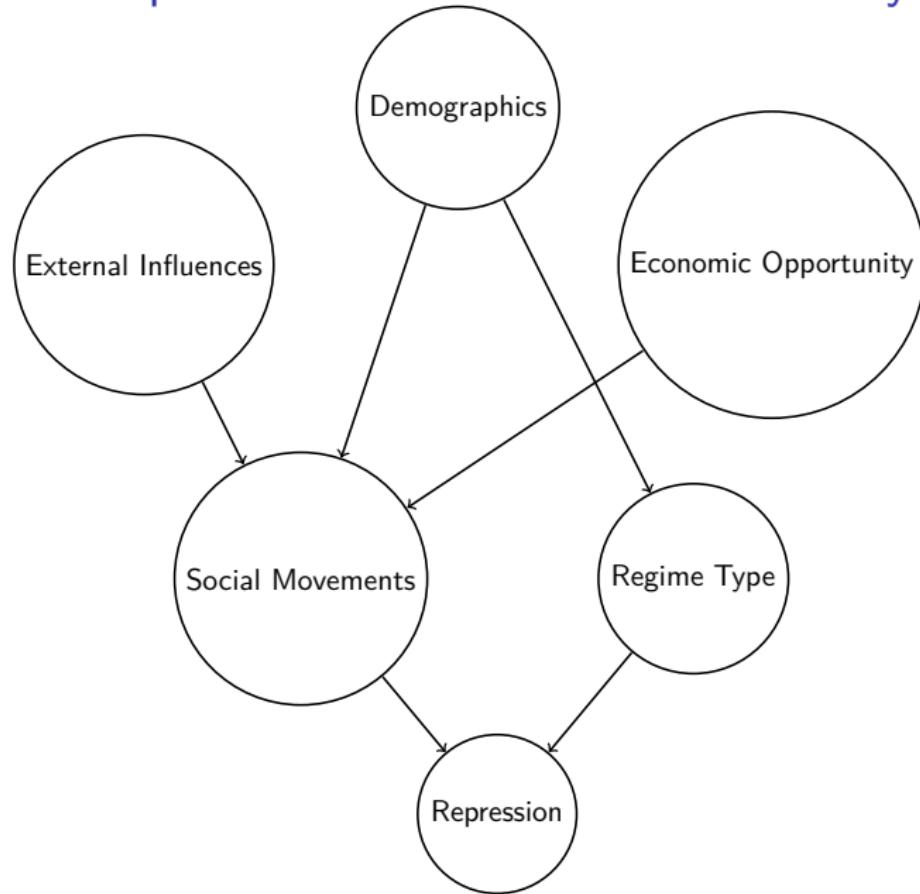
# Repression



# Conventional Data Analysis in the Social Sciences

- linear models and generalizations thereof are most common
- substantive interpretation is the focus

# Assumptions of Conventional Data Analysis



# Problems with Conventional Data Analysis

- functional form assumptions often not implied by theory
- robustness check = informal specification search

# Statistical Learning Methods

machine learning with statistical properties

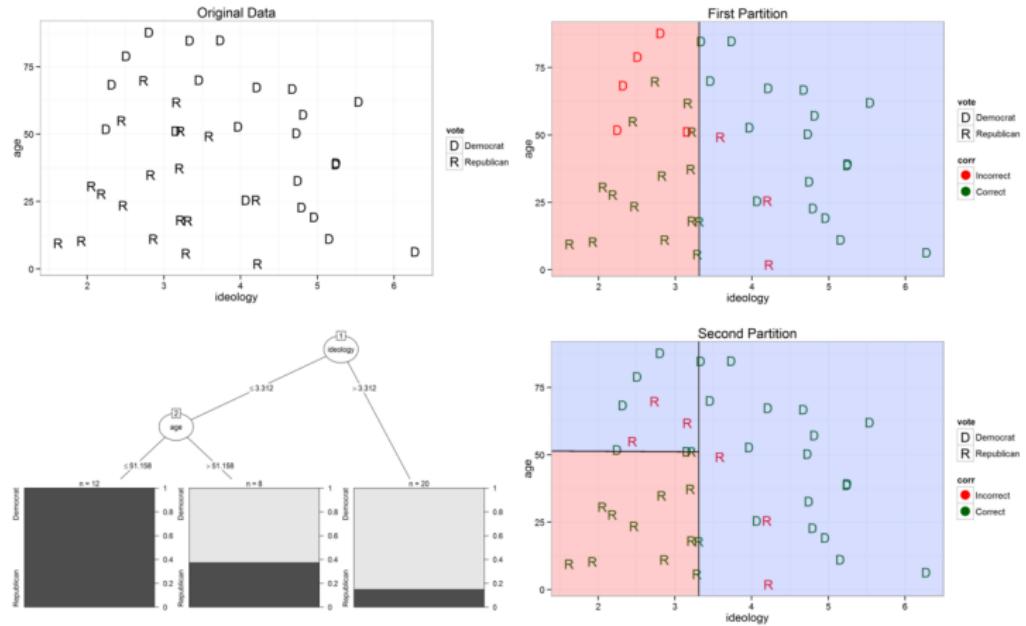
- developed with a focus on model generalizability
- few limits on functional form

