

Machine Learning and Causal Inference

MIXTAPE TRACK



Allow me to introduce myself

- ▶ Economics professor at Brigham Young University in Utah



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- ▶ 4 kids, most of whom can now run and mountain bike faster than me



Allow me to introduce myself

- ▶ Economics professor at Brigham Young University in Utah
- ▶ 4 kids, most of whom can now run and mountain bike faster than me
- ▶ A big fan of causal inference in observational settings:
 - ▶ Quasi-experimental evaluations of the effects of unions
(Frandsen 2016, 2017, 2021; Chen, Frandsen, Grabowski, Town, Sojourner 2015)
 - ▶ Distributional effects
(Frandsen and Lefgren 2018, 2021; Frandsen, Froelich, Melly 2012)
- ▶ And of exploring machine learning in applied economics:
 - ▶ Teach Machine Learning for Economists at BYU
 - ▶ Research on the power of ML in empirical strategies
(Angrist and Frandsen 2022)

Welcome to the Machine: Where we're going

Machine Learning + Causal Inference I

Day 1 (today)

- ▶ Prediction vs. Causality
- ▶ Conceptual and practical (python!) intro to supervised machine learning methods
 - ▶ Lasso
 - ▶ Ridge
 - ▶ Elastic nets
 - ▶ Random Forests
- ▶ Day 2: How modern prediction methods can be deployed in the service of causal inference
 - ▶ Post double selection lasso (PDS lasso)
 - ▶ Double/de-biased machine learning (DML)

Machine Learning + Causal Inference II (starts Nov 15)

- ▶ Predicting heterogeneous treatment effects
- ▶ Random Causal Forests

Prediction vs. Causality

Imagine you are a life insurance underwriter. You receive an application for life insurance from someone with the following characteristics:

- ▶ male

Prediction vs. Causality

Imagine you are a life insurance underwriter. You receive an application for life insurance from someone with the following characteristics:

- ▶ male
 - ▶ age 67

Prediction vs. Causality

Imagine you are a life insurance underwriter. You receive an application for life insurance from someone with the following characteristics:

- ▶ male
- ▶ age 67
- ▶ high blood pressure

Prediction vs. Causality

Imagine you are a life insurance underwriter. You receive an application for life insurance from someone with the following characteristics:

- ▶ male
- ▶ age 67
- ▶ high blood pressure
- ▶ high cholesterol

Prediction vs. Causality

Imagine you are a life insurance underwriter. You receive an application for life insurance from someone with the following characteristics:

- ▶ male
- ▶ age 67
- ▶ high blood pressure
- ▶ high cholesterol
- ▶ family history of heart disease

Prediction vs. Causality

Imagine you are a life insurance underwriter. You receive an application for life insurance from someone with the following characteristics:

- ▶ male
- ▶ age 67
- ▶ high blood pressure
- ▶ high cholesterol
- ▶ family history of heart disease
- ▶ and . . .

Prediction vs. Causality

Imagine you are a life insurance underwriter. You receive an application for life insurance from someone with the following characteristics:

- ▶ male
- ▶ age 67
- ▶ high blood pressure
- ▶ high cholesterol
- ▶ family history of heart disease
- ▶ and . . .
- ▶ was admitted to the hospital yesterday



Prediction vs. Causality

Now imagine you are a loved one of someone with the following characteristics:

- ▶ male

Prediction vs. Causality

Now imagine you are a loved one of someone with the following characteristics:

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 - ▶ age 67

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- ▶ and . . .

Prediction vs. Causality

Now imagine you are a loved one of someone with the following characteristics:

- ▶ male
- ▶ age 67
- ▶ high blood pressure
- ▶ high cholesterol
- ▶ family history of heart disease
- ▶ and . . .
- ▶ is having chest pains.

Prediction vs. Causality

Now imagine you are a loved one of someone with the following characteristics:

- ▶ male
- ▶ age 67
- ▶ high blood pressure
- ▶ high cholesterol
- ▶ family history of heart disease
- ▶ and . . .
- ▶ is having chest pains.
- ▶ Should you take him to the hospital?



Prediction vs. Causality: Purpose



Prediction vs. Causality: Purpose



Prepare

- ▶ A loan officer wants to know the likelihood of an individual repaying a loan based on income, employment, and other characteristics.



Prediction vs. Causality: Purpose



Prepare

- ▶ A loan officer wants to know the likelihood of an individual repaying a loan based on income, employment, and other characteristics.



Influence

- ▶ A mortgage lender wants to know if direct debit will increase loan repayments



Prediction vs. Causality: Purpose



Prepare

- ▶ In order to decide whether to invest in a start-up, an investor needs to know how likely the start-up is to succeed, given the entrepreneur's experience and the characteristics of the industry.



Influence



Prediction vs. Causality: Purpose



Prepare

- ▶ In order to decide whether to invest in a start-up, an investor needs to know how likely the start-up is to succeed, given the entrepreneur's experience and the characteristics of the industry.



Influence

- ▶ An entrepreneur needs to know what the effect of receiving funding from a private equity investor (rather than getting a loan) is on the ultimate success of an enterprise.



Prediction vs. Causality: Purpose



Prepare

- ▶ A bail hearing judge needs to know how likely a defendant is to flee before trial, given his or her charges, criminal history, and other characteristics



Influence



Prediction vs. Causality: Purpose



Prepare

- ▶ A bail hearing judge needs to know how likely a defendant is to flee before trial, given his or her charges, criminal history, and other characteristics



Influence

- ▶ A policy maker needs to know the effect of being released on bail (rather than detained) prior to trial on ultimate conviction



Prediction vs. Causality: Purpose



Prepare



Influence

- ▶ A home seller wants to know what price homes with the characteristics of his or her home typically sell for



Prediction vs. Causality: Purpose



Prepare

- ▶ A home seller wants to know what price homes with the characteristics of his or her home typically sell for



Influence

- ▶ A home seller wants to know by how much installing new windows will raise the value of his or her home



Prediction vs. Causality: Purpose



Prepare

- ▶ A Harvard admissions officer wants to know how likely an applicant with given credentials is to graduate in 4 years



Influence



Prediction vs. Causality: Purpose



Prepare

- ▶ A Harvard admissions officer wants to know how likely an applicant with given credentials is to graduate in 4 years



