

# **Classification and Regression Trees**

# Objectives

- Describe the output of a decision tree to someone without a data science background
- Describe how the algorithm creates the decision tree
- Predict the likelihood of a binary event using the decision tree algorithm in scikit-learn
- Create a decision tree visualization
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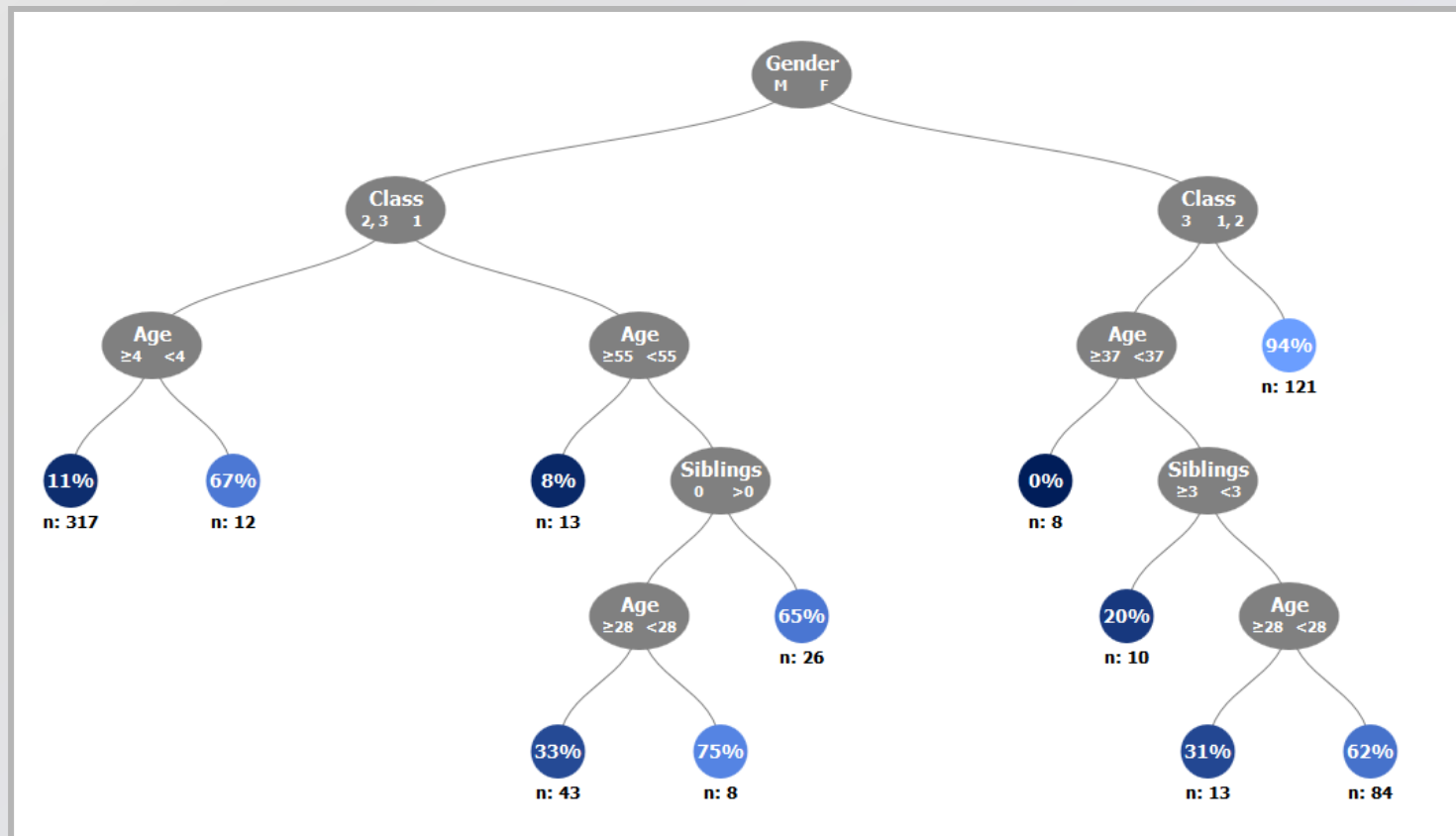
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- Are prone towards high-variance.
- We will focus on the CART algorithm.

