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# Why Locating Local Optima Is Sometimes More Complicated Than Locating Global Ones

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## Abstract

In most applications, practitioners are interested in locating global optima. In such applications, local optima that result from some optimization algorithms are an unnecessary side effect. In other words, in such applications, locating global optima is a much more computationally complex problem than locating local optima. In several practical applications, however, local optima themselves are of interest. Somewhat surprisingly, it turned out that in many such applications, locating all local optima is a much more computationally complex problem than locating all global optima. In this paper, we provide a theoretical explanation for this surprising empirical phenomenon.

## 1 Formulation of the Problem

**A usual understanding is that global optimization is harder.** There are many optimization techniques, starting with the simple gradient descent. A usual problem with these techniques is that when they converge, they often lead to a *local* optimum, not to a global one. It takes a special effort to come up with a global optimum instead of a local one.

From this viewpoint, it looks like global optimization is more difficult than locating local optima; see, e.g., [1, 2, 3, 5, 6].

**While locating a local optimum may be easier, locating all local optima is difficult.** What is indeed relatively easy is locating *a* local optimum. In some practical situations, however, we are actually interested in *all* local optima (see, e.g., [7]); for example:

- in spectral analysis, chemical species are identified by local maxima of the spectrum;
- in radioastronomy, radiosources and their components are identified as local maxima of the brightness distribution; see, e.g., [8];

- elementary particles are identified by locating local maxima of the dependence of scattering intensity on the energy.

It turns out that empirically, the computation problem of finding all local optima is much more computationally complicated than the problem of finding all global optima; see, e.g., [4].

**Problem – and what we do in this paper.** While empirically, computing local optima is often more complex than computing global ones, there has been, to the best of our knowledge, no convincing theoretical explanation for this complexity.

The main goal of this paper is to provide such a theoretical explanation.

## 2 Local Optima Are Often More Complex to Locate Than Global Optima: A Possible Theoretical Explanation

**Approximating the objective function: a frequent way to solve optimization problems.** Often, the computational complexity of an optimization problem is due to the complexity of the objective function. Thus, a reasonable idea is:

- to approximate the original objective function  $f(x)$  by a close simpler one  $f_\varepsilon(x)$ ,
- solve the corresponding optimization problem for this simpler objective function  $f_\varepsilon(x)$ , and
- to use the resulting solution  $x_\varepsilon$  as a first approximation to the solution of the original optimization problem.

This idea indeed helps in solving global optimization problems, see, e.g., [1, 2, 3, 5, 6].

**What we do in this paper.** What we will prove is that this simplifying idea cannot be used for locating local optima. This is our first theoretical explanation of why locating local optima is often more computationally complicated than locating global optima.

**Definitions and the main result.** Let us first explain why the above idea is helpful for locating global maxima: namely, that the above idea helps us dismiss some locations as definitely not containing locations of global optima:

**Proposition 1.** *Let  $f(x)$  and  $f_\varepsilon(x)$  be two functions which are  $\varepsilon$ -close, i.e., for which  $|f(x) - f_\varepsilon(x)| \leq \varepsilon$  for all  $x$ , and let  $x_\varepsilon$  be a location of the global maximum of the function  $f_\varepsilon(x)$ , i.e.,  $f_\varepsilon(x_\varepsilon) = \max_x f_\varepsilon(x)$ . Then, for each location  $x_{\max}$  of the global maximum of the function  $f(x)$ , we have  $f_\varepsilon(x_{\max}) \geq f_\varepsilon(x_\varepsilon) - 2\varepsilon$ .*

**Proof.** From the fact that  $x_{\max}$  is a location of the global maximum of the function  $f(x)$ , we conclude, in particular, that  $f(x_{\max}) \geq f(x_\varepsilon)$ . Here,

$$|f(x) - f_\varepsilon(x)| \leq \varepsilon$$

for all  $x$ , in particular,  $f_\varepsilon(x_{\max}) \geq f(x_{\max}) - \varepsilon$  and  $f(x_\varepsilon) \geq f_\varepsilon(x_\varepsilon) - \varepsilon$ . Thus,

$$f_\varepsilon(x_{\max}) \geq f(x_{\max}) - \varepsilon \geq f(x_\varepsilon) - \varepsilon \geq (f_\varepsilon(x_\varepsilon) - \varepsilon) - \varepsilon = f_\varepsilon(x_\varepsilon) - 2\varepsilon.$$

The proposition is proven.

