

Ensemble Learning

Nipun Batra and teaching staff

July 26, 2025

IIT Gandhinagar

Table of Contents

Introduction to Ensemble Learning

Ensemble Methods

Use multiple models for prediction.

Most winning entries of Kaggle competitions use ensemble learning.

Ensemble Methods

Use multiple models for prediction.

Most winning entries of Kaggle competitions use ensemble learning.

Example:

Classifier 1 - Good

Classifier 2 - Good

Classifier 3 - Bad

Using Majority Voting, we predict Good.

Ensemble Methods

Use multiple models for prediction.

Most winning entries of Kaggle competitions use ensemble learning.

Example:

Regressor 1 - 20

Regressor 2 - 30

Regressor 3 - 30

Using averaging, we predict $\frac{80}{3}$

Intuition

Based on [Ensemble methods in ML by Dietterich](#)

Three reasons why ensembles make sense:

Intuition

Based on [Ensemble methods in ML by Dietterich](#)

Three reasons why ensembles make sense:

1) Statistical: Sometimes if **data is limited, many competing hypotheses can be learned** all giving the same accuracy on training data.

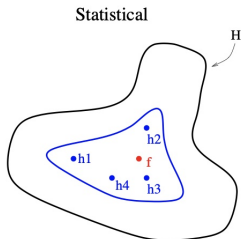
Intuition

Based on [Ensemble methods in ML by Dietterich](#)

Three reasons why ensembles make sense:

1) Statistical: Sometimes if **data is limited, many competing hypotheses can be learned** all giving the same accuracy on training data.

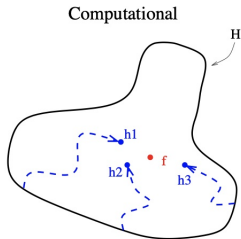
E.g., we can learn many decision trees for the same data giving the same accuracy.



2) Computational: Even if data is sufficient, some **classifiers/regressors can get stuck in local optima or apply greedy strategies**. Computationally learning the “best” hypothesis can be non-trivial.

2) Computational: Even if data is sufficient, some **classifiers/regressors can get stuck in local optima or apply greedy strategies**. Computationally learning the “best” hypothesis can be non-trivial.

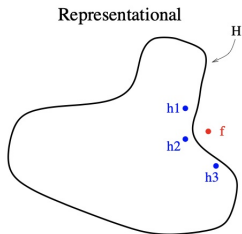
E.g., decision trees employ greedy criteria



3) Representational: Some **classifiers/regressors cannot learn the true form or representation.**

3) Representational: Some **classifiers/regressors cannot learn the true form or representation.**

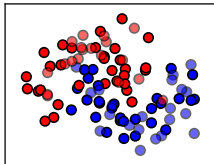
E.g., decision trees can only learn axis-parallel splits.



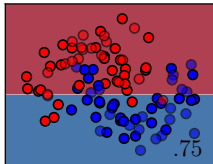
Representation of Limited Depth DTs vs RFs

Notebook: [ensemble-representation.html](#)

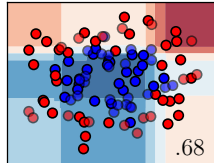
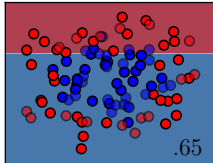
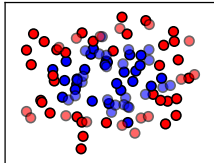
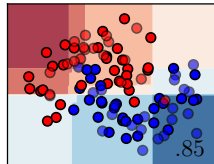
Input data



Decision Tree (Depth 1)



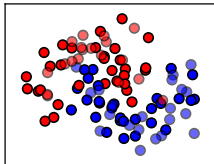
Random Forest



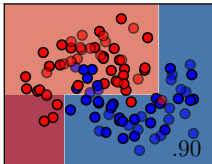
Representation of Limited Depth DTs vs RFs

Notebook: [ensemble-representation.html](#)

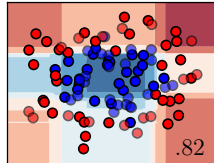
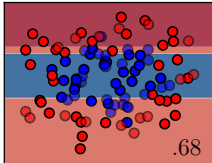
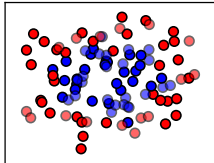
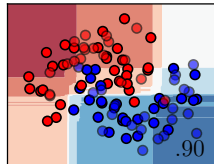
Input data



Decision Tree (Depth 2)



Random Forest



Necessary and Sufficient Conditions

Necessary and Sufficient Conditions

1) A necessary and sufficient condition for an ensemble of classifiers to be more accurate than any of its individual members is if the classifiers are accurate and diverse.

Necessary and Sufficient Conditions

- 1) A necessary and sufficient condition for an ensemble of classifiers to be more accurate than any of its individual members is if the classifiers are accurate and diverse.
- 2) An accurate classifier:

Necessary and Sufficient Conditions

- 1) A necessary and sufficient condition for an ensemble of classifiers to be more accurate than any of its individual members is if the classifiers are accurate and diverse.
- 2) An accurate classifier: is one that has an error rate of better than random guessing on new x values.

Necessary and Sufficient Conditions

- 1) A necessary and sufficient condition for an ensemble of classifiers to be more accurate than any of its individual members is if the classifiers are accurate and diverse.
- 2) An accurate classifier: is one that has an error rate of better than random guessing on new x values.
- 3) Two classifiers are diverse:

Necessary and Sufficient Conditions

- 1) A necessary and sufficient condition for an ensemble of classifiers to be more accurate than any of its individual members is if the classifiers are accurate and diverse.
- 2) An accurate classifier: is one that has an error rate of better than random guessing on new x values.
- 3) Two classifiers are diverse: if they make different errors on new data points

Necessary and Sufficient Conditions

Imagine that we have an ensemble of three classifiers (h_1, h_2, h_3) and consider a new case x .

Necessary and Sufficient Conditions

Imagine that we have an ensemble of three classifiers (h_1, h_2, h_3) and consider a new case x .

If the three classifiers are identical, i.e. not diverse, then when $h_1(x)$ is wrong $h_2(x)$ and $h_3(x)$ will also be wrong.

Necessary and Sufficient Conditions

Imagine that we have an ensemble of three classifiers (h_1, h_2, h_3) and consider a new case x .

If the three classifiers are identical, i.e. not diverse, then when $h_1(x)$ is wrong $h_2(x)$ and $h_3(x)$ will also be wrong.

However, if the errors made by the classifiers are uncorrelated, then when $h_1(x)$ is wrong, $h_2(x)$ and $h_3(x)$ may be correct, so that a majority vote will correctly classify.

