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MATHEMATICS

Differentiate $f(x) = x^T A x$

Asked 8 years, 7 months ago Active 2 months ago Viewed 37k times



Calculate the differential of the function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ given by

16

$$f(x) = x^T A x$$



with A symmetric. Also, differentiate this function with respect to x^T .



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How exactly does this work in the case of vectors and matrices? Could anyone please help me out?

[matrices](#) [multivariable-calculus](#) [derivatives](#) [quadratic-forms](#)

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edited Sep 15 '19 at 16:40



Rodrigo de Azevedo

1

asked Feb 23 '13 at 15:59



dreamer

3.029 6 36 73

And yes, I will soon try to learn to use Latex :). – dreamer Feb 23 '13 at 16:03

2 I've edited your math formatting, could you look through it and see that it is still correct? – Arthur Feb 23 '13 at 16:06

1 Write math between $\$...$$, you can find symbols etc. here: codecogs.com/latex/eqneditor.php – Kasper Feb 23 '13 at 16:06 

1 try a 2×2 case explicitly and see if you can guess the general form of answer. – Maesumi Feb 23 '13 at 16:09 

1 This is the composition of the linear map $x \mapsto (x, x)$ and the bilinear map $(x, y) \mapsto x^t A y$. You can use the chain rule. – Julien Feb 23 '13 at 16:10 

4 Answers

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There is another way to solve the problem:

20 Let $\mathbf{x}^{n \times 1} = (x_1, \dots, x_n)'$ be a vector, the derivative of $\mathbf{y} = f(\mathbf{x})$ with respect to the vector \mathbf{x} is defined by

$$\frac{\partial f}{\partial \mathbf{x}} = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{pmatrix}$$



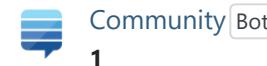
Let

$$\begin{aligned} \mathbf{y} &= f(\mathbf{x}) \\ &= \mathbf{x}' A \mathbf{x} \\ &= \sum_{i=1}^n \sum_{j=1}^n a_{ij} x_i x_j \\ &= \sum_{i=1}^n a_{i1} x_i x_1 + \sum_{j=1}^n a_{1j} x_1 x_j + \sum_{i=2}^n \sum_{j=2}^n a_{ij} x_i x_j \\ \frac{\partial f}{\partial x_1} &= \sum_{i=1}^n a_{i1} x_i + \sum_{j=1}^n a_{1j} x_j \end{aligned}$$

$$\begin{aligned}
 &= \sum_{i=1}^n a_{1i} x_i + \sum_{i=1}^n a_{1i} x_i \quad [\text{since } a_{1i} = a_{i1}] \\
 &= 2 \sum_{i=1}^n a_{1i} x_i \\
 \frac{\partial f}{\partial \mathbf{x}} &= \begin{pmatrix} 2 \sum_{i=1}^n a_{1i} x_i \\ \vdots \\ 2 \sum_{i=1}^n a_{ni} x_i \end{pmatrix} \\
 &= 2 \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \\
 &= 2A\mathbf{x}
 \end{aligned}$$

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edited Jun 12 '20 at 10:38



answered Feb 23 '13 at 20:05



Thanks for showing me this way as well :). Gives me more options :) – dreamer Feb 24 '13 at 10:01

- 1 The only thing that is slightly unclear to me is how $\mathbf{x}' A \mathbf{x}$ becomes the double summation ($a_{ij} x_i x_j$). Why is the order reversed here? I mean, why aren't the a 's in the middle anymore? @Argha – dreamer Feb 24 '13 at 10:04

Note that $\mathbf{x}' A \mathbf{x} = (x_1, \dots, x_n) \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$ and simply multiplying we get required result. Also note order of \mathbf{x}' is $1 \times n$ and order of A is $n \times n$. So order of $\mathbf{x}' A \mathbf{x}$ is 1×1 . – Argha Feb 24 '13 at 11:24

Note that $a_{ij} x_i x_j \equiv x_i a_{ij} x_j$. So there is no problem at all. – Argha Feb 24 '13 at 11:36

- 1 On the first summation of the line that says [since $a_{1i} = a_{i1}$, how did you swap the indices from the previous step? – Michael Chav Sep 28 '17 at 23:40



As a start, things work "as usual": You calculate the difference between $f(\mathbf{x} + h)$ and $f(\mathbf{x})$ and check how it depends on h , looking for a dominant linear part as $h \rightarrow 0$. Here, $f(\mathbf{x} + h) = (\mathbf{x} + h)^T A (\mathbf{x} + h) = \mathbf{x}^T A \mathbf{x} + h^T A \mathbf{x} + \mathbf{x}^T A h + h^T A h = f(\mathbf{x}) + 2\mathbf{x}^T A h$, so

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$$+ h^T A h$$

 $f(x + h) - f(x) = 2x^T A \cdot h + h^T A h$. The first summand is linear in h with a factor $2x^T A$, the second summand is quadratic in h , i.e. goes to 0 faster than the first / is negligible against the first for small h . So the row vector $2x^T A$ is our derivative (or transposed: $2Ax$ is the derivative with respect to x^T).

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answered Feb 23 '13 at 16:13



Hagen von Eitzen

1

Thank you. This is also what I tried. However, what confused me is that the question mentions that you should differentiate with respect to x^T . From your answer, I see that you took the transpose of the 'ordinary' derivative. Does that imply that the ordinary derive is always taken with respect to x so that you can just take the transpose when you differentiate with respect to x^T ? – dreamer Feb 23 '13 at 16:21

2 Are you sure that $x^T A h = h^T A x$? Why? – mavavilj Nov 17 '16 at 13:24

@mavavilj it's not. The dimensions don't necessarily check out. – Michael Chav Sep 28 '17 at 23:28

3 Actually, it's because A is symmetric. – Michael Chav Sep 28 '17 at 23:43

 @Hagen von Eitzen's answer is certainly the fastest route here, but since you asked, here is a chain rule.

3 Here are two useful facts about linear and bilinear bounded maps from normed vectors spaces to normed vector spaces.

 If f is linear and bounded, then trivially:

$$df_x(h) = f(h).$$

And if g is bilinear and bounded ($\|g(h, k)\| \leq C\|h\|\|k\|$), we have

$$dg_{(x,y)}(h, k) = g(x, k) + g(h, y).$$

Now take $f(x) = (x, x)$ and $g(x, y) = x^T A y$. The former is linear and bounded, the latter is bilinear and bounded.

So, by the chain rule, $g \circ f(x) = x^T A x$ is differentiable and

$$d(g \circ f)_x(h) = dg_{f(x)} \circ df_x(h) = dg_{(x,x)}(h, h) = x^T A h + h^T A x.$$

This is true for any matrix A . Now if A is symmetric, this can be simplified since

$$x^T A h + h^T A x = x^T A h + h^T A^T x = x^T A h + (A h)^T x = 2x^T A h.$$

Removing h , this gives

$$d(g \circ f)_x = 2x^T A.$$

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edited Feb 23 '13 at 16:41

answered Feb 23 '13 at 16:34



Julien

42.1k 3 68 149

Thank you. The other answer is indeed quicker but I am glad that I know now how to do it in this way as well. Much appreciated :). – dreamer Feb 23 '13 at 17:03

2 @user48288 You're welcome. And I am sure these general facts about bounded linear and bilinear maps will prove useful sooner or later. – Julien Feb 23 '13 at 17:04

Can I know in detail? I want to know this, but it can be hard to understand. – jakