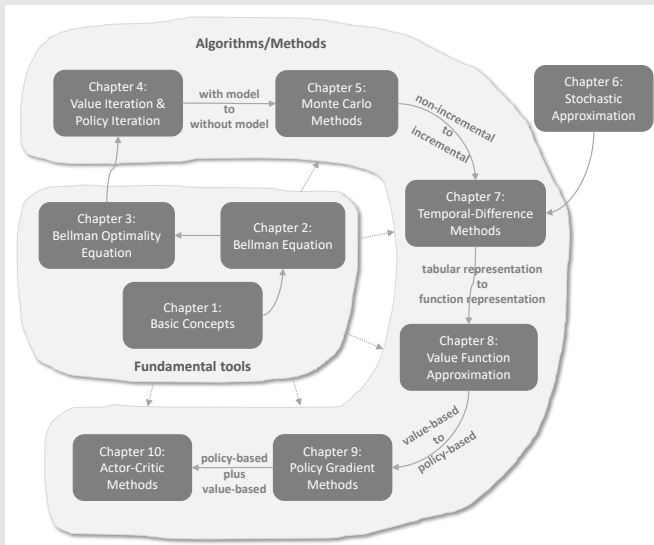


Lecture 6:
Stochastic Approximation
and
Stochastic Gradient Descent

Shiyu Zhao



- In the last lecture, we introduced Monte-Carlo learning.
- In the next lecture, we will introduce temporal-difference (TD) learning.
- In this lecture, we press the pause button to get us better prepared.

Why?

- The ideas and expressions of TD algorithms are very different from the algorithms we studied so far.
- Many students who see the TD algorithms the first time many wonder why these algorithms were designed in the first place and why they work effectively.
- There is a knowledge gap!

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- There is a **knowledge gap**!

In this lecture,

- We fill the knowledge gap between the previous and upcoming lectures by introducing basic **stochastic approximation (SA)** algorithms.
- We will see in the next lecture that the **temporal-difference algorithms are special SA algorithms**. As a result, it will be much easier to understand these algorithms.
- We will also understand the important algorithm of **stochastic gradient descent (SGD)**.

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 - Convergence analysis
 - Application to mean estimation
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Motivating example: mean estimation, again

Revisit the mean estimation problem:

- Consider a random variable X .
- Suppose that we collected a sequence of iid samples $\{x_i\}_{i=1}^N$.
- Our aim is to estimate $\mathbb{E}[X]$.
- The expectation of X can be approximated by

$$\mathbb{E}[X] \approx \bar{x} := \frac{1}{N} \sum_{i=1}^N x_i.$$

- This approximation is the basic idea of Monte Carlo estimation.
- We know that $\bar{x} \rightarrow \mathbb{E}[X]$ as $N \rightarrow \infty$.

Why do we care about mean estimation so much?

- Many quantities in RL such as action values and gradients are defined as expectations!

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New question: how to calculate the mean \bar{x} ?

$$\mathbb{E}[X] \approx \bar{x} := \frac{1}{N} \sum_{i=1}^N x_i.$$

We have two ways.

- **The first way**, which is trivial, is to collect all the samples then calculate the average.
 - The drawback of such way is that, if the samples are collected one by one over a period of time, we have to wait until all the samples to be collected.
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Motivating example: mean estimation

In particular, suppose

$$w_{k+1} = \frac{1}{k} \sum_{i=1}^k x_i, \quad k = 1, 2, \dots$$

and hence

$$w_k = \frac{1}{k-1} \sum_{i=1}^{k-1} x_i, \quad k = 2, 3, \dots$$

Then, w_{k+1} can be expressed in terms of w_k as

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Therefore, we obtain the following iterative algorithm:

$$w_{k+1} = w_k - \frac{1}{k}(w_k - x_k).$$

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to calculate the mean \bar{x} incrementally:

$$w_1 = x_1,$$

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Remarks about this algorithm:

$$w_{k+1} = w_k - \frac{1}{k}(w_k - x_k).$$

- An **advantage** of this algorithm is that it is **incremental**. A mean estimate can be obtained immediately once a sample is received. Then, the mean estimate can be used for other purposes immediately.
- The mean estimate is not accurate in the beginning due to insufficient samples (that is $w_k \neq \mathbb{E}[X]$). However, **it is better than nothing**. As more samples are obtained, the estimate can be improved gradually (that is $w_k \rightarrow \mathbb{E}[X]$ as $k \rightarrow \infty$).

Furthermore, consider an algorithm with a more general expression:

$$w_{k+1} = w_k - \alpha_k (w_k - x_k),$$

where $1/k$ is replaced by $\alpha_k > 0$.

- Does this algorithm still converge to the mean $\mathbb{E}[X]$? We will show that the answer is yes if $\{\alpha_k\}$ satisfy some mild conditions.
- We will also show that this algorithm is a special SA algorithm and also a special stochastic gradient descent algorithm.
- In the next lecture, we will see that the temporal-difference algorithms have similar (but more complex) expressions.

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- SA refers to a broad class of stochastic iterative algorithms solving root finding or optimization problems.
- Compared to many other root-finding algorithms such as gradient-based methods, SA is powerful in the sense that it does *not* require to know the expression of the objective function nor its derivative.

Robbins-Monro (RM) algorithm:

- This is a pioneering work in the field of stochastic approximation.
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Problem statement: Suppose we would like to find the root of the equation

$$g(w) = 0,$$

where $w \in \mathbb{R}$ is the variable to be solved and $g : \mathbb{R} \rightarrow \mathbb{R}$ is a function.

- Many problems can be eventually converted to this root finding problem. For example, suppose $J(w)$ is an objective function to be minimized. Then, the optimization problem can be converted to

$$g(w) = \nabla_w J(w) = 0$$

- Note that an equation like $g(w) = c$ with c as a constant can also be converted to the above equation by rewriting $g(w) - c$ as a new function.

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How to calculate the root of $g(w) = 0$?

- Model-based: If the expression of g is known, there are many numerical algorithms that can solve this problem.
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The Robbins-Monro (RM) algorithm that can solve this problem is as follows:

$$w_{k+1} = w_k - a_k \tilde{g}(w_k, \eta_k), \quad k = 1, 2, 3, \dots$$

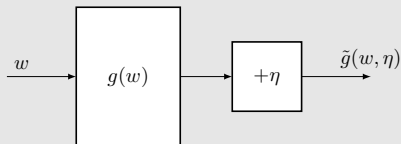
where

- w_k is the k th estimate of the root
- $\tilde{g}(w_k, \eta_k) = g(w_k) + \eta_k$ is the k th noisy observation
- a_k is a positive coefficient.

Robbins-Monro algorithm – The algorithm

This algorithm relies on data instead of model:

- Input sequence: $\{w_k\}$
- Noisy output sequence: $\{\tilde{g}(w_k, \eta_k)\}$



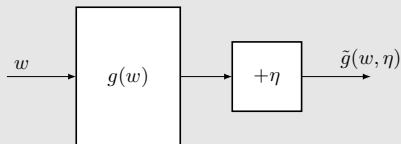
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$$w_2 = w_1 - a_1 g(w_1) = 20 - 0.5 * 10 = 15 \implies g(w_2) = 5$$

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\vdots

$$w_k \rightarrow 10$$

Robbins-Monro algorithm – Illustrative examples

Another example: solve $g(w) = w^3 - 5$ using the RM algorithm.

- The true root is $5^{1/3} \approx 1.71$.
- We only know $\tilde{g}(w) = g(w) + \eta$.
- Suppose η_k is iid and obeys a standard normal distribution with a mean of zero and standard deviation of 1.
- The initial guess is $w_1 = 0$ and a_k is selected to be $a_k = 1/k$.

The evolution of w_k is shown in the figure. As can be seen, the estimate w_k can converge to the true root.

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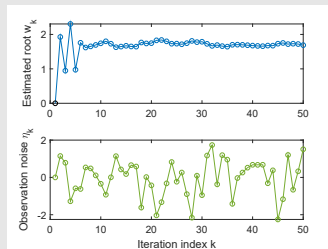


Figure: An illustrative example of the RM algorithm.

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Why can the RM algorithm find the root of $g(w) = 0$?

- First present an illustrative example.
- Second give the rigorous convergence analysis.

An illustrative example:

- $g(w) = \tanh(w - 1)$
- The true root of $g(w) = 0$ is $w^* = 1$.
- Parameters: $w_1 = 3$, $a_k = 1/k$, $\eta_k \equiv 0$ (no noise for the sake of simplicity)

The RM algorithm in this case is

$$w_{k+1} = w_k - a_k g(w_k)$$

since $\tilde{g}(w_k, \eta_k) = g(w_k)$ when $\eta_k = 0$.

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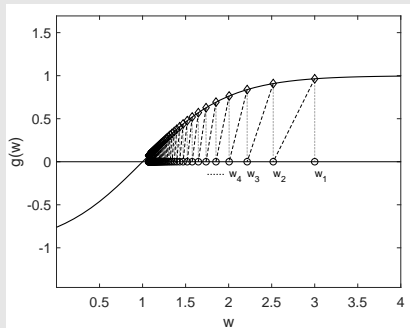
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Robbins-Monro algorithm – Convergence properties

Simulation result: w_k converges to the true root $w^* = 1$.

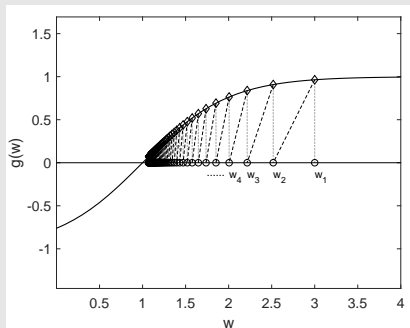


Intuition: w_{k+1} is closer to w^* than w_k .

- When $w_k > w^*$, we have $g(w_k) > 0$. Then, $w_{k+1} = w_k - a_k g(w_k) < w_k$ and hence w_{k+1} is closer to w^* than w_k .
- When $w_k < w^*$, we have $g(w_k) < 0$. Then, $w_{k+1} = w_k - a_k g(w_k) > w_k$ and w_{k+1} is closer to w^* than w_k .

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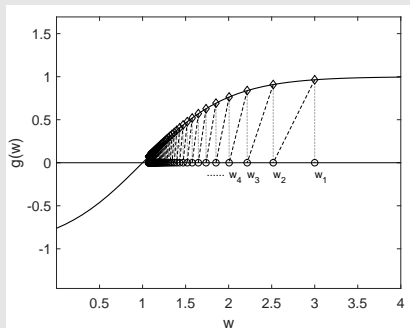


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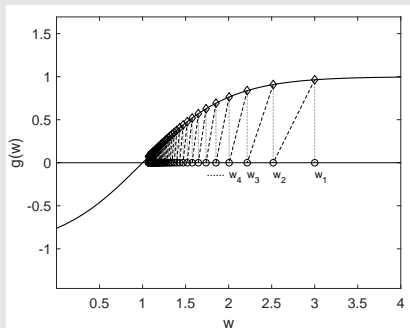


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The above analysis is intuitive, but not rigorous. A rigorous convergence result is given below.

Theorem (Robbins-Monro Theorem)

In the Robbins-Monro algorithm, if

- 1) $0 < c_1 \leq \nabla_w g(w) \leq c_2$ for all w ;*
- 2) $\sum_{k=1}^{\infty} a_k = \infty$ and $\sum_{k=1}^{\infty} a_k^2 < \infty$;*
- 3) $\mathbb{E}[\eta_k | \mathcal{H}_k] = 0$ and $\mathbb{E}[\eta_k^2 | \mathcal{H}_k] < \infty$;*

where $\mathcal{H}_k = \{w_k, w_{k-1}, \dots\}$, then w_k converges with probability 1 (w.p.1) to the root w^ satisfying $g(w^*) = 0$.*

Explanation of the three conditions:

- **Condition 1:** $0 < c_1 \leq \nabla_w g(w) \leq c_2$ for all w
 - g should be monotonically increasing, which ensures that the root of $g(w) = 0$ exists and is unique
 - The gradient is bounded from the above.
 - This condition is not strict. Consider the example $g(w) = \nabla_w J(w) = 0$. This condition requires that $g(w)$ is convex.
- **Condition 2:** $\sum_{k=1}^{\infty} a_k = \infty$ and $\sum_{k=1}^{\infty} a_k^2 < \infty$
 - $\sum_{k=1}^{\infty} a_k^2 < \infty$ ensures that a_k converges to zero as $k \rightarrow \infty$.
 - $\sum_{k=1}^{\infty} a_k = \infty$ ensures that a_k do not converge to zero too fast.
- **Condition 3:** $\mathbb{E}[\eta_k | \mathcal{H}_k] = 0$ and $\mathbb{E}[\eta_k^2 | \mathcal{H}_k] < \infty$
 - A special yet common case is that $\{\eta_k\}$ is an iid stochastic sequence satisfying $\mathbb{E}[\eta_k] = 0$ and $\mathbb{E}[\eta_k^2] < \infty$. The observation error η_k is not required to be Gaussian.

Explanation of the three conditions:

- **Condition 1:** $0 < c_1 \leq \nabla_w g(w) \leq c_2$ for all w
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Examine the second condition more closely:

$$\sum_{k=1}^{\infty} a_k^2 < \infty \quad \sum_{k=1}^{\infty} a_k = \infty$$

- First, $\sum_{k=1}^{\infty} a_k^2 < \infty$ indicates that $a_k \rightarrow 0$ as $k \rightarrow \infty$.
- Why is this condition important?

Since

$$w_{k+1} - w_k = -a_k \tilde{g}(w_k, \eta_k),$$

- If $a_k \rightarrow 0$, then $a_k \tilde{g}(w_k, \eta_k) \rightarrow 0$ and hence $w_{k+1} - w_k \rightarrow 0$.
- We need the fact that $w_{k+1} - w_k \rightarrow 0$ if w_k converges eventually.
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Summarizing $w_2 = w_1 - a_1 \tilde{g}(w_1, \eta_1)$, $w_3 = w_2 - a_2 \tilde{g}(w_2, \eta_2)$, \dots ,
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Robbins-Monro algorithm – Convergence properties

What $\{a_k\}$ satisfies the two conditions? $\sum_{k=1}^{\infty} a_k^2 < \infty, \sum_{k=1}^{\infty} a_k = \infty$

One typical sequence is

$$a_k = \frac{1}{k}$$

- It holds that

$$\lim_{n \rightarrow \infty} \left(\sum_{k=1}^n \frac{1}{k} - \ln n \right) = \kappa,$$

where $\kappa \approx 0.577$ is called the Euler-Mascheroni constant (also called Euler's constant).

- It is notable that

$$\sum_{k=1}^{\infty} \frac{1}{k^2} = \frac{\pi^2}{6} < \infty.$$

The limit $\sum_{k=1}^{\infty} 1/k^2$ also has a specific name in the number theory: Basel problem.

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If the three conditions are not satisfied, the algorithm may not work.

- For example, $g(w) = w^3 - 5$ does not satisfy the first condition on gradient boundedness. If the initial guess is good, the algorithm can converge (locally). Otherwise, it will diverge.

We will see that a_k is often selected as a sufficiently small constant in many RL algorithms. Although the second condition is not satisfied in this case, the algorithm can still work effectively.

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$$w_{k+1} = w_k + \alpha_k(x_k - w_k).$$

is the mean estimation algorithm.

We know that

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$$g(w) \doteq w - \mathbb{E}[X].$$

Our aim is to solve $g(w) = 0$. If we can do that, then we can obtain $\mathbb{E}[X]$.

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$$\tilde{g}(w, x) \doteq w - x,$$

because we can only obtain samples of X . Note that

$$\begin{aligned}\tilde{g}(w, \eta) &= w - x = w - x + \mathbb{E}[X] - \mathbb{E}[X] \\ &= (w - \mathbb{E}[X]) + (\mathbb{E}[X] - x) \doteq g(w) + \eta,\end{aligned}$$

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Dvoretzky's convergence theorem (optional)

Theorem (Dvoretzky's Theorem)

Consider a stochastic process

$$w_{k+1} = (1 - \alpha_k)w_k + \beta_k \eta_k,$$

where $\{\alpha_k\}_{k=1}^{\infty}$, $\{\beta_k\}_{k=1}^{\infty}$, $\{\eta_k\}_{k=1}^{\infty}$ are stochastic sequences. Here $\alpha_k \geq 0$, $\beta_k \geq 0$ for all k .

