

# Stochastic Gradient Descent with Momentum and Line Searches

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## Abstract

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# 1 Introduction

## 2 Mini-batch gradient descent variants

### 2.1 Fixed step-size

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Mini-batch Gradient Descent with fixed step-size

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1 dati  $w^0 \in \mathbb{R}^n$ ,  $f(w) = \sum_{i=1}^N \log(1 + \exp(-y^{(i)} w^T x^{(i)})) + \lambda \|w\|^2$ ,  $k = 0$  e  $\{\alpha_k\} \mid \alpha_k = \alpha$ 
2 while  $(\|\nabla f(w^k)\| > \varepsilon)$ 
3   shuffle  $\{1, \dots, N\}$  in  $N/M$  blocchi  $B_1, \dots, B_{N/M}$  di dimensione  $1 < |B_t| = M \ll N$ 
4    $y_0 = w^k$ 
5   for  $t = 1, \dots, N/M$ 
6      $y_t = y_{t-1} - \alpha_k \frac{1}{M} \sum_{j \in B_t} \nabla f_j(y_{t-1})$ 
7   end for
8    $w^{k+1} = y_{N/M}$ 
9    $k = k + 1$  fine epoca
10 end while

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