

Gradient descent implementation example applied to Celestial mechanics

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Abstract

This document aims to describe gradient descent algorithm, its implementations and how it can be used on a simple celestial mechanics example.

1 Introduction

1 Gradient descent is an optimization algorithm. The aim of gradient descent is to converge to a local minimum/maximum of a function. We call it a first order derivative iterative algorithm. It is labeled first order derivative, since we use first derivative of the function during the iterations.

There are plethora of applications, easy to imagine, that requires converging to a local minimum/maximum (Machine Learning, mechanics, biology...), often the function we want to minimize is called cost function noted $J(\theta_n)$.

Since Gradient descent is widely used, you can find easily an implementation in many programming languages.

Here we will go through the basics of the theory, then we will apply it on a practical case, Earth Sun orbital system.

2 Requirement

In order to apply the gradient descent algorithm using a function these conditions must be met.

Given $f : R^n \rightarrow R$, $f(x_n)$ then $\forall x_n \exists f'(x_n)$

Where for a given a we have $f'(a) = \lim_{h \rightarrow 0} \frac{f(a+h) - f(a)}{h}$ exists

2.1 Few differentiable functions

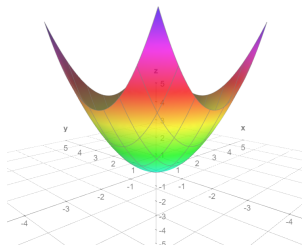


Figure 1: $x^2 + y^2$

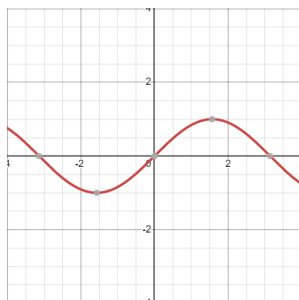


Figure 2: $\sin(x)$

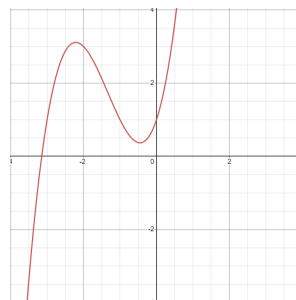


Figure 3: $(x+1)^3 + x^2(x)$

2.2 Few non differentiable functions

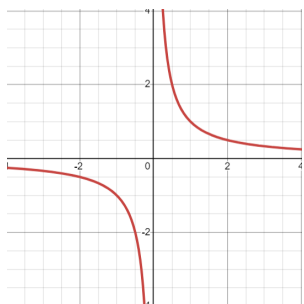


Figure 4: $1/x$

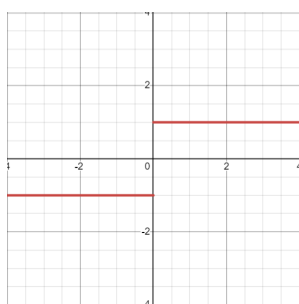


Figure 5: $x/|x|$

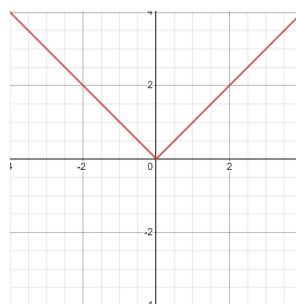


Figure 6: $|x|$

Note: that the algorithm, can fall on what we call a saddle point, meaning for a given point (x_0, y_0) we have $f_x(x_0, y_0) = 0$ and $f_y(x_0, y_0) = 0$ so defined as critical point, but since it is not an extremum, it ends up being only a saddle point. To sort it out we can use the Hessian matrix for a second partial derivatives test

3 Gradient descent algorithm description

The algorithm consist in finding the minimum through an iterative process. The value S_{min} will be updated and will end with the value we are looking for.

Let's define some parameters

1. $f : R^n \rightarrow R$, noted $f(x_n)$ where $x_n \in R$
2. α a scalar as learning rate
3. M as number of iterations
4. i current iteration
5. S_i current point

$$6. \nabla f(S_i) \text{ where the gradient is } \nabla f(x_1, x_2, \dots, x_n) = \begin{bmatrix} \frac{\partial f}{\partial x_1}(x_1, x_2, \dots, x_n) \\ \frac{\partial f}{\partial x_2}(x_1, x_2, \dots, x_n) \\ \vdots \\ \frac{\partial f}{\partial x_n}(x_1, x_2, \dots, x_n) \end{bmatrix}$$

```

1:  $S_i \leftarrow [a_0, a_1..]$                                 ▷ initialize starting point
2:  $S_{min} \leftarrow S_i$                                     ▷ initialize mininum
3:  $M \leftarrow 50$                                           ▷ maxmium of iterations
4:  $\alpha \leftarrow random([0, 1[)$                             ▷ ranged learning rate
5: for  $i = 0, i < M, i++$  do
6:    $S_{i+1} \leftarrow S_i - \alpha * \nabla f(S_i)$ 
7:   if  $f(S_{i+1}) < f(S_{min})$  then
8:      $S_{min} \leftarrow S_{i+1}$                                 ▷ update minium if necessary
9:   end if
10: end for

```

4 Application on orbital Earth Sun system

Let's apply this algorithmic on a concrete case. Earth Sun system could be an interesting candidate.

