Stochastic gradient descent

GD minimizes:

$$E_{\text{in}}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^{N} \underbrace{\mathrm{e}\left(h(\mathbf{x}_n), y_n\right)}_{\ln\left(1+e^{-y_n \mathbf{w}^{\mathsf{T}} \mathbf{x}_n}\right)} \quad \longleftarrow \text{ in logistic regression}$$

by iterative steps along $-\nabla E_{\text{in}}$:

$$\Delta \mathbf{w} = -\,\eta\, \nabla E_{\text{in}}(\mathbf{w})$$

∇E_{in} is based on all examples $(\mathbf{x}_n, y_n)$

"**batch**" GD

The stochastic aspect

Pick <u>one</u> $(\mathbf{x}_n, y_n)$ at a time. Apply GD to $\mathbf{e}\left(h(\mathbf{x}_n), y_n\right)$

"Average" direction:

$$\mathbb{E}_n\left[-\nabla \mathbf{e}\left(h(\mathbf{x}_n), y_n\right)\right] = \frac{1}{N}\sum_{n=1}^{N} -\nabla \mathbf{e}\left(h(\mathbf{x}_n), y_n\right)$$

$$= -\nabla\, E_{\text{in}}$$

randomized version of GD

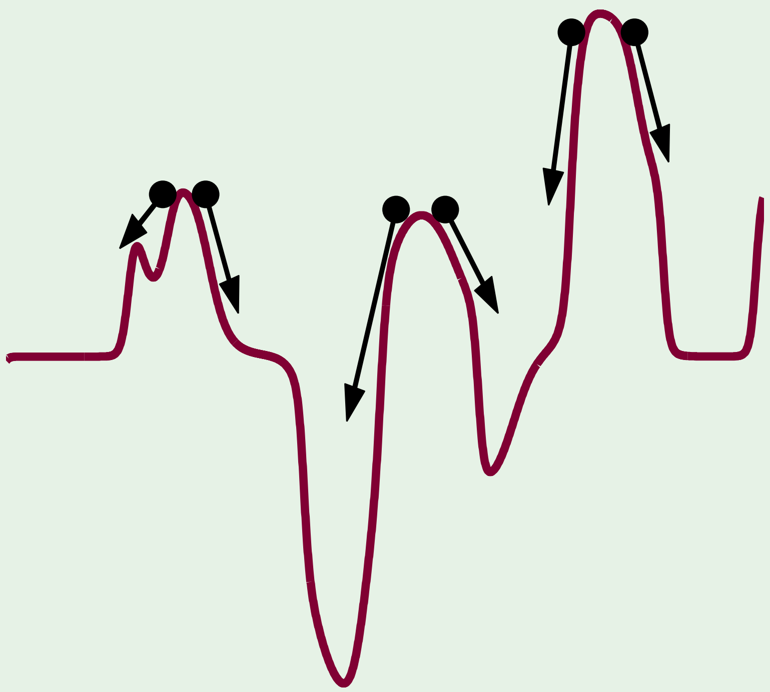
stochastic gradient descent (SGD)

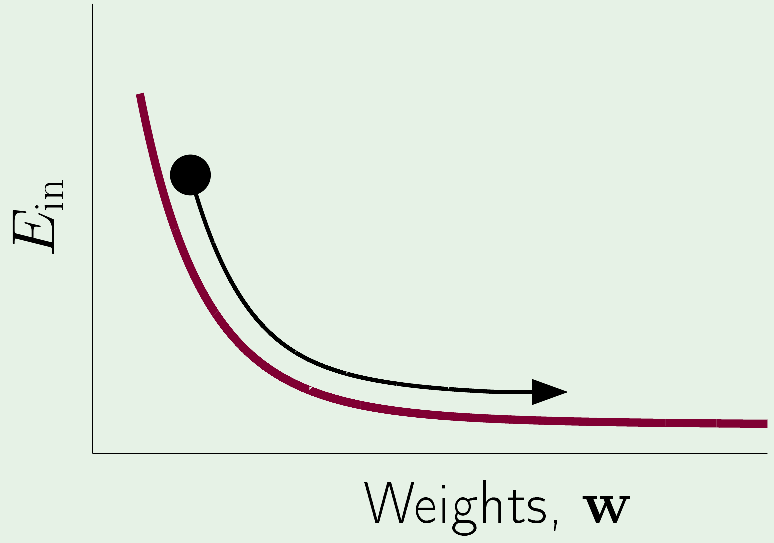
Benefits of SGD

1. cheaper computation
2. randomization
3. simple

Rule of thumb:

$\eta = 0.1$ works





randomization helps