CS 405/605 Data Science

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Random Forest

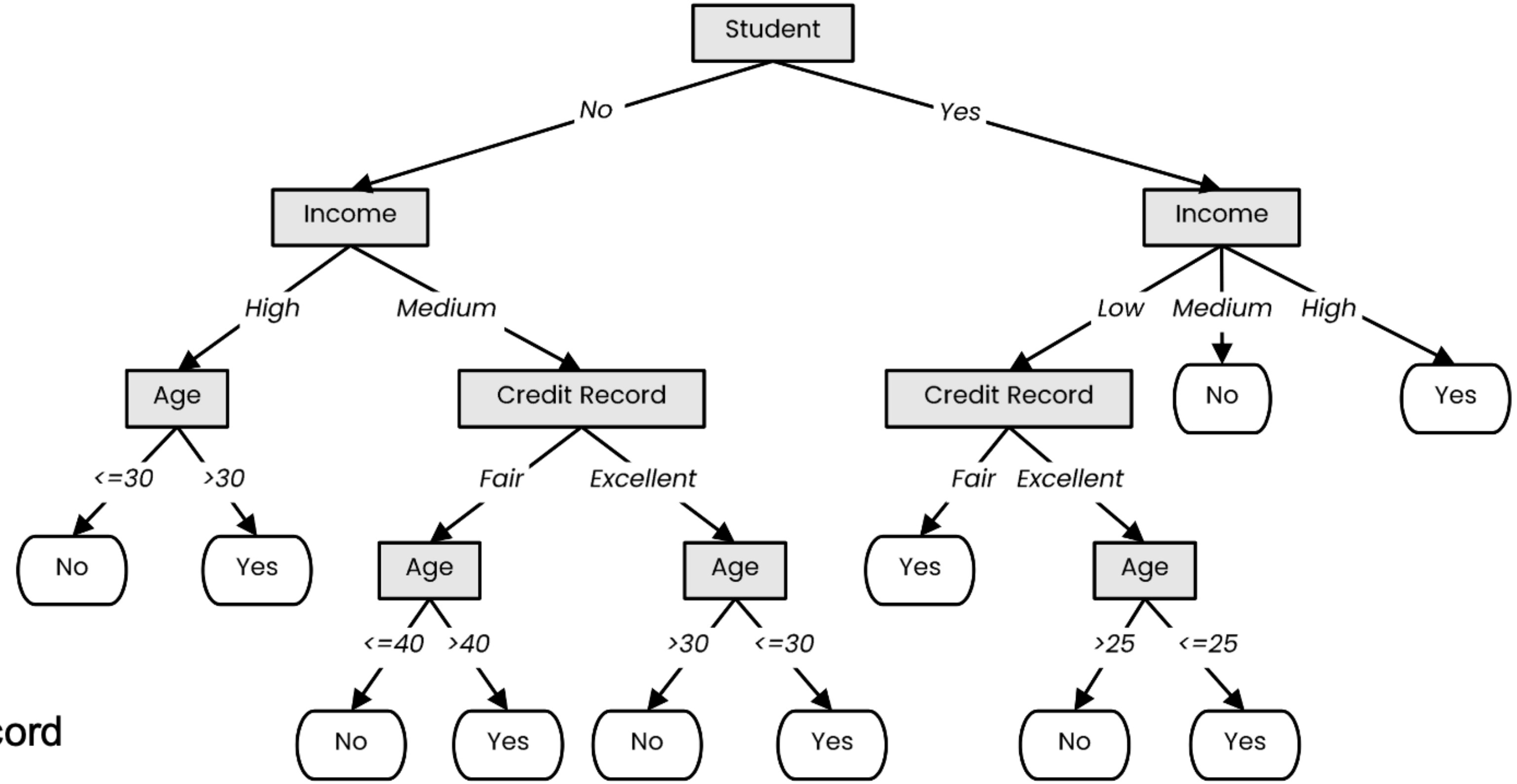
Recap Decision Tree

- A tree-like model that illustrates series of events leading to certain decisions
- Each node represents a test on an attribute and each branch is an outcome of that test

Who to loan?

- Not a student
- 45 years old
- Medium income
- Fair credit record

- Student
- 27 years old
- Low income
- Excellent credit record



Random Forest

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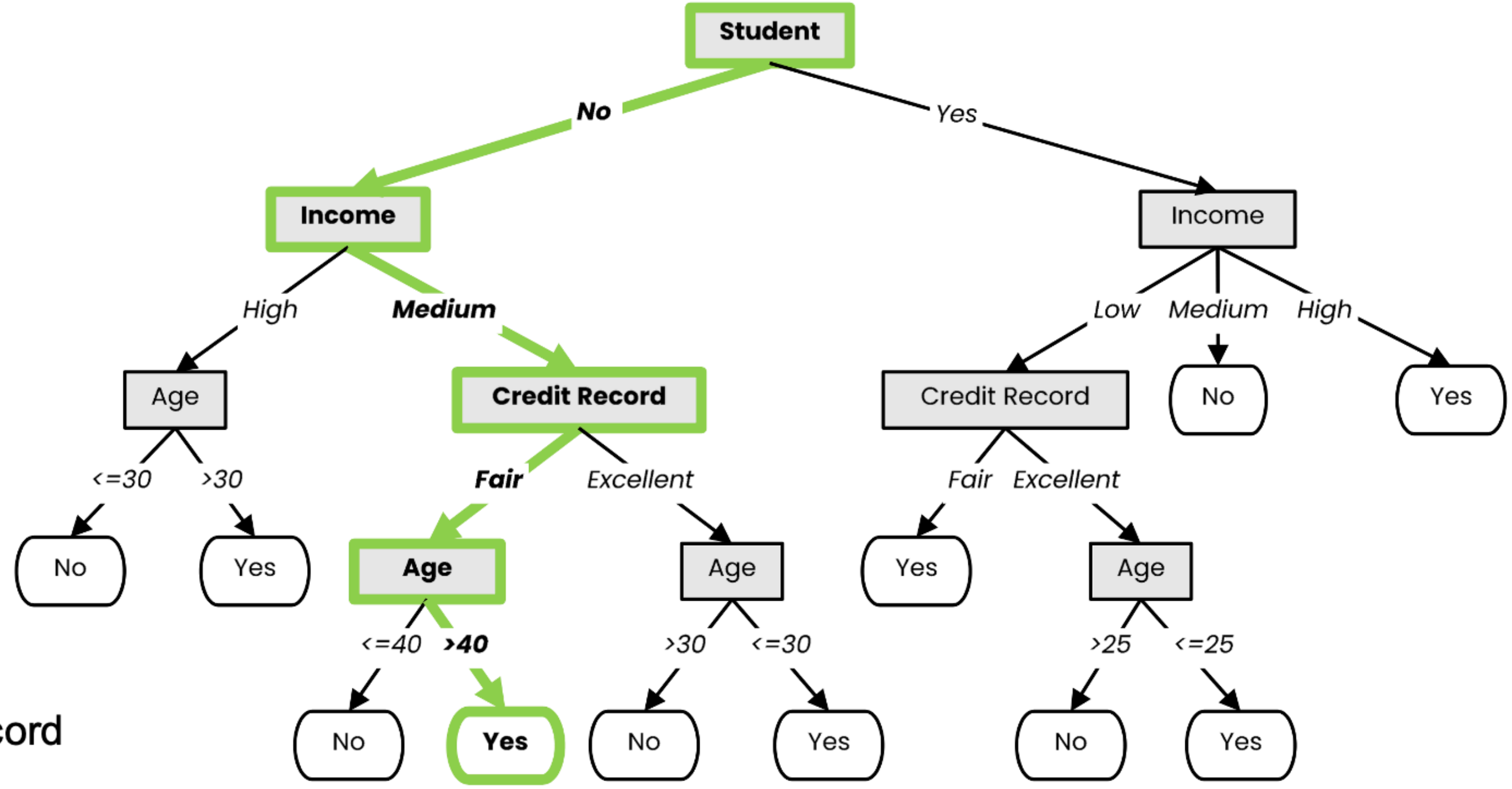

Random Forest

Recap Decision Tree

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Who to loan?

