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The gradient descent acts like follows:

$$x_{k+1} = x_k - \frac{\alpha_k}{n} \sum_{i=1}^n \nabla f_i(x)$$

• Convergence with constant α or line search.

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Let's switch from the full gradient calculation to its unbiased estimator, when we randomly choose
$$i_k$$
 index of point at each iteration uniformly:
$$x_{k+1} = x_k - \alpha_k \nabla f_{i_k}(x_k) \tag{SGD}$$

With $p(i_k = i) = \frac{1}{n}$, the stochastic gradient is an unbiased estimate of the gradient, given by:

$$\mathbb{E}[\nabla f_{i_k}(x)] = \sum_{i=1}^n p(i_k = i) \nabla f_i(x) = \sum_{i=1}^n \frac{1}{n} \nabla f_i(x) = \frac{1}{n} \sum_{i=1}^n \nabla f_i(x) = \nabla f(x)$$

This indicates that the expected value of the stochastic gradient is equal to the actual gradient of f(x). $f \to \min_{x,y,z}$ Finite-sum problem

(GD)

Stochastic iterations are n times faster, but how many iterations are needed?

If ∇f is Lipschitz continuous then we have:

Assumption	Deterministic Gradient Descent	Stochastic Gradient Descent
PL	$O(\log(1/\varepsilon))$	$O(1/\varepsilon)$
Convex	O(1/arepsilon)	$O(1/\varepsilon^2)$
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 - Sublinear rate even in strongly-convex case.
 - Bounds are unimprovable under standard assumptions.
 - Oracle returns an unbiased gradient approximation with bounded variance.
- Momentum and Quasi-Newton-like methods do not improve rates in stochastic case. Can only improve constant factors (bottleneck is variance, not condition number).

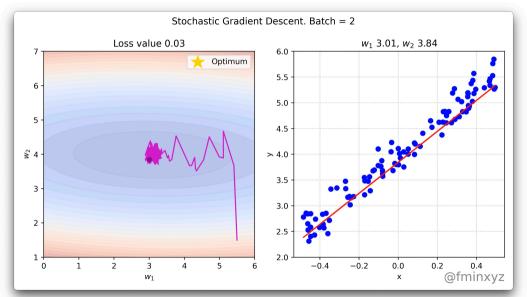
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Stochastic Gradient Descent (SGD)





Typical behaviour







Lipschitz continiity implies:

$$f(x_{k+1}) \leq f(x_k) + \langle \nabla f(x_k), x_{k+1} - x_k \rangle + \frac{L}{2} \|x_{k+1} - x_k\|^2$$

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using (SGD):

$$f(x_{k+1}) \leq f(x_k) - \alpha_k \langle \nabla f(x_k), \nabla f_{i_k}(x_k) \rangle + \alpha_k^2 \frac{L}{2} \| \nabla f_{i_k}(x_k) \|^2$$

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Now let's take expectation with respect to i_{ι} :

$$\mathbb{E}[f(x_{k+1})] \leq \mathbb{E}[f(x_k) - \alpha_k \langle \nabla f(x_k), \nabla f_{i_k}(x_k) \rangle + \alpha_k^2 \frac{L}{2} \|\nabla f_{i_k}(x_k)\|^2]$$

 $f \to \min_{x,y,z}$ Stochastic Gradient Descent (SGD)

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Since uniform sampling implies unbiased estimate of gradient: $\mathbb{E}[\nabla f_{i_k}(x_k)] = \nabla f(x_k)$:

$$\mathbb{E}[f(x_{k+1})] \leq f(x_k) - \alpha_k \|\nabla f(x_k)\|^2 + \alpha_k^2 \frac{L}{2} \mathbb{E}[\|\nabla f_{i_k}(x_k)\|^2]$$

$$\frac{1}{2}\|\nabla f(x)\|_2^2 \geq \mu(f(x) - f^*), \forall x \in \mathbb{R}^p$$

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This inequality simply requires that the gradient grows faster than a quadratic function as we move away from the optimal function value. Note, that strong convexity implies PL, but not vice versa. Using PL we can write:

$$\mathbb{E}[f(x_{k+1})] - f^* \leq (1 - 2\alpha_k \mu)[f(x_k) - f^*] + \alpha_k^2 \frac{L}{2} \mathbb{E}[\|\nabla f_{i_k}(x_k)\|^2]$$

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This bound already indicates, that we have something like linear convergence if far from solution and gradients are similar, but no progress if close to solution or have high variance in gradients at the same time.