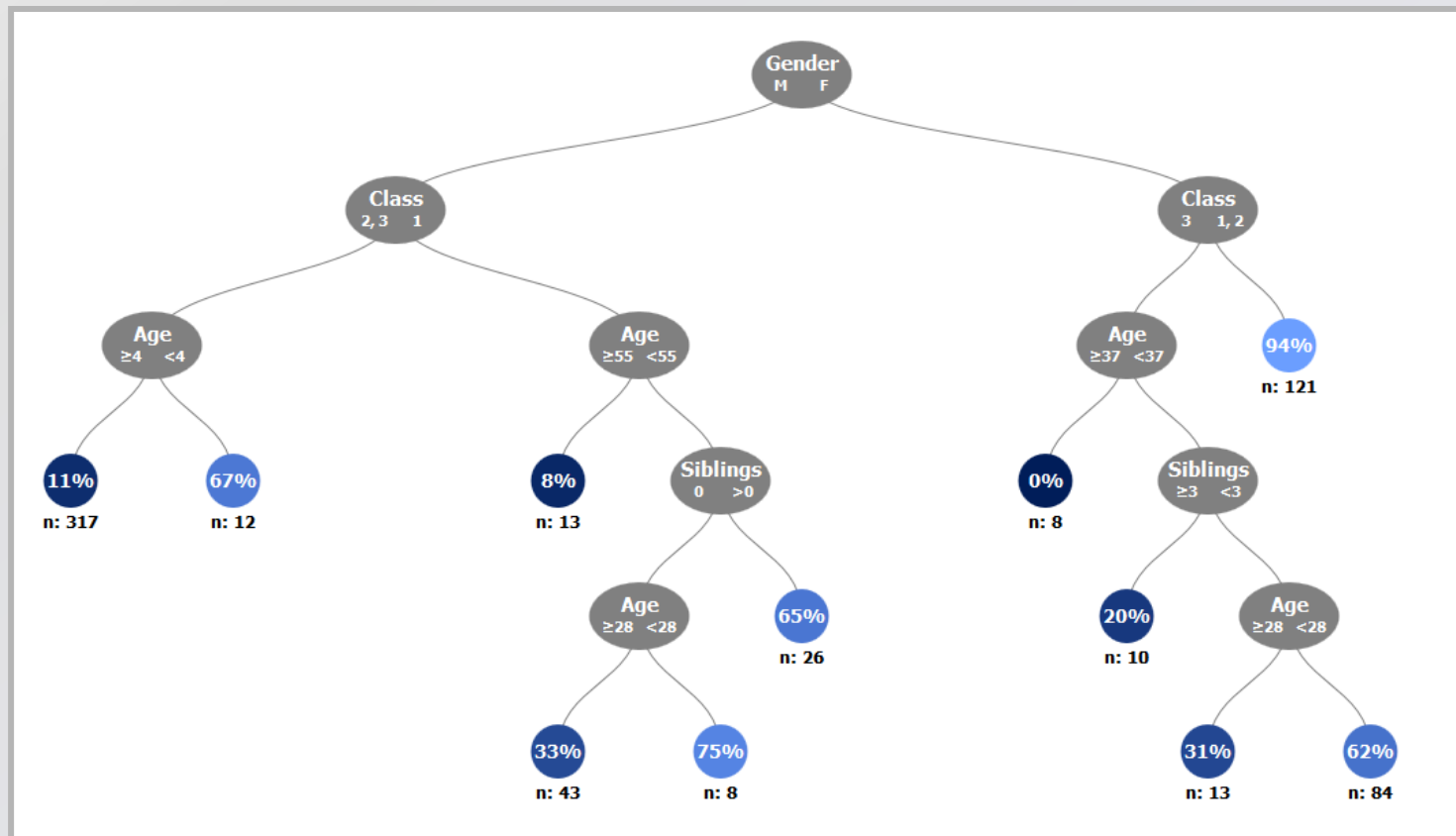
# Description

Best place to start understanding decision trees is to look at one of them. The diagram below shows a decision tree trained on the titanic data set.