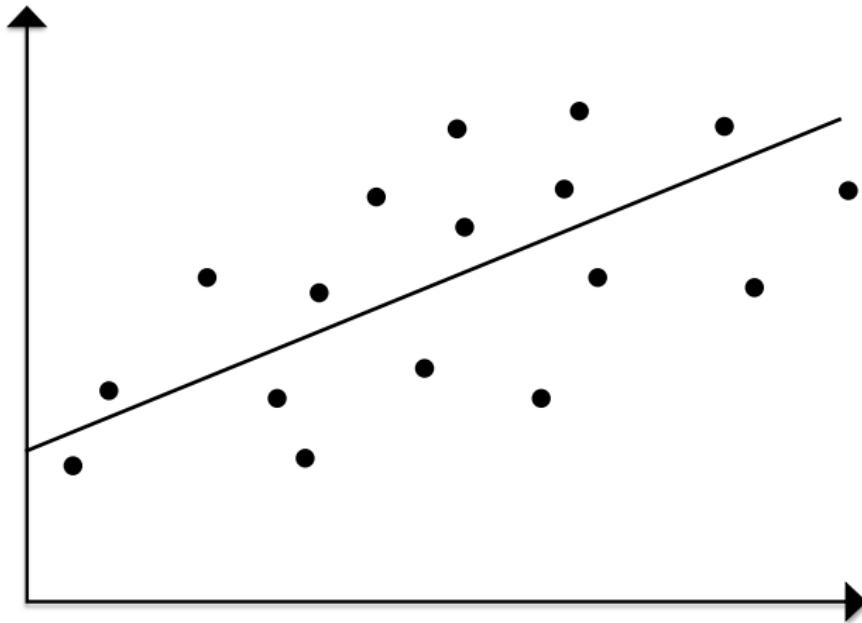
Influence

- ▶ A labor economist wants to know whether individuals of a certain ethnic background are less likely to get into Harvard than applicants with similar academic credentials



Prediction vs. Causality: Target

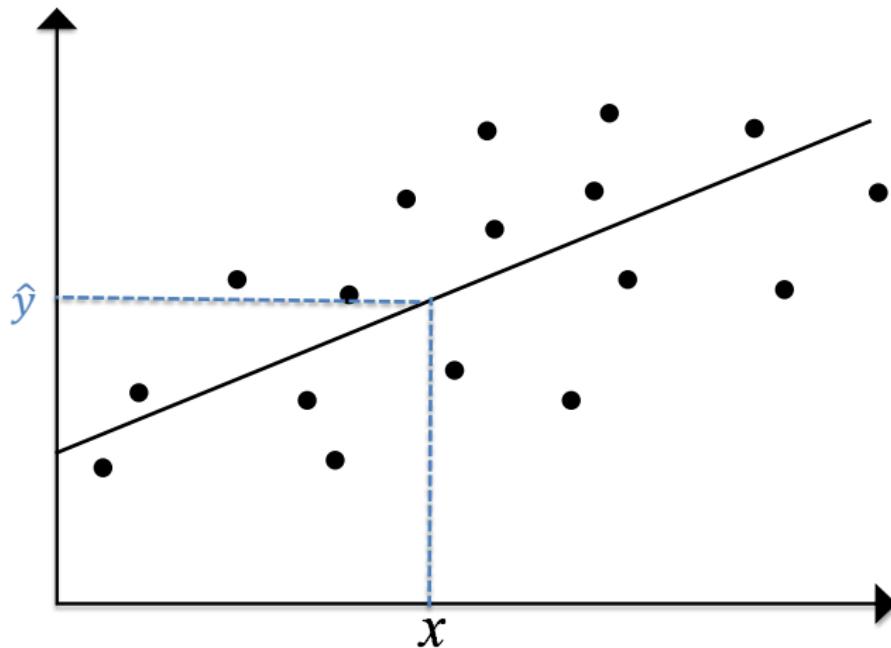
$$y_i = \alpha + \beta x_i + \varepsilon_i$$



Prediction vs. Causality: Target

Prediction

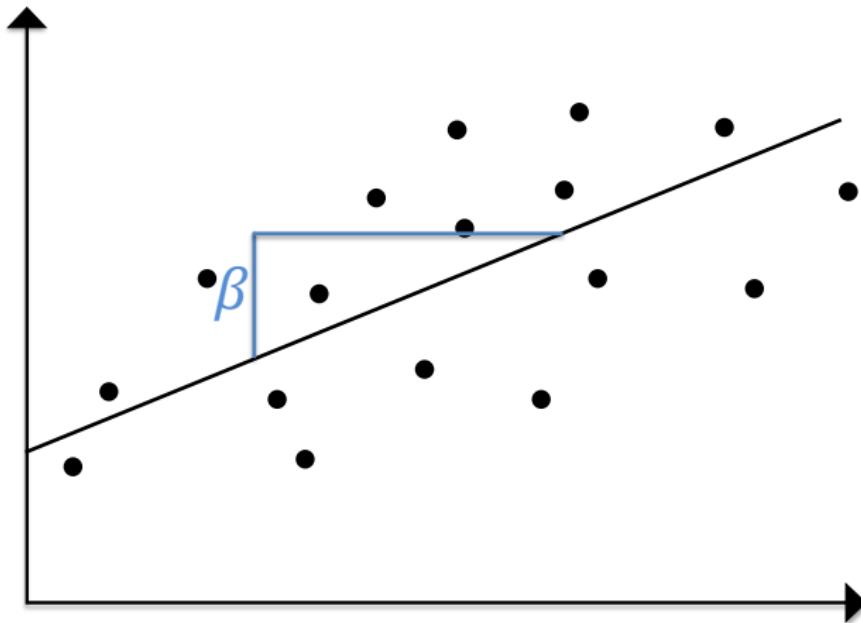
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Prediction vs. Causality: Target

Causality

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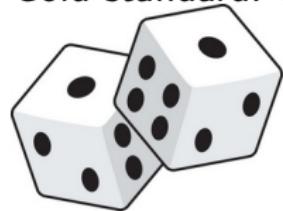
Prediction vs. Causality: Methods

