EXIT TICKETS

- Maybe you can elaborate more to us about how clustering is used in the real world.
- There was a significant amount of walkthrough on the code - that's good but smaller tidbits would be good.
- How do you verify the authenticity of data? What are some good ways to ensure that the data is not tampered with?
- Is it possible to have a quick 5-10 mins demo pitch to showcase how "results" are communicated for e.g. housing dataset ?
- Still not very familiar with some data visualization tools such as those plotting functions
- Agglomerative Clustering. A quick walkthrough summarizing Classification and Logistic Regression, odds, odds ratio will be helpful...
- 1. After showing a clustering methods on a plot, i may wish to identify a particular point within a cluster. How woud I know which point it is? For example, if Ali, Bob, and Charlie belong to Cluster 1, when they are displayed on a plot, how do you know which point is Ali?
  2. Odds are the "odd of a factors affecting an outcome. Coefficients show the impact of a factor/variable on an outcome. But actually, at work, when to use odds, when to use co-efficients?

GENERAL ASSEMBLY

DECISION TREES AND RANDOM FORESTS

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LEARNING OBJECTIVES

- Understand and build decision tree models for classification and regression
- Understand the differences between linear and non-linear models
- Understand and build random forest models for classification and regression
- Know how to extract the most important predictors in a random forest model

OPENING

DECISION TREES AND RANDOM FORESTS

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

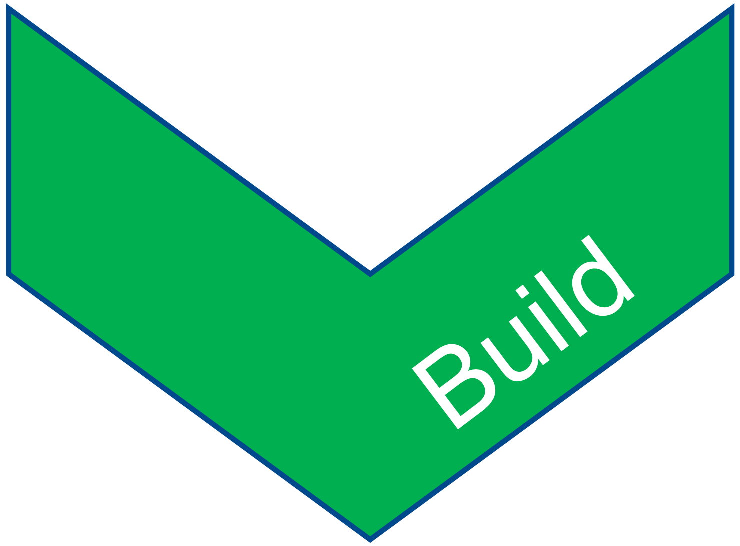
1. Define the difference between the precision and recall of a model.
2. What are some common components and use cases for logistic regression?

DELIVERABLE

Answers to the above questions

OVERVIEW OF THE DATA SCIENCE WORKFLOW

- In this lesson, we will focus on mining the dataset and building a model. We will focus on refining our model for the best predictive ability.



BUILD A DATA MODEL

- Select appropriate model
- Build model
- Evaluate and refine model

GUIDED PRACTICE

EXPLORE THE DATASET

ACTIVITY: EXPLORE THE DATASET

EXERCISE

DIRECTIONS (25 minutes)

We will be using a dataset from StumbleUpon, a service that recommends webpages to users based upon their interests. They like to recommend "evergreen" sites, ones that are always relevant. This usually means websites that avoid topical content and focus on recipes, how-to guides, art projects, etc. We want to determine important characteristics for "evergreen" websites. Follow these prompts to get started:

1. Break into groups.
2. Prior to looking at the data, brainstorm 3-5 characteristics that would be useful for predicting evergreen websites.
3. After looking at the dataset, can you model or quantify any of the characteristics you wanted? See the Notebook for data dictionary and starter code.
4. Does being a news site affect evergreeness? Compute or plot the percent of evergreen news sites.

ACTIVITY: EXPLORE THE DATASET

EXERCISE

DIRECTIONS (25 minutes)

5. In general, does category affect evergreeness? Plot the rate of evergreen sites for all Alchemy categories.
6. How many articles are there per category?
7. Create a feature for the title containing “recipe”. Is the percentage of evergreen websites higher or lower on pages that have “recipe” in the title?

Check: Were you able to plot the requested features? Can you explain how you would approach this type of dataset?