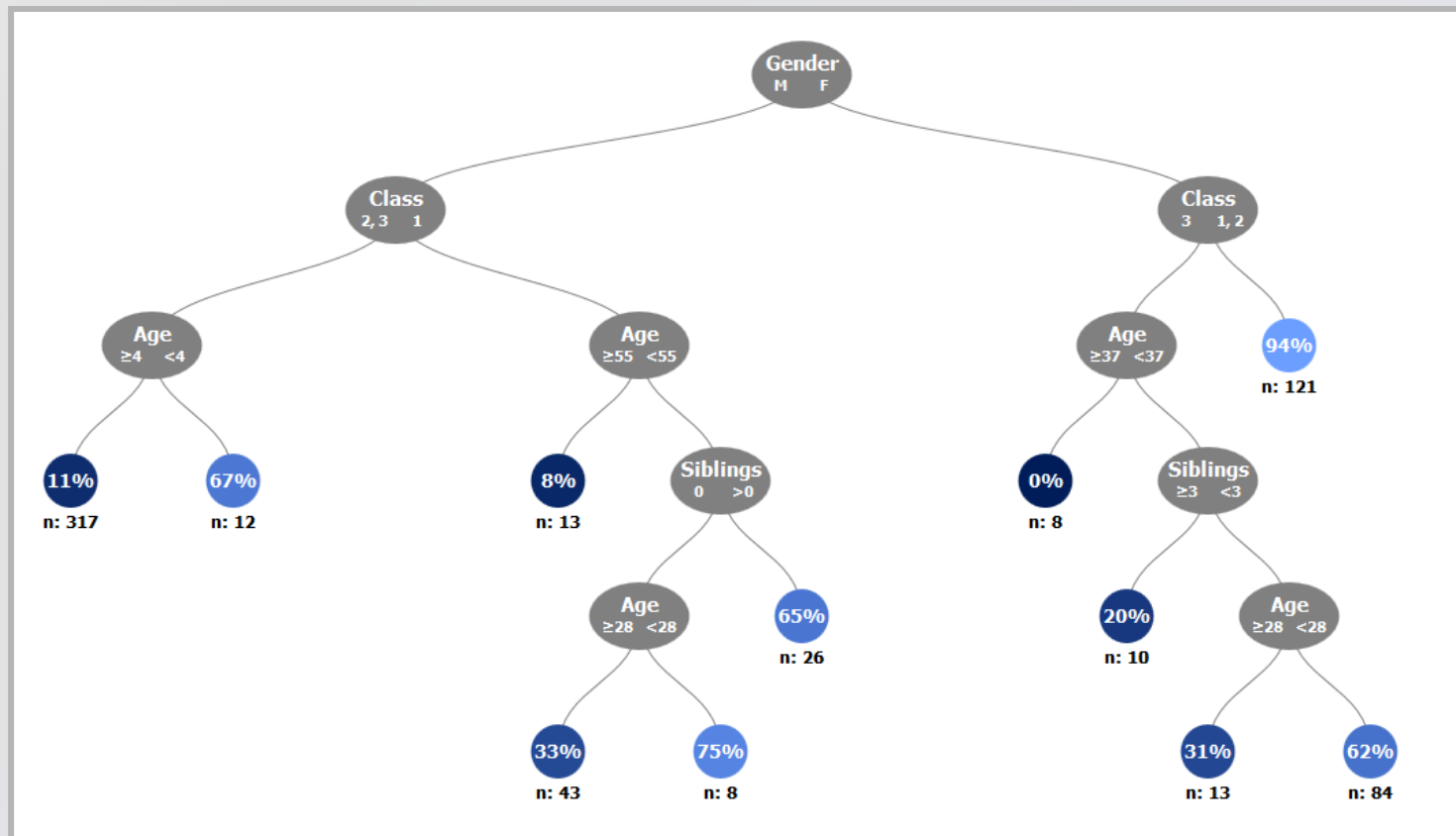
# Description

Decision Trees are made up of interconnected nodes, which act as a series of questions / test conditions (e.g., is the passenger male or female?)



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Terminal nodes show the output metric, in this case the percentage of titanic survivors for a given combination of variables.



# This raises questions

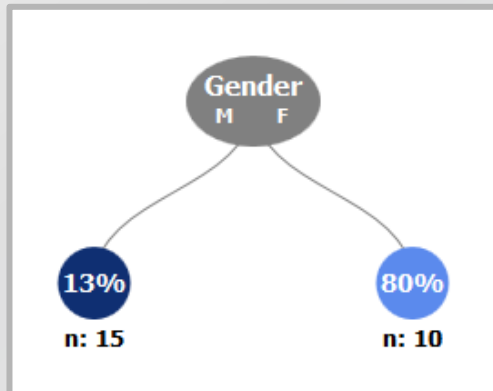
- How does the algorithm choose which variables to include on the tree?
- How does the algorithm choose where variables should be located on the tree?
- How does the algorithm choose when to stop the tree?

# Objectives

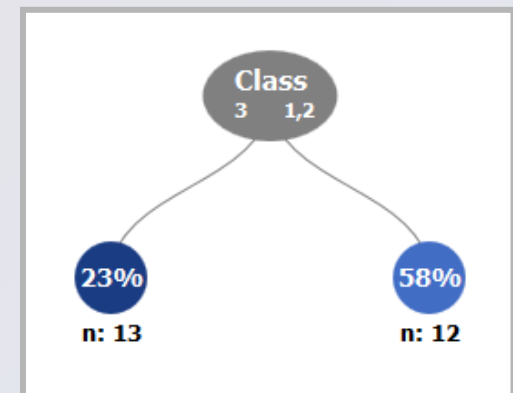
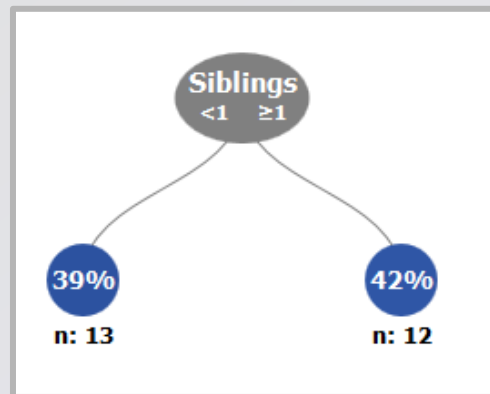
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# The Algorithm, Introduced

Different variables and split options are evaluated to determine which split will provide the greatest separation between classes.



