

Social Data Science

Soc 114
Winter 2025

Supervised Machine Learning

Learning goals for today

By the end of class, you will be able to

- ▶ use statistical learning to estimate when data are sparse
- ▶ work with models that are “wrong”

Prediction function

A **prediction function** is an input-output function:

- ▶ input a vector of predictors \vec{x}
- ▶ output a predicted outcome $\hat{y} = \hat{f}(\vec{x})$



Example:

{Sex, Age}

Probability of
Employment
Given Sex
and Age

	Age	Sex	Employed
cases for learning	26	F	1
	40	M	1
	61	M	0
	32	F	1
case to predict	63	F	?

OLS is a prediction function

Input $\vec{x} \rightarrow$ Output \hat{y}

$$\hat{y} = \hat{f}(\vec{x}) = \hat{\beta}_0 + \hat{\beta}_1(\text{Sex} = \text{Male}) + \hat{\beta}_2(\text{Age})$$

- ▶ Learn \hat{f} in a **learning sample** with $\{\vec{x}_i, y_i\}_{i=1}^n$
 - ▶ Computer finds $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2$ that predict well in the learning sample
- ▶ At a new \vec{x} value, predict $\hat{f}(\vec{x})$

Logistic regression is a prediction function

Input $\vec{x} \rightarrow$ Output \hat{y}

$$\hat{y} = \hat{f}(\vec{x}) = \text{logit}^{-1} \left(\hat{\beta}_0 + \hat{\beta}_1(\text{Sex} = \text{Male}) + \hat{\beta}_2(\text{Age}) \right)$$

- ▶ Learn \hat{f} in a **learning sample** with $\{\vec{x}_i, y_i\}_{i=1}^n$
 - ▶ Computer finds $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2$ that predict well in the learning sample
- ▶ At a new \vec{x} value, predict $\hat{f}(\vec{x})$

Matching is a prediction function

Input $\vec{x} \rightarrow$ Output \hat{y}

$$\hat{y} = \hat{f}(\vec{x}) = y_j$$

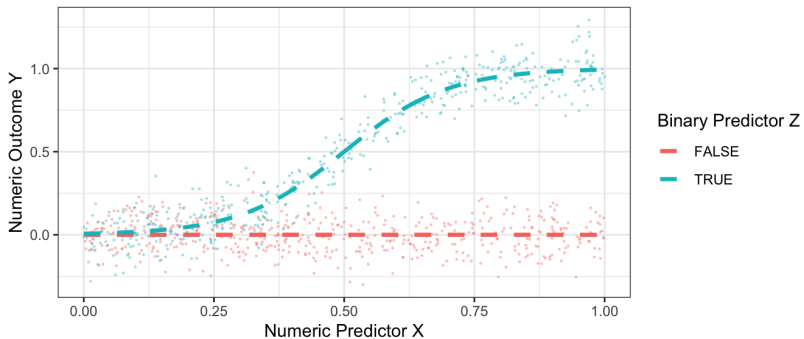
where unit j is the best match among the learning sample, which minimizes a distance from the case to predict: $d(\vec{x}, \vec{x}_j)$ is small

- ▶ Learn \hat{f} in a **learning sample** with $\{\vec{x}_i, y_i\}_{i=1}^n$
 - ▶ Computer finds j with \vec{x}_j most similar to \vec{x}
- ▶ At a new \vec{x} value, predict $\hat{f}(\vec{x})$

There are many prediction functions

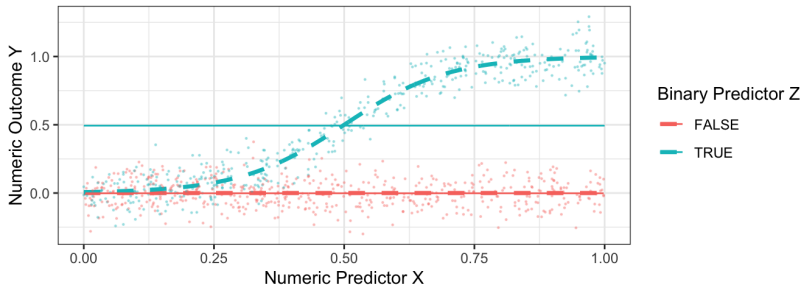
- ▶ input a vector of predictors \vec{x}
- ▶ output a predicted outcome $\hat{y} = \hat{f}(\vec{x})$

