ADAM : A Method for Stochastic Optimization in ICLR 2015 By Diederik P. Kingma Jimmy Lei Ba

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Motivation

1. Learning rate affect model performance. We want cost function sensitive to some directions in parameter space and insensitive to others.

2. This method computes individual adaptive learning rates for different parameters from estimates of first and second moments of the gradients; the name Adam is derived from adaptive moment estimation

Related Work

AdaGrad

Learning rate scaled by inverse of square of sum of all the previous squared values of the gradient

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)

$v_t \leftarrow v_{t-1} + g_t^2$ (update biased second moment estimate)

$\theta_t \leftarrow \theta_{t-1} - \frac{\alpha}{\sqrt{v_t + \epsilon}} \odot g_t (updateParameter)$

end while

return θ_t (resulting parameter)

Related Work

RMSprop

Uses an exponentially weighted moving average to discard history from the extreme past

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)

v$_t \leftarrow \beta_1 v_{t-1} + (1 - \beta_1) g_t^2$ (update biased second moment estimate)

$\theta_t \leftarrow \theta_{t-1} - \frac{\alpha}{\sqrt{v_t + \epsilon}} \odot g_t (updateParameter)$

end while

return θ_t (resulting parameter)

Proposed Work

ADAM

It is a combination of RMSprop and SGD with momentum. It uses the squared gradients to scale the learning rate like RMSprop and it takes advantage of momentum by using moving average of the gradient like SGD with momentum

Algorithm

g_t^2 indicates the element wise square $g_t \odot g_t$
$\beta_1 = 0.9$,$\beta_2 = 0.999$ and $\epsilon = 10^{-8}$
Require : α : *Stepsize*
Require : $\beta_1, \beta_2 \, \epsilon$ [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 1^{st} moment vector)
$v_0 \leftarrow 0$ (Initialize 2^{nd} moment vector)
$t \leftarrow 0$ (initialize timestep)

Algorithm

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$_t \leftarrow \beta_1 m_{t-1} + (1 - \beta_1).g_t$ (update biased first moment estimate)

v$_t \leftarrow \beta_2.v_{t-1} + (1 - \beta_2).g_t^2$ (update biased second moment estimate)

m$_t^{'} \leftarrow m_t/(1 - \beta_1^t)$ (compute bias-corrected first moment estimate)

v$_t^{'} \leftarrow v_t/(1 - \beta_2^t)$ (compute bias-corrected second raw moment estimate)

$\theta_t \leftarrow \theta_{t-1} - \alpha.m_t^{'}/(\sqrt{v_t^{'}} + \epsilon)$ (update parameters)

end while

return θ_t (resulting parameter)

Results

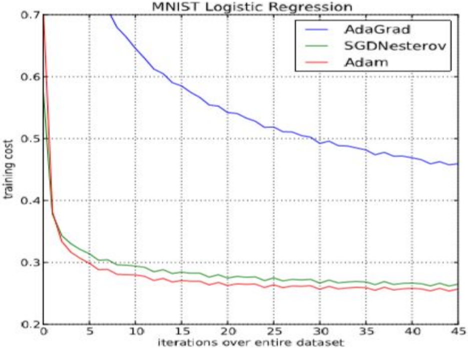

Fig : Logistic Regression on MNIST Images

Adam yields similar convergence as SGD with momentum and both converge faster than Adagrad.

Results

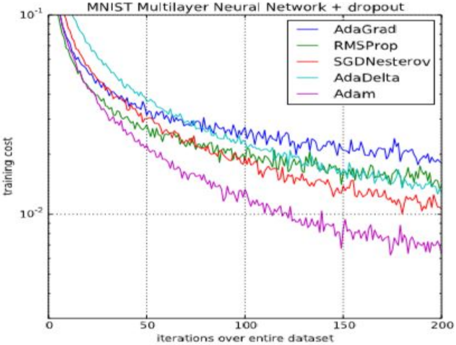

Fig : Multilayer Neural Network on MNIST images

References

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[3] Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization." arXiv preprint arXiv:1412.6980 (2014).