- Not a student
- 45 years old
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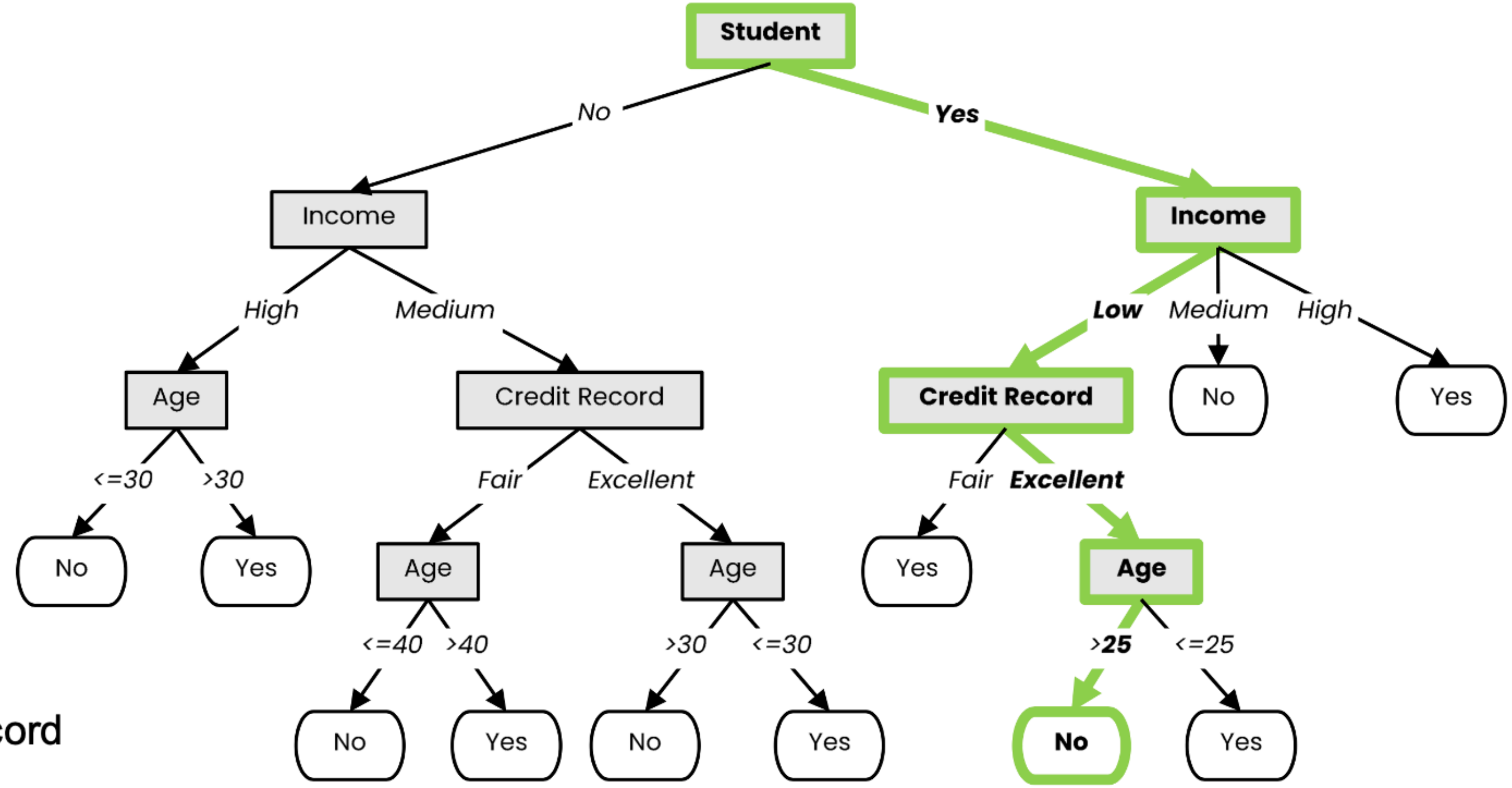
- ➢ Yes

- Student
- 27 years old
- Low income
- Excellent credit record
- ➢ No



Random Forest

Recap Decision Tree

- We use labeled data to obtain a suitable decision tree for future predictions
  - ➢ We want a decision tree that works well on unseen data, while asking as few questions as possible

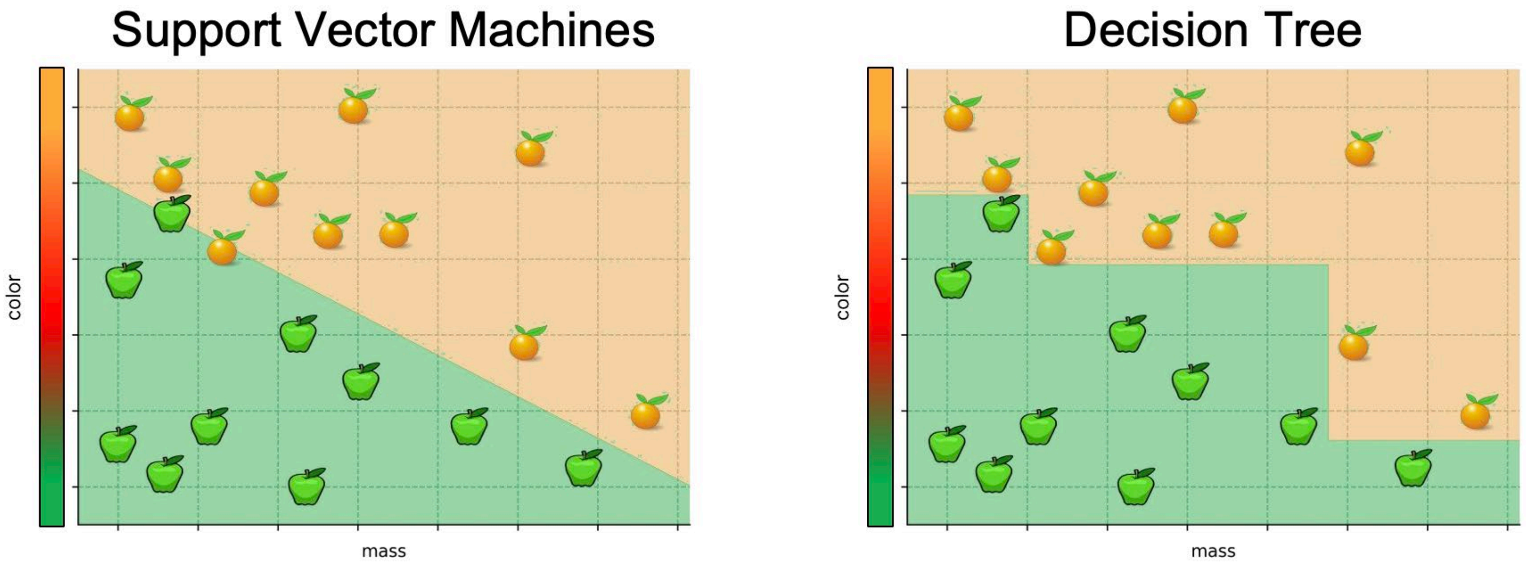
- Basic step: choose an attribute and, based on its values, split the data into smaller sets
  - ➢ Recursively repeat this step until we can surely decide the label

