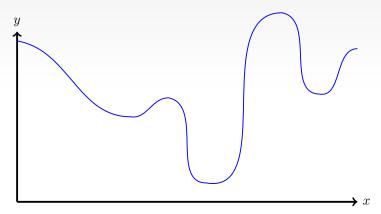
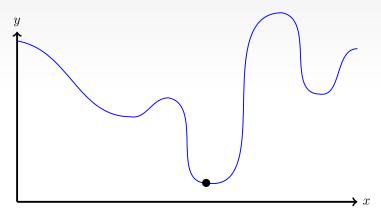
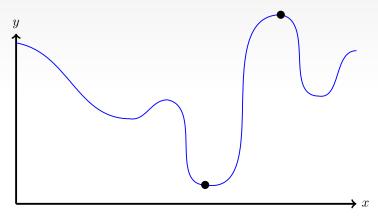
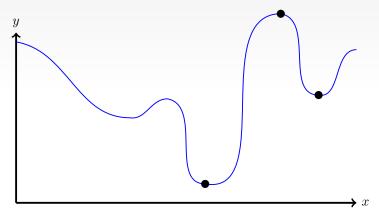
# Artificial Intelligence: Modeling Human Intelligence with Networks

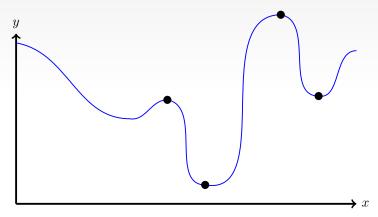
Jeová Farias Sales Rocha Neto jeova\_farias@brown.edu

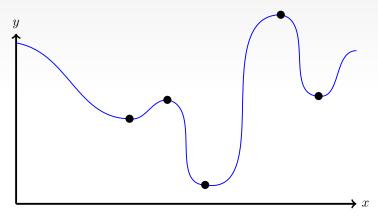




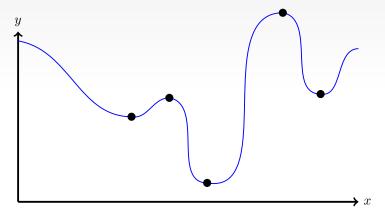








■ Which points in the following curve have derivative equals to zero?



■ Does anyone spot something important about (some of) these points?

## **Gradient Descent**

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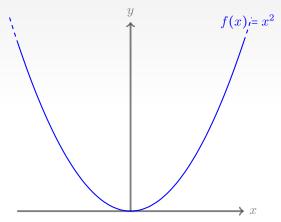
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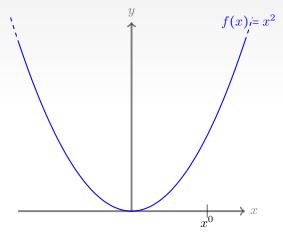
- In order to minimize it, we can't change the data X (it was given to us), but we can try to find the best w!
- The **Gradient descent** algorithm!

