

Thursday, 9/8

What about something a little harder?

Let's compute:

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Big-O

$$f(x) = O(g(x)) \text{ as } x \rightarrow a$$

$$\Leftrightarrow \exists \delta > 0 \exists M > 0$$

$$\text{st } 0 < |x - a| < \delta$$

$$\Rightarrow |f(x)| \leq M g(x)$$

$$\text{or } \lim_{x \rightarrow a} \frac{f(x)}{g(x)} < \infty$$

OK:

$$D \|y - Ae\|_2^2 = D(y - Ae)^T (y - Ae)$$

Also review MVE
show how to do it
using PDS

$$(y - A(c + \delta c))^T (y - A(c - \delta c))$$

$$= y^T y - y^T A(c + \delta c) - [A(c - \delta c)]^T y + [A(c - \delta c)]^T [A(c - \delta c)]$$

$$= y^T y - y^T A c - (A c)^T y + (A c)^T (A c)$$

$$+ y^T A \delta c + (A \delta c)^T y - (A c)^T A \delta c - (A \delta c)^T A c$$

$$+ (A \delta c)^T A \delta c$$

$$= (y - A c)^T (y - A c) + 2 y^T A \delta c - 2 (A c)^T A \delta c$$

$$+ (A \delta c)^T A \delta c$$

$$= \underbrace{\|y - A c\|_2^2}_{"S(c)"} + \underbrace{2 (y - A c)^T A \delta c}_{D \|y - A c\|_2^2} + O(\|\delta c\|_2^2)$$

transpose

$$\Rightarrow \nabla_c \|y - A c\|_2^2 = 2 A^T (y - A c)$$

Problem: compute $\nabla f(x)$, where $x \in \mathbb{R}^n$, and

$$f(x) = \frac{1}{2} x^T A x + b^T x + c$$

• These were examples of linear least squares.

• Why linear? We fit a function which is a linear model, i.e.,

$$f(x, c) = c_0 f_0(x) + c_1 f_1(x) + \dots + c_m f_m(x).$$

The functions f_i may be nonlinear, but they are a linear combination. Hence, fitting reduces to solving a nonlinear system.

• We can also have a nonlinear dependence on the model parameters, e.g.,

$$f(x, c) = \frac{c_0 + c_1 x}{1 + c_2 x}$$

• This leads to nonlinear least squares.

$$\text{minimize } \|y - f(c)\|_2^2 = \sum_{i=0}^n (y_i - f(x_i, c))^2.$$

How to solve? Let $F(c) = \|y - f(c)\|_2^2$. Take gradient, set equal to zero, solve. Let's see:

$$\begin{aligned} DF(c) &= D \|y - f(c)\|_2^2 = D (y - f(c))^T (y - f(c)) \\ &= D (y^T y - 2 f(c)^T y + f(c)^T f(c)) \\ &= D - 2 D f(c)^T y + 2 D f(c)^T f(c) \\ &= -2 D f(c)^T (y - f(c)). \end{aligned}$$

OK... we have:

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$$DS(c)^T (y - f(c)) = 0 \Rightarrow DS(c)^T y = DS(c)^T f(c).$$

Not totally clear how to proceed...

Let's try the following trick: Let's introduce an iteration

$$f(c) = f(c^{(0)}, c^{(1)}, \dots)$$

where $c^{(n+1)} = c^{(n)} + \Delta c^{(n)}$

Let's apply our equation at $c^{(n)}$ to get:

$$\begin{aligned} DS(c^{(n+1)})^T y &= DS(c^{(n+1)})^T f(c^{(n+1)}) \\ &= DS(c^{(n+1)})^T f(c^{(n)} + \Delta c^{(n)}) \\ &= DS(c^{(n+1)})^T \left[f(c^{(n)}) + DS(c^{(n)}) \Delta c^{(n)} + O(\|\Delta c^{(n)}\|^2) \right] \end{aligned}$$

Let's assume c^* is the true solution to the nonlinear least squares problem and that $c^{(n)} \rightarrow c^*$ as $n \rightarrow \infty$.

This implies that $\|c^{(n+1)} - c^{(n)}\|_2 = \|\Delta c^{(n)}\|_2 \rightarrow 0$

as $n \rightarrow \infty$, hence, we are justified in ignoring the quadratic term " $O(\|\Delta c^{(n)}\|_2^2)$ " and consider instead: (roughly);

$$\begin{aligned} DS(c^{(n)})^T y &\approx DS(c^{(n)})^T \left[f(c^{(n)}) + DS(c^{(n)}) \Delta c^{(n)} \right] \\ \Rightarrow \Delta c^{(n)} &\approx \left[DS(c^{(n)})^T DS(c^{(n)}) \right]^{-1} DS(c^{(n)})^T (y - f(c^{(n)})) \end{aligned}$$