DELIVERABLE

Requested features and answers to questions

INTRODUCTION

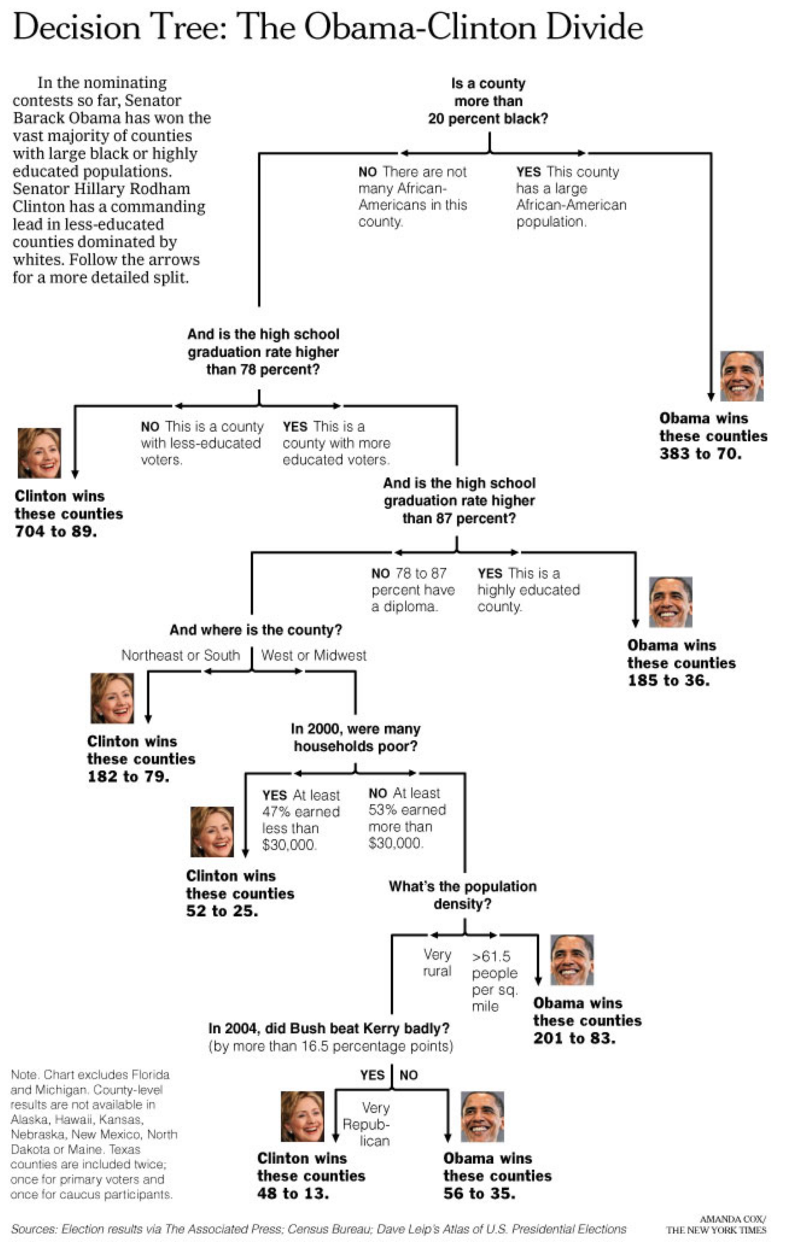
TRAINING DECISION TREES

INTUITION BEHIND DECISION TREES

- Decision trees are like the game “20 questions”. They make decision by answering a series of questions, most often binary questions (yes or no).

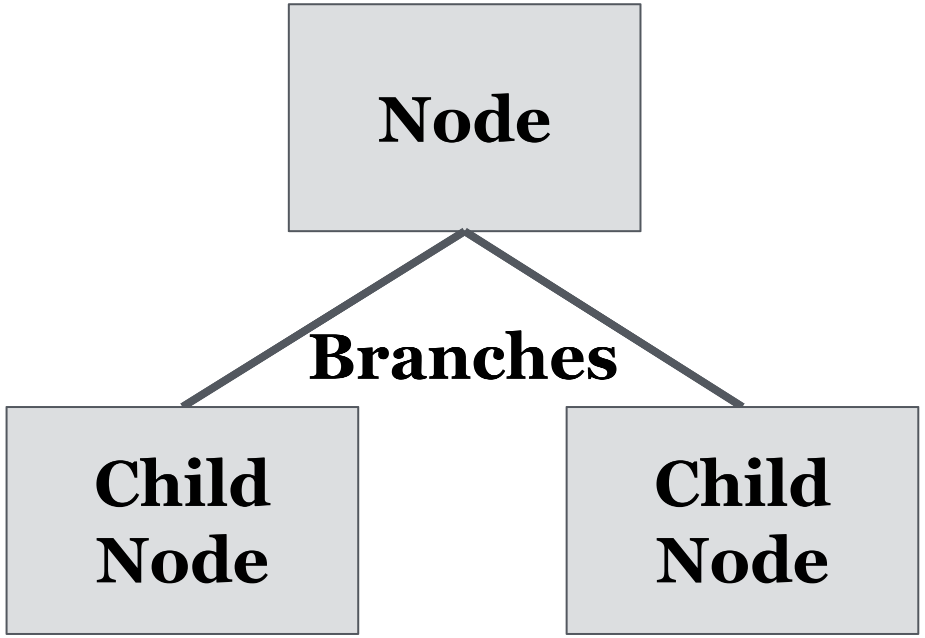
- We want the smallest set of questions to get to the right answer.

- Each questions should reduce the search space as much as possible.