## Definitions

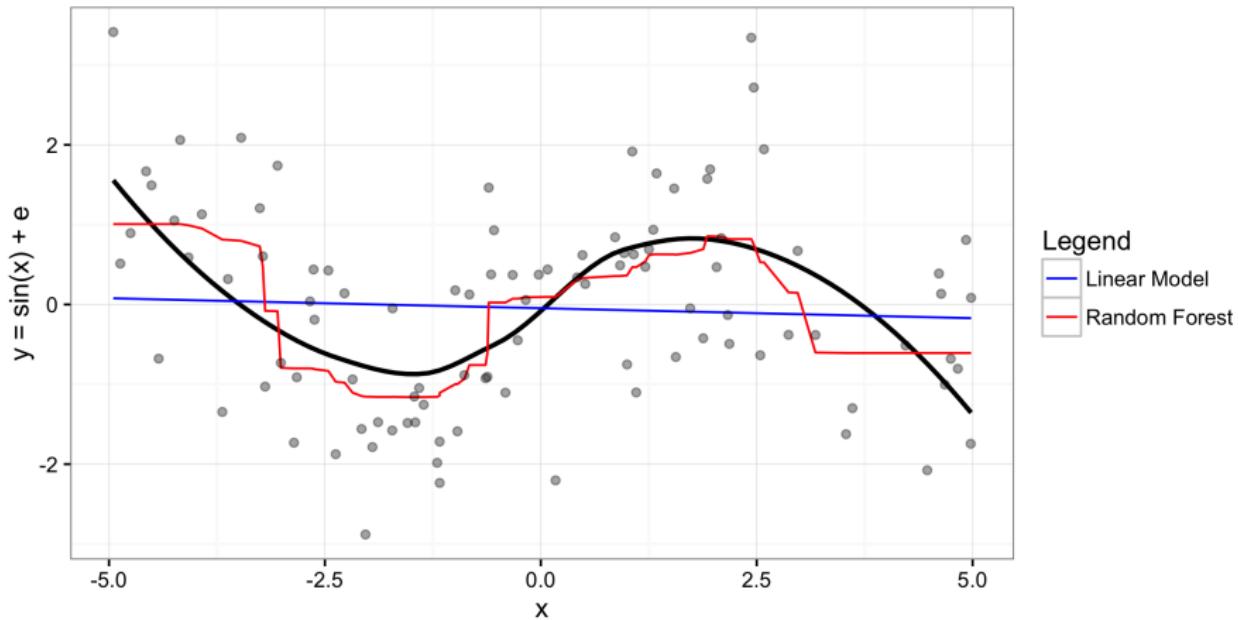
**conventional** methods have a finite, fixed number of parameters

**statistical learning** methods have a data-adaptive number of parameters

# Decision Trees



# Conventional versus Statistical Learning Methods



# Why Don't We Use Statistical Learning Methods to Analyze Our Data?

interpretability!

solved by my software

# Interpreting Models

- interpretation is how we test theory
- interpretability  $\approx$  simplicity
- simplicity is inappropriate if the data are generated by a complex process

Minimize the cost of interpretability!