Random Forest

Recap Decision Tree

Decision Boundaries

- Decision trees produce non-linear decision boundaries



Random Forest

Recap Decision Tree

- Decision trees represent a tool based on a tree-like graph of decisions and their possible outcomes
- Decision tree learning is a machine learning method that employs a decision tree as a predictive model
- While decision trees classify quickly, the time for building a tree may be higher than another type of classifier
- Decision trees suffer from a problem of errors propagating throughout a tree
  A very serious problem as the number of classes increases
- **Decision Trees have very high variance**

Random Forests

(Ensemble learning with decision trees)

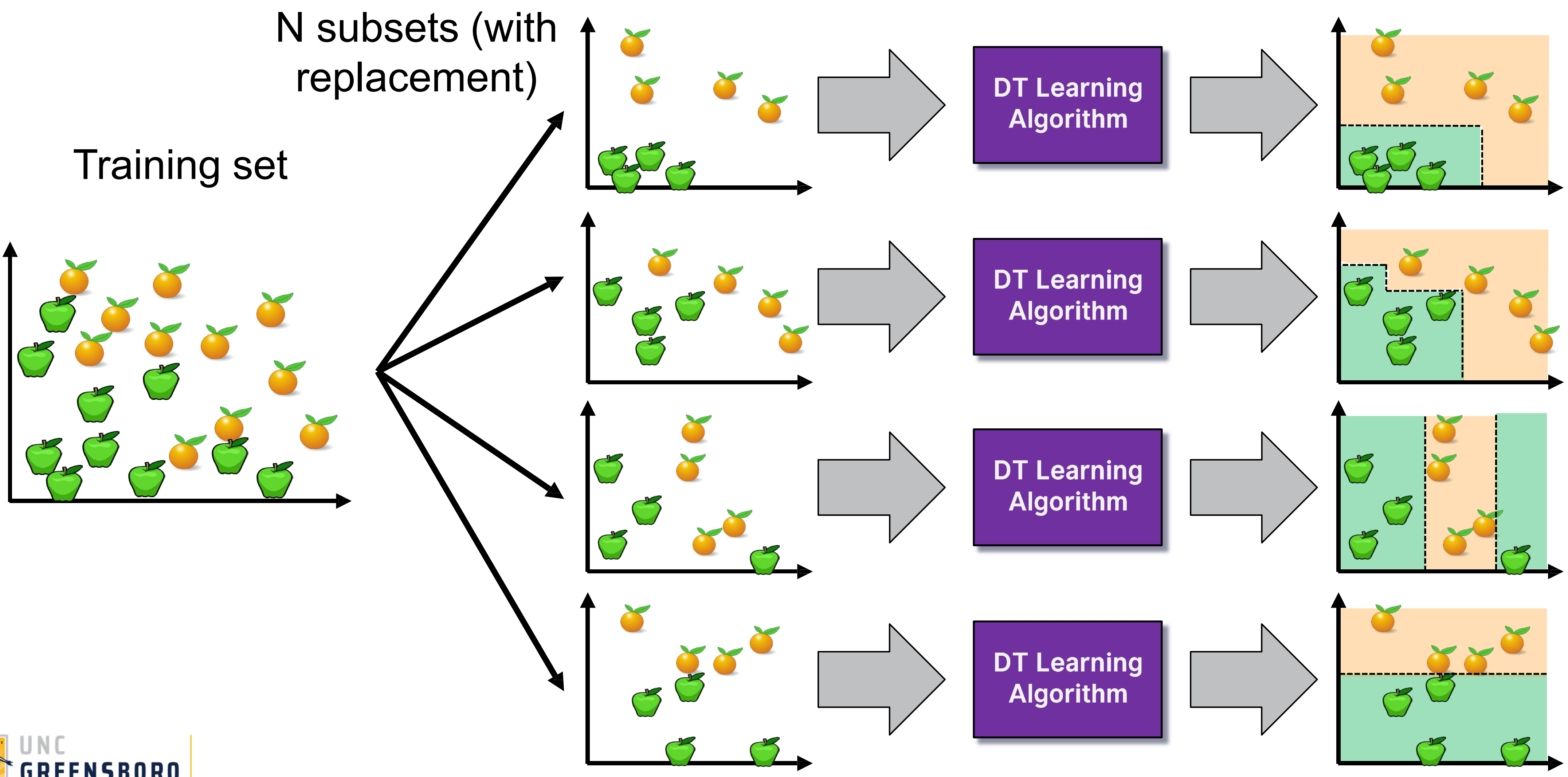
Random Forest

- Random Forests:
  - ➢ Instead of building a single decision tree and use it to make predictions, build many slightly different trees and combine their predictions
- We have a single data set, so how do we obtain slightly different trees?

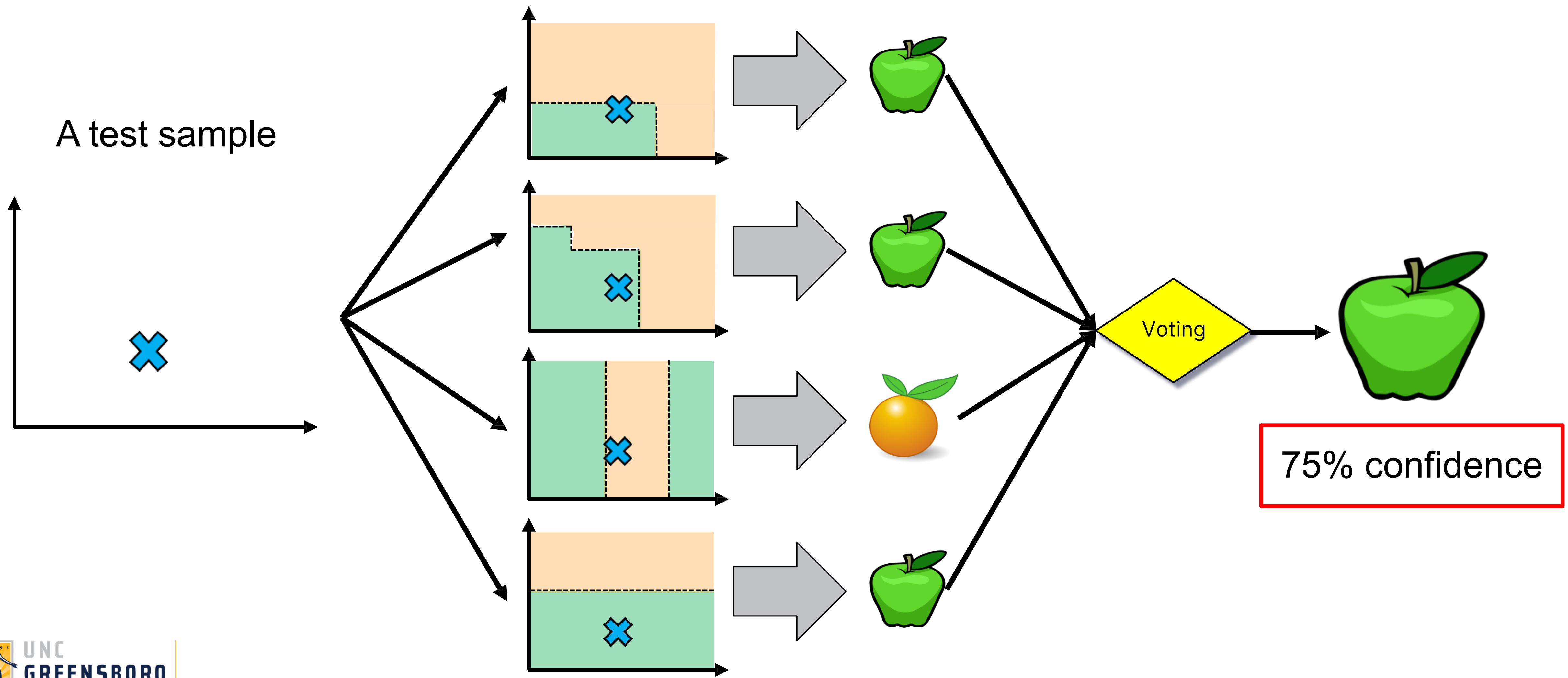
1. Bagging (**B**ootstrap **Agg**regat**ing**):
   - ➢ Take random subsets of data points from the training set to create N smaller data sets
   - ➢ Fit a decision tree on each subset

