

A Gentle Introduction to Gradient Boosting

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Gradient Boosting

- ▶ a powerful machine learning algorithm
- ▶ it can do
 - ▶ regression
 - ▶ classification
 - ▶ ranking
- ▶ won Track 1 of the Yahoo Learning to Rank Challenge

Our implementation of Gradient Boosting is available at
<https://github.com/cheng-li/pyramid>

Outline of the Tutorial

- 1 What is Gradient Boosting
- 2 A brief history
- 3 Gradient Boosting for regression
- 4 Gradient Boosting for classification
- 5 A demo of Gradient Boosting
- 6 Relationship between Adaboost and Gradient Boosting
- 7 Why it works

Note: This tutorial focuses on the intuition. For a formal treatment, see [Friedman, 2001]

What is Gradient Boosting

Gradient Boosting = Gradient Descent + Boosting

Adaboost

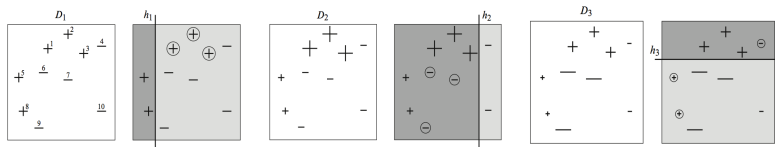


Figure: AdaBoost. Source: Figure 1.1 of [Schapire and Freund, 2012]

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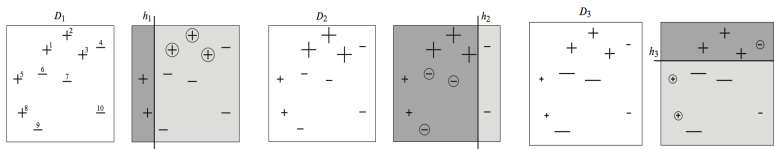


Figure: AdaBoost. Source: Figure 1.1 of [Schapire and Freund, 2012]

- ▶ Fit an additive model (ensemble) $\sum_t \rho_t h_t(x)$ in a forward stage-wise manner.
- ▶ In each stage, introduce a weak learner to compensate the shortcomings of existing weak learners.
- ▶ In Adaboost, “shortcomings” are identified by high-weight data points.

What is Gradient Boosting

Gradient Boosting = Gradient Descent + Boosting
Adaboost

$$H(x) = \sum_t \rho_t h_t(x)$$

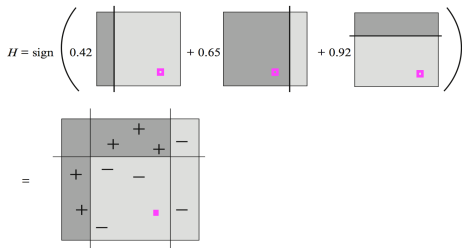


Figure: AdaBoost. Source: Figure 1.2 of [Schapire and Freund, 2012]

What is Gradient Boosting

Gradient Boosting = Gradient Descent + Boosting

Gradient Boosting

- ▶ Fit an additive model (ensemble) $\sum_t \rho_t h_t(x)$ in a forward stage-wise manner.
- ▶ In each stage, introduce a weak learner to compensate the shortcomings of existing weak learners.
- ▶ In Gradient Boosting, “shortcomings” are identified by gradients.
- ▶ Recall that, in Adaboost, “shortcomings” are identified by high-weight data points.
- ▶ Both high-weight data points and gradients tell us how to improve our model.

What is Gradient Boosting

Why and how did researchers invent Gradient Boosting?

A Brief History of Gradient Boosting

- ▶ Invent Adaboost, the first successful boosting algorithm [Freund et al., 1996, Freund and Schapire, 1997]
- ▶ Formulate Adaboost as gradient descent with a special loss function [Breiman et al., 1998, Breiman, 1999]
- ▶ Generalize Adaboost to Gradient Boosting in order to handle a variety of loss functions [Friedman et al., 2000, Friedman, 2001]

Gradient Boosting for Regression

Gradient Boosting for Different Problems

Difficulty:

regression \implies classification \implies ranking

Gradient Boosting for Regression

Let's play a game...

You are given $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$, and the task is to fit a model $F(x)$ to minimize square loss.

Suppose your friend wants to help you and gives you a model F .

You check his model and find the model is good but not perfect.

There are some mistakes: $F(x_1) = 0.8$, while $y_1 = 0.9$, and

$F(x_2) = 1.4$ while $y_2 = 1.3$... How can you improve this model?

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Rule of the game:

- ▶ You are not allowed to remove anything from F or change any parameter in F .

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Rule of the game:

- ▶ You are not allowed to remove anything from F or change any parameter in F .
- ▶ You can add an additional model (regression tree) h to F , so the new prediction will be $F(x) + h(x)$.

Gradient Boosting for Regression

Simple solution:

You wish to improve the model such that

$$F(x_1) + h(x_1) = y_1$$

$$F(x_2) + h(x_2) = y_2$$

...

$$F(x_n) + h(x_n) = y_n$$

Gradient Boosting for Regression

Simple solution:

Or, equivalently, you wish

$$h(x_1) = y_1 - F(x_1)$$

$$h(x_2) = y_2 - F(x_2)$$

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How?

Just fit a regression tree h to data

$$(x_1, y_1 - F(x_1)), (x_2, y_2 - F(x_2)), \dots, (x_n, y_n - F(x_n))$$

Gradient Boosting for Regression

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$(x_1, y_1 - F(x_1)), (x_2, y_2 - F(x_2)), \dots, (x_n, y_n - F(x_n))$

Congratulations, you get a better model!

Gradient Boosting for Regression

Simple solution:

$y_i - F(x_i)$ are called **residuals**. These are the parts that existing model F cannot do well.

