# Optimization Techniques

Laboratory 3

Derivative-based optimization



### Gradient Descent

Hiker algorithm that wants to climb down a hill Each step is determined by:

- Steepness of the mountain (gradient)
- Leg length of the hiker (learning rate)

$$x \leftarrow x \ - \stackrel{\downarrow}{\alpha} \nabla_x f(x)$$

#### Given:

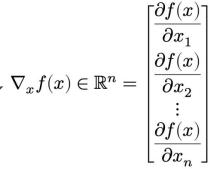
Function f , initial point  $x_0$  , step size  $\alpha>0$ 

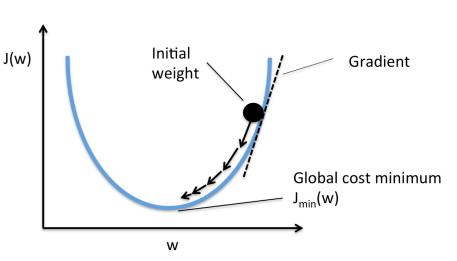
#### Initialize:

$$x \leftarrow x_0$$

#### Repeat until convergence:

$$x \leftarrow x - \alpha \nabla_x f(x)$$





### Newton Method

Second-order method - approximates the right step-size

Uses the **steepness** and **curvature** to determine the next step

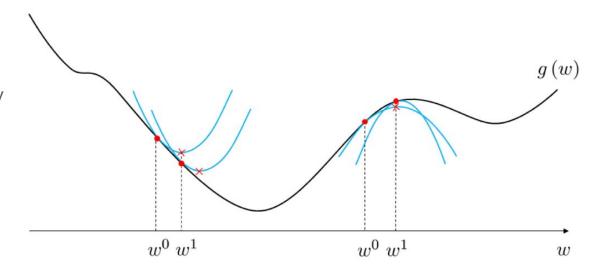
#### Pros:

 When f is quadratic, it jumps to the minimum straight away

#### Cons:

- Computational burden
- Attracts saddle points

$$\mathbf{x}^* = \mathbf{x}^{(0)} - H(f)(\mathbf{x}^{(0)})^{-1} \nabla_x f(\mathbf{x}^{(0)})$$



## Broyden-Fletcher-Goldfarb-Shanno

(BFGS)

<u>Limitation of Newton's method</u> is that it requires the calculation of the inverse of the Hessian matrix

Quasi-Newton method - approximates the inverse of the Hessian matrix using the gradient

**BFGS** uses a line search in the chosen direction to determine how far to move in that direction

```
k = 0
                                                                                      Initialize iteration counter
\alpha_{\text{init}} = 1
                                                                             Initial step length for line search
while \|\nabla f_k\|_{\infty} > \tau do
                                                                                             Optimality condition
     if k = 0 or reset = true then
          \tilde{V}_k = \frac{1}{\|\nabla f\|} I
     else
          s = x_k - x_{k-1}
                                                                                                            Last step
          y = \nabla f_k - \nabla f_{k-1}
                                                                                       Curvature along last step
          \sigma = \frac{1}{s^{\mathsf{T}} y}
          \tilde{V}_k = (I - \sigma s y^{\mathsf{T}}) \tilde{V}_{k-1} (I - \sigma y s^{\mathsf{T}}) + \sigma s s^{\mathsf{T}}
                                                                                           Quasi-Newton update
     end if
     p = -\tilde{V}_k \nabla f_k
                                                                                  Compute quasi-Newton step
     \alpha = linesearch(p, \alpha_{init})
                                                                Should satisfy the strong Wolfe conditions
     x_{k+1} = x_k + \alpha p
                                                                                        Update design variables
     k = k + 1
                                                                                      Increment iteration index
end while
```