

## Topic 5: Review of Optimization

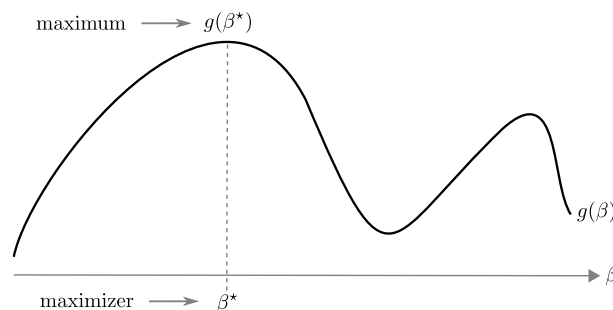
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## 5.1 Introduction

Most data science problems can be posed as finding the *maximizer* of a function  $g(\beta)$ , that is, the value  $\beta^*$  such that  $g(\beta^*) \geq g(\beta)$  for every  $\beta$  in the domain of  $g$ :



**Example 5.1.** Suppose  $\beta$  denotes the moment of your life when you stop studying, and start working, e.g., after high school, after college, after a masters, after a Ph.D, after a postdoc, or somewhere in between.. Let  $g$  be the amount of money that you will earn throughout your life as a function of  $\beta$ . The more you study, the higher pay you'll earn when you start working; on the other hand, the sooner you start working, the more experience you'll gain, the sooner you can get a promotion and a raise. You want to find the sweet spot (maximizer)  $\beta^*$  that produces the maximum pay  $g(\beta^*)$ .

## 5.2 Optimizing Simple Convex Functions

If  $g$  is concave and *simple* enough,  $\beta^*$  can be determined using our elemental calculus recipe:

1. Take derivative of  $g(\beta)$
2. Set derivative to zero, and solve for the maximizer.

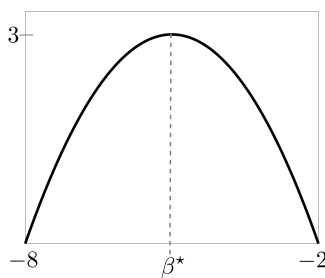
**Example 5.2.** Consider  $g(\beta) = 3 - (\beta + 5)^2$ . We can follow our recipe to find its maximizer:

1. The derivative of  $g$  is given by  $\nabla g(\beta) = -2(\beta + 5)$ .

2. Setting the derivative to zero and solving for  $\beta$  we obtain:

$$\begin{aligned} -2(\beta + 5) &= 0 \\ \beta &= -5. \end{aligned}$$

Since  $g$  is concave (can you show this?), we conclude that its maximizer is  $\beta^* = -5$ , as depicted below:



## 5.3 Gradient Ascent

Some functions, however, are too complex to solve for  $\beta$  in step 2. For example, consider the following function that describes the likelihood of a Bernoulli random variable:

$$\ell(\beta) = \sum_{i=1}^n y_i \log \left( \frac{1}{1 + e^{-\beta^T \mathbf{x}_i}} \right) + (1 - y_i) \log \left( 1 - \frac{1}{1 + e^{-\beta^T \mathbf{x}_i}} \right).$$

Its gradient is given by:

$$\nabla \ell(\beta | \mathbf{Y}, \mathbf{X}) = \sum_{i=1}^N \left( y_i - \frac{1}{1 + e^{-\beta^T \mathbf{x}_i}} \right) \mathbf{x}_i.$$

If we set this to zero, can you solve for  $\beta$ ?

For cases where our calculus 101 recipe does not work, we use *optimization*, which is the field of mathematics that deals with finding maximums (and minimums). In particular, we will use one of the most elemental tools of optimization: gradient ascent.

The setting is this: you have a function  $g(\beta)$ . You want to find its maximum. You cannot solve for it directly using the derivative trick, so what can you do? You can *test* the value of  $g$  for different values of  $\beta$ . For example, you can test  $g(0)$ , then maybe  $g(1)$ , then maybe  $g(-1)$ , then maybe  $g(1.5)$ , and so on, until you find the maximizer. Of course, depending on the domain of  $g$ , there could be infinitely many options, so testing them all would be infeasible.

As the name suggests, the main idea of gradient ascent is to test some initial value  $\beta_0$  (for example 0), and iteratively use the gradient (another name for derivative) to determine which value of  $\beta$  to test next, such that the each new value  $\beta_{t+1}$  produces a higher value for  $g$ , until we find the maximum. The main intuition is that the gradient  $\nabla g(\beta)$  tells us the slope of  $g$  at  $\beta$ . If this slope is positive, then we know that  $g$  is increasing, and we should try a larger value of  $\beta$ , say  $\beta_{t+1} = \beta_t + \eta$ , where  $\eta$  is often referred to as *step-size*.