The role of h is to compensate the shortcoming of existing model F .

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How is this related to gradient descent?

Gradient Boosting for Regression

Gradient Descent

Minimize a function by moving in the opposite direction of the gradient.

$$\theta_i := \theta_i - \rho \frac{\partial J}{\partial \theta_i}$$

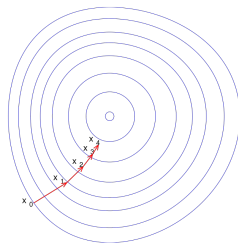


Figure: Gradient Descent. Source:

http://en.wikipedia.org/wiki/Gradient_descent

Gradient Boosting for Regression

How is this related to gradient descent?

Loss function $L(y, F(x)) = (y - F(x))^2/2$

We want to minimize $J = \sum_i L(y_i, F(x_i))$ by adjusting $F(x_1), F(x_2), \dots, F(x_n)$.

Notice that $F(x_1), F(x_2), \dots, F(x_n)$ are just some numbers. We can treat $F(x_i)$ as parameters and take derivatives

$$\frac{\partial J}{\partial F(x_i)} = \frac{\partial \sum_i L(y_i, F(x_i))}{\partial F(x_i)} = \frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} = F(x_i) - y_i$$

So we can interpret residuals as negative gradients.

$$y_i - F(x_i) = -\frac{\partial J}{\partial F(x_i)}$$

Gradient Boosting for Regression

How is this related to gradient descent?

$$F(x_i) := F(x_i) + h(x_i)$$

$$F(x_i) := F(x_i) + y_i - F(x_i)$$

$$F(x_i) := F(x_i) - 1 \frac{\partial J}{\partial F(x_i)}$$

$$\theta_i := \theta_i - \rho \frac{\partial J}{\partial \theta_i}$$

Gradient Boosting for Regression

How is this related to gradient descent?

For regression with **square loss**,

residual \Leftrightarrow *negative gradient*

fit h to residual \Leftrightarrow *fit h to negative gradient*

update F based on residual \Leftrightarrow *update F based on negative gradient*

Gradient Boosting for Regression

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So we are actually updating our model using **gradient descent**!

Gradient Boosting for Regression

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update F based on residual \Leftrightarrow *update F based on negative gradient*

So we are actually updating our model using **gradient descent**!

It turns out that the concept of **gradients** is more general and useful than the concept of **residuals**. So from now on, let's stick with gradients. The reason will be explained later.

Gradient Boosting for Regression

Regression with square Loss

Let us summarize the algorithm we just derived using the concept of gradients. Negative gradient:

$$-g(x_i) = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} = y_i - F(x_i)$$

start with an initial model, say, $F(x) = \frac{\sum_{i=1}^n y_i}{n}$

iterate until converge:

- calculate negative gradients $-g(x_i)$

- fit a regression tree h to negative gradients $-g(x_i)$

- $F := F + \rho h$, where $\rho = 1$

Gradient Boosting for Regression

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The benefit of formulating this algorithm using gradients is that it allows us to consider other loss functions and derive the corresponding algorithms in the same way.

Loss Functions for Regression Problem

Why do we need to consider other loss functions? Isn't square loss good enough?

Gradient Boosting for Regression

Loss Functions for Regression Problem

Square loss is:

✓ Easy to deal with mathematically

✗ Not robust to outliers

Outliers are heavily punished because the error is squared.

Example:

y_i	0.5	1.2	2	5*
$F(x_i)$	0.6	1.4	1.5	1.7
$L = (y - F)^2/2$	0.005	0.02	0.125	5.445

Consequence?

Gradient Boosting for Regression

Loss Functions for Regression Problem

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Consequence?

Pay too much attention to outliers. Try hard to incorporate outliers into the model. Degrade the overall performance.

Loss Functions for Regression Problem

- ▶ Absolute loss (more robust to outliers)

$$L(y, F) = |y - F|$$

Loss Functions for Regression Problem

- ▶ Absolute loss (more robust to outliers)

$$L(y, F) = |y - F|$$

- ▶ Huber loss (more robust to outliers)

$$L(y, F) = \begin{cases} \frac{1}{2}(y - F)^2 & |y - F| \leq \delta \\ \delta(|y - F| - \delta/2) & |y - F| > \delta \end{cases}$$

Gradient Boosting for Regression

Loss Functions for Regression Problem

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y_i	0.5	1.2	2	5*
$F(x_i)$	0.6	1.4	1.5	1.7
Square loss	0.005	0.02	0.125	5.445
Absolute loss	0.1	0.2	0.5	3.3
Huber loss($\delta = 0.5$)	0.005	0.02	0.125	1.525

Gradient Boosting for Regression

Regression with Absolute Loss

Negative gradient:

$$-g(x_i) = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} = \text{sign}(y_i - F(x_i))$$

start with an initial model, say, $F(x) = \frac{\sum_{i=1}^n y_i}{n}$

iterate until converge:

calculate gradients $-g(x_i)$

fit a regression tree h to negative gradients $-g(x_i)$

$F := F + \rho h$

Gradient Boosting for Regression

Regression with Huber Loss

Negative gradient:

$$\begin{aligned} -g(x_i) &= -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \\ &= \begin{cases} y_i - F(x_i) & |y_i - F(x_i)| \leq \delta \\ \delta \operatorname{sign}(y_i - F(x_i)) & |y_i - F(x_i)| > \delta \end{cases} \end{aligned}$$

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Gradient Boosting for Regression

Regression with loss function L : general procedure

Give any differentiable loss function L

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fit a regression tree h to negative gradients $-g(x_i)$

$F := F + \rho h$

In general,

negative gradients $\not\leftrightarrow$ residuals

We should follow negative gradients rather than residuals. Why?

