6.03 Random Forests

Ensemble Methods

- ML methods that combine several base models to produce one optimal predictive model
- Combine decisions from multiple models to improve the overall performance
- Ensemble learning involves creating a collection (or “ensemble”) of multiple algos for purpose of generating a single model that outperforms its base models

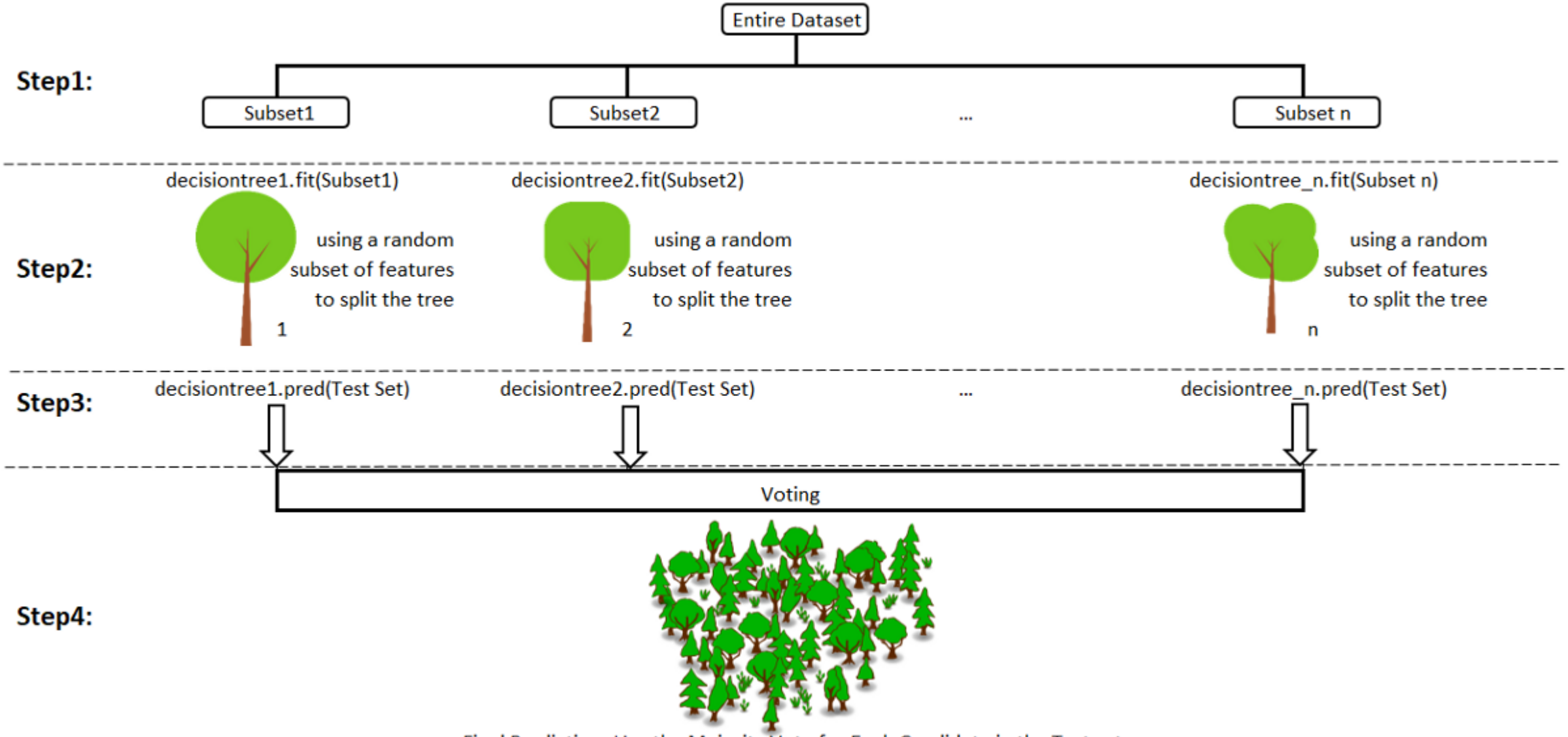
Random Forest (RF)

- Ensemble of decision trees using randomly sampled data
- Uses a variant of Bagging method where each time a split is considered only a portion of features are considered split candidates, so as to avoid the case with Bagging where very strong features can result in most trees using that feature as the top split
- Useful for both classification and regression

