# Big Data and Economics

## Regression Trees

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# Prologue

# Prologue

- Last week we talked about the basics of machine learning
- You take a bunch of data, split it into training and testing sets, fit a model to the training data, then test it on the testing data
- Let's look at a particular type of machine learning model: decision trees
- Decision trees are a type of machine learning model that are easy to interpret
    - They allow for non-linear relationships between the dependent and independent variables
    - But the math is a lot more complicated than an OLS regression
    - The visualizations are more straight-forward
- Trees **stratify**, **segment**, or **partition** the data into subgroups
    - Each subgroup predicts a different value of the dependent variable
    - These lend themselves to flowcharts!

# Questions

# Hack-a-thon

- Fill out survey please
- Right now we have three participants

# Attribution

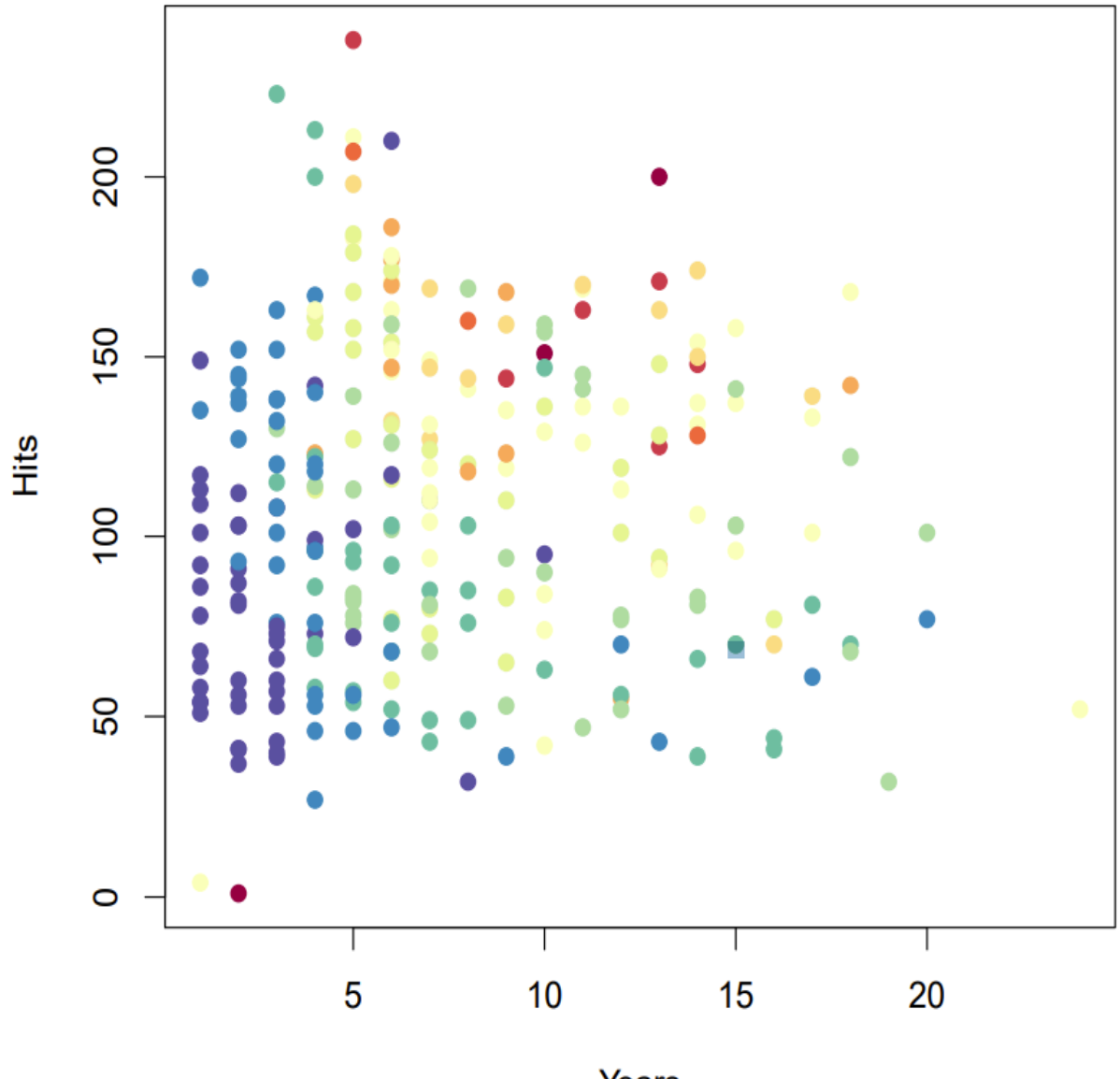
- This lecture is based on the following resources:
- Introduction to Statistical Learning, Chapter 8
- Tyler Ransom's lecture notes

