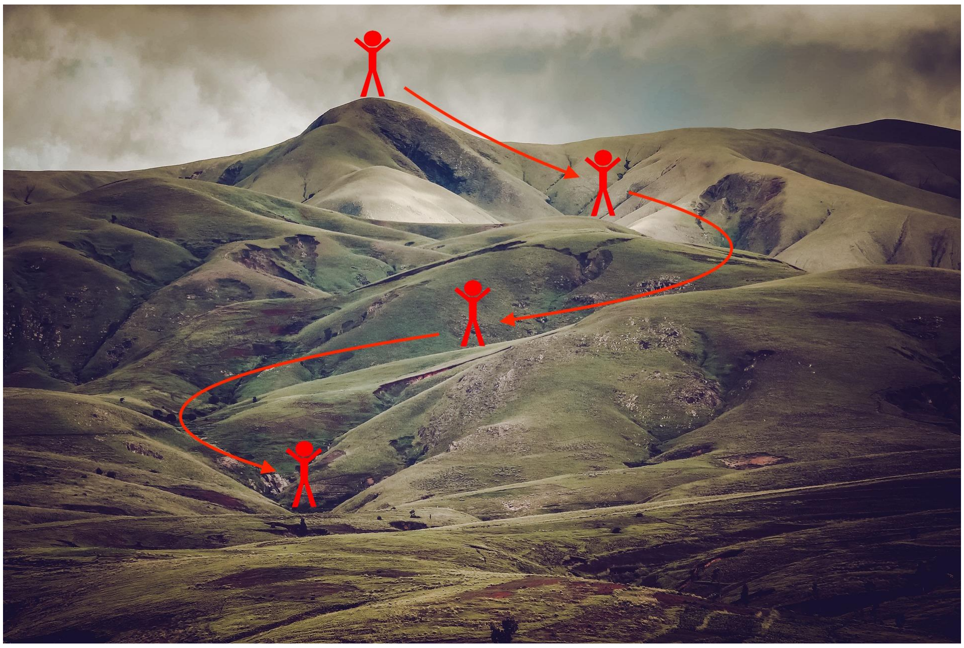
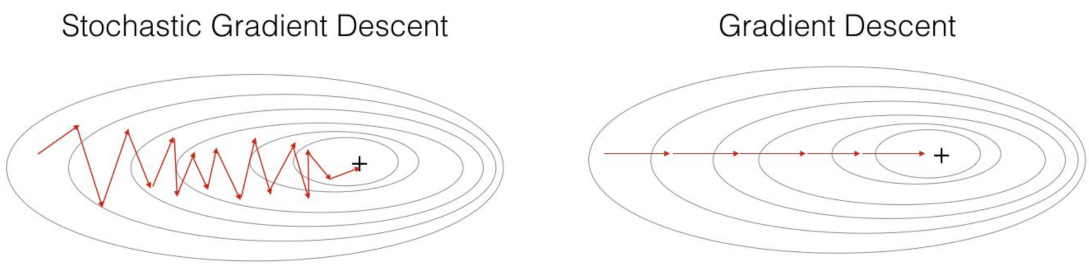
Optimization Methods

Supporting Figures

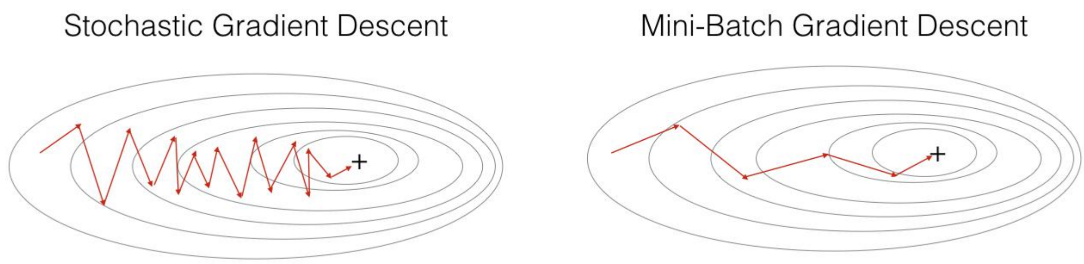
S0_Figure1_Assigment_optimization_methods