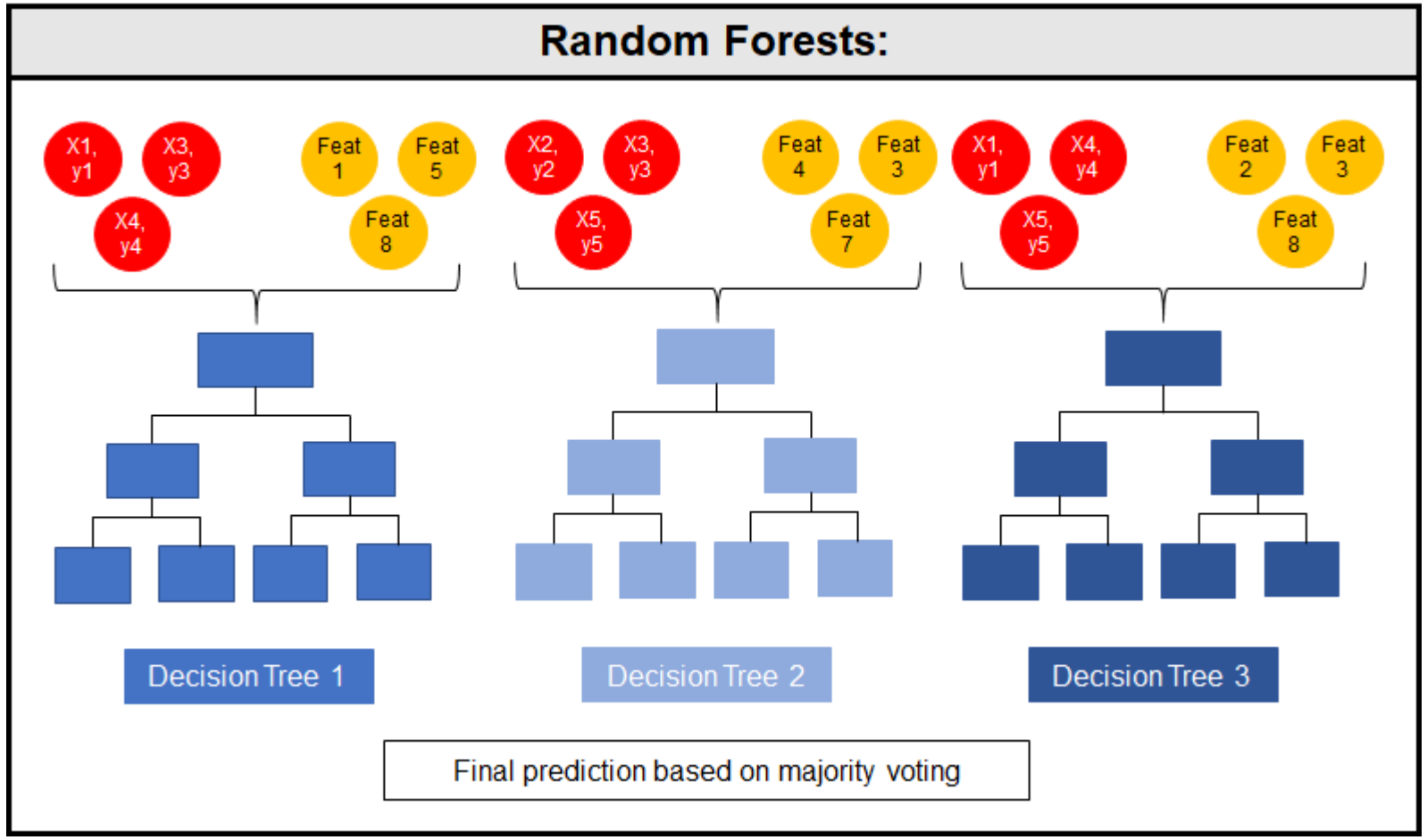
Random Forest

- When predicting a new value for a target feature, each tree is either using regression or classification to derive a value a.k.a. “vote”
- Random Forest algo then takes an average value or most popular category of all the trees in the ensemble
- This average is the predicted value of the target variable

Random Forest



Random Forest



Visualization of the random forests algorithm. Subsamples of the training samples and of the features are used to grow multiple weak learners (decision trees)

Random Forest Process

1. Create a random sample from the original data
2. Randomly select a set of features at each node in the decision tree
3. Decide the best split
4. For each data sample, create a separate base model
5. Compute the final prediction by average the predictions from all the individual models

Random Forests Pros

- Easy to understand
- Useful for data exploration
- Reduced data cleaning (scaling not required)
- Handle multiple data types
- Highly flexible and gives a good accuracy
- Works well on large datasets
- Overfitting is avoided (due to averaging)

Random Forests Cons

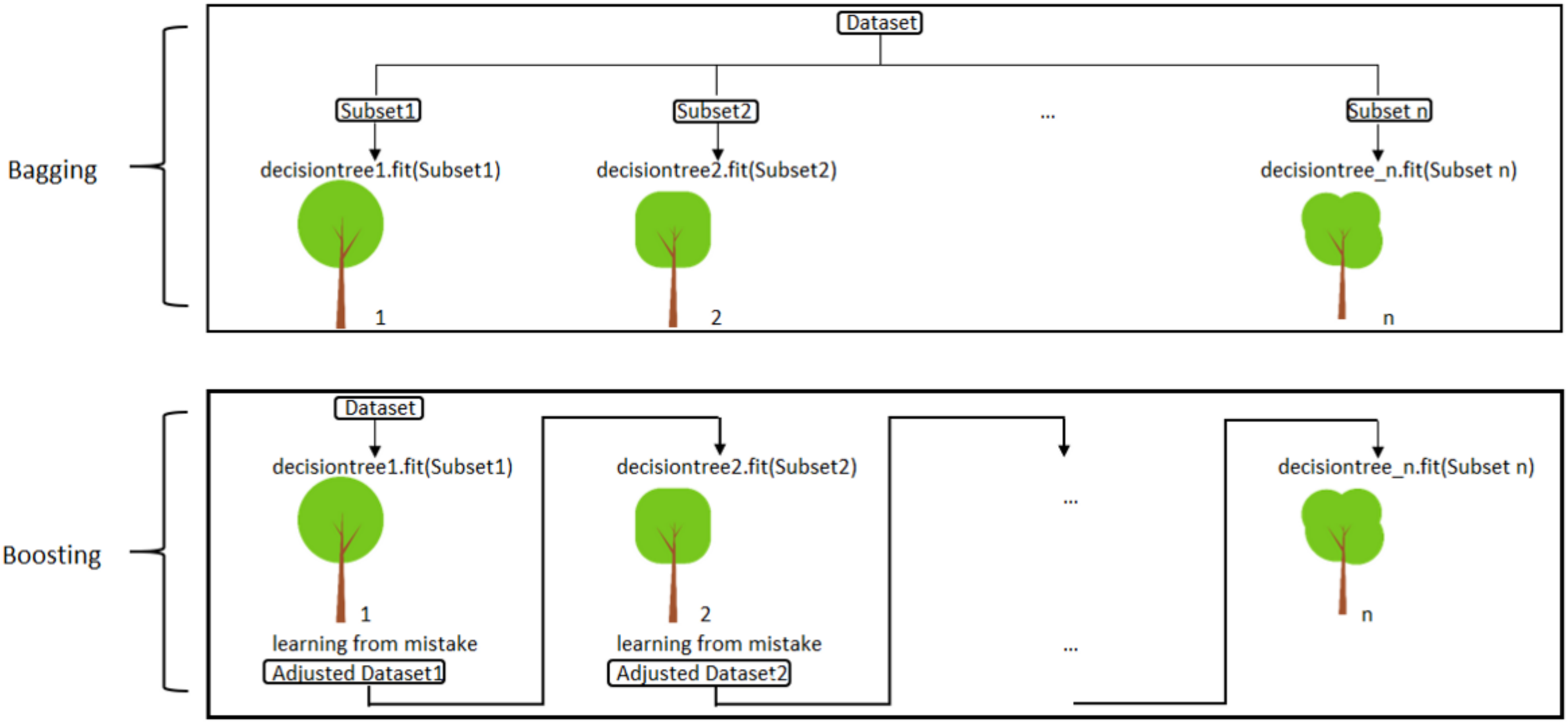
- Does not work well with sparse datasets
- Computationally expensive
- No interpretability

6.04 Boosting

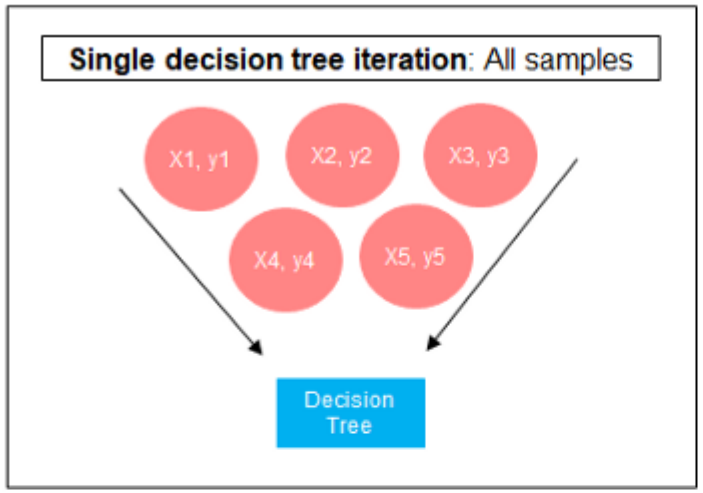
Boosting

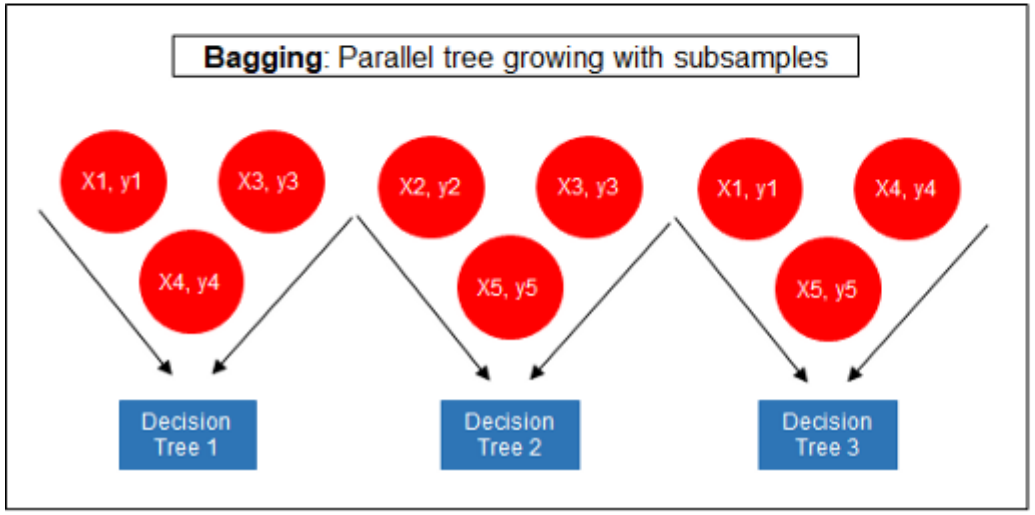
- Ensemble method that aggregates a number of weak models to create one strong model
  - A weak model is one that's only slightly better than random guessing
  - A strong model is one that's strongly correlated w/ true classification
- Boosting effectively learns from its mistakes with each iteration

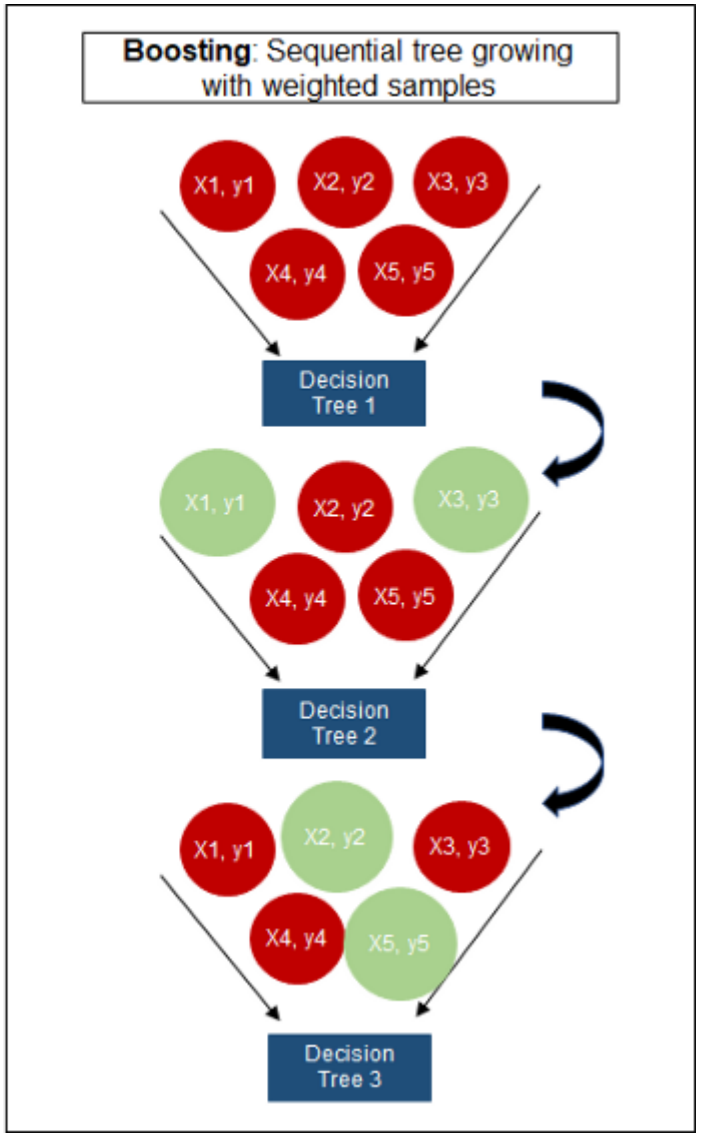
Difference between Bagging and Boosting



Difference between Bagging and Boosting







Boosting

When to Use It?