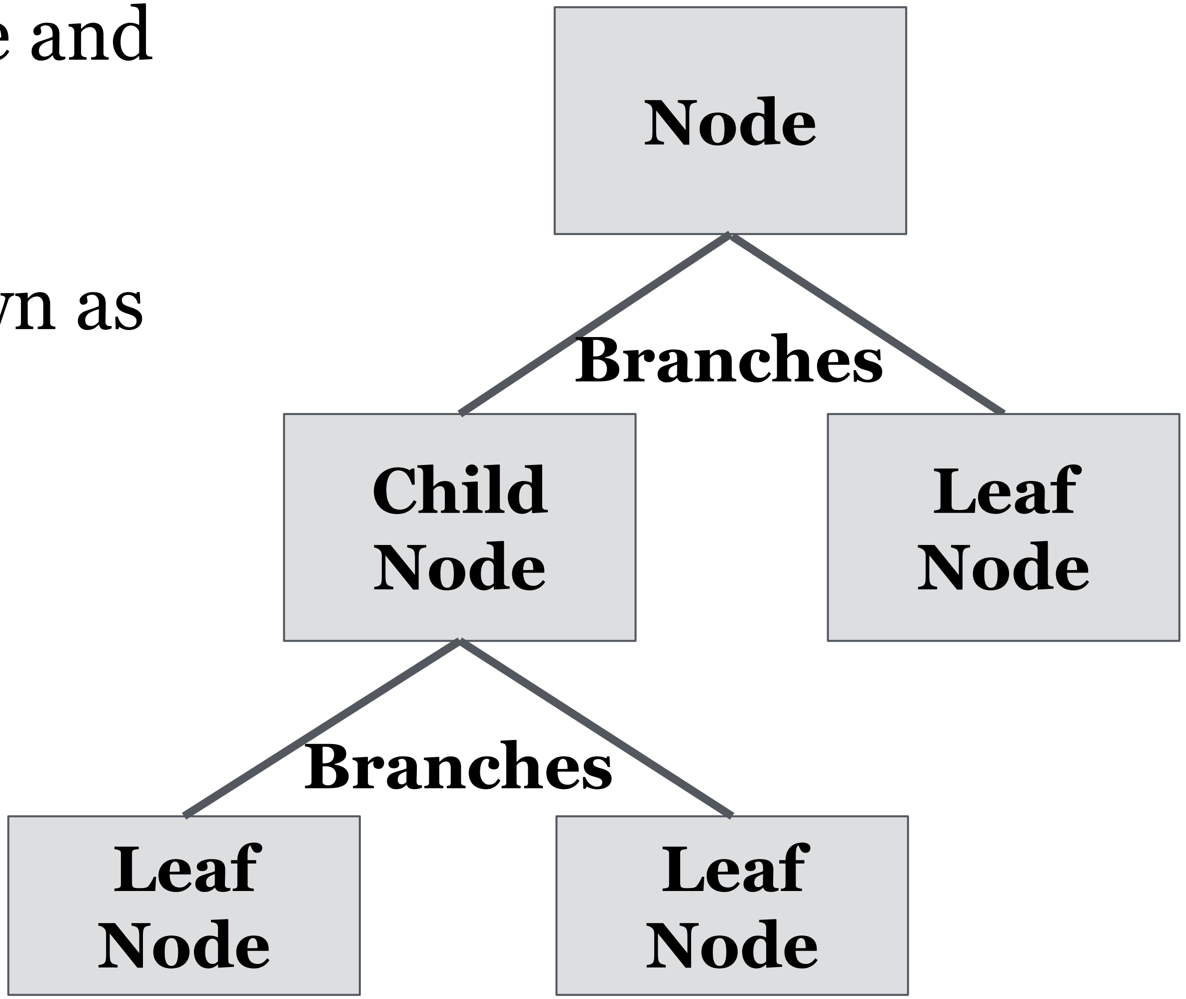
TREES

- Trees are a data structure made up of *nodes* and *branches*.
- Each node typically has two or more branches that connect it to its children.



TREES

- Each child is another node in the tree and contains its own *subtree*.
- Nodes without any children are known as *leaf* nodes.