Trees as a prediction function



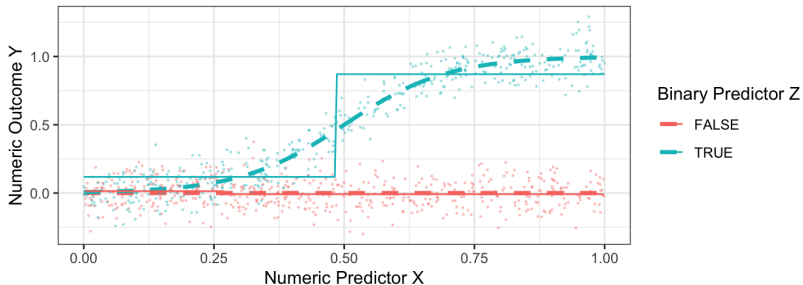
Trees as a prediction function

Solid lines represent predicted values
after one split on Z

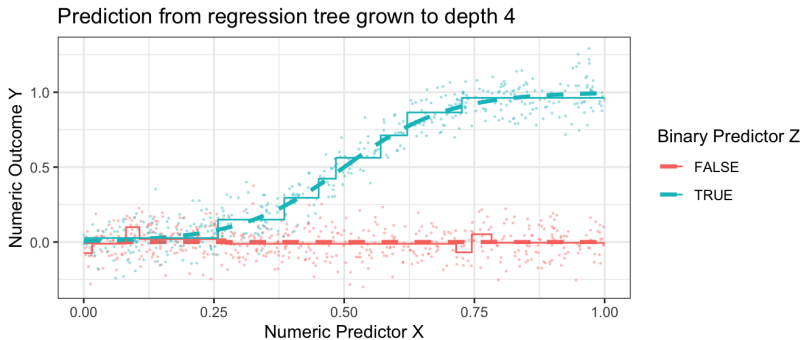


Trees as a prediction function

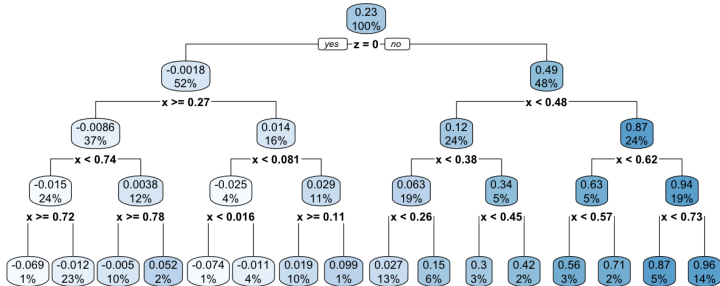
Solid lines represent predicted values
after two splits on (Z, X)