- Categorical or continuous target variable
- Useful on nearly any type of problem
- Interested in significance of predictors
- Prediction time is important

When Not to Use It?

- Transparency is important
- Training time is important or compute power is limited
- Data is really noisy

Boosting Techniques

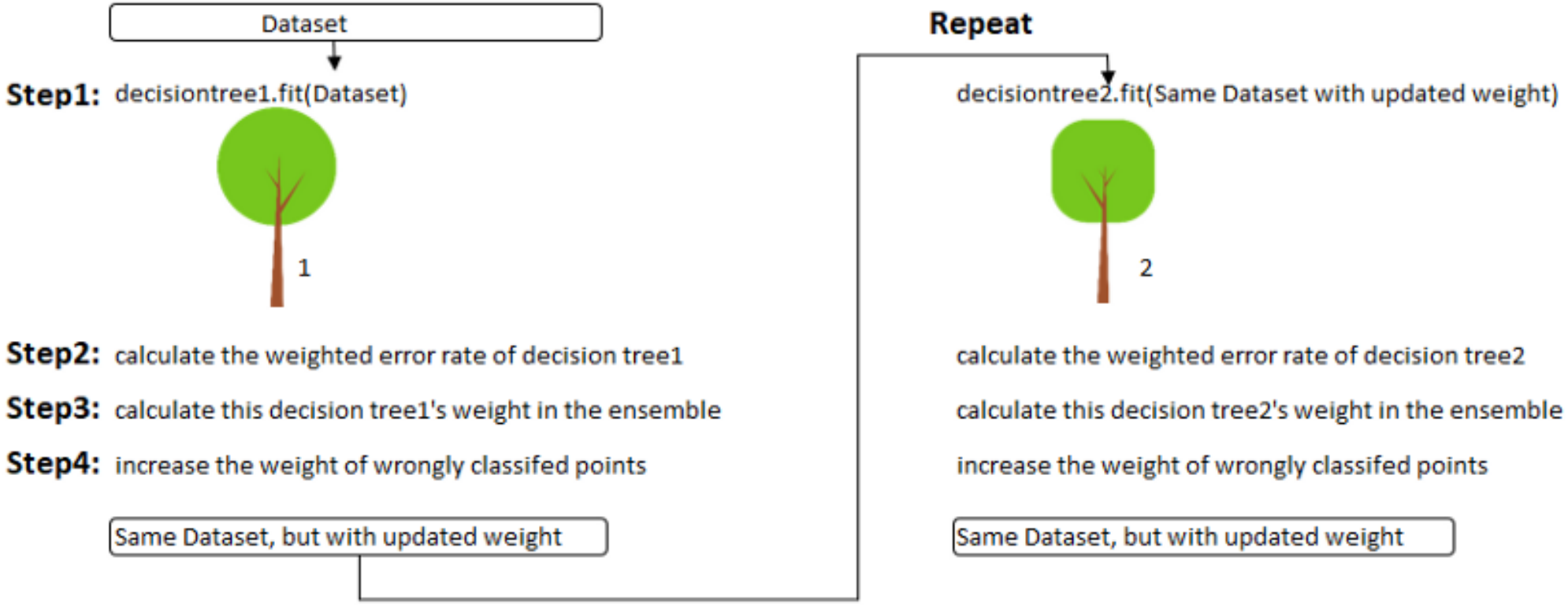
1. AdaBoost

2. Gradient Boosting

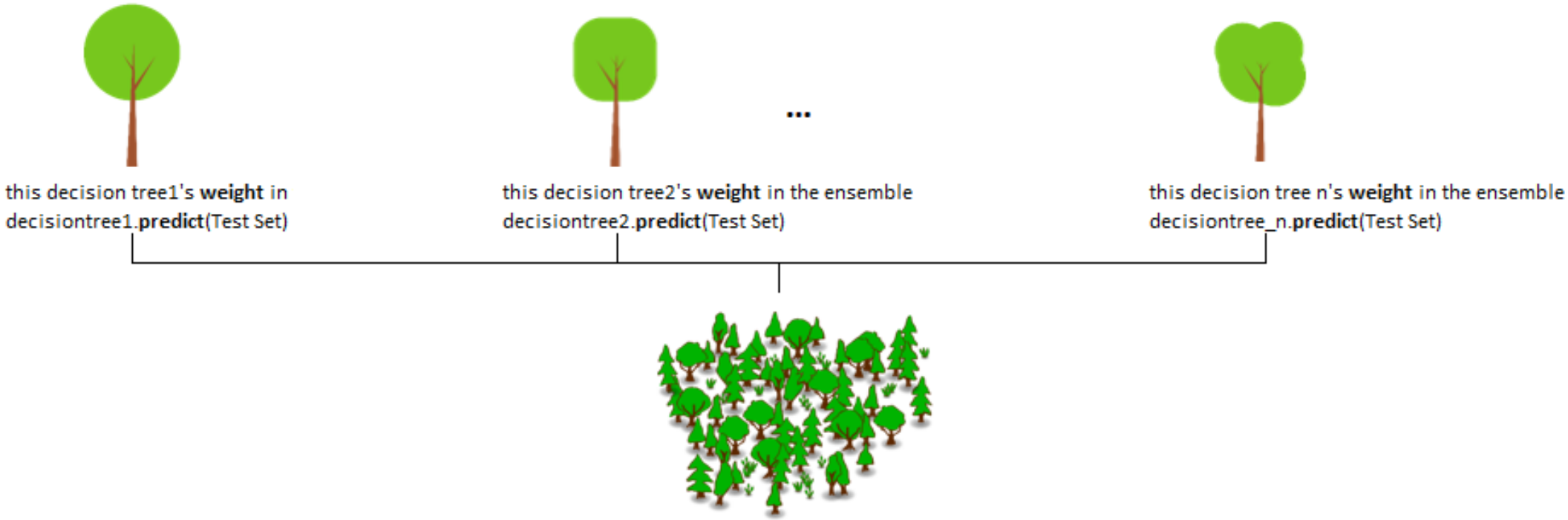
AdaBoost (Adaptive Boosting)

- Boosting ensemble model that works especially well with the decision tree.
- Boosting model's key is learning from the previous mistakes, e.g. misclassification data points.
- AdaBoost learns from the mistakes by increasing the weight of misclassified data points.

AdaBoost (Adaptive Boosting)



AdaBoost (Adaptive Boosting)



AdaBoost Process

- Step 0: Initialize the weights of data points. if the training set has 100 data points, then each point's initial weight should be 1/100 = 0.01.

- Step 1: Train a decision tree

- Step 2: Calculate the weighted error rate (e) of the decision tree. The weighted error rate (e) is just how many wrong predictions out of total and you treat the wrong predictions differently based on its data point's weight. The higher the weight, the more the corresponding error will be weighted during the calculation of the (e).

AdaBoost Process

- Step 3: **Calculate this decision tree's weight** in the ensemble
- the weight of this tree = learning rate * log((1 — e) / e)