# Decision Trees

# Motivating example

- Imagine you want to predict the income mobility of those raised in the 25th percentile for some county
    - **Remember we are not making causal inferences here, just predictions**
- You have tons of predictors: job growth, health, education, crime rates, share of each race, median HH income, college degrees, bankruptcies, religiosity, and more
- The correlations between these variables and mobility is likely non-linear
- The correrlations between mobility and median HH income could change depending on the rate of education
- Would a regression capture all of that?
- Probably not...

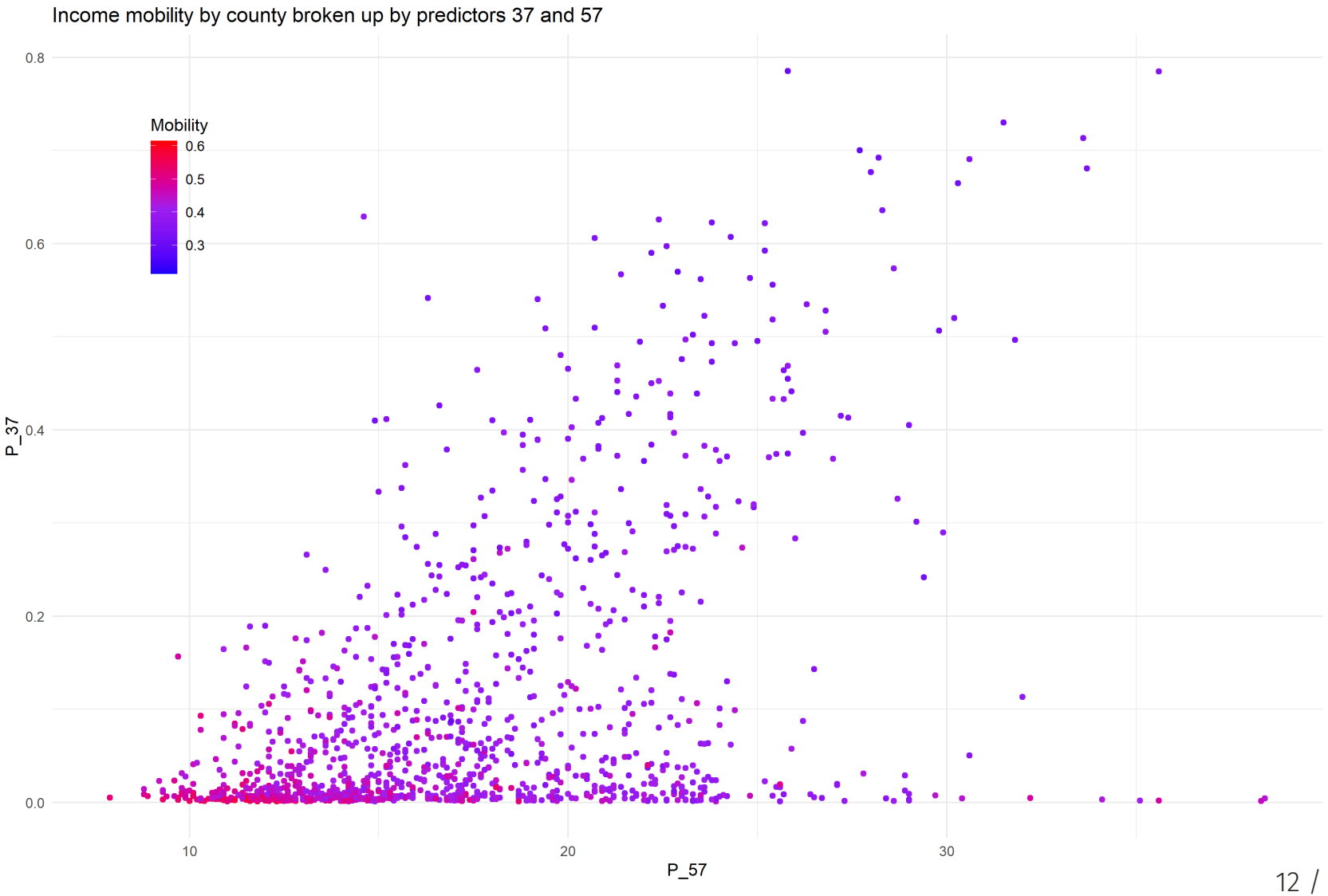
