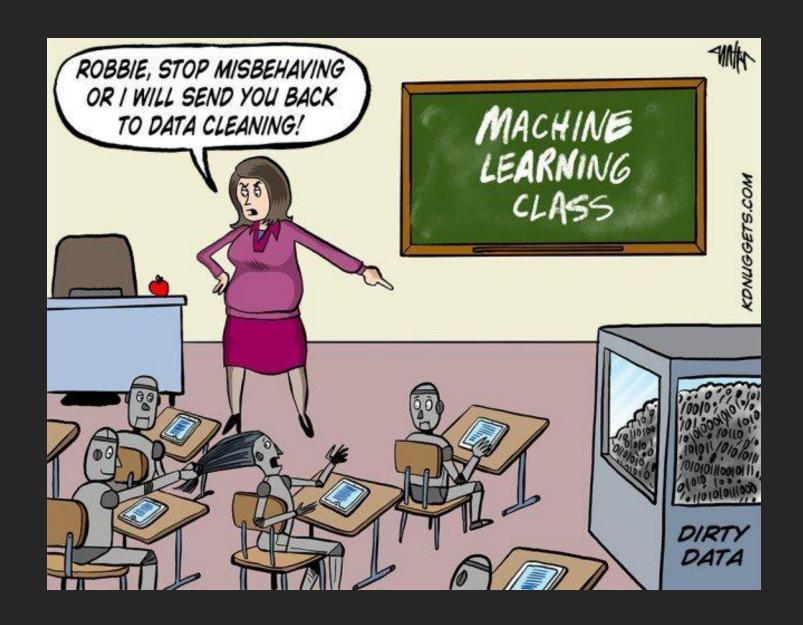
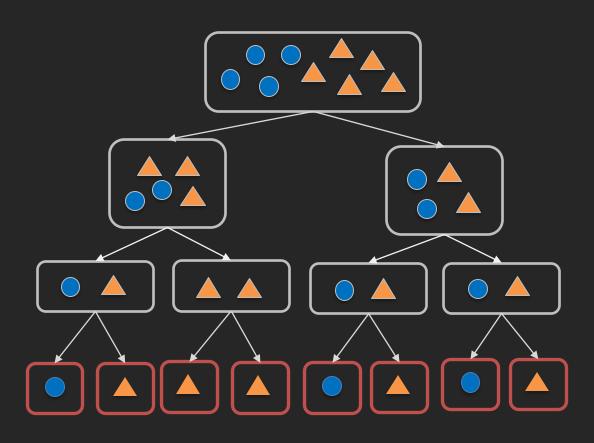


Outline

- Motivation
- Decision Trees Classification
 - Intuition
 - Predictions
 - Splitting Criteria
 - Stopping Conditions



Question: If we don't terminate the decision tree algorithm manually, what will the leaf nodes of the decision tree look like?

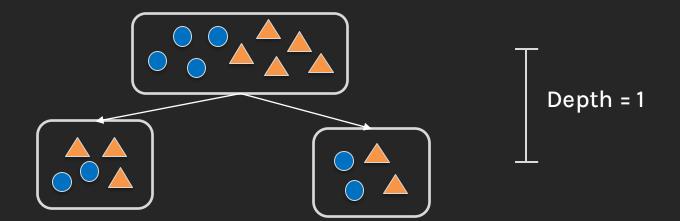


The tree will continue to grow until each region contains **exactly one training point** and the model attains 100% **training** accuracy.

Question: How can we prevent this from happening?

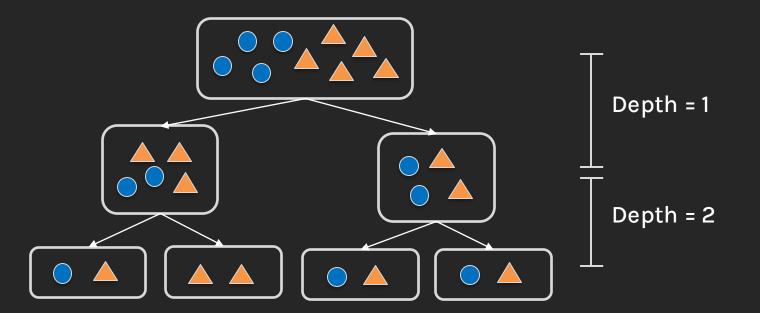
The most common stopping condition is to limit the maximum depth $(max \ depth)$ of the tree.