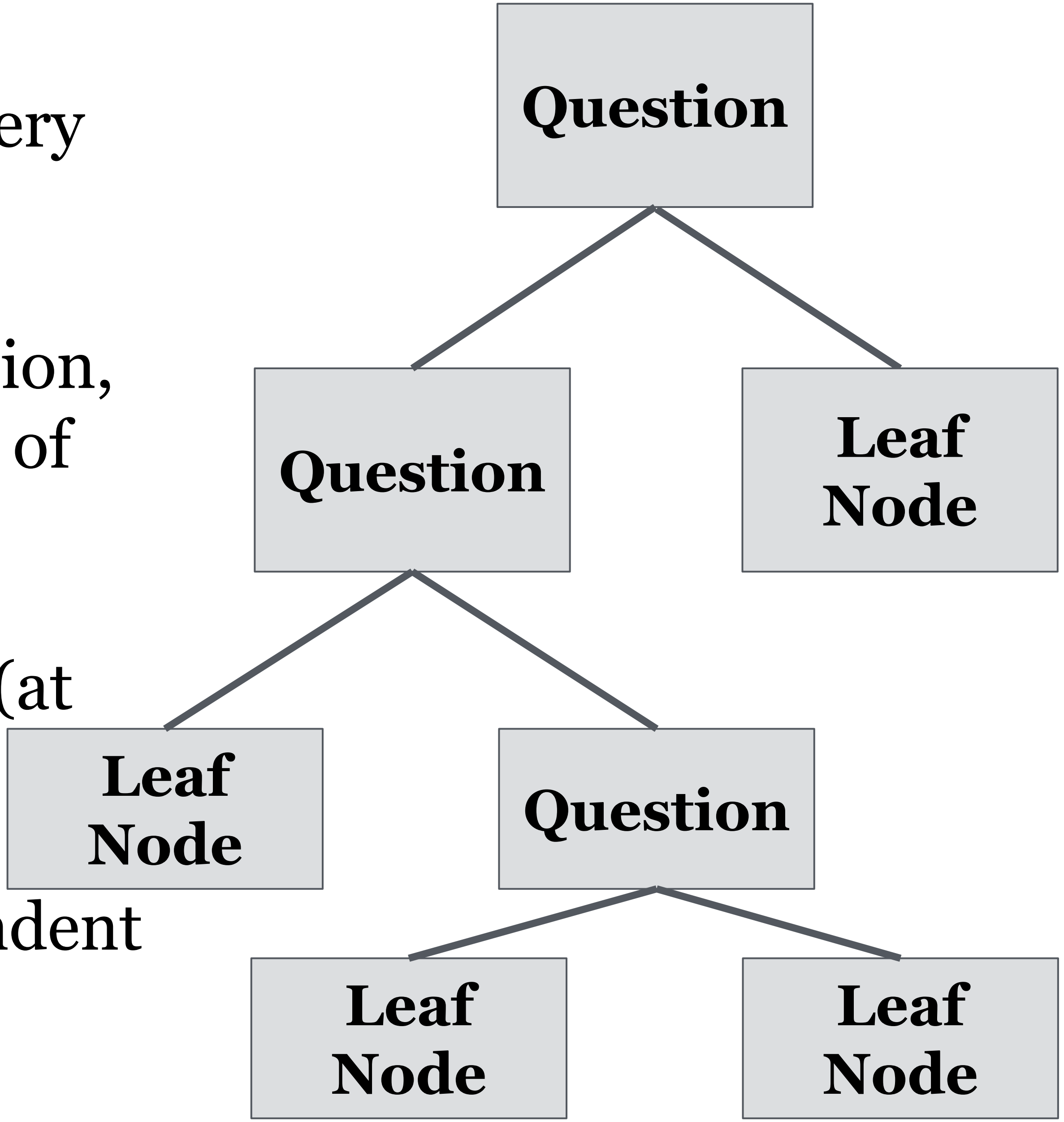
DECISION TREES

- A *decision tree* contains a question at every node.

- Depending upon the answer to the question, we proceed down the left or right branch of the tree and ask another question.

- Once we don't have any more questions (at the *leaf* nodes), we make a prediction.

- Note: The next question is always dependent on the last.



DECISION TREES

- Let’s suppose we want to predict if an article is a news article.
- What questions should we ask to make a prediction?
- How many questions should we ask?

DECISION TREES

- We may start by asking: does it mention a President?
- If it does, it must be a news article.
- If not, let's ask another question: does the article contain other political features?
- If not, does the article contain references to political topics?
- We could keep going on in this manner until we were satisfied.

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

Let's work as a class to accomplish the following:

1. Using our StumpleUpon dataset, try to predict whether a given article is evergreen.
2. Build a decision tree to determine the above.

DELIVERABLE

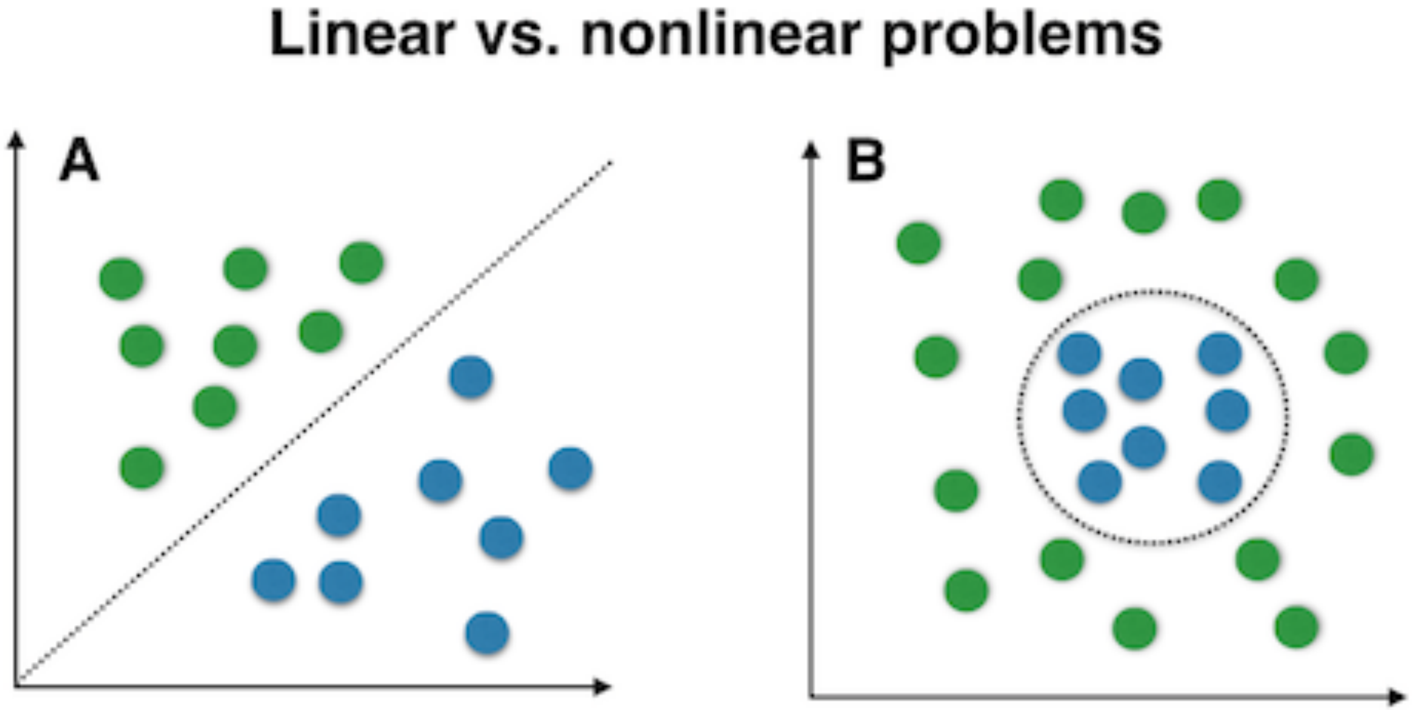
Our decision tree

COMPARISON TO PREVIOUS MODELS

- Decision trees are *non-linear*, an advantage over logistic regression.
- A *linear* model is one in which a change in an input variable has a constant change on the output variable.

COMPARISON TO PREVIOUS MODELS

- Linear vs. non-linear classification models



COMPARISON TO PREVIOUS MODELS

- An example of this difference is the relationship between years of education and salary. In a *linear* model, the increase in salary from 10 to 15 years of education would be the same as the increase in salary from 15 to 20 years of education. In a *non-linear* model, salary can change dramatically for years 0-15 and negligibly from years 15-20.

- Trees automatically contain interaction of features, since each question is dependent on the last.

