

Recap with some changes in notations:

In gradient descent, the core formula was:

$$X_{(i+1)} = X_i - h * d/dx f(x)$$

But the above formula is valid only for a Loss function with one variable x. For a loss function in two variables, this formula will become like this:

$$X_{(i+1)} = X_i - h * [d/dx f(x, y) + d/dy f(x, y)]$$

For n number of variables:

$$x_{t+1} = x_t - \eta \left[\frac{\partial}{\partial x_1} f(x_1, x_2, \dots, x_n) + \frac{\partial}{\partial x_2} f(x_1, x_2, \dots, x_n) + \dots + \frac{\partial}{\partial x_n} f(x_1, x_2, \dots, x_n) \right]$$

$$\therefore x_{t+1} = x_t - \eta \sum_{i=1}^n \frac{\partial}{\partial x_i} f$$

Now by replacing x_t by θ_t or θ^t & x_{t+1} by θ_{t+1} or θ^{t+1} :

$$\theta^{t+1} = \theta^t - \eta \sum \frac{\partial}{\partial \theta_i^t} f$$

Constrained Optimization Problem:

As we know, our loss function is-
$$L = \sum \frac{\vec{\omega}^T \vec{x} + \omega_0}{\|\vec{\omega}\|} \cdot y_i$$

While computing gradient, we will need to differentiate this function and the division will add complexity in the differentiation.

Constrained optimization problem is a strategy in which we simplify our problem by adding some constraints (some limitation) so that it becomes easy (less complex) to optimize it.

In this case, $\|\vec{\omega}\|$ in the denominator is increasing the complexity so, let's take a constraint - $\|\vec{\omega}\| = 1$

Now with this constraint, we want to find the values of $\vec{\omega}$ & ω_0 for which the value of Loss function becomes minimum. This can be also written as the following

along with our constraint:

$$\underset{(\vec{w}, w_0)}{\text{argmin}} \quad - \sum \frac{\vec{w}^T \cdot \vec{x}_i + w_0}{\|\vec{w}\|} \cdot y_i \quad \text{s.t.} \quad \|\vec{w}\| = 1$$

↳ such that / Subject to

Now, let's calculate the gradient ∇L

$$\begin{aligned} \frac{\partial}{\partial w_1} L &= - \frac{\partial}{\partial w_1} (w_1 x_1 y_1 + w_2 x_2 y_2 + \dots + w_n x_n y_n + w_0 y_0) \\ &= -x_1 y_1 \end{aligned}$$

$$\frac{\partial}{\partial w_2} L = -x_2 y_2 \quad \dots \quad \frac{\partial}{\partial w_n} L = -x_n y_n$$

$$\nabla L = \frac{\partial}{\partial w_1} L + \frac{\partial}{\partial w_2} L + \dots + \frac{\partial}{\partial w_n} L = -(x_1 y_1 + x_2 y_2 + \dots + x_n y_n)$$

$$\nabla L = - \sum x_i y_i$$

Now, putting this into gradient descent formula to predict next value of w

$$w_{i+1} = w_i - \eta \nabla L$$

$$w_{i+1} = w_i - \eta (- \sum x_i y_i)$$

The above formula is valid for all components of \vec{w} other than w_0

For w_0 ,

$$\omega_o^{t+1} = \omega_o^t - \eta (-\sum y_i)$$

A deeper dive into constrained optimization:

Example - 1:

Suppose there is a function $f(x) = x^2 - 3x - 3$ that we want to minimize and, we also want to put a constraint that our minima must also satisfy the function $g(x) = x^2 - 2x - 3$ then our constrained optimized problem can be represented as:

$$\underset{x}{\operatorname{argmin}} f(x) \quad \text{s.t.} \quad g(x)$$

The goal here is to minimize the $f(x)$ in a way that the constraint $g(x)$ is also taken care of. But there is a problem with the above equation - how to differentiate a formula with "s.t." part in it? Answer to this question is known as - **Lagrange's Multiplier**.

Instead of differentiating (or working with) the above equation, we will first transform it in the following form:

$$\underset{x, \lambda}{\operatorname{argmin}} \quad \underbrace{f(x)}_{\text{Minimization}} + \underbrace{\lambda g(x)}_{\text{Taking care of the constraint}}$$

(I)

Now this equation doesn't have the "s.t." part in it hence this form is called "Unconstrained Problem".

