Introduction to Machine Learning and Stochastic Optimization

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Solving the Finite Sum Training Problem

Optimization Sum of Terms

A Datum Function

$$f_i(w) := \ell\left(h_w(x^i), y^i\right) + \lambda R(w)$$

$$\begin{aligned}\frac{1}{n}\sum_{i=1}^{n} \ell\left(h_w(x^i), y^i\right) + \lambda R(w) &= \frac{1}{n}\sum_{i=1}^{n}\left(\ell\left(h_w(x^i), y^i\right) + \lambda R(w)\right)\\ &= \frac{1}{n}\sum_{i=1}^{n} f_i(w)\end{aligned}$$

Finite Sum Training Problem

$$\min_{w \in \mathbf{R}^d} \frac{1}{n}\sum_{i=1}^{n} f_i(w) =: f(w)$$

The Training Problem

Solving the *training problem*:

$$\min_{w \in \mathbf{R}^d} \frac{1}{n} \sum_{i=1}^{n} f_i(w)$$

Reference method: Gradient descent

$$\nabla \left(\frac{1}{n} \sum_{i=1}^{n} f_i(w) \right) = \frac{1}{n} \sum_{i=1}^{n} \nabla f_i(w)$$

Gradient Descent Algorithm

Set $w^0 = 0$, choose $\alpha > 0$.

for $t = 1, 2, 3, \ldots, T$

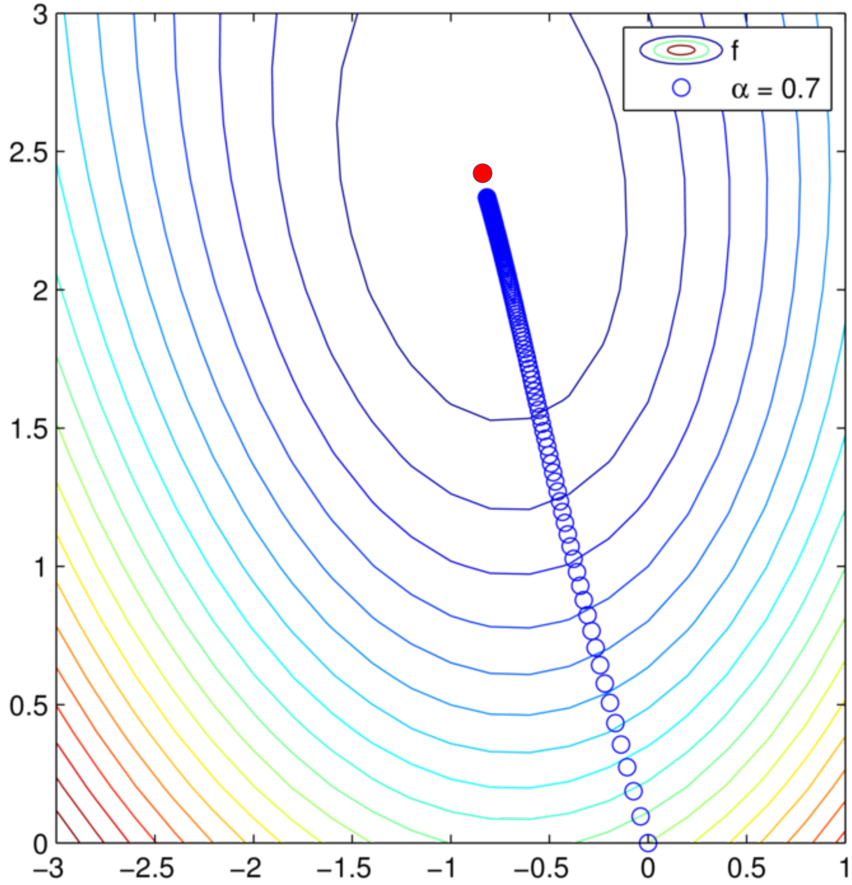
$$w^{t+1} = w^t - \frac{\alpha}{n} \sum_{i=1}^{n} \nabla f_i(w^t)$$

Output w^{T+1}

Gradient Descent Example

A Logistic Regression problem using the fourclass labelled data from LIBSVM

$(n,\ d) = (862,2)$



Gradient Descent Example

Optimal point

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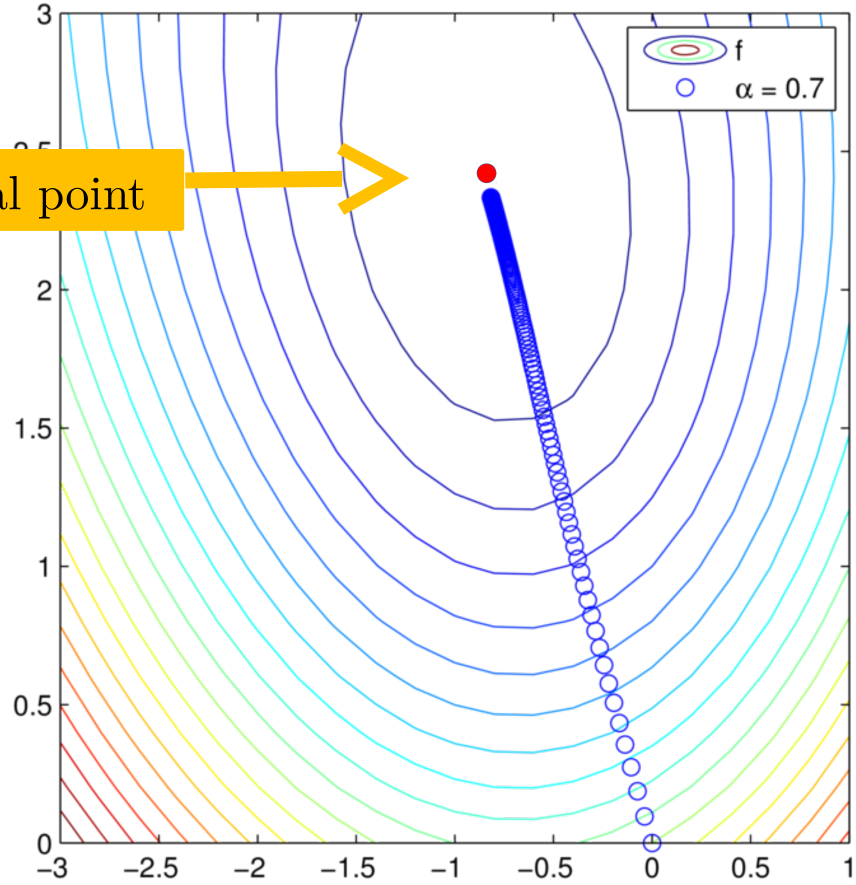

The Training Problem

Solving the *training problem*:

$$\min_{w \in \mathbf{R}^d} \frac{1}{n} \sum_{i=1}^{n} f_i(w)$$

Problem with Gradient Descent:
Each iteration requires computing a gradient $\nabla f_i(w)$ for each data point. One gradient for each cat on the internet!

Gradient Descent Algorithm

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Stochastic Gradient Descent

Is it possible to design a method that uses only the gradient of a **single** data function $f_i(w)$ at each iteration?

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Unbiased Estimate

Let j be a random index sampled from {*1*, *...*, *n*} selected uniformly at random. Then

$$\mathbb{E}_j\left[\nabla f_j(w)\right] = \frac{1}{n}\sum \nabla f_i(w) = \nabla f(w)$$

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Use $\nabla f_j(w) \approx \nabla f(w)$