max depth = 1



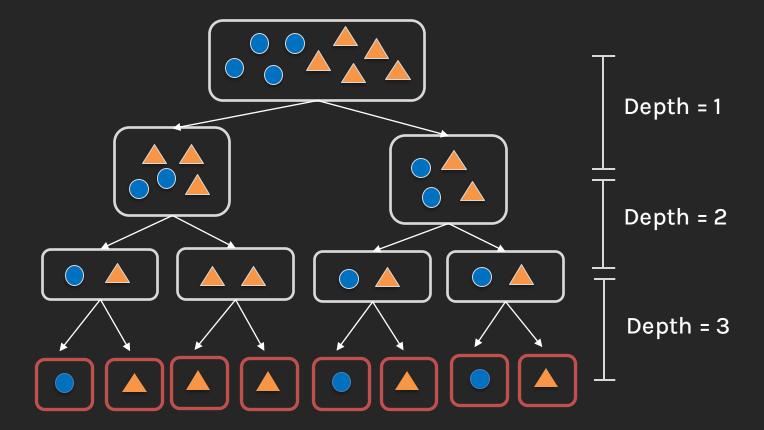
The most common stopping condition is to limit the maximum depth (max depth) of the tree.

$$max_depth = 2$$



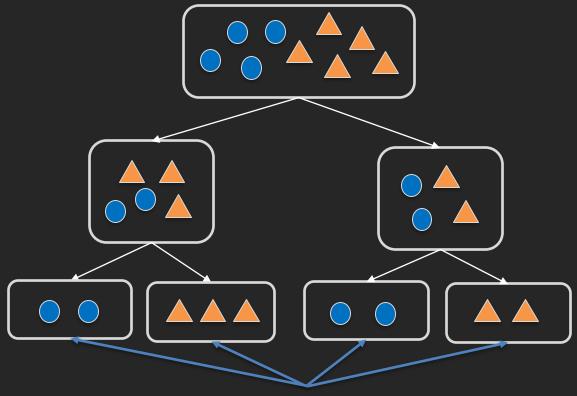
The most common stopping condition is to limit the maximum depth (max depth) of the tree.

$$max_depth = 3$$



Other common simple stopping conditions are:

Don't split a region if all instances in the region belong to the same class.

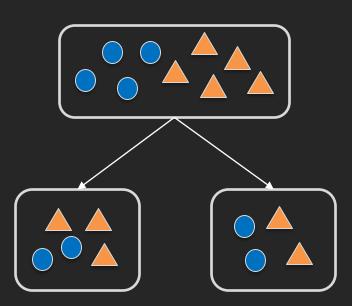


Pure leaf Nodes

Other common simple stopping conditions are:

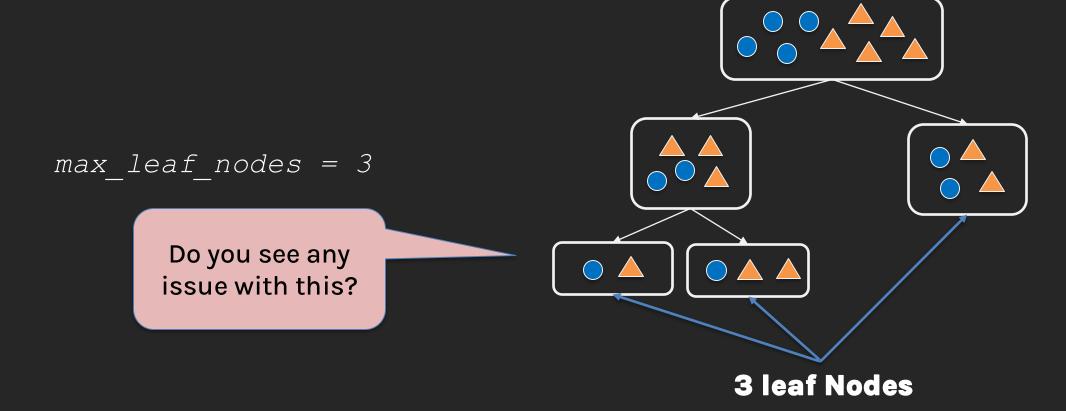
Don't split a region if the number of instances in any of the sub-regions will fall below pre-defined threshold (min_samples_leaf).

$$min_samples_leaf = 4$$



Other common simple stopping conditions are:

• Don't split a region if the total number of leaves in the tree will exceed a predefined threshold (max leaf nodes).



