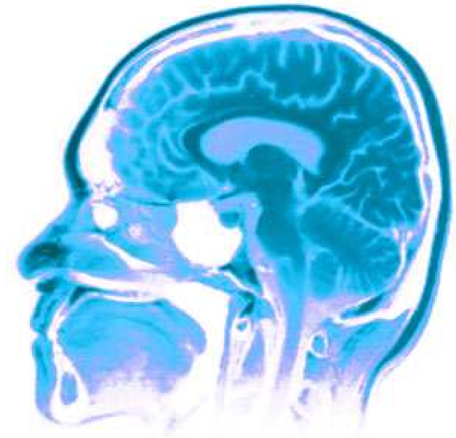
CPSC540



Optimization: gradient descent and Newton's method

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Outline of the lecture

Many machine learning problems can be cast as optimization problems. This lecture introduces optimization. The objective is for you to learn:

- ❑ The definitions of gradient and Hessian.
- ❑ The gradient descent algorithm.
- ❑ Newton’s algorithm.
- ❑ The stochastic gradient descent algorithm for online learning.
- ❑ How to apply all these algorithms to linear regression.

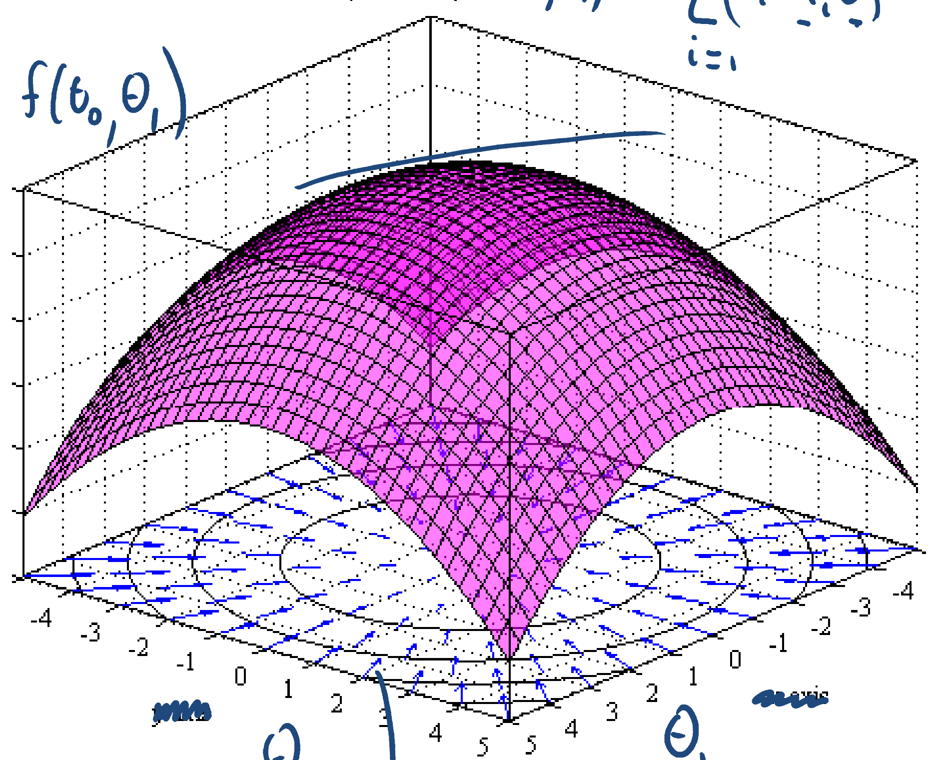
Gradient vector

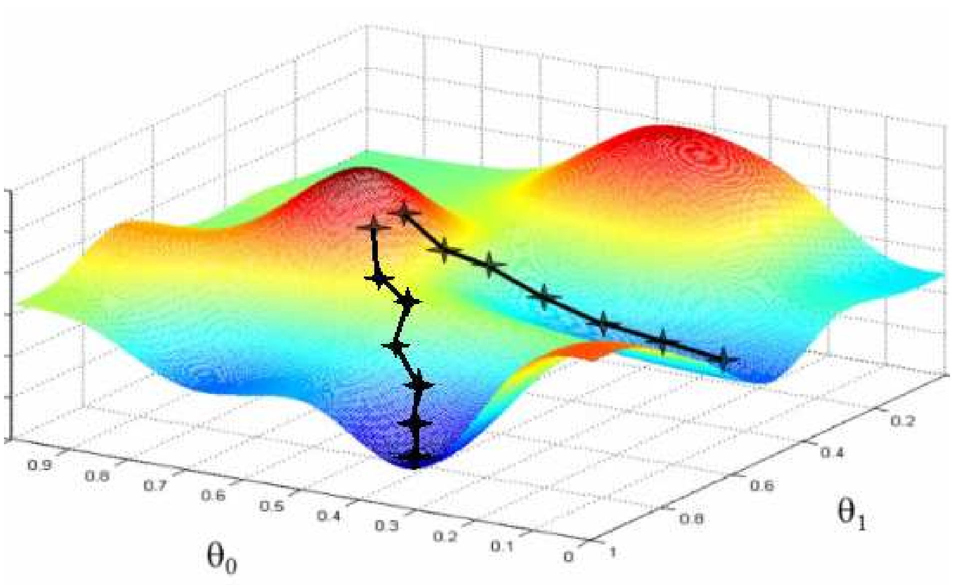
$\Theta = (\theta_0, \theta_1)$

Let $\boldsymbol{\theta}$ be an d-dimensional vector and $f(\boldsymbol{\theta})$ a scalar-valued function. The gradient vector of $f(\cdot)$ with respect to $\boldsymbol{\theta}$ is:

$f(\theta_0, \theta_1) = -\sum_{i=1}^{n} (y_i - x_i \theta)^2$

$$\nabla_{\boldsymbol{\theta}} f(\boldsymbol{\theta}) = \begin{bmatrix} \frac{\partial f(\boldsymbol{\theta})}{\partial \theta_1} \\ \frac{\partial f(\boldsymbol{\theta})}{\partial \theta_2} \\ \vdots \\ \frac{\partial f(\boldsymbol{\theta})}{\partial \theta_n} \end{bmatrix}$$





$$\nabla_\theta f(\theta) = \begin{bmatrix} \partial f(\theta) / \partial \theta_0 \\ \partial f(\theta) / \partial \theta_1 \end{bmatrix}_{\theta = \theta^*}$$

Hessian matrix

The **Hessian** matrix of $f(\cdot)$ with respect to $\boldsymbol{\theta}$, written $\nabla^2_{\boldsymbol{\theta}} f(\boldsymbol{\theta})$ or simply as $\mathbf{H}$, is the $d \times d$ matrix of partial derivatives,