Then, w_k would converge to zero with probability 1 if the following conditions are satisfied:

- 1) $\sum_{k=1}^{\infty} \alpha_k = \infty$, $\sum_{k=1}^{\infty} \alpha_k^2 < \infty$; $\sum_{k=1}^{\infty} \beta_k^2 < \infty$ uniformly w.p.1;
- 2) $\mathbb{E}[\eta_k | \mathcal{H}_k] = 0$ and $\mathbb{E}[\eta_k^2 | \mathcal{H}_k] \leq C$ w.p.1;

where $\mathcal{H}_k = \{w_k, w_{k-1}, \dots, \eta_{k-1}, \dots, \alpha_{k-1}, \dots, \beta_{k-1}, \dots\}$.

- A more general result than the RM theorem. It can be used to prove the RM theorem
- It can also directly analyze the mean estimation problem.
- An extension of it can be used to analyze Q-learning and TD learning algorithms.

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Next, we introduce stochastic gradient descent (SGD) algorithms:

- SGD is widely used in the field of machine learning and also in RL.
- SGD is a special RM algorithm.
- The mean estimation algorithm is a special SGD algorithm.

Problem setup: Suppose we aim to solve the following optimization problem:

$$\min_w J(w) = \mathbb{E}[f(w, X)]$$

- w is the parameter to be optimized.
- X is a random variable. The expectation is with respect to X .
- w and X can be either scalars or vectors. The function $f(\cdot)$ is a scalar.

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$$w_{k+1} = w_k - \alpha_k \nabla_w \mathbb{E}[f(w_k, X)] = w_k - \alpha_k \mathbb{E}[\nabla_w f(w_k, X)]$$

How to calculate the expectation? Model-based or model-free

We focus on model-free here.

Method 2: batch gradient descent (BGD)

$$\mathbb{E}[\nabla_w f(w_k, X)] \approx \frac{1}{n} \sum_{i=1}^n \nabla_w f(w_k, x_i).$$

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Method 3: stochastic gradient descent (SGD)

$$w_{k+1} = w_k - \alpha_k \nabla_w f(w_k, x_k),$$

- Compared to the gradient descent method: Replace the **true gradient** $\mathbb{E}[\nabla_w f(w_k, X)]$ by the **stochastic gradient** $\nabla_w f(w_k, x_k)$.
- Compared to the batch gradient descent method: let $n = 1$.

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We next consider an example:

$$\min_w J(w) = \mathbb{E}[f(w, X)] = \mathbb{E} \left[\frac{1}{2} \|w - X\|^2 \right],$$

where

$$f(w, X) = \|w - X\|^2 / 2 \quad \nabla_w f(w, X) = w - X$$

Excises:

- Excise 1: Show that the optimal solution is $w^* = \mathbb{E}[X]$.
- Excise 2: Write out the GD algorithm for solving this problem.
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Answer:

- The GD algorithm for solving the above problem is

$$\begin{aligned}w_{k+1} &= w_k - \alpha_k \nabla_w J(w_k) \\&= w_k - \alpha_k \mathbb{E}[\nabla_w f(w_k, X)] \\&= w_k - \alpha_k \mathbb{E}[w_k - X].\end{aligned}$$

- The SGD algorithm for solving the above problem is

$$w_{k+1} = w_k - \alpha_k \nabla_w f(w_k, x_k) = w_k - \alpha_k (w_k - x_k)$$

- Note:
 - It is the same as the mean estimation algorithm we presented before.
 - That mean estimation algorithm is a special SGD algorithm.

