Optimisation

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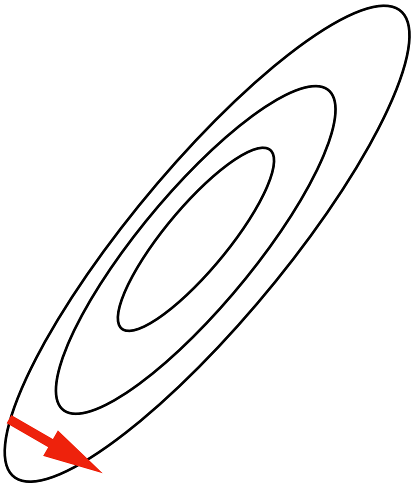
[1] Some of the material in this lecture is based on Andrew Ng's lectures on Optimisation

Why learning can be slow



Why learning can be slow

- If the ellipse is very elongated, the direction of steepest descent is almost perpendicular to the direction towards the minimum
- The gradient vector will have a large component along the short axis of the ellipse and a small component along the long axis of the ellipse.
- This is the opposite of what we want to optimise efficiently

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$v_{100} = 0.1\theta_{100} + 0.9 * 0.1 * \theta_{99} + 0.1 * (0.9)^2 * \theta_{98} + 0.1(0.9)^3\theta_{97} + \dots$

Momentum

- The momentum method allows to accumulate velocity in directions of low curvature that persist across multiple iterations
- This leads to accelerated progress in low curvature directions compared to gradient descent

Gradient Descent (GD) with Momentum

Learning with momentum is given by

On iteration t:

Compute dW_t on the current mini-batch

$$V_t = \beta V_{t-1} + (1-\beta) dW_t \tag{1}$$

$$w_t = w_{t-1} - \eta V_t \tag{2}$$

Note that dW_t represents the gradient of the cost function (as computed in standard GD). η is the learning rate and $\beta = 0.9$ is a good choice for the exponentially weighted average parameter.

RMSProp

Learning with RMSProp is given by

On iteration t:
    Compute dW on current mini-batch

$$S_{dW_t} = \beta S_{dW_{t-1}} + (1-\beta) dW_t^2 \tag{3}$$

$$w_t = w_{t-1} - \eta \frac{dW_t}{\sqrt{S_{dW_t}}} \tag{4}$$

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- $t = 2$: $\frac{v_2}{1-(0.9)^2} = 5.263 * v_2$
- ...
- $t = 10$: $\frac{v_{10}}{1-(0.9)^{10}} = 1.535 * v_{10}$
- ...
- $t = 20$: $\frac{v_{20}}{1-(0.9)^{20}} = 1.138 * v_{20}$

Adam

Initialize parameters: $V_{dW} = 0, S_{dW} = 0$

On iteration t:

Compute dW_t on current mini-batch

$$V_{dW} = \beta_1 V_{dW} + (1 - \beta_1) dW, \quad V_{dW}^{corr} = \frac{V_{dW}}{(1 - \beta_1^t)} \tag{5}$$

$$S_{dW} = \beta_2 S_{dW} + (1 - \beta_2) dW^2, \quad S_{dW}^{corr} = \frac{S_{dW}}{(1 - \beta_2^t)} \tag{6}$$

$$w := w - \eta \frac{V_{dW}^{corr}}{\sqrt{(}S_{dW}^{corr} + \epsilon)} \tag{7}$$