S1_Figure1_SGD vs GD



S2_Figure 2_SGD vs Mini-Batch GD

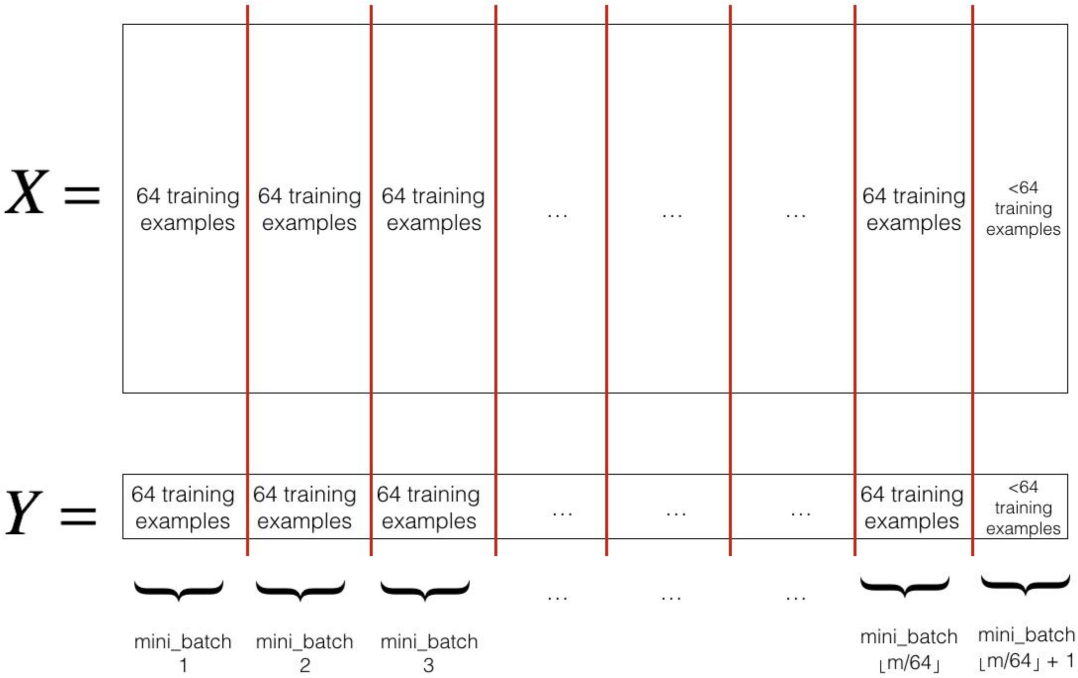


S3_Shuffle

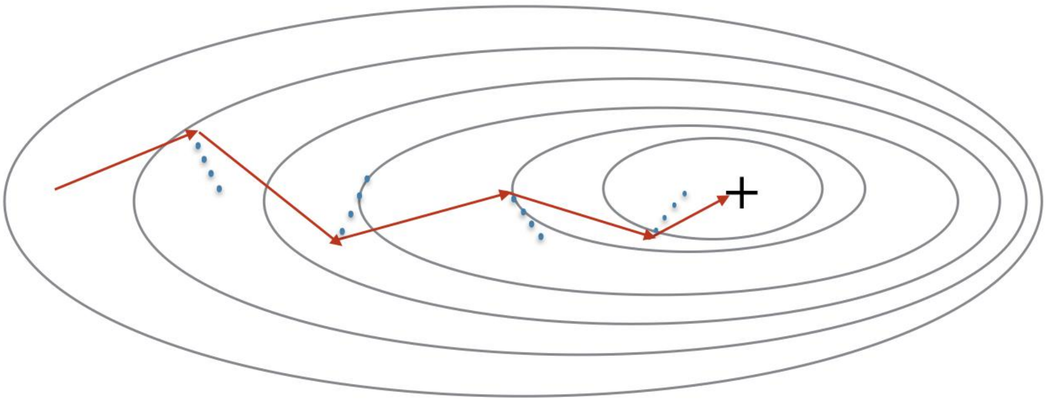
$$X = \begin{pmatrix} x_0^{(1)} & x_0^{(2)} & \dots & x_0^{(m-1)} & x_0^{(m)} \\ x_1^{(1)} & x_1^{(2)} & \dots & x_1^{(m-1)} & x_1^{(m)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{12286}^{(1)} & x_{12286}^{(2)} & \dots & x_{12286}^{(m-1)} & x_{12286}^{(m)} \\ x_{12287}^{(1)} & x_{12287}^{(2)} & \dots & x_{12287}^{(m-1)} & x_{12287}^{(m)} \end{pmatrix} \qquad Y = \begin{pmatrix} y^{(1)} & y^{(2)} & \dots & y^{(m-1)} & y^{(m)} \end{pmatrix}$$