Gradient Boosting for Regression

Negative Gradient vs Residual: An Example

Huber loss

$$L(y, F) = \begin{cases} \frac{1}{2}(y - F)^2 & |y - F| \leq \delta \\ \delta(|y - F| - \delta/2) & |y - F| > \delta \end{cases}$$

Update by Negative Gradient:

$$h(x_i) = -g(x_i) = \begin{cases} y_i - F(x_i) & |y_i - F(x_i)| \leq \delta \\ \delta \text{sign}(y_i - F(x_i)) & |y_i - F(x_i)| > \delta \end{cases}$$

Update by Residual:

$$h(x_i) = y_i - F(x_i)$$

Difference: negative gradient pays less attention to outliers.

Gradient Boosting for Regression

Summary of the Section

- ▶ Fit an additive model $F = \sum_t \rho_t h_t$ in a forward stage-wise manner.
- ▶ In each stage, introduce a new regression tree h to compensate the shortcomings of existing model.
- ▶ The “shortcomings” are identified by negative gradients.
- ▶ For any loss function, we can derive a gradient boosting algorithm.
- ▶ Absolute loss and Huber loss are more robust to outliers than square loss.

Things not covered

How to choose a proper learning rate for each gradient boosting algorithm. See [Friedman, 2001]

Gradient Boosting for Classification

Problem

Recognize the given hand written capital letter.

- ▶ Multi-class classification
- ▶ 26 classes. A,B,C,...,Z



Data Set

- ▶ <http://archive.ics.uci.edu/ml/datasets/Letter+Recognition>
- ▶ 20000 data points, 16 features

Gradient Boosting for Classification

Feature Extraction



1	horizontal position of box	9	mean y variance
2	vertical position of box	10	mean x y correlation
3	width of box	11	mean of $x * x * y$
4	height of box	12	mean of $x * y * y$
5	total number on pixels	13	mean edge count left to right
6	mean x of on pixels in box	14	correlation of x-edge with y
7	mean y of on pixels in box	15	mean edge count bottom to top
8	mean x variance	16	correlation of y-edge with x

Feature Vector = (2, 1, 3, 1, 1, 8, 6, 6, 6, 6, 5, 9, 1, 7, 5, 10)

Label = G

Gradient Boosting for Classification

Model

- ▶ 26 score functions (our models): $F_A, F_B, F_C, \dots, F_Z$.
- ▶ $F_A(x)$ assigns a score for class A
- ▶ scores are used to calculate probabilities

$$P_A(x) = \frac{e^{F_A(x)}}{\sum_{c=A}^Z e^{F_c(x)}}$$

$$P_B(x) = \frac{e^{F_B(x)}}{\sum_{c=A}^Z e^{F_c(x)}}$$

...

$$P_Z(x) = \frac{e^{F_Z(x)}}{\sum_{c=A}^Z e^{F_c(x)}}$$

- ▶ predicted label = class that has the highest probability

Loss Function for each data point

Step 1 turn the label y_i into a (true) probability distribution $Y_c(x_i)$

For example: $y_5=G$,

$$Y_A(x_5) = 0, Y_B(x_5) = 0, \dots, Y_G(x_5) = 1, \dots, Y_Z(x_5) = 0$$

Gradient Boosting for Classification

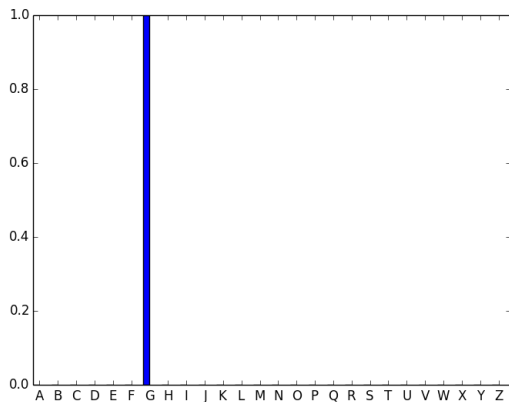


Figure: true probability distribution

Loss Function for each data point

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For example: $y_5=G$,

$$Y_A(x_5) = 0, Y_B(x_5) = 0, \dots, Y_G(x_5) = 1, \dots, Y_Z(x_5) = 0$$

Step 2 calculate the predicted probability distribution $P_c(x_i)$ based on the current model F_A, F_B, \dots, F_Z .

$$P_A(x_5) = 0.03, P_B(x_5) = 0.05, \dots, P_G(x_5) = 0.3, \dots, P_Z(x_5) = 0.05$$

Gradient Boosting for Classification

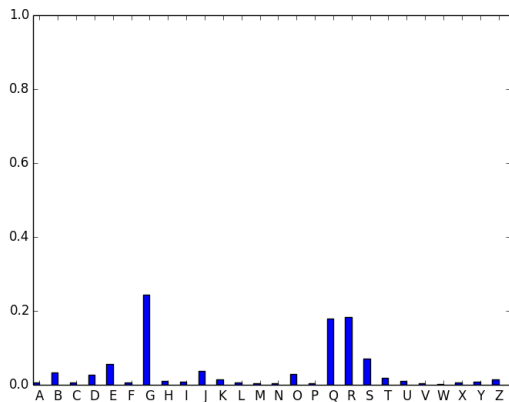


Figure: predicted probability distribution based on current model

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Step 3 calculate the difference between the true probability distribution and the predicted probability distribution. Here we use KL-divergence

Gradient Boosting for Classification

Goal

- ▶ minimize the total loss (KL-divergence)
- ▶ for each data point, we wish the predicted probability distribution to match the true probability distribution as closely as possible

