Gradient Boosting

Theory and Intuition

Similar idea to AdaBoost, where weak learners are created in series in order to produce a strong ensemble model.

Uses residual error for learning.

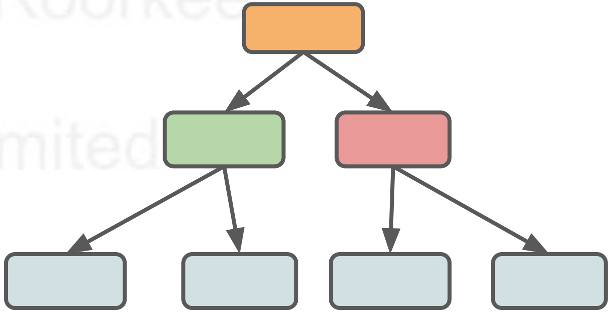
Gradient Boosting vs. Adaboost:

- Larger Trees allowed in Gradient Boosting.
- Gradual series learning is based on training on the **residuals** of the previous model.

Area m^2	Bedrooms	Bathrooms	Price
200	3	2	$500,000
190	2	1	$462,000
230	3	3	$565,000

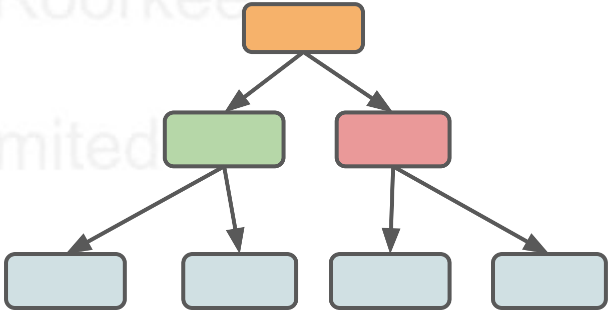
Train a decision tree on data

Area m^2	Bedrooms	Bathrooms	Price
200	3	2	$500,000
190	2	1	$462,000
230	3	3	$565,000



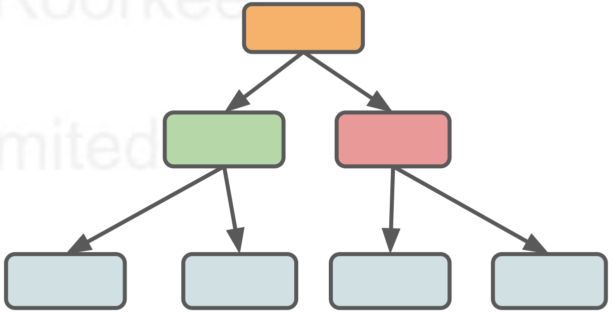
Get predicted ŷ value

y	ŷ
$500,000	$509,000
$462,000	$509,000
$565,000	$509,000



Residual: **e = y-ŷ**

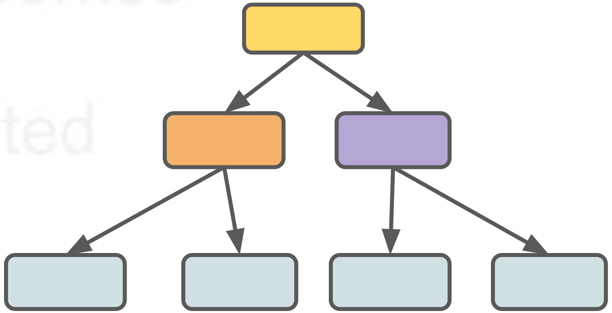
y	ŷ	e
$500,000	$509,000	-$9,000
$462,000	$509,000	-$47,000
$565,000	$509,000	$56,000



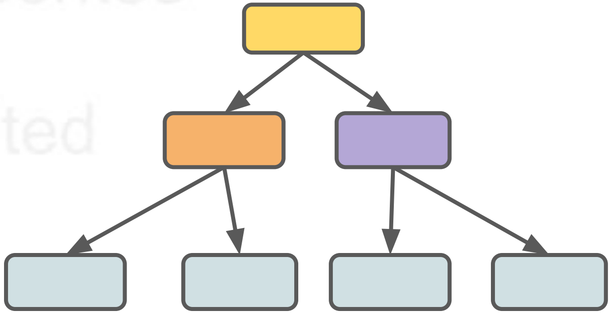
Create new model to predict the **error**

y	ŷ	e
$500,000	$509,000	-$9,000
$462,000	$509,000	-$47,000
$565,000	$509,000	$56,000

