Notes to Google's Machine Learning Crash Course

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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 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

$$L_2Loss = \sum(x, y) \in D(y - prediction(x))^2 \tag{1}$$

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')$^{\mathbf{2}}$ 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

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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 **Stocahastic 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:

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

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

$$\frac{\partial f}{\partial x} \tag{3}$$

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:

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

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

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

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

$$\nabla f \tag{6}$$

for instance, if

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

then

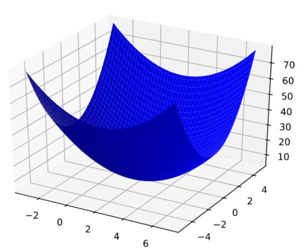
$$\nabla f(x,y) = \left(\frac{\partial f}{\partial x}(x,y), \frac{\partial f}{\partial y}(x,y)\right) = (e^{2y}\cos x, 2e^{2y}\sin x) \tag{8}$$

N.B. ∇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:

$$f(x,y) = 4 + (x-2)^2 + 2y^2 \tag{9}$$

when viewed in three dimenions 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.