$$\nabla^2_{\boldsymbol{\theta}} f(\boldsymbol{\theta}) = \begin{bmatrix} \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_1^2} & \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_1 \partial \theta_2} & \cdots & \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_1 \partial \theta_n} \\ \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_2 \partial \theta_1} & \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_2^2} & \cdots & \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_2 \partial \theta_d} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_d \partial \theta_1} & \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_d \partial \theta_2} & \cdots & \frac{\partial^2 f(\boldsymbol{\theta})}{\partial \theta_d^2} \end{bmatrix}$$

In **offline** learning, we have a **batch** of data $\mathbf{x}_{1:n} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$. We typically optimize cost functions of the form

$$f(\boldsymbol{\theta}) = f(\boldsymbol{\theta}, \mathbf{x}_{1:n}) = \frac{1}{n}\sum_{i=1}^{n} f(\boldsymbol{\theta}, \mathbf{x}_i)$$

The corresponding gradient is

$$g(\boldsymbol{\theta}) = \nabla_{\boldsymbol{\theta}} f(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n} \nabla_{\boldsymbol{\theta}} f(\boldsymbol{\theta}, \mathbf{x}_i)$$

For linear regression with training data $\{\mathbf{x}_i, y_i\}_{i=1}^{n}$, we have have the quadratic cost

$$f(\boldsymbol{\theta}) = f(\boldsymbol{\theta}, \mathbf{X}, \mathbf{y}) = (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\theta}) = \sum_{i=1}^{n}(y_i - \mathbf{x}_i\boldsymbol{\theta})^2$$