2. Random Subspace Method (also known as Feature Bagging):
   - ➢ Fit N different decision trees by constraining each one to operate on a random subset of features

Bagging at training time



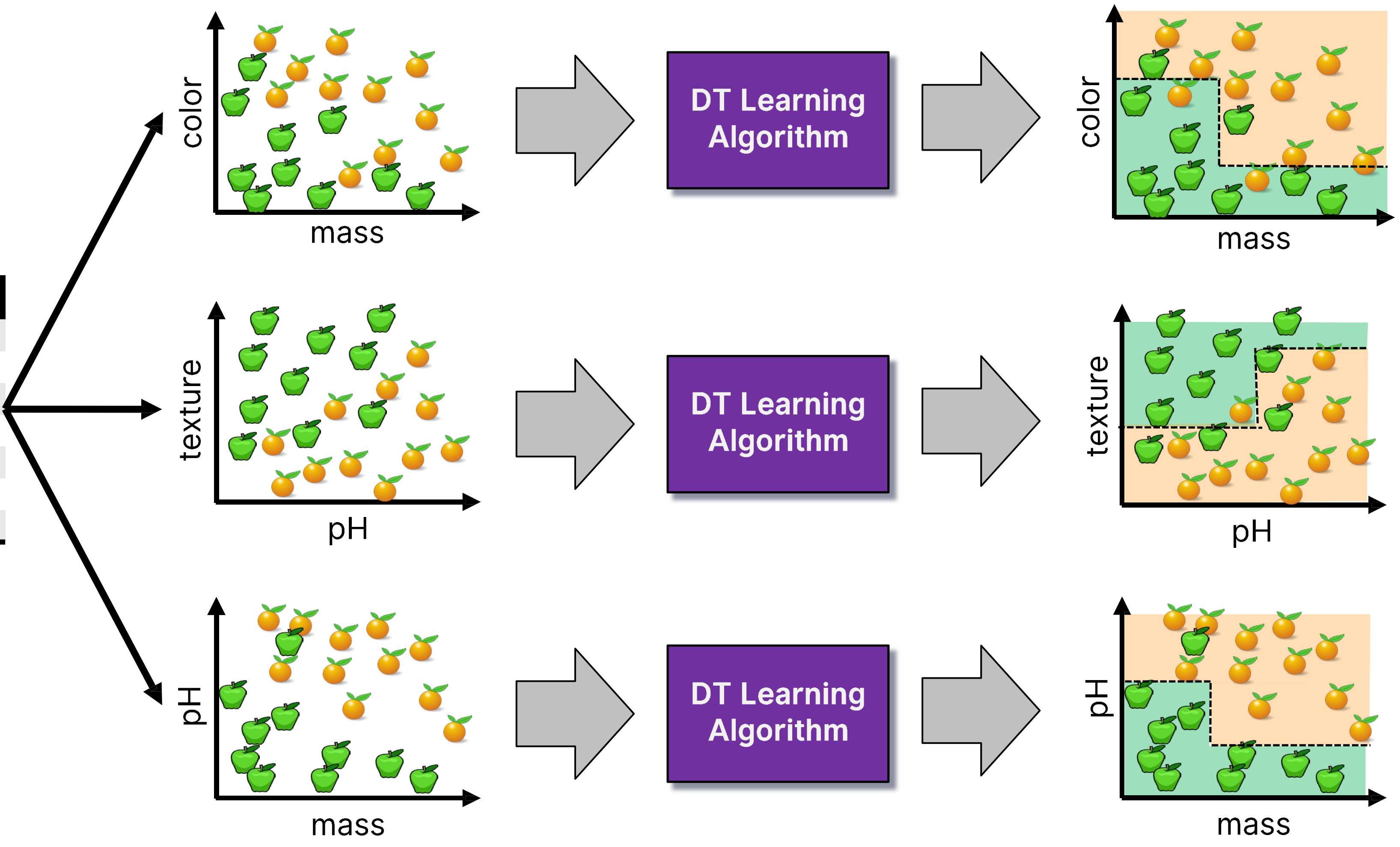
Bagging at inference time



Random Subspace Method at training time

Training data

Mass (g)	Color	Texture	pH	Label
84	Green	Smooth	3.5	**Apple**
121	Orange	Rough	3.9	**Orange**
85	Red	Smooth	3.3	**Apple**
101	Orange	Smooth	3.7	**Orange**
111	Green	Rough	3.5	**Apple**
…				
117	Red	Rough	3.4	**Orange**