Intuition for Ensemble Methods from Quantitative Perspective

Intuition for Ensemble Methods from Quantitative Perspective

Error Probability of each model = $\varepsilon = 0.3$

$$\begin{aligned} Pr(\text{ensemble being wrong}) &= {}^3C_2(\varepsilon^2)(1-\varepsilon)^{3-2} + {}^3C_3(\varepsilon^3)(1-\varepsilon)^{3-3} \\ &= 0.19 \leq 0.3 \end{aligned}$$

Some calculations

Number of Models	Ensemble Error	Individual Error
1	0.3	0.3
3	0.216	0.3
5	0.163	0.3

Some calculations

Number of Models	Ensemble Error	Individual Error
1	0.6	0.6
3	0.648	0.6
5	0.683	0.6

Where does ensemble learning not work well?

Where does ensemble learning not work well?

- The base model is bad.
- All models give similar prediction or the models are highly correlated.

Bagging

Also known as *Bootstrap Aggregation*.

Bagging

Also known as *Bootstrap Aggregation*.

Key idea : Reduce Variance

Bagging

Also known as *Bootstrap Aggregation*.

Key idea : Reduce Variance

How to learn different classifiers while feeding in the same data?

Bagging

Also known as *Bootstrap Aggregation*.

Key idea : Reduce Variance

How to learn different classifiers while feeding in the same data?

Think about cross-validation!

Bagging

Also known as *Bootstrap Aggregation*.

Key idea : Reduce Variance

How to learn different classifiers while feeding in the same data?

Think about cross-validation!

We will create multiple datasets from our single dataset using
"sampling with replacement".

Bagging

Consider our dataset has n samples: $D_1, D_2, D_3, \dots, D_n$.

For each model in the ensemble, we create a new dataset of size n by sampling uniformly with replacement.

Bagging

Consider our dataset has n samples: $D_1, D_2, D_3, \dots, D_n$.

For each model in the ensemble, we create a new dataset of size n by sampling uniformly with replacement.

Round 1: $D_1, D_3, D_6, D_1, \dots, D_n$

Round 2: $D_2, D_4, D_1, D_{80}, \dots, D_3$

\vdots

Bagging

Consider our dataset has n samples: $D_1, D_2, D_3, \dots, D_n$.

For each model in the ensemble, we create a new dataset of size n by sampling uniformly with replacement.

Round 1: $D_1, D_3, D_6, D_1, \dots, D_n$

Round 2: $D_2, D_4, D_1, D_{80}, \dots, D_3$

\vdots

Repetition of samples is possible.

Bagging

Consider our dataset has n samples: $D_1, D_2, D_3, \dots, D_n$.

For each model in the ensemble, we create a new dataset of size n by sampling uniformly with replacement.

Round 1: $D_1, D_3, D_6, D_1, \dots, D_n$

Round 2: $D_2, D_4, D_1, D_{80}, \dots, D_3$

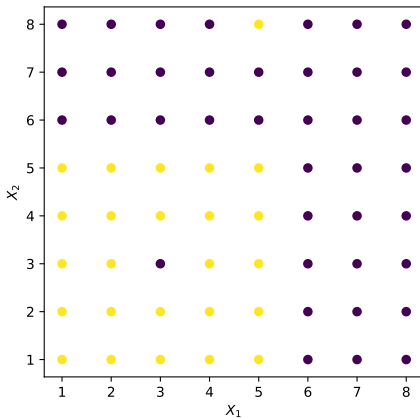
\vdots

Repetition of samples is possible.

We can train the same classifier/models on each of these different “Bagging Rounds”.

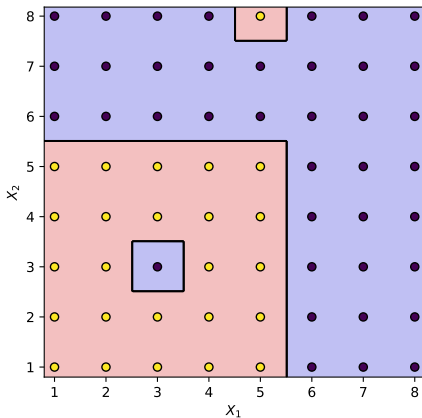
Bagging : Classification Example

Consider the dataset below. Points (3,3) and (5,8) are anomalies.



Bagging : Classification Example

Decision Boundary for decision tree with depth 6.



Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

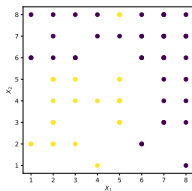
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

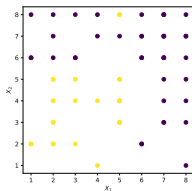
Round - 1



Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

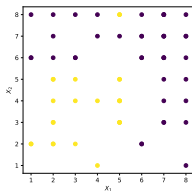
Round - 1



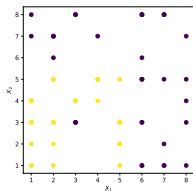
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

Round - 1



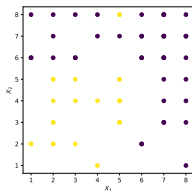
Round - 2



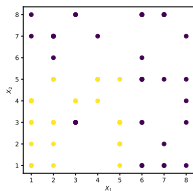
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

Round - 1



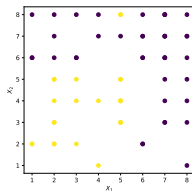
Round - 2



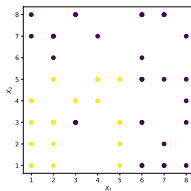
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

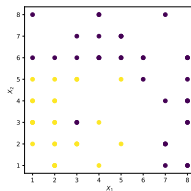
Round - 1



Round - 2



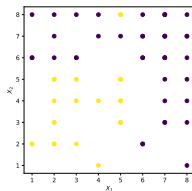
Round - 3



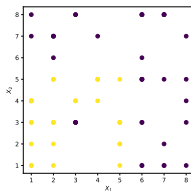
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

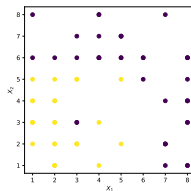
Round - 1



Round - 2



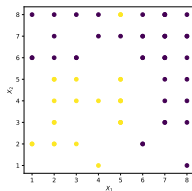
Round - 3



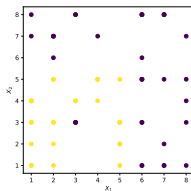
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

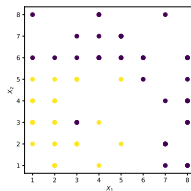
Round - 1



Round - 2



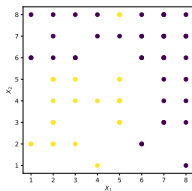
Round - 3



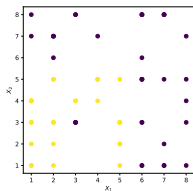
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

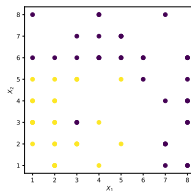
Round - 1



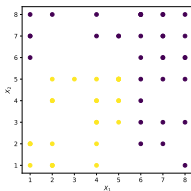
Round - 2



Round - 3



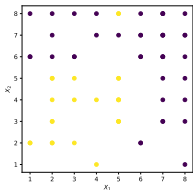
Round - 4



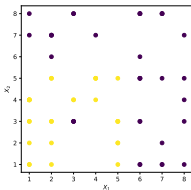
Bagging : Classification Example

Let's use bagging with an ensemble of 5 trees.