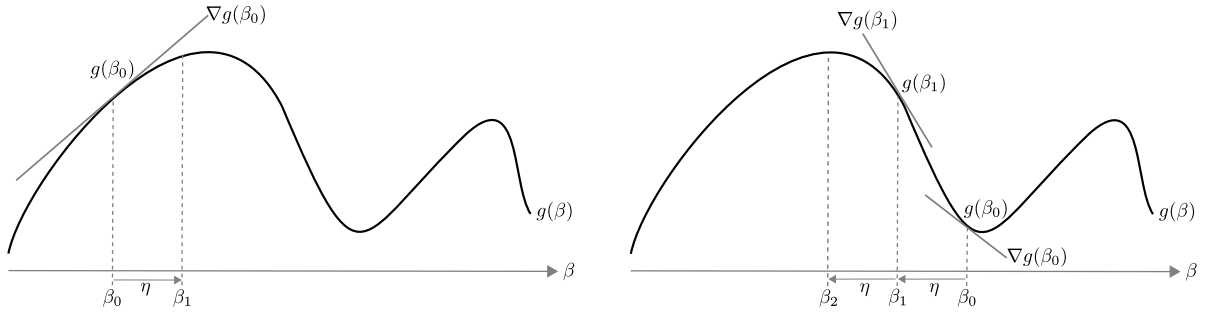


Figure 5.1: Start at some point  $\beta_0$ . If the gradient is positive (left figure), try a larger value of  $\beta$ , say  $\beta_1 = \beta_0 + \eta$ . If the gradient is negative (right figure), try a smaller value of  $\beta$ , say  $\beta_1 = \beta_0 - \eta$ . Repeat this until convergence.

If the slope is negative, then we know that  $g$  is decreasing, and we should try a smaller value of  $\beta$ , say  $\beta_{t+1} = \beta_t - \eta$  (see Figure 5.1 to build some intuition).

The same insight extends to multivariable functions. If  $g$  is a function of a vector  $\beta \in \mathbb{R}^d$ , then  $\nabla g(\beta) \in \mathbb{R}^d$  gives the slope of  $g$  in each of the  $d$  coordinates of  $\beta$ . Based on this insight, gradient ascent can be summarized as follows:

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**Algorithm 1:** Gradient Ascent

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**Input:** Function  $g$ , step-size parameter  $\eta > 0$ .

**Initialize**  $\beta_0$ . For example,  $\beta_0 = \mathbf{0}$ .

**Repeat until convergence:**  $\beta_{t+1} = \beta_t + \eta \nabla g(\beta_t)$ .

**Output:**  $\beta^* = \beta_t$ .

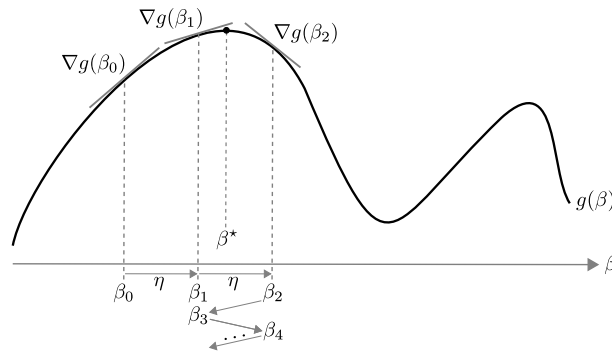
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### 5.3.1 Step-size $\eta$

The keen reader will be wondering, what if we move too far? In our example of Figure 5.1, we could run into an infinite loop, where

$$\begin{aligned}\beta_1 &= \beta_3 = \beta_5 = \beta_7 = \dots \\ \beta_2 &= \beta_4 = \beta_6 = \beta_8 = \dots,\end{aligned}$$

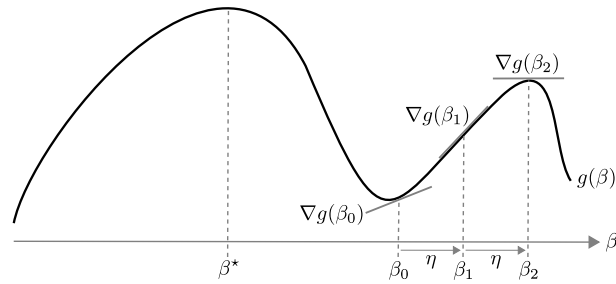
without ever achieving  $\beta^*$ , as depicted below:



How would you solve this?

### 5.3.2 Initialization

The keen reader will also be wondering: what if we start at the wrong place, as depicted below:



In cases like these we could run into a so-called local maximum, that is, a point that is larger than all other points in its vicinity, but not necessarily the maximum over the whole domain of  $g$ . In the figure above,  $\beta_2$  is a local maximizer.

How would you solve this?