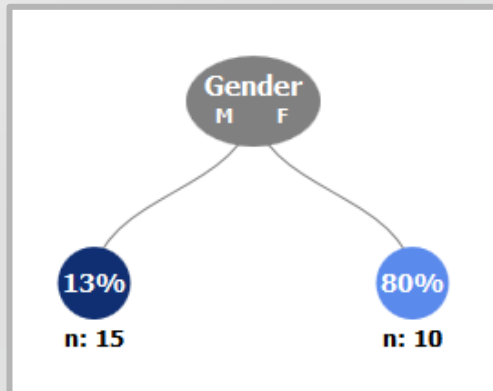
Which split option would you select?



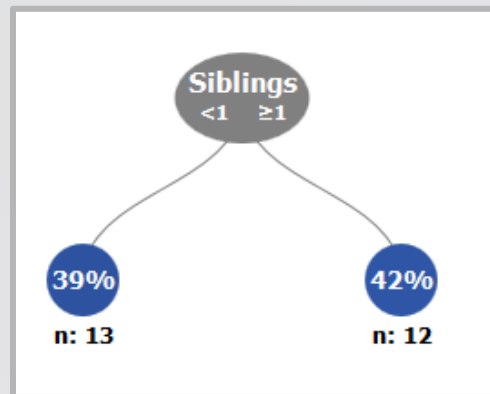


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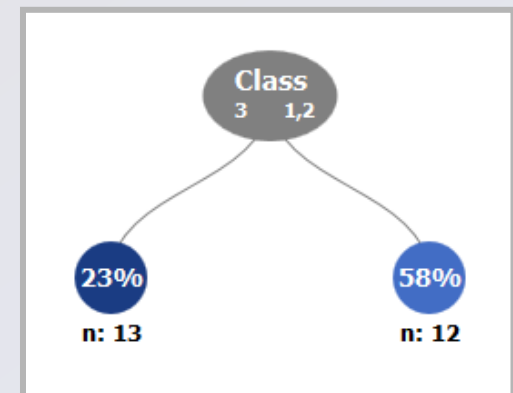
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Which split option would you select?



How can we determine the best split analytically?