Normally, Sklearn grows trees in what is called 'level-order'-fashion until a stopping condition such as $max \ depth$ is met.

However, if a value for max_leaf_nodes is specified, Sklearn will instead grow the tree in a 'best-first' fashion.

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But what do level-order and best-first growth *mean*?

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However, if a value for max_leaf_nodes is specified, Sklearn will instead grow the tree in a 'best-first' fashion.

But what do level-order and best-first growth *mean*?

Level-order is also sometimes called 'breadth-first'-search but we will use the term 'level-order' so it won't be confused with the similar sounding 'best-first' search.

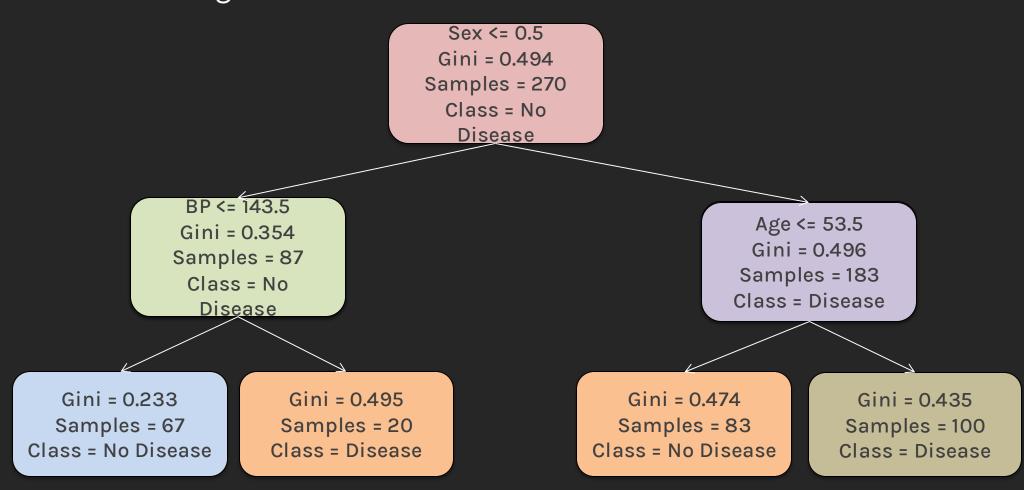
Example 1: Level-Order

Consider the following decision tree with max_depth=2 that predicts if a person has heart disease based on age, sex, BP and cholesterol:

Gini = 0.494 Samples = 270 Class = No Disease

Example 1: Level-Order

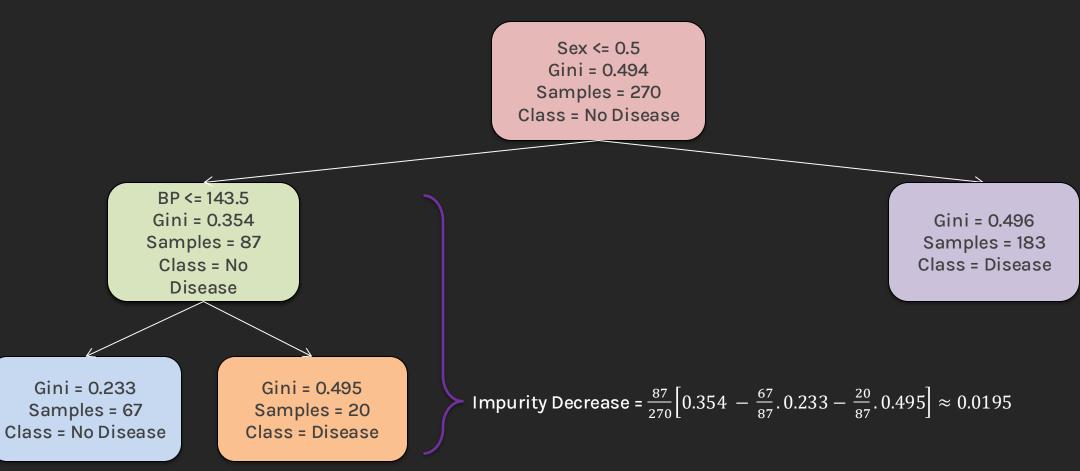
Consider the following decision tree with max_depth=2 that predicts if a person has heart disease based on age, sex, BP and cholesterol:

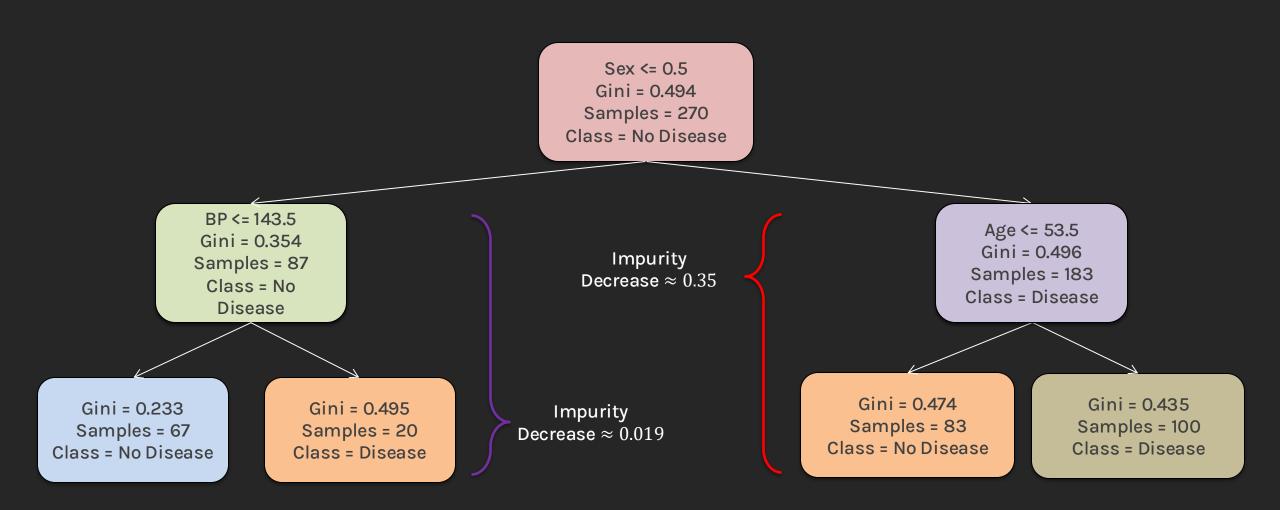


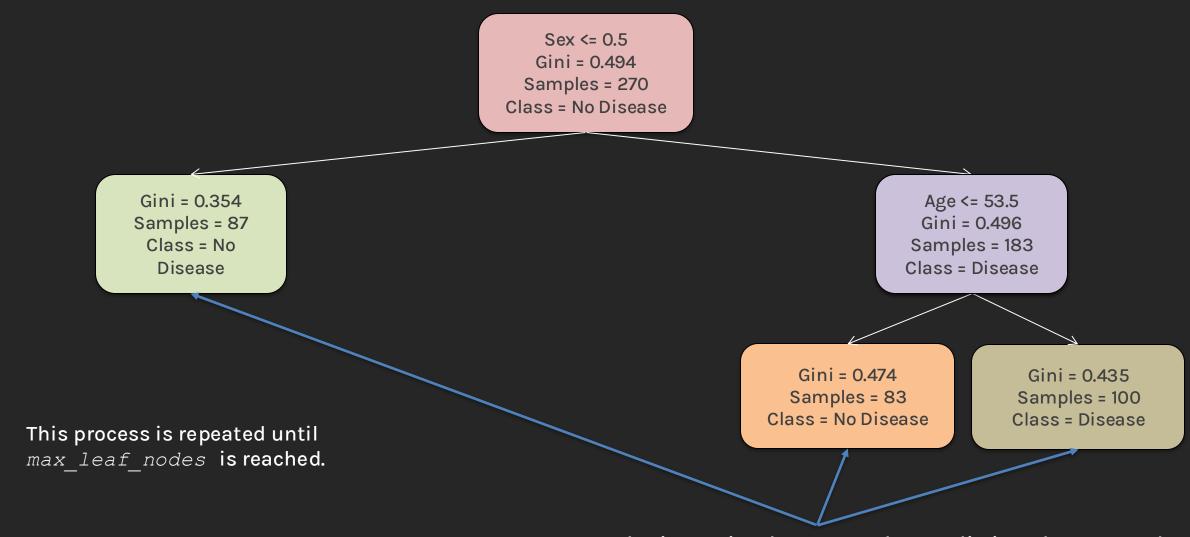
Sklearn determines the best split based on **impurity decrease**. The resulting tree will be the same when fully grown, just the order in which it is built is different.