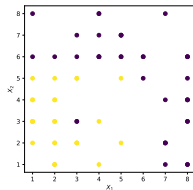
Round - 1



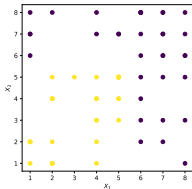
Round - 2



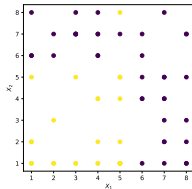
Round - 3



Round - 4



Round - 5

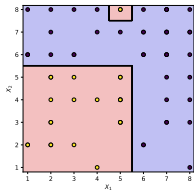


Bagging : Classification Example

Bagging : Classification Example

Bagging : Classification Example

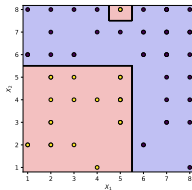
Round - 1



Tree Depth = 4

Bagging : Classification Example

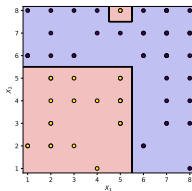
Round - 1



Tree Depth = 4

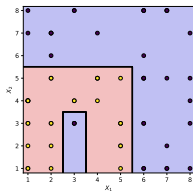
Bagging : Classification Example

Round - 1



Tree Depth = 4

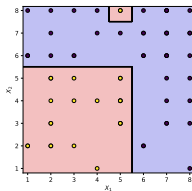
Round - 2



Tree Depth = 5

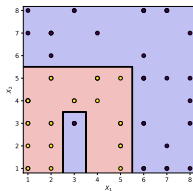
Bagging : Classification Example

Round - 1



Tree Depth = 4

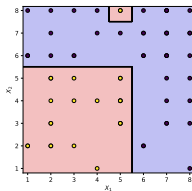
Round - 2



Tree Depth = 5

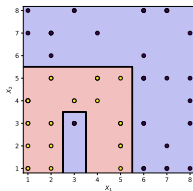
Bagging : Classification Example

Round - 1



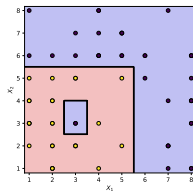
Tree Depth = 4

Round - 2



Tree Depth = 5

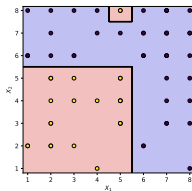
Round - 3



Tree Depth = 5

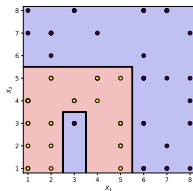
Bagging : Classification Example

Round - 1



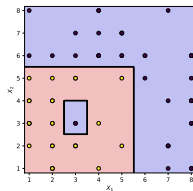
Tree Depth = 4

Round - 2



Tree Depth = 5

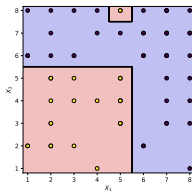
Round - 3



Tree Depth = 5

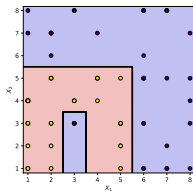
Bagging : Classification Example

Round - 1



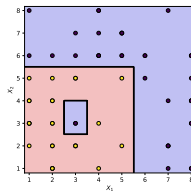
Tree Depth = 4

Round - 2



Tree Depth = 5

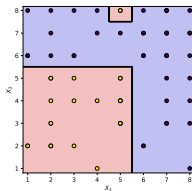
Round - 3



Tree Depth = 5

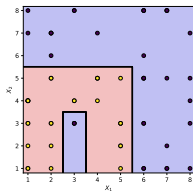
Bagging : Classification Example

Round - 1



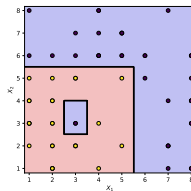
Tree Depth = 4

Round - 2



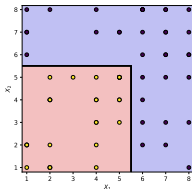
Tree Depth = 5

Round - 3



Tree Depth = 5

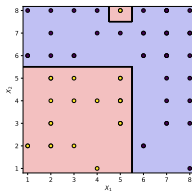
Round - 4



Tree Depth = 2

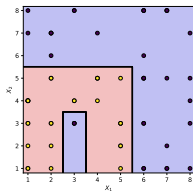
Bagging : Classification Example

Round - 1



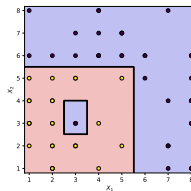
Tree Depth = 4

Round - 2



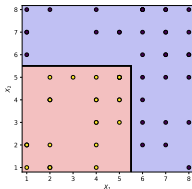
Tree Depth = 5

Round - 3



Tree Depth = 5

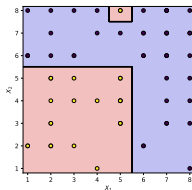
Round - 4



Tree Depth = 2

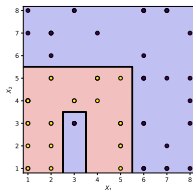
Bagging : Classification Example

Round - 1



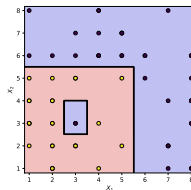
Tree Depth = 4

Round - 2



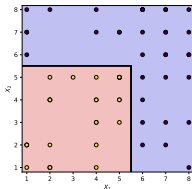
Tree Depth = 5

Round - 3



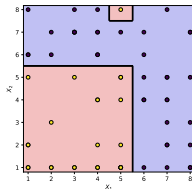
Tree Depth = 5

Round - 4



Tree Depth = 2

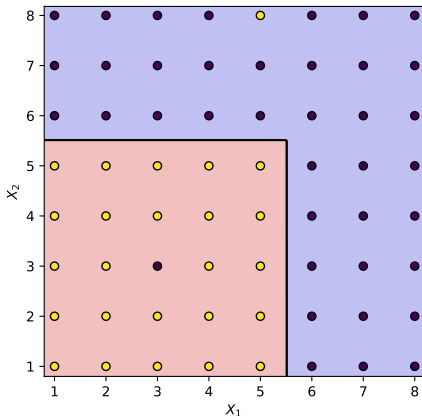
Round - 5



Tree Depth = 4

Bagging : Classification Example

Using majority voting to combine all predictions, we get the decision boundary below.



Summary

- We take “strong” learners and combine them to reduce variance.

Summary

- We take “strong” learners and combine them to reduce variance.
- All learners are independent of each other.

- We take “weak” learners and combine them to reduce bias.

- We take “weak” learners and combine them to reduce bias.

Boosting

- We take “weak” learners and combine them to reduce bias.
- All learners are incrementally built.

Boosting

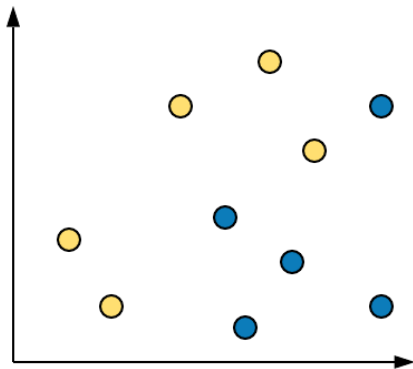
- We take “weak” learners and combine them to reduce bias.
- All learners are incrementally built.

