



# **W3. Decision Tree, Random Forests with Python**

**Bio and Health Informatics Lab**

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# Decision Trees

- **Decision Trees (DTs)** are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.
- Also by building trees and observing its hierarchy, you will learn what features are of high importance. This can be further used for feature selection
- The interpretation of the data is very helpful and easy.

# Drawbacks of Decision Trees

- If data is highly unbalanced, the model may not predict well
- Errors within the training set may propagate to child nodes
- DTs are prone to overfitting



# Installing python libraries for DT and RF analysis

- pip install sklearn
- pip install graphviz



# Practice 1-1: Building DTs for classifying flowers using the Iris data

- Classes: 3={Iris-Setosa, Iris-Versicolour, Iris-Virginica}



Can you tell any difference?

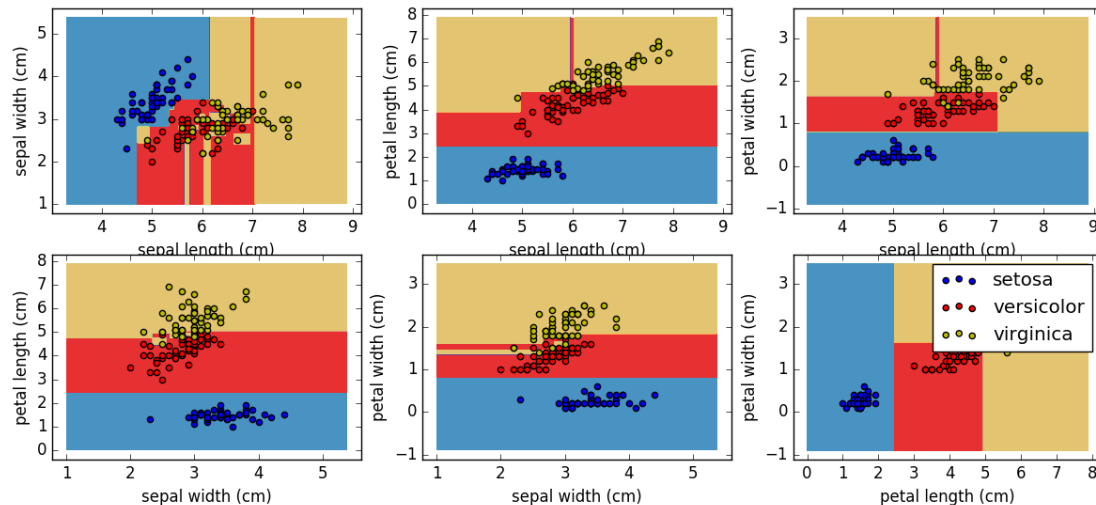
- Features: 4={Sepal length, sepal width, petal length, petal width}
- Data:

Sepal length	Sepal width	Petal length	Petal width	Species
4.9	3.0	1.4	0.2	<i>I. setosa</i>
4.7	3.2	1.3	0.2	<i>I. setosa</i>
4.6	3.1	1.5	0.2	<i>I. setosa</i>
5.0	3.6	1.4	0.3	<i>I. setosa</i>
5.4	3.9	1.7	0.4	<i>I. setosa</i>
4.6	3.4	1.4	0.3	<i>I. setosa</i>
5.0	3.4	1.5	0.2	<i>I. setosa</i>
4.4	2.9	1.4	0.2	<i>I. setosa</i>
4.9	3.1	1.5	0.1	<i>I. setosa</i>
5.4	3.7	1.5	0.2	<i>I. setosa</i>
4.8	3.4	1.6	0.2	<i>I. setosa</i>
4.8	3.0	1.4	0.1	<i>I. setosa</i>
4.3	3.0	1.1	0.1	<i>I. setosa</i>
5.8	4.0	1.2	0.2	<i>I. setosa</i>