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Now we assume, that the variance of the stochastic gradients is bounded:

$$\mathbb{E}[\|\nabla f_i(x_k)\|^2] \le \sigma^2$$

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Thus, we have

$$\mathbb{E}[f(x_{k+1}) - f^*] \le (1 - 2\alpha_k \mu)[f(x_k) - f^*] + \frac{L\sigma^2 \alpha_k^2}{2}.$$

1. Consider decreasing stepsize strategy with $\alpha_k = \frac{2k+1}{2u(k+1)^2}$ we obtain

$$\mathbb{E}[f(x_{k+1}) - f^*] \leq \frac{k^2}{(k+1)^2} [f(x_k) - f^*] + \frac{L\sigma^2 (2k+1)^2|}{8\mu^2 (k+1)^4}$$

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2. Multiplying both sides by $(k+1)^2$ and letting $\delta_f(k) \equiv k^2 \mathbb{E}[f(x_k) - f^*]$ we get

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$$\begin{split} \delta_f(k+1) & \leq \delta_f(k) + \frac{L\sigma^2(2k+1)^2}{8\mu^2(k+1)^2} \\ & \leq \delta_f(k) + \frac{L\sigma^2}{2\mu^2}, \end{split}$$

where the second line follows from $\frac{2k+1}{k+1} < 2$. Summing up this inequality from k=0 to k and using the fact that $\delta_f(0)=0$ we get

$$\delta_f(k+1) \leq \delta_f(0) + \frac{L\sigma^2}{2\mu^2} \sum_{i=0}^k 1 \leq \frac{L\sigma^2(k+1)}{2\mu^2} \Rightarrow (k+1)^2 \mathbb{E}[f(x_{k+1}) - f^*] \leq \frac{L\sigma^2(k+1)}{2\mu^2}$$

which gives the stated rate.

3. Constant step size: Choosing $\alpha_k = \alpha$ for any $\alpha < 1/2\mu$ yields

$$\begin{split} \mathbb{E}[f(x_{k+1}) - f^*] &\leq (1 - 2\alpha\mu)^k [f(x_0) - f^*] + \frac{L\sigma^2\alpha^2}{2} \sum_{i=0}^k (1 - 2\alpha\mu)^i \\ &\leq (1 - 2\alpha\mu)^k [f(x_0) - f^*] + \frac{L\sigma^2\alpha^2}{2} \sum_{i=0}^\infty (1 - 2\alpha\mu)^i \\ &= (1 - 2\alpha\mu)^k [f(x_0) - f^*] + \frac{L\sigma^2\alpha}{4\mu}, \end{split}$$

where the last line uses that $\alpha < 1/2\mu$ and the limit of the geometric series.

Convergence. Smooth convex case.



Convergence. Non-smooth convex case.



Mini-batch SGD



Mini-batch SGD



Mini-batch SGD

Approach 1: Control the sample size

The deterministic method uses all n gradients:

$$\nabla f(x_k) = \frac{1}{n} \sum_{i=1}^n \nabla f_i(x_k).$$

The stochastic method approximates this using just 1 sample:

$$\nabla f_{ik}(x_k) \approx \frac{1}{n} \sum_{i=1}^n \nabla f_i(x_k).$$

A common variant is to use a larger sample B_k ("mini-batch"):

$$\frac{1}{|B_k|} \sum_{i \in B_k} \nabla f_i(x_k) \approx \frac{1}{n} \sum_{i=1}^n \nabla f_i(x_k),$$

particularly useful for vectorization and parallelization.

For example, with 16 cores set $|B_k| = 16$ and compute 16 gradients at once.

Mini-Batching as Gradient Descent with Error

The SG method with a sample B_k ("mini-batch") uses iterations:

$$x_{k+1} = x_k - \alpha_k \left(\frac{1}{|B_k|} \sum_{i \in B_k} \nabla f_i(x_k) \right).$$

Let's view this as a "gradient method with error":

$$x_{k+1} = x_k - \alpha_k(\nabla f(x_k) + e_k),$$

where e_k is the difference between the approximate and true gradient.