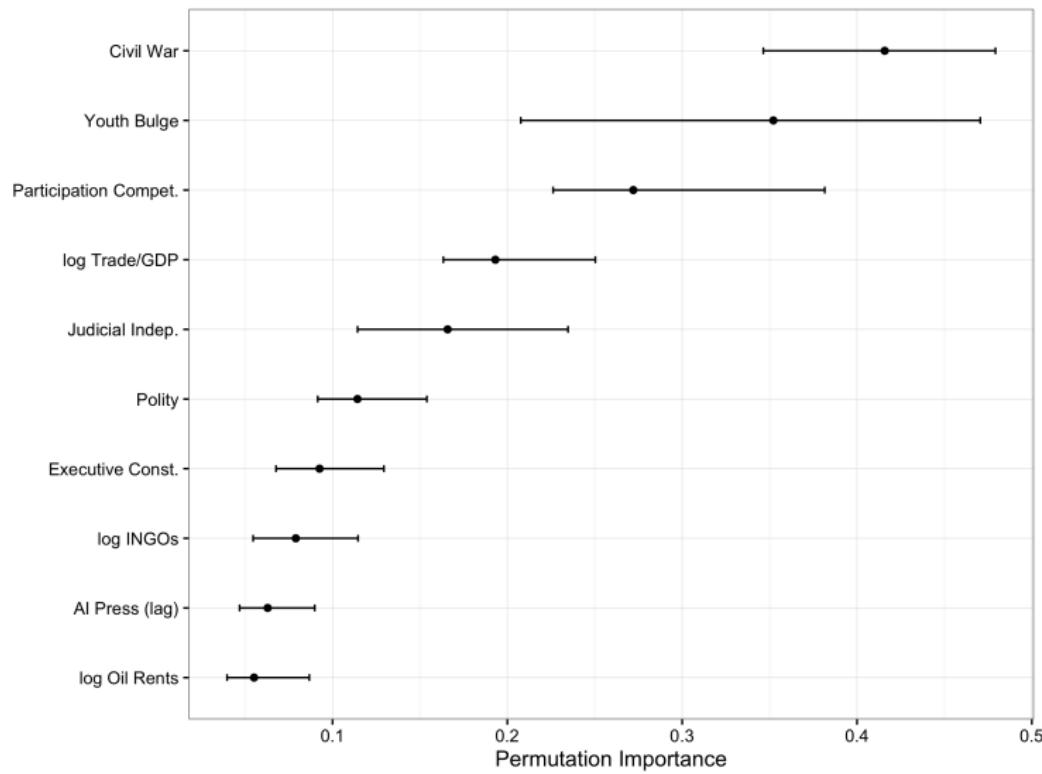
# Components of Model Interpretation

component	conventional	statistical learning
size	$ \beta $	permutation importance
shape	sign of $\beta$ or marginal effect	partial dependence
variability	prespecified	interaction detection
reliability	standard error, CI	extrapolation, variance

## Permutation Importance

- identifies covariates important for variation in predictions
- randomly shuffling covariates makes them useless to the model (if they are important)

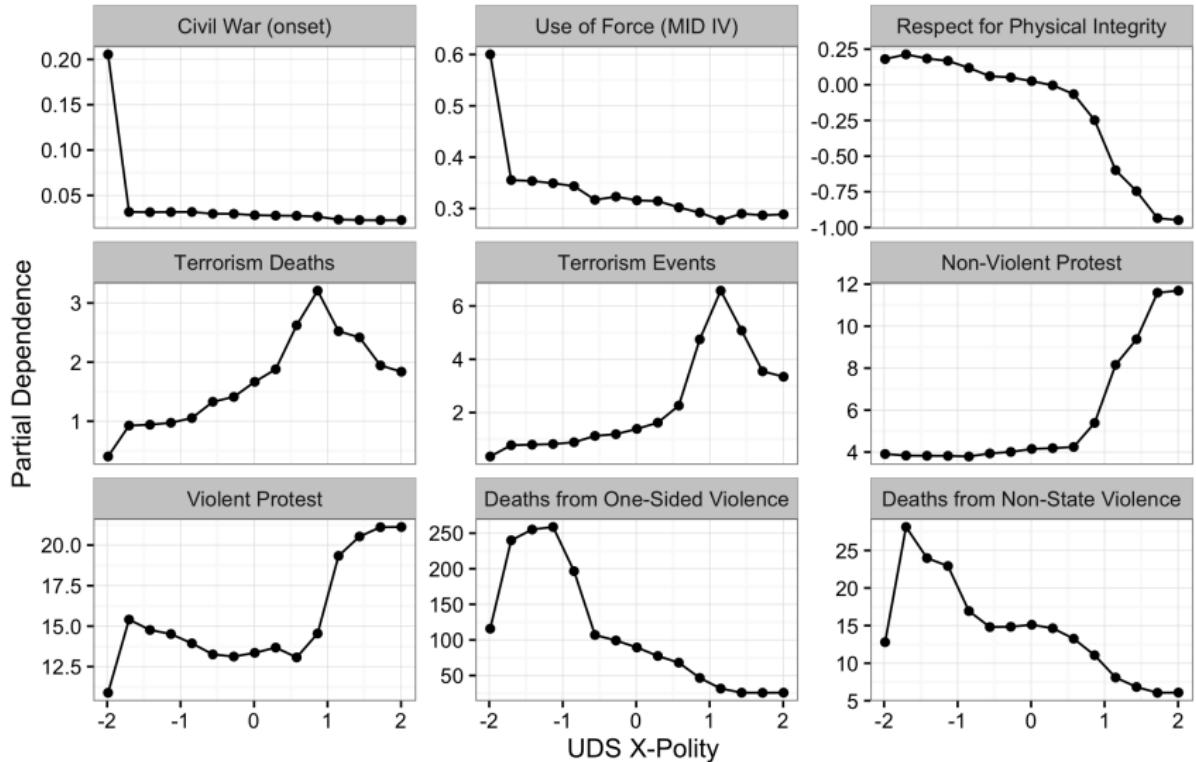
# Permutation Importance (Hill and Jones 2014)