Stochastic Gradient Descent

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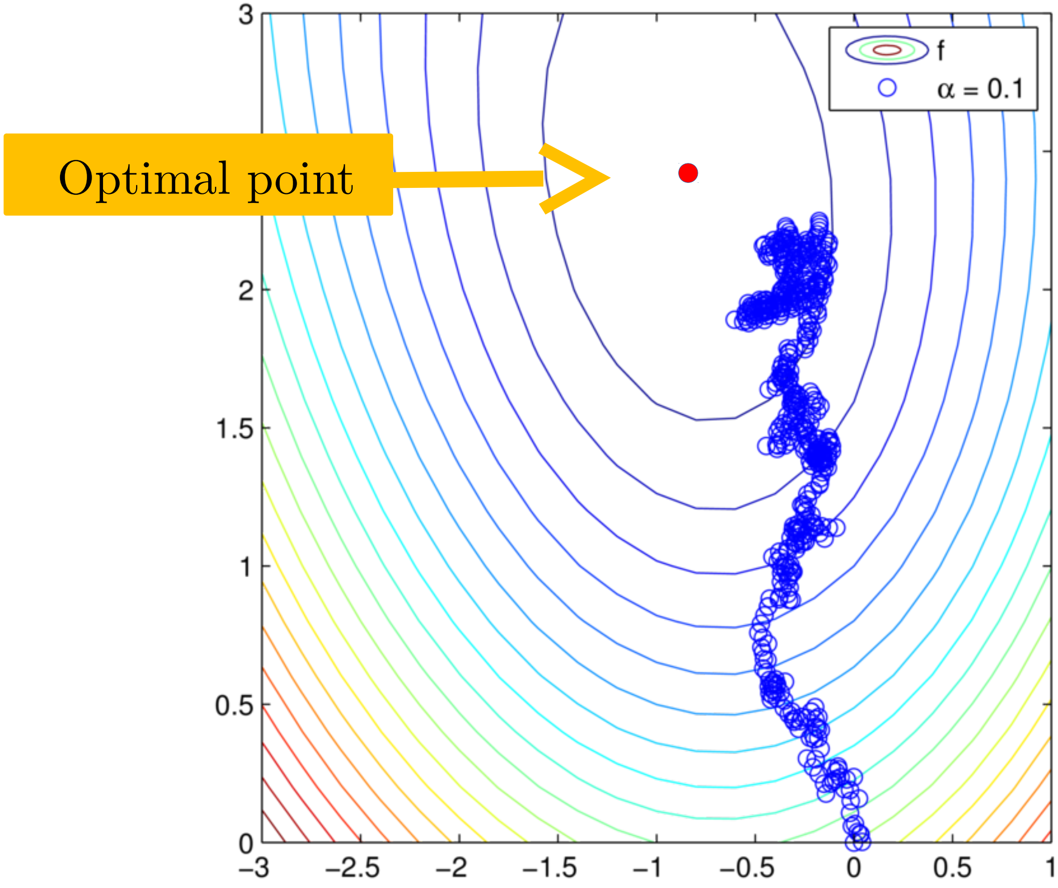

Assumptions for Convergence

Strong Convexity

$$f(w) \geq f(y) + \langle \nabla f(y), w - y \rangle + \frac{\lambda}{2} ||w - y||_2^2$$

$$2\langle \nabla f(w), w - w^* \rangle \geq \lambda ||w - w^*||_2^2$$

EXE: Using that

$$\frac{\sigma_{\min}(A)^2}{2} ||w - y||_2^2 \leq \frac{1}{2} ||A(w - y)||_2^2$$

Show that

$$\frac{1}{2} ||Aw - b||_2^2 \geq \frac{1}{2} ||Ay - b||_2^2 + \langle A^\top (Ay - b), w - y \rangle + \frac{\sigma_{\min}(A)^2}{2} ||w - y||_2^2$$

Assumptions for Convergence

Often the same as the regularization parameter

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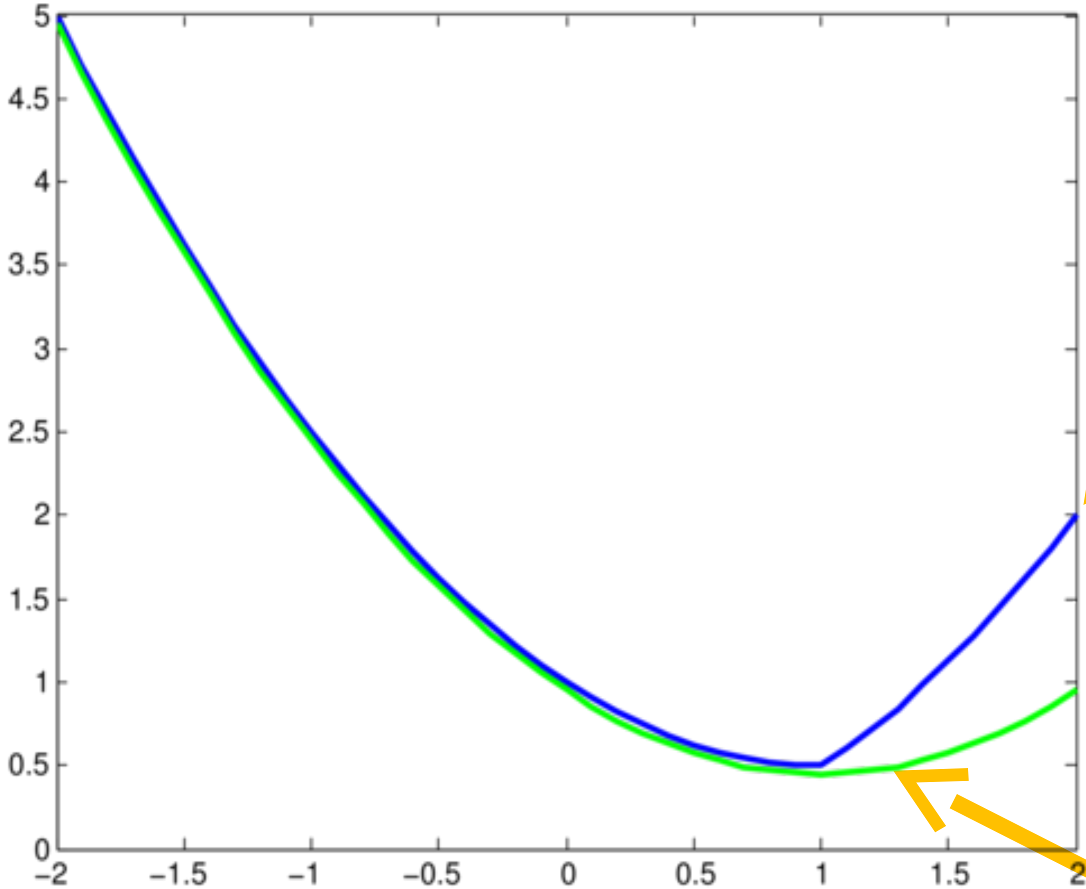
Strong convexity parameter!

Expected Bounded Stochastic Gradients

$$\mathbb{E}\left[||\nabla f_j(w^t)||_2^2 \right] \leq B^2, \text{ for all iterates } w^t \text{ of SGD}$$

Example of Strong Convexity



Hinge loss + L2

$$\max\{0, 1 - x\} + \frac{1}{2}||x||_2^2$$

Quadratic lower bound

Complexity / Convergence

Theorem

If $\frac{1}{\lambda} \geq \alpha > 0$ then the iterates of the SGD method satisfy

$$\mathbb{E}\left[||w^t - w^*||_2^2\right] \leq (1 - \alpha\lambda)^t \mathbb{E}\left[||w^0 - w^*||_2^2\right] + \frac{\alpha}{\lambda} B^2$$

Shows that $\alpha \approx \frac{1}{\lambda}$

Shows that $\alpha \approx 0$

Proof:

$$||w^{t+1} - w^*||_2^2 = ||w^t - w^* - \alpha \nabla f_j(w^t)||_2^2$$

$$= ||w^t - w^*||_2^2 - 2\alpha\langle \nabla f_j(w^t), w^t - w^*\rangle + \alpha^2 ||\nabla f_j(w^t)||_2^2.$$

Taking expectation with respect to j

Unbiased estimator

$$\mathbb{E}_j\left[||w^{t+1} - w^*||_2^2\right] = ||w^t - w^*||_2^2 - 2\alpha\langle \nabla f(w^t), w^t - w^*\rangle + \alpha^2 \mathbb{E}_j\left[||\nabla f_j(w^t)||_2^2\right]$$

$$\leq ||w^t - w^*||_2^2 - 2\alpha\langle \nabla f(w^t), w^t - w^*\rangle + \alpha^2 B^2$$

Strong conv.

$$\leq (1-\alpha\lambda)||w^t - w^*||_2^2 + \alpha^2 B^2$$

Bounded Stoch grad

Taking total expectation

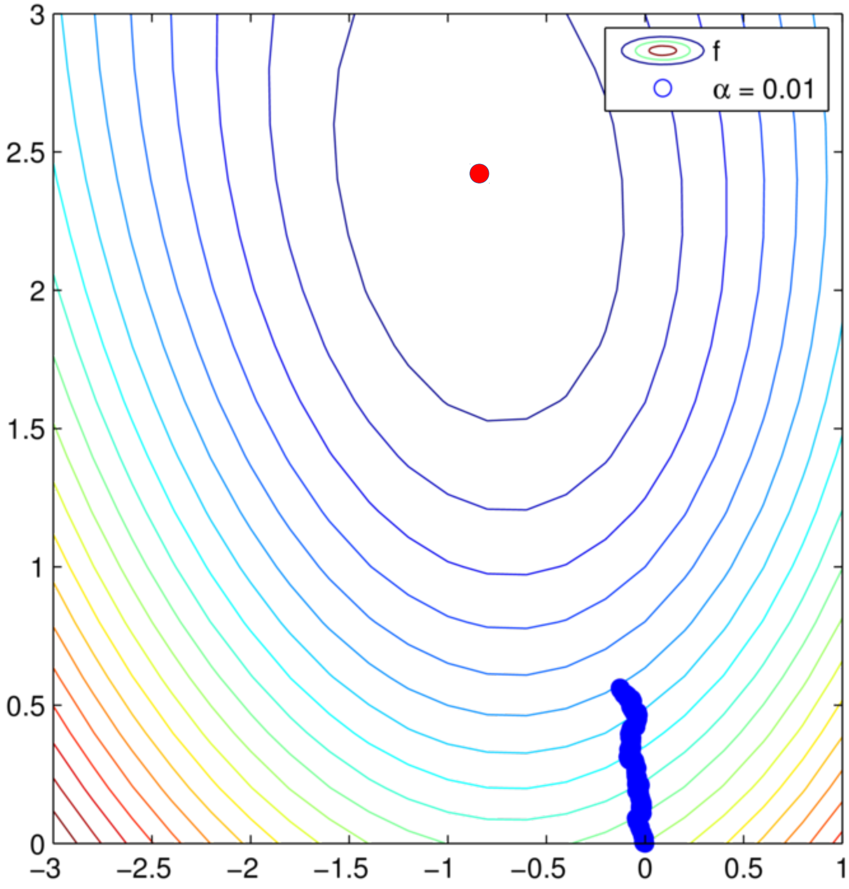
$$\mathbb{E}\left[||w^{t+1} - w^*||_2^2\right] \leq (1-\alpha\lambda)\mathbb{E}\left[||w^t - w^*||_2^2\right] + \alpha^2 B^2$$

$$= (1-\alpha\lambda)^{t+1}||w^0 - w^*||_2^2 + \textstyle\sum_{i=0}^t (1-\alpha\lambda)^i \alpha^2 B^2$$

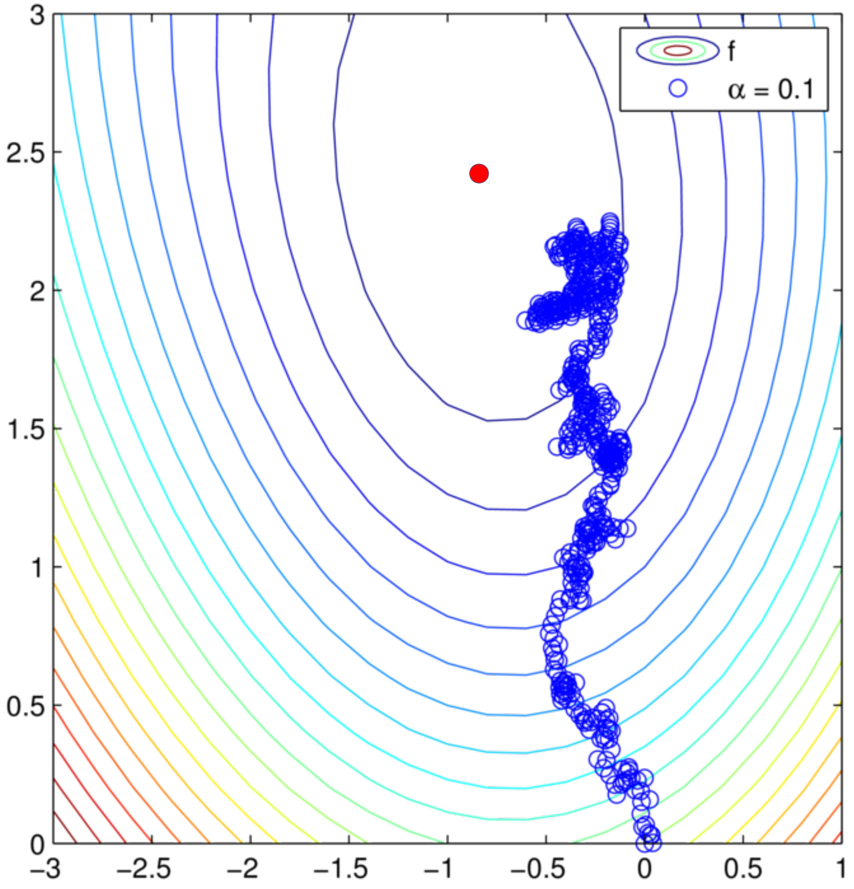
Using the geometric series sum $\displaystyle\sum_{i=0}^{t}(1-\alpha\lambda)^i = \frac{1-(1-\alpha\mu)^{t+1}}{\alpha\lambda} \leq \frac{1}{\alpha\lambda}$

$$\mathbb{E}\left[||w^{t+1} - w^*||_2^2\right] \leq (1-\alpha\lambda)^{t+1}||w^0 - w^*||_2^2 + \tfrac{\alpha}{\lambda} B^2$$

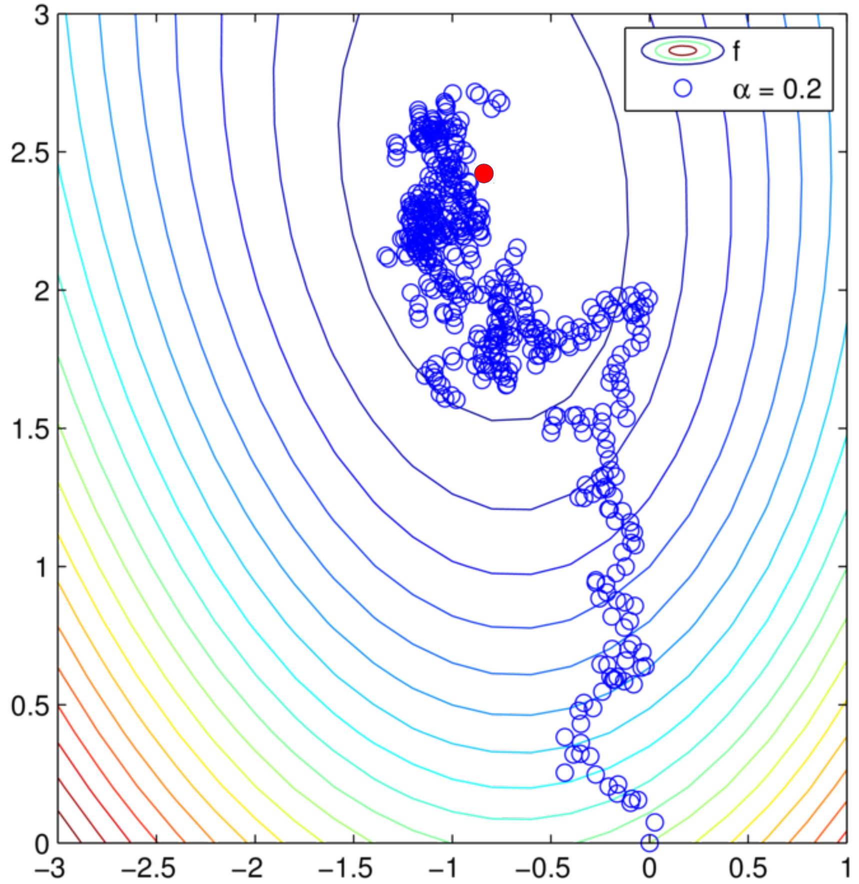
Stochastic Gradient Descent
$\alpha = 0.01$