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Stochastic gradient descent – Convergence

From GD to SGD:

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$$w_{k+1} = w_k - \alpha_k \nabla_w f(w_k, x_k)$$

- $\mathbb{E}[\nabla_w f(w_k, X)]$: true gradient
- $\nabla_w f(w_k, X)$: stochastic gradient

The stochastic gradient is a noisy measurement or an approximation of the true gradient:

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where η is the noise. Since

$$\nabla_w f(w_k, x_k) \neq \mathbb{E}[\nabla_w f(w, X)]$$

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We next show that **SGD is a special RM algorithm**. Then, the convergence naturally follows.

The aim of SGD is to minimize

$$J(w) = \mathbb{E}[f(w, X)]$$

This problem can be converted to a root-finding problem:

$$\nabla_w J(w) = \mathbb{E}[\nabla_w f(w, X)] = 0$$

Let

$$g(w) = \nabla_w J(w) = \mathbb{E}[\nabla_w f(w, X)].$$

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What we can measure is

$$\begin{aligned}\tilde{g}(w, \eta) &= \nabla_w f(w, x) \\ &= \underbrace{\mathbb{E}[\nabla_w f(w, X)]}_{g(w)} + \underbrace{\nabla_w f(w, x) - \mathbb{E}[\nabla_w f(w, X)]}_{\eta}.\end{aligned}$$

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Since SGD is a special RM algorithm, its convergence naturally follows.

Theorem (Convergence of SGD)

In the SGD algorithm, if

- 1) $0 < c_1 \leq \nabla_w^2 f(w, X) \leq c_2$;*
- 2) $\sum_{k=1}^{\infty} a_k = \infty$ and $\sum_{k=1}^{\infty} a_k^2 < \infty$;*
- 3) $\{x_k\}_{k=1}^{\infty}$ is iid;*

then w_k converges to the root of $\nabla_w \mathbb{E}[f(w, X)] = 0$ with probability 1.

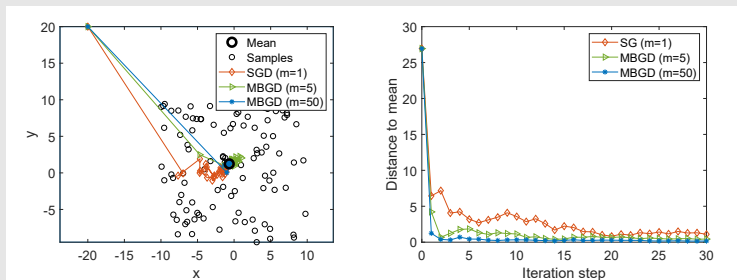
For the proof see the book.

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Question: Since the stochastic gradient is random and hence the approximation is inaccurate, *whether the convergence of SGD is slow or random?*

Stochastic gradient descent – Convergence pattern

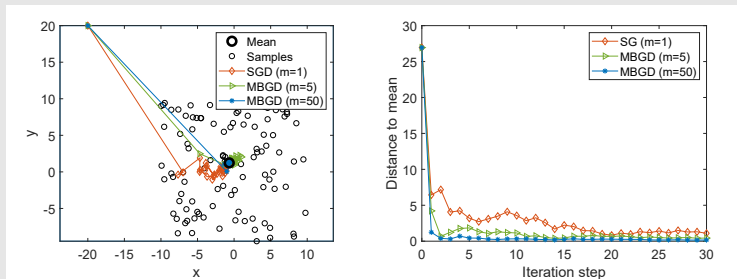
Example: $X \in \mathbb{R}^2$ represents a random position in the plane. Its distribution is uniform in the square area centered at the origin with the side length as 20. The true mean is $\mathbb{E}[X] = 0$. The mean estimation is based on 100 iid samples $\{x_i\}_{i=1}^{100}$.



- When the estimate (e.g., the initial guess) is far away from the true value, the SGD estimate can approach the neighborhood of the true value fast.
- When the estimate is close to the true value, it exhibits certain randomness but still approaches the true value gradually.

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Question: Why such a pattern?