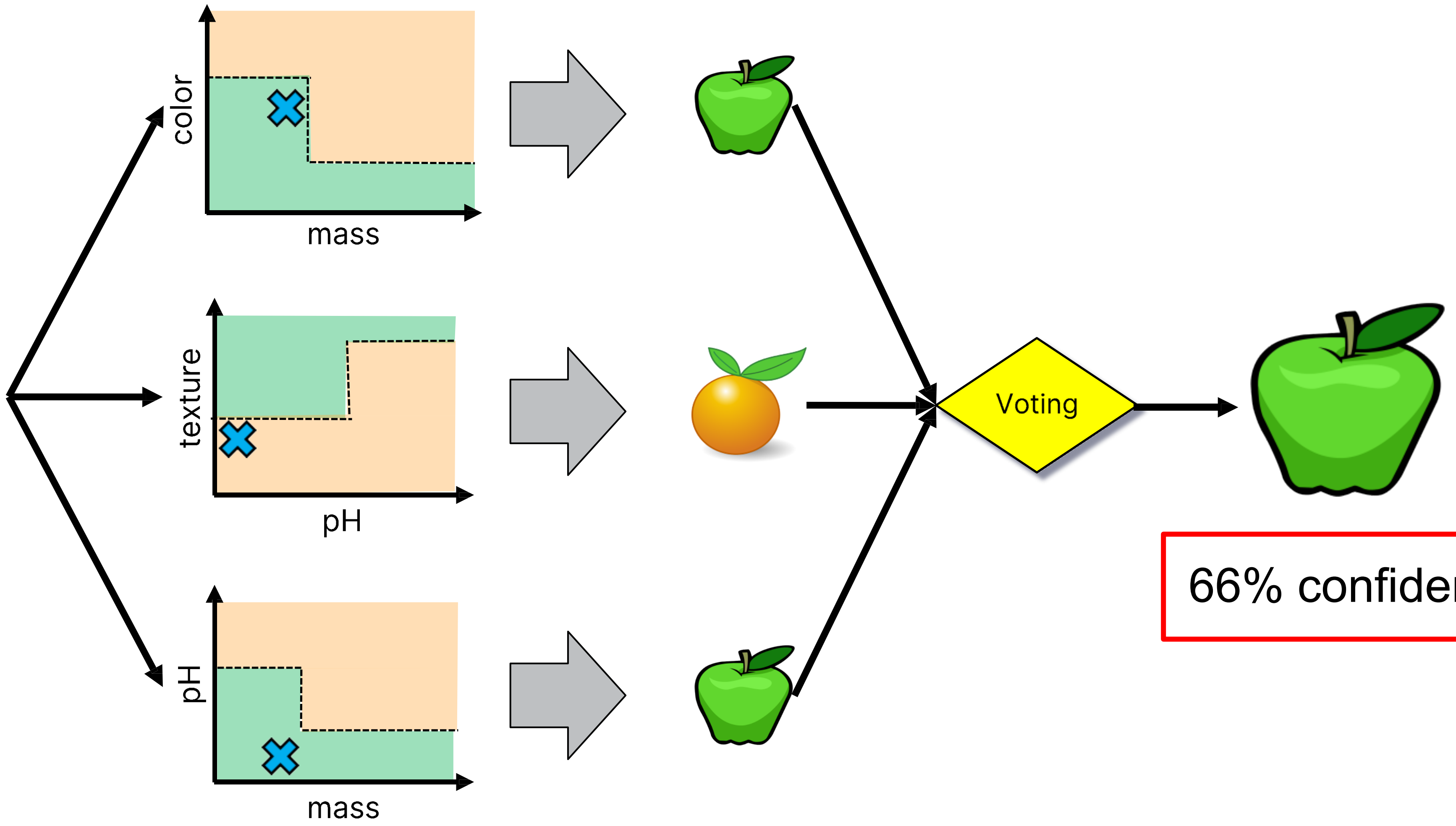


UNC GREENSBORO

Random Subspace Method at inference time

A test sample

87	Red	Smooth	3.1



66% confidence

Random Forest

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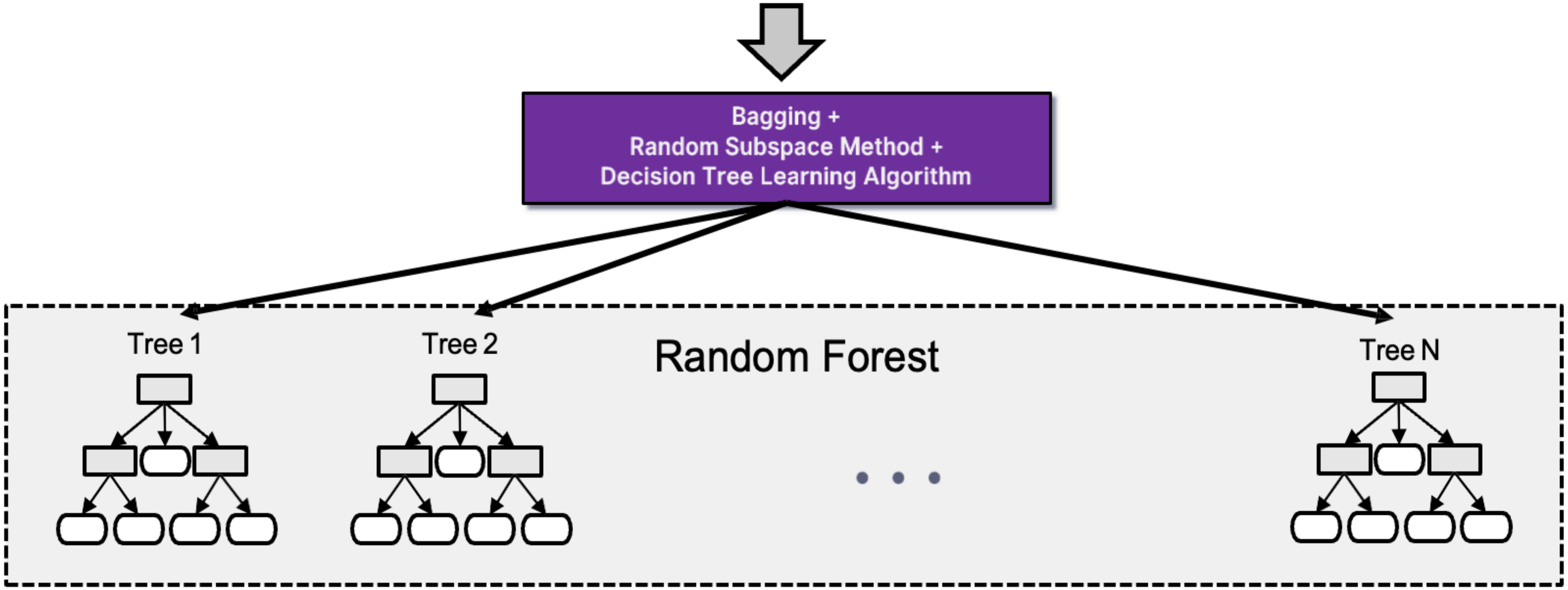


History of Random Forests

- Introduction of the Random Subspace Method
  - “Random Decision Forests” [Ho, 1995] and “The Random Subspace Method for Constructing Decision Forests” [Ho, 1998]

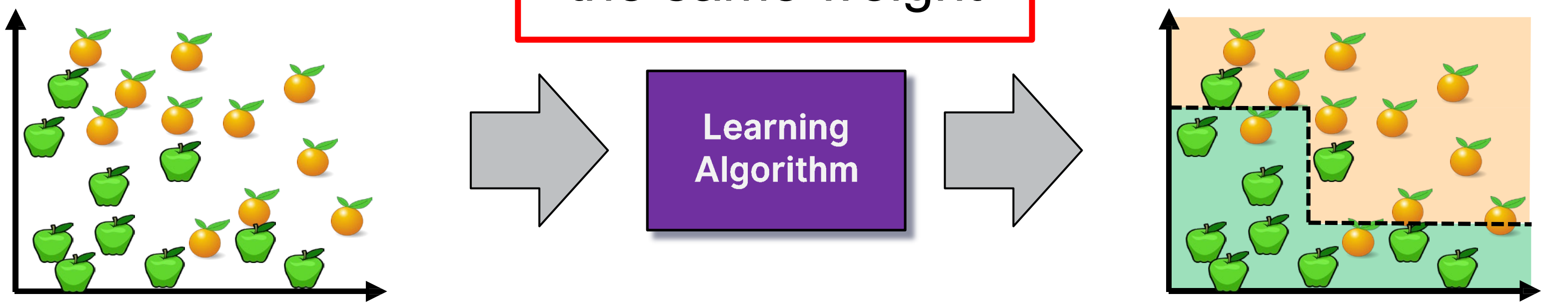
- Combined the Random Subspace Method with Bagging. Introduce the term Random Forest (a trademark of Leo Breiman and Adele Cutler)
  - “Random Forests” [Breiman, 2001]

Ensemble Learning

- Ensemble Learning:
  - ➢ Method that combines multiple learning algorithms to obtain performance improvements over its components
- **Random Forests** are one of the most common examples of ensemble learning
- Other commonly-used ensemble methods:
  - ➢ Bagging: multiple models on random subsets of data samples
  - ➢ Random Subspace Method: multiple models on random subsets of features
  - ➢ Boosting: train models iteratively, while making the current model focus on the mistakes of the previous ones by increasing the weight of misclassified samples