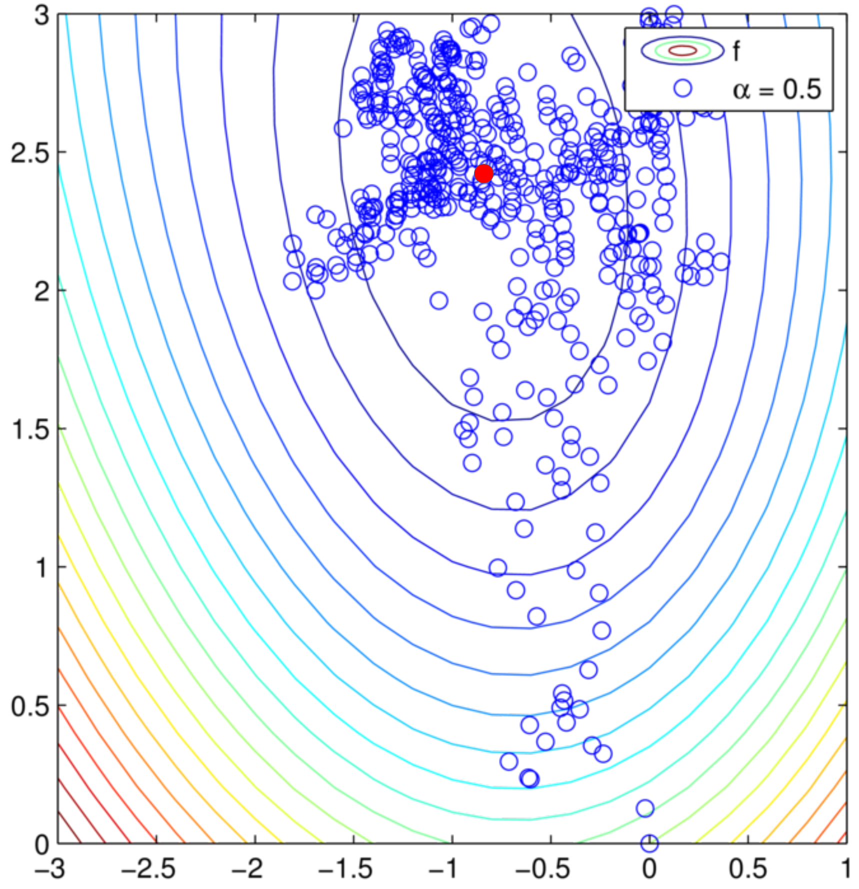
Stochastic Gradient Descent
α =0.1



Stochastic Gradient Descent
α =0.2



Stochastic Gradient Descent
α =0.5



Complexity / Convergence

Theorem (Shrinking stepsize)

If $\alpha_t = \frac{1}{t\lambda}$ then the iterates of the SGD method satisfy

$$\mathbb{E}\left[||w^t - w^*||_2^2\right] \leq \frac{4B^2}{t}$$

Stochastic Gradient Descent Algorithm

Set $w^0 = 0, \alpha_t = \frac{1}{t\lambda}$.
for $t = 1, 2, 3, \ldots, T$
Sor $j \in \{1, \ldots, n\}$
$w^{t+1} = w^t - \alpha_t \nabla f_j(w^t)$
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Sublinear convergence

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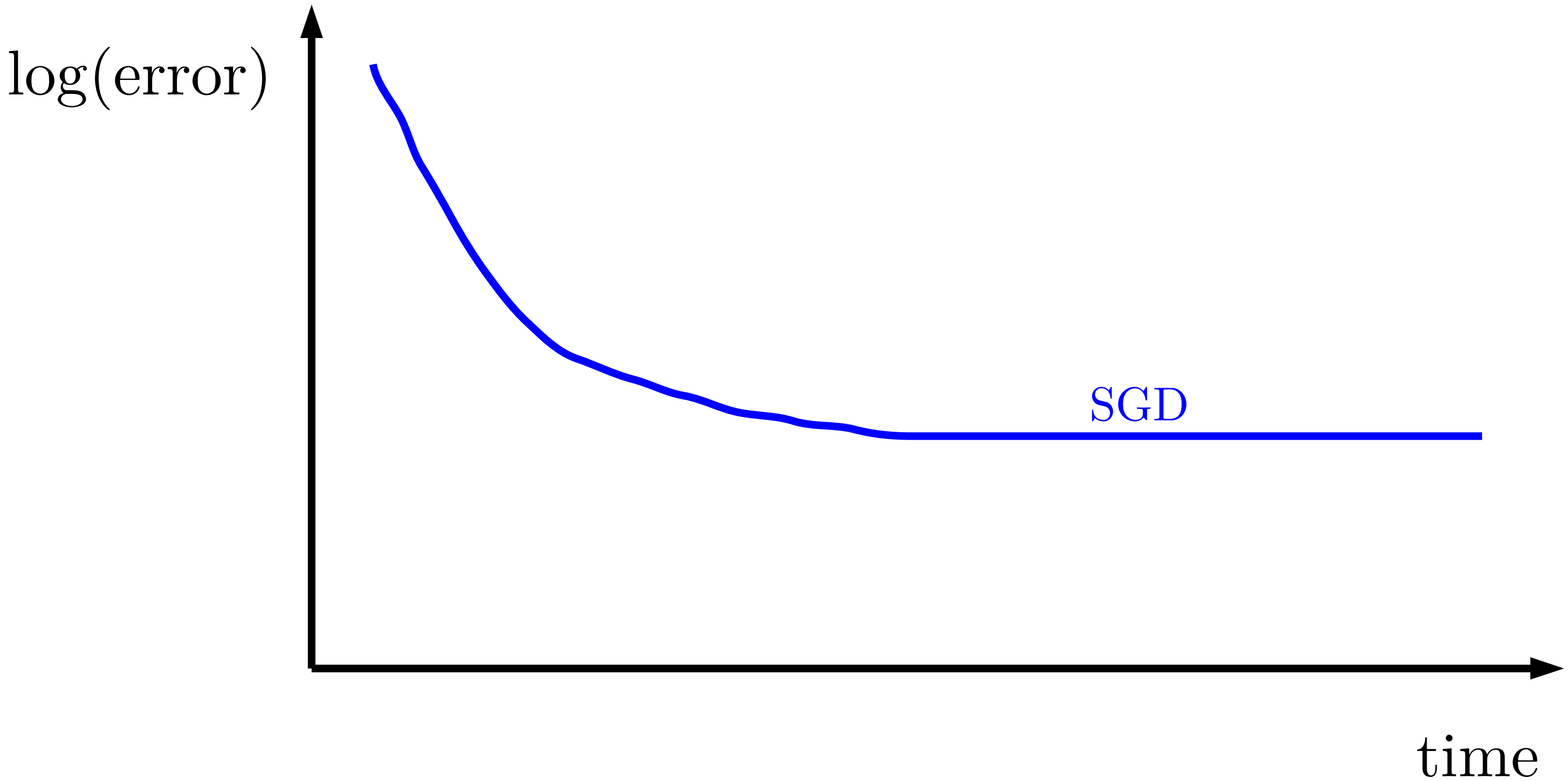
Shrinking Stepsize

Comparison SGD vs GD



M. Schmidt, N. Le Roux, F. Bach (2016)
Mathematical Programming
Minimizing Finite Sums with the Stochastic Average Gradient.