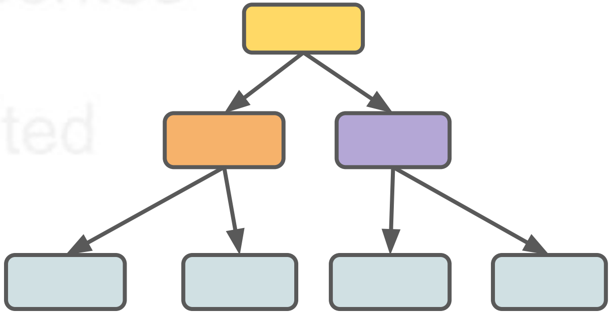
y	ŷ	e
$500,000	$509,000	-$9,000
$462,000	$509,000	-$47,000
$565,000	$509,000	$56,000



y	ŷ	e	f1
$500,000	$509,000	-$9,000	-$8,000
$462,000	$509,000	-$47,000	-$50,000
$565,000	$509,000	$56,000	$50,000

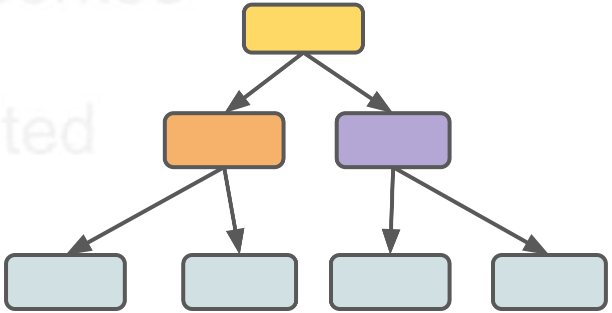


y	ŷ	e	f1
$500,000	$509,000	-$9,000	-$8,000
$462,000	$509,000	-$47,000	-$50,000
$565,000	$509,000	$56,000	$50,000



Area m^2	Bedrooms	Bathrooms
200	3	2
190	2	1
230	3	3

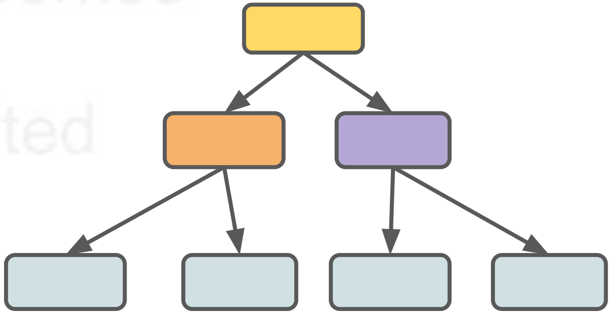
y	ŷ	e	f1
$500,000	$509,000	-$9,000	-$8,000
$462,000	$509,000	-$47,000	-$50,000
$565,000	$509,000	$56,000	$50,000



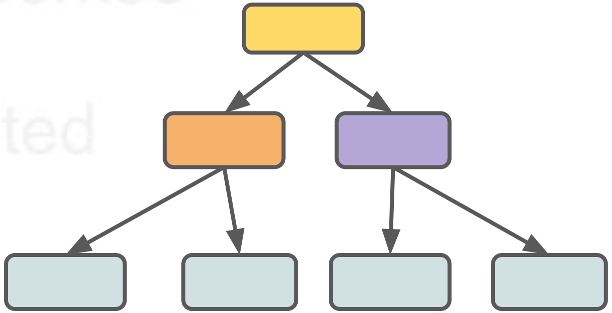
Area m²	Bedrooms	Bathrooms
200	3	2
190	2	1
230	3	3

Update prediction using **error prediction**

y	ŷ	e	f1	F1 = ŷ + f1
$500,000	$509,000	-$9,000	-$8,000	
$462,000	$509,000	-$47,000	-$50,000	
$565,000	$509,000	$56,000	$50,000	



y	ŷ	e	f1	F1 = ŷ + f1
$500,000	$509,000	-$9,000	-$8,000	$501,000
$462,000	$509,000	-$47,000	-$50,000	$459,000
$565,000	$509,000	$56,000	$50,000	$559,000



Gradient Boosting Process

$$F_m = F_{m-1} + f_m$$

$$F_m = F_{m-1} + f_m$$

$$F_m = F_{m-1} + (\text{learning rate} * f_m)$$

Gradient Boosting Process

- Create initial model: f_0
- Train another model on error
  - $e = y - f_0$
- Create new prediction
  - $F_1 = f_0 + \eta f_1$
- Repeat as needed
  - $F_m = f_{m-1} + \eta f_m$

Note: for classification we can use the logit as an error metric:

$$\hat{y} = \log\left(\frac{\hat{p}}{1-\hat{p}}\right) \qquad \hat{p} = \frac{1}{1+e^{-\hat{y}}}$$

The learning rate is the same for each new model in the series and **not** unique to each subsequent model (unlike AdaBoost's alpha coefficient).

