

Optimization Theory

Lecture 13

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- 1 Stochastic Gradient Decent
- 2 Variance Reduction Methods

1 Stochastic Gradient Decent

2 Variance Reduction Methods

Large Scale Optimization

In machine learning, we usually learn model parameter $\mathbf{x} \in \mathbb{R}^d$ from

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \frac{1}{n} \sum_{i=1}^n f_i(\mathbf{x}),$$

where n may be very large.

More generally, we also consider the stochastic optimization problem

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \mathbb{E}_{\xi}[F(\mathbf{x}; \xi)],$$

where the random variable $\xi \sim \mathcal{D}$.

Stochastic Subgradient Descent

We consider the problem

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \mathbb{E}_{\xi}[F(\mathbf{x}; \xi)],$$

where each $F(\mathbf{x}; \xi)$ is convex but possibly nonsmooth.

Algorithm 1 Stochastic Subgradient Descent

- 1: **Input:** $\mathbf{x}_0, \{\eta_t\}_{t=0}^{T-1}$
 - 2: **for** $t = 0, \dots, T - 1$
 - 3: draw $\xi_t \sim \mathcal{D}$
 - 4: let $\mathbf{g}_t \in \partial F(\mathbf{x}_t; \xi_t)$
 - 5: $\mathbf{x}_{t+1} = \mathbf{x}_t - \eta_t \mathbf{g}_t$
 - 6: **end for**
 - 7: **Output:** $\bar{\mathbf{x}}_T = \left(\sum_{t=0}^{T-1} \eta_t \right)^{-1} \sum_{t=0}^{T-1} \eta_t \mathbf{x}_t$
-

Stochastic Subgradient Descent

Suppose each $F(\mathbf{x}; \xi)$ is convex and G -Lipschitz such that $\|\mathbf{g}\|_2 \leq G$ for any $\mathbf{g} \in \partial F(\mathbf{x}; \xi)$, then stochastic subgradient descent holds

$$\mathbb{E}[f(\bar{\mathbf{x}}_T)] \leq f(\hat{\mathbf{x}}) + \frac{\|\mathbf{x}_0 - \hat{\mathbf{x}}\|_2^2 + \sum_{t=0}^{T-1} G^2 \eta_t^2}{2 \sum_{t=0}^{T-1} \eta_t}.$$

Taking $\eta_t = \eta_0 / \sqrt{T}$, we have

$$\mathbb{E}[f(\bar{\mathbf{x}}_T)] \leq f(\hat{\mathbf{x}}) + \frac{\|\mathbf{x}_0 - \hat{\mathbf{x}}\|_2^2 + \eta_0^2 G^2}{2\eta_0 \sqrt{T}}.$$

Stochastic Subgradient Descent

We additionally suppose each $f(\mathbf{x})$ is μ -strongly convex and take $\eta_t = 2/(\mu(t+1))$, then we have

$$\mathbb{E}[f(\bar{\mathbf{x}}_T)] \leq f(\hat{\mathbf{x}}) + \frac{2G^2}{\mu(T-1)},$$

where

$$\bar{\mathbf{x}}_T = \sum_{t=0}^{T-1} \frac{t\mathbf{x}_t}{T(T-1)}.$$

Stochastic Gradient Descent

We consider the problem

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \mathbb{E}_{\xi}[F(\mathbf{x}; \xi)],$$

where each $F(\mathbf{x}; \xi)$ is L -smooth and convex.

We consider mini-batch stochastic gradient descent.

Algorithm 2 Mini-Batch Stochastic Gradient Descent

- 1: **Input:** $\mathbf{x}_0, \{\eta_t\}_{t=0}^{T-1}, b$
 - 2: **for** $t = 0, \dots, T - 1$
 - 3: draw $\xi_{t,1}, \dots, \xi_{t,b} \stackrel{\text{i.i.d.}}{\sim} \mathcal{D}$
 - 4: $\mathbf{x}_{t+1} = \mathbf{x}_t - \eta_t \cdot \frac{1}{b} \sum_{i=1}^b \nabla F(\mathbf{x}_t; \xi_{t,i})$
 - 5: **end for**
 - 6: **Output:** $\bar{\mathbf{x}}_T$ be weighed average of $\{\mathbf{x}_t\}_{t=0}^{T-1}$
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Running mini-batch SGD with $\eta_t = \eta \leq 1/(3L)$, we have