Causality

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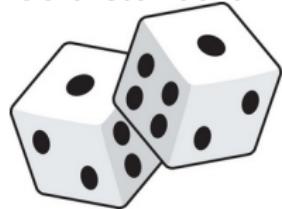
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Prediction vs. Causality: Methods

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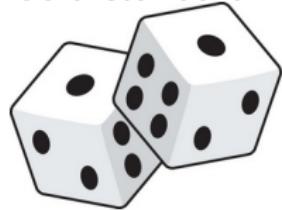


- ▶ Aluminum standard: Regression or IV strategies that approximate controlled experiments

Prediction vs. Causality: Methods

Causality

- ▶ Gold standard: RCT



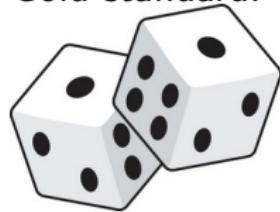
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Prediction

Prediction vs. Causality: Methods

Causality

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- ▶ Aluminum standard: Regression or IV strategies that approximate controlled experiments

Prediction

- ▶ Supervised machine learning algorithms

Prediction vs. Causality: Where shall the twain meet?

We've seen that prediction and causality

- ▶ answer different questions

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Different strokes for different folks, or complementary tools in an applied economist's toolkit?

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Different strokes for different folks, or **complementary tools in an applied economist's toolkit?**

Prediction vs. Causality: Where shall the twain meet?

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Different strokes for different folks, or **complementary tools in an applied economist's toolkit?**

- ▶ Illustrate using the Oregon Health Insurance Experiment (go to python)

Where ML fits into causal inference

Traditional regression strategy:

1. Regress Y_i on X_i and compute the residuals,

$$\begin{aligned}\tilde{Y}_i &= Y_i - \hat{Y}_i^{OLS}, \\ \hat{Y}_i^{OLS} &= X'_i (X'X)^{-1} X' Y\end{aligned}$$

2. Regress D_i on X_i and compute the residuals,

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When OLS might not be the right tool for the job:

- ▶ there are many variables in X_i
- ▶ the relationship between X_i and Y_i or D_i may not be linear

Where ML fits into causal inference

ML-augmented regression strategy:

1. Predict Y_i using X_i with ML and compute the residuals,

$$\tilde{Y}_i = Y_i - \hat{Y}_i^{ML},$$

\hat{Y}_i^{ML} = prediction generated by ML

2. Predict D_i using X_i with ML and compute the residuals,

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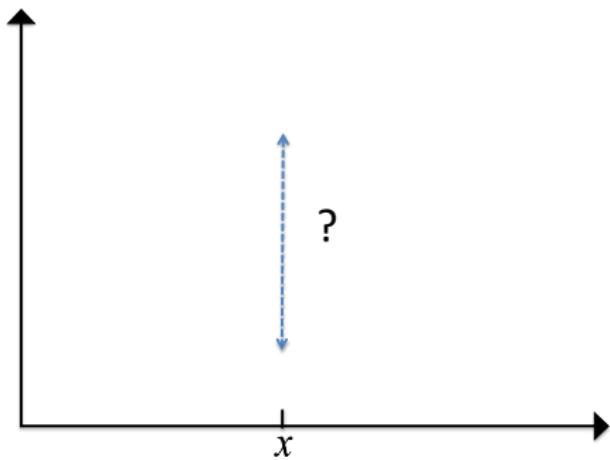
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Most common ML methods in applied economics:

- ▶ Lasso
- ▶ Ridge
- ▶ Elastic net
- ▶ Random forest

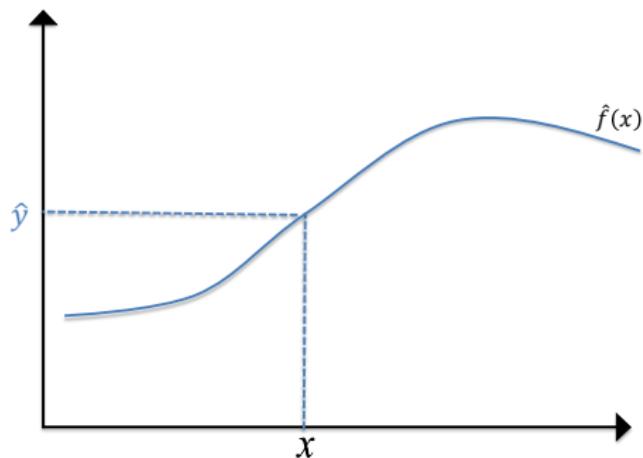
Getting serious about prediction

- ▶ **Goal:** Predict an out-of-sample outcome Y



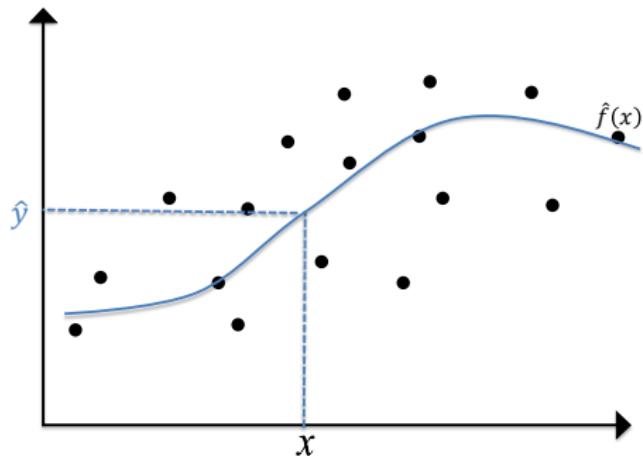
Getting serious about prediction

- ▶ **Goal:** Predict an out-of-sample outcome Y
- ▶ as a function, $\hat{f}(X)$, of **features** $X = (1, X_1, X_2, \dots, X_K)'$.