TRAINING A DECISION TREE MODEL

- Training a decision model is deciding the best set of questions to ask.
- A good question will be one that best segregates the positive group from the negative group and then narrows in on the correct answer.
- For example, in our news article decision tree, the best question is one that creates two groups, one that is mostly news stories and one that is mostly non-news stories.

TRAINING A DECISION TREE MODEL

- We can quantify the *purity* of the separation of groups using Classification Error, Entropy, or Gini Coefficient.

- We want to choose the question that gives us the best *change* in our purity measure. At each step, we can ask, “Given our current set of data points, which question will make the largest change in purity?”

- This is done *recursively* for each new set of two groups until we reach a stopping point.

TRAINING A DECISION TREE MODEL

- Classification Error: Fraction of training observations in the region that do not belong to the most common class

$$E = 1 - \max_k(\hat{p}_{mk})$$

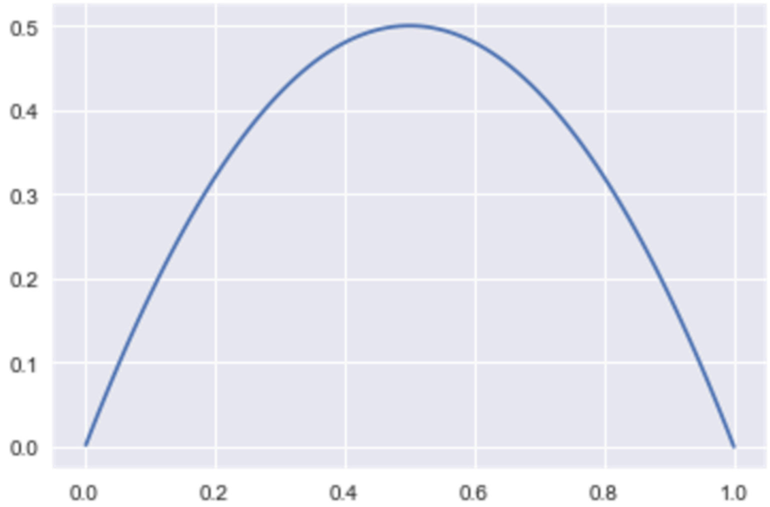
- $\hat{p}_{mk}$ represents the proportion of training observations in the mth region that are from the kth class

- Classification error however is generally not sufficiently sensitive for tree-growing and in practice the two other measures are preferable

TRAINING A DECISION TREE MODEL

- Gini Index is defined by:

$$G = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk})$$



- The Gini Index takes on a small value if all the $\hat{p}_{mk}$ are close to zero or one. For this reason the Gini Index is referred to as a measure of node purity

0.9, 0.1 => G = 0.9 * (1-0.9) + 0.1 * (1-0.1) = 0.18

0.4, 0.6 => G = 0.4 * (1-0.4) + 0.6*(1-0.6) = 0.48

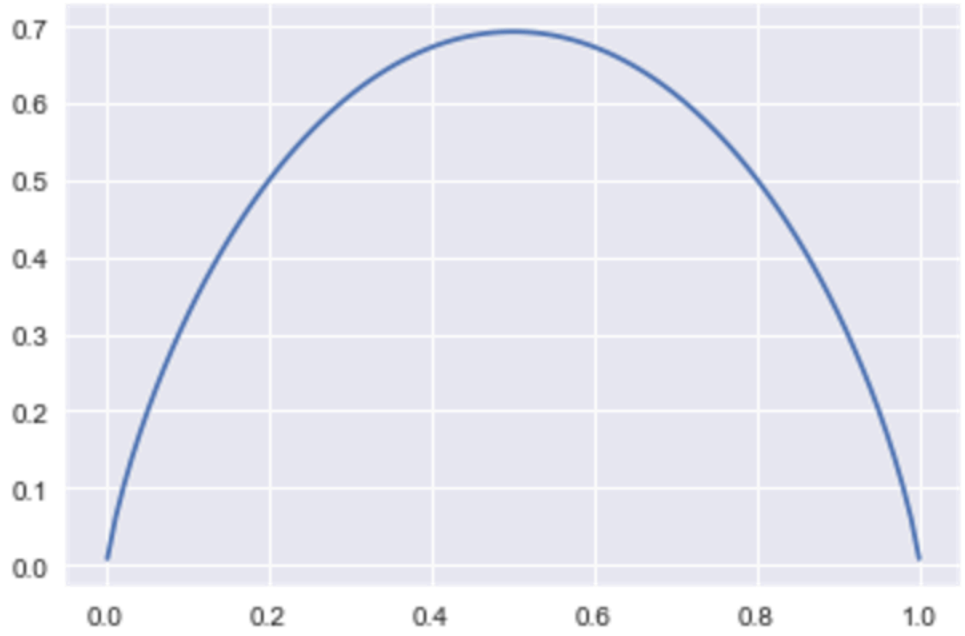
TRAINING A DECISION TREE MODEL

- Cross Entropy is defined by:

$$D = -\sum_{k=1}^{K} \hat{p}_{mk} \log(\hat{p}_{mk})$$

- Since $0 \leq \hat{p}_{mk} \leq 1$ it follows that $0 \leq -\hat{p}_{mk} \log(\hat{p}_{mk})$