Gradient vector and Hessian matrix

$$f(\boldsymbol{\theta}) = f(\boldsymbol{\theta}, \mathbf{X}, \mathbf{y}) = (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\theta}) = \sum_{i=1}^{n}(y_i - \mathbf{x}_i^T\boldsymbol{\theta})^2$$

$$\nabla_\theta f(\theta) = 2X^TX\theta - 2X^Ty \equiv \nabla_\theta f(\theta) = -2\sum_{i=1}^{n} x_i^T(y_i - x_i^T\theta)$$

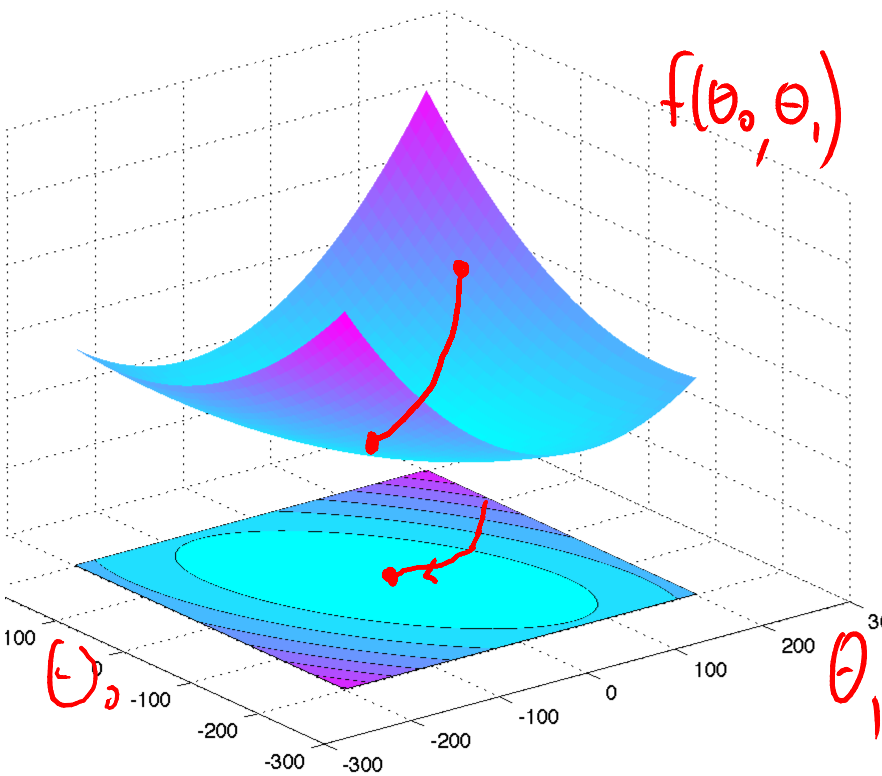
$$H = \nabla_\theta^2 f(\theta) = 2X^TX$$