Getting serious about prediction

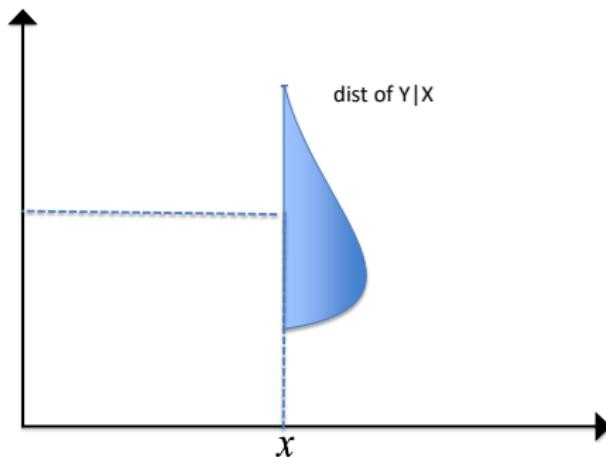
- ▶ **Goal:** Predict an out-of-sample outcome Y
- ▶ as a function, $\hat{f}(X)$, of **features** $X = (1, X_1, X_2, \dots, X_K)'$.
- ▶ Estimate the function \hat{f} (aka “train the model”) based on **training sample** $\{(Y_i, X_i); i = 1, \dots, N\}$



Cutting our losses

- Want our prediction to be “close,” i.e. minimize the **expected loss function**:

$$\min_{f(x)} E [L(f(x) - Y)|X = x]$$

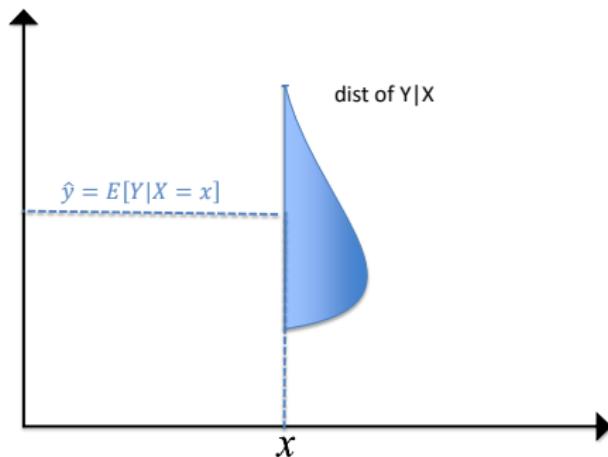


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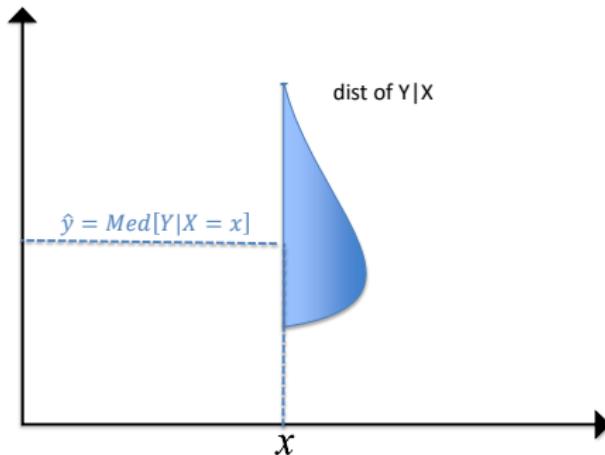


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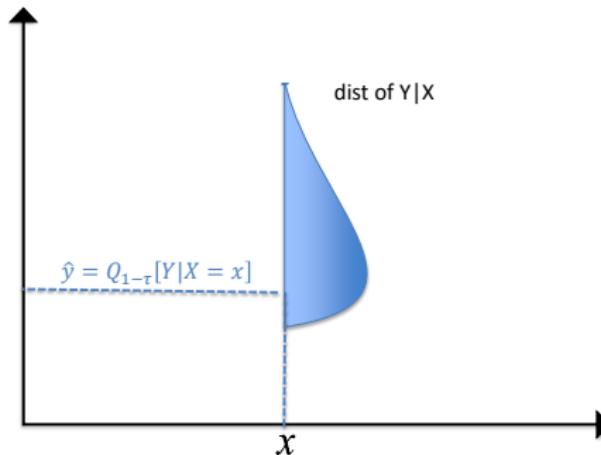
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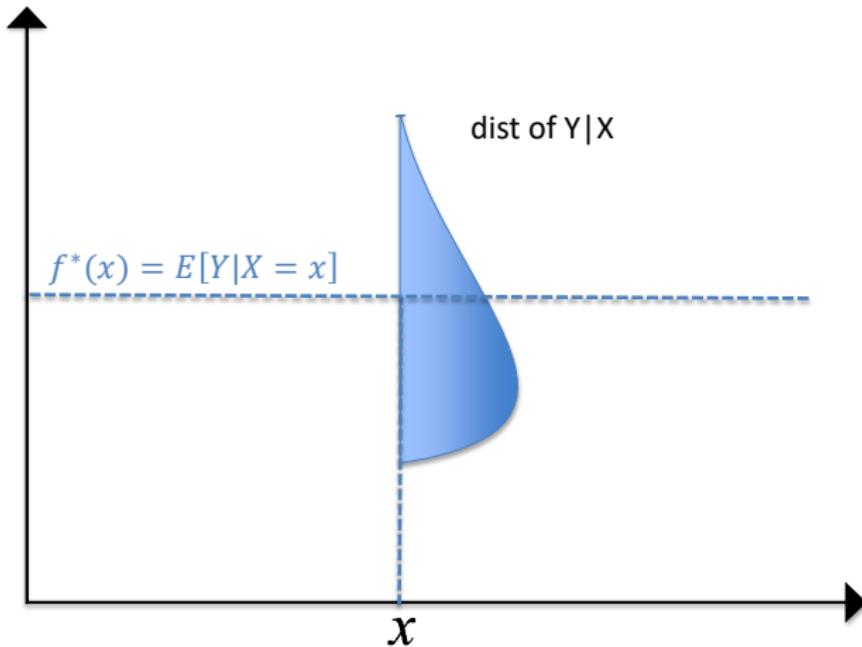
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- Asymmetric loss:**