If you use $\alpha_k = \frac{1}{L}$, then using the descent lemma, this algorithm has:

$$f(x_{k+1}) \leq f(x_k) - \frac{1}{2L} \|\nabla f(x_k)\|^2 + \frac{1}{2L} \|e_k\|^2,$$

for any error e_k .

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Effect of Error on Convergence Rate

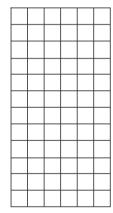
Our progress bound with $\alpha_k = \frac{1}{L}$ and error in the gradient of e_k is:

$$f(x_{k+1}) \le f(x_k) - \frac{1}{2L} \|\nabla f(x_k)\|^2 + \frac{1}{2L} \|e_k\|^2.$$



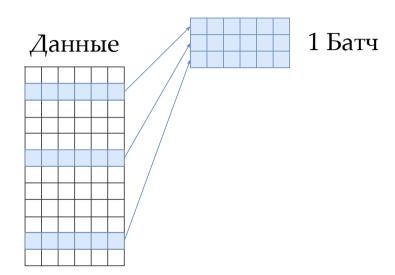
Идея SGD и батчей

Данные



Mini-batch SGD

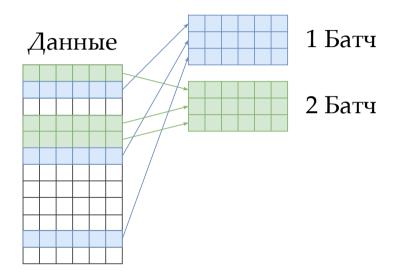
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Mini-batch SGD

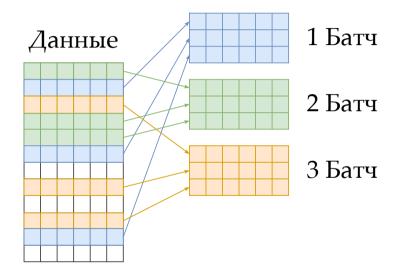
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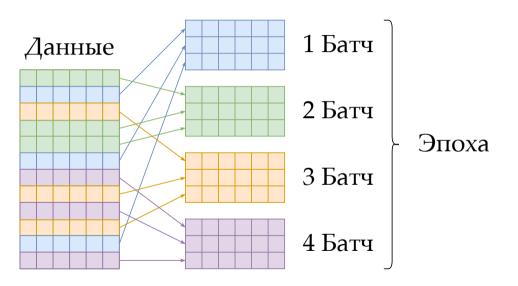
Mini-batch SGD

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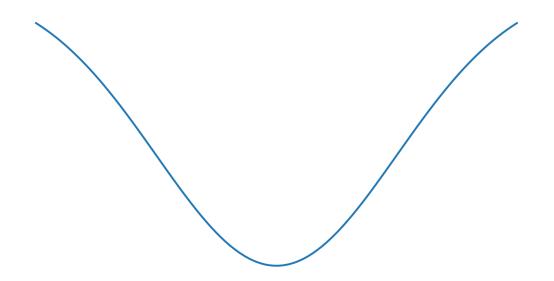
Mini-batch SGD

