

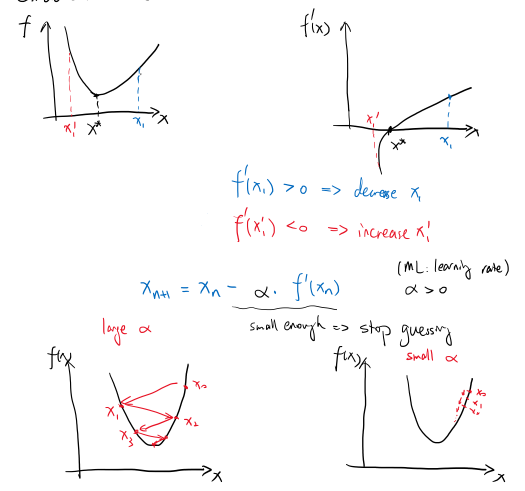
$$\nabla f = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right)$$

Necessary condition $\nabla f = 0 \Rightarrow \frac{\partial f}{\partial x_i} = 0 \quad i=1, \dots, n$

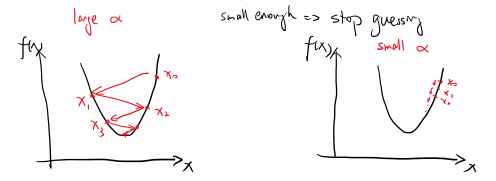
(check the Hessian for min/max)

- 1) finite-difference $f(x_1, \dots, x_n)$
 $\epsilon = 1e^{-8} \quad \frac{\partial f}{\partial x_i} \approx \frac{f(x_1, \dots, x_i + \epsilon, \dots, x_n) - f(x_1, \dots, x_n)}{\epsilon}$
- 2) using symbolic der.:
 $f = x^2 \Rightarrow f' = 2x$
- 3) automatic differentiation (reverse mode \approx back propagation)

Gradient descent

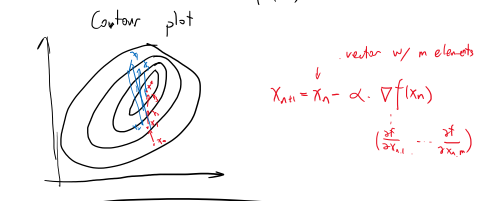


$$x_{n+1} = x_n - \alpha \cdot f'(x_n) \quad (\text{ML: learning rate})$$



Newton method

$$x_{n+1} = x_n - \frac{f'(x_n)}{f''(x_n)}$$



vector w/ n elements

$$x_{n+1} = x_n - \alpha \cdot \nabla f(x_n)$$
$$\left(\frac{\partial f}{\partial x_1}, \dots, \frac{\partial f}{\partial x_n} \right)$$

max $U(A, B)$

s.t. $p_A \cdot A + p_B \cdot B \leq W$

$$\frac{MU_A}{MU_B} = MRS_{A,B} = \frac{P_A}{P_B} \quad (\text{ECON 101})$$

$$\mathcal{L} = U(A, B) - \lambda (p_A A + p_B B - W)$$

$$\frac{\partial \mathcal{L}}{\partial A} = \frac{\partial U}{\partial A} - \lambda \cdot p_A \Rightarrow \frac{\partial U / \partial A}{\partial U / \partial B} = \frac{P_A}{P_B} \quad (\text{ECON 200})$$

inter. micro.