Social Science Inquiry II
Week 9: Beyond linear regression

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Loading packages for this class

```
> set.seed(60637)
> library(ggplot2)
```

- Housekeeping

Machine learning

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- A body of *algorithmic* methods . . . (an algorithm is just a recipe)
- Somehow part of *artificial intelligence*. . . (basically, how computers perform tasks)
- In general, a flexible, *data-driven* approach to make predictions, classify data, or take decisions.

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  - e.g., is this a picture of banana or a cat? Will this person be more likely to click on an ad for sneakers or cookware?
- Is there overlap between the two?

Model fit vs. prediction

- In linear regression, propose a model:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \cdots + \hat{\beta}_K X_{Ki}$$

- Select $\hat{\beta}_0 \ldots \hat{\beta}_K$ to minimize

$$\sum_{i=1}^{N} \hat{\varepsilon_i}^2 = \sum_{i=1}^{N} \left(\hat{Y}_i - Y_i \right)^2$$

Model fit vs. prediction

- For prediction tasks, we could use the same model,

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \cdots + \hat{\beta}_K X_{Ki}$$

- But select $\hat{\beta}_0 \ldots \hat{\beta}_K$ to minimize squared prediction error for the next observation:

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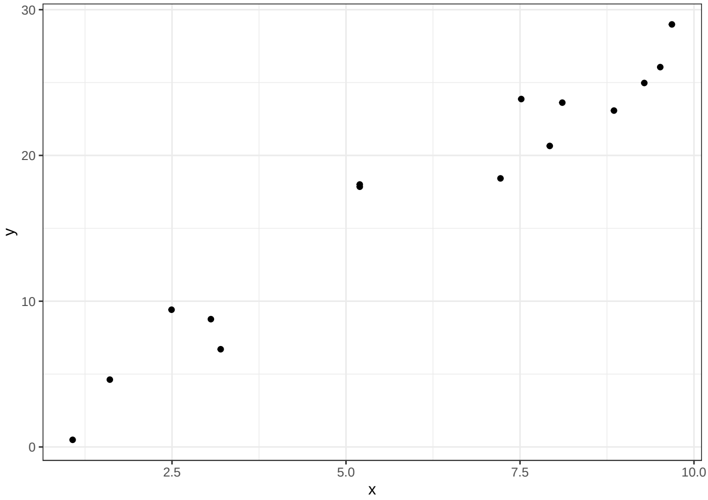
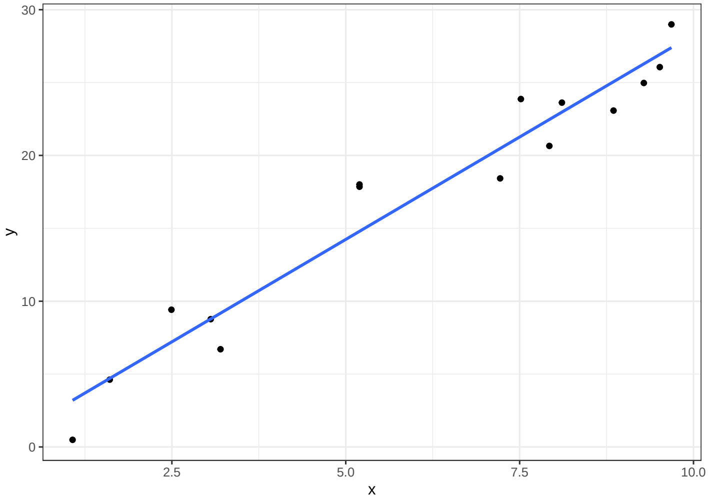
Some ML tools

- A major concern of ML: *overfit*
  - If your model fits the data *too* perfectly, it's not useful for prediction

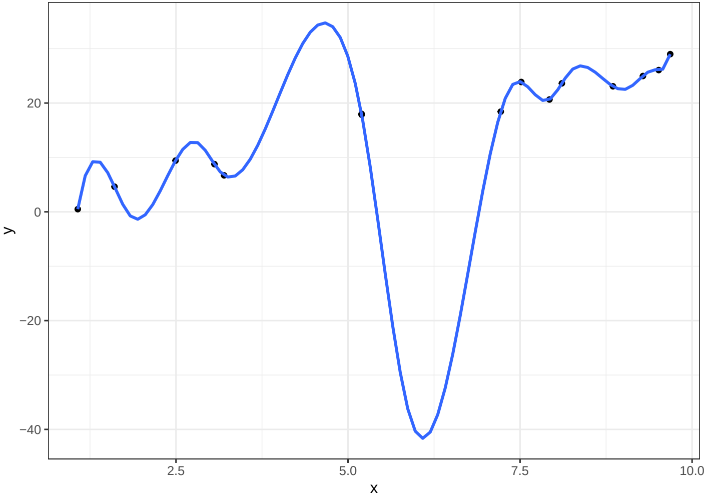
Suppose we would like to fit a model to the following data:



We could use a single line:



Or we could fit a curve that goes between every point:



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- ML methods propose a way to check this, by separating data into training and test sets.
- You can fit different models on the training set, and then see which one does the best job of predicting response in the test set. (This is not a new idea.)
- There are some different ways to do this:
  - Leave-k-out
  - Leave-one-out
  - k-fold cross validation

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- What should the expectation be taken over? Can/should we hold the data we used for fitting the model fixed?

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- We may be interested in $\mathrm{Err}_{\mathcal{T}}$, in practice most estimating methods will give us estimates of Err.

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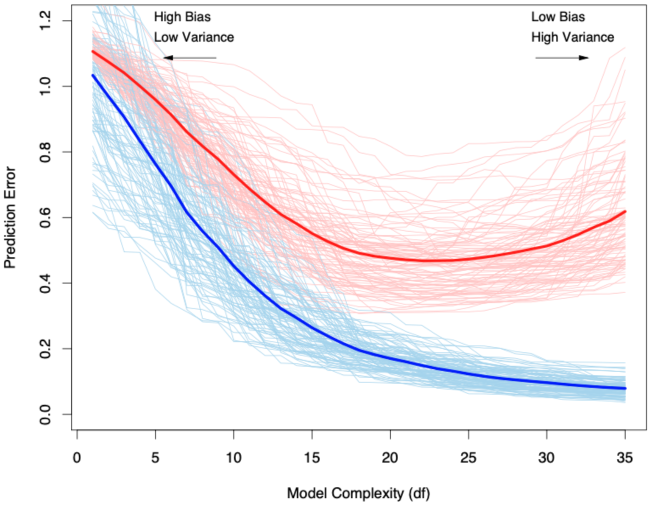

Hastie et al. (2009)

Blue is in-sample error, red is out-of-sample error.

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- We may want to use expected test error to **select among models**, or versions of models.
- And, once we have selected a version of a model, we may want to **assess** how a selected model performs.

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- We can't measure expected test error directly.

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- Why do we need to estimate the prediction error of the selected model *again*? Winner's curse.

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- We can potentially get more out of our data by cross-validating.

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Version 2	Training	Training	Training	Validation	Training
Version 3	Training	Training	Validation	Training	Training
Version 4	Training	Validation	Training	Training	Training
Version 5	Validation	Training	Training	Training	Training

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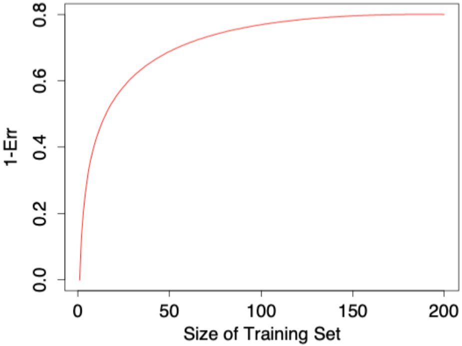

Hastie et al. (2009)

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- Rule of thumb is often 5 or 10.

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- This is a common problem when we think about an industry setting, where for every customer a business might have a large number of measurements. Which ones should they use to predict an outcome?

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- With regularization, we shrink some of the $\hat{\beta}_k$ nearly all the way or all the way to zero.
- For *ridge regression* or *lasso*, we select the $\hat{\beta}_k$ using:

$$\underset{\boldsymbol{\beta}}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \left(Y_i - \beta_0 + \sum_{k=1}^{K} X_{ki} \beta_k \right)^2 + \lambda \sum_{k=1}^{K} |\beta_k|^q \right\}$$