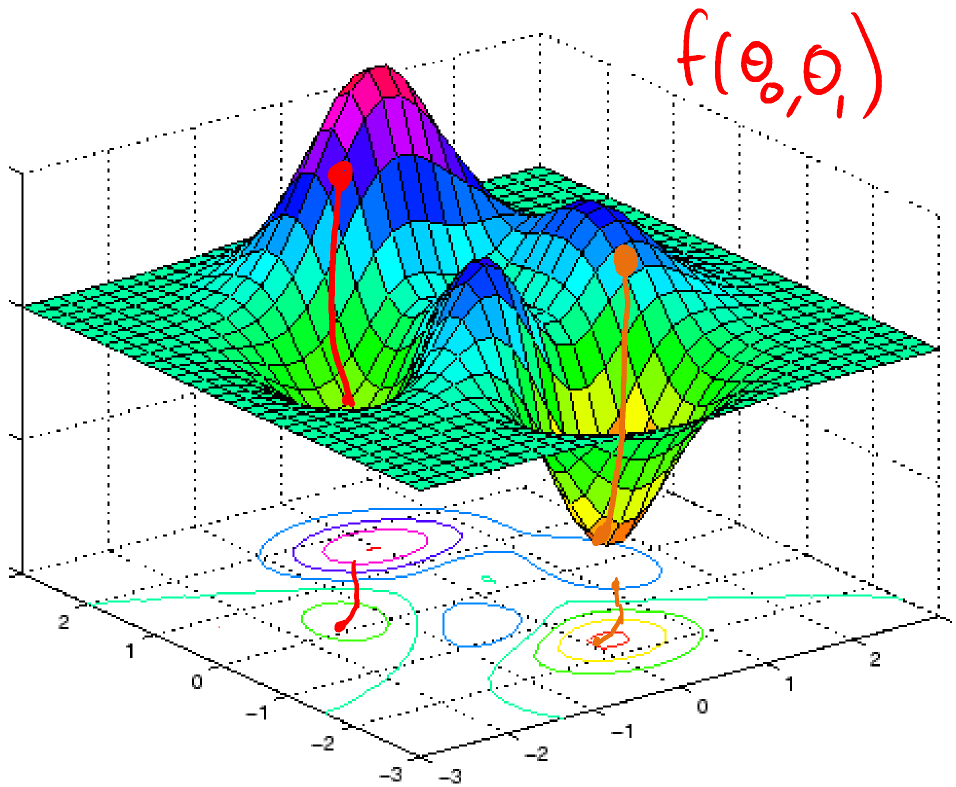
Steepest gradient descent algorithm

One of the simplest optimization algorithms is called **gradient descent** or **steepest descent**. This can be written as follows:

$$\underbrace{\overset{d\times 1}{\boldsymbol{\theta}_{k+1}}} = \overset{d\times 1}{\boldsymbol{\theta}_k} - \eta_k \overset{d\times 1}{\mathbf{g}_k} = \boldsymbol{\theta}_k - \eta_k \nabla f(\boldsymbol{\theta}_k)$$

where k indexes steps of the algorithm, $\mathbf{g}_k = \mathbf{g}(\boldsymbol{\theta}_k)$ is the gradient at step k, and $\eta_k > 0$ is called the **learning rate** or **step size**.





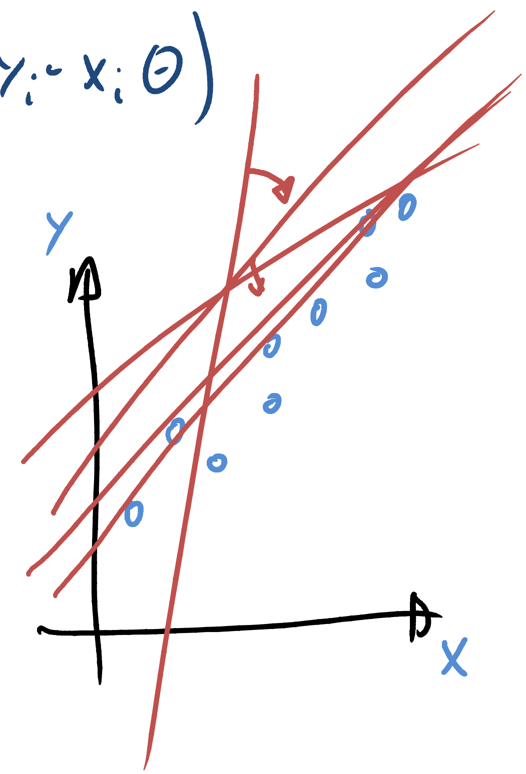
Steepest gradient descent algorithm for least squares

$$f(\boldsymbol{\theta}) = f(\boldsymbol{\theta}, \mathbf{X}, \mathbf{y}) = (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\theta}) = \sum_{i=1}^{n}(y_i - \mathbf{x}_i\boldsymbol{\theta})^2$$

$$\nabla f(\theta) = 2X^TX\theta - 2X^Ty = -2\sum_{i=1}^{n} x_i^T(y_i - x_i\theta)$$