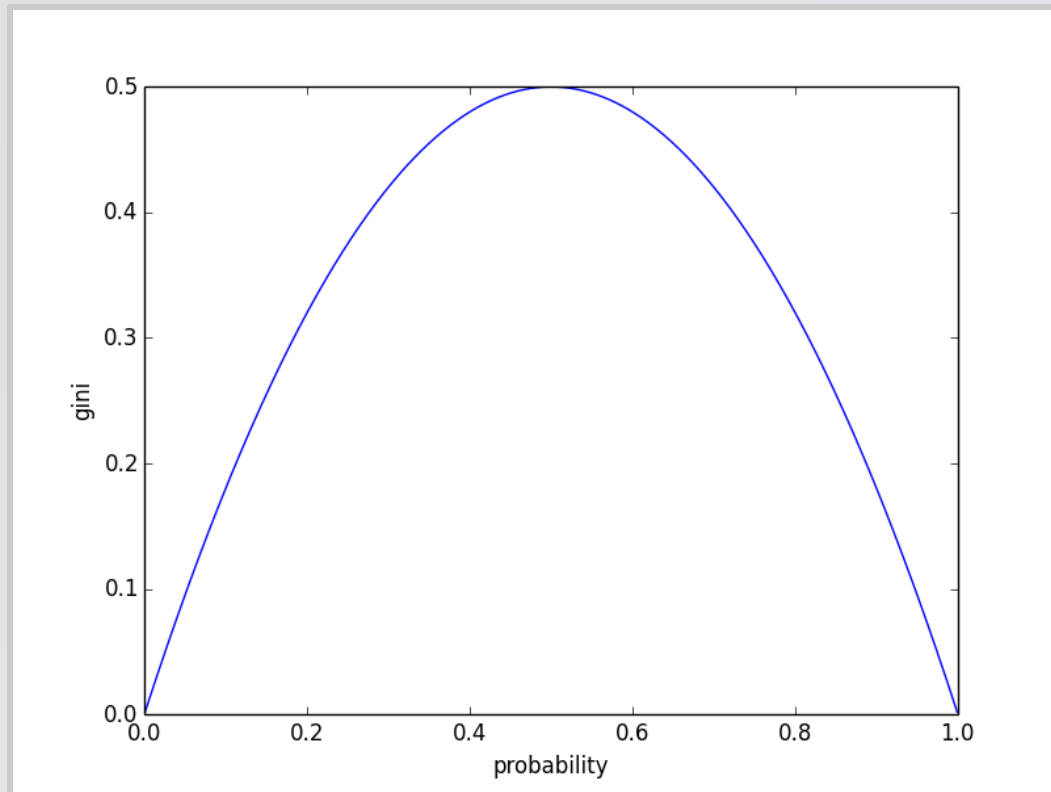
# Measuring Purity

For decision trees, splits are chosen by measuring the class purity before and after the split. Purity can be calculated by the Gini index.

$$Gini = 1 - \sum_{i=1}^{\text{class proportion}} p_i^2$$

# Measuring Purity

A Gini index of 0.5 indicates equal representation between both classes, and a Gini index of 0 indicates perfect separation between classes (i.e., perfect purity)



# The Algorithm – Overview

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**Let's go through an example**

# Before the Split

Before Split	All
Survived	10
Died	15

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What is the gini coefficient?

# Before the Split

Before Split	All
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Died	15

$$1 - \sum \left( \frac{class_i}{total} \right)^2$$

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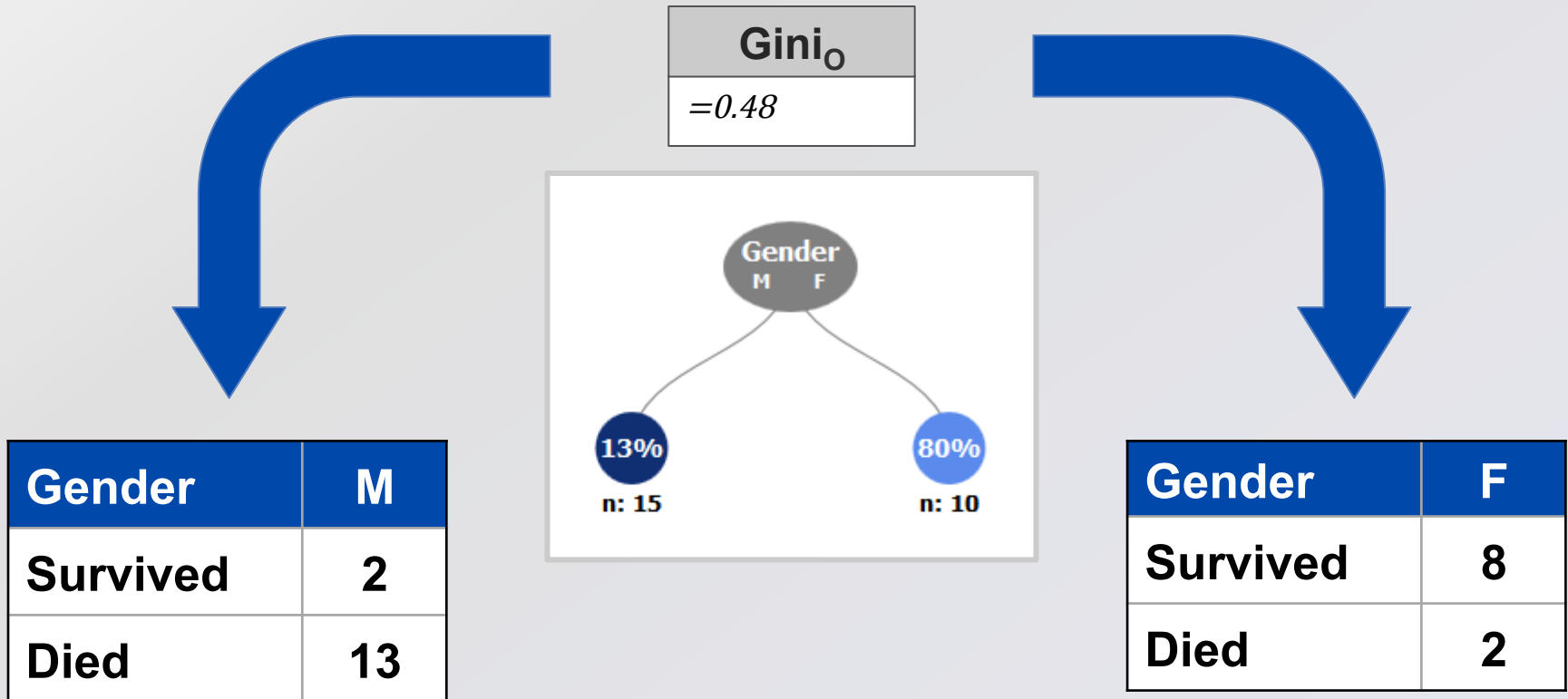
$$1 - \left( \frac{\textit{survived}}{\textit{total}} \right)^2 - \left( \frac{\textit{died}}{\textit{total}} \right)^2$$