- We take “weak” learners and combine them to reduce bias.
- All learners are incrementally built.
- Incremental building: Incrementally try to classify “harder” samples correctly.

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

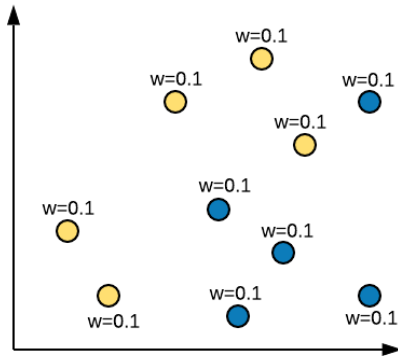


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

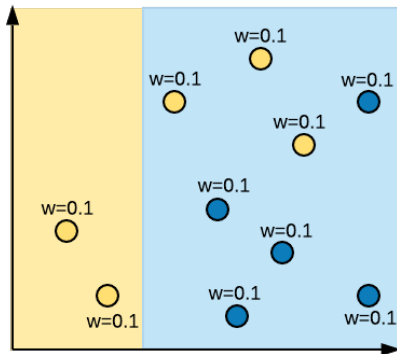


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

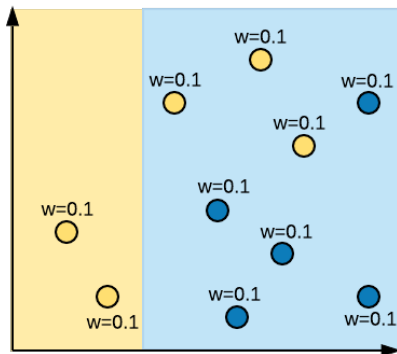


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

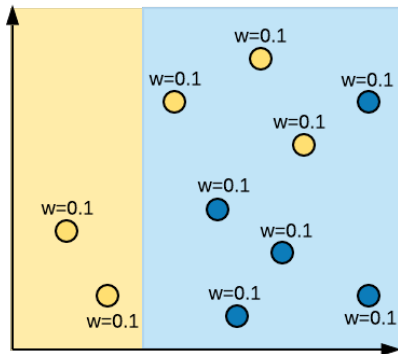


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

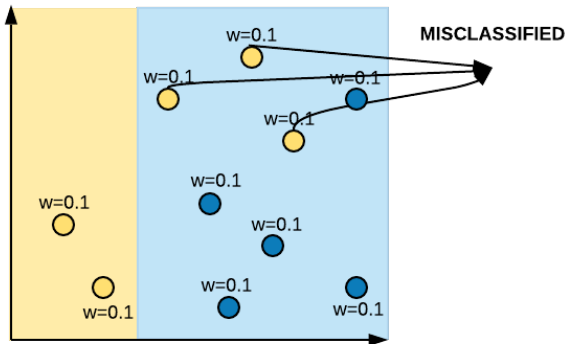


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

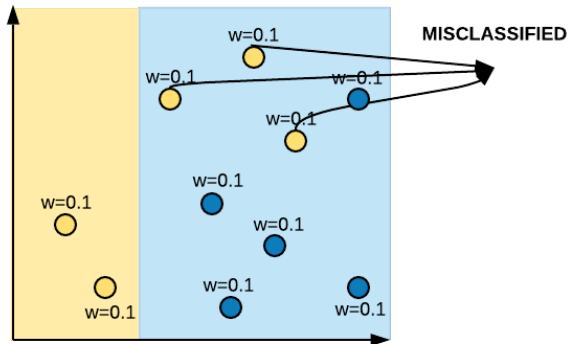


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's



Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

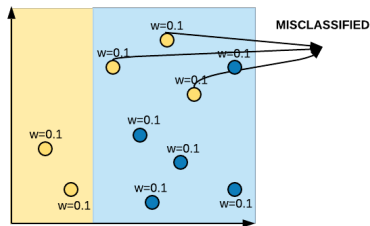
1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

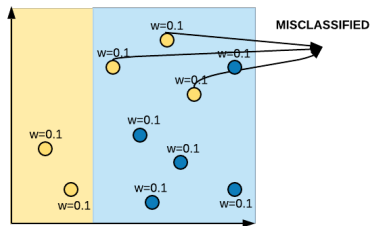


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $err_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$



$$err_1 = \frac{0.3}{1}$$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

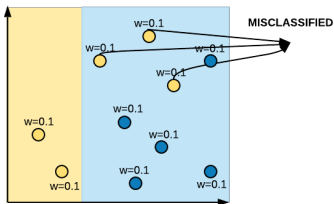
1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i (\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

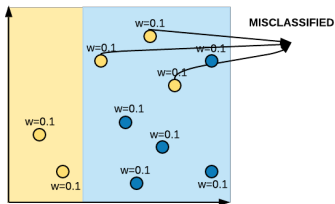


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $err_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - err_m}{err_m} \right)$



$$err_1 = \frac{0.3}{1}$$
$$\alpha_1 = \frac{1}{2} \log \left(\frac{1 - 0.3}{0.3} \right) = 0.42$$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$

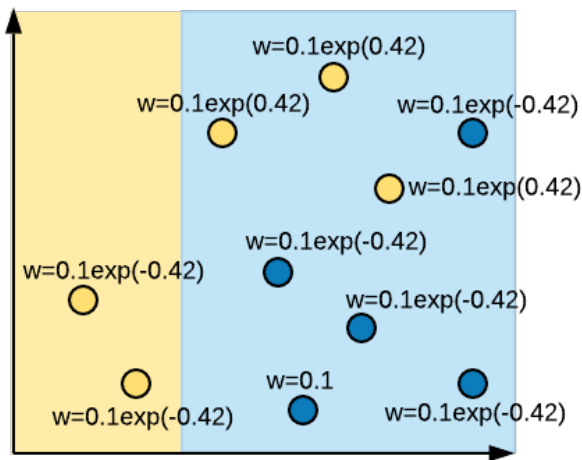
Boosting : AdaBoost

Consider we have a dataset of N samples.