Gini = 0.494 Samples = 270 Class = No Disease

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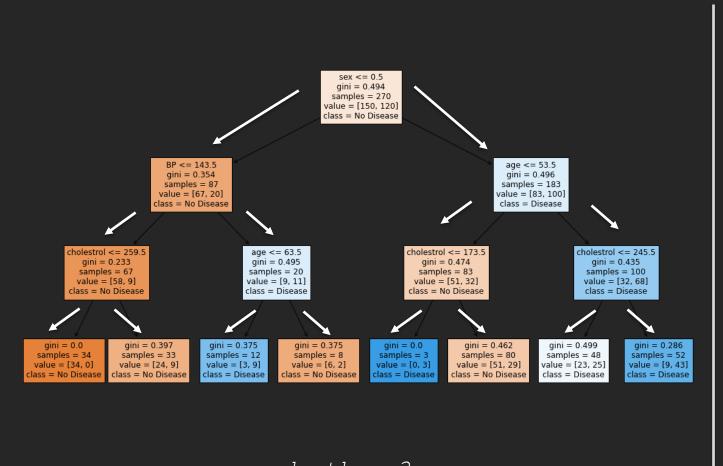


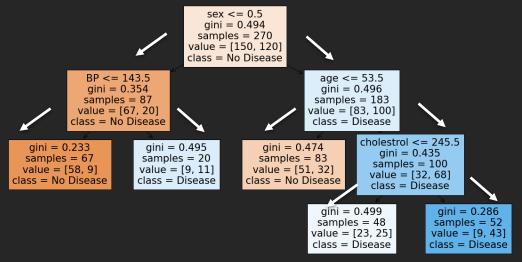




Now we compare the impurity decrease when splitting these 3 nodes!

Example 2: Level-order vs Best-first growth





$$max_leaf_nodes = 5$$

 $\overline{max} \underline{depth} = 3$

A more restrictive stopping condition is:

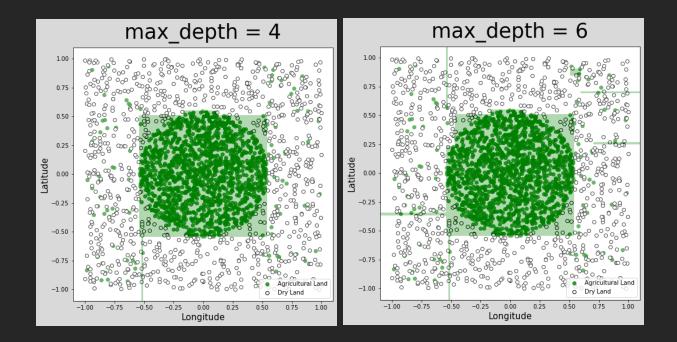
Compute the gain in purity of splitting a region R into R_1 and R_2 :