# Stratifying baseball data



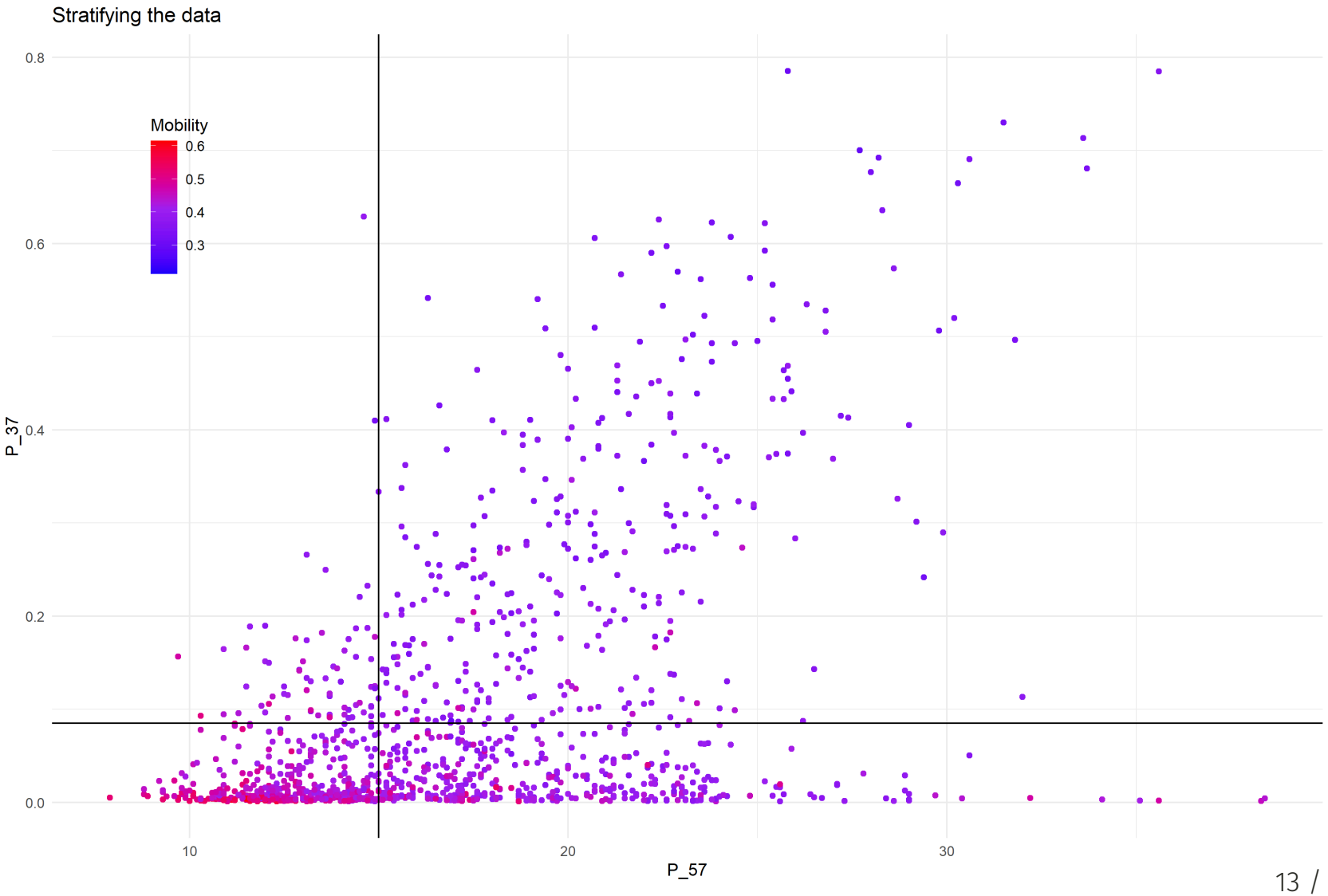
# Opportunity Atlas data

Couldn't load plugin.

# Stratify opp atlas data



# Strata lines



# What is a decision tree?

- A decision tree organizes variables into tree-like structure
    - It is essentially, a really fancy flowchart
- At each node, pick the variable that best meets a decision rule
- At node 1, the algorithm cycles through each $X$ variable and finds the split in the data that best meets the decision rule
    - It picks the best $X$ variable
    - It follows the branch down and creates nodes by looking at the remaining $X$'s that best meet the decision rule