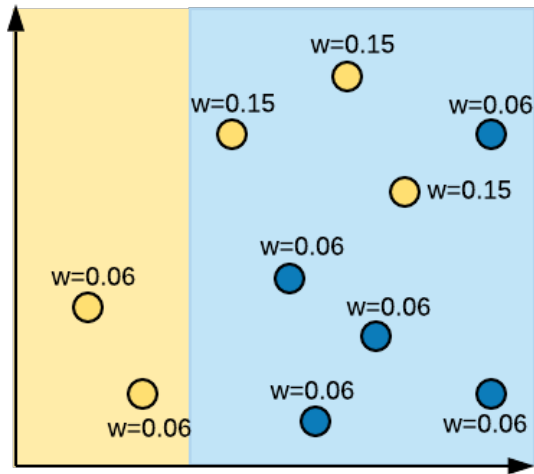
Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$
 - 2.5 For samples which were predicted incorrectly: $w_i = w_i e^{\alpha_m}$

Boosting : AdaBoost



Boosting : AdaBoost



Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $err_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1-err_m}{err_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$
 - 2.5 For samples which were predicted incorrectly: $w_i = w_i e^{\alpha_m}$

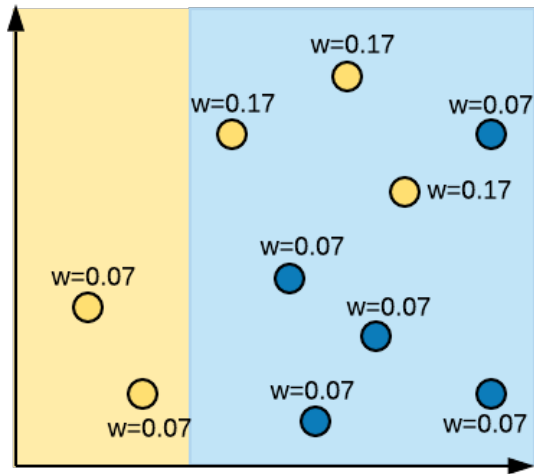
Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $err_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1-err_m}{err_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$
 - 2.5 For samples which were predicted incorrectly: $w_i = w_i e^{\alpha_m}$
 - 2.6 Normalize w_i 's to sum to 1.

Boosting : AdaBoost



Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

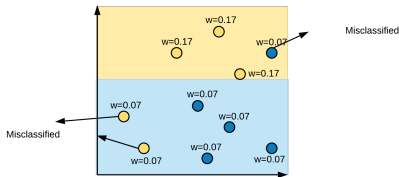
1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

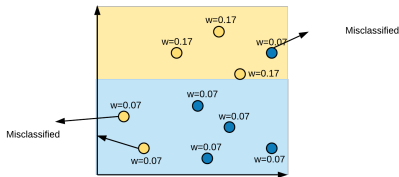


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $err_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - err_m}{err_m} \right)$



$$err_2 = \frac{0.21}{1}$$
$$\alpha_2 = \frac{1}{2} \log \left(\frac{1 - 0.21}{0.21} \right) = 0.66$$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$

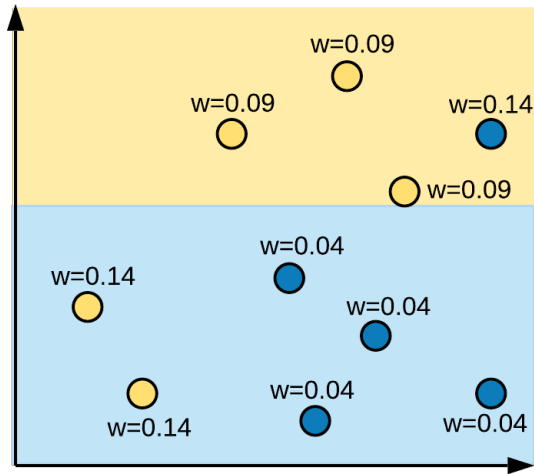
Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$
 - 2.5 For samples which were predicted incorrectly: $w_i = w_i e^{\alpha_m}$

Boosting : AdaBoost



Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $err_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1-err_m}{err_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$
 - 2.5 For samples which were predicted incorrectly: $w_i = w_i e^{\alpha_m}$

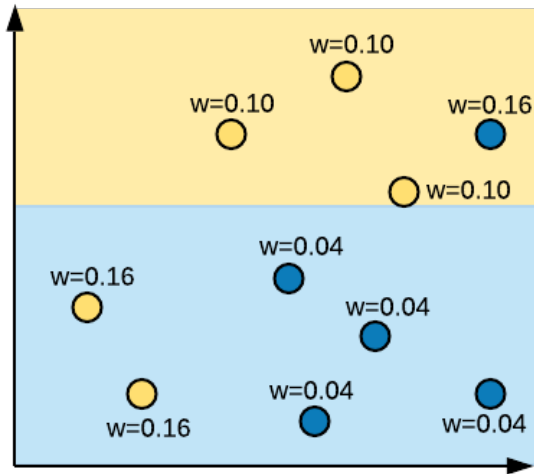
Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$
 - 2.4 For samples which were predicted correctly: $w_i = w_i e^{-\alpha_m}$
 - 2.5 For samples which were predicted incorrectly: $w_i = w_i e^{\alpha_m}$
 - 2.6 Normalize w_i 's to sum to 1.

Boosting : AdaBoost



Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

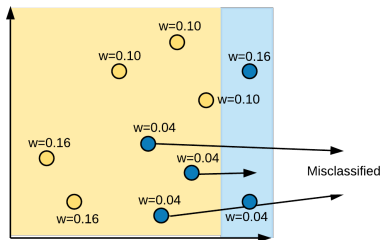
1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $\text{err}_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - \text{err}_m}{\text{err}_m} \right)$

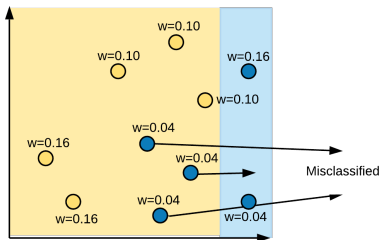


Boosting : AdaBoost

Consider we have a dataset of N samples.

Sample i has weight w_i . There are M classifiers in the ensemble.

1. Initialize weights of data samples: $w_i = \frac{1}{N}$
2. For $m = 1, \dots, M$:
 - 2.1 Learn classifier using current weights w_i 's
 - 2.2 Compute the weighted error: $err_m = \frac{\sum_i w_i(\text{incorrect})}{\sum_i w_i}$
 - 2.3 Compute $\alpha_m = \frac{1}{2} \log_e \left(\frac{1 - err_m}{err_m} \right)$



$$err_3 = \frac{0.12}{1}$$
$$\alpha_3 = \frac{1}{2} \log \left(\frac{1 - 0.12}{0.12} \right) = 0.99$$

Boosting: Adaboost

Intuitively, after each iteration, importance of wrongly classified samples is increased by increasing their weights and importance of correctly classified samples is decreased by decreasing their weights.

Testing

- For each sample x , compute the prediction of each classifier $h_m(x)$.