Boosting

All samples have the same weight



Boosting

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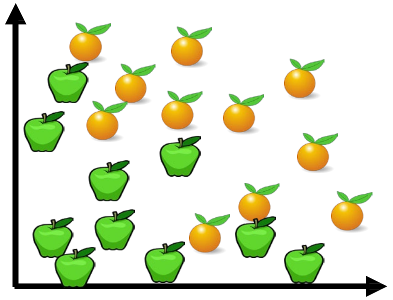
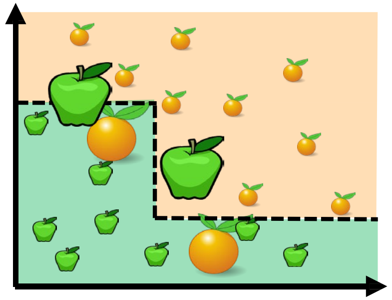
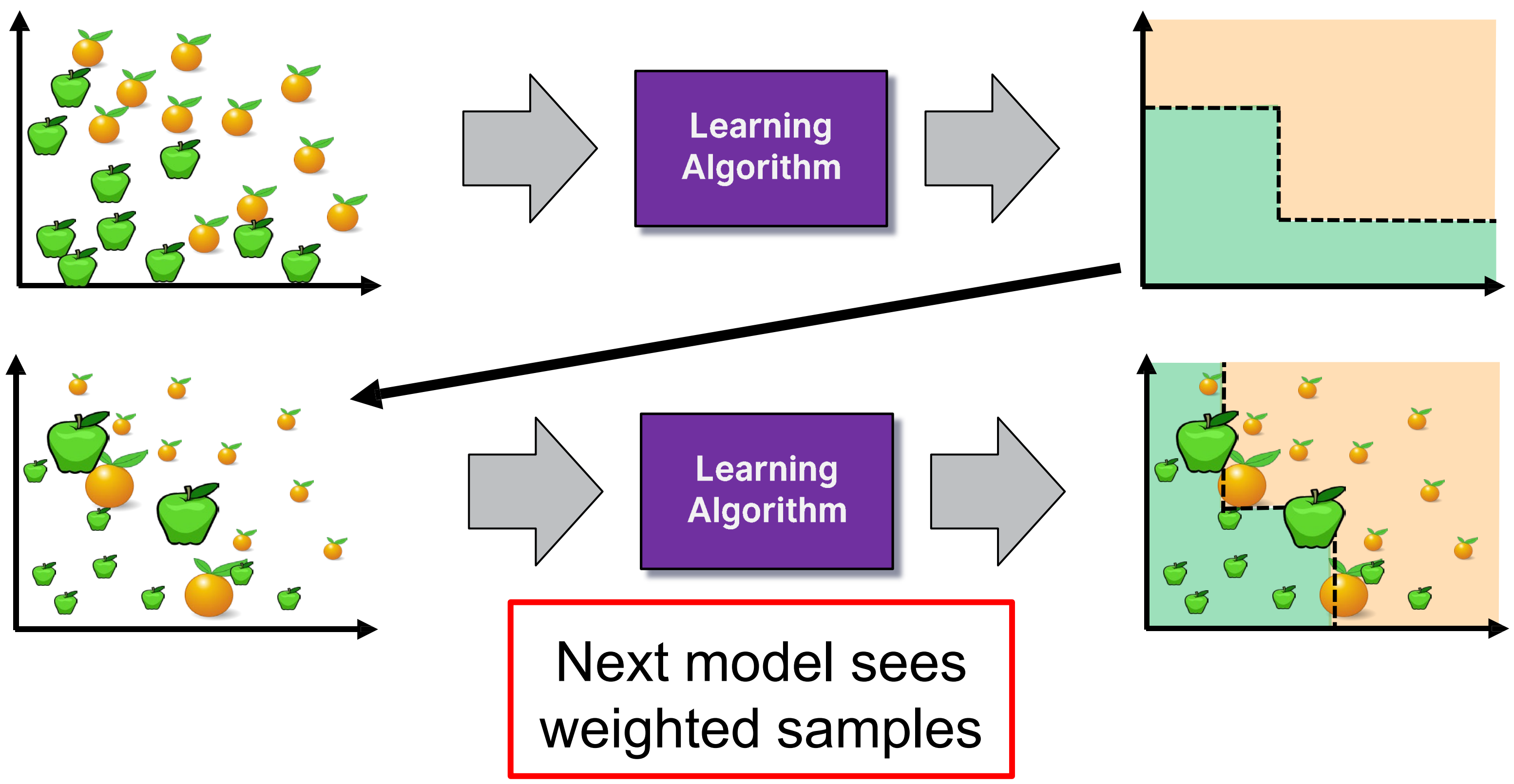