# Before the Split

Before Split	All
Survived	10
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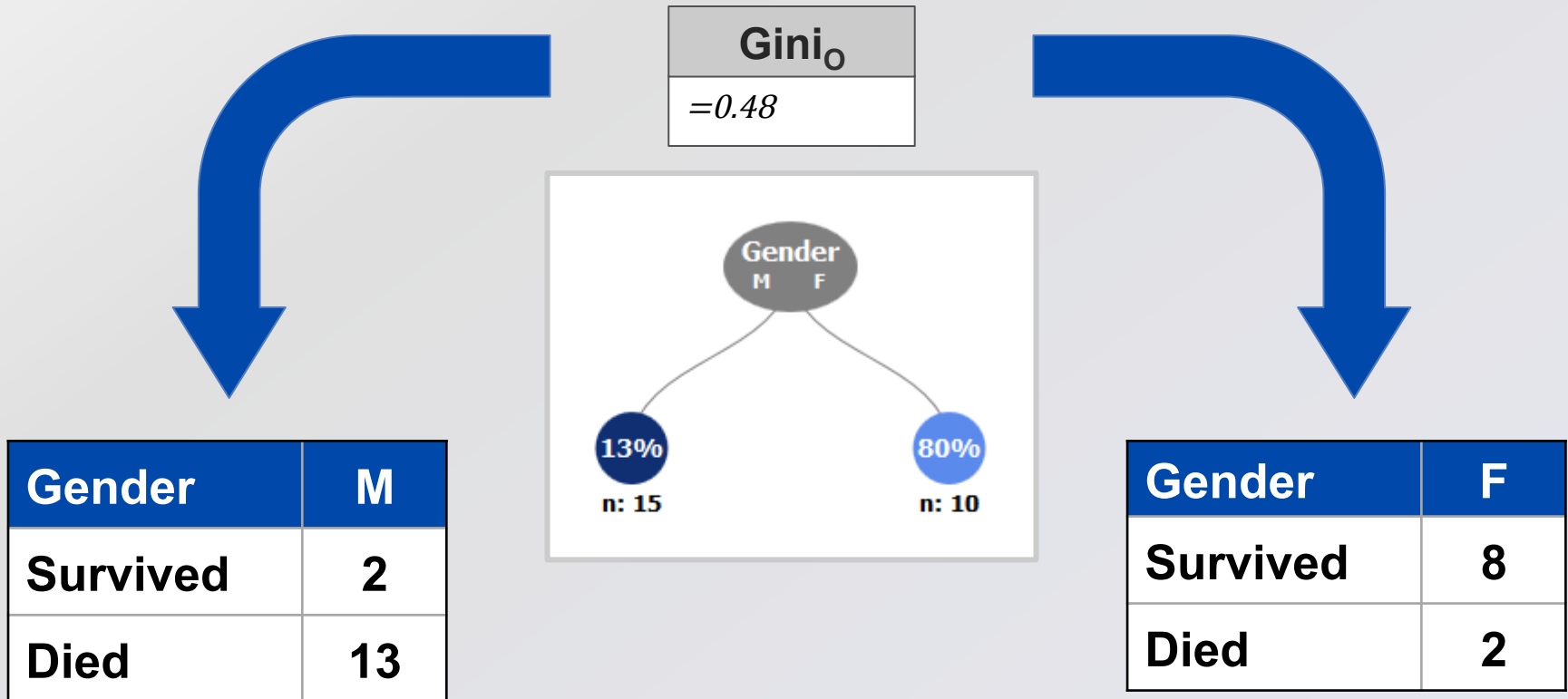
$$1 - \left( \frac{\textit{survived}}{\textit{total}} \right)^2 - \left( \frac{\textit{died}}{\textit{total}} \right)^2$$
$$1 - \left( \frac{10}{25} \right)^2 - \left( \frac{15}{25} \right)^2 = 0.48$$

# After the Split





# After the Split



What is the gini coefficient?