Testing

- For each sample x , compute the prediction of each classifier $h_m(x)$.
- Final prediction is the sign of the sum of weighted predictions, given as:

Testing

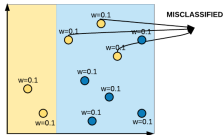
- For each sample x , compute the prediction of each classifier $h_m(x)$.
- Final prediction is the sign of the sum of weighted predictions, given as:
- $\text{SIGN}(\alpha_1 h_1(x) + \alpha_2 h_2(x) + \dots + \alpha_M h_M(x))$

Example

Example

Boosting: Adaboost

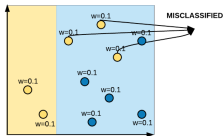
Example



$$\alpha_1 = 0.42$$

Boosting: Adaboost

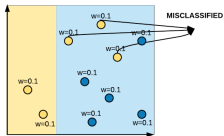
Example



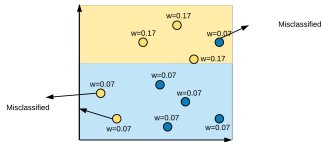
$$\alpha_1 = 0.42$$

Boosting: Adaboost

Example



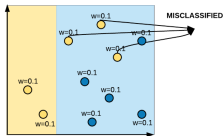
$$\alpha_1 = 0.42$$



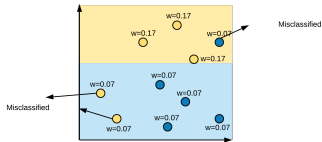
$$\alpha_2 = 0.66$$

Boosting: Adaboost

Example



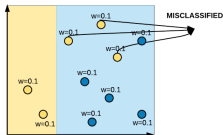
$$\alpha_1 = 0.42$$



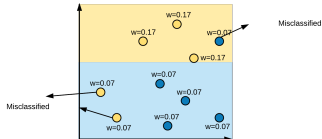
$$\alpha_2 = 0.66$$

Boosting: Adaboost

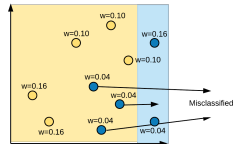
Example



$$\alpha_1 = 0.42$$



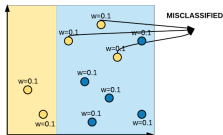
$$\alpha_2 = 0.66$$



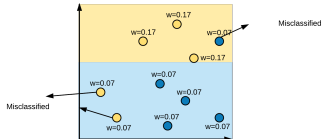
$$\alpha_3 = 0.99$$

Boosting: Adaboost

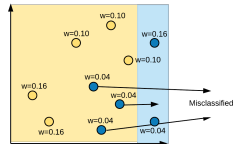
Example



$$\alpha_1 = 0.42$$



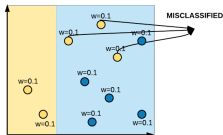
$$\alpha_2 = 0.66$$



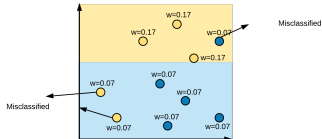
$$\alpha_3 = 0.99$$

Boosting: Adaboost

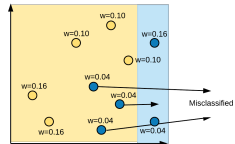
Example



$$\alpha_1 = 0.42$$



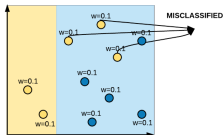
$$\alpha_2 = 0.66$$



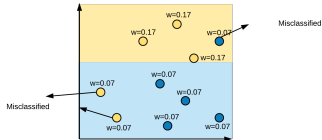
$$\alpha_3 = 0.99$$

Boosting: Adaboost

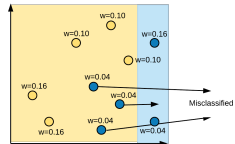
Example



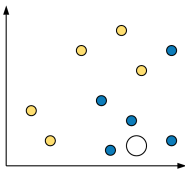
$$\alpha_1 = 0.42$$



$$\alpha_2 = 0.66$$

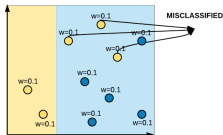


$$\alpha_3 = 0.99$$

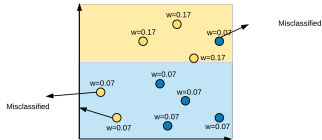


Boosting: Adaboost

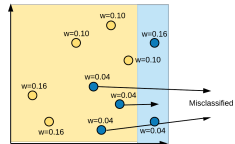
Example



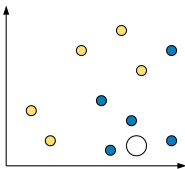
$$\alpha_1 = 0.42$$



$$\alpha_2 = 0.66$$

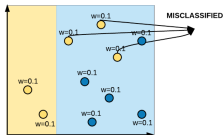


$$\alpha_3 = 0.99$$

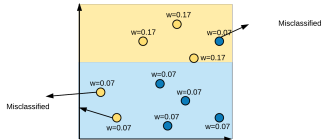


Boosting: Adaboost

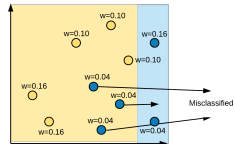
Example



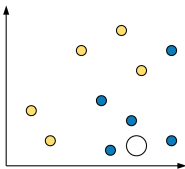
$$\alpha_1 = 0.42$$



$$\alpha_2 = 0.66$$

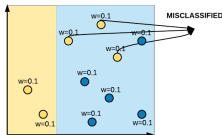


$$\alpha_3 = 0.99$$

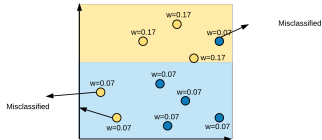


Boosting: Adaboost

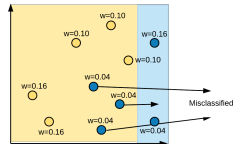
Example



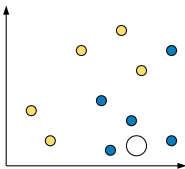
$$\alpha_1 = 0.42$$



$$\alpha_2 = 0.66$$



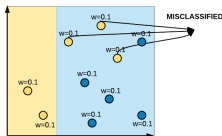
$$\alpha_3 = 0.99$$



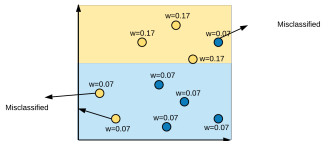
Let us say, yellow class is $+1$ and blue class is -1

Boosting: Adaboost

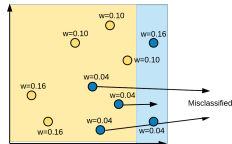
Example



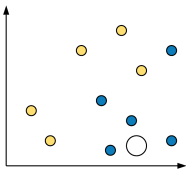
$$\alpha_1 = 0.42$$



$$\alpha_2 = 0.66$$



$$\alpha_3 = 0.99$$



Let us say, yellow class is +1 and
blue class is -1

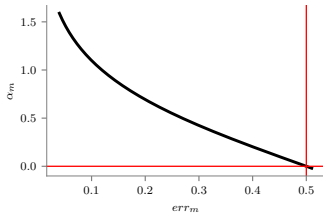
Prediction = $\text{SIGN}(0.42 \cdot -1 + 0.66 \cdot -1 + 0.99 \cdot +1)$ = Negative
= blue

Intuition behind weight update formula

Intuition behind weight update formula

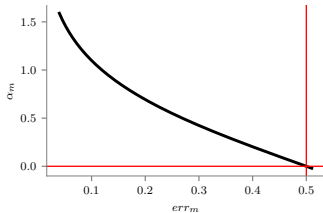
Intuition behind weight update formula

Notebook: [boosting-explanation.html](#)



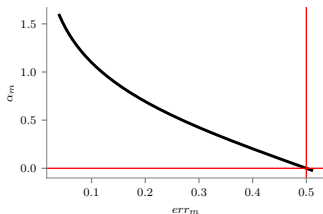
Intuition behind weight update formula

Notebook: [boosting-explanation.html](#)

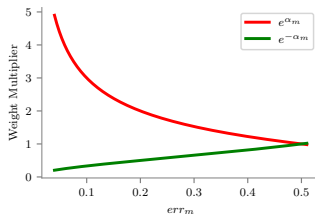


Intuition behind weight update formula

Notebook: [boosting-explanation.html](#)



Notebook: [boosting-explanation.html](#)



From Paper: Improving Regressors using Boosting Techniques

Our problem will be that the modeling error is also nonzero because we have to determine the model in the presence of noise. Since we don't know the probability distributions, we approximate the expectation of the ME and PE using the sample ME (if the truth is known) and sample PE and then average over multiple experiments.