Gradient Boosting is fairly robust to overfitting, allowing for the number of estimators to be set high be default (~100).

Gradient Boosting Intuition

We optimize the series of trees by learning on the residuals, forcing subsequent trees to attempt to correct for the error in the previous trees.

The trade-off is training time.

A learning rate is between 0-1, which means a very low value would mean each subsequent tree has little "say", meaning more trees need to be created, causing a longer computational training time.

Let’s explore Gradient Boosting in Jupyter Notebook!

Naive Bayes and NLP

Using raw string text for machine learning models.

This idea in general is known as “Natural Language Processing”.

Overview

- Naive Bayes Algorithm and NLP
- Extracting Features from Text Data

Part One: Bayes' Theorem

Naive Bayes is the shorthand for a set of algorithms that use Bayes' Theorem.

Bayes' Theorem leverages previously known probabilities to define probability of related events occuring.

Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' Theorem.

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

Bayes' Theorem

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

- **A** and **B** are events
- **P(A|B)** is probability of event **A** given that **B** is True.
- **P(B|A)** is probability of event **B** given that **A** is True.
- **P(A)** is probability of A occurring.
- **P(B)** is probability of B occurring.

Assume following situation:

- Every apartment in a building is fit with a fire alarm detection system.
- However, there are false alarms where smoke is detected but there is not a dangerous fire to put out (e.g. smoke from an oven).

The associated probabilities:

- Actual dangerous fires occur only 1% of the time.
- Smoke alarms are not good, and go off about 10% of the time.
- When there is an actual dangerous fire, 95% of the time the smoke alarms go off.

If you get a smoke alarm detecting a fire, what is the probability that there actually is a dangerous fire?

Event A: Dangerous Fire

Event B: Smoke Alarm Triggered

- P(A|B):
  - Probability of Fire given Smoke Alarm
- P(B|A):
  - Probability of Smoke Alarm given a dangerous fire

- Actual dangerous fires occur only 1% of the time. **P(Fire) = 1/100**
- Smoke alarms are not good and go off about 10% of the time. **P(Smoke) = 1/10**
- When there is an actual dangerous fire, 95% of the time the smoke alarms go off.
  - **P(Smoke|Fire) = 95/100**

Using Bayes' Theorem:

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

P(Fire|Smoke) = P(Smoke|Fire)*P(Fire)/P(Smoke)

Using Bayes' Theorem:

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

P(Fire|Smoke) = P(Smoke|Fire)*P(Fire)/P(Smoke)
P(Fire|Smoke) = 0.95 * 0.01 / 0.1
P(Fire|Smoke) = 0.095
P(Fire|Smoke) = 9.5%

Let's see how Bayes' Theorem can be extended to perform classification.

We'll focus on using Bayes' Theorem for Natural Language Processing Classification.

Part Two: Naive Bayes

Model the probability of belonging to a class given a vector of features.

$$\mathbf{x} = (x_1, \ldots, x_n)$$

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)} \quad \Rightarrow \quad p(C_k \mid \mathbf{x}) = \frac{p(C_k)\, p(\mathbf{x} \mid C_k)}{p(\mathbf{x})}$$

The numerator is equivalent to a joint probability model:

$$p(C_k \mid \mathbf{x}) = \frac{p(C_k)\; p(\mathbf{x} \mid C_k)}{p(\mathbf{x})} \Rightarrow p(C_k \mid \mathbf{x}) = \frac{p(C_k, x_1, \dots, x_n)}{p(\mathbf{x})}$$

The chain rule can rewrite this numerator as a series of products of conditional probabilities:

$$
\begin{aligned}
p(C_k, x_1, \ldots, x_n) &= p(x_1, \ldots, x_n, C_k) \\
&= p(x_1 \mid x_2, \ldots, x_n, C_k)\, p(x_2, \ldots, x_n, C_k) \\
&= p(x_1 \mid x_2, \ldots, x_n, C_k)\, p(x_2 \mid x_3, \ldots, x_n, C_k)\, p(x_3, \ldots, x_n, C_k) \\
&= \cdots \\
&= p(x_1 \mid x_2, \ldots, x_n, C_k)\, p(x_2 \mid x_3, \ldots, x_n, C_k) \cdots p(x_{n-1} \mid x_n, C_k)\, p(x_n \mid C_k)\, p(C_k)
\end{aligned}
$$

Finally we need to make an assumption that all x features are **mutually independent** of each other.

