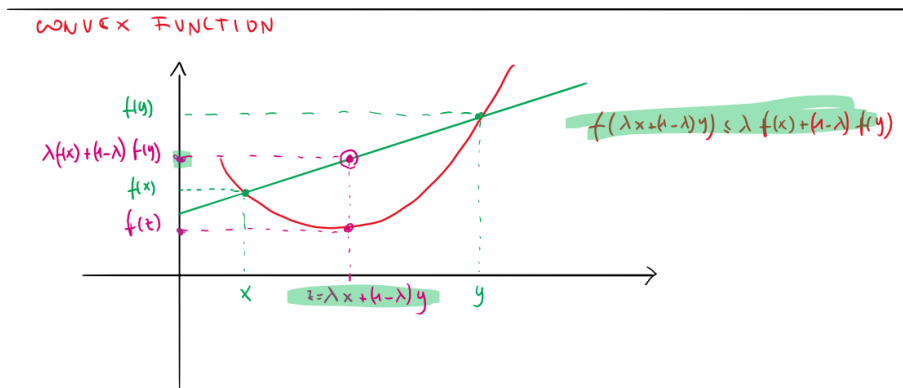


**convex** function = any function that has a shape like a bowl

$$f(tx + (1 - t)y) \leq tf(x) + (1 - t)f(y) \quad \text{for all } x, y \in \mathcal{X}, t \in [0, 1]. \quad - (1)$$

Notice the equal in the “ $\leq$ ” sign!

From Rinaldi’s whiteboard:



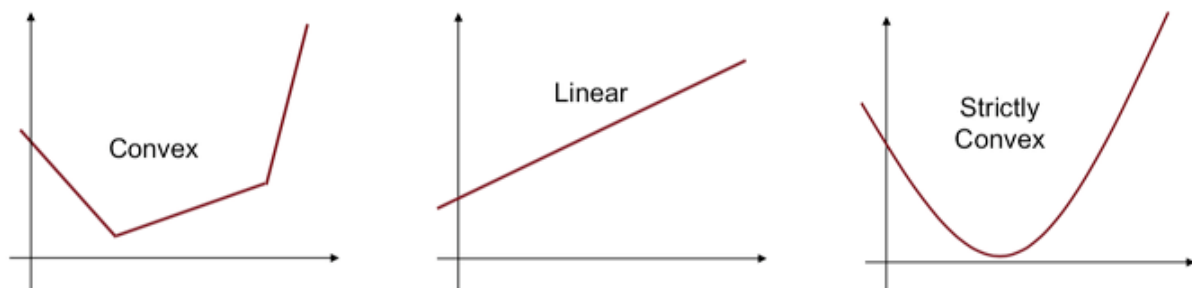
Interpretation: For any two points, we draw a line between them, and for any point on that line, the value of the function in this point is below the point on the line.

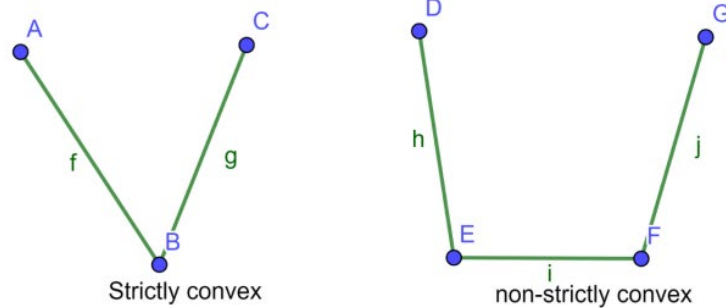
**strictly convex** function = has only one minimum (local = global)

$$f(tx + (1 - t)y) < tf(x) + (1 - t)f(y) \quad \text{for all } x \neq y \in \mathcal{X}, t \in (0, 1).$$

Here we don’t have the equal in the sign!