$$\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[f(\mathbf{x}_t)] - f(\mathbf{x}^*) \leq \frac{3 \|\mathbf{x}_0 - \mathbf{x}^*\|_2^2}{2\eta T} + \frac{3V^*\eta}{b},$$

where $V^* = \mathbb{E}_\xi \|\nabla F(\mathbf{x}^*; \xi) - \nabla f(\mathbf{x}^*)\|_2^2$ and

$$\bar{\mathbf{x}}_T = \frac{1}{T} \sum_{t=0}^{T-1} \mathbf{x}_t.$$

We consider μ -strongly convex case

- ① Taking $\eta_t = \eta \leq 1/(2L)$, we have

$$\mathbb{E} \|\mathbf{x}_T - \mathbf{x}^*\|_2^2 \leq (1 - 2\eta\mu)^T \|\mathbf{x}_0 - \mathbf{x}^*\|_2^2 + \frac{2\eta V^*}{2b\mu}.$$

- ② Taking $\eta_t = 2/(8L + \mu t)$, we have

$$\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[f(\mathbf{x}_t) - f(\mathbf{x}^*)] \leq \frac{4L}{T} \|\mathbf{x}_0 - \mathbf{x}^*\|_2^2 + \frac{4V^* \ln(T+1)}{b\mu T}.$$

Outline

- 1 Stochastic Gradient Decent
- 2 Variance Reduction Methods

Stochastic Gradient Descent

We consider the finite-sum problem

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \frac{1}{n} \sum_{i=1}^n f_i(\mathbf{x}),$$

where $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is μ -strongly convex and $f_i : \mathbb{R}^d \rightarrow \mathbb{R}$ is convex and L -smooth.

The convergence of SGD

$$\mathbf{x}_{t+1} = \mathbf{x}_t - \eta_t \nabla f_i(\mathbf{x}_t)$$

requires η_t converging to zero.

Variance Reduction Methods

We hope the iteration

$$\mathbf{x}_{t+1} = \mathbf{x}_t - \eta_t \mathbf{v}_t$$

such that \mathbf{v}_t converges to $\nabla f(\mathbf{x}_t)$ when \mathbf{x}_t converges to \mathbf{x}^* .

There are several variance reduction methods:

- 1 SAG (Stochastic Average Gradient)
- 2 SVRG (Stochastic Variance Reduced Gradient)
- 3 SAGA (What is the full name?)
- 4 Katyusha (A Russian of Soviet era folk-based song)
- 5 SARAH (StochAstic Recursive grAdient algorithM)
- 6 SPIDER (Stochastic Path-Integrated Differential Estimator)

Stochastic Average Gradient (SAG)

The SAG iterations take the form

$$\mathbf{x}_{t+1} = \mathbf{x}_t - \eta_t \cdot \frac{1}{n} \sum_{i=1}^n \mathbf{g}_{i,t},$$

where at each iteration a random index i_t is selected and we set

$$\mathbf{g}_{i,t} = \begin{cases} \nabla f_i(\mathbf{x}_t) & \text{if } i = i_t, \\ \mathbf{g}_{i,t-1} & \text{otherwise.} \end{cases}$$

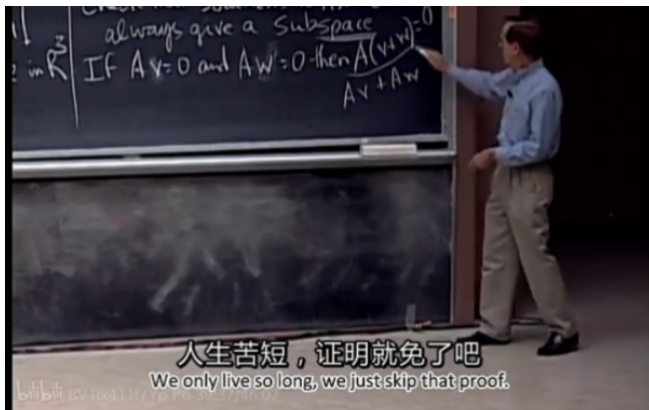
Taking $\eta_t = 1/(16L)$, we have

$$\mathbb{E}[f(\mathbf{x}_t)] - f(\mathbf{x}^*) \leq \left(1 - \min \left\{ \frac{\mu}{16L}, \frac{1}{n} \right\}\right)^t C_0$$

for some constant $C_0 > 0$.