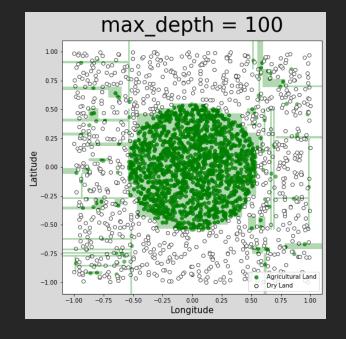
$$Gain(R) = \Delta(R) = m(R) - \frac{N_1}{N}m(R_1) - \frac{N_2}{N}m(R_2)$$

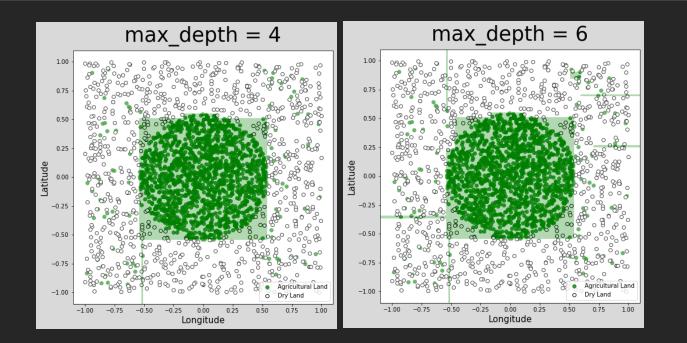
Classification Error/Gini Index/Entropy

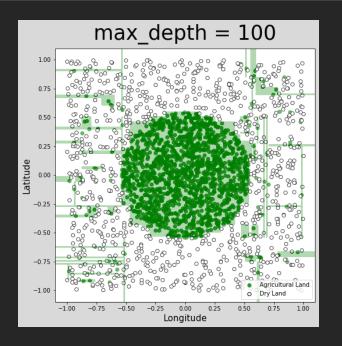
Don't split if the gain is less than some pre-defined threshold (min_impurity_decrease).

How do we decide what is the appropriate stopping condition or stopping method?