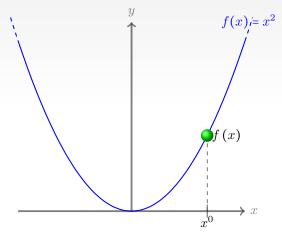
#### Gradient descent

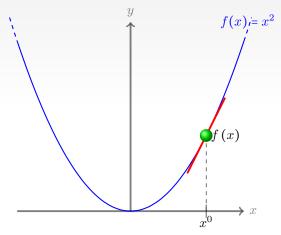
#### Algorithm 1 Gradient descent - v1

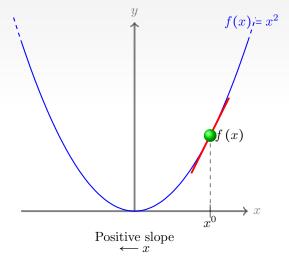
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Input: A function f(x)
  Output: A number x.
1: Initialize x
2: step\_size = 1
3: for some repetitions do
      if Slope at f(x) is negative then
4:
        x = x + step\_size
5:
     end if
6.
7:
     if Slope at f(x) is positive then
8:
        x = x - step\_size
     end if
9:
10: end for
```

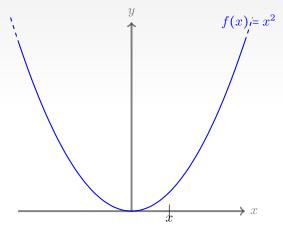


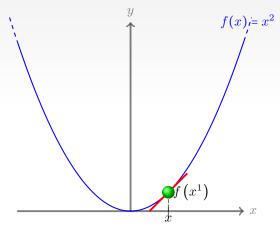


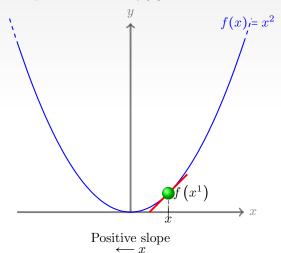


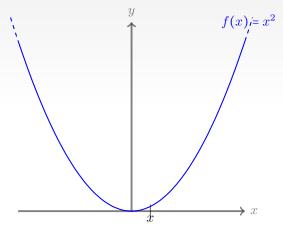


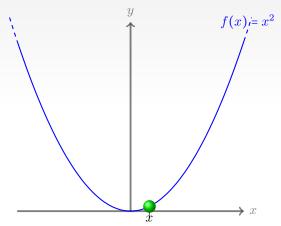


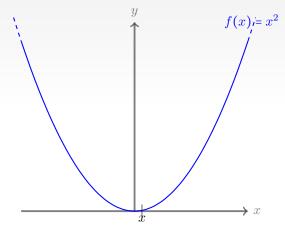


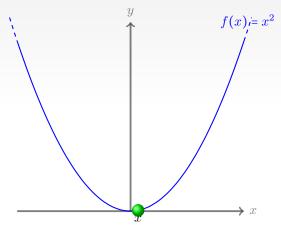


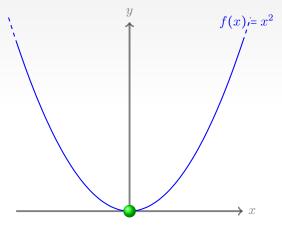




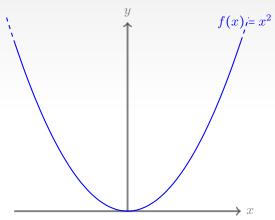


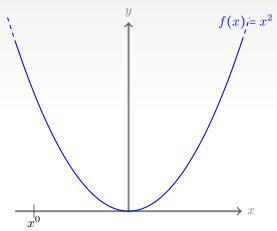


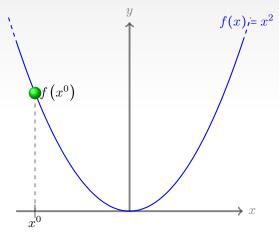


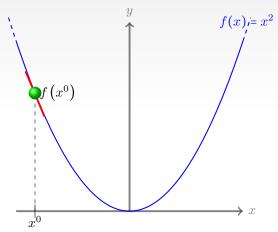


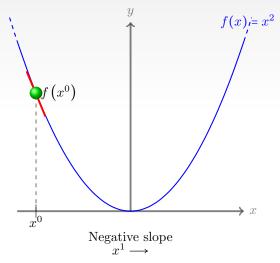
That's the minimum!!

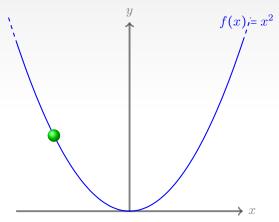


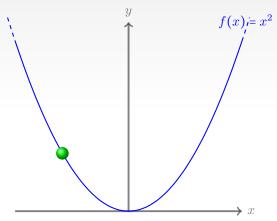


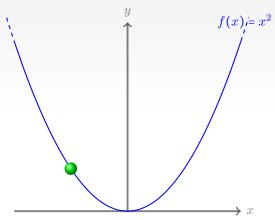


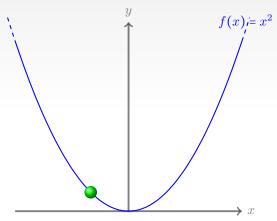


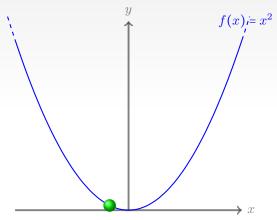


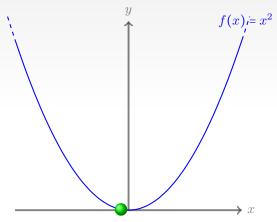


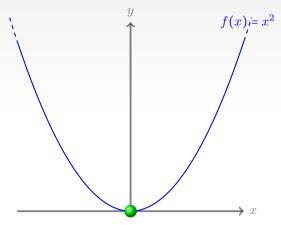












That's the minimum!!

#### Gradient descent

#### **Algorithm 2** GradientDescent - v1

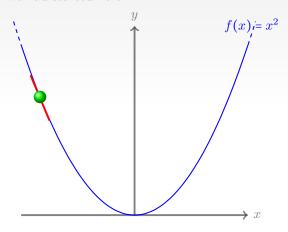
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#### Gradient descent

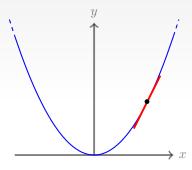
#### **Algorithm 3** GradientDescent - v2