Gradient Boosting for Classification

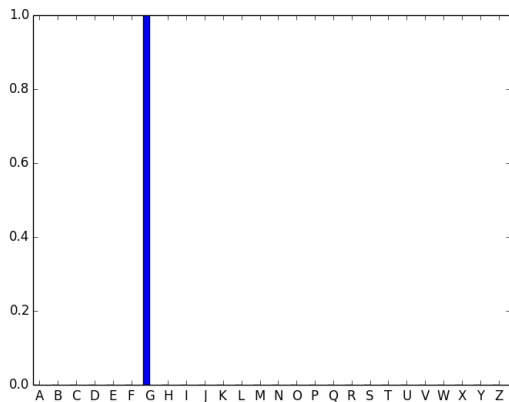


Figure: true probability distribution

Gradient Boosting for Classification

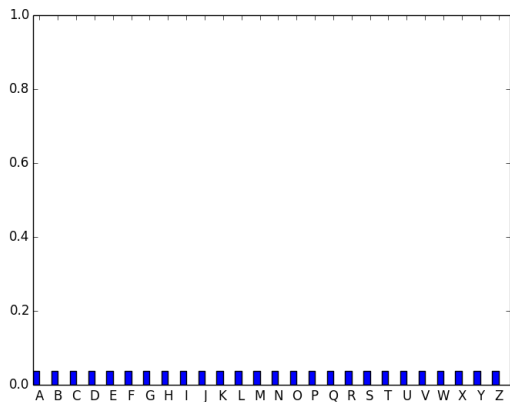


Figure: predicted probability distribution at round 0

Gradient Boosting for Classification

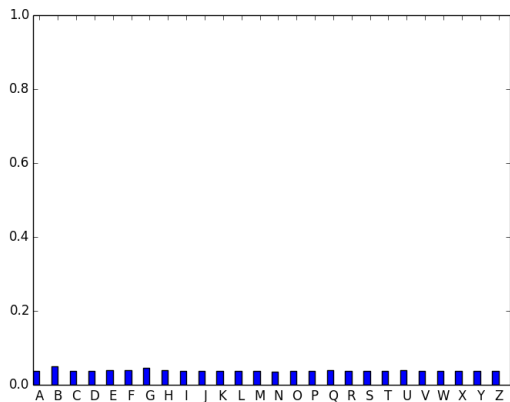


Figure: predicted probability distribution at round 1

Gradient Boosting for Classification

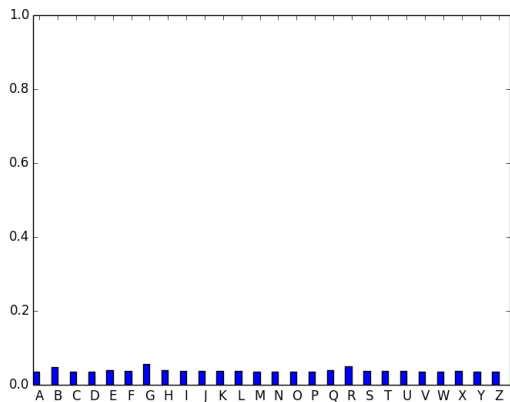


Figure: predicted probability distribution at round 2

Gradient Boosting for Classification

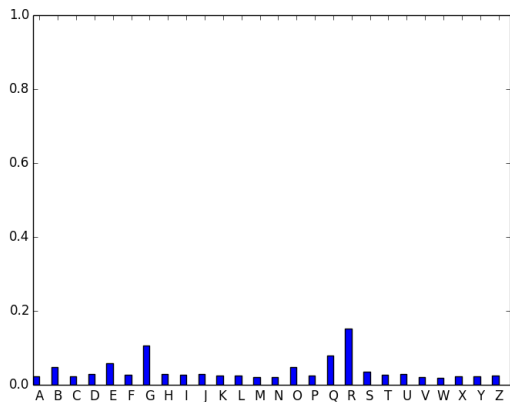


Figure: predicted probability distribution at round 10

Gradient Boosting for Classification

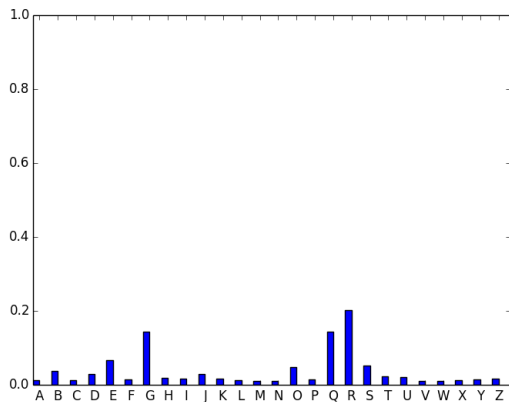


Figure: predicted probability distribution at round 20

Gradient Boosting for Classification

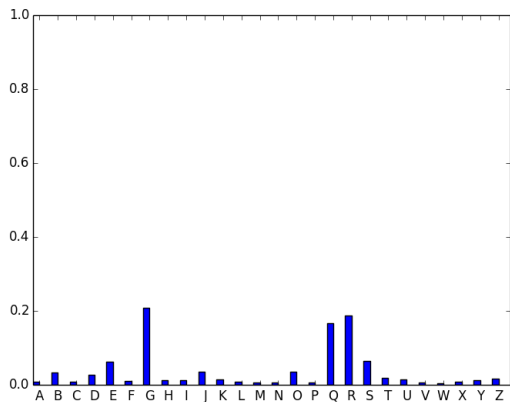


Figure: predicted probability distribution at round 30

Gradient Boosting for Classification

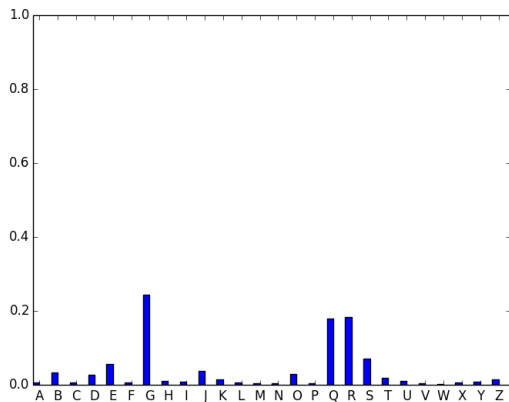


Figure: predicted probability distribution at round 40

Gradient Boosting for Classification

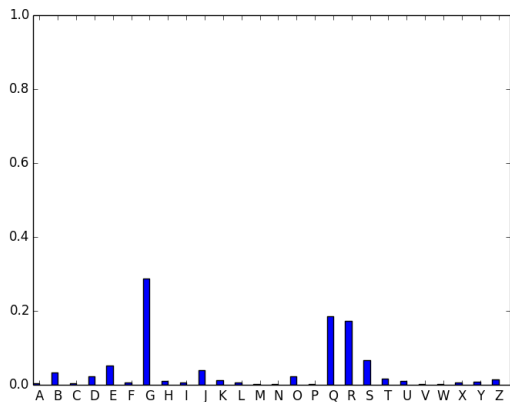


Figure: predicted probability distribution at round 50

Gradient Boosting for Classification

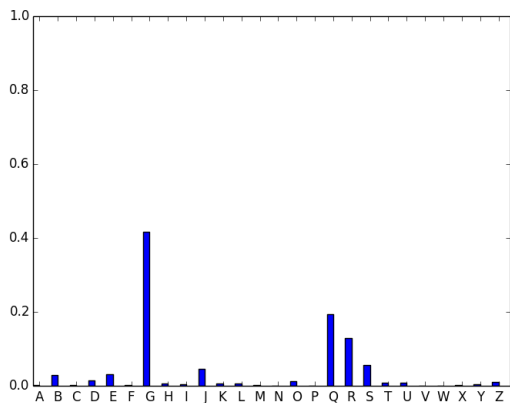


Figure: predicted probability distribution at round 100

Gradient Boosting for Classification

Goal

- ▶ minimize the total loss (KL-divergence)
- ▶ for each data point, we wish the predicted probability distribution to match the true probability distribution as closely as possible
- ▶ we achieve this goal by adjusting our models F_A, F_B, \dots, F_Z .

Gradient Boosting for Regression: Review

Regression with loss function L : general procedure

Give any differentiable loss function L

start with an initial model F

iterate until converge:

calculate negative gradients $-g(x_i) = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}$

fit a regression tree h to negative gradients $-g(x_i)$

$F := F + \rho h$

Gradient Boosting for Classification

Differences

- ▶ F_A, F_B, \dots, F_Z vs F
- ▶ a matrix of parameters to optimize vs a column of parameters to optimize

$F_A(x_1)$	$F_B(x_1)$...	$F_Z(x_1)$
$F_A(x_2)$	$F_B(x_2)$...	$F_Z(x_2)$