Answer: We answer this question by considering the **relative error** between the stochastic and batch gradients:

$$\delta_k \doteq \frac{|\nabla_w f(w_k, x_k) - \mathbb{E}[\nabla_w f(w_k, X)]|}{|\mathbb{E}[\nabla_w f(w_k, X)]|}.$$

Since $\mathbb{E}[\nabla_w f(w^*, X)] = 0$, we further have

$$\delta_k = \frac{|\nabla_w f(w_k, x_k) - \mathbb{E}[\nabla_w f(w_k, X)]|}{|\mathbb{E}[\nabla_w f(w_k, X)] - \mathbb{E}[\nabla_w f(w^*, X)]|} = \frac{|\nabla_w f(w_k, x_k) - \mathbb{E}[\nabla_w f(w_k, X)]|}{|\mathbb{E}[\nabla_w^2 f(\tilde{w}_k, X)(w_k - w^*)]|}.$$

where the last equality is due to the mean value theorem and $\tilde{w}_k \in [w_k, w^*]$.

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Suppose f is strictly convex such that

$$\nabla_w^2 f \geq c > 0$$

for all w, X , where c is a positive bound.

Then, the denominator of δ_k becomes

$$\begin{aligned} |\mathbb{E}[\nabla_w^2 f(\tilde{w}_k, X)(w_k - w^*)]| &= |\mathbb{E}[\nabla_w^2 f(\tilde{w}_k, X)](w_k - w^*)| \\ &= |\mathbb{E}[\nabla_w^2 f(\tilde{w}_k, X)]| |w_k - w^*| \geq c |w_k - w^*|. \end{aligned}$$

Substituting the above inequality to δ_k gives

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The above equation suggests an interesting convergence pattern of SGD.

- The relative error δ_k is inversely proportional to $|w_k - w^*|$.
- When $|w_k - w^*|$ is large, δ_k is small and SGD behaves like GD.
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Suppose we would like to minimize $J(w) = \mathbb{E}[f(w, X)]$ given a set of random samples $\{x_i\}_{i=1}^n$ of X . The BGD, SGD, MBGD algorithms solving this problem are, respectively,

$$w_{k+1} = w_k - \alpha_k \frac{1}{n} \sum_{i=1}^n \nabla_w f(w_k, x_i), \quad (\text{BGD})$$

$$w_{k+1} = w_k - \alpha_k \frac{1}{m} \sum_{j \in \mathcal{I}_k} \nabla_w f(w_k, x_j), \quad (\text{MBGD})$$

$$w_{k+1} = w_k - \alpha_k \nabla_w f(w_k, x_k). \quad (\text{SGD})$$

- In the BGD algorithm, all the samples are used in every iteration. When n is large, $(1/n) \sum_{i=1}^n \nabla_w f(w_k, x_i)$ is close to the true gradient $\mathbb{E}[\nabla_w f(w_k, X)]$.
- In the MBGD algorithm, \mathcal{I}_k is a subset of $\{1, \dots, n\}$ with the size as $|\mathcal{I}_k| = m$. The set \mathcal{I}_k is obtained by m times iid samplings.
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$$w_{k+1} = w_k - \alpha_k \frac{1}{m} \sum_{j \in \mathcal{I}_k} \nabla_w f(w_k, x_j), \quad (\text{MBGD})$$

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- **In the BGD algorithm**, all the samples are used in every iteration. When n is large, $(1/n) \sum_{i=1}^n \nabla_w f(w_k, x_i)$ is close to the true gradient $\mathbb{E}[\nabla_w f(w_k, X)]$.
- **In the MBGD algorithm**, \mathcal{I}_k is a subset of $\{1, \dots, n\}$ with the size as $|\mathcal{I}_k| = m$. The set \mathcal{I}_k is obtained by m times iid samplings.
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Compare MBGD with BGD and SGD:

- Compared to SGD, MBGD has less randomness because it uses more samples instead of just one as in SGD.
- Compared to BGD, MBGD does not require to use all the samples in every iteration, making it more flexible and efficient.
- If $m = 1$, MBGD becomes SGD.
- If $m = n$, MBGD does NOT become BGD strictly speaking because MBGD uses randomly fetched n samples whereas BGD uses all n numbers. In particular, MBGD may use a value in $\{x_i\}_{i=1}^n$ multiple times whereas BGD uses each number once.