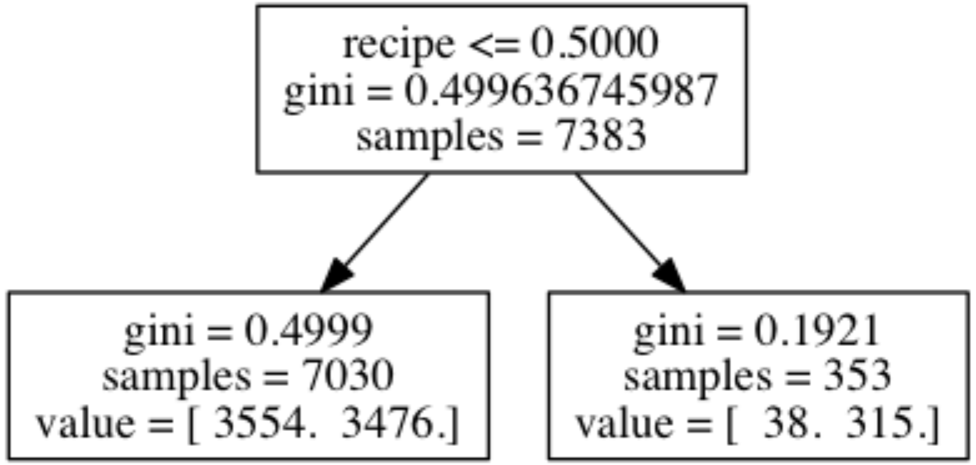
- The Cross Entropy will take on a value near zero if all the $\hat{p}_{mk}$ are all near zero or near one



TRAINING A DECISION TREE MODEL

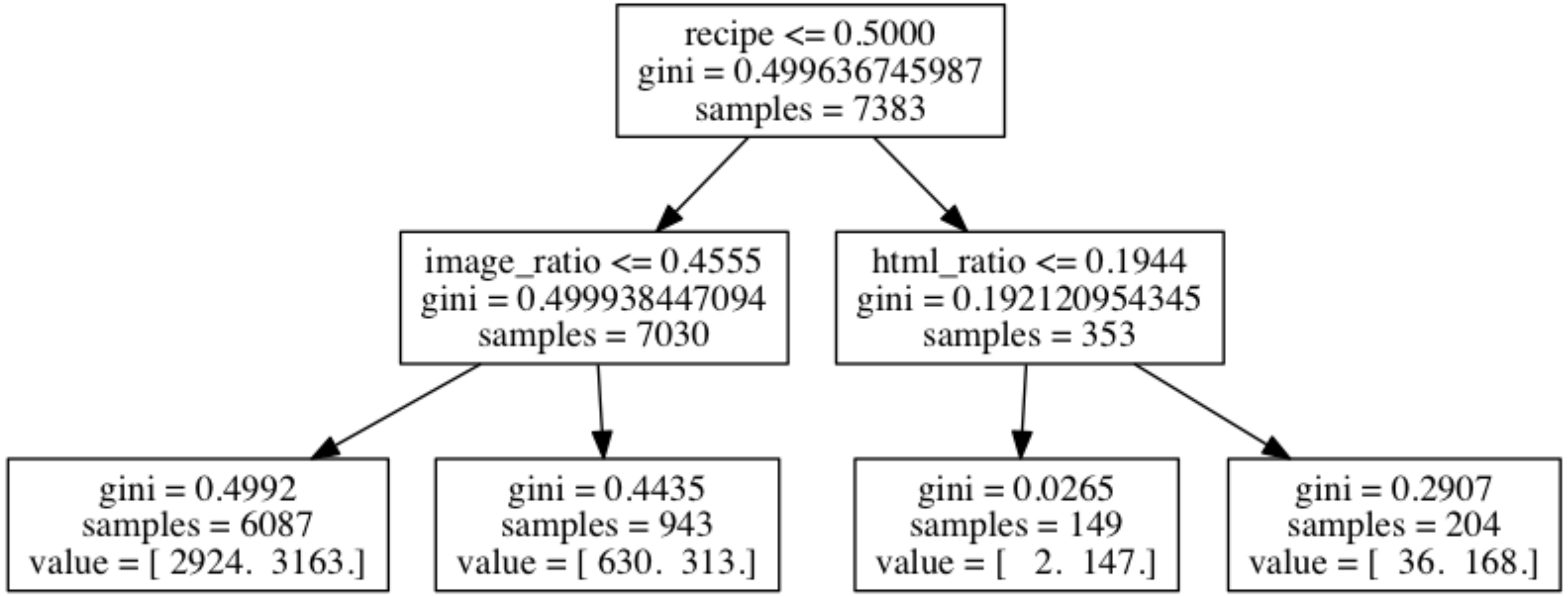
- Let's build a sample tree for our evergreen prediction problem. Assume our features are whether the article contains a recipe, the image ratio, the html ratio.

- First, let's choose the feature that gives us the highest purity, the recipe feature.



TRAINING A DECISION TREE MODEL

- We can take each side of the tree and repeat the process.



- We can continue this process until we have asked as many questions as we want or until our leaf nodes are completely pure.

MAKING PREDICTIONS FROM A DECISION TREE

- Predictions are made by answering each of the questions.

- Once we reach a leaf node, our prediction is made by taking the majority label of the training samples that fulfill the questions.

- In our sample tree, if we want to classify a new article, ask:
    - Does the article contain the word recipe?
    - If it doesn't, does the article have a lot of images?
    - If it does, then 313 / 943 article are evergreen.
    - So we can assign a 0.33 probability for evergreen sites.

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. How do we classify a new article?
2. How do we make predictions from a decision tree?

DELIVERABLE

Answers to the above questions

GUIDED PRACTICE

DECISION TREES IN SCIKIT-LEARN

ACTIVITY: DECISION TREES IN SCIKIT-LEARN

EXERCISE

DIRECTIONS (15 minutes)

1. In the starter code notebook, work through the exercises titled "Decision Trees in scikit-learn".
2. In your groups from earlier, work on evaluating the decision tree using cross-validation methods.
3. What metrics would work best? Why?

Check: Are you able to evaluate the decision tree model using cross-validation methods?