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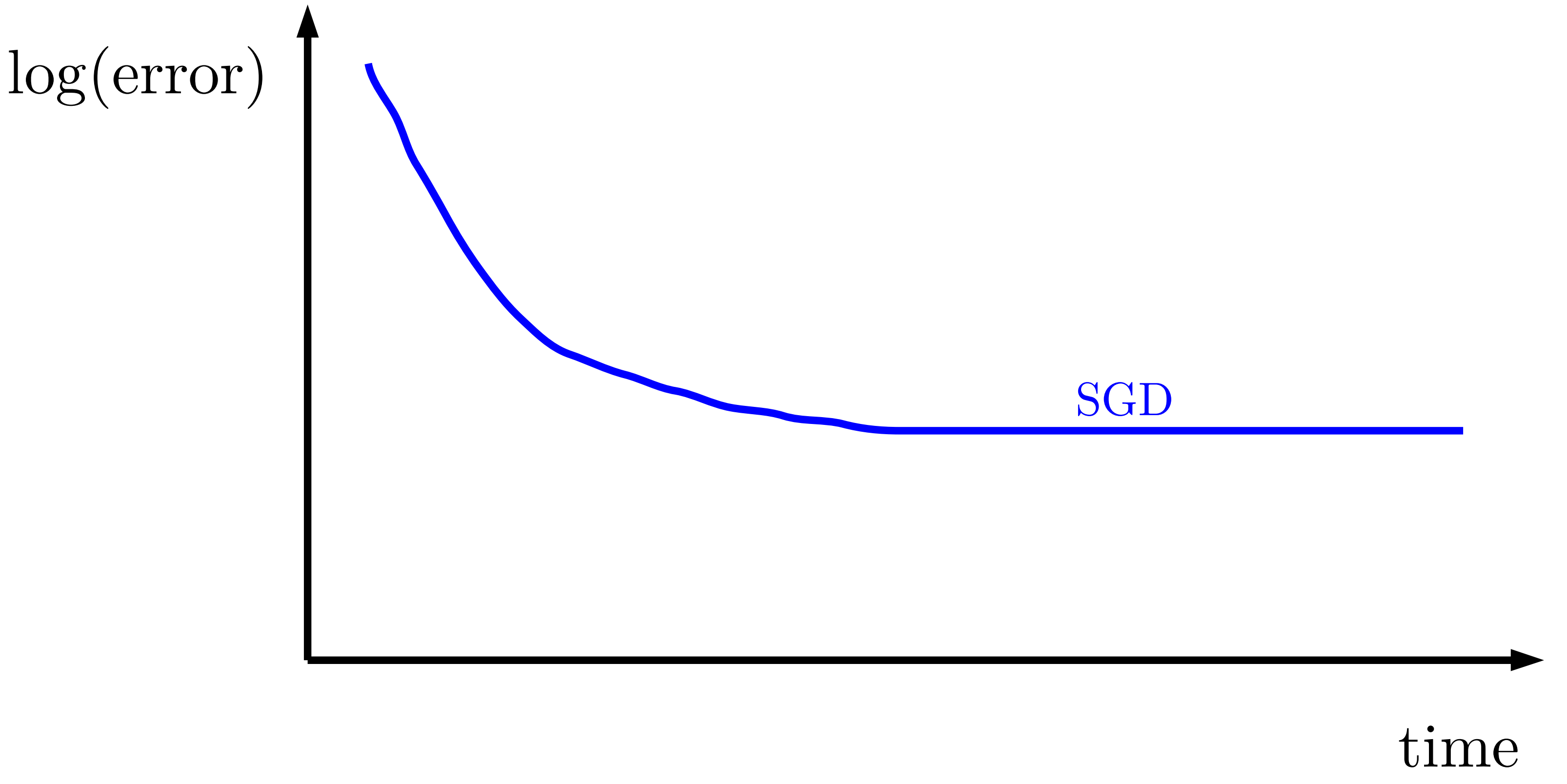

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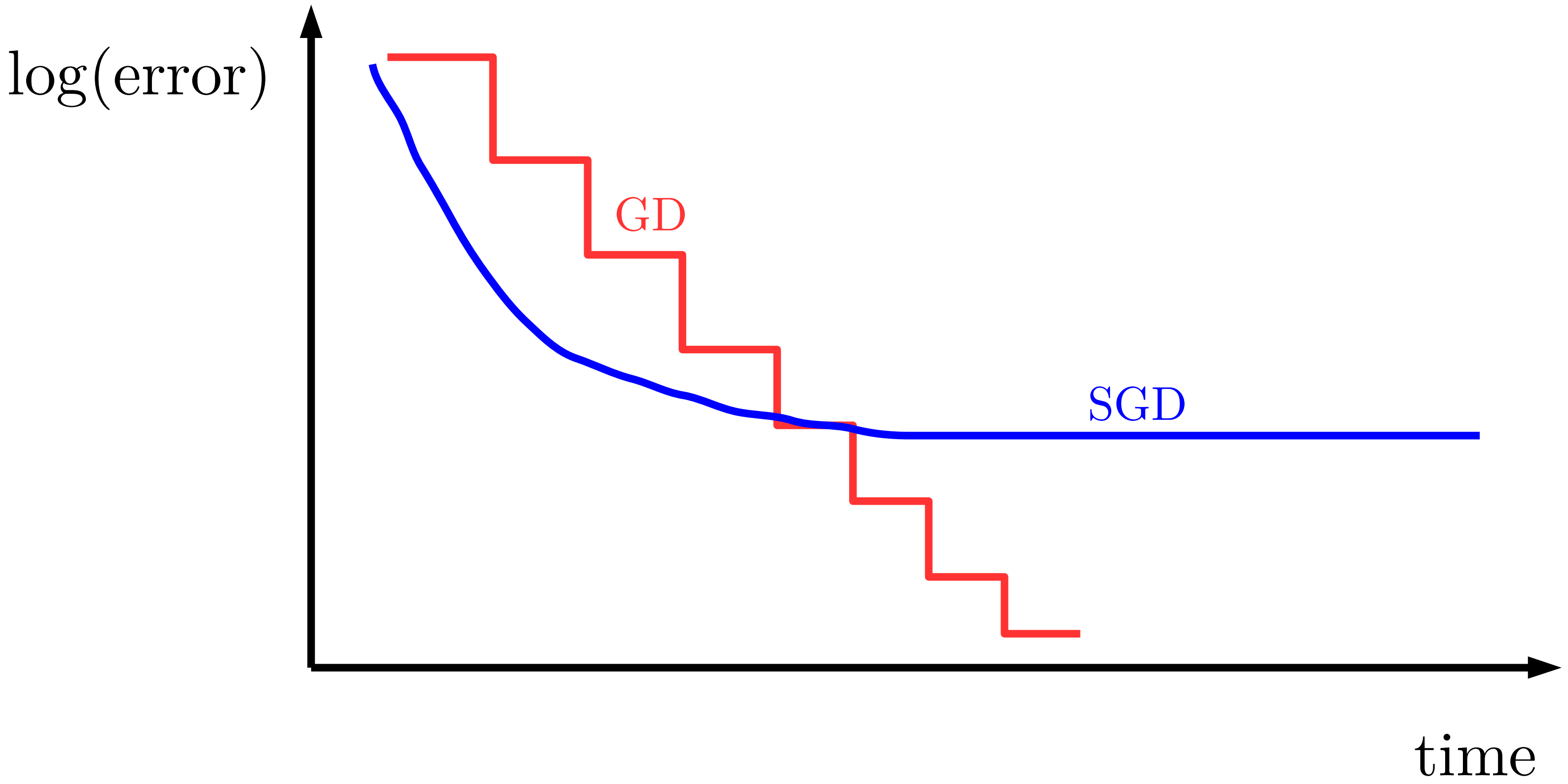

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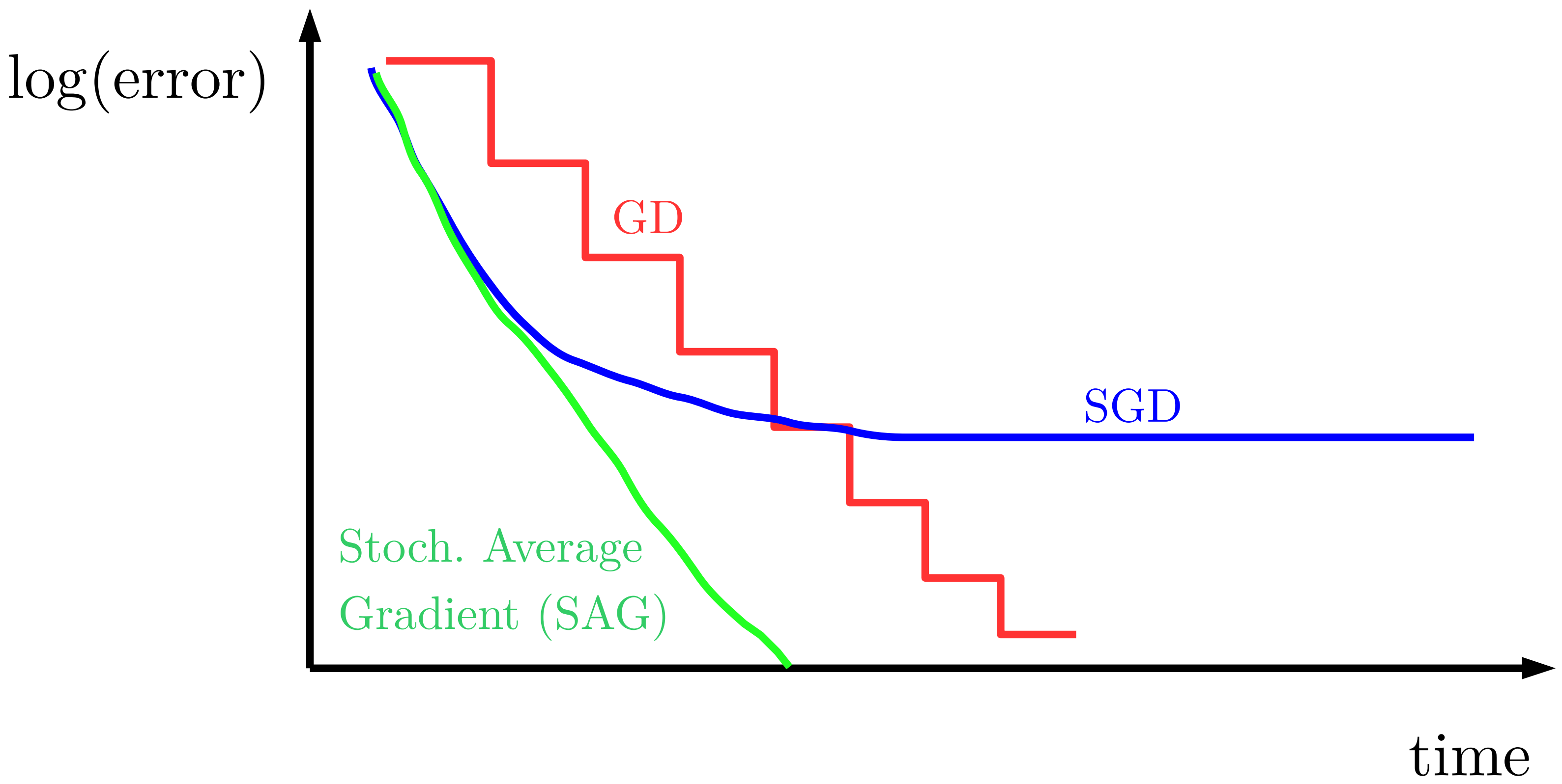