## Partial Dependence (Friedman 2001)

- Monte-Carlo method for estimating how a model depends on a subset of the covariates
- similar to marginal effects

# Partial Dependence (Jones and Lupu 2016)



# Software

- using interpretable statistical learning methods requires substantial time, programming skill
  - ▶ using statistical learning methods well
  - ▶ implementing interpretation methods
- two easy-to-use packages in R
  - ▶ **M**achine **L**earning with **R** (`mlr`)
  - ▶ **E**xploratory **D**ata **A**nalysis using **R**andom **F**orests (`edarf`)

## Future Research

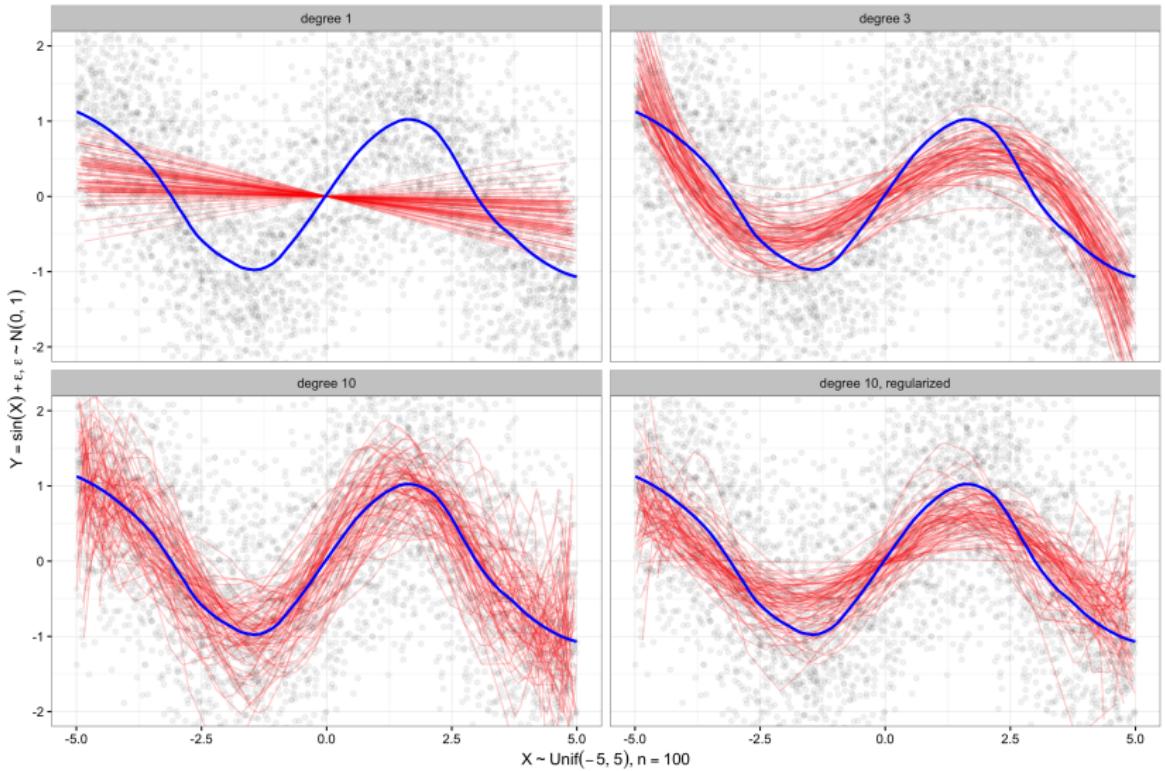
- further methodological development
  - ▶ enhancements
  - ▶ statistical properties
  - ▶ faster (bigger data)
- applications! collaboration!