  - the higher weighted error rate of a tree, the less decision power the tree will be given during the later voting
  - the lower weighted error rate of a tree, the higher decision power the tree will be given during the later voting

AdaBoost Process

- Step 4: **Update weights** of wrongly classified points
- the weight of each data point =
  - if the model got this data point correct, the weight stays the same
  - if the model got this data point wrong, the new weight of this point = old weight * np.exp(weight of this tree)

- Note: The higher the weight of the tree (more accurate this tree performs), the more boost (importance) the misclassified data point by this tree will get. The weights of the data points are normalized after all the misclassified points are updated.

AdaBoost Process

- Step 5: **Repeat** Step 1(until the number of trees we set to train is reached)
- Step 6: **Make the final prediction**

- The AdaBoost makes a new prediction by adding up the weight (of each tree) multiply the prediction (of each tree). Obviously, the tree with higher weight will have more power of influence the final decision.

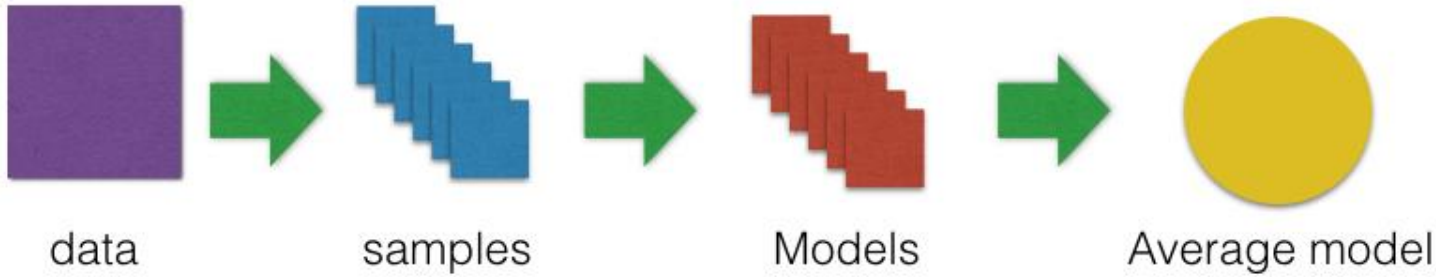
Gradient Boosting

- Ensemble learning method that takes an iterative approach to combining weak learners to create a strong learner by focusing on mistakes of prior iterations
- Takes results from multiple models and combines them to get a final result
- Process overview: create subsets of the original data and run different models on the subsets; run the models sequentially