This equation (I) is considering only one constraint. What if we have multiple constraints?

$$\underset{x, \lambda_1, \lambda_2, \dots, \lambda_n}{\operatorname{argmin}} \quad f(x) + \lambda_1 g_1(x) + \lambda_2 g_2(x) + \dots + \lambda_n g_n(x)$$

In the above formula, $\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_n$ are called **Lagrange's Multipliers**.

Now let's try to solve the **Example - 1** using this approach:

$$f(x) = x^2 - 3x - 3, \quad g(x) = x^2 - 2x - 3$$

$$\operatorname{argmin}_{x, \lambda} f(x) + \lambda g(x) = \operatorname{argmin}_{x, \lambda} x^2 - 3x - 3 + \lambda(x^2 - 2x - 3) = h(x, \lambda)$$

To minimize this, we need to calculate its gradient:

$$\nabla h = \begin{bmatrix} \frac{\partial}{\partial x} h(x, \lambda) \\ \frac{\partial}{\partial \lambda} h(x, \lambda) \end{bmatrix} = \begin{bmatrix} 2x - 3 + 2\lambda x - 2\lambda \\ x^2 - 2x - 3 \end{bmatrix}$$

At the minima, the differentiation (gradient) is 0.

$$\therefore \nabla h = 0$$

$$\therefore 2x - 3 + 2\lambda x - 2\lambda = 0 \quad \& \quad L(A)$$

$$x^2 - 2x - 3 = 0$$

$$x^2 - 3x + x - 3 = 0$$

$$x(x-3) + 1(x-3) = 0$$

$$\boxed{x = -1} \text{ OR } \boxed{x = 3}$$

By putting $x = -1$ & $x = 3$ into (A):

$$\boxed{x = -1:}$$

$$2(-1) - 3 + 2\lambda(-1) - 2\lambda = 0$$

$$\therefore -2 - 3 - 2\lambda - 2\lambda = 0$$

$$\therefore -4\lambda = 5 \Rightarrow \boxed{\lambda = -\frac{5}{4}}$$

$$\text{For } \boxed{x = 3:} \quad 2(3) - 3 + 2\lambda(3) - 2\lambda = 0$$

$$\therefore 3 + 6\lambda - 2\lambda = 0$$

$$\boxed{\lambda = -\frac{3}{4}}$$

\therefore The two minima/maxima are $(-1, -\frac{5}{4})$ & $(3, -\frac{3}{4})$

To identify the minimum of these two:

$$f(x) + \lambda g(x) \text{ for } x = -1 \text{ and } \lambda = \left(-\frac{5}{4}\right):$$

$$x^2 - 3x - 3 + \lambda x^2 - 2\lambda x - 3\lambda = 1 + \beta - \beta - \frac{5}{4} - \frac{2 \times 5}{4} + \frac{3 \times 5}{4}$$

$$= \frac{4 - 5 - 10 + 15}{4} = \frac{4}{4} = 1 \quad \therefore$$

$$\boxed{f(x) + \lambda g(x) = 1 \text{ for } x = -1 \text{ and } \lambda = -\frac{5}{4}}$$

similarly for $x = 3$ and $\lambda = -\frac{3}{4}$:

$$x^2 - 3x - 3 + \frac{-3}{4}x^2 - 2 \times \frac{(-3)}{4}x - 3\left(\frac{-3}{4}\right) = \frac{-12 - 27 + 18 + 9}{4}$$

$$= \frac{-12}{4} = -3$$

$$\therefore f(x) + \lambda g(x) = -3 \text{ for } x = 3 \text{ and } \lambda = -\frac{3}{4}$$

\therefore Our minim is at $\left(3, -\frac{3}{4}\right)$ — solution

Now let's apply this approach to minimize the loss function of our G.D.

$$f(x) = L = - \sum \frac{\vec{\omega}^T \cdot \vec{x} + \omega_0}{\|\vec{\omega}\|} \cdot y_i \quad \text{s.t.} \quad \underbrace{\|\vec{\omega}\| = 1}_{\downarrow}$$