```
Input: A function f(x)
  Output: A number x.
1: Initialize x
2: step\_size = 1
3: for some repetitions do
    if f'(x) < 0 then
       x = x + step\_size
5:
   end if
6.
   if f'(x) > 0 then
8:
       x = x - step\_size
     end if
9:
10: end for
```

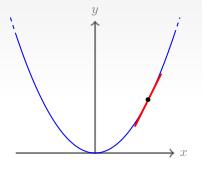
# Python Notebooks!

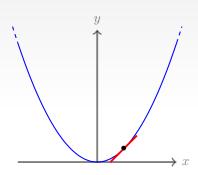


■ Take this two points:

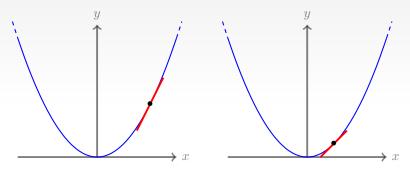


■ Take this two points:



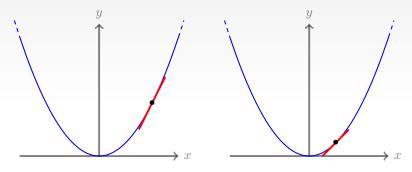


■ Take this two points:



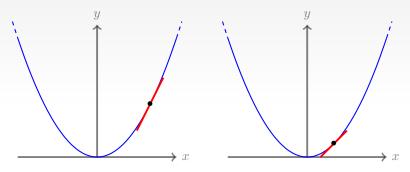
■ Which one of the following is the closest to the minumum?

■ Take this two points:



- Which one of the following is the closest to the minumum?
- Which one has the steeper slope?

■ Take this two points:



- Which one of the following is the closest to the minumum?
- Which one has the steeper slope?
- What if we could walk different step sizes in different points?

#### Gradient descent

#### **Algorithm 4** GradientDescent - v3

