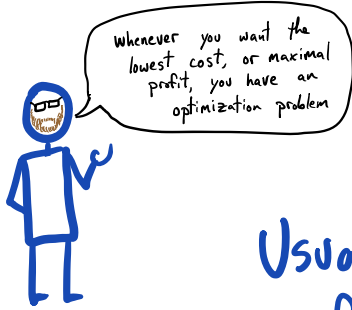
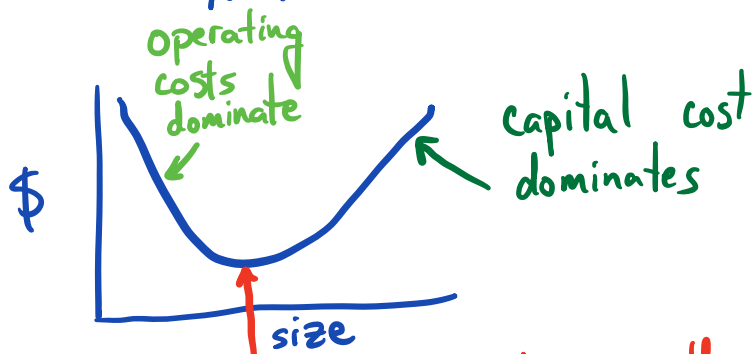


# Optimization

AKA Give me the best solution



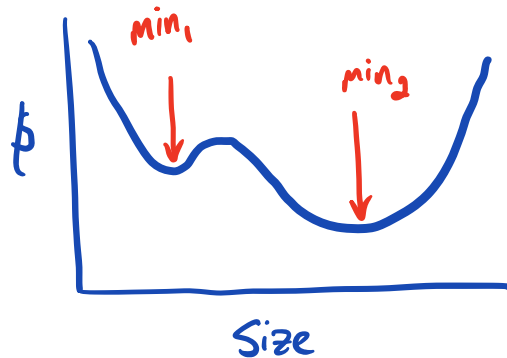
Usually we seek to minimize a function. Take the cost of a process. The capital costs often decrease as a process gets smaller, but operating costs increase because it takes longer to run



minimum cost, i.e. the optimal size

The minimum here is defined by the first derivative  $\frac{d\phi}{d\text{size}} = 0$  and by the second derivative at the minimum being positive (i.e. the cost function is concave up).

Depending on your cost function there may be many minima:



$\text{min}_1$  and  $\text{min}_2$  are both minima but  $\text{min}_2$  is lower than  $\text{min}_1$ . Our job as engineers is to decide which one is a better solution.

$\text{min}_1$  is called a local minimum

$\text{min}_2$  (at least in this interval) is the global minimum.

## Finding minima

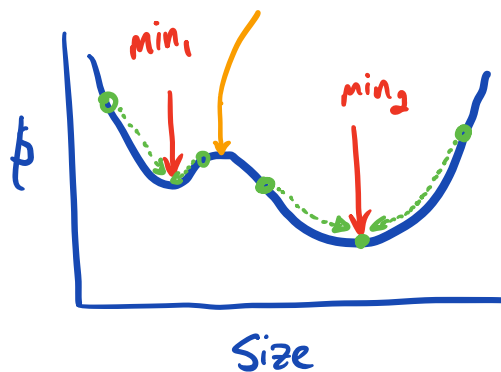
Newton's method can be adapted to find minima; basically we solve

$$f'(x) = 0!$$

whoa... we used fsolve for that

That's right!  
And just like fsolve, this is an iterative method that needs an initial guess and that finds the closest minimum.

Bad place to start!  $f'(\text{size}) = 0$



Similar to `fsolve`, there is

`scipy.optimize.minimize`

```
def objective(x):  
    return some_func(x)
```

`minimize(objective, guess) ⇒ sol`

`sol` is a data structure containing the solution.

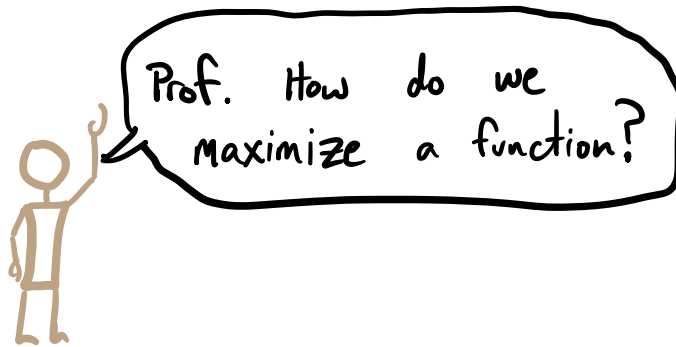
`sol.status == 0` when the minimization succeeded

`sol.success == True`

`sol.message == 'Optimization terminated successfully'`

`sol.x` contains an array of the solution

`sol.fun` is the value of `objective(sol.x)`



## Maximizing a function

Maximizing a function is equivalent to minimizing the negative of that function.

