# Boosting

## **Learning Objectives**

- Understand the differences between bagging and boosting
- Understand how boosting is an ensemble method
- Learn the intuition behind AdaBoost



## Review: what is bagging?

- Bootstrapping: sampling with replacement on the original training data
- **Aggregating**: using predictions made by many models in aggregate



## A simple diagram



## Some properties of bagged models

- Fit in parallel
- Decreased variance
- Individual models may still be correlated with each other
  - Random forests introduce additional randomness by limiting the features each split is allowed to consider

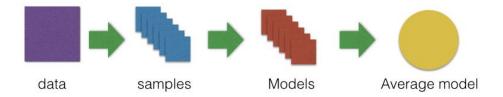


## What is boosting?

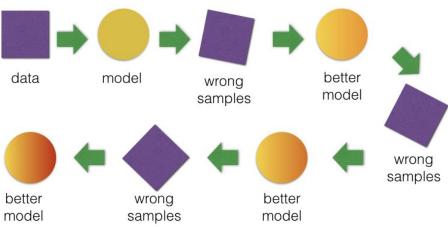
- Boosted models are ensemble models fit sequentially instead of in parallel
- Boosting is much slower
- Can achieve very high performance
- More prone to overfitting



#### **Bagging**



#### **Boosting**







## What is boosting?

Use many **weak learners**, often **decision stumps**, to develop a single **strong learner** 

- Weak learner: a model/learner/estimator that performs poorly, often just better than chance
- Decision stump: a decision tree with just one split
- Strong learner: a model that performs well



#### **AdaBoost**

- AdaBoost is the original boosting algorithm
- Fit a sequence of weak learners on repeatedly modified versions of the data
  - Each subsequent weak learner is fit on a boostrapped sample, but training data that was misclassified is more likely to be sampled. Over time, difficult-to-classify observations become 'focused on'
- Each weak learner is weighted to produce the final prediction
  - More useful weak learners will be upweighted, and less useful weak learners will be downweighted



## Other boosting algorithms

- Focus on AdaBoost this morning
- Also gradient boosting
  - Big on Kaggle
  - Fits subsequent models to the residuals of the last model instead of resampling with misclassified observations upweighted



Let's implement it in code!