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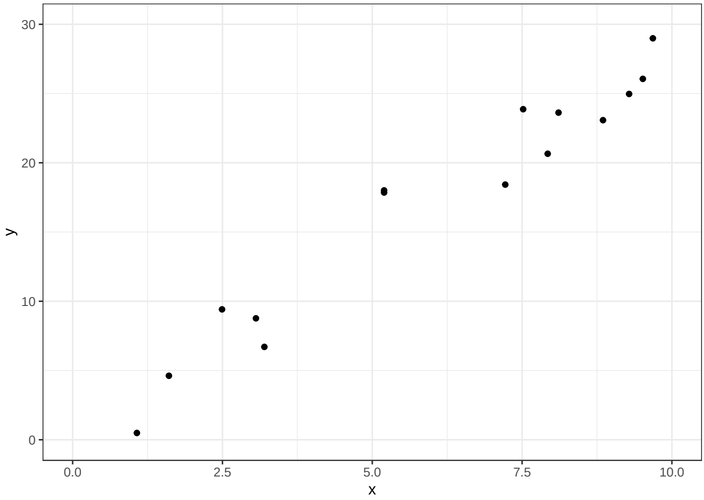
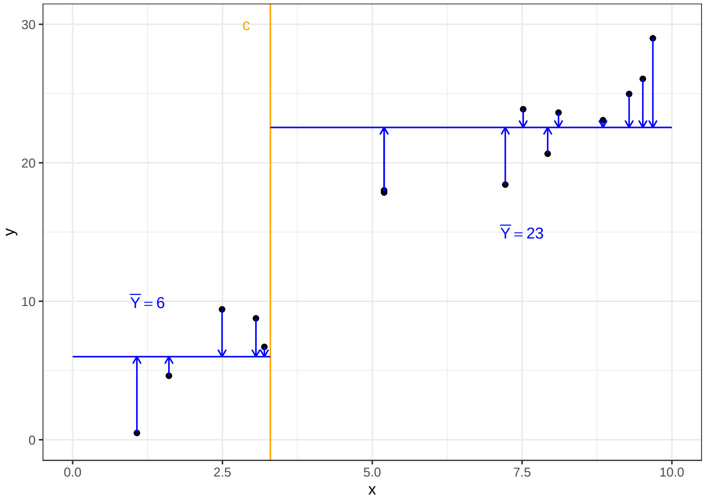
- …and for each sub-sample, predict $\hat{Y}$ as the mean of the Y_i within each sample.
- We want to pick c to minimize:

$$Q = \sum_{i:X_i \leq c} (Y_i - \bar{Y}_{\text{lower}})^2 + \sum_{i:X_i > c} (Y_i - \bar{Y}_{\text{upper}})^2$$



30
20
10
0
y
0.0
2.5
5.0
7.5
10.0
x


c
$\overline{Y} = 6$
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- Generally, we'll define the depth of the tree as 2 or three variables; first we'll split on X_k, then we'll split on $X_j \ldots$

Honesty

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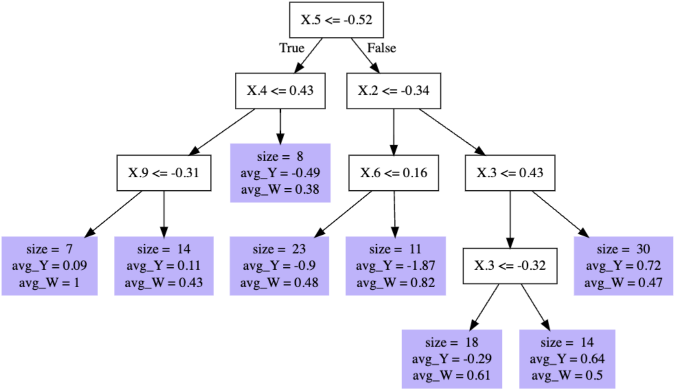
- This can result in some leaves being empty. Prune them?
- This procedure reduces bias relative to those proposed by Breiman (2001).

An honest tree algorithm

```
> library(grf)
> set.seed(60637)
> n <- 500
> p <- 10
> X <- matrix(rnorm(n * p), n, p)
> W <- rbinom(n, 1, 0.5)
> Y <- pmax(X[, 1], 0) * W + X[, 2] +
+   pmin(X[, 3], 0) + rnorm(n)
> c.forest <- causal_forest(X, Y, W)
```

An honest tree



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- The question: how to best recommend to them movies that they have not yet rated?
- The challenge: come up with the best recommendation algorithm, winner gets $1 million.
- This can be framed as a matrix completion problem: put users on rows, movies on columns, predict all of the missing rankings.

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  - Fit prediction models separately to treatment and control, so we can do a better job of estimating treatment effects at different covariate values.

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  - For observational data, predict propensity to be in treatment vs. control group, based on covariates.

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- Causal interpretations are based on assumptions about the data generating process, or knowledge of assignment procedures. These are outside the realm of machine learning methods.

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- Applying these solutions to prediction under multiple linear regression

References I

Athey, S. and Imbens, G. W. (2019). Machine learning methods that economists should know about. Annual Review of Economics, 11:685–725.

Breiman, L. (2001). Random forests. Machine learning, 45:5–32.

Hastie, T., Tibshirani, R., Friedman, J. H., and Friedman, J. H. (2009). The elements of statistical learning: data mining, inference, and prediction, volume 2. Springer.