Variance reduction for stochastic gradient methods

Axel Böhm

September 10, 2021

Introduction

A common Task in (supervised) machine learning:

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) := \frac{1}{n} \sum_{i=1}^n \underbrace{\mathsf{loss for } i\text{-th sample}}_{\mathsf{regularize}} + \underbrace{\psi(\mathbf{x})}_{\mathsf{regularize}}$$

where the *i*-th sample is (a_i, y_i) .

- linear regression: $f_i(x) = (a_i^T x y_i)^2$, and $\psi = 0$
- logistic regression: $f_i(x) = \log(1 + e^{-y_i a_i^T x})$, and $\psi = 0$ "sigmoid function" and logistic loss.
- Lasso: f_i as for linear regression but $\psi(x) = ||x||_i$
- SVM: $f_i(x) = \max\{0, 1 y_i a_i^T x\}$ and $\psi(x) = \|x\|^2$

Stochastic gradient descent

We already noticed that:

• large stepsizes fail to supress variability