DELIVERABLE

Completed exercises and answer to #3

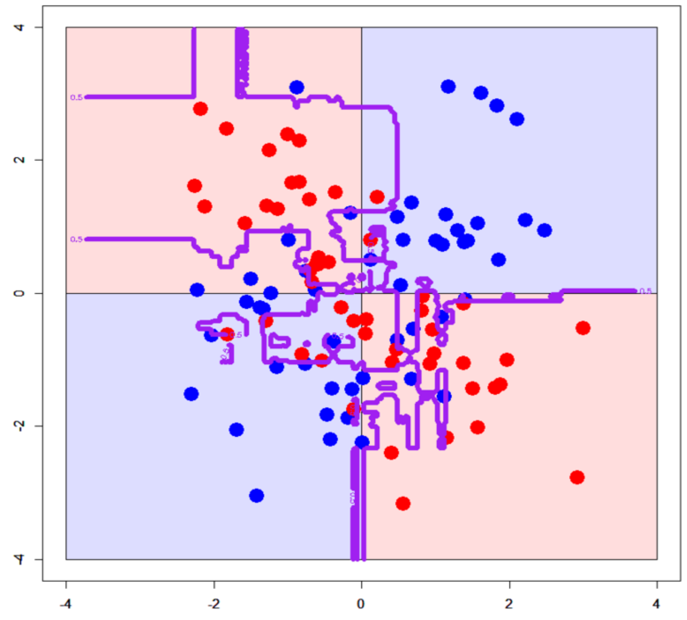
DEMO

OVERFITTING IN DECISION TREES

OVERFITTING IN DECISION TREES

- Decision trees tend to be weak models because they can easily memorize or overfit to a dataset.

- A model is *overfit* when it memorizes or bends to a few specific data points rather than picking up general trends in the data.



OVERFITTING IN DECISION TREES

- An unconstrained decision tree can learn an extreme tree (e.g. one feature for each word in a news article).

- We can limit our decision trees using a few methods.
  - Limiting the number of questions (nodes) a tree can have).
  - Limiting the number of samples in the leaf nodes.

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. Why are decision trees generally thought of as weak models?
2. How can we limit our decision trees?

DELIVERABLE

Answers to the above questions

ADVANTAGES AND DISADVANTAGES OF DECISION TREES

- Advantages:
  - Trees are very easy to explain to people
  - Some people believe that decision trees more closely mirror human decision-making than other approaches
  - Trees can be displayed graphically and are easily interpreted even by a non-expert

- Disadvantages:
  - Trees generally do not have the same level of predictive accuracy as other approaches
  - Trees can be very non-robust, i.e. a small change in the data can cause a large change in the final estimated tree

GUIDED PRACTICE

ADJUSTING DECISION TREES TO AVOID OVERFITTING

ACTIVITY: ADJUSTING DECISION TREES TO AVOID OVERFITTING

EXERCISE

DIRECTIONS (15 minutes)

1. You can control for overfitting in decision trees by adjusting one of the following parameters:
   a. `max_depth`: Control the maximum number of questions.
   b. `min_samples_in_leaf`: Control the minimum number of records in each node.
2. Test each of these parameters in the starter code notebook.

DELIVERABLE

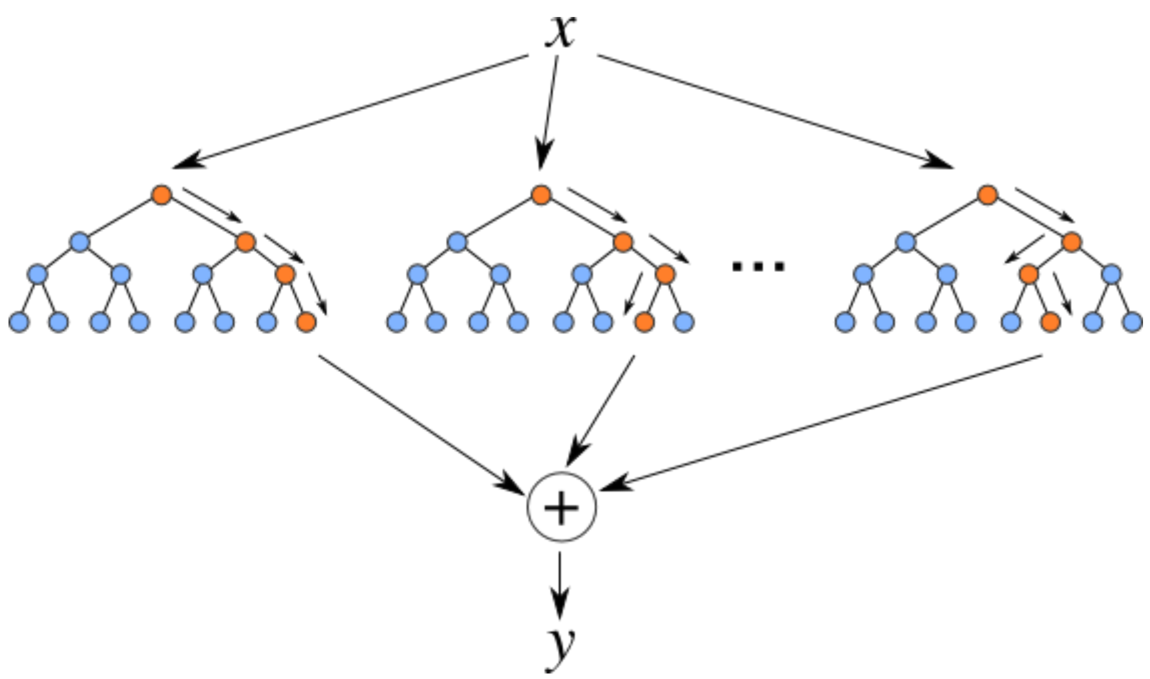
Code using the above parameters

INTRODUCTION

RUNNING THROUGH THE RANDOM FORESTS

RUNNING THROUGH THE RANDOM FORESTS

- Random forest models are one of the most widespread classifiers used.
- They are relatively simple to use and help avoid overfitting.
- Random Forests are an *ensemble* or collection of individual decision trees.