...
$F_A(x_n)$	$F_B(x_n)$...	$F_Z(x_n)$

- ▶ a matrix of gradients vs a column of gradients

$\frac{\partial L}{\partial F_A(x_1)}$	$\frac{\partial L}{\partial F_B(x_1)}$...	$\frac{\partial L}{\partial F_Z(x_1)}$
$\frac{\partial L}{\partial F_A(x_2)}$	$\frac{\partial L}{\partial F_B(x_2)}$...	$\frac{\partial L}{\partial F_Z(x_2)}$
...
$\frac{\partial L}{\partial F_A(x_n)}$	$\frac{\partial L}{\partial F_B(x_n)}$...	$\frac{\partial L}{\partial F_Z(x_n)}$

Gradient Boosting for Classification

start with initial models $F_A, F_B, F_C, \dots, F_Z$

iterate until converge:

calculate negative gradients for class A: $-g_A(x_i) = -\frac{\partial L}{\partial F_A(x_i)}$

calculate negative gradients for class B: $-g_B(x_i) = -\frac{\partial L}{\partial F_B(x_i)}$

...

calculate negative gradients for class Z: $-g_Z(x_i) = -\frac{\partial L}{\partial F_Z(x_i)}$

fit a regression tree h_A to negative gradients $-g_A(x_i)$

fit a regression tree h_B to negative gradients $-g_B(x_i)$

...

fit a regression tree h_Z to negative gradients $-g_Z(x_i)$

$F_A := F_A + \rho_A h_A$

$F_B := F_A + \rho_B h_B$

...

$F_Z := F_A + \rho_Z h_Z$

Gradient Boosting for Classification

start with initial models $F_A, F_B, F_C, \dots, F_Z$

iterate until converge:

calculate negative gradients for class A: $-g_A(x_i) = Y_A(x_i) - P_A(x_i)$

calculate negative gradients for class B: $-g_B(x_i) = Y_B(x_i) - P_B(x_i)$

...

calculate negative gradients for class Z: $-g_Z(x_i) = Y_Z(x_i) - P_Z(x_i)$

fit a regression tree h_A to negative gradients $-g_A(x_i)$

fit a regression tree h_B to negative gradients $-g_B(x_i)$

...

fit a regression tree h_Z to negative gradients $-g_Z(x_i)$

$$F_A := F_A + \rho_A h_A$$

$$F_B := F_A + \rho_B h_B$$

...

$$F_Z := F_A + \rho_Z h_Z$$

Gradient Boosting for Classification

round 0

i	y	Y _A	Y _B	Y _C	Y _D	Y _E	Y _F	Y _G	Y _H	Y _I	Y _J	Y _K	Y _L	Y _M	Y _N	Y _O	Y _P	Y _Q	Y _R	Y _S	Y _T	Y _U	Y _V	Y _W	Y _X	Y _Y	Y _Z	
1	T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2	I	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	D	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	N	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	G	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
...