In the following discussion, we detail both bagging and boosting. We then discuss how to build trees which are the basic building blocks of our regression machines and use these ensembles on some standard test functions.

2. BAGGING

The following is a paraphrase of Breiman (1996b) with some difference in notation. Suppose we pick with replacement N_1 examples from the training set of size N_1 and call the k 'th set of observations O_k . Based on these observations, we form a predictor $y^{(p)}(\mathbf{x}, O_k)$. Because we are sampling with replacement, we may have multiple observations or no observations of a particular training example. Sampling with replacement is sometimes termed bootstrap sampling [Efron and Tibshirani (1993)] and therefore this method is called bootstrap aggregating or bagging for short. The ensemble predictor is formed from the approximation to the expectation over all the observation sets, i.e. $E_O[y^{(p)}(\mathbf{x}, O)]$ by using the average of the outputs of all the predictors. Breiman discusses which algorithms are good candidates for predictors and concludes that the best predictors are unstable, i.e., a small change in the training set O_k causes a large change in the predictor $y^{(p)}(\mathbf{x}, O_k)$. Good candidates are regression trees and neural nets.

3. BOOSTING

In bagging, each training example is equally likely to be picked. In boosting, the probability of a particular example being in the training set of a particular machine depends on the performance of the prior machines on that example. The following is a modification of *Adaboost.R* [Freund and Schapire (1996a)].

Initially, to each training pattern we assign a weight $w_i=1 \quad i=1, \dots, N_1$

Repeat the following while the average loss \bar{L} defined

set. Each machine makes a hypothesis: $h_i: \mathbf{x} \rightarrow y$

3. Pass *every* member of the training set through this machine to obtain a prediction $y_i^{(p)}(\mathbf{x}_i) \quad i=1, \dots, N_1$.

4. Calculate a loss for each training sample $L_i = L \left[\left| y_i^{(p)}(\mathbf{x}_i) - y_i \right| \right]$. The loss L may be of any functional form as long as $L \in [0, 1]$. If we let

$$D = \sup \left| y_i^{(p)}(\mathbf{x}_i) - y_i \right| \quad i=1, \dots, N_1$$

then we have three candidate loss functions:

$$L_i = \frac{\left| y_i^{(p)}(\mathbf{x}_i) - y_i \right|}{D} \quad (\text{linear})$$

$$L_i = \frac{\left| y_i^{(p)}(\mathbf{x}_i) - y_i \right|^2}{D^2} \quad (\text{square law})$$

$$L_i = 1 - \exp \left[\frac{- \left| y_i^{(p)}(\mathbf{x}_i) - y_i \right|}{D} \right] \quad (\text{exponential})$$

5. Calculate an average loss: $\bar{L} = \sum_{i=1}^{N_1} L_i p_i$

6. Form $\beta = \frac{\bar{L}}{1 - \bar{L}}$. β is a measure of confidence in the predictor. Low β means high confidence in the prediction.

7. Update the weights: $w_i \rightarrow w_i \beta^{**} [1 - L_i]$, where $**$ indicates exponentiation. The smaller the loss, the more the weight is reduced making the probability smaller that this pattern will be picked as a member of the training set for the next machine in the ensemble.

8. For a particular input \mathbf{x}_i , each of the T machines makes a prediction $h_i, i=1, \dots, T$. Obtain the cumulative prediction h_T using the T predictors:

Random Forest

- Random Forest is an ensemble of decision trees.

Random Forest

- Random Forest is an ensemble of decision trees.
- We have two types of bagging: bootstrap (on data) and random subspace (of features).

Random Forest

- Random Forest is an ensemble of decision trees.
- We have two types of bagging: bootstrap (on data) and random subspace (of features).
- As features are randomly selected, we learn decorrelated trees and helps in reducing variance.

Random Forest

There are 3 parameters while training a random forest number of trees, number of features (m), maximum depth.

Training Algorithm

- For i^{th} tree ($i \in \{1 \cdots N\}$), select n samples from total N samples with replacement.

Learning Decision Tree (for RF)

Random Forest

There are 3 parameters while training a random forest number of trees, number of features (m), maximum depth.

Training Algorithm

- For i^{th} tree ($i \in \{1 \cdots N\}$), select n samples from total N samples with replacement.
- Learn Decision Tree on selected samples for i^{th} round.

Learning Decision Tree (for RF)

Random Forest

There are 3 parameters while training a random forest number of trees, number of features (m), maximum depth.

Training Algorithm

- For i^{th} tree ($i \in \{1 \cdots N\}$), select n samples from total N samples with replacement.
- Learn Decision Tree on selected samples for i^{th} round.

Learning Decision Tree (for RF)

- For each split, select m features from total available M features and train a decision tree on selected features