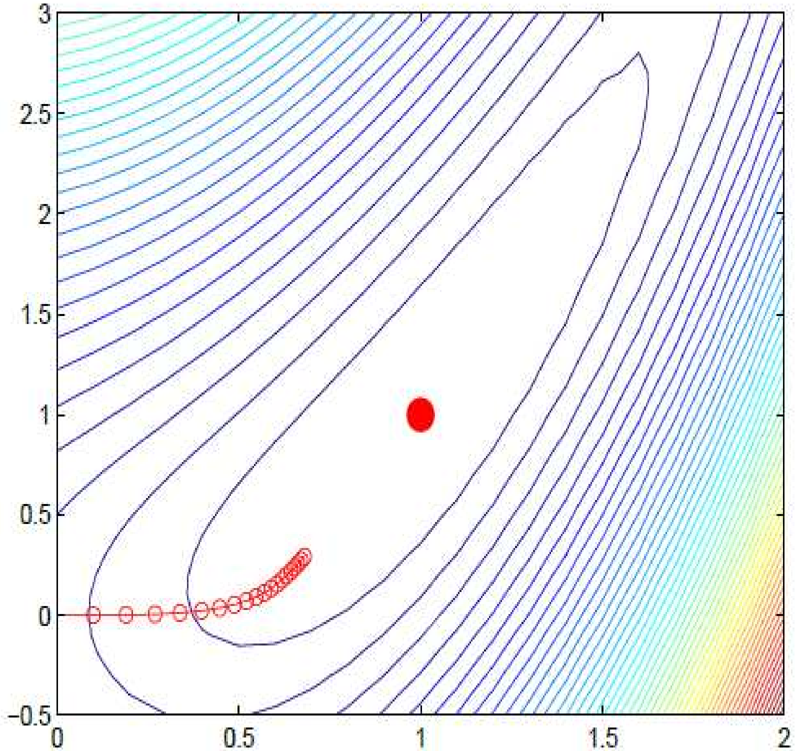
$$\theta_{k+1} = \theta_k - 2\eta\left[X^TX\theta_k - X^Ty\right]$$

$$\theta_{k+1} = \theta_k + 2\eta\sum_{i=1}^{n} x_i^T(y_i - x_i\theta)$$



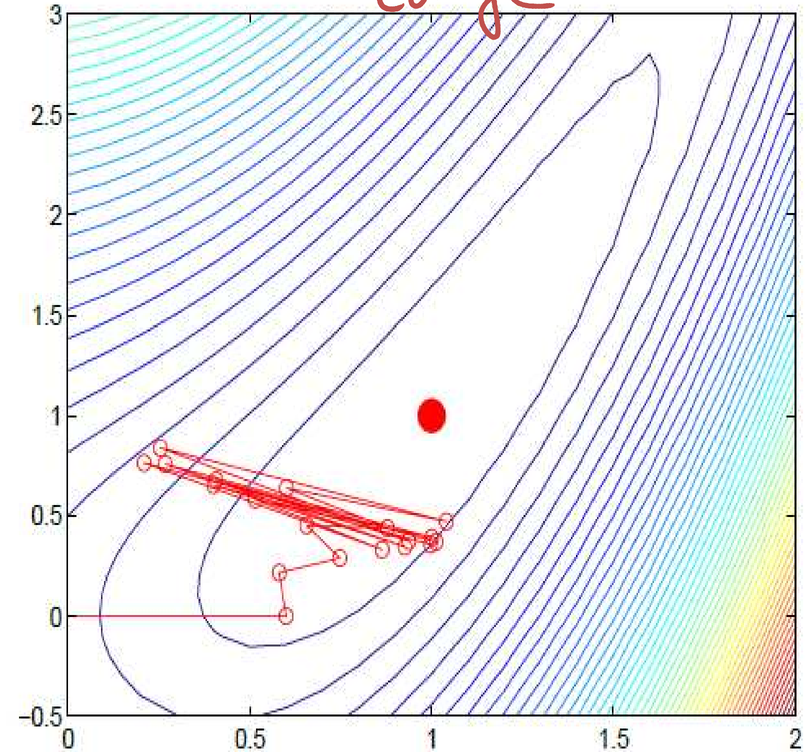
How to choose the step size ?