Learning Algorithm

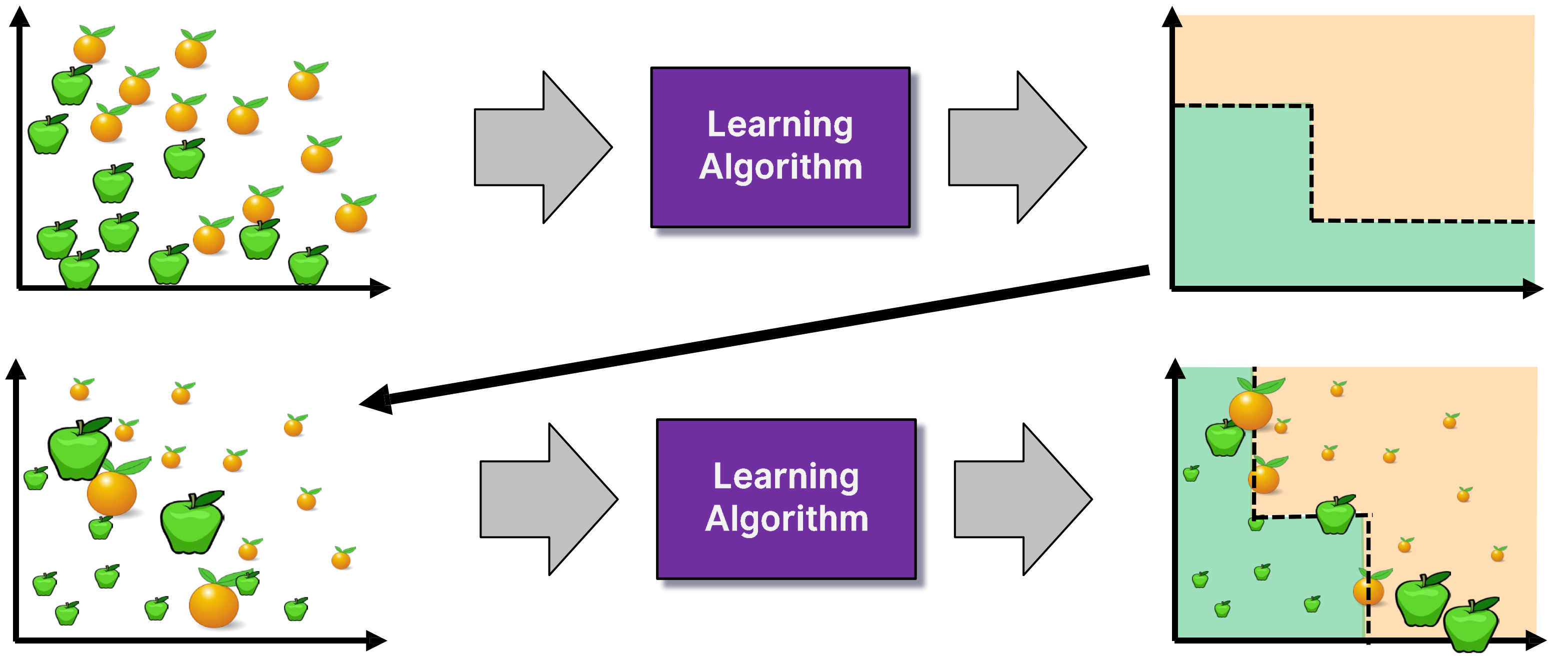


Reweight based on model's mistakes

Boosting

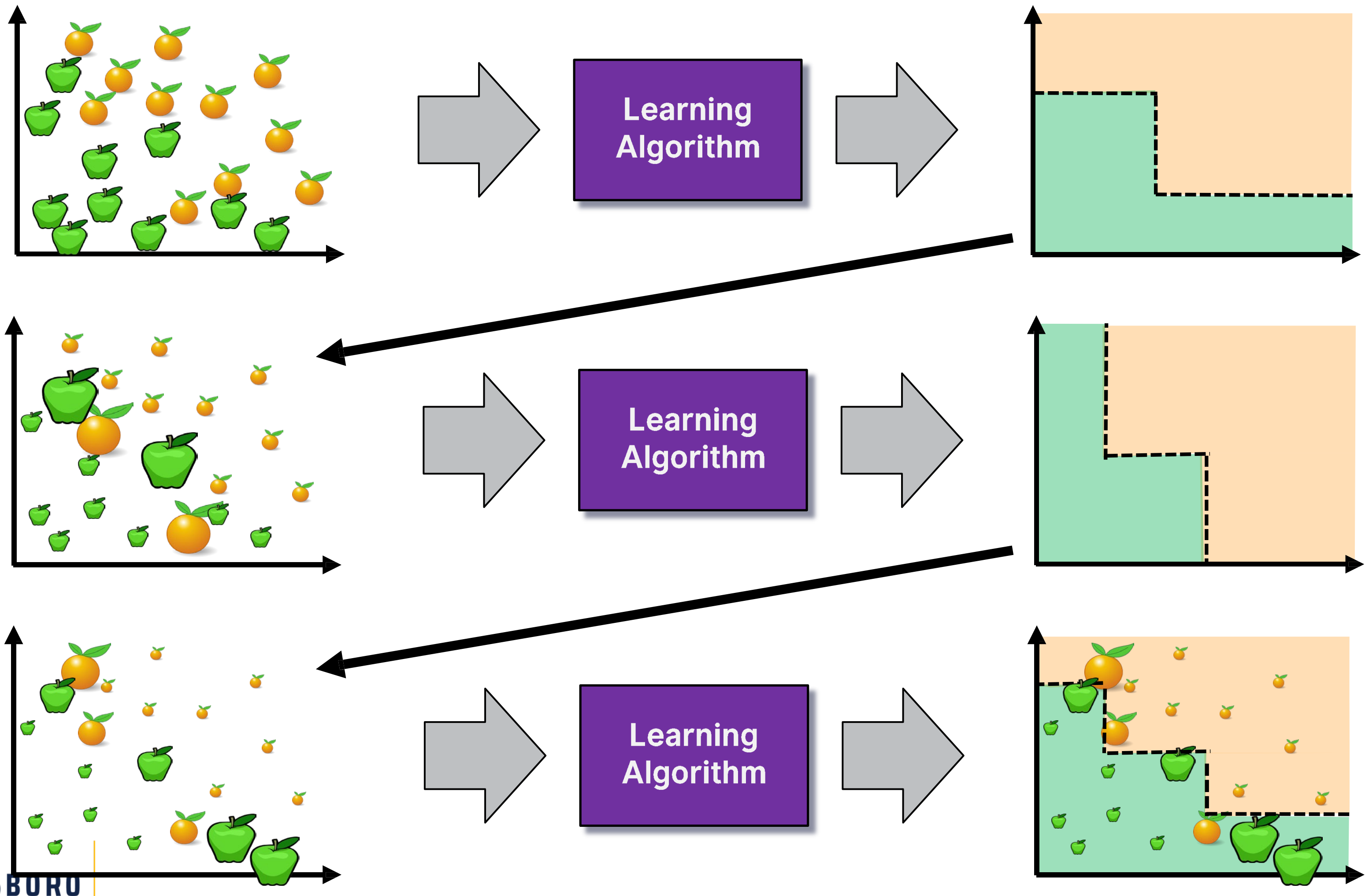

Learning
Algorithm
Learning
Algorithm
Next model sees
weighted samples

Boosting

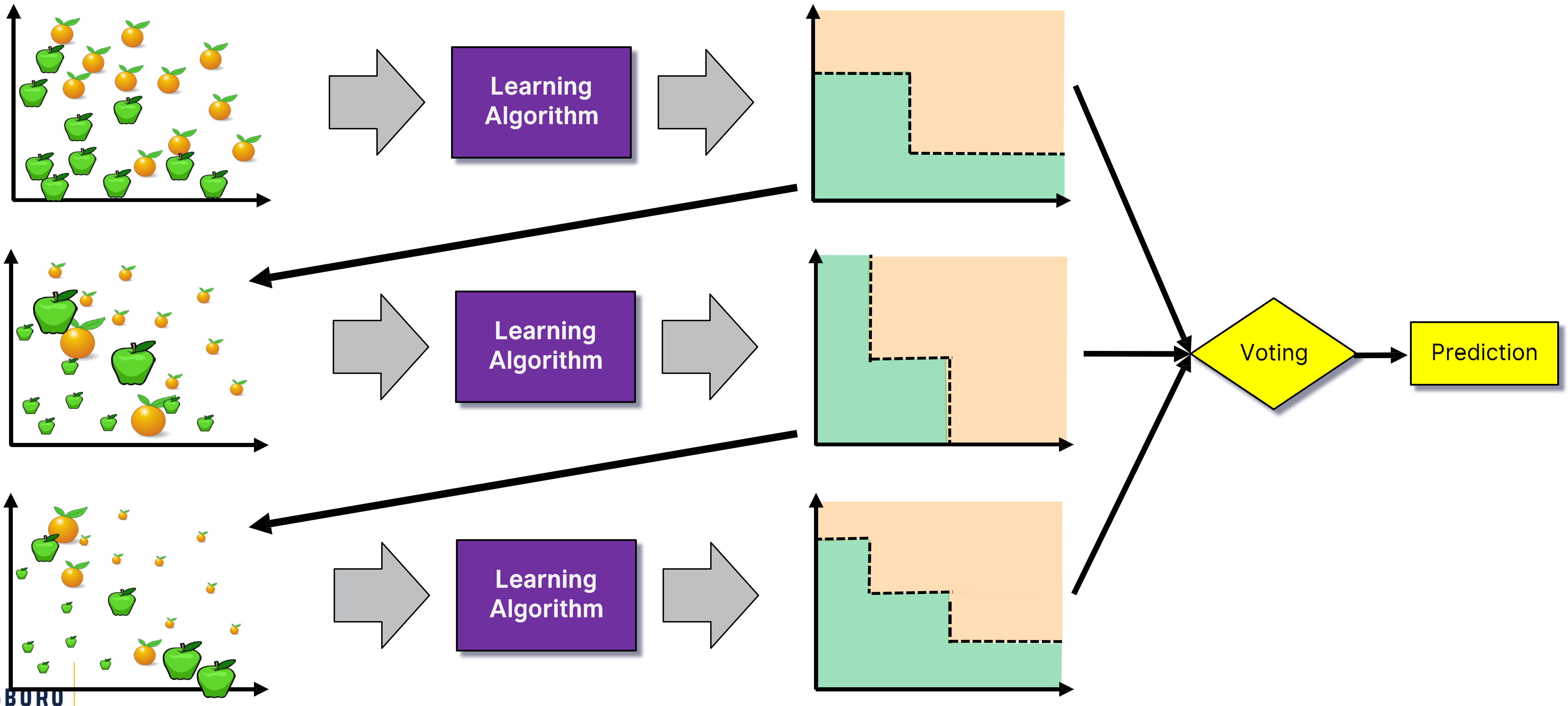


Reweight based on current model's mistakes

Boosting


Learning Algorithm
Learning Algorithm
Learning Algorithm

Boosting



Learning Algorithm
Learning Algorithm
Learning Algorithm
Voting
Prediction

Random Forest – scikit-learn

Objective:
Predict the class of wine based on its chemical composition and compare the performance of a Decision Tree classifier with that of a Random Forest classifier.

```python
from sklearn import datasets
import pandas as pd

# Load the wine dataset
wine = datasets.load_wine()
df = pd.DataFrame(data=wine.data, columns=wine.feature_names)
df['class'] = wine.target
print(df.head())
```

```python
from sklearn.model_selection import train_test_split

X = wine.data
y = wine.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
   alcohol  malic_acid   ash  alcalinity_of_ash  magnesium  total_phenols  \
0    14.23        1.71  2.43               15.6      127.0           2.80
1    13.20        1.78  2.14               11.2      100.0           2.65
2    13.16        2.36  2.67               18.6      101.0           2.80
3    14.37        1.95  2.50               16.8      113.0           3.85
4    13.24        2.59  2.87               21.0      118.0           2.80

   flavanoids  nonflavanoid_phenols  proanthocyanins  color_intensity   hue  \
0        3.06                  0.28             2.29             5.64  1.04
1        2.76                  0.26             1.28             4.38  1.05
2        3.24                  0.30             2.81             5.68  1.03
3        3.49                  0.24             2.18             7.80  0.86
4        2.69                  0.39             1.82             4.32  1.04

   od280/od315_of_diluted_wines  proline  class
0                          3.92   1065.0      0
1                          3.40   1050.0      0
2                          3.17   1185.0      0
3                          3.45   1480.0      0
4                          2.93    735.0      0
```

Random Forest – scikit-learn

Build and Train a Decision Tree Model