- When making a decision about an observation, follow the tree down the branches

# Types of decision trees

## Regression trees

- The decision rule is what variable $X$ best predicts $y$ when split at some cutoff point $\bar{X}$
    - Typically the predicted $\hat{y}$ is the average of $y$ conditional on $X$ being less than or greater than $\bar{X}$
    - Alternatively, it could be the mode
- At the terminal node, the prediction $\hat{y}$ is the average of $y$ for all observations in that node

## Classification trees

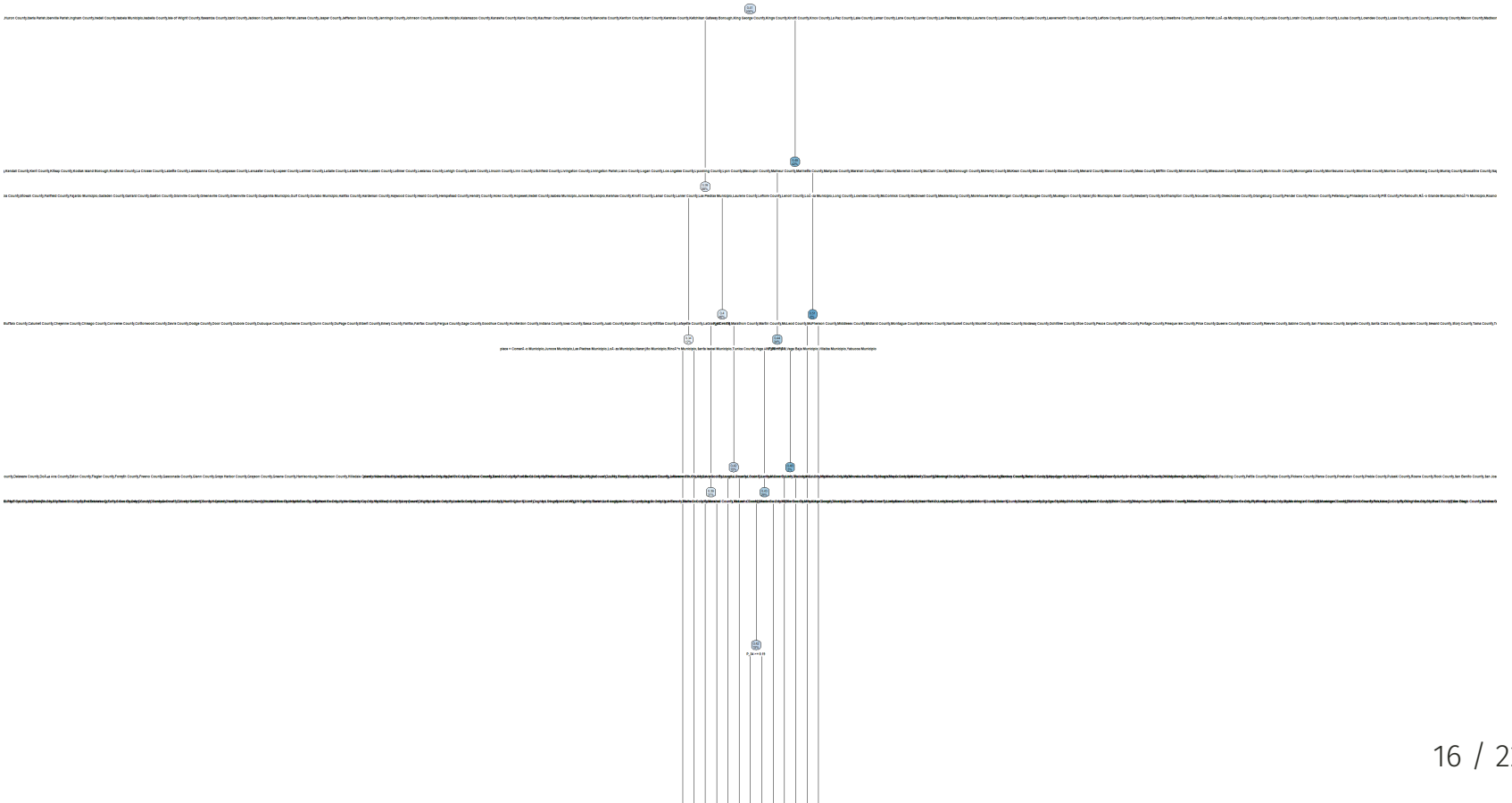
- Your outcome is now a categorical variable
- These predict the probability that an observation fits in some category