# Conclusion

- statistical learning methods can replace or be used as a robustness check for conventional methods
- try out my software!
- more information at [zmjones.com/hire\\_me](http://zmjones.com/hire_me)

Thanks!

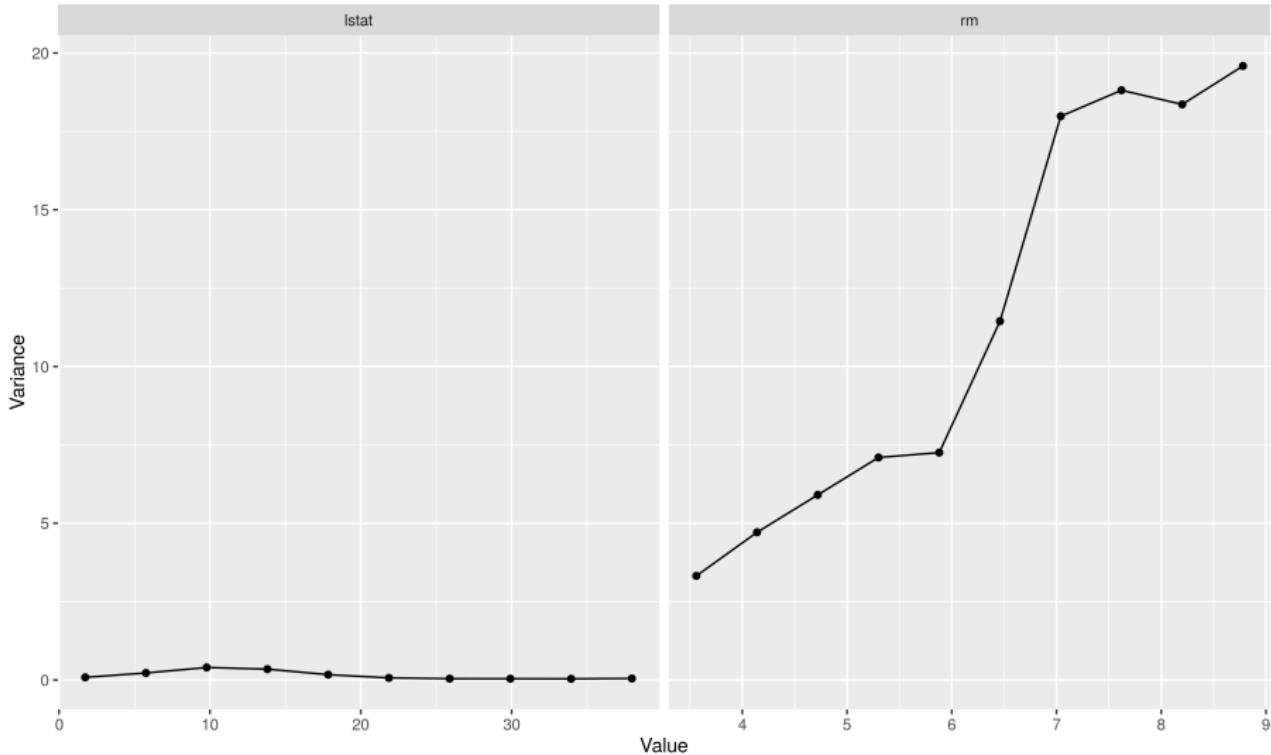
# The Bias/Variance Tradeoff



# Partial Dependence

$$\hat{f}_u(x_u) = \frac{1}{n} \sum_{i=1}^n \hat{f}(x_u, x_{-u,i})$$

# Variations on Partial Dependence (Goldstein et. al., 2015)



# Functional ANOVA

$$f(x) = f_0 + \sum_{i=1}^p f_i(x_i) + \sum_{i \neq j} f_{ij}(x_{ij}) + \dots$$

$$f_u(x) = \int_{x_{-u}} \left( f(x) - \sum_{v \subset u} f_v(x) \right) dx_{-u}$$

# Extrapolation

- Behavior of models at points far from the sample data is variable.
- Different models behave differently far from the data.

# Methods for Detecting Extrapolation

- joint density estimation
- data depth
- anomaly/outlier detection

# Weighted Functional ANOVA (Hooker 2012)

$$f_u(x) = \int_{x-u} \left( f(x) - \sum_{v \subset u} f_v(x) \right) w(x) dx_{-u}$$

# Weighted Functional ANOVA

