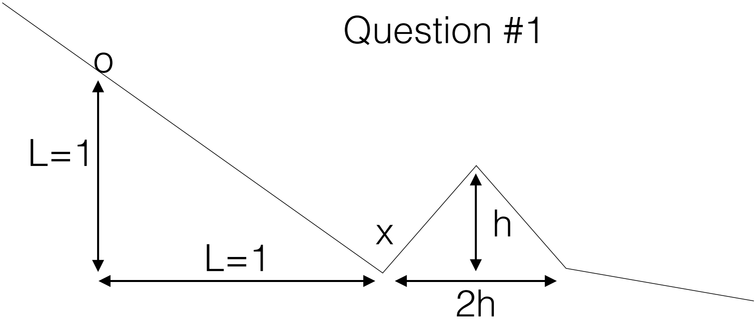
Assignment 2

Due week 6 before class time

Question #1



The diagram above shows a plot of a 1D function and gradient descend is applied to minimise the function at the point ‘o’. there is a bump a distance L away with bump dimensions given as h x 2h. Let L = 1, a = 0.3 and h > a where a is the learning rate

(1) what will happen if you apply standard gradient descend?

(2) if you apply adam optimisation with parameters given in the next slide, what is the max height ‘h’ of the bump in which the adam optimiser will escape the local min at ‘x’? use \epsilon = 0 instead of \epsilon = 1e-8 in your calculations.

Algorithm 1: *Adam*, our proposed algorithm for stochastic optimization. See section 2 for details, and for a slightly more efficient (but less clear) order of computation. g_t^2 indicates the elementwise square $g_t \odot g_t$. Good default settings for the tested machine learning problems are $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$. All operations on vectors are element-wise. With β_1^t and β_2^t we denote β_1 and β_2 to the power t.

Require: α: Stepsize
Require: $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates
Require: $f(\theta)$: Stochastic objective function with parameters θ
Require: θ_0: Initial parameter vector
  $m_0 \leftarrow 0$ (Initialize 1st moment vector)
  $v_0 \leftarrow 0$ (Initialize 2nd moment vector)
  $t \leftarrow 0$ (Initialize timestep)
  while θ_t not converged **do**
    $t \leftarrow t + 1$
    $g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)
    $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)
    $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)
    $\widehat{m}_t \leftarrow m_t / (1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)
    $\widehat{v}_t \leftarrow v_t / (1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)
    $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)
  end while
  return θ_t (Resulting parameters)

Question #2

(a) Design an auto encoder to take in MNIST images with latent space dimension of 2,16,256.

Train auto encoder with L1-norm reconstruction loss

Do a 2D plot of the latent space for different digits for latent space of 2D. K-means clustering for latent space of dimensions 16,256. Use one color for each digit. Report all results.

What do you notice about the reconstructed images?

Question #2

(b) Design another neural network “dis_net” to discriminate between blur images and clear images. Blur images can be generated by taking the original MNIST data and do some gaussian blur.

Train auto encoder with L1-norm reconstruction loss + discriminator loss. Make reconstructed images as clear as possible, that is, the auto encoder will need to be trained so that “dis_net” score it as a clear image

Compare results between (a) and (b)