$$L_\tau(d) = d(\tau - 1(d < 0)) \implies f^*(x) = Q_{1-\tau}[Y|X = x]$$



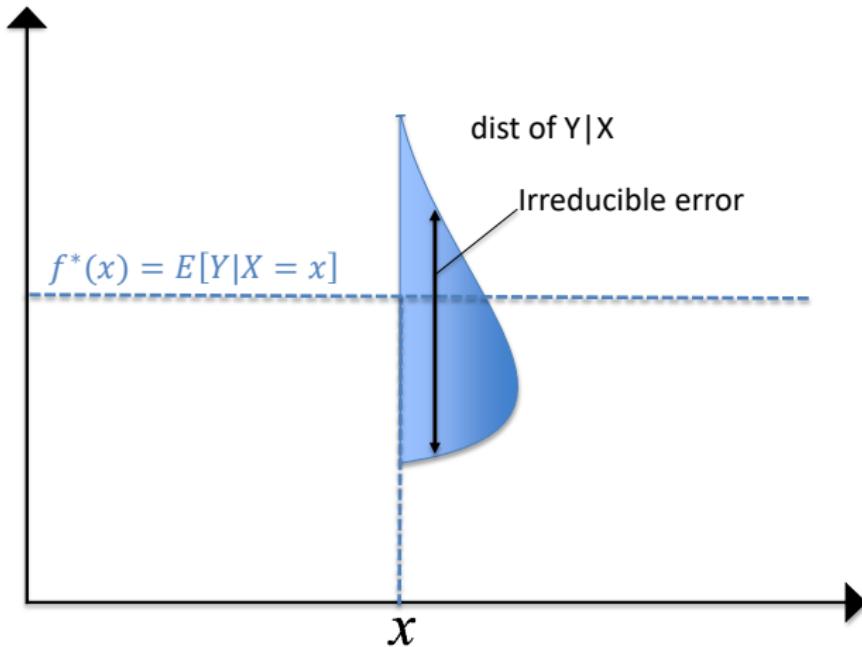
Navigating the Bias-Variance Tradeoff

- ▶ Prediction problem solved if we knew $f^*(x) = E [Y|X = x]$



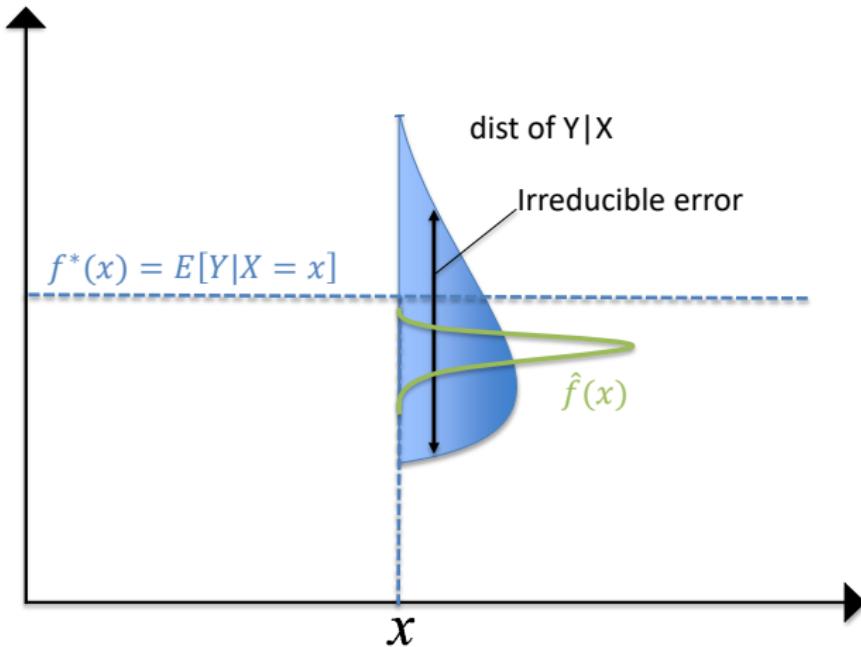
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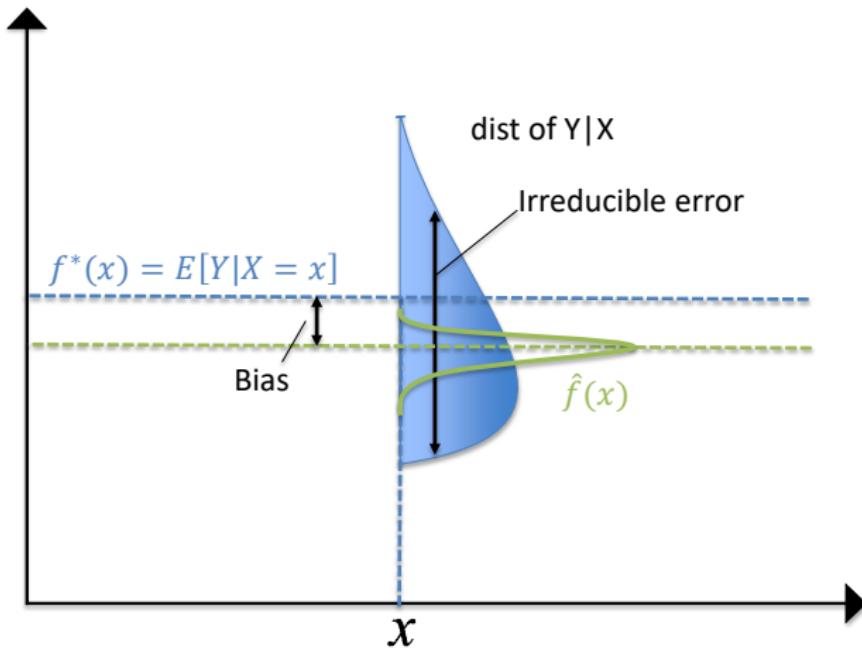
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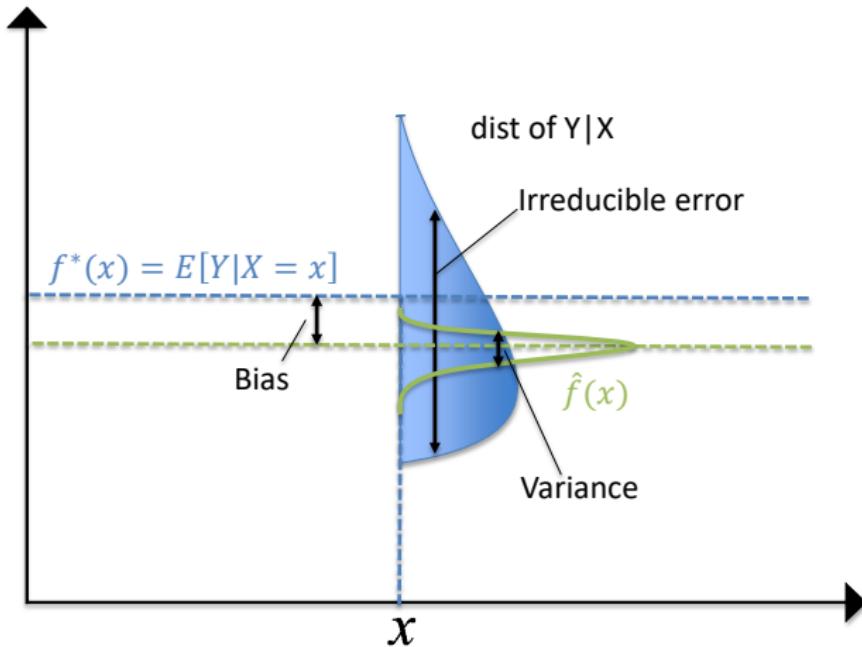
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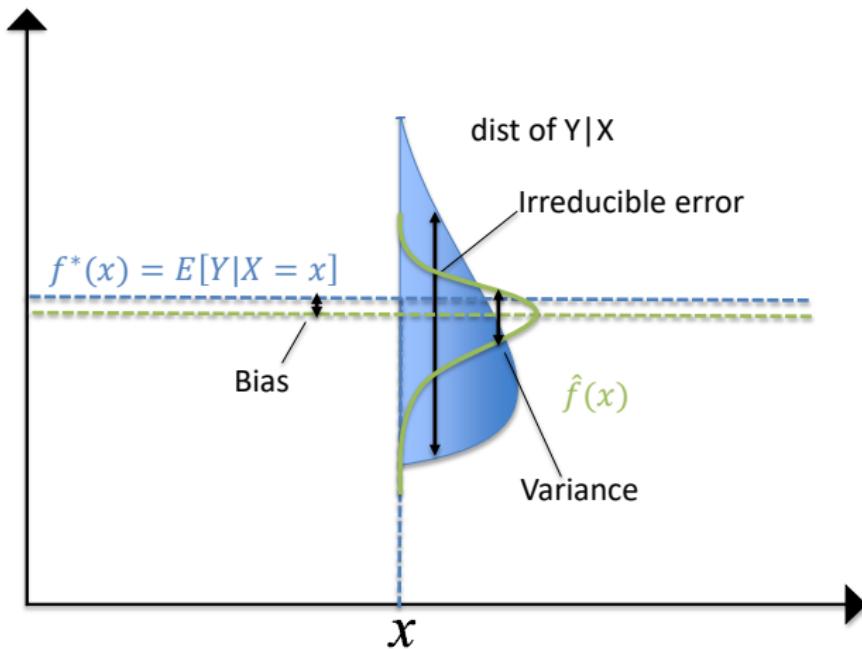
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Navigating the Bias-Variance Tradeoff