Thus, allowing for this conditional probability:

$$p(x_i \mid x_{i+1}, \ldots, x_n, C_k) = p(x_i \mid C_k)$$

Then the joint model (the full Naive Bayes model) is fully written as:
(Where $\propto$ denotes proportionality)

$$
\begin{aligned}
p(C_k \mid x_1, \ldots, x_n) &\propto p(C_k, x_1, \ldots, x_n) \\
&\propto p(C_k)\, p(x_1 \mid C_k)\, p(x_2 \mid C_k)\, p(x_3 \mid C_k)\, \cdots \\
&\propto p(C_k) \prod_{i=1}^{n} p(x_i \mid C_k)\,,
\end{aligned}
$$

Let's walk through an example of using this Naive Bayes model.

Variations of Naive Bayes models, including:

- Multinomial Naive Bayes
- Gaussian Naive Bayes
- Complement Naive Bayes
- Bernoulli Naive Bayes
- Categorical Naive Bayes

Check documentation of sklearn!

We will focus on Multinomial Naive Bayes, since its used most often in the context of NLP.

Imagine we want to create a movie review aggregation website where we need to classify movie reviews into two categories: positive or negative.

Using previous reviews, we can have someone manually label them in order to create a labeled data set.

Then in the future, we could use our machine learning algorithm to automatically classify a new text review for us.

But how do we actually train on this text data?

Multinomial Bayes can work quite well with a simple count vectorization model (counting the frequency of each word in each document).

Start by separating out document classes:

Create “prior” probabilities for each class:

P(pos) = 25/35

P(neg) = 10/35

We will use these later!

P(pos) = 25/35

P(neg) = 10/35

Start with count vectorization on classes:

10	2	8	4
movie	actor	great	film

8	10	0	2
movie	actor	great	film

Calculate conditional probabilities:

10	2	8	4
movie	actor	great	film

P(movie|pos) = 10/24=0.42

8	10	0	2
movie	actor	great	film

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

8	10	0	2
movie	actor	great	film

$$P(\text{movie}|\text{pos}) = 10/24 = 0.42$$
$$P(\text{actor}|\text{pos}) = 2/24 = 0.08$$
$$P(\text{great}|\text{pos}) = 8/24 = 0.33$$
$$P(\text{film}|\text{pos}) = 4/24 = 0.17$$

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

$$P(\text{movie}|\text{neg}) = 8/20 = 0.4$$
$$P(\text{actor}|\text{neg}) = 10/20 = 0.5$$
$$P(\text{great}|\text{neg}) = 0/20 = 0$$
$$P(\text{film}|\text{neg}) = 2/20 = 0.1$$

Now a new review was created:

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

“movie actor”

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

Start with prior probability

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

“movie actor”

P(pos) = (25/35)

Continue with conditional probabilities

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

"movie actor"

P(pos)×P(movie|pos)

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film


25


0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

"movie actor"

$$P(\text{pos}) \times P(\text{movie}|\text{pos}) \times P(\text{actor}|\text{pos})$$


10


0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

"movie actor"

$$(0.71)\times(0.42)\times(0.08) = 0.024$$

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

Score is proportional to P(pos|“movie actor”)

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

“movie actor”

0.024 ∝ P(pos| “movie actor”)

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

Repeat same process with negative class

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

"movie actor"

P(neg)×P(movie|neg)×P(actor|neg)

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

25

0.42	0.08	0.33	0.17
10	2	8	4
movie	actor	great	film

“movie actor”

$$(10/35)\times(0.4)\times(0.5) = 0.057$$

10

0.4	0.5	0	0.1
8	10	0	2
movie	actor	great	film

Score is proportional to P(neg|“movie actor”)

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

“movie actor”

$$0.057 \propto P(neg|\text{“movie actor”})$$

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

1. Compare both scores against each other
2. Classify based on highest score
3. Hence, this is classified as a negative review

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

“movie actor”

0.057 ∝ P(neg| “movie actor”)
0.024 ∝ P(pos| “movie actor”)

What about 0 count words?

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

“great movie”

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

Probability is zero! Regardless of text!