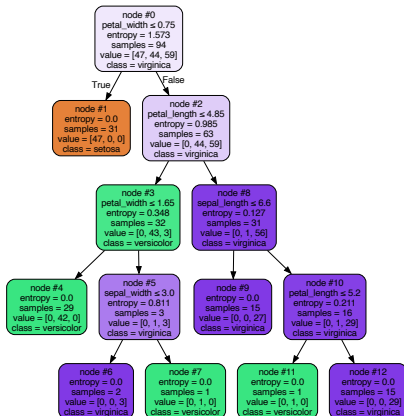
Dataset

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

150 rows × 5 columns

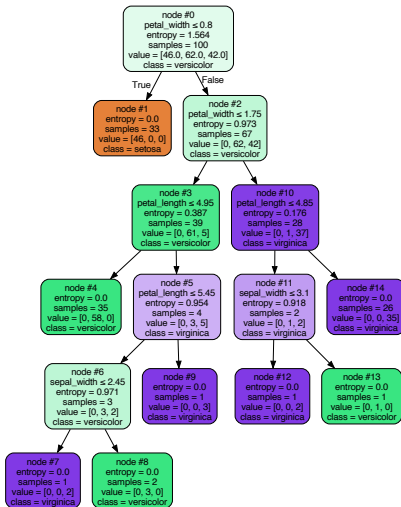
Decision Tree # 0

Notebook: ensemble-feature-importance.html



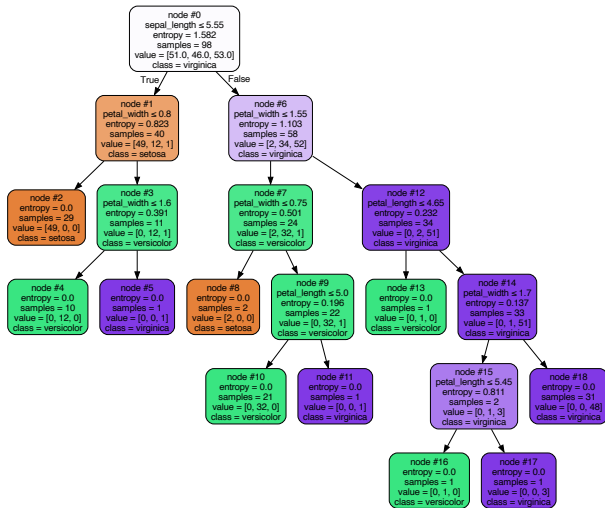
Decision Tree # 1

Notebook: ensemble-feature-importance.html



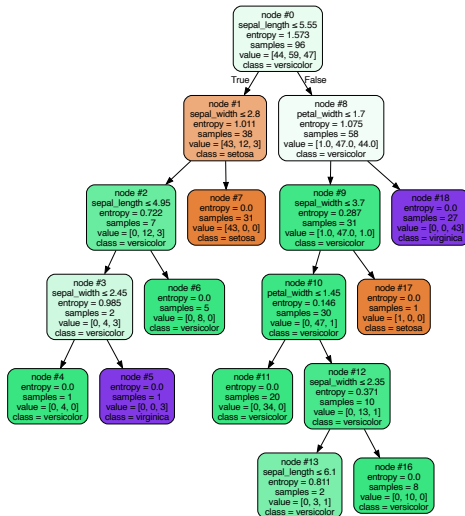
Decision Tree # 2

Notebook: ensemble-feature-importance.html



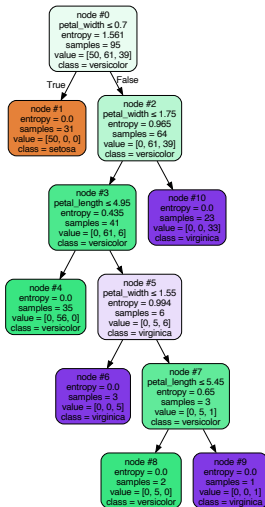
Decision Tree # 3

Notebook: ensemble-feature-importance.html



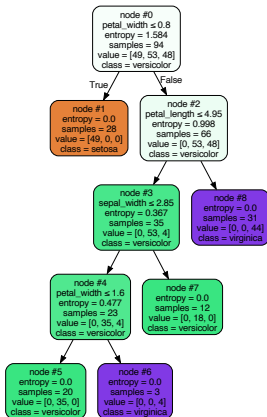
Decision Tree # 4

Notebook: ensemble-feature-importance.html



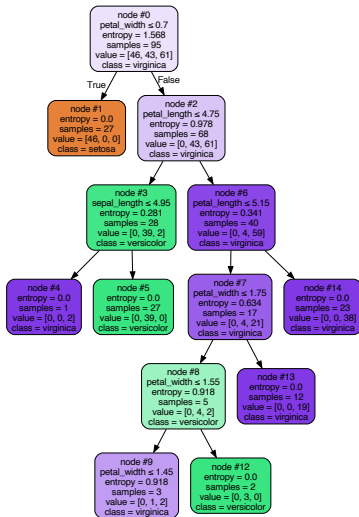
Decision Tree # 5

Notebook: ensemble-feature-importance.html



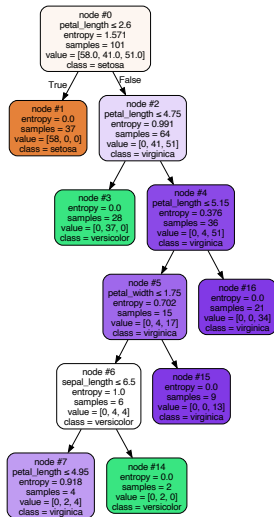
Decision Tree # 6

Notebook: ensemble-feature-importance.html



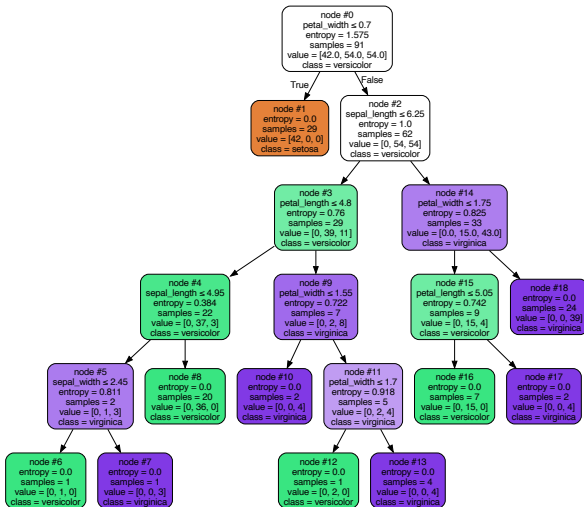
Decision Tree # 7

Notebook: ensemble-feature-importance.html



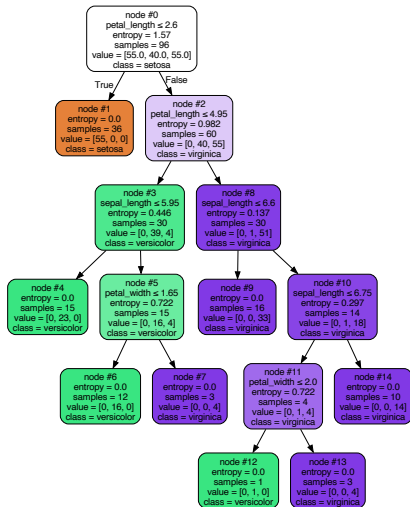
Decision Tree # 8

Notebook: ensemble-feature-importance.html

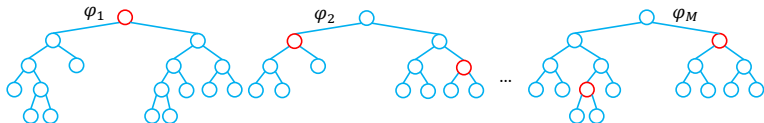


Decision Tree # 9

Notebook: ensemble-feature-importance.html



Feature Importance¹



Importance of variable X_j for an ensemble of M trees φ_m is:

$$\text{Imp}(X_j) = \frac{1}{M} \sum_{m=1}^M \sum_{t \in \varphi_m} 1(j_t = j) \left[p(t) \Delta i(t) \right],$$

where j_t denotes the variable used at node t , $p(t) = N_t/N$ and $\Delta i(t)$ is the impurity reduction at node t :

$$\Delta i(t) = i(t) - \frac{N_{t_L}}{N_t} i(t_L) - \frac{N_{t_R}}{N_t} i(t_R)$$

¹Slide Courtesy Gilles Louppe

Computed Feature Importance

Notebook: [ensemble-feature-importance.html](#)