i	y	F _A	F _B	F _C	F _D	F _E	F _F	F _G	F _H	F _I	F _J	F _K	F _L	F _M	F _N	F _O	F _P	F _Q	F _R	F _S	F _T	F _U	F _V	F _W	F _X	F _Y	F _Z	
1	T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2	I	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3	D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
5	G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
...

i	y	P _A	P _B	P _C	P _D	P _E	P _F	P _G	P _H	P _I	P _J	P _K	P _L	P _M	P _N	P _O	P _P	P _Q	P _R	P _S	P _T	P _U	P _V	P _W	P _X	P _Y	P _Z	
1	T	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
2	I	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
3	D	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
4	N	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
5	G	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
...

i	y	Y _A - P _A	Y _B - P _B	Y _C - P _C	Y _D - P _D	Y _E - P _E	Y _F - P _F	Y _G - P _G	Y _H - P _H	Y _I - P _I	Y _J - P _J	Y _K - P _K	Y _L - P _L	Y _M - P _M	Y _N - P _N	Y _O - P _O	Y _P - P _P	Y _Q - P _Q	Y _R - P _R	Y _S - P _S	Y _T - P _T	Y _U - P _U	Y _V - P _V	Y _W - P _W	Y _X - P _X	Y _Y - P _Y	Y _Z - P _Z
1	T	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
2	I	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
3	D	-0.04	-0.04	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
4	N	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
5	G	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
...

Gradient Boosting for Classification

$$h_A(x) = \begin{cases} 0.98 & \text{feature 10 of } x \leq 2.0 \\ -0.07 & \text{feature 10 of } x > 2.0 \end{cases}$$

$$h_B(x) = \begin{cases} -0.07 & \text{feature 15 of } x \leq 8.0 \\ 0.22 & \text{feature 15 of } x > 8.0 \end{cases}$$

...

$$h_Z(x) = \begin{cases} -0.07 & \text{feature 8 of } x \leq 8.0 \\ 0.82 & \text{feature 8 of } x > 8.0 \end{cases}$$

$$F_A := F_A + \rho_A h_A$$

$$F_B := F_B + \rho_B h_B$$

...

$$F_Z := F_Z + \rho_Z h_Z$$

Gradient Boosting for Classification

round 1

i	y	Y _A	Y _B	Y _C	Y _D	Y _E	Y _F	Y _G	Y _H	Y _I	Y _J	Y _K	Y _L	Y _M	Y _N	Y _O	Y _P	Y _Q	Y _R	Y _S	Y _T	Y _U	Y _V	Y _W	Y _X	Y _Y	Y _Z	
1	T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2	I	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	D	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	N	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	G	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
...

i	y	F _A	F _B	F _C	F _D	F _E	F _F	F _G	F _H	F _I	F _J	F _K	F _L	F _M	F _N	F _O	F _P	F _Q	F _R	F _S	F _T	F _U	F _V	F _W	F _X	F _Y	F _Z
1	T	-0.08	-0.07	-0.06	-0.07	-0.02	-0.02	-0.08	-0.02	-0.03	-0.03	-0.06	-0.04	-0.08	-0.08	-0.07	-0.07	-0.02	-0.04	-0.04	0.59	-0.01	-0.07	-0.07	-0.05	-0.06	-0.07
2	I	-0.08	0.23	-0.06	-0.07	-0.02	-0.02	0.16	-0.02	-0.03	-0.03	-0.06	-0.04	-0.08	-0.08	-0.07	-0.07	-0.02	-0.04	-0.04	-0.07	-0.01	-0.07	-0.07	-0.05	-0.06	-0.07
3	D	-0.08	0.23	-0.06	-0.07	-0.02	-0.02	-0.08	-0.02	-0.03	-0.03	-0.06	-0.04	-0.08	-0.08	-0.07	-0.07	-0.02	-0.04	-0.04	-0.07	-0.01	-0.07	-0.07	-0.05	-0.06	-0.07
4	N	-0.08	-0.07	-0.06	-0.07	-0.02	-0.02	0.16	-0.02	-0.03	-0.03	0.26	-0.04	-0.08	0.3	-0.07	-0.07	-0.02	-0.04	-0.04	-0.07	-0.01	-0.07	-0.07	-0.05	-0.06	-0.07
5	G	-0.08	0.23	-0.06	-0.07	-0.02	-0.02	0.16	-0.02	-0.03	-0.03	-0.06	-0.04	-0.08	-0.08	-0.07	-0.07	-0.02	-0.04	-0.04	-0.07	-0.01	-0.07	-0.07	-0.05	-0.06	-0.07
...

i	y	P _A	P _B	P _C	P _D	P _E	P _F	P _G	P _H	P _I	P _J	P _K	P _L	P _M	P _N	P _O	P _P	P _Q	P _R	P _S	P _T	P _U	P _V	P _W	P _X	P _Y	P _Z
1	T	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.07	0.04	0.04	0.04	0.04	0.04	0.04
2	I	0.04	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
3	D	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
4	N	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
5	G	0.04	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
...

i	y	Y _A -P _A	Y _B -P _B	Y _C -P _C	Y _D -P _D	Y _E -P _E	Y _F -P _F	Y _G -P _G	Y _H -P _H	Y _I -P _I	Y _J -P _J	Y _K -P _K	Y _L -P _L	Y _M -P _M	Y _N -P _N	Y _O -P _O	Y _P -P _P	Y _Q -P _Q	Y _R -P _R	Y _S -P _S	Y _T -P _T	Y _U -P _U	Y _V -P _V	Y _W -P _W	Y _X -P _X	Y _Y -P _Y	Y _Z -P _Z
1	T	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	0.93	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
2	I	-0.04	-0.05	-0.04	-0.04	-0.04	-0.04	-0.05	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
3	D	-0.04	-0.05	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
4	N	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.05	-0.04	-0.04	-0.04	-0.05	-0.04	-0.04	0.95	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
5	G	-0.04	-0.05	-0.04	-0.04	-0.04	-0.04	0.95	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
...