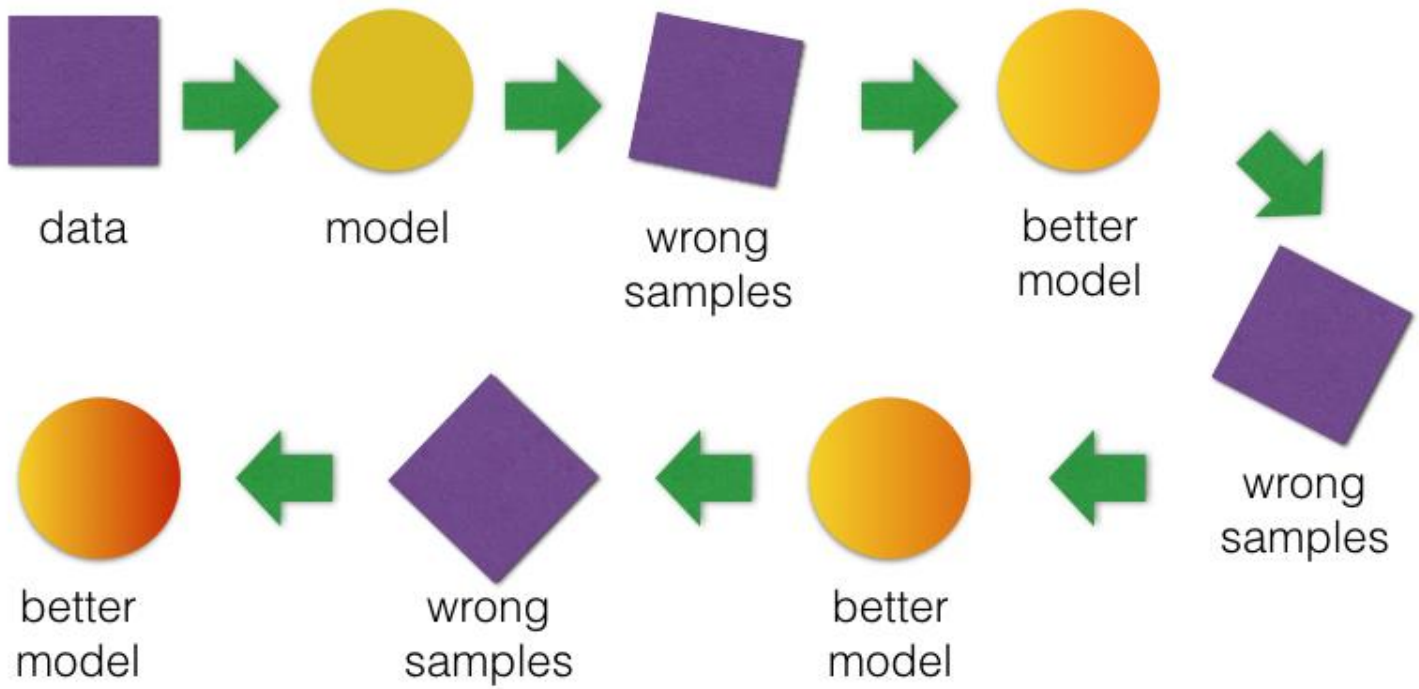
Gradient Boosting Process

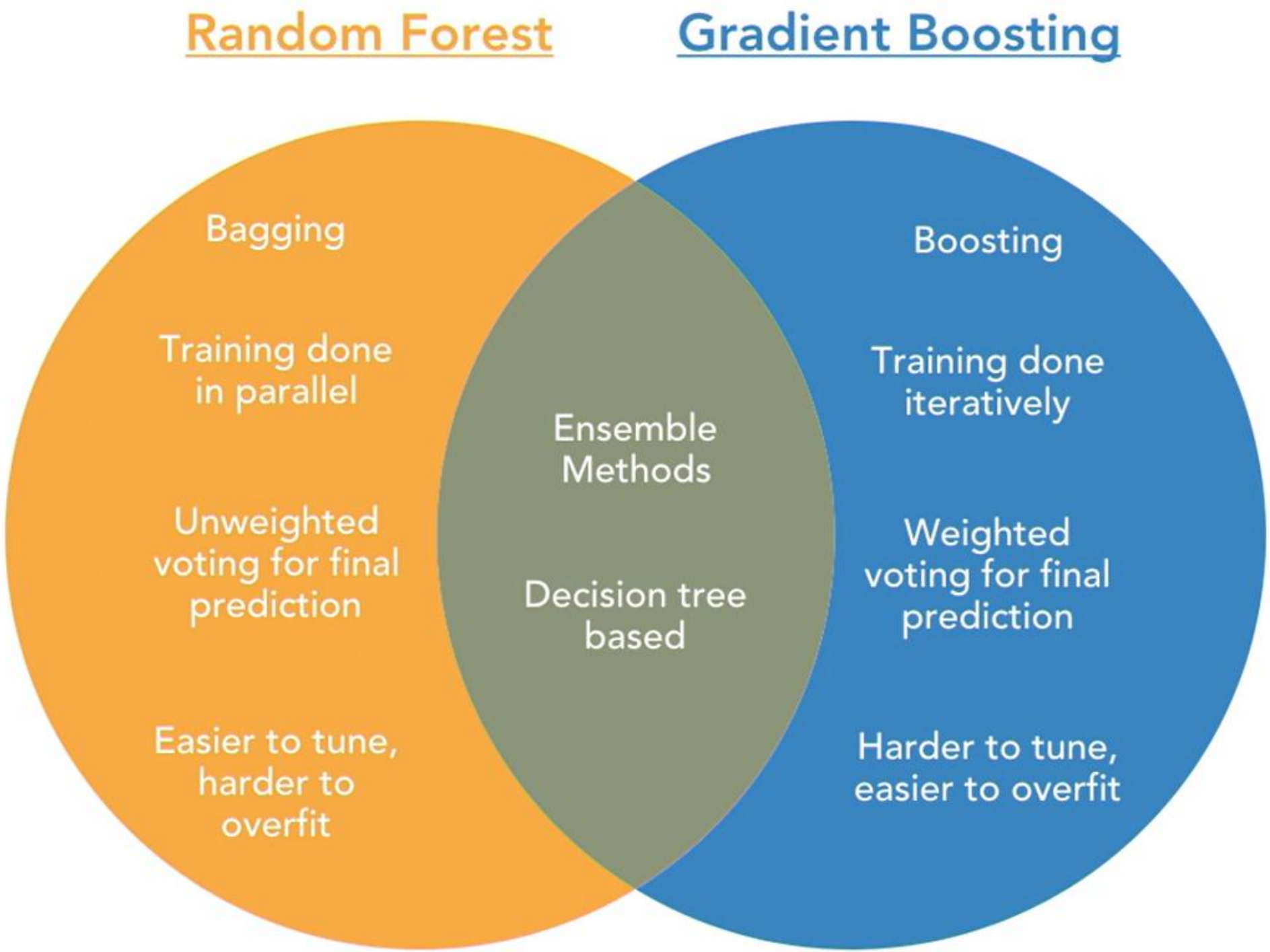
- Create a subset of data
- Run a model on subset of data and get the predictions
- Calculate errors on these predictions
- Assign weights to the incorrect predictions
- Create a better model with the same data
- Repeat cycle until a “strong learner” is created

Bagging



Boosting




Random Forest
Gradient Boosting
Bagging
Training done in parallel
Unweighted voting for final prediction
Easier to tune, harder to overfit
Ensemble Methods
Decision tree based
Boosting
Training done iteratively
Weighted voting for final prediction
Harder to tune, easier to overfit

Gradient Boosting Trade-offs

- Pros
  - Extremely powerful
  - Accepts various types of inputs
  - Can be used for classification or regression
  - Outputs feature importance
- Cons
  - Longer to train (can't parallelize)
  - More likely to overfit
  - More difficult to properly tune

Differences Between Bagging and Boosting

S.NO	Bagging	Boosting
1.	The simplest way of combining predictions that belong to the same type.	A way of combining predictions that belong to the different types.
2.	Aim to decrease variance, not bias.	Aim to decrease bias, not variance.
3.	Each model receives equal weight.	Models are weighted according to their performance.
4.	Each model is built independently.	New models are influenced by the performance of previously built models.
5.	Different training data subsets are selected using row sampling with replacement and random sampling methods from the entire training dataset.	Every new subset contains the elements that were misclassified by previous models.

Differences Between Bagging and Boosting

S.NO	Bagging	Boosting
6.	Bagging tries to solve the over-fitting problem.	Bagging tries to solve the under-fitting problem.
7.	If the classifier is unstable (high variance), then apply bagging.	If the classifier is stable and simple (high bias) the apply boosting.
8.	Base classifiers are trained parallelly.	Base classifiers are trained sequentially.
9	Example: The Random forest model uses Bagging.	Example: The AdaBoost uses Boosting techniques