At this place it must be of the form $g(x) = 0$

$$\therefore L = - \sum \underbrace{\frac{\vec{\omega}^T \cdot \vec{x} + \omega_0}{\|\vec{\omega}\|}}_{f(x)} \cdot y_i \quad \text{s.t.} \quad \underbrace{\|\vec{\omega}\| - 1 = 0}_{g(x)}$$

$$\overbrace{f(x)}$$

$$g(x)$$

$$\therefore L = \underset{\vec{w}, \lambda}{\text{argmin}} \quad - \sum (\vec{w}^T \cdot \vec{x} + w_0) \cdot y_i + \lambda (\|\vec{w}\| - 1) = h(\vec{w}, \lambda)$$

$$\therefore \nabla h = \begin{bmatrix} \frac{\partial}{\partial \vec{w}} h(\vec{w}, \lambda) \\ \frac{\partial}{\partial \lambda} h(\vec{w}, \lambda) \end{bmatrix} \begin{matrix} \rightarrow \text{component-1} \\ \rightarrow \text{component-2} \end{matrix}$$

Before calculating these components, let's see 3 interesting results:

$$\|\vec{w}\| = \sqrt{w_1^2 + w_2^2 + \dots + w_n^2}$$

$$\frac{d}{dx} \sqrt{x} = \frac{d}{dx} x^{\frac{1}{2}}$$

$$\|\vec{w}\| = \sqrt{[w_1, w_2, \dots, w_n] \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}}$$

$$= \frac{1}{2} x^{\frac{1}{2} - 1}$$

$$= \frac{1}{2} x^{-\frac{1}{2}}$$

$$= \frac{1}{2 x^{\frac{1}{2}}}$$

$$\|\vec{w}\| = \sqrt{\vec{w}^T \cdot \vec{w}} \quad \text{--- (I)}$$

$$\frac{d}{dx} \sqrt{x} = \frac{1}{2\sqrt{x}} \quad \text{--- (II)}$$

$$\frac{\partial}{\partial x} \vec{x}^T \cdot \vec{x} = 2\vec{x}$$

(III)

--- Try to prove it yourself.

First component :- $\frac{\partial}{\partial \vec{w}} h(\vec{w}, \lambda)$:

$$\frac{\partial}{\partial \vec{w}} h(x, \lambda) = - \sum \frac{\partial}{\partial \vec{w}} (\vec{w}^T \cdot \vec{x} + w_0) \cdot y_i + \frac{\partial}{\partial \vec{w}} \lambda (\|\vec{w}\| - 1)$$

$$\sim \vec{w} \rightarrow \vec{w}$$

$$\begin{aligned}
&= - \sum y_i (\vec{x} + 0) + \lambda \left(\frac{\partial}{\partial \vec{\omega}} \sqrt{\vec{\omega}^T \cdot \vec{\omega}} - 0 \right) \\
&= - \sum y_i \vec{x} + \lambda \left(\frac{1}{2\sqrt{\vec{\omega}^T \cdot \vec{\omega}}} \cdot \frac{\partial}{\partial \vec{\omega}} \vec{\omega}^T \cdot \vec{\omega} \right) \text{--- from (I)} \\
&= - \sum y_i x_i + \lambda \left(\frac{1}{2\sqrt{\vec{\omega}^T \cdot \vec{\omega}}} \cdot 2\vec{\omega} \right) \text{--- from (II)} \\
&= - \sum y_i x_i + \lambda \left(\frac{\vec{\omega}}{\sqrt{\vec{\omega}^T \cdot \vec{\omega}}} \right)
\end{aligned}$$

$$\frac{\partial}{\partial \vec{\omega}} h = - \sum y_i x_i + \lambda \frac{\vec{\omega}}{\|\vec{\omega}\|}$$

Second component: $\frac{\partial}{\partial \lambda} h(x, \lambda)$:

$$\begin{aligned}
&= \frac{\partial}{\partial \lambda} \left[- \sum (\vec{\omega}^T \cdot \vec{x} + \omega_0) \cdot y_i + \lambda (\|\vec{\omega}\| - 1) \right] \\
&= - \sum (0 + (\|\vec{\omega}\| - 1) \cdot 1)
\end{aligned}$$

$$\frac{\partial}{\partial \lambda} h(x, \lambda) = - \sum (\|\vec{\omega}\| - 1)$$