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BGD, MBGD, and SGD – Illustrative examples

Given some numbers $\{x_i\}_{i=1}^n$, our aim is to calculate the mean $\bar{x} = \sum_{i=1}^n x_i/n$.

This problem can be equivalently stated as the following optimization problem:

$$\min_w J(w) = \frac{1}{2n} \sum_{i=1}^n \|w - x_i\|^2$$

The three algorithms for solving this problem are, respectively,

$$w_{k+1} = w_k - \alpha_k \frac{1}{n} \sum_{i=1}^n (w_k - x_i) = w_k - \alpha_k (w_k - \bar{x}), \quad (\text{BGD})$$

$$w_{k+1} = w_k - \alpha_k \frac{1}{m} \sum_{j \in \mathcal{I}_k} (w_k - x_j) = w_k - \alpha_k (w_k - \bar{x}_k^{(m)}), \quad (\text{MBGD})$$

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where $\bar{x}_k^{(m)} = \sum_{j \in \mathcal{I}_k} x_j/m$.

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where $\bar{x}_k^{(m)} = \sum_{j \in \mathcal{I}_k} x_j / m$.

Furthermore, if $\alpha_k = 1/k$, the above equation can be solved as

$$w_{k+1} = \frac{1}{k} \sum_{j=1}^k \bar{x} = \bar{x}, \quad (\text{BGD})$$

$$w_{k+1} = \frac{1}{k} \sum_{j=1}^k \bar{x}_j^{(m)}, \quad (\text{MBGD})$$

$$w_{k+1} = \frac{1}{k} \sum_{j=1}^k x_j. \quad (\text{SGD})$$

- The estimate of BGD at each step is exactly the optimal solution $w^* = \bar{x}$.
- The estimate of MBGD approaches the mean faster than SGD because $\bar{x}_k^{(m)}$ is already an average.

Let $\alpha_k = 1/k$. Given 100 points, using different mini-batch sizes leads to different convergence speed.

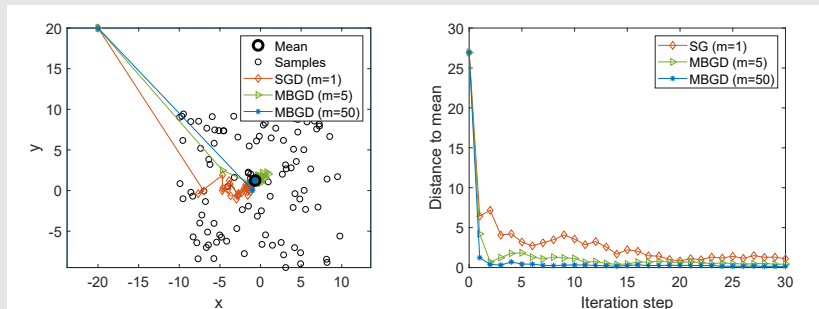


Figure: An illustrative example for mean estimation by different GD algorithms.

- 1 Motivating examples
- 2 Robbins-Monro algorithm
 - Algorithm description
 - Illustrative examples
 - Convergence analysis
 - Application to mean estimation
- 3 Stochastic gradient descent
 - Algorithm description
 - Examples and application
 - Convergence analysis
 - Convergence pattern
 - BGD, MBGD, and SGD
- 4 Summary

- Mean estimation: compute $\mathbb{E}[X]$ using $\{x_k\}$

$$w_{k+1} = w_k - \frac{1}{k}(w_k - x_k).$$

- RM algorithm: solve $g(w) = 0$ using $\{\tilde{g}(w_k, \eta_k)\}$

$$w_{k+1} = w_k - a_k \tilde{g}(w_k, \eta_k)$$

- SGD algorithm: minimize $J(w) = \mathbb{E}[f(w, X)]$ using $\{\nabla_w f(w_k, x_k)\}$

$$w_{k+1} = w_k - \alpha_k \nabla_w f(w_k, x_k),$$

These results are useful:

- We will see in the next chapter that the temporal-difference learning algorithms can be viewed as stochastic approximation algorithms and hence have similar expressions.
- They are important optimization techniques that can be applied to many other fields.