Too small



$\eta = 0.1.$

Too Large



$\eta = 0.6.$

$$\Theta_{k+1} = \Theta_k - \underbrace{(0.1)\,\nabla f(\Theta_k)}_{\approx 0}$$

Newton's algorithm

The most basic second-order optimization algorithm is **Newton's algorithm**, which consists of updates of the form

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k - \mathbf{H}_K^{-1}\mathbf{g}_k$$

This algorithm is derived by making a second-order Taylor series approximation of $f(\boldsymbol{\theta})$ around $\boldsymbol{\theta}_k$:

$$\frac{1}{2}\left[\theta^T H_k \theta - 2\theta^T H_k \theta_k + \cancel{\theta_k^T H_k \theta_k}\right]$$

$$f_{quad}(\boldsymbol{\theta}) = f(\boldsymbol{\theta}_k) + \mathbf{g}_k^T(\boldsymbol{\theta} - \boldsymbol{\theta}_k) + \frac{1}{2}(\boldsymbol{\theta} - \boldsymbol{\theta}_k)^T\mathbf{H}_k(\boldsymbol{\theta} - \boldsymbol{\theta}_k)$$

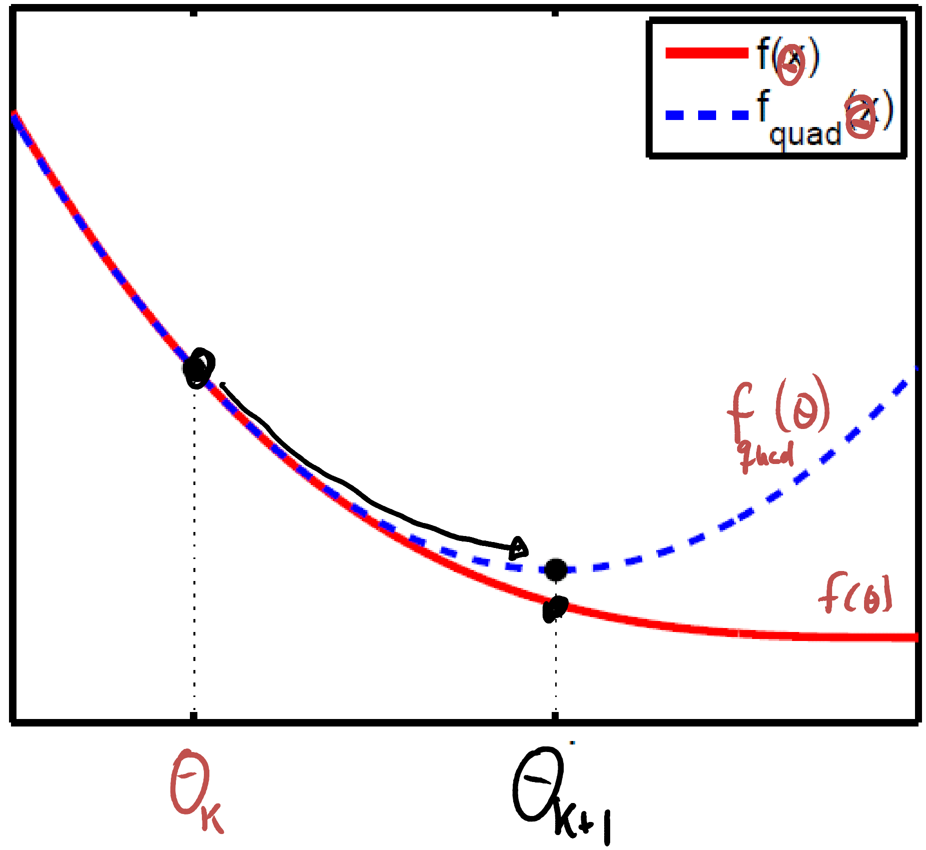
differentiating and equating to zero to solve for $\boldsymbol{\theta}_{k+1}$.