## Causal Trees

- Instead of splitting based on prediction of $y$, split to maximize the difference in the average treatment effect (ATE) between the two branches
- At each node, the $X$ covariate that maximizes the difference in the ATE is selected

# Regression Tree of income mobility

- Each node shows the share of observations and the average income mobility for thse observations
- Each branch shows the decision rule as a cutoff in whatever variable minimizes the residual sum of squares



# Random Forests

# Many trees make a forest

- Decision trees are fairly easily to interpret once you make one
- But one drawback is that they are very sensitive to the data
    - Too many nodes and you could overfit
    - Too few nodes and you'll just have noise
- So what if we made many trees and averaged the predictions?
    - Technically this is just called "bagging" (bootstrap aggregating)
    - Random forests also randomize the variables available to split the nodes
    - See more at Introduction to Statistical Learning, Chapter 8.2
- But won't we just repeat the same tree over and over?

# Pull yourself up by your bootstraps

- How could we use bootstrapping?

# Pull yourself up by your bootstraps

- How could we use bootstrapping?
- If you bootstrap the data $B$ times, you create $B$ new samples of the data indexed $b$

1. For each bootstrap sample $b$, create a decision tree $T_b$ using the bootstrap sample $b$
2. For each observation $i$ in the original sample, predict the outcome $y_i$ using all $B$ trees
3. Average the predictions as $\hat{y}_i = \frac{1}{B} \sum_{b=1}^{B} T_b(X_i)$

- This is called bagging (bootstrap aggregating)
- **Intuition**: With many trees, you can average out the noise and get a better prediction
- Random forests add a twist to bagging by randomly selecting a subset of $X$ variables to split the nodes in the tree
    - This ensures the trees are uncorrelated with each other
    - Minimizes variance

**Intuition**: By randomizing the $X$ variables available to a tree, they are less likely to only use the same variables to split the nodes in the tree. As a result, the algorithm evaluates other variables in the data.

# Use cases of random forests

- Random forests are a very popular machine learning technique
- They are used for prediction, classification, and causal inference
- Kleinberg et al. (2018) use random forests to predict the judicial bail decisions in NYC

# What next?

- Get your hands dirty!
- Navigate to the Generalized Random Forest vignette

```
#install.packages('grf')
library(grf)
```

- This will walk you through how to use the **grf** package to estimate causal forests
- Once you finish, try the **grf** guided tour
    - I recommend you try the application to school program evaluation example
- This package is full of vignettes that you could use for the problem set

# Next lecture: Least Absolute Shrinkage and Selection Operator (LASSO)