- ▶ Prediction problem solved if we knew $f^*(x) = E[Y|X=x]$
- ▶ But we have to settle for an estimate: $\hat{f}(x)$;

$E \left[(Y - \hat{f}(x))^2 \middle| X = x \right]$ becomes:

$$\begin{aligned} & \left(E \left[\hat{f}(x) - f^*(x) \right] \right)^2 && \text{prediction bias squared} \\ & + E \left[\left(\hat{f}(x) - E \left[\hat{f}(x) \right] \right)^2 \right] && \text{prediction variance} \\ & + E[(Y - f^*(x))^2 | X = x] && \text{irreducible error.} \end{aligned}$$

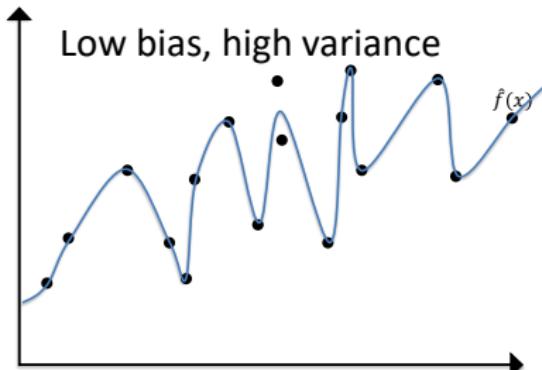
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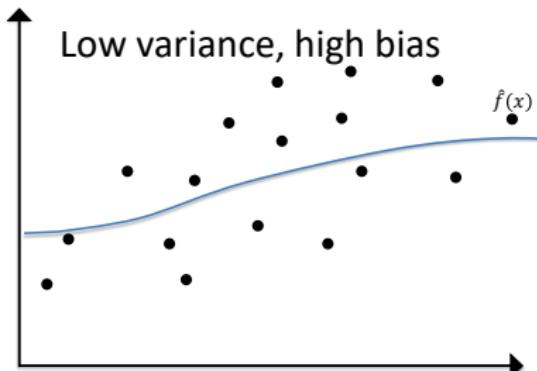


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Python example: predicting earnings in the NLSY

Penalized Regression: Lasso

- ▶ When is it the right tool for the job:
 - ▶ When you have a large number of potential regressors (including powers or other transformations), maybe even more than the sample size!
 - ▶ Out of these, only a relatively few (but you don't know which) really matter (what do we mean by "matter?"). We call this **approximate sparsity**
- ▶ Theoretical definition:

$$\arg \min_b \sum_{i=1}^n (y_i - x'_i b)^2 + \lambda \sum_{j=1}^k |b_j|$$

What does λ do and how do we choose it?

