Algorithms

Decision trees and random forests

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Learning from data

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- Training set: data points with "ground-truth" labels.
- Test set: data points with unknown labels.

Random forest: Intuition

Figures by Richard Kershner

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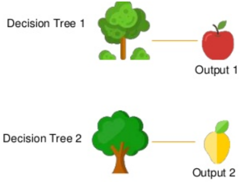

Construct multiple decision trees.

Each decision tree outputs a prediction for a given input.

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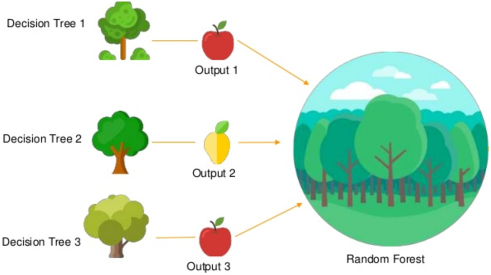

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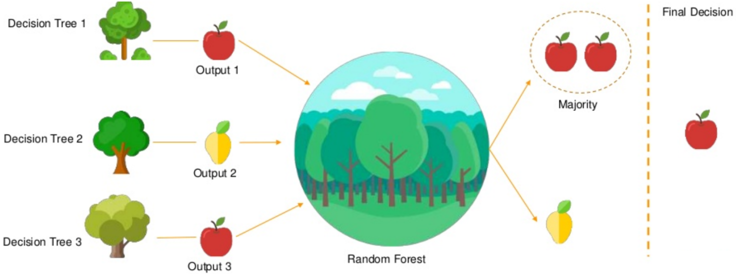

Construct multiple decision trees.

Each decision tree outputs a prediction for a given input.

The predictions from each tree are combined into one final prediction.

In the example, the final decision is "apple with probability 66%".

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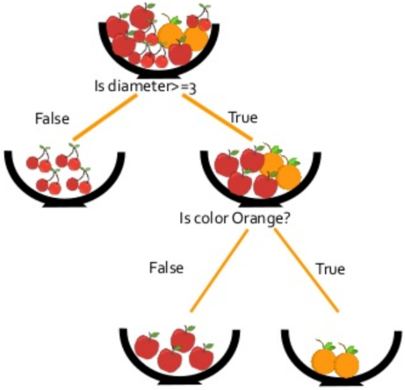
Decision tree

A decision tree is a binary tree in which each branch represents a possible decision. A path through the tree is therefore a course of action.



The data is iteratively partitioned into subsets from the root to the leaves.

Information gain

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Each leaf node stores the final decision (i.e. the classification result).

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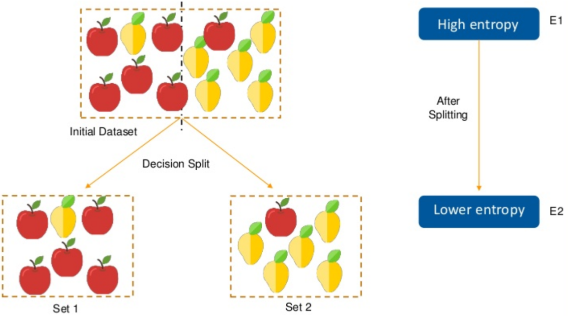

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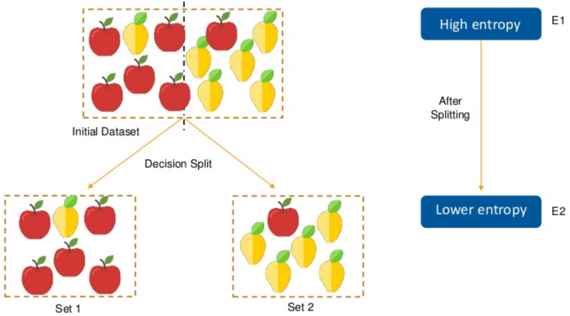

Ideally we want each split to be as discriminative as possible, and thus maximize the information gain $E2 - E1$.

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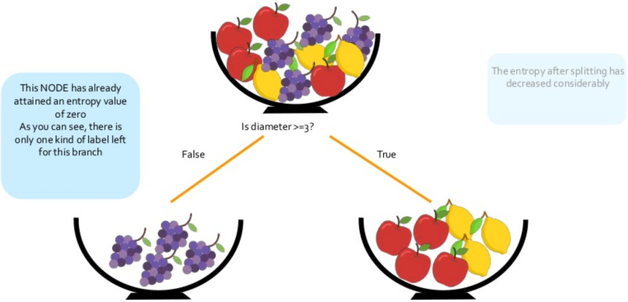
Keep splitting until the dataset is empty or accuracy is high enough.

Accuracy



A leaf is where no more splitting is required or possible (zero entropy).

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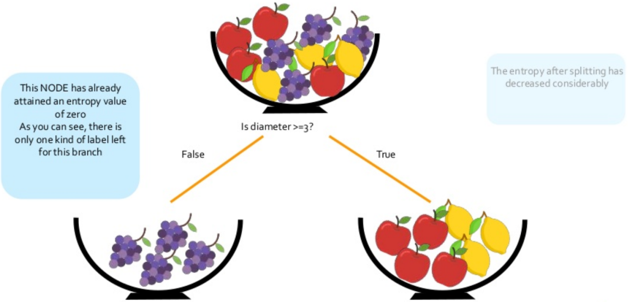

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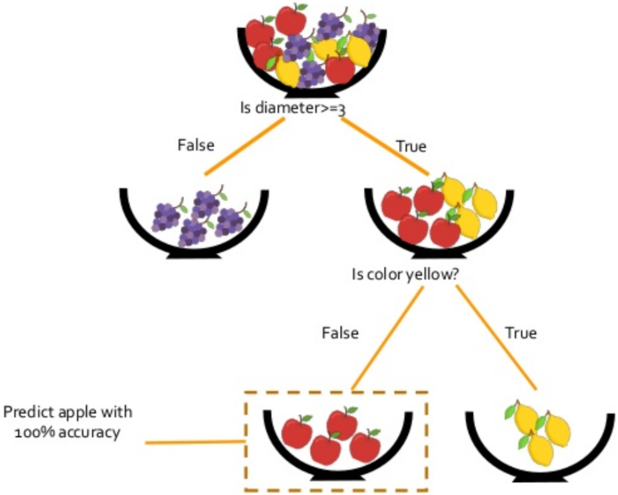
At each leaf, accuracy with respect to label ℓ is measured as:

$$\frac{\#\text{ data points with label }\ell}{\#\text{ data points}}$$

Accuracy



Is diameter>=3
False
True
Is color yellow?
False
True
Predict apple with
100% accuracy

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- Split the given training data into random partitions (bagging).

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- Given a new data point (test set), route it through each tree.

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- Given a new data point (test set), route it through each tree.

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  Average the tree predictions to get the forest prediction.

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Example

In scikit-learn:

`https://scikit-learn.org/stable/modules/ensemble.html`

Exercise: Use the iris dataset to predict flower species.

Reading: "Understanding random forests: from theory to practice"

`https://arxiv.org/pdf/1407.7502`