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Mini-batch SGD

Градиентный спуск сходится к локальному минимуму



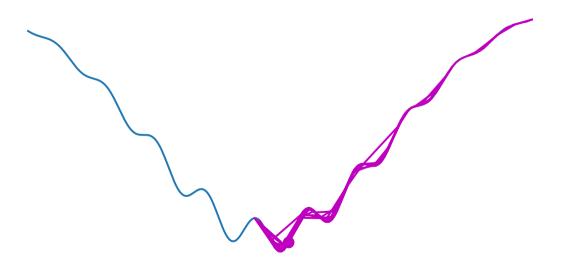


Градиентный спуск сходится к локальному минимуму





Стохастический градиентный спуск выпрыгивает из локальных минимумов



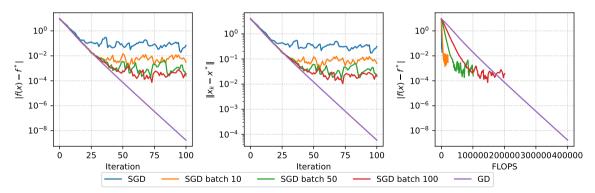




Main problem of SGD

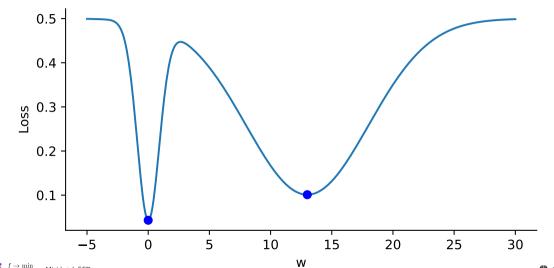
$$f(x) = \frac{\mu}{2} \|x\|_2^2 + \frac{1}{m} \sum_{i=1}^m \log(1 + \exp(-y_i \langle a_i, x \rangle)) \to \min_{x \in \mathbb{R}^n}$$

Strongly convex binary logistic regression. m=200, n=10, mu=1.



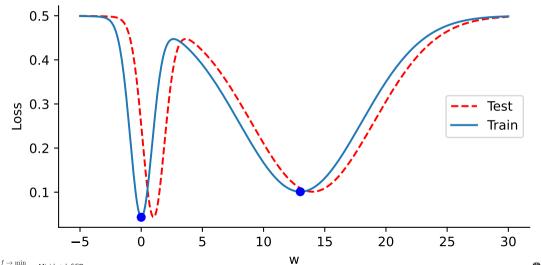
Ширина локальных минимумов

Узкие и широкие локальные минимумы



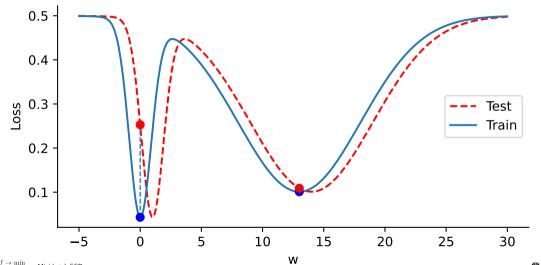
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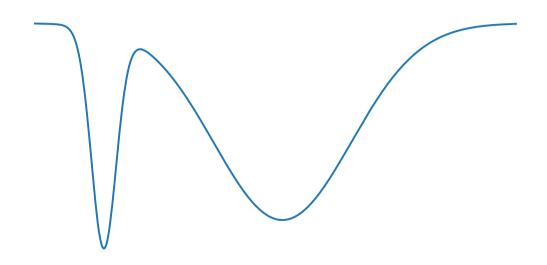


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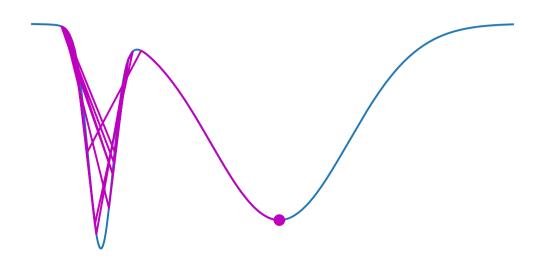


Градиентный спуск с маленьким шагом сходится в узкий локальный минимум





Градиентный спуск с большим шагом избегает узкого локального минимума







Основные результаты сходимости SGD

Пусть f - L-гладкая μ -сильно выпуклая функция, а дисперсия стохастического градиента конечна $(\mathbb{E}[\|\nabla f_i(x_k)\|^2] \leq \sigma^2)$. Тогда траектория стохастического градиентного спуска с постоянным шагом $\alpha < \frac{1}{2\mu}$ будет гарантировать:

$$\mathbb{E}[f(x_{k+1}) - f^*] \le (1 - 2\alpha\mu)^k [f(x_0) - f^*] + \frac{L\sigma^2\alpha}{4\mu}.$$



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$$\mathbb{E}[f(x_{k+1}) - f^*] \le \frac{L\sigma^2}{2\mu^2(k+1)}$$

 $f \to \min_{x,y,z}$

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- Two-phase Newton-like method achieves $\mathcal{O}\left(\frac{1}{h}\right)$ without strong convexity.