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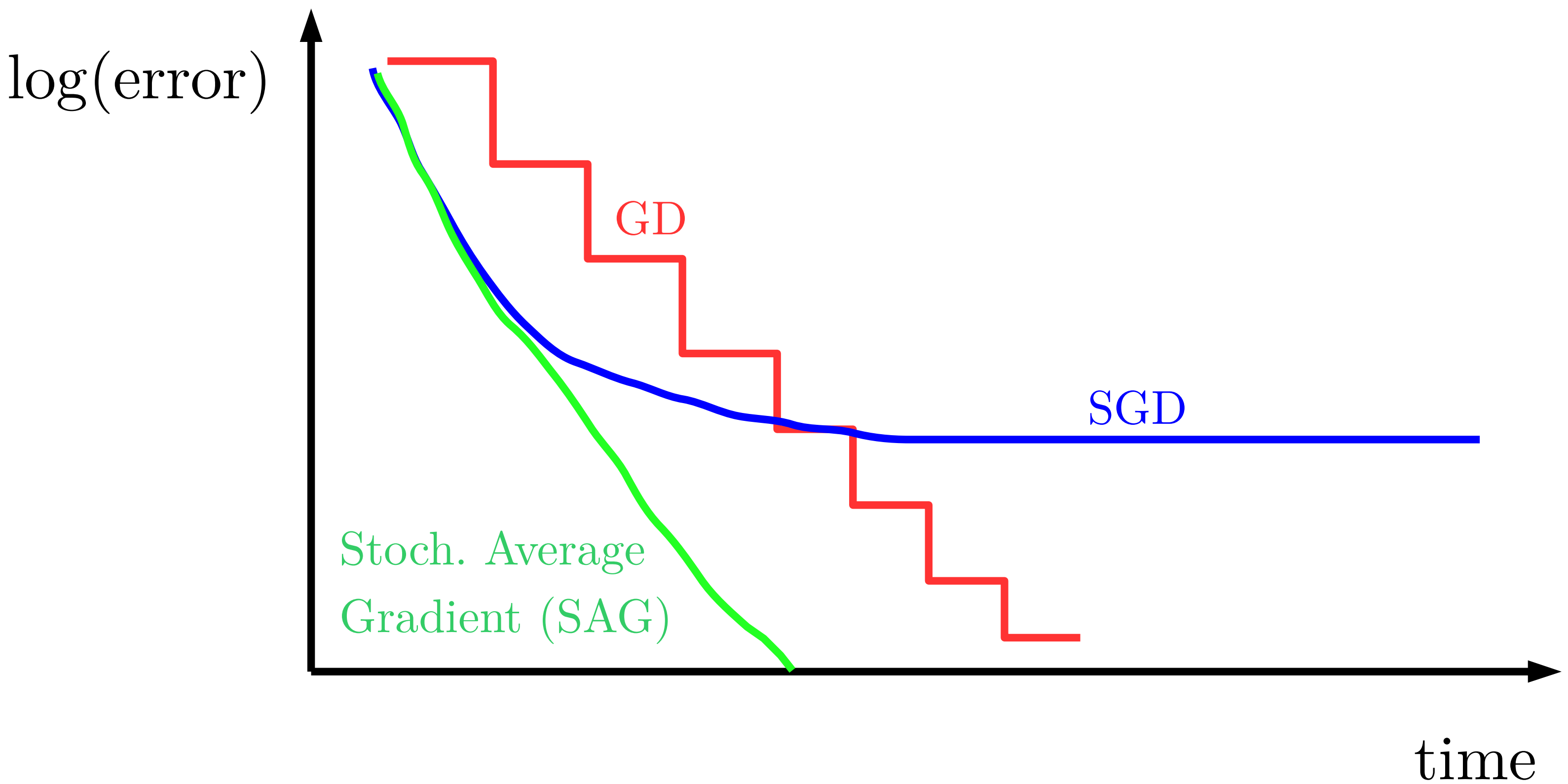

Maybe just an unbiased estimate is not enough.

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Variance reduced methods through Sketching

Build an Estimate of the Gradient

Instead of using directly $\nabla f_j(w^t) \approx \nabla f(w^t)$
Use $\nabla f_j(w^t)$ to update estimate $g_t \approx \nabla f(w^t)$

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We would like gradient estimate such that:

Unbiased

$$\mathbb{E}[g^t] = \nabla f(w^t)$$

Converges in *L2*

$$\mathbb{E}||g^t - \nabla f(w^t)||_2^2 \underset{w^t \to w^*}{\longrightarrow} 0$$

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We would like gradient estimate such that:

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$$\mathbb{E}[g^t] = \nabla f(w^t)$$

Solves problem of
$||\nabla f_j(w)||_2^2 \leq B^2$

Converges in *L2*

$$\mathbb{E}||g^t - \nabla f(w^t)||_2^2 \underset{w^t \to w^*}{\longrightarrow} 0$$

Example: The Stochastic Average Gradient

Maintain $J^t \approx [\nabla f_1(w^t), \ldots, \nabla f_n(w^t)]$ and iterate

$$w^{t+1} = w^t - \frac{\alpha}{n} \sum_{i=1}^{n} J_i^t = w^t - \alpha g^t$$

Update J_i^t's by sampling $j \in \{1, \ldots, n\}$ uniformly at random and setting:

$$J_i^t = \begin{cases} J_i^t = \nabla f_i(w^t) & \text{if } i = j \\ J_i^t = J_i^{t-1} & \text{if } i \neq j \end{cases}$$

