Lecture 7: Classification Models and Cross Validation

INFO 1998: Introduction to Machine Learning



Agenda

- 1. Decision Trees
- 2. Logistic Regression and Its Applications
- 3. Cross Validation

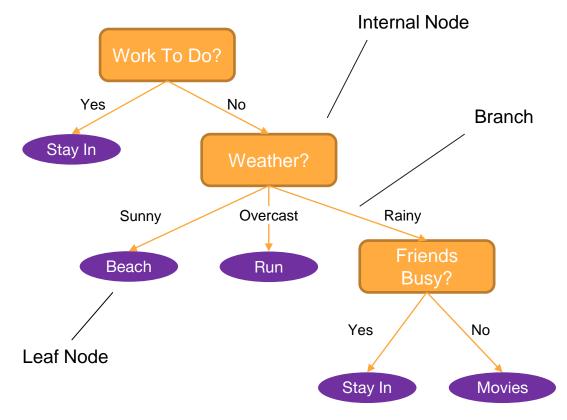


Decision Trees



How Should I Spend My Weekends

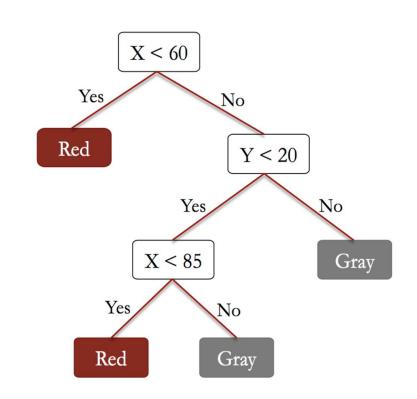
A decision tree is a supervised machine learning model used to predict a target by learning decision rules from features. As the name suggests, we can think of this model as **breaking down** our data by making a decision based on asking a series of questions.





CART (Classification and Regression Trees)

- Used for Classification and Regression
- At each node, split on variables
- Each split minimizes error function
- Very interpretable
- Models a non-linear relationship!







Pros and Cons of Using Decision Trees

Pros	Cons
Easy to interpret	Overfitting (2)
Requires little data preparation (robust to missing data)	Requires parameter tuning (max depth)
Can use a lot of features	
Can capture non-linear relationships	





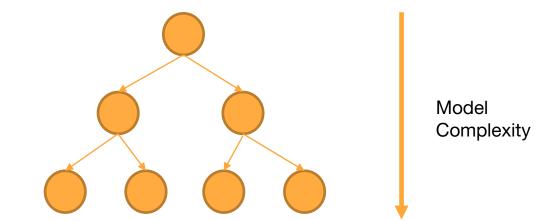
How to Reduce Overfitting

1. Limit the max depth of the tree



Depth = 1

Depth = 2



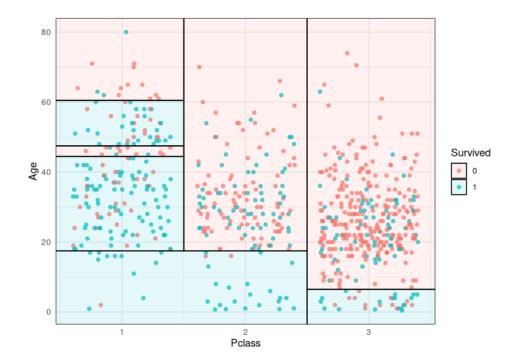
When training a decision tree, we have to specify the maximum depth a constructed tree can have





How to Reduce Overfitting

- There are no "curves" for each decision tree boundary line
- Limiting the depth of the tree limits the number of lines you are splitting on



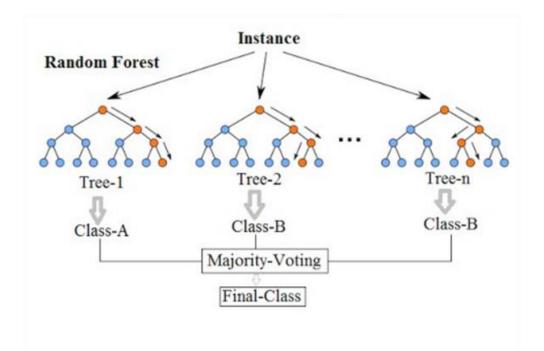




How to Reduce Overfitting

2) Train multiple decision trees and determine final output based on output of each decision tree

This is called a Random Forest Classifier







Demo



Logistic Regression



Logistic Regression

Used for Binary Classification:

$$Y = \begin{cases} 1 \\ 0 \end{cases}$$

- Fits a linear relationship between the variables
- Transforms the linear relationship of probability that the outcome is 1 by using the sigmoid function

Formula:

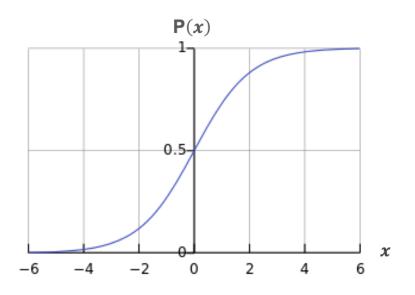
$$P(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k)}} \longrightarrow \ln\left(\frac{P}{1 - P}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$





Logistic Function

$$\mathbf{P}(x) = \frac{1}{1+e^{-x}}$$



The Logistic Function "squeezes" numbers to be between 0 and 1



Allows us to interpret our prediction as a "probability" that something is true

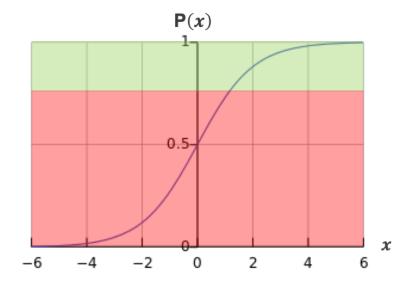




Threshold

At what point point do we differentiate between our classifications?

- f(x) below threshold: predict 0
- f(x) above threshold: predict 1







Pros and Cons of Using Logistic Regression

Pros	Cons
Easy to interpret (probability)	Only Capable of Binary Classification
Computationally efficient to compute	
Does not require parameter tuning	

Logistic Regression is a simple model, therefore, oftentimes it is used as a good "baseline" to compare more complex models to





Demo



Cross Validation





Often used in practice with k=5 or k=10.

Create equally sized *k* partitions, or **folds**, of training data

For each fold:

- Treat the *k-1* other folds as training data.
- Test on the chosen fold.

The average of these errors is the validation error





Dataset





Fold 1 Fold 2 Fold 3 Fold 4 Fold 5





Test Sample

Training Sample

Training Sample

Training Sample

Training Sample

Calculate MSE = mse1





Training Sample

Test Sample

Training Sample

Training Sample

Training Sample

Calculate MSE = mse2





Training Sample

Training Sample

Test Sample

Training Sample

Training Sample

Calculate MSE = mse3





And so on





Fold 1 Fold 2 Fold 3 Fold 4 Fold 5

MSE = Avg(mse1...5)





Matters less how we divide up

Selection bias not present





Leave-1-Out Cross Validation

For each sample:

- Treat all other data as training data.
- Test on that one sample

The average of these errors is the validation error

Pro: Better on small datasets

Pro: More realistic (trained on most of the data)

Con: Takes longer to run





Demo



Coming Up

- Assignment 7: Due on November 2nd, 2022
- Next Lecture: Linear Classifiers and Model Validation
- Last Day for Mid-Semester Check In: November 2nd, 2022