Stochastic Average Gradient (SAG)

“The analysis of SAG is notoriously difficult, which is perhaps due to the estimator of gradient being biased.” — Francis Bach



Stochastic Variance Reduced Gradient (SVRG)

We keep a snap shot point $\tilde{\mathbf{x}}$ and maintain

$$\tilde{\mu} = \nabla f(\tilde{\mathbf{x}}) = \frac{1}{n} \sum_{i=1}^n \nabla f_i(\tilde{\mathbf{x}}).$$

We apply the update

$$\mathbf{x}_{t+1} = \mathbf{x}_t - \eta_t (\nabla f_i(\mathbf{x}_t) - \nabla f_i(\tilde{\mathbf{x}}) + \tilde{\mu}),$$

where i is randomly sampled from $\{1, \dots, n\}$.

If \mathbf{x}_t and $\tilde{\mathbf{x}}$ tends to \mathbf{x}^* , then

$$\nabla f_i(\mathbf{x}_t) - \nabla f_i(\tilde{\mathbf{x}}) + \tilde{\mu} \rightarrow 0.$$

We also have

$$\mathbb{E}_i [\nabla f_i(\mathbf{x}_t) - \nabla f_i(\tilde{\mathbf{x}}) + \tilde{\mu}] = \nabla f(\mathbf{x}_t).$$

Stochastic Variance Reduced Gradient (SVRG)

Algorithm 3 Stochastic Variance Reduced Gradient

```
1: Input:  $\mathbf{x}_0, \eta, m$ 
2:  $\tilde{\mathbf{x}}^{(0)} = \mathbf{x}_0$ 
3: for  $s = 0, \dots, S - 1$ 
4:    $\tilde{\mu} = \nabla f(\tilde{\mathbf{x}}^{(s)})$ 
5:    $\mathbf{x}_0 = \tilde{\mathbf{x}} = \tilde{\mathbf{x}}^{(s)}$ 
6:   for  $t = 0, \dots, m - 1$ 
7:     draw  $i_t$  from  $\{1, \dots, n\}$  uniformly
8:      $\mathbf{x}_{t+1} = \mathbf{x}_t - \eta_t(\nabla f_{i_t}(\mathbf{x}_t) - \nabla f_{i_t}(\tilde{\mathbf{x}}) + \tilde{\mu}),$ 
9:   end for
10:  Option I:  $\tilde{\mathbf{x}}^{(s)} = \mathbf{x}_m$ 
11:  Option II:  $\tilde{\mathbf{x}}^{(s)} = \mathbf{x}_t$  for randomly chosen  $t \in \{0, \dots, m - 1\}$ 
12: end for
13: Output:  $\tilde{\mathbf{x}}^{(S)}$ 
```

Stochastic Variance Reduced Gradient (SVRG)

Assume $\eta < 1/(2L)$ and m is sufficient large so that

$$\rho = \frac{1}{\mu\eta(1-2L\eta)m} + \frac{2L\eta}{1-2L\eta} < 1,$$

then SVRG holds that

$$\mathbb{E}[f(\tilde{\mathbf{x}}^{(s)}) - f(\mathbf{x}^*)] \leq \rho^s(f(\tilde{\mathbf{x}}_0) - f(\mathbf{x}^*)).$$

The incremental first-order oracle complexity to achieve

$$\mathbb{E}[f(\tilde{\mathbf{x}}^{(s)}) - f(\mathbf{x}^*)] \leq \epsilon$$

is at most $\mathcal{O}((\kappa + n) \log(1/\epsilon))$.