**Proposition 2.** *For every  $\varepsilon > 0$ , for every continuous function  $f_\varepsilon(x)$ , and for every point  $x_0$ , there exists a function  $f(x)$  which is  $\varepsilon$ -close to  $f_\varepsilon(x)$  and which attains a local maximum at the point  $x_0$ .*

**Discussion.** Thus, even if we know everything about the approximating function, we cannot dismiss any point  $x$  as a possible location of a local maximum – in other words, the above idea indeed does not work for locating local optima.

**Proof.** Since the function  $f_\varepsilon(x)$  is continuous, there exists a  $\delta > 0$  for which  $d(x_0, x) \leq \delta$  implies that  $|f_\varepsilon(x) - f_\varepsilon(x_0)| \leq \frac{\varepsilon}{2}$ .

Let us define an auxiliary function  $g(x)$  which is equal to:

- $g(x) = f_\varepsilon(x_0)$  when  $d(x, x_0) \geq \frac{\delta}{2}$  and
- $g(x) = f_\varepsilon(x_0) + \frac{\varepsilon}{2} - d(x, x_0) \cdot \frac{\varepsilon}{\delta}$  for all other  $x$ .

One can easily see that this function is continuous, and that it has a local maximum (actually, even global maximum) for  $x = x_0$ .

For values  $x$  for which  $d(x, x_0) \leq \delta$ , the largest possible difference

$$|g(x) - f_\varepsilon(x_0)|$$

between  $g(x)$  and  $f_\varepsilon(x_0)$  is attained in the second case at the point  $x_0$ , when the distance  $d(x, x_0) = 0$ . In this case, the difference is equal to  $|g(x_0) - f_\varepsilon(x_0)| = \frac{\varepsilon}{2}$ .

Thus, for all  $x$ , we have  $|f_\varepsilon(x_0) - g(x)| \leq \frac{\varepsilon}{2}$ . So, for all these  $x$ , we have

$$|f_\varepsilon(x) - g(x)| \leq |f_\varepsilon(x) - f_\varepsilon(x_0)| + |f_\varepsilon(x_0) - g(x)| \leq \frac{\varepsilon}{2} + \frac{\varepsilon}{2} = \varepsilon.$$

Hence, when  $x$  is  $\delta$ -close to  $x_0$ , the values  $g(x)$  and  $f_\varepsilon(x)$  are  $\varepsilon$ -close.

Let us now consider the second auxiliary function  $w(x)$ , which is equal to:

- $w(x) = 1$  when  $d(x, x_0) \leq \frac{\delta}{2}$ ;
- $w(x) = 1 - \frac{d(x, x_0)}{\delta/2}$  when  $\frac{\delta}{2} \leq d(x, x_0) \leq \delta$ ; and

- $w(x) = 0$  when  $d(x, x_0) \geq \delta$ .

One can check that this function  $w(x)$  is also continuous, and its values are always between 0 and 1.

Thus, the convex combination  $f(x) \stackrel{\text{def}}{=} w(x) \cdot g(x) + (1 - w(x)) \cdot f_\varepsilon(x)$  is continuous and  $\varepsilon$ -close to the original function  $f_\varepsilon(x)$ . For points  $x$  for which  $d(x, x_0) \leq \frac{\delta}{2}$ , we have  $f(x) = g(x)$ , and thus, the function  $f(x)$  indeed attains a local maximum for  $x = x_0$ . The proposition is proven.

**Additional theoretical explanation.** An additional theoretical explanation for the empirical computational complexity of locating local optima is that this problem also has a higher logical complexity, i.e., needs more quantifiers to describe.

Indeed, the fact that a function  $f(x)$  attains its global maximum at a point  $x_0$  is naturally described by a one-quantifier formula  $\forall x (f(x) \leq f(x_0))$ . However, to describe the fact that there is a local maximum at the point  $x_0$ , we need two quantifiers:  $\exists \delta \forall x (d(x, x_0) \leq \delta \rightarrow f(x) \leq f(x_0))$ .

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