# After the Split

**Gini<sub>O</sub>**

*=0.48*

Gender  
M F

13%

n: 15

80%

n: 10

**Gender**

**M**

**Survived**

**2**

**Died**

**13**

**Gender**

**F**

**Survived**

**8**

**Died**

**2**

**Gini<sub>M</sub>**

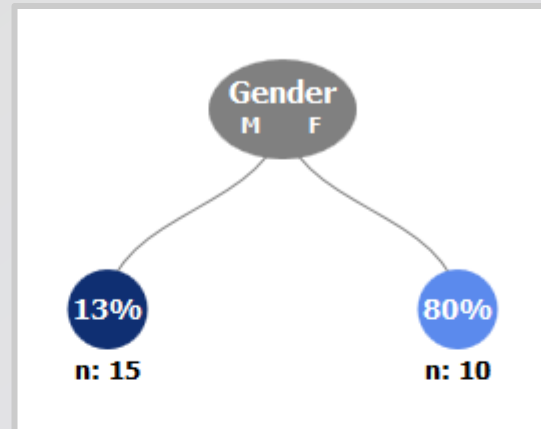
$$1 - (2/15)^2 - (13/15)^2 = 0.23$$

**Gini<sub>F</sub>**

$$1 - (8/10)^2 - (2/10)^2 = 0.32$$

# After the Split (continued)

<b>Gini<sub>O</sub></b>
$=0.48$



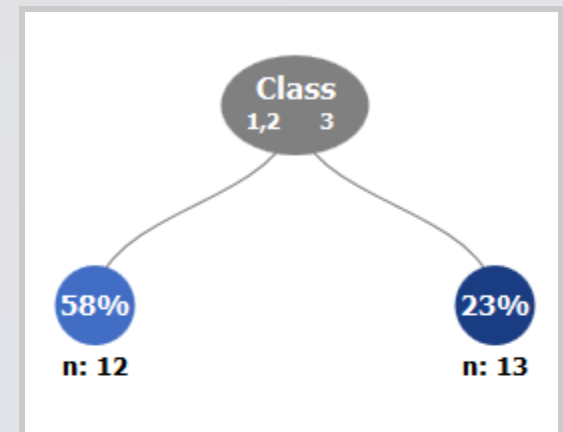
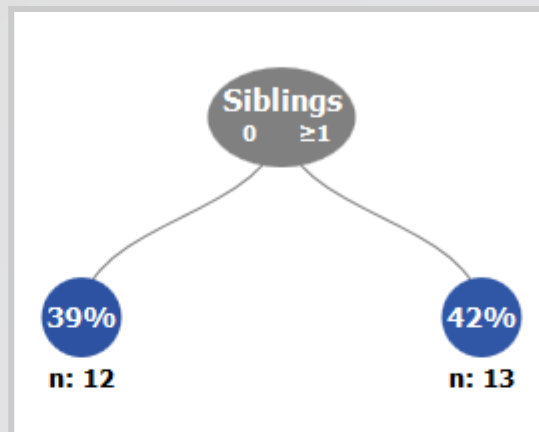
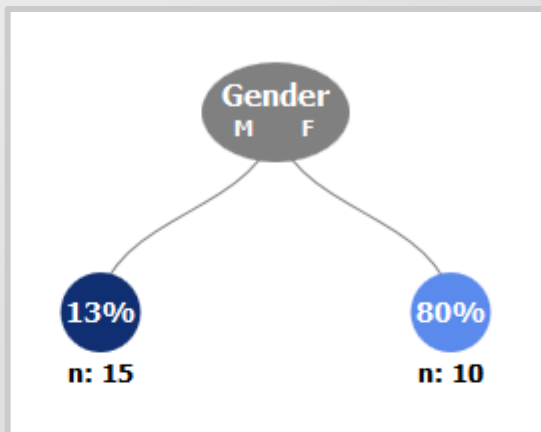
<b>Gini<sub>M</sub></b>
$=0.23$

<b>Gini<sub>F</sub></b>
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<b>Gini<sub>C</sub></b>
$Gini_M (M/M+F) + Gini_F (F/M+F) =$ $0.23(15/10+15) + 0.32(10/10+15) = 0.27$

# Choosing the Split

How does the gini coefficient compare for the Siblings and class variables?



