Estimation of the Gradient I

- Recall the function is

$$f(\boldsymbol{\theta}) = \frac{1}{2C}\boldsymbol{\theta}^T\boldsymbol{\theta} + \frac{1}{l}\sum_{i=1}^{l} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i})$$

- The gradient is

$$\frac{\boldsymbol{\theta}}{C} + \frac{1}{l}\nabla_{\boldsymbol{\theta}} \sum_{i=1}^{l} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i})$$

$$= \frac{\boldsymbol{\theta}}{C} + \frac{1}{l}\sum_{i=1}^{l} \nabla_{\boldsymbol{\theta}} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i})$$

Estimation of the Gradient II

- Going over all data is time consuming
- If data are from the same distribution

$$E(\nabla_{\boldsymbol{\theta}}\xi(\boldsymbol{\theta}; \boldsymbol{y}, Z^1)) = \frac{1}{l}\nabla_{\boldsymbol{\theta}} \sum_{i=1}^{l} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i})$$

then we may just use a subset S

$$\frac{\boldsymbol{\theta}}{C} + \frac{1}{|S|}\nabla_{\boldsymbol{\theta}} \sum_{i:i\in S} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i})$$

Stochastic Gradient Algorithm I

1: Given an initial learning rate η.
2: **while do**
3: Choose $S \subset \{1, \ldots, l\}$.
4: Calculate

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta\left(\frac{\boldsymbol{\theta}}{C} + \frac{1}{|S|}\nabla_{\boldsymbol{\theta}} \sum_{i:i\in S} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i})\right)$$

5: May adjust the learning rate η
6: **end while**

- It's known that deciding a suitable learning rate is difficult

Stochastic Gradient Algorithm II

- Too small learning rate: very slow convergence
- Too large learning rate: the procedure may diverge

Stochastic Gradient "Descent" I

- In comparison with gradient descent you see that we don't do line search
- Indeed we cannot. Without the full gradient, the sufficient decrease condition may never hold.

$$f(\boldsymbol{\theta} + \alpha\Delta\boldsymbol{\theta}) < f(\boldsymbol{\theta}) + \nu\nabla f(\boldsymbol{\theta})^T(\alpha\Delta\boldsymbol{\theta})$$

- Therefore, we don't have a "descent" algorithm here
- It's possible that

$$f(\boldsymbol{\theta}^{\text{next}}) > f(\boldsymbol{\theta})$$

- Though people frequently use "SGD," it's unclear if "D" is suitable in the name of this method

Momentum I

- This is a method to improve the convergence speed
- A new vector $\boldsymbol{v}$ and a parameter $\alpha \in [0, 1)$ are introduced

$$\boldsymbol{v} \leftarrow \alpha \boldsymbol{v} - \eta\left(\frac{\boldsymbol{\theta}}{C} + \frac{1}{|S|}\nabla_{\boldsymbol{\theta}} \sum_{i:i\in S} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i})\right)$$

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \boldsymbol{v}$$

Momentum II

- Essentially what we do is

$$\begin{aligned}\boldsymbol{\theta} \leftarrow \quad & \boldsymbol{\theta} - \eta(\text{current sub-gradient}) \\ & -\alpha\eta(\text{prev. sub-gradient}) \\ & -\alpha^2\eta(\text{prev. prev. sub-gradient}) - \cdots\end{aligned}$$

- There are some reasons why doing so can improve the convergence speed, though details are not discussed here

AdaGrad I

- Scaling learning rates inversely proportional to the square root of sum of past gradient squares (Duchi et al., 2011)
- Update rule:

$$\begin{aligned} \boldsymbol{g} &\leftarrow \frac{\boldsymbol{\theta}}{C} + \frac{1}{|S|}\nabla_{\boldsymbol{\theta}} \sum_{i:i\in S} \xi(\boldsymbol{\theta}; \boldsymbol{y}^i, Z^{1,i}) \\ \boldsymbol{r} &\leftarrow \boldsymbol{r} + \boldsymbol{g} \odot \boldsymbol{g} \\ \boldsymbol{\theta} &\leftarrow \boldsymbol{\theta} - \frac{\epsilon}{\sqrt{\boldsymbol{r}} + \delta} \odot \boldsymbol{g} \end{aligned}$$

- $\boldsymbol{r}$: sum of past gradient squares

AdaGrad II

ϵ and δ are given constants

- $\odot$: Hadamard product (element-wise product of two vectors/matrices)
- A large $\boldsymbol{g}$ component

  $\Rightarrow$ a larger $\boldsymbol{r}$ component

  $\Rightarrow$ fast decrease of the learning rate
- Conceptual explanation from Duchi et al. (2011):
  - frequently occurring features $\Rightarrow$ low learning rates
  - infrequent features $\Rightarrow$ high learning rates

AdaGrad III

"the intuition is that each time an infrequent feature is seen, the learner should take notice."

- But how is this explanation related to $\boldsymbol{g}$ components?
- Let's consider linear classification. Recall our optimization problem is

$$\frac{\boldsymbol{w}^T\boldsymbol{w}}{2} + C\sum_{i=1}^{l}\xi(\boldsymbol{w}; y_i, \boldsymbol{x}_i)$$

AdaGrad IV

- For methods such as SVM or logistic regression, the loss function can be written as a function of $\boldsymbol{w}^T\boldsymbol{x}$

$$\xi(\boldsymbol{w}; y, \boldsymbol{x}) = \hat{\epsilon}(\boldsymbol{w}^T\boldsymbol{x})$$

  Then the gradient is

$$\boldsymbol{w} + C\sum_{i=1}^{l} \hat{\epsilon}'(\boldsymbol{w}^T\boldsymbol{x}_i)\boldsymbol{x}_i$$

- Thus the gradient is related to the density of features

AdaGrad V

- The above analysis is for linear classification
- But now we have a non-convex neural network!
- Empirically, people find that the sum of squared gradient since the beginning causes too fast decrease of the learning rate

RMSProp I

- The original reference seems to be the lecture slides at `https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec6.pdf`
- Idea: they think AdaGrad's learning rate may be too small before reaching a locally convex region
- That is, OK to sum all past gradient squares in convex, but not non-convex
- Thus they do "exponentially weighted moving average"

RMSProp II

- Update rule

$$\begin{aligned} \boldsymbol{r} &\leftarrow \rho \boldsymbol{r} + (1-\rho)\boldsymbol{g} \odot \boldsymbol{g} \\ \boldsymbol{\theta} &\leftarrow \boldsymbol{\theta} - \frac{\epsilon}{\sqrt{\delta + \boldsymbol{r}}} \odot \boldsymbol{g} \end{aligned}$$

- AdaGrad:

$$\begin{aligned} \boldsymbol{r} &\leftarrow \boldsymbol{r} + \boldsymbol{g} \odot \boldsymbol{g} \\ \boldsymbol{\theta} &\leftarrow \boldsymbol{\theta} - \frac{\epsilon}{\sqrt{\boldsymbol{r}} + \delta} \odot \boldsymbol{g} \end{aligned}$$

RMSProp III

- Somehow the setting is a bit heuristic and the reason behind the change (from AdaGrad to RMSProp) is not really that strong

References I

J. Duchi, E. Hazan, and Y. Singer. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, 12:2121–2159, 2011.