Examples for strictly convex:





Every strictly convex function is convex, but the reverse is not true. (see pictures above)

**Strongly convex** function = how “convex” or “curved” a convex function is.

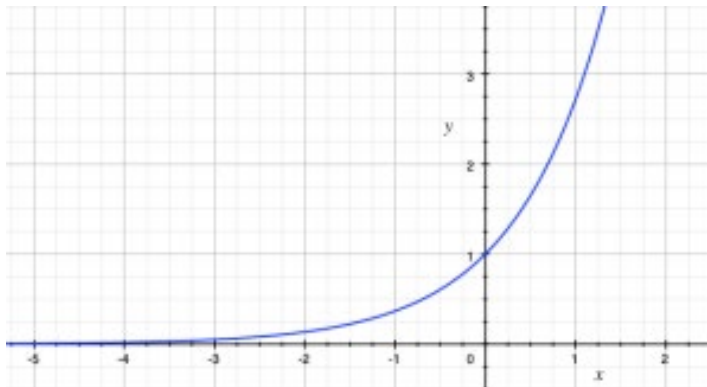
It can be seen as a kind of “parameterized strict convexity”.

[we add this term here](#)

$$f(tx + (1 - t)y) \leq tf(x) + (1 - t)f(y) - \frac{1}{2}mt(1 - t)\|x - y\|_2^2$$

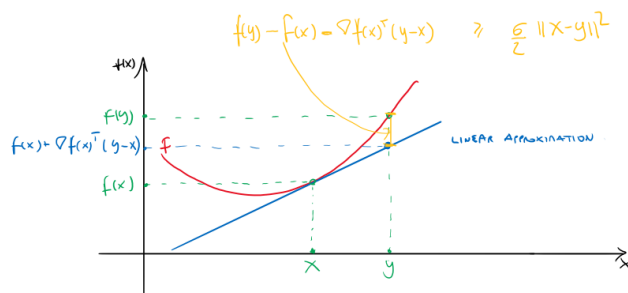
$$\text{for all } x, y \in \mathcal{X}, t \in [0, 1]. \quad - (4)$$

You can think of the parameter  $m$  as measuring how “curved” the function is: the larger  $m$  is the more curved  $f$  is. That is why  $f(x) = \exp(x)$  is not strongly convex: as  $x$  goes to infinity, the curve becomes flatter and flatter ( $m \rightarrow 0$ ).



From Rinaldi's whiteboard: (sigma is the same as m above)

1ST ORDER STRONG CONVEXITY



Between two strongly convex functions, the function with the larger m is more strongly convex.  
 => this function's curvature grows more rapidly

Extras for strong convexity:

From Rinaldi's slides (here lambda refers to t in above's equation):

Finally, by taking limit  $\lambda \rightarrow 0$ , we can write

$$f(x) \geq f(x^*) + \frac{\sigma}{2} \|x - x^*\|^2,$$

## Strong Convexity

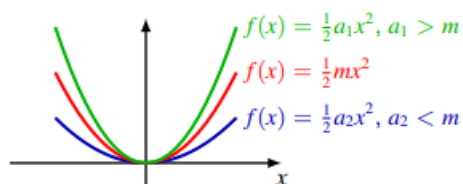
A function  $f$  is **strongly convex** with parameter  $m > 0$ , or simply  **$m$ -strongly convex**, if

$$\tilde{f}(x) = f(x) - \frac{m}{2} \|x\|^2$$

is convex.

**Note.**  $f(x) = \frac{m}{2} \|x\|^2 + \tilde{f}(x)$ , i.e.  $f$  is  $\frac{m}{2} \|x\|^2$  plus an extra convex term. Informally, " $m$ -strongly convex" means at least as "convex" as  $\frac{m}{2} \|x\|^2$ .

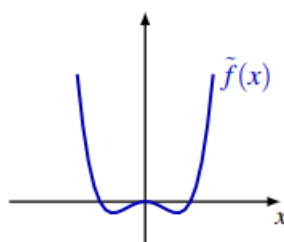
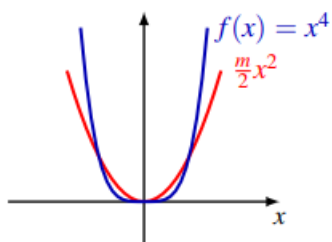
**Example.**  $f(x) = \frac{a}{2} \|x\|^2$  is  $m$ -strongly convex iff  $a \geq m$



**Example.**  $f(x) = x^4$  is **not**  $m$ -strongly convex for any  $m > 0$ , as  $\tilde{f}(x) = x^4 - \frac{m}{2}x^2$  is not convex,

$$\tilde{f}''(x) = 12x^2 - m < 0$$

for  $|x| < \sqrt{m/12}$ .



Useful link:

[\(Strictly/strongly\) convex functions | Statistical Odds & Ends \(wordpress.com\)](#)