Gradient Boosting for Classification

$$h_A(x) = \begin{cases} 0.37 & \text{feature 10 of } x \leq 2.0 \\ -0.07 & \text{feature 10 of } x > 2.0 \end{cases}$$

$$h_B(x) = \begin{cases} -0.07 & \text{feature 14 of } x \leq 5.0 \\ 0.22 & \text{feature 14 of } x > 5.0 \end{cases}$$

...

$$h_Z(x) = \begin{cases} -0.07 & \text{feature 8 of } x \leq 8.0 \\ 0.35 & \text{feature 8 of } x > 8.0 \end{cases}$$

$$F_A := F_A + \rho_A h_A$$

$$F_B := F_B + \rho_B h_B$$

...

$$F_Z := F_Z + \rho_Z h_Z$$

Gradient Boosting for Classification

round 2

i	y	Y _A	Y _B	Y _C	Y _D	Y _E	Y _F	Y _G	Y _H	Y _I	Y _J	Y _K	Y _L	Y _M	Y _N	Y _O	Y _P	Y _Q	Y _R	Y _S	Y _T	Y _U	Y _V	Y _W	Y _X	Y _Y	Y _Z	
1	T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2	I	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	D	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	N	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	G	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
...

i	y	F _A	F _B	F _C	F _D	F _E	F _F	F _G	F _H	F _I	F _J	F _K	F _L	F _M	F _N	F _O	F _P	F _Q	F _R	F _S	F _T	F _U	F _V	F _W	F _X	F _Y	F _Z
1	T	-0.15	-0.14	-0.12	-0.14	-0.03	0.28	-0.14	-0.04	1.49	-0.07	-0.11	-0.08	-0.14	-0.17	-0.13	-0.13	-0.04	-0.11	-0.07	1.05	0.19	0.25	-0.16	-0.09	0.33	-0.14
2	I	-0.15	0.16	-0.12	-0.14	-0.03	-0.08	0.33	-0.04	-0.07	-0.07	-0.11	-0.08	-0.14	-0.17	-0.13	-0.13	-0.04	-0.11	-0.07	-0.11	-0.07	-0.15	-0.16	-0.09	-0.13	-0.14
3	D	-0.15	0.16	-0.12	-0.14	-0.03	-0.08	0.1	-0.04	-0.07	-0.07	-0.11	-0.08	-0.14	-0.17	-0.13	-0.13	-0.04	0.19	-0.07	-0.11	-0.07	-0.15	-0.16	-0.09	-0.13	-0.14
4	N	-0.15	-0.14	-0.12	-0.14	-0.03	-0.08	0.1	-0.04	-0.07	-0.07	0.46	-0.08	-0.14	0.5	-0.13	-0.13	-0.04	-0.11	-0.07	-0.11	-0.07	-0.15	0.25	-0.09	-0.13	-0.14
5	G	-0.15	0.16	-0.12	-0.14	-0.03	-0.08	0.33	-0.04	-0.07	-0.07	-0.11	-0.08	-0.14	-0.17	-0.13	-0.13	-0.04	0.19	-0.07	-0.11	-0.07	-0.15	-0.16	-0.09	-0.13	-0.14
...

i	y	P _A	P _B	P _C	P _D	P _E	P _F	P _G	P _H	P _I	P _J	P _K	P _L	P _M	P _N	P _O	P _P	P _Q	P _R	P _S	P _T	P _U	P _V	P _W	P _X	P _Y	P _Z	
1	T	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.15	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.09	0.04	0.04	0.03	0.03	0.05	0.03
2	I	0.04	0.05	0.04	0.04	0.04	0.04	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
3	D	0.04	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
4	N	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.06	0.04	0.03	0.06	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.05	0.04	0.03	0.03
5	G	0.03	0.05	0.04	0.04	0.04	0.04	0.06	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.04
...

i	y	Y _A -P _A	Y _B -P _B	Y _C -P _C	Y _D -P _D	Y _E -P _E	Y _F -P _F	Y _G -P _G	Y _H -P _H	Y _I -P _I	Y _J -P _J	Y _K -P _K	Y _L -P _L	Y _M -P _M	Y _N -P _N	Y _O -P _O	Y _P -P _P	Y _Q -P _Q	Y _R -P _R	Y _S -P _S	Y _T -P _T	Y _U -P _U	Y _V -P _V	Y _W -P _W	Y _X -P _X	Y _Y -P _Y	Y _Z -P _Z	
1	T	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.03	-0.03	-0.15	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	0.91	-0.04	-0.04	-0.03	-0.03	-0.05	-0.03
2	I	-0.04	-0.05	-0.04	-0.04	-0.04	-0.04	-0.06	-0.04	0.96	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
3	D	-0.04	-0.05	-0.04	0.96	-0.04	-0.04	-0.05	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.05	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
4	N	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.06	-0.04	-0.03	0.94	-0.03	-0.03	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.03	-0.05	-0.04	-0.03	-0.03
5	G	-0.03	-0.05	-0.04	-0.04	-0.04	-0.04	0.94	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.03	-0.04	-0.04	-0.04	-0.04	-0.05	-0.04	-0.04	-0.04	-0.04	-0.03	-0.04	-0.04	-0.04
...