```
from sklearn.tree import DecisionTreeClassifier

dt_clf = DecisionTreeClassifier()
dt_clf.fit(X_train, y_train)

dt_pred = dt_clf.predict(X_test)
print("Decision Tree Accuracy:", accuracy_score(y_test, dt_pred))
```

```
Decision Tree Accuracy: 0.9444444444444444
```

Build and Train a Random Forest Model

```
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(n_estimators=100)
rf_clf.fit(X_train, y_train)

rf_pred = rf_clf.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, rf_pred))
```

```
Random Forest Accuracy: 1.0
```

Random Forest – scikit-learn

Comparison of Feature Importance between Decision Tree and Random Forest

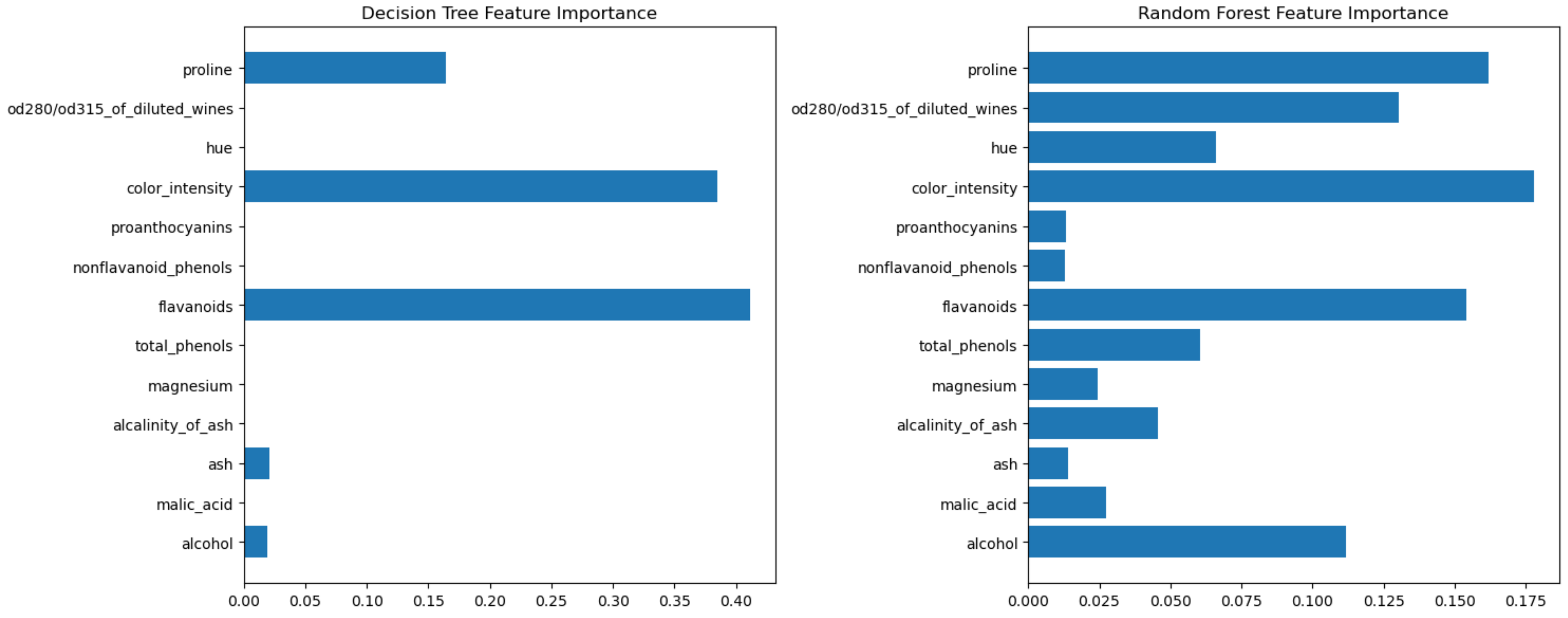
```
import matplotlib.pyplot as plt

# Plot feature importance for decision tree
plt.figure(figsize=(15, 6))
plt.subplot(1, 2, 1)
plt.barh(wine.feature_names, dt_clf.feature_importances_)
plt.title('Decision Tree Feature Importance')

# Plot feature importance for random forest
plt.subplot(1, 2, 2)
plt.barh(wine.feature_names, rf_clf.feature_importances_)
plt.title('Random Forest Feature Importance')
plt.tight_layout()
plt.show()
```

Random Forest – scikit-learn

Comparison of Feature Importance between Decision Tree and Random Forest



Random Forest

Summary

- Ensemble Learning methods combine multiple learning algorithms to obtain performance improvements over its components
- Commonly-used ensemble methods:
  - ➢ Bagging (multiple models on random subsets of data samples)
  - ➢ Random Subspace Method (multiple models on random subsets of features)
  - ➢ Boosting (train models iteratively, while making the current model focus on the mistakes of the previous ones by increasing the weight of misclassified samples)
- **Random Forests** are an ensemble learning method that employ decision tree learning to build multiple trees through **bagging** and **random subspace method**.
  - ➢ They rectify the overfitting problem of decision trees!

Exercise

Objective: Predict the species of iris flowers based on the length and width of their sepals and petals.

1. Data Loading and Exploration
2. Split Data into Training and Testing Sets
3. Build and Train a Decision Tree Model & Random Forest Model
4. Evaluate the Model
5. Feature Importance comparison between decision tree and random forest.