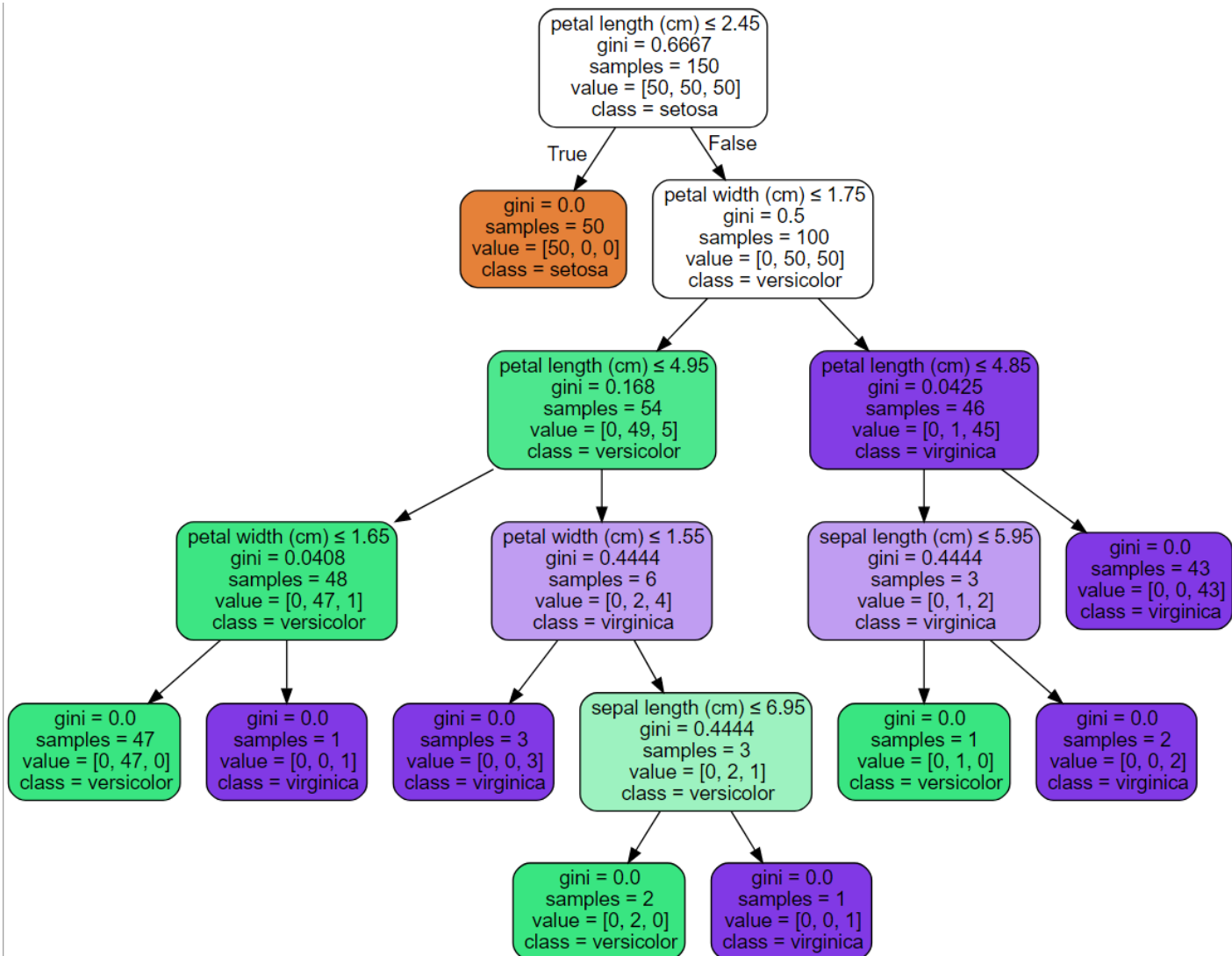
# Practice 1-1: Draw the DT for this data

- Load Iris data and observe the data (data, target or labels)
- Create a decision tree and fit the data
- Perform prediction on input data
- Draw a more interpretable DT using the graphviz package
- Visualize the pair-wise decision surface of the DT

Decision surface of a decision tree using paired features



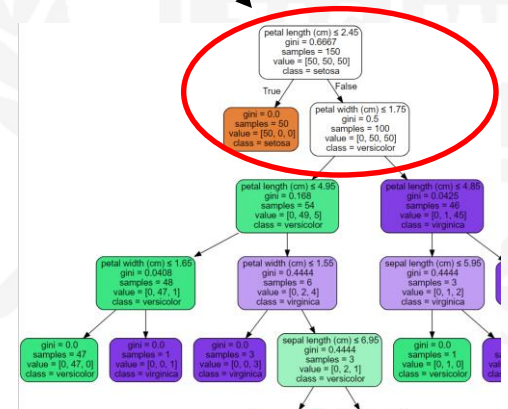
# Decision Tree of the Iris data





# Practice 1-2: Decide where to split the DT

- Implement the GINI index formula
- Implement the  $\text{GINI}_{\text{split}}$  formula
- Calculate the  $\text{GINI}_{\text{split}}$  for the first branch
  - How should we split the data?
- What are the  $\text{GINI}_{\text{split}}$  values of each feature?



# Practice 2-1:

## Building Random Forests using the Iris data

- Load Iris data
- Create a data frame using pandas package
- Split the Iris data to training and testing sets
  - Ratio 75:15
- Create Random Forest(RF) classifier
- Fit data into RF
- Predict the species of the testing data
- Check accuracy
- What are the variable importance values of each feature?
- Visualize the first estimator tree of the RF
  - How many trees did RF generate?

## Practice 2-2:

# Build a Digit Recognizer using RF

- Load MNIST digit train data ("train.csv")
  - Split data into train, test data
  - Generate and fit a RF using train data
  - Measure accuracy using test data
- 
- Use the whole train data
  - Load the test data ("test.csv")
  - Predict the digit of each image in "test.csv"
  - Check the prediction

## Practice 2-3:

# Classify your own handwritten digits

- Draw your digit using <https://sketch.io/sketchpad/>
- Save your drawing as .png file
- Convert it into computable format (np.array format)
  - image2data.py imagefile
- Load it as a test data and classify the image

