

# PadhAI: Variants of Gradient Descent

## One Fourth Labs

### Epochs and Steps

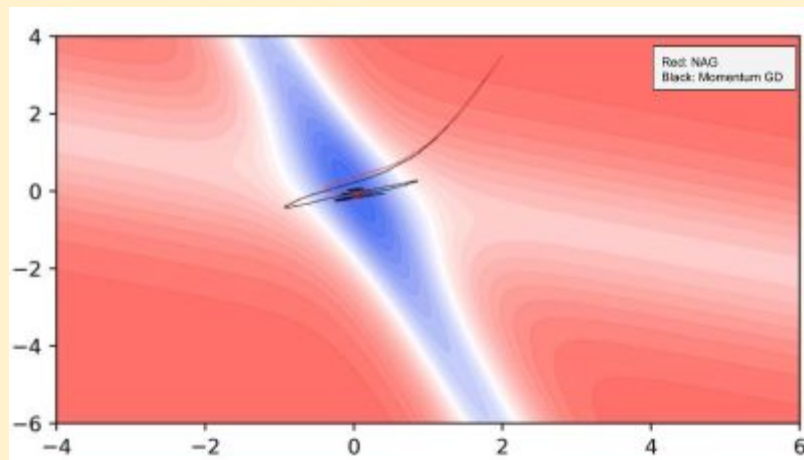
What is an epoch and what is a step?

- Let us go over the definitions of an epoch and a step
  - 1 epoch = one pass over the entire data
  - 1 step = one update of the parameters
  - $N$  = number of data points
  - $B$  = mini-batch size
- Let's analyse the algorithms using epochs and steps

| Algorithm                   | Number of steps in one epoch |
|-----------------------------|------------------------------|
| Batch Gradient Descent      | 1                            |
| Stochastic Gradient Descent | $N$                          |
| Mini-Batch Gradient Descent | $N/B$                        |

- Let's look at stochastic version of NAG and Momentum based GD

| Stochastic Momentum GD  | Stochastic NAG  |
|---|---|
| <pre>def do_stochastic_momentum_gradient_descent():     w, b, eta, max_epochs = -2, -2, 1.0, 1000     v_w, v_b = 0.0, 0.0     gamma = 0.7     for i in range(max_epochs):         dw, db = 0, 0         for x, y in zip(X, Y):             dw += grad_w(w, b, x, y)             db += grad_b(w, b, x, y)             v_w = gamma*v_w + eta*dw             v_b = gamma*v_b + eta*db          w = w - v_w         b = b - v_b</pre> | <pre>def do_stochastic_nag_gradient_descent():     w, b, eta, max_epochs = -2, -2, 1.0, 1000     v_w, v_b = 0, 0     gamma = 0.9     for i in range(max_epochs):         dw, db = 0, 0          #Compute the lookahead value         w = w - gamma*v_w         b = b - gamma*v_b          for x, y in zip(X, Y):             #Compute the derivatives using the lookahead value             dw += grad_w(w, b, x, y)             db += grad_b(w, b, x, y)          #Now move further in the direction of that gradient         w = w - eta*dw         b = b - eta*db          #Now update the history         v_w = gamma * v_w + eta * dw         v_b = gamma * v_b + eta * db</pre> |



- Since there is a history component, NAG and Momentum GD have slightly smoother oscillations.