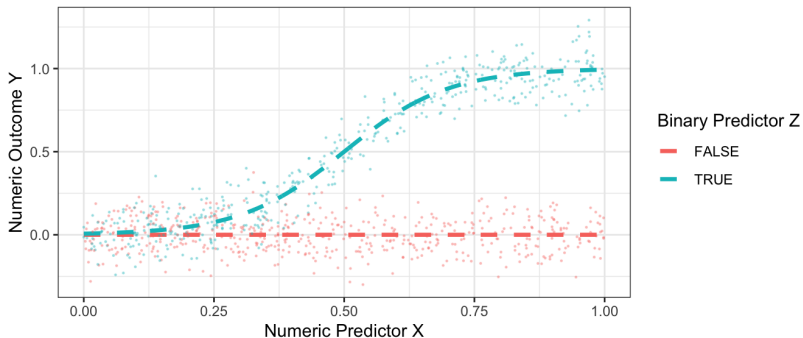
Trees as a prediction function



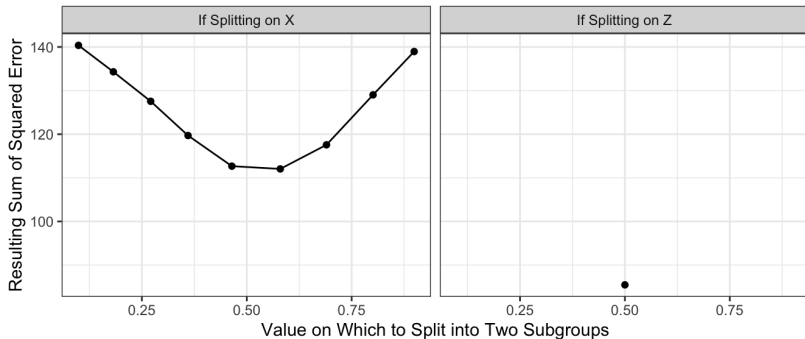
Trees as a prediction function



Trees as a prediction function: How that worked

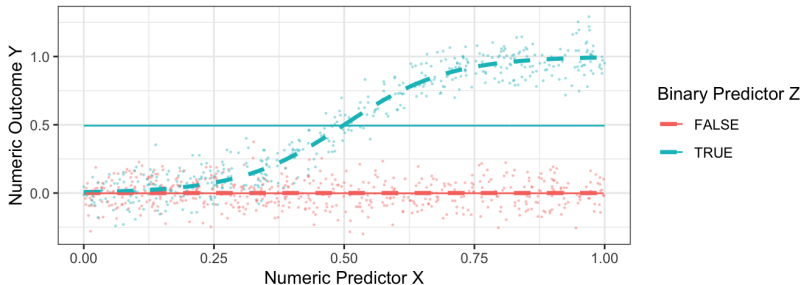


Trees as a prediction function: How that worked

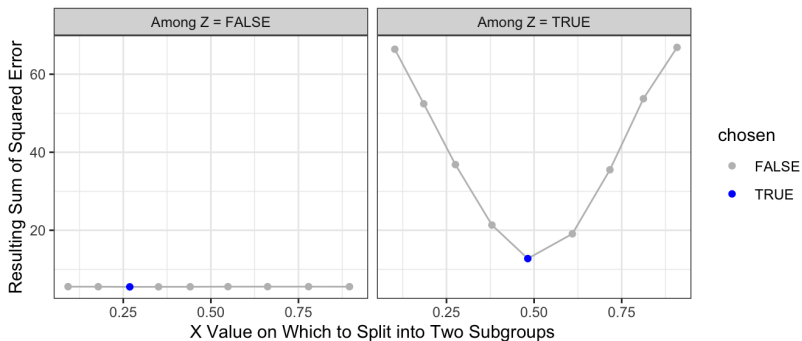


Trees as a prediction function: How that worked

Solid lines represent predicted values
after one split on Z

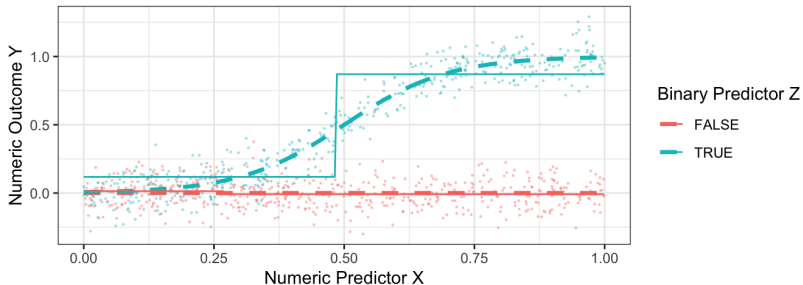


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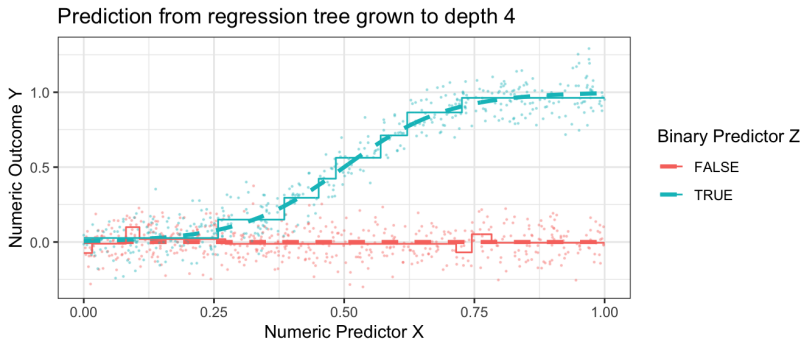


Trees as a prediction function: How that worked

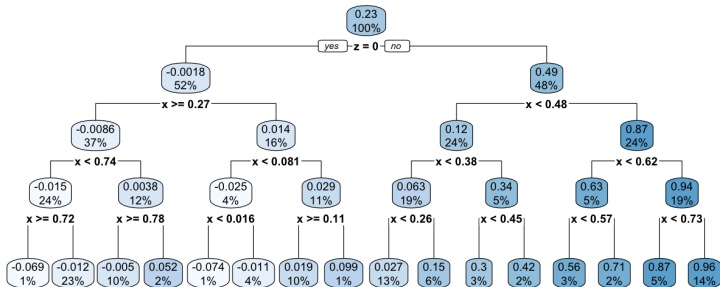
Solid lines represent predicted values
after two splits on (Z,X)



Trees as a prediction function: How that worked



Trees as a prediction function: How that worked



A tree can be interpretable

TODO: real data example

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