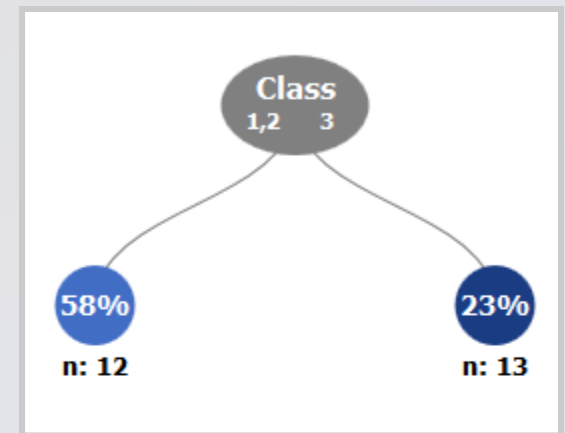
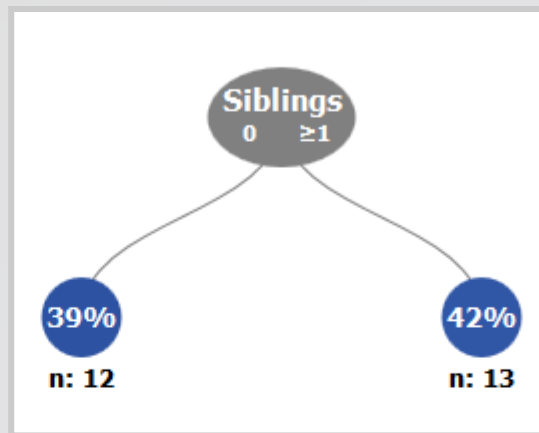
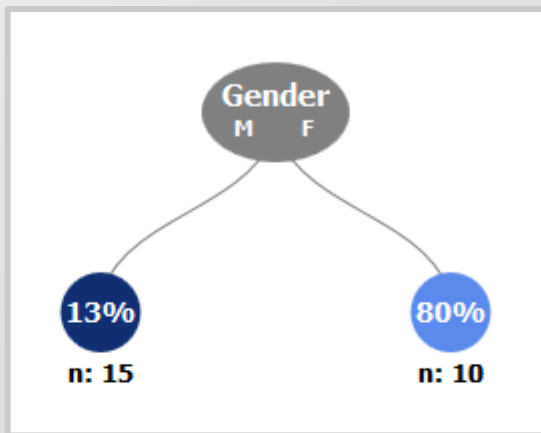
Gender	M	F
Survived	2	8
Died	13	2
Gini <sub>C</sub>	0.27	

Siblings	0	≥1
Survived	5	5
Died	7	8
Gini <sub>C</sub>	??	

Class	1,2	3
Survived	7	3
Died	5	10
Gini <sub>C</sub>	??	

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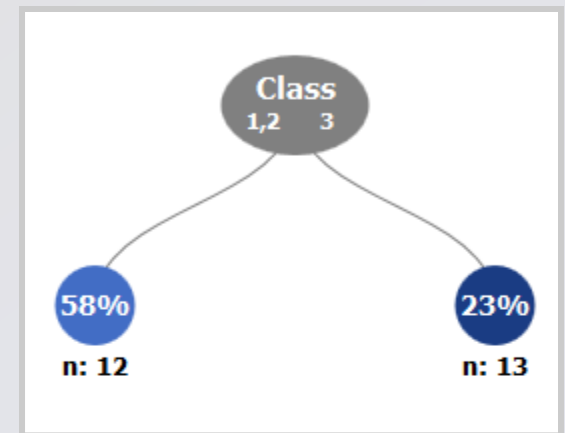
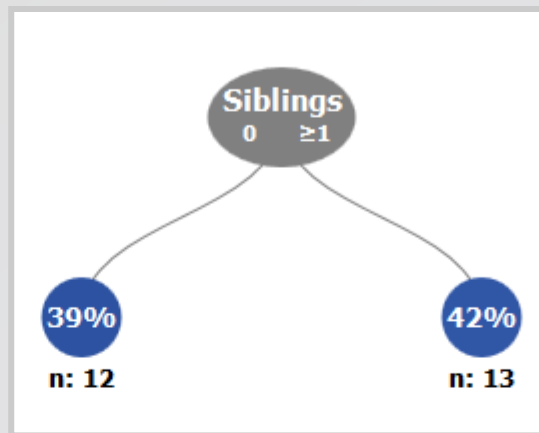
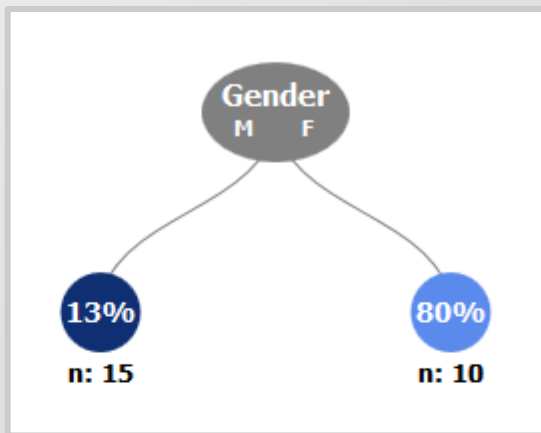
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# Choosing the Split

In this example, the algorithm will select the Gender variable since it provides the greatest increase in purity.



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What do you think?

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## Disadvantages:

- The decision Tree tends to perform worse than more sophisticated modeling techniques due to their **high** variance