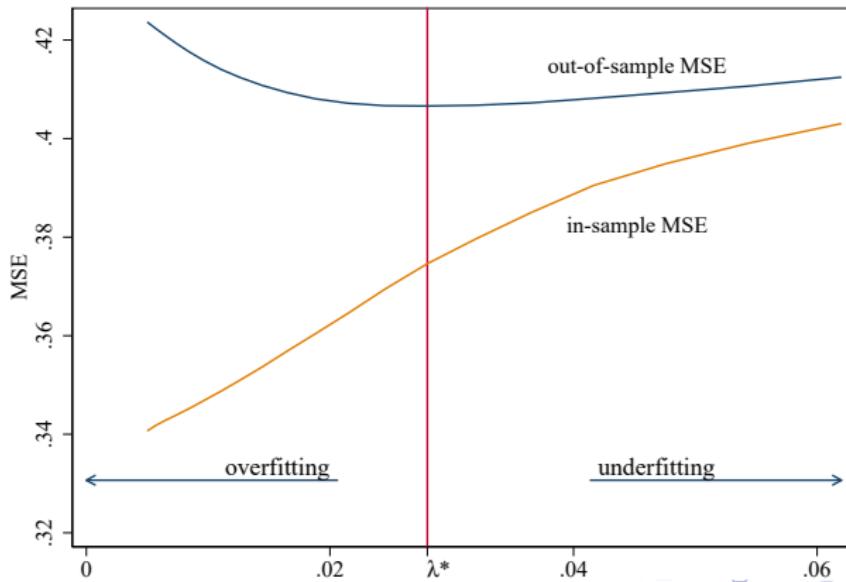
- ▶ Caveats and considerations:
 - ▶ Important to standardize regressors pre-lasso
 - ▶ Can give unexpected results with dummy variables
 - ▶ Resist the temptation to interpret coefficients or the included variables as the "true model!"
- ▶ Let's give it a go in python!

Choosing Tuning Parameters: Cross-Validation

All supervised ML methods have tuning parameters:

- ▶ Lasso: λ
- ▶ Ridge: α
- ▶ Random forests: tree depth, etc.

Tuning parameters are the rudder by which we navigate the bias-variance tradeoff.



Choosing Tuning Parameters: Cross-Validation

	Y	X1	X2	X3
Fold 1				
Fold 2				
Fold 3				

Cross-validation procedure: Divide sample in K folds

- ▶ Choose some value of the tuning parameter, λ
- ▶ For each fold $k = 1, \dots, K$
 1. Train model leaving out fold k
 2. Generate predictions in fold k
 3. Compute MSE for fold k : $MSE_k = \frac{1}{n_k} \sum_{i \in k} (Y_i - \hat{Y}_i)^2$
- ▶ Compute overall MSE corresponding to the current choice of λ : $MSE(\lambda) = \frac{1}{K} \sum_{k=1}^K MSE_k$

Repeat the above for many values of λ , and choose the value λ^* with the lowest cross-validated MSE—time for python!

Penalized Regression: Ridge

- ▶ When is it the right tool for the job:
 - ▶ When you have a large number of regressors including highly collinear ones
- ▶ Theoretical definition:

$$\begin{aligned} \arg \min_b & \sum_{i=1}^n (y_i - x'_i b)^2 + \alpha \sum_{j=1}^k b_j^2 \\ & = (X'X + \alpha I)^{-1} X'Y \end{aligned}$$

- ▶ Caveats and considerations:
 - ▶ Important to standardize regressors pre-ridge
 - ▶ Shrinks (biases) coefficients towards zero, but not all the way (unlike lasso)
- ▶ Let's give it a go in python!

Penalized Regression: Elastic Net

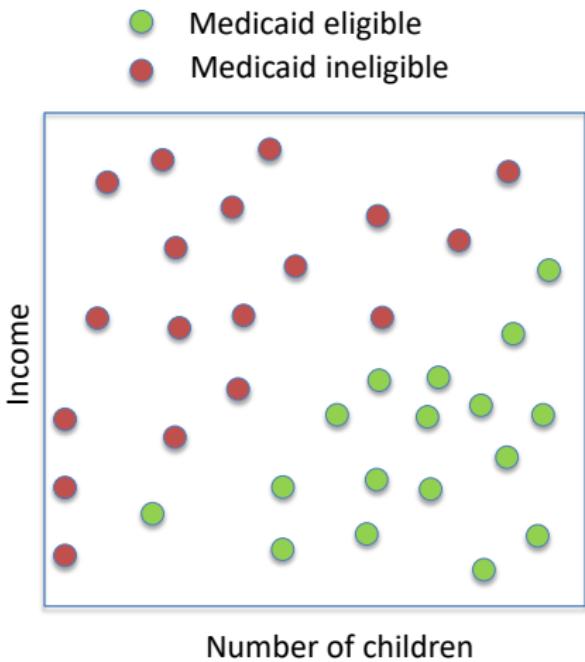
- ▶ Combines lasso and ridge approaches
- ▶ Theoretical definition:

$$\arg \min_b \sum_{i=1}^n (y_i - x_i' b)^2 + \alpha \gamma \sum_{j=1}^k |b_j| + .5\alpha (1 - \gamma) \sum_{j=1}^k b_j^2$$

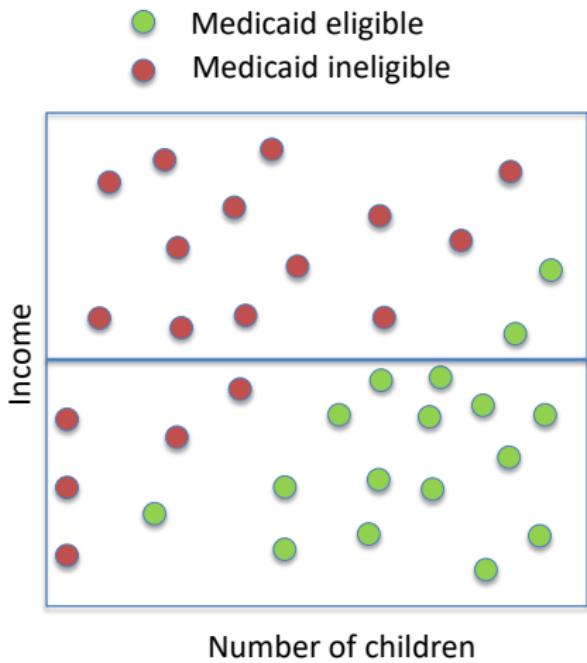
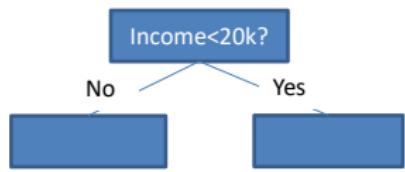
- ▶ Caveats and considerations:
 - ▶ Two tuning parameters: α and γ
 - ▶ Important to standardize regressors pre-ridge
 - ▶ Zeros out many regressors, shrinks (biases) remaining coefficients towards zero
- ▶ Let's give it a go in python!