25

0.42	**0.08**	**0.33**	**0.17**
10	2	8	4
movie	actor	great	film

10

0.4	**0.5**	**0**	**0.1**
8	10	0	2
movie	actor	great	film

"great movie"

$$P(neg)\times P(great|neg)\times P(movie|neg)$$

Alpha smoothing parameter

25

10**+1**	2**+1**	8**+1**	4**+1**
movie	actor	great	film

"great movie"

$$\mathbf{P(\textcolor{darkred}{neg})\times P(great|\textcolor{darkred}{neg})\times P(movie|\textcolor{darkred}{neg})}$$

10

8**+1**	10**+1**	0**+1**	2**+1**
movie	actor	great	film

Note how a higher alpha value will be more “smoothing”, giving each word less distinct importance.

Now let’s move on to focusing on feature extraction in general.

Are there better ways than just simply word frequency counts to extract features from text?

Extracting Features From Text Data

Theory and Intuition

Most classic ML algorithms can’t take in raw text as data.

Instead we need to perform a feature “extraction” from the raw text in order to pass numerical features to the ML algorithm.

Main Methods for Feature Extraction:

- Count Vectorization
- TF-IDF:
  - Term Frequency - Inverse Document Frequency

Count Vectorization

Create a vocabulary of all possible words

You are good
I feel good
I am good

Create a vocabulary of all possible words

YOU	ARE	GOOD	I	FEEL	AM

Create a vector of frequency counts

	YOU	ARE	GOOD	I	FEEL	AM
You are good	1	1	1	0	0	0
I feel good	0	0	1	1	1	0
I am good	0	0	1	1	0	1

```python
messages = ["Hey, lets go to the game today!",
            "Call your sister.",
            "Want to go walk your dogs?"]
```

Document Term Matrix (DTM)

call	dogs	game	go	hey	lets	sister	the	to	today	walk	want	your
0	0	1	1	1	1	0	1	1	1	0	0	0
1	0	0	0	0	0	1	0	0	0	0	0	1
0	1	0	1	0	0	0	0	1	0	1	1	1

Count Vectorization treats every word as a feature, Frequency counts act as a “strength” of the feature/word.

For larger documents, matrices are stored as a **sparse matrix** to save space, since so many values will be zero.

Issues:

Very common words (e.g. “a” , “the”, “about”).

Words common to a particular set of documents (e.g. “run” in a set of different sports articles).

Stop Words are words common enough throughout a language that its usually safe to remove them.

Many NLP libraries have a built-in list of common stop words.

We can address the issue of document frequency by using a TF-IDF Vectorization process.

Instead of filling the DTM with word frequency counts it calculates term frequency-inverse document frequency value for each word(TF-IDF).

Term frequency **tf(t,d)**: is the raw count of a term in a document:

The number of times that term **t** occurs in document **d**.

Term Frequency alone isn’t enough for a thorough feature analysis of the text!

Let’s imagine very common terms, like “a” or “the”...

Because the term "the" is so common, term frequency will tend to incorrectly emphasize documents which happen to use the word "the" more frequently, without giving enough weight to the more meaningful terms "red" and "dogs".

We also need to consider a group of documents where non stop words are common throughout all the documents

The word “run” in documents about various sports.

An inverse document frequency factor is incorporated which diminishes the weight of terms that occur very frequently in the document set and increases the weight of terms that occur rarely.

It is the logarithmically scaled inverse fraction of the documents that contain the word (obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that quotient)

- The IDF is how common or rare a word is in the entire document set.
- **The closer it is to 0, the more common a word is**.
- Calculated by taking the **total number of documents**, **dividing it by the number of documents that contain a word**, and **calculating the logarithm.**

TF-IDF = term frequency * (1 / document frequency)

TF-IDF = term frequency * inverse document freq

$$\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \cdot \mathrm{idf}(t, D)$$

$$\mathrm{idf}(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

Scikit-learn can calculate all these terms for us through the use of its API.

```
from sklearn.feature_extraction.text import TfidfVectorizer

vect = TfidfVectorizer()
dtm = vect.fit_transform(messages)
```


call	dogs	game	go	hey	lets	sister	the	to	today	walk	want	your
0.000	0.00	0.403	0.307	0.403	0.403	0.000	0.403	0.307	0.403	0.00	0.00	0.000
0.623	0.00	0.000	0.000	0.000	0.000	0.623	0.000	0.000	0.000	0.00	0.00	0.474
0.000	0.46	0.000	0.349	0.000	0.000	0.000	0.000	0.349	0.000	0.46	0.46	0.349

Let's Code !!