$$\frac{\partial f_{quad}(\theta)}{\partial(\theta)} = 0 + g_k + H_k(\theta - \theta_k) \to 0$$

$$-g_k = H_k\theta - H_k\theta_k$$

$$-H_k^{-1}g_k = \theta - \theta_k$$

Newton's as bound optimization



Newton's algorithm for linear regression

$$f(\boldsymbol{\theta}) = f(\boldsymbol{\theta}, \mathbf{X}, \mathbf{y}) = (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\theta}) = \sum_{i=1}^{n}(y_i - \mathbf{x}_i\boldsymbol{\theta})^2$$

$$g = Df(\theta) = 2X^TX\theta - 2X^Ty$$

$$H = 2X^TX$$

$$\theta_{k+1} = \theta_k - \frac{2}{2}(X^TX)^{-1}\left[X^TX\theta_k - X^Ty\right]$$

$$= \theta_k - (X^TX)^{-1}(X^TX)\theta_k + (X^TX)^{-1}X^Ty$$

$$= (X^TX)^{-1}X^Ty$$

exercise

show this is

$(X^TX)^{-1}X^Ty$

Advanced: Newton CG algorithm

Rather than computing $\mathbf{d}_k = -\mathbf{H}_k^{-1}\mathbf{g}_k$ directly, we can solve the linear system of equations $\mathbf{H}_k\mathbf{d}_k = -\mathbf{g}_k$ for $\mathbf{d}_k$.

One efficient and popular way to do this, especially if $\mathbf{H}$ is sparse, is to use a conjugate gradient method to solve the linear system.

Initialize $\boldsymbol{\theta}_0$

for $k = 1, 2, \ldots$ *until convergence* **do**

    Evaluate $\mathbf{g}_k = \nabla f(\boldsymbol{\theta}_k)$

    Evaluate $\mathbf{H}_k = \nabla^2 f(\boldsymbol{\theta}_k)$

    Solve $\mathbf{H}_k\mathbf{d}_k = -\mathbf{g}_k$ for $\mathbf{d}_k$

    Use line search to find stepsize η_k along $\mathbf{d}_k$

    $\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \eta_k\mathbf{d}_k$

Online learning
aka stochastic gradient descent

Batch

$$\Theta_{k+1} = \Theta_k + \eta \sum_{i=1}^{n} x_i^T (y_i - x_i \theta_k) \quad \left(\begin{array}{c} n \\ \text{data} \\ \text{points} \end{array}\right)$$