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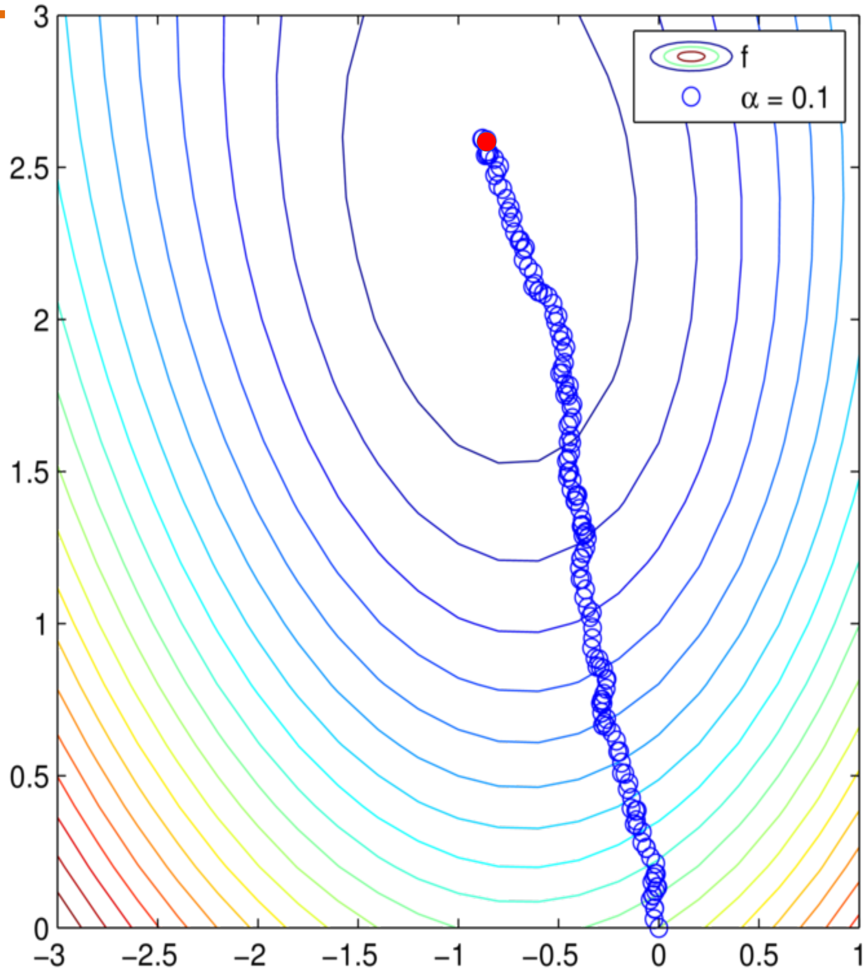
The Stochastic Average Gradient



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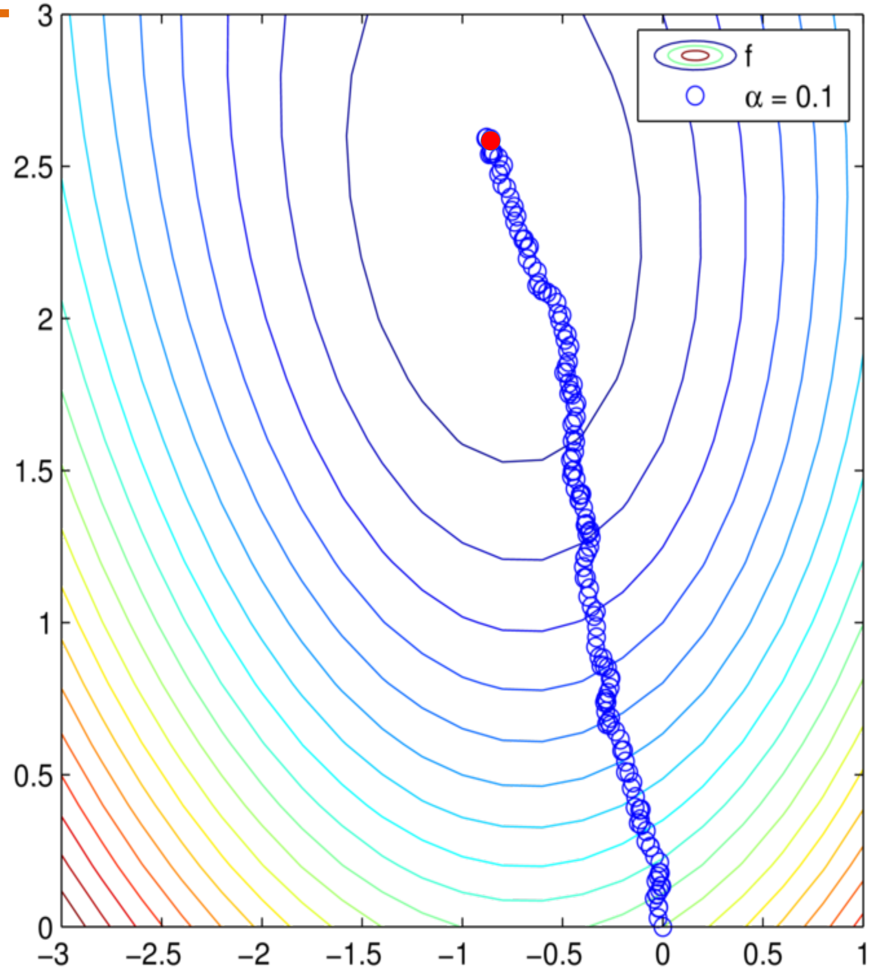

How to prove this converges? Is this the only option?

Introducing the Jacobian

$$\min_{w \in \mathbf{R}^d} f(w) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^{n} f_i(w)$$

$$F(w) \stackrel{\text{def}}{=} (f_1(w), \ldots, f_n(w))$$

$$DF(w) = (\nabla f_1(w), \ldots, \nabla f_n(w))$$

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$\nabla f(w)$ is a *dense* linear meassurement of $DF(w)$

The Stochastic Average Gradient

Maintain $J^t \approx [\nabla f_1(w^t), \ldots, \nabla f_n(w^t)] = DF(w^t)$ and iterate

$$w^{t+1} = w^t - \frac{\alpha}{n} \sum_{i=1}^{n} J_i^t$$

Update J_i^t's by sampling $j \in \{1, \ldots, n\}$ uniformly at random and setting:

$$J_i^t = \begin{cases} J_i^t = \nabla f_i(w^t) & \text{if } i = j \\ J_i^t = J_i^{t-1} & \text{if } i \neq j \end{cases}$$

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Estimate of $\frac{1}{n} DF(w^t)\mathbf{1}$

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Stoch. Linear Measurement $DF(w^t)e_j$

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Is this the only option? How to prove this converges?

Stochastic Sparse Sketches

Sparse Stochastic Matrix

$$S \in \mathbf{R}^{n \times \tau} \text{ a sparse matrix and } \tau \ll d$$

$$S \sim \mathcal{D} \text{ fixed distribution}$$

Stochastic Sketch

$$DF(w)S = \sum_{i=1}^{\tau} DF(w)S_{:i}$$

Stochastic Sparse Sketches

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Stochastic Sketch

$$DF(w)S = \sum_{i=1}^{\tau} DF(w)S_{:i}$$

Eg: SGD Sketch

$$S = e_j \in \mathbf{R}^d \text{ the } j\text{th unit coordinate vector}$$

$$\text{with } \mathbb{P}(S = e_j) = \frac{1}{n}$$

$$DF(x)S = \nabla f_j(w)$$

Stochastic Sparse Sketches

Eg: Mini-batch SGD Sketch

$S = I_C \in \mathbf{R}^{n\times\tau}$ where $C \subset \{1,\ldots,n\}$

$$DF(w)S = [\nabla f_{C_1}(w),\ldots,\nabla f_{C_\tau}(w)]$$

Exe. $\tau = 3, n = 6, \quad S = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ and $DF(w)S = [\nabla f_1(w), \nabla f_4(w), \nabla f_6(w)]$

Many examples: Sparse Rademacher matrices, sampling with replacement, nonuniform...etc

A Jacobian Based Method

Maintain Jacobian Estimate

$$J^{t-1} \approx DF(w^{t-1})$$

+

Sample Stochastic Sketch

$$S \sim \mathcal{D}$$

$$DF(w^t)S$$

A Jacobian Based Method

Maintain Jacobian Estimate

$$J^{t-1} \approx DF(w^{t-1})$$

Sample Stochastic Sketch

$$S \sim \mathcal{D}$$

$$DF(w^t)S$$

? ?

Improved Guess

$$J^t \approx DF(w^t)$$

A Jacobian Based Method

Jacobian Sketching Algorithm

Set $\alpha > 0, w^1 = 0, J^0 \in \mathbb{R}^{d \times n}$
For $t = 1, \ldots, T$
  Sample $S \sim \mathcal{D}$
  Calculate Sketch $DF(w^t)S$
  Update J^t using $DF(w^t)S$ and J^{t-1}
  Calculate $g^t = \frac{1}{n} J^t \mathbf{1}$
  Step $w^{t+1} = w^t - \alpha g^t$.

A Jacobian Based Method

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  Calculate $g^t = \frac{1}{n} J^t \mathbf{1}$
  Step $w^{t+1} = w^t - \alpha g^t$.

$\approx \frac{1}{n} DF(w)\mathbf{1}$

A Jacobian Based Method

Jacobian Sketching Algorithm

Set $\alpha > 0, w^1 = 0, J^0 \in \mathbb{R}^{d \times n}$
For $t = 1, \ldots, T$
  Sample $S \sim \mathcal{D}$
  Calculate Sketch $DF(w^t)S$
? Update J^t using $DF(w^t)S$ and J^{t-1} ?
  Calculate $g^t = \frac{1}{n} J^t \mathbf{1}$
  Step $w^{t+1} = w^t - \alpha g^t$.

