

# Notes to Google's Machine Learning Crash Course

Michael Sendker

June 27, 2021

## 1 Definitions

---

**Definition 1 - label.**

A label is  $Y$

---

---

**Definition 2 - feature.**

The feature is  $X$

---

---

**Definition 3 - inference.**

running trained model on unlabeled data

---

---

**Definition 4 - regression.**

predicting continuous values (e.g., median house values)

---

---

**Definition 5 - classification.**

predicting discrete values (e.g., hot dog, not a hot dog) also includes multi-value classification (e.g., dog, cat, or hamster)

---

---

**Definition 6 - hyperparameters.**

the configuration settings used to tune how the model is trained

---

---

**Definition 7 - empirical risk minimization.**

In supervised learning, a machine learning algorithm builds a model by examining many examples and attempting to find a model that minimizes loss; this process is called **empirical risk minimization**.

## 2 Conceptual understanding

Tom helped me understand: all ML is finding a plane in n-dimensional space that segregates distinct Ys. The different methods, like Forests, Trees, etc., are just different methods of generating functions to distinguish those Ys from their Xs.

## 3 Reducing Loss

$$L_2 Loss = \sum (x, y) \in D (y - prediction(x))^2 \quad (1)$$

Sometimes useful to average over all examples so divide by  $\|D\|$

We use the square of the difference to get a nice concave graph that allows easy stepping to reduce the loss.

The Derivative of  $(y-y')^2$  with respect to the weights and biases tells us how loss changes for a given example.

Repeatedly take small steps in the direction that minimizes loss. These are called (negative) Gradient Steps. This strategy is called Gradient Descent

---

### Definition 8 - Gradient Descent.

---

The strategy whereby one takes repeated small steps in the direction that minimizes loss.

If your batch is large, testing a lot of steps is extremely expensive, you could test with one example at a time, or do batches of 10-1000 and average over time. One example at a time is called **Stochastic Gradient Descent** and small batches is **Mini-Batch Gradient Descent**.

I really want to understand the mathy stuff because it's super cool and hard and I believe I can do it, so, infobox from Google:

### 3.1 Partial Derivatives

A multivariable function is a function with more than one argument, such as:

$$f(x, y) = e^{2y} \sin x \quad (2)$$

The partial derivative of  $f$  with respect to  $x$ , denoted as

$$\frac{\partial f}{\partial x} \quad (3)$$

is the derivative of  $f$  as a function of  $x$  considered alone. To find  $\frac{\partial f}{\partial x}$  hold  $y$  constant and take the derivative of  $f$  with respect to  $x$ .

That seems easy enough. (I'm copying a lot of this verbatim.)

In general, thinking of  $y$  as fixed, the partial derivative of  $f$  with respect to  $x$  is calculated as follows:

$$\frac{\partial f}{\partial x}(x, y) = e^{2y} \cos x \quad (4)$$

and the reverse,  $f$  with respect to  $y$  holding  $x$  fixed:

$$\frac{\partial f}{\partial y}(x, y) = 2e^{2y} \sin x \quad (5)$$

It does seem obvious ("intuitive") that the partial derivative of  $f$  with respect to either  $x$  or  $y$  just tells you how much perturbation in  $f$  you get from either  $x$  or  $y$ .

### 3.2 Gradients

A **gradient** of a function is the vector of partial derivatives with respect to all the independent variables, denoted as

$$\nabla f \quad (6)$$

for instance, if

$$f(x, y) = e^{2y} \sin(x) \quad (7)$$

then

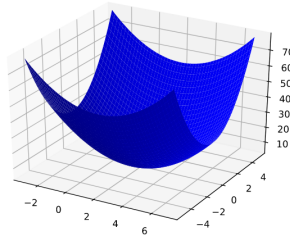
$$\nabla f(x, y) = \left( \frac{\partial f}{\partial x}(x, y), \frac{\partial f}{\partial y}(x, y) \right) = (e^{2y} \cos x, 2e^{2y} \sin x) \quad (8)$$

**N.B.**  $\nabla f$  points toward the greatest increase of the function, and  $-\nabla f$  points toward the greatest decrease of the function.

The number of dimensions in the vector is equal to the number of variables in the formula for  $f$ ; in other words, the vector falls within the domain space of the function. For instance, the graph of the following function:

$$f(x, y) = 4 + (x - 2)^2 + 2y^2 \quad (9)$$

when viewed in three dimensions with  $z = f(x, y)$  looks like a valley with a minimum at (2,0,4):



## 4 Gradient Descents

A gradient is a vector with a direction and a magnitude. To determine the next point along the loss function curve, the gradient descent algorithm adds some fraction of the gradient's magnitude to the starting point. This means we get diminishing steps.

That's cool, reminds me of Proportional in PID. You halve the distance between your target and your value. But, like, the gradient is unknown, so your magnitude is as well, when you're adjusting, and that's the point of the steps. So how do you know what your Gradient Descent Algorithm (henceforth GDA) should use as a step?

I guess that's the rub. Or is this something I would just know intuitively from linear algebra? You know a point, not actually a direction, so it's 50/50 which way to go on your next iteration.

"The ideal learning rate in one-dimension is  $\frac{1}{f'(x)''}$ .

The ideal learning rate for 2 or more dimensions is the inverse of the Hessian (matrix of second partial derivatives)."

What is a Hessian you ask?

---

**Definition 9.**

---

In mathematics, the Hessian matrix or Hessian is a square matrix of second-order partial derivatives of a scalar-valued function, or scalar field. It describes the local curvature of a function of many variables. The Hessian matrix was developed in the 19th century by the German mathematician Ludwig Otto Hesse and later named after him. Hesse originally used the term "functional determinants".

Okay, so that's just a matrix of second-order partial derivatives of a scalar-valued function or scalar field.

I actually get what that is, sort of.