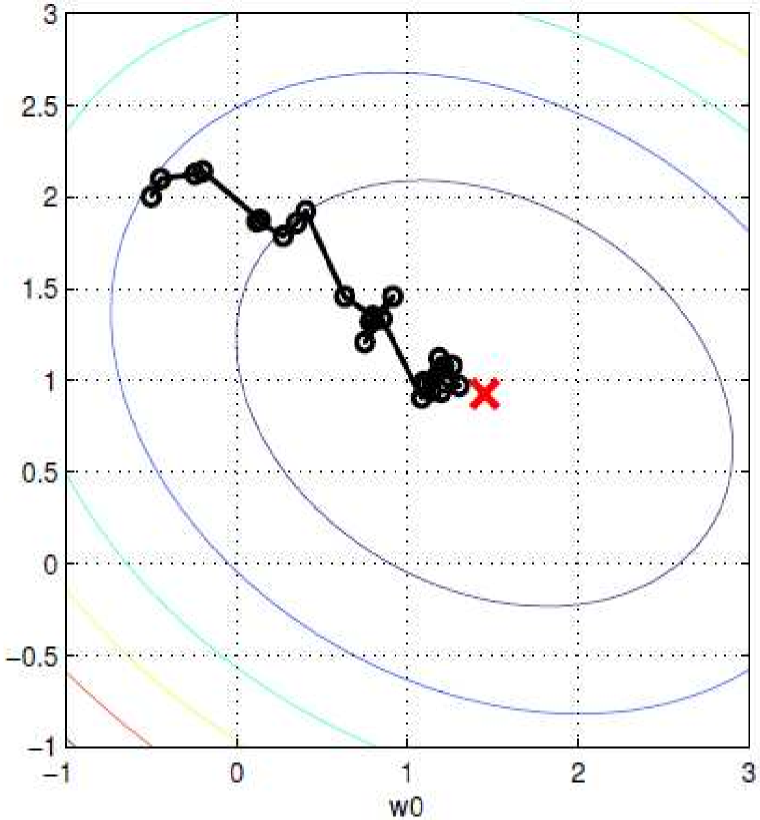
Online

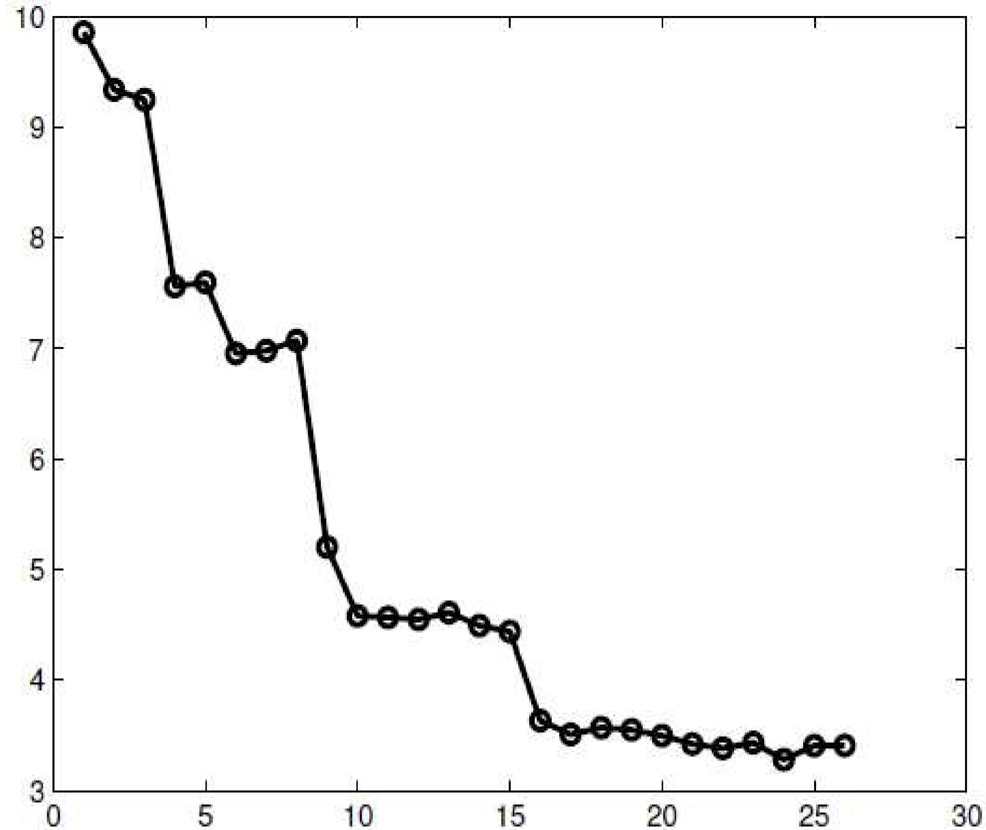
$$\Theta_{k+1} = \Theta_k + \eta\, x_k^T (y_k - x_k \Theta_k)$$

mini-batch

$$\Theta_{k+1} = \Theta_k + \eta \sum_{j=1}^{20} x_j^T (y_j - x_j \Theta_k)$$

The online learning algorithm





Stochastic gradient descent

SGD can also be used for offline learning, by repeatedly cycling through the data; each such pass over the whole dataset is called an **epoch**. This is useful if we have **massive datasets** that will not fit in main memory. In this offline case, it is often better to compute the gradient of a **mini-batch** of B data cases. If $B = 1$, this is standard SGD, and if $B = N$, this is standard steepest descent. Typically $B \sim 100$ is used.

Intuitively, one can get a fairly good estimate of the gradient by looking at just a few examples. Carefully evaluating precise gradients using large datasets is often a waste of time, since the algorithm will have to recompute the gradient again anyway at the next step. It is often a better use of computer time to have a noisy estimate and to move rapidly through parameter space.

SGD is often less prone to getting stuck in shallow local minima, because it adds a certain amount of "noise". Consequently it is quite popular in the machine learning community for fitting models such as neural networks and deep belief networks with non-convex objectives.

Next lecture

In the next lecture, we apply these ideas to learn a neural network with a single neuron (logistic regression).