

# ADAGRAD / 2

## Algorithm AdaGrad

```
1: require Global step size  $\alpha$ 
2: require Initial parameter  $\theta$ 
3: require Small constant  $\beta$ , perhaps  $10^{-7}$ , for numerical stability
4: Initialize gradient accumulation variable  $r = \mathbf{0}$ 
5: while stopping criterion not met do
6:   Sample minibatch of  $m$  examples from the training set  $\{\tilde{\mathbf{x}}^{(1)}, \dots, \tilde{\mathbf{x}}^{(m)}\}$ 
7:   Compute gradient estimate:  $\hat{\mathbf{g}} = \frac{1}{m} \nabla_{\theta} \sum_i L(y^{(i)}, f(\tilde{\mathbf{x}}^{(i)} || \theta))$ 
8:   Accumulate squared gradient  $r \leftarrow r + \hat{\mathbf{g}} \odot \hat{\mathbf{g}}$ 
9:   Compute update:  $\nabla \theta = -\frac{\alpha}{\sqrt{r}} \odot \hat{\mathbf{g}}$  (operations element-wise)
10:  Compute update:  $\nabla \theta = -\frac{\alpha}{\sqrt{r}} \odot \hat{\mathbf{g}}$  (operations element-wise)
11:  Apply update:  $\theta \leftarrow \theta + \nabla \theta$ 
11: end while
11: end while
```

⊗: element-wise product (Hadamard)

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## RMSPROP / 2

### Algorithm RMSProp

```
1: require Global step size  $\alpha$  and decay rate  $\rho \in [0, 1)$ 
2: require Initial parameter  $\theta$ 
3: require Small constant  $\beta$ , perhaps  $10^{-6}$ , for numerical stability
4: Initialize gradient accumulation variable  $r = 0$ 
5: while stopping criterion not met do
6:   Sample minibatch of  $m$  examples from the training set  $\{\tilde{x}^{(1)}, \dots, \tilde{x}^{(m)}\}$ 
7:   Compute gradient estimate:  $\hat{g} \leftarrow \frac{1}{m} \nabla_{\theta} \sum_i L(y^{(i)}, f(\tilde{x}^{(i)} | \theta))$ 
8:   Accumulate squared gradient  $r \leftarrow \rho r + (1 - \rho) \hat{g} \odot \hat{g}$ 
8:   Accumulate squared gradient  $r \leftarrow \rho r + (1 - \rho) g \odot g$ 
9:   Compute update:  $\nabla \theta = -\frac{\alpha}{\sqrt{r}} \odot g$ 
9:   Compute update:  $\nabla \theta = -\frac{\alpha}{\sqrt{r}} \odot g$ 
10:  Apply update:  $\theta \leftarrow \theta + \nabla \theta$ 
10:  Apply update:  $\theta \leftarrow \theta + \nabla \theta$ 
11: end while
11: end while
```



**Algorithm Adam**


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```

1: require Global step size  $\alpha$  (suggested default: 0.001)
2: require Exponential decay rates for moment estimates,  $\rho_1$  and  $\rho_2$  in  $[0, 1]$  (suggested de-
   faults: 0.9 and 0.999 respectively)
3: require Small constant  $\beta$  (suggested default  $10^{-8}$ )
4: require Initial parameters  $\theta$ 
5: Initialize time step  $t = 0$ 
6: Initialize 1st and 2nd moment variables  $s^{[0]} = 0, r^{[0]} = 0$ 
7: while stopping criterion not met do
8:    $t \leftarrow t + 1$ 
9:   Sample a minibatch of  $m$  examples from the training set  $\{\tilde{x}^{(1)}, \dots, \tilde{x}^{(m)}\}$ 
10:  Compute gradient estimate:  $\hat{g}^{[t]} \leftarrow \frac{1}{m} \nabla_{\theta} \sum_i L(y^{[i]}, f(\tilde{x}^{[i]} | \theta))$ 
11:  Update biased first moment estimate:  $\hat{s}^{[t]} \leftarrow \rho_1 s^{[t-1]} + (1 - \rho_1) \hat{g}^{[t]}$ 
12:  Update biased second moment estimate:  $\hat{r}^{[t]} \leftarrow \rho_2 r^{[t-1]} + (1 - \rho_2) \hat{g}^{[t]} \otimes \hat{g}^{[t]}$ 
13:  Correct bias in first moment:  $\hat{s} \leftarrow \frac{\hat{s}^{[t]}}{1 - \rho_1^{[t]}}$ 
14:  Correct bias in second moment:  $\hat{r} \leftarrow \frac{\hat{r}^{[t]}}{1 - \rho_2^{[t]}}$ 
15:  Compute update:  $\nabla \theta \equiv -\alpha \frac{\hat{s}}{\sqrt{\hat{r} + \beta}}$ 
16:  Apply update:  $\theta \leftarrow \theta + \nabla \theta$ 
17: end while

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