# Introduction to Data Science

### **Data Science Essentials**



### **Goals for today**

- Review last session coding tasks
- Machine Learning, Part 2 Tree-Based Models



## Review last session coding tasks

week5\_review notebook



#### **Parametric Methods**

Assume that your model takes a particular functional form. Fitting the model boils down to finding the best set of parameters.

Common examples: linear regression, logistic regression, neural networks

$$mpg = \beta_0 + \beta_1 \cdot (hp) + \beta_2 \cdot (cyl)$$
Parameters



### Nonparametric Methods

Do not assume a particular functional form for your model. Instead, use an estimate that gets as close as possible to the training data.

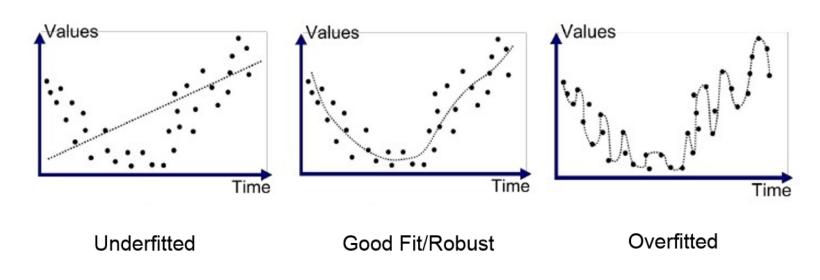
Common examples: decision trees, random forests, gradient boosted trees, k-nearest neighbors



### Parametric vs. Nonparametric

Parametric methods will be low accuracy if the particular form that you chose is incorrect. Prone to **underfitting** - not fitting the training or the test data very well.

Nonparametric methods can fit the training data extremely well but not generalize well to new data. Prone to **overfitting** - fitting the noise. Larger amount of training data is needed to obtain an accurate model.

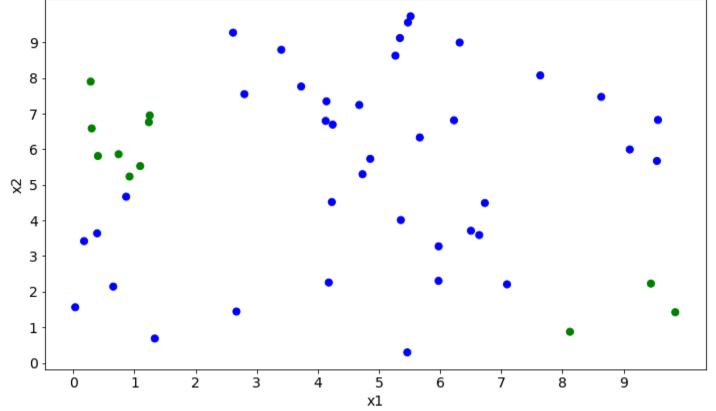




#### **Decision Trees**

Makes predictions by using a set of sequential, hierarchical decisions leading to a final outcome. Can work on datasets that would be difficult to predict using parametric

methods.



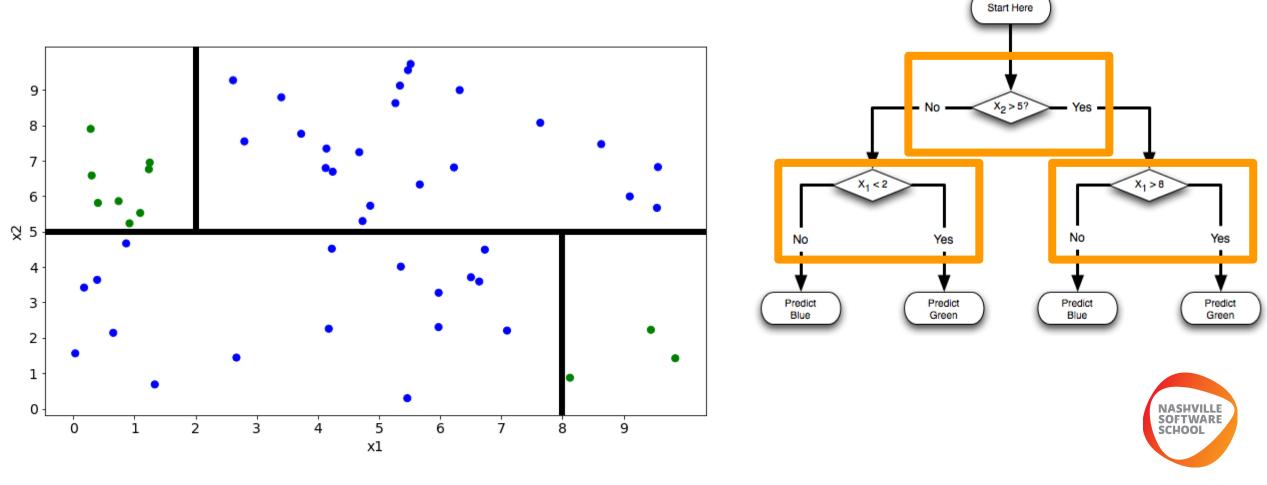
Can we build a model that distinguishes blue points from green points?

It is impossible to separate these points by a straight line, so we could not use a traditional logistic regression model here (unless we applied a complicated transformation to the dataset).

Instead, we can opt for a decision tree model.

#### **Decision Trees**

Makes predictions by using a set of sequential, hierarchical decisions leading to a final outcome. Can work on datasets that would be difficult to predict using parametric methods.



#### **Random Forests**

Single decision trees will often not generalize well to new data.

One common way to improve this is by building multiple trees and aggregating the predictions (aka creating an **ensemble**).

**Random Forest** models create a large number of decision trees, each trained on a subset of the training data and a subset of the features in order to decorrelate and reduce the variance of predictions.

To make the final prediction, the predictions from each tree are averaged.



## Model building and evaluation

Model\_evaluation\_Part2 notebook



#### **Next Steps:**

Your turn! Find more data to try and improve your model. Try using a random forest model to predict whether a county's cost-income ratio is above or below the mean for TN (hint: first create a label for the data that answers that).

- October 16 data storytelling and presentation; work in teams to create a 7-10 minute presentation of your findings
- October 23 Team presentations + panel with data scientists who have walked in your shoes



## **Questions?**