```
Input: A function f(x)
  Output: A number x.
1: Initialize x
2: step\_size = 1
3: for some repetitions do
    if f'(x) < 0 then
        x = x + step\_size \times f'(x)
5:
    end if
6.
    if f'(x) > 0 then
        x = x - step\_size \times f'(x)
8:
      end if
9:
10: end for
```

#### Gradient descent

#### $\overline{\textbf{Algorithm 5}} \ \overline{\textbf{G}radientDesce} nt$ - Final

**Input**: A function f(x)

Output: A number x.

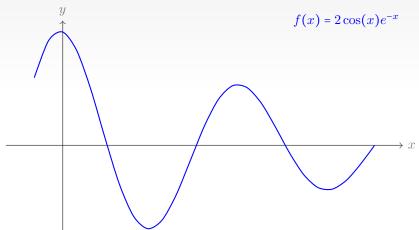
1: Initialize x

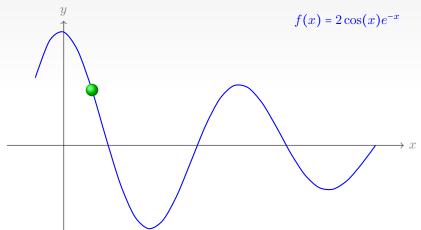
2:  $step\_size = 1$ 

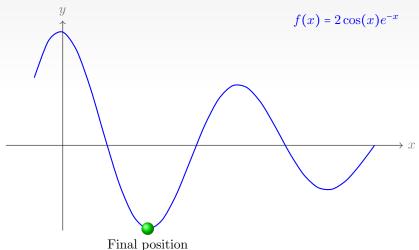
3: **for** some repetitions **do** 

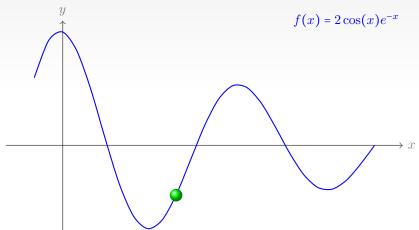
4:  $x = x - step\_size \times f'(x)$ 

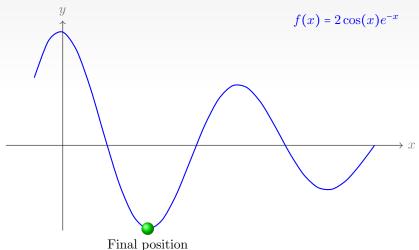
5: end for

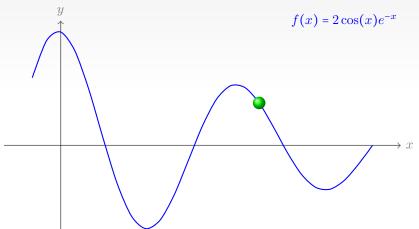


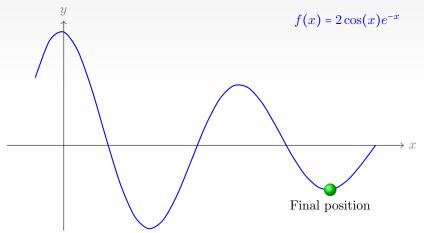


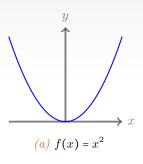


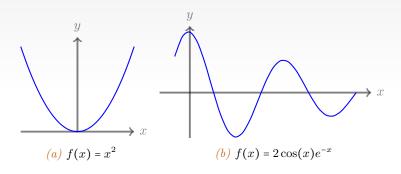




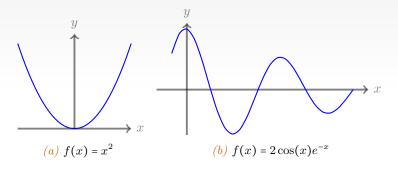




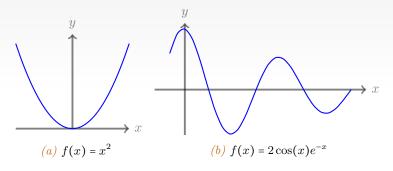




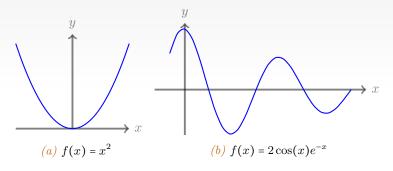
■ What is the difference between these functions?



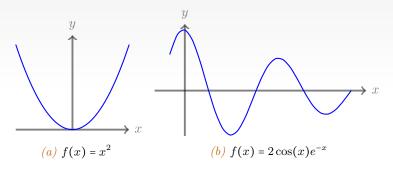
• One is convex (a) and the other is non-convex (b).



- One is convex (a) and the other is non-convex (b).
- Wait,



- One is convex (a) and the other is non-convex (b).
- Wait, WHAT THE HECK IS CONVEXITY???



- One is convex (a) and the other is non-convex (b).
- Wait, WHAT THE HECK IS CONVEXITY???
- How does this influence the gradient descent algorithm?