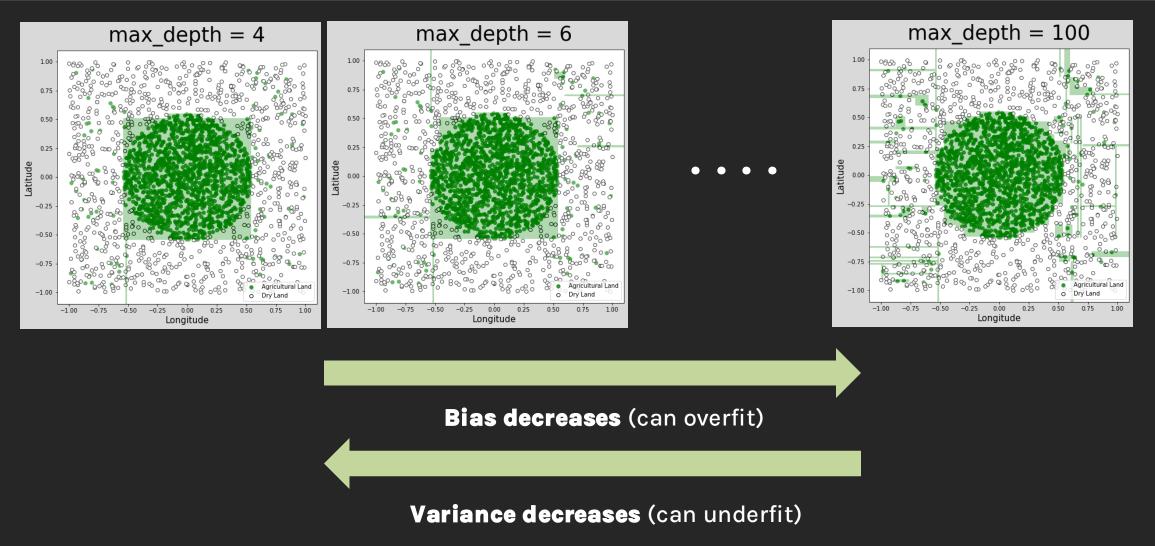




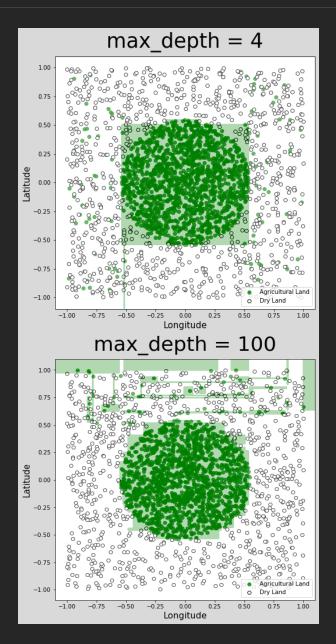




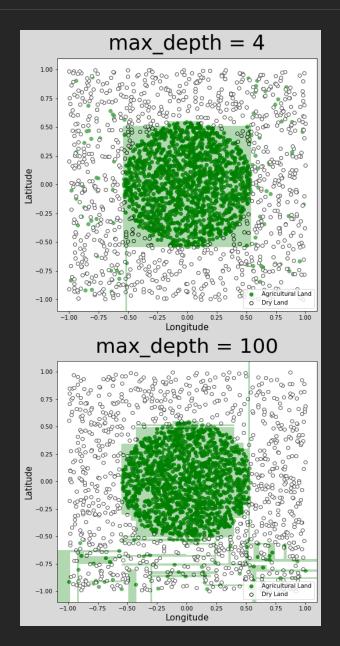
Bias decreases (can overfit)



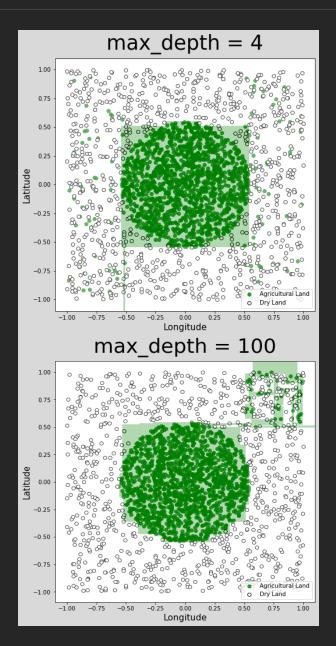
Complex trees are also harder to interpret and more computationally expensive to



- **High Bias:** Trees of low depth are not a good fit for the training data it's unable to capture the nonlinear boundary separating the two classes.
- Low Variance: Trees of low depth are robust to slight perturbations in the training data the square carved out by the model is stable if you move the boundary points a bit.
- Low Bias: With a high depth, we can obtain a model that correctly classifies all points on the boundary (by zig-zagging around each point).



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- Low Variance: Trees of low depth are robust to slight perturbations in the training data the square carved out by the model is stable if you move the boundary points a bit.
- Low Bias: With a high depth, we can obtain a model that correctly classifies all points on the boundary (by zig-zagging around each point).
- High Variance: Trees of high depth are sensitive to perturbations in the training data, especially to changes in the boundary points.



```
min_samples_leaf
```

min_impurity_decrease

How can we determine the appropriate hyperparameters?

cross-validation

Game time





Consider the ROC plot below. A, B, C, and D represent 4 different binary classification models.

Arrange the model names such that they correspond to the sequence of statements below:

- 1. This model is the perfect/optimal classifier.
- 2. The model is the worst classifier.
- 3. The classifier is a chance based classifier, each class has an equal probability.
- 4. The model is a good classifier.

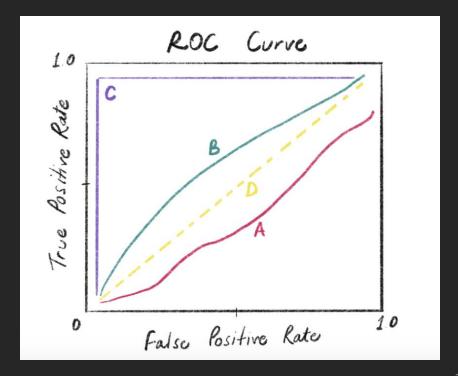
Options

A. 1-A, 2-B, 3-C, 4-D

B. 1-C, 2-A, 3-D, 4-B

C. 1-C, 2-D, 3-B, 4-A

D. 1-B, 2-A, 3-C, 4-D



Thank you