$$X = \begin{pmatrix} x_0^{(5)} & x_0^{(16)} & \dots & x_0^{(2)} & x_0^{(m-1)} \\ x_1^{(5)} & x_1^{(16)} & \dots & x_1^{(2)} & x_1^{(m-1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{12286}^{(5)} & x_{12286}^{(16)} & \dots & x_{12286}^{(2)} & x_{12286}^{(m-1)} \\ x_{12287}^{(5)} & x_{12287}^{(16)} & \dots & x_{12287}^{(2)} & x_{12287}^{(m-1)} \end{pmatrix} \qquad Y = \begin{pmatrix} y^{(5)} & y^{(16)} & \dots & y^{(2)} & y^{(m-1)} \end{pmatrix}$$

S4_Partion



S5_ Figure 3: The red arrows show the direction taken by one step of mini-batch gradient descent with momentum. The blue points show the direction of the gradient (with respect to the current mini-batch) on each step. Rather than just following the gradient, the gradient is allowed to influence v and then take a step in the direction of v.



S6_How does Adam work

The update rule is, for $l = 1, \dots, L$:

$$
\begin{cases}
v_{dW^{[l]}} = \beta_1 v_{dW^{[l]}} + (1 - \beta_1)\frac{\partial \mathcal{J}}{\partial W^{[l]}} \\
v^{corrected}_{dW^{[l]}} = \frac{v_{dW^{[l]}}}{1-(\beta_1)^t} \\
s_{dW^{[l]}} = \beta_2 s_{dW^{[l]}} + (1 - \beta_2)(\frac{\partial \mathcal{J}}{\partial W^{[l]}})^2 \\
s^{corrected}_{dW^{[l]}} = \frac{s_{dW^{[l]}}}{1-(\beta_2)^t} \\
W^{[l]} = W^{[l]} - \alpha \frac{v^{corrected}_{dW^{[l]}}}{\sqrt{s^{corrected}_{dW^{[l]}}} + \varepsilon}
\end{cases}
$$

where:

- t counts the number of steps taken of Adam
- L is the number of layers
- β_1 and β_2 are hyperparameters that control the two exponentially weighted averages.
- α is the learning rate
- ε is a very small number to avoid dividing by zero

S7_Excercise6_ update_parameters_with_adam

Exercise 6 - update_parameters_with_adam

Now, implement the parameters update with Adam. Recall the general update rule is, for $l = 1, \ldots, L$:

$$\begin{cases} v_{dW^{[l]}} = \beta_1 v_{dW^{[l]}} + (1 - \beta_1) \frac{\partial \mathcal{J}}{\partial W^{[l]}} \\ v^{corrected}_{dW^{[l]}} = \frac{v_{dW^{[l]}}}{1 - (\beta_1)^t} \\ s_{dW^{[l]}} = \beta_2 s_{dW^{[l]}} + (1 - \beta_2) (\frac{\partial \mathcal{J}}{\partial W^{[l]}})^2 \\ s^{corrected}_{dW^{[l]}} = \frac{s_{dW^{[l]}}}{1 - (\beta_2)^t} \\ W^{[l]} = W^{[l]} - \alpha \frac{v^{corrected}_{dW^{[l]}}}{\sqrt{s^{corrected}_{dW^{[l]}}} + \varepsilon} \end{cases}$$

Note that the iterator `l` starts at 1 in the `for` loop as the first parameters are $W^{[1]}$ and $b^{[1]}$.