Gradient Boosting for Classification

round 100

i	y	Y _A	Y _B	Y _C	Y _D	Y _E	Y _F	Y _G	Y _H	Y _I	Y _J	Y _K	Y _L	Y _M	Y _N	Y _O	Y _P	Y _Q	Y _R	Y _S	Y _T	Y _U	Y _V	Y _W	Y _X	Y _Y	Y _Z	
1	T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2	I	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	D	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	N	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	G	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
...

i	y	F _A	F _B	F _C	F _D	F _E	F _F	F _G	F _H	F _I	F _J	F _K	F _L	F _M	F _N	F _O	F _P	F _Q	F _R	F _S	F _T	F _U	F _V	F _W	F _X	F _Y	F _Z
1	T	-3.26	-2.7	-2.2	-2.22	-2.48	-0.31	-2.77	-1.19	2.77	0.1	-1.49	-1.02	-1.64	-0.8	-2.4	-3.57	-0.9	-2.45	-0.2	4.61	0.5	-0.71	-1.21	-0.24	0.49	-1.66
2	I	-1.64	-1.09	-2.29	-1.8	0.45	-0.43	2.14	-1.56	1.19	1.09	-1.5	-0.5	-3.64	-3.98	-0.39	-2.3	1.42	-0.59	0.27	-2.88	-1.96	-1.67	-4.38	-2.06	-2.95	-1.76
3	D	-2.45	0.18	-3.01	0.18	-2.79	-1.7	-2.21	0.43	-1.12	0.32	0.67	-2.16	-2.91	-2.76	-1.92	-3.04	-1.47	-0.48	-1.48	-1.25	-2.25	-3.23	-4.38	0.17	-2.95	-2.65
4	N	-3.95	-3.38	-0.22	-0.94	-1.33	-1.38	-1.22	-0.12	-2.33	-3.13	0.58	-0.65	-0.25	2.96	-2.84	-1.82	0.19	0.55	-1.22	-1.25	0.45	-1.8	0.11	-0.69	-1.6	-3.78
5	G	-3.14	-0.04	-2.37	-0.78	0.02	-2.68	2.6	-1.48	-1.93	0.42	-1.44	-1.45	-3.36	-3.98	-0.94	-3.42	1.84	1.44	0.62	-1.25	-1.33	-4.41	-4.71	-2.62	-2.15	-1.09
...





i	y	P _A	P _B	P _C	P _D	P _E	P _F	P _G	P _H	P _I	P _J	P _K	P _L	P _M	P _N	P _O	P _P	P _Q	P _R	P _S	P _T	P _U	P _V	P _W	P _X	P _Y	P _Z
1	T	0	0	0	0	0.01	0	0	0.13	0.01	0	0	0	0	0	0	0	0	0.01	0.79	0.01	0	0	0.01	0.01	0	0
2	I	0.01	0.01	0	0.01	0.06	0.02	0.32	0.01	0.12	0.11	0.01	0.02	0	0	0.03	0	0.16	0.02	0.05	0	0.01	0.01	0	0	0	0.01
3	D	0.01	0.11	0	0.11	0.01	0.02	0.01	0.14	0.03	0.12	0.17	0.01	0	0.01	0.01	0	0.02	0.05	0.02	0.03	0.01	0	0	0.11	0	0.01
4	N	0	0	0.02	0.01	0.01	0.01	0.03	0	0	0.05	0.02	0.02	0.59	0	0	0.04	0.05	0.01	0.01	0.05	0.01	0.03	0.02	0.01	0	0
5	G	0	0.03	0	0.01	0.03	0	0.42	0.01	0	0.05	0.01	0.01	0	0	0.01	0	0.19	0.13	0.06	0.01	0.01	0	0	0	0	0.01
...




i	y	Y _A - P _A	Y _B - P _B	Y _C - P _C	Y _D - P _D	Y _E - P _E	Y _F - P _F	Y _G - P _G	Y _H - P _H	Y _I - P _I	Y _J - P _J	Y _K - P _K	Y _L - P _L	Y _M - P _M	Y _N - P _N	Y _O - P _O	Y _P - P _P	Y _Q - P _Q	Y _R - P _R	Y _S - P _S	Y _T - P _T	Y _U - P _U	Y _V - P _V	Y _W - P _W	Y _X - P _X	Y _Y - P _Y	Y _Z - P _Z
1	T	-0	-0	-0	-0	-0	-0.01	-0	-0	-0.13	-0.01	-0	-0	-0	-0	-0	-0	-0	-0	-0.01	0.21	-0.01	-0	-0	-0.01	-0.01	-0
2	I	-0.01	-0.01	-0	-0.01	-0.06	-0.02	-0.32	-0.01	0.88	-0.11	-0.01	-0.02	-0	-0	-0.03	-0	-0.16	-0.02	-0.05	-0	-0.01	-0.01	-0	-0	-0	-0.01
3	D	-0.01	-0.11	-0	0.89	-0.01	-0.02	-0.01	-0.14	-0.03	-0.12	-0.01	-0.01	-0	-0.01	-0.01	-0	-0.02	-0.05	-0.02	-0.03	-0.01	-0	-0	-0.11	-0	-0.01
4	N	-0	-0	-0.02	-0.01	-0.01	-0.01	-0.01	-0.03	-0	-0	-0.05	-0.02	-0.02	0.41	-0	-0	-0.04	-0.05	-0.01	-0.01	-0.05	-0.01	-0.03	-0.02	-0.01	-0
5	G	-0	-0.03	-0	-0.01	-0.03	-0	0.58	-0.01	-0	-0.05	-0.01	-0.01	-0	-0	-0.01	-0	-0.19	-0.13	-0.06	-0.01	-0.01	-0	-0	-0	-0	-0.01
...

Things not covered

- ▶ How to choose proper learning rates. See [Friedman, 2001]
- ▶ Other possible loss functions. See [Friedman, 2001]

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