Decision Trees

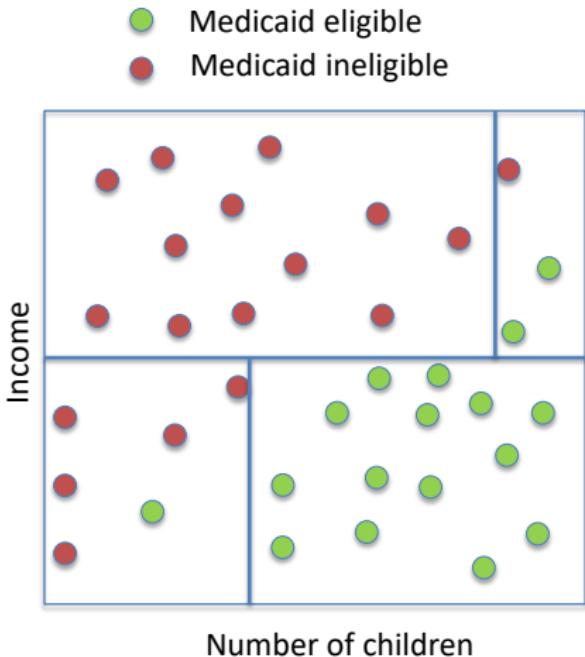
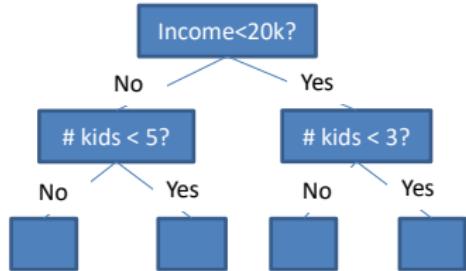
Initial node



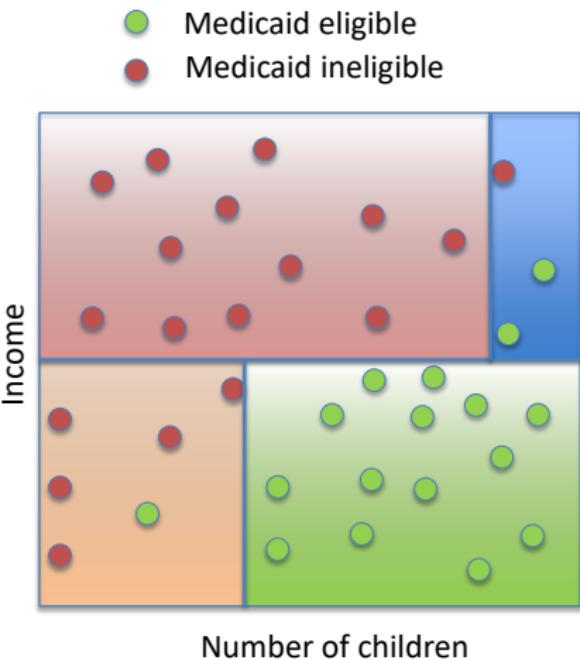
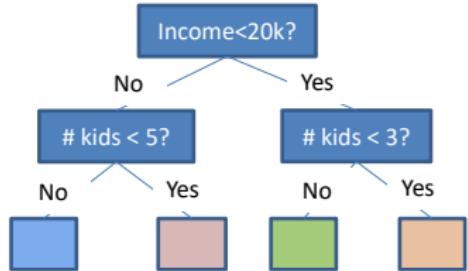
Decision Trees



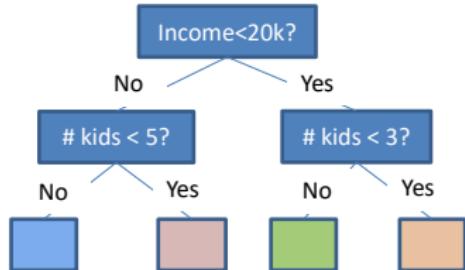
Decision Trees



Decision Trees



Decision Trees

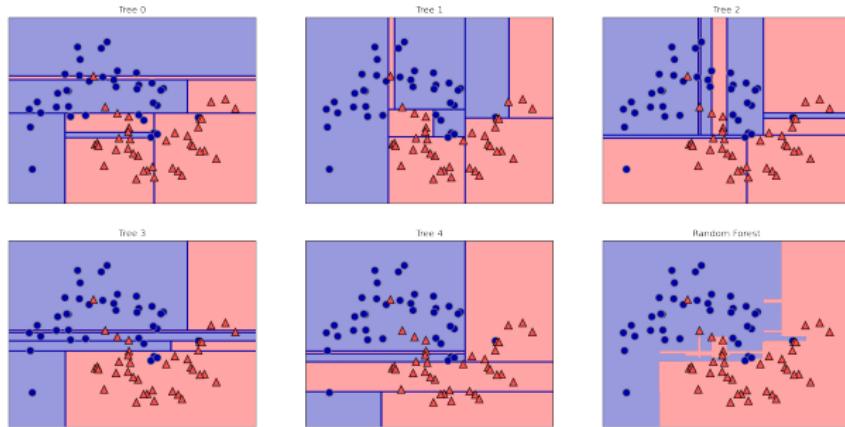


- ▶ Where to split:
Choose the feature from $\{x_1, \dots, x_p\}$ and the value of that feature to minimize MSE in the resulting child nodes
- ▶ Tuning parameters
 - ▶ Max depth
 - ▶ Min training obs per leaf
 - ▶ Min improvement in fit in order to go ahead with a split
- ▶ Let's try it in python!

Wisdom of the crowd: predict my father's age!



Forest for the Trees



- ▶ Value proposition: reduce variance by averaging together multiple predictions
- ▶ The catch: individual trees need to be **de-correlated**
- ▶ Algorithm:
 - ▶ Grow B trees, each on a different bootstrapped sample
 - ▶ At each split, consider only a random subset of features
 - ▶ Average together the individual predictions
- ▶ Let's grow some trees in python!