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Updating the Jacobian Estimate: Sketch and project

$$J^t \quad = \quad DF(w^t)$$

Updating the Jacobian Estimate: Sketch and project

$$J^t S \;=\; DF(w^t)S, \qquad S \sim \mathcal{D}$$

Updating the Jacobian Estimate: Sketch and project

$$J^t = \arg\min_{J \in \mathbb{R}^{d\times n}} ||J - J^{t-1}||_F^2$$

$$J^t S \;=\; DF(w^t)S, \qquad S \sim \mathcal{D}$$

Updating the Jacobian Estimate: Sketch and project

Sketch and Project the Jacobian

$$
\begin{aligned}
J^t = \arg \min_{J \in \mathbb{R}^{d \times n}} & \; ||J - J^{t-1}||_F^2 \\
J^t S \; = & \quad DF(w^t) S, \qquad S \sim \mathcal{D}
\end{aligned}
$$

Updating the Jacobian Estimate: Sketch and project

Sketch and Project the Jacobian

$$
\begin{aligned}
J^t = \arg \min_{J \in \mathbb{R}^{d\times n}} & \; \|J - J^{t-1}\|_F^2 \\
J^t S \; = & \quad DF(w^t)S, \qquad S \sim \mathcal{D}
\end{aligned}
$$

RMG and Peter Richtarik (2015)
Randomized iterative methods for linear systems
SIAM Journal on Matrix Analysis and Applications 36(4)

Exercise

$$J^t = \arg\min_{J \in \mathbb{R}^{d\times n}} ||J - J^{t-1}||_F^2$$
$$\text{subject to} \quad JS = DF(w^t)S$$

Show that the solution J^t is given by

Solution: $$J^t = J^{t-1} - (J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top$$

Proof: The Lagrangian is given by

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$$\begin{aligned} L(J, Y) \quad &:= \tfrac{1}{2}||J - J^{t-1}||_F^2 + \langle Y, (DF^t - J)S \rangle \\ &= \tfrac{1}{2}||J - J^{t-1}||_F^2 + \langle YS^\top, DF^t - J \rangle \end{aligned}$$

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Differentiating in J and setting to zero: $\quad YS^\top = J - J^{t-1} \qquad (1)$

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Right multiplying by $S(S^\top S)^{-1}$ gives : $\quad Y = (DF^t - J^{t-1})S(S^\top S)^{-1} \quad (2)$

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Substituting (1) into (2) gives the solution.

Sketch and project the Jacobian

$$J^t = \arg\min_{J \in \mathbb{R}^{d\times n}} ||J - J^{t-1}||_F^2$$
$$\text{subject to} \quad JS = DF(w^t)S$$

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$$J^t = J^{t-1} - (J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top$$

$$g^t = \frac{1}{n}J^{t-1}\mathbf{1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top \mathbf{1}$$

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If $\eta = 1$ then $\mathrm{g}^t = \frac{1}{n}J^t\mathbf{1}$

Sketch and project the Jacobian

$$J^t = \arg\min_{J \in \mathbb{R}^{d \times n}} ||J - J^{t-1}||^2_{F(W)}$$
$$\text{subject to} \quad JS = DF(w^t)S$$

Solution:

$$J^t = J^{t-1} - (J^{t-1} - DF(w^t))S(S^\top W^{-1} S)^{-1} S^\top W^{-1}$$

$$g^t = \frac{1}{n} J^{t-1}\mathbf{1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))S(S^\top W^{-1} S)^{-1} S^\top W^{-1}\mathbf{1}$$

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Solution:

$$J^t = J^{t-1} - (J^{t-1} - DF(w^t))\underbrace{S(S^\top S)^{-1}S^\top}_{} =: P_S$$

$$g^t = \frac{1}{n}J^{t-1}\mathbf{1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top\mathbf{1}$$

Unbiased Condition

Lemma. If $(\frac{1}{\eta}, \mathbf{1})$ is an eigenpair of $\mathbb{E}[P_S]$ then

$$\mathbb{E}_S[g^t] = \nabla f(w^t)$$

consequently g^t is an unbiased estimator.

Proof: $$g^t = g^{t-1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top \mathbf{1}$$

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Proof:

$$g^t = g^{t-1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top \mathbf{1}$$

$$\begin{aligned}
\mathbb{E}_S[g^t] &= \frac{1}{n}J^{t-1}\mathbf{1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))\mathbb{E}_S[\underbrace{S(S^\top S)^{-1}S^\top}_{P_S}]\mathbf{1} \\
&= \frac{1}{n}J^{t-1}\mathbf{1} - \frac{\eta}{n\eta}(J^{t-1} - DF(w^t))\mathbf{1} \\
&= \cancel{\frac{1}{n}J^{t-1}}\mathbf{1} - \cancel{\frac{1}{n}J^{t-1}}\mathbf{1} + \frac{1}{n}DF(w^t))\mathbf{1} \quad = \quad \nabla f(w^t)
\end{aligned}$$

Exercise

Let $\mathbb{P}[S = e_i] = \dfrac{1}{n}$ for $i = 1, \ldots, n$. Show that

$$\mathbb{E}[P_S]\mathbf{1} = \mathbb{E}[S(S^\top S)^{-1} S^\top]\mathbf{1} = \frac{1}{n}\mathbf{1}$$

Proof:

Exercise

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$$\mathbb{E}[P_S]\mathbf{1} = \mathbb{E}[S(S^\top S)^{-1}S^\top]\mathbf{1} = \frac{1}{n}\mathbf{1}$$

Proof:

$$\begin{aligned}
\mathbb{E}[S(S^\top S)^{-1}S^\top]\mathbf{1} &= \textstyle\sum_{i=1}^n \frac{1}{n}\frac{e_i e_i^\top}{e_i^\top e_i} \\
&= \frac{1}{n}\sum_{i=1}^n e_i e_i^\top \mathbf{1} \\
&= \frac{1}{n} I\mathbf{1} = \frac{1}{n}\mathbf{1}
\end{aligned}$$

A Jacobian Based Method

Archetype Jacobian Sketching Algorithm

Choose distribution $\mathcal{D}$ and unbiased $\eta > 0$
Set $\alpha > 0, w^1 = 0, J^0 \in \mathbb{R}^{d \times n}$
For $t = 1, \ldots, T$
  Sample $S \sim \mathcal{D}$
  Calculate Sketch $DF(w^t)S$
  Update $J^t = J^{t-1} - (J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top$
  Calculate $g^t = \frac{1}{n}J^{t-1}\mathbf{1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top \mathbf{1}$
  Step $w^{t+1} = w^t - \alpha g^t$

A Jacobian Based Method

Archetype Jacobian Sketching Algorithm

Choose distribution $\mathcal{D}$ and unbiased $\eta > 0$

Set $\alpha > 0, w^1 = 0, J^0 \in \mathbb{R}^{d\times n}$

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Sample $S \sim \mathcal{D}$

Calculate Sketch $DF(w^t)S$

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Calculate $g^t = \frac{1}{n}J^{t-1}\mathbf{1} - \frac{\eta}{n}(J^{t-1} - DF(w^t))S(S^\top S)^{-1}S^\top\mathbf{1}$

Step $w^{t+1} = w^t - \alpha g^t$

Looks expensive and complicated. Investigate

Example: minibatch-SAGA

Homework:

$$\mathbb{E}[P_S]\mathbf{1} = \frac{\tau}{n}\mathbf{1}$$

Let $C \subset \{1,\ldots,n\}$ with $|C| = \tau$ and $\mathbb{P}[S = I_C] = \frac{1}{\binom{n}{\tau}}$

Exe. $\tau = 3, n = 6, \quad S = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ and $DF(w)S = [\nabla f_1(w), \nabla f_4(w), \nabla f_6(w)]$

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Jacobain update

$$J_j^t = \begin{cases} \nabla f_j(w^t) & \text{if } j \in C, \\ J_j^{t-1} & \text{if } j \neq C. \end{cases}$$

Gradiant estimate

$$g^t = \frac{1}{n} J^{t-1}\mathbf{1} - \frac{1}{\tau}\sum_{j \in C}(J_j^{t-1} - \nabla f_j(w^t))$$

Proving Convergence of Variance reduced methods