In our Solar system Earth orbits around the Sun along an ellipse in a period of $\simeq 365$ days with an average speed of $29.7827 km.s^{-1}$.

Here is a figure that helps visualize (ellipse is flattened on purpose) :



Few elements that characterizes an ellipse d :

- 4

- Aphelion 152,097,597 *km*, distance when Earth is the furthest from the Sun
- Perihelion 147,098,450 *km*, distance when Earth is the nearest from the Sun
- Semi-major axis 149,598,023 *km* (ellipse figure is flattened for visibility)
- Eccentricity 0.0167086
- Vis-Viva equation: $OrbitalSpeed = \sqrt{G \times SunMass \times (\frac{2}{radius} - \frac{1}{SemiMajorAxis})}$

5 Example of implementation

5.1 Code relative to Earth Sun System

5.1.1 Compute Radius from Sun \equiv focus on the right, in Km

```
public double getRadiusFromFocusInKm(double semiMajorAxisInMeter, double eccentricity, double angleInDegree){
    return (semiMajorAxisInMeter * (1 - Math.pow(eccentricity, 2))) /
           (1 + (eccentricity * Math.cos(getRadianFromDegree(angleInDegree))));
}
```

5.1.2 Compute orbital speed around massive object

```
public double getOrbitalSpeed(double massObjectInKg, double radiusInMeter, double semiMajorAxisInMeter){
    return Math.sqrt(G * massObjectInKg * ((2 / radiusInMeter) - (1 / semiMajorAxisInMeter)));
}
```

5.2 Example of Gradient descent Implementation

```
public GradientDescent<Double> getMinByGradientDescent(int maxIteration, Double learningRate, Double start){
    Derivative2DFunction function = computationService.getEarthOrbitalSpeed2D();
    Double min = start;
    List<Double[]> path = new ArrayList<>();
    for (int i = 0; i < maxIteration; i++) {
        double scaledGradient = learningRate * function.getDerivative(start);
        path.add(new Double[]{start, function.apply(start)});
        Double newPoint = start - scaledGradient;
        start = newPoint;
        if (function.apply(newPoint) < function.apply(min)) {
            min = newPoint;
        }
    }
    return new GradientDescent<>(path, min);
}
```

In red we see the orbital speed oscillating between \equiv 30,3 km/s and 29,3 km/s.

If we draw the function for degrees more than 360°, we will see more clearly

5.3 Gradient descent plot

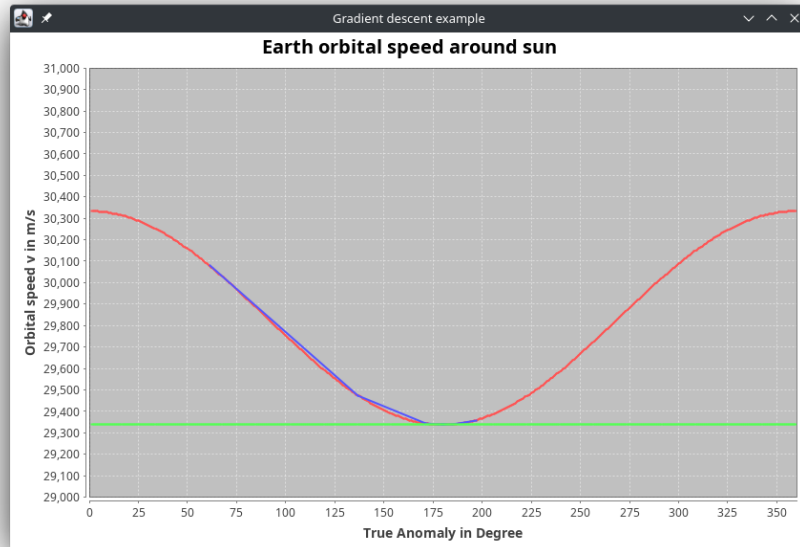


Figure 8: Orbital Earth Sun system

that the function is periodic with a period of $360^\circ (2\pi$ in gradient).

Then we see in blue the path followed by the gradient descent (α learning rate has been put high on purpose to see the broken line).

We can notice that over the iterations, the blue, follows the red curve. The blue curve is a broken line, the gradient direction scaled by the learning rate. Behind the scenes, the algorithm keeps track of the minimum. Here we can see that green line, is drawn at $180^\circ (e.q \pi \text{ radians})$.

5.4 Comments on results

The above implementation shows how a local minimum can be found by using a first derivative order, and a simple structured algorithm. Gradient descent, can be scaled to a function with higher dimensions.

We will see in a next article in the context of machine learning, how we can leverage Gradient descent to solve a polynomial regression problem, by minimizing the cost function