PROS AND CONS OF RANDOM FORESTS

- Advantages
  - Easy to tune
  - Built-in protection against overfitting
  - Non-linear
  - Built-in interaction effects

- Disadvantages
  - Slow
  - Black-box
  - No “coefficients”
  - Harder to explain

TRAINING A RANDOM FOREST

- Training a random forest model involves training many decision tree models.

- Since decision trees overfit easily, we use many decision trees together and randomize the way they are created.

TRAINING A RANDOM FOREST

- Random Forest Algorithm

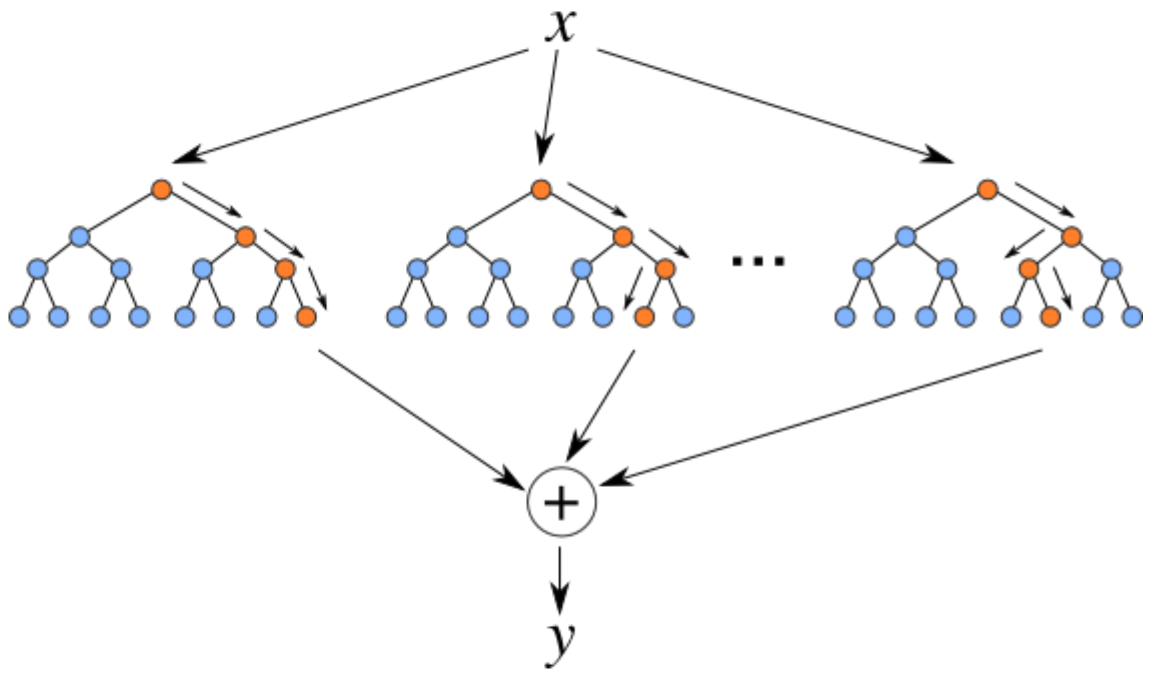
  a. Take a bootstrap sample of the dataset.

  b. Train a decision tree on the bootstrap sample. For each split/feature selection, only evaluate a *limited* number of features to find the best decision tree.

  c. Repeat this for *N* trees.

PREDICTIONS USING A RANDOM FOREST

- Predictions for a random forest model come from each decision tree.
- Make an individual prediction with each decision tree.
- Combine the individual predictions and take the majority vote.



GUIDED PRACTICE

REGRESSION WITH DECISION TREES AND RANDOM FORESTS

REGRESSION TREES

- For regression trees, the prediction is the mean value of all the values in the node
- The goal is to find nodes R_1, … R_J based on minimizing the RSS

$$\sum_{j=1}^{J} \sum_{i \epsilon R_j} \left(y_i - \hat{y}_{R_j} \right)^2$$

ACTIVITY: REGRESSION WITH DECISION TREES & RANDOM FORESTS

EXERCISE

DIRECTIONS (20 minutes)

1. Build a random forest model to predict the evergreeness of a website. Remember to use the parameter `n_estimators` to control the number of trees used in the model.
2. Take note of the features that give the best splits to determine the most important features.
3. Decision trees and random forests can be used for both classification and regression. In regression, predictions are made by taking the average value of the samples in the leaf node. You can take the average of the individual trees' predictions. Build a regression based random forest model.

DELIVERABLE

The models mentioned above

INDEPENDENT PRACTICE

EVALUATE RANDOM FOREST USING CROSS-VALIDATION

ACTIVITY: EVALUATE RANDOM FOREST USING CROSS-VALIDATION

EXERCISE

DIRECTIONS (25 minutes)

1. Building upon the previous Guided Practice, add any input variables to the model that you think may be relevant.

2. For each feature:
    a. Evaluate the model for improved predictive performance using cross-validation.
    b. Evaluate the importance of the feature.

3. **Bonus**: Just like the 'recipe' feature, add in similar text features and evaluate their performance.

DELIVERABLE

Newly created features and models

CONCLUSION

TOPIC REVIEW

REVIEW Q&A

- What are decision trees?
- What does training involve?
- What are some common problems with decision trees?
- What are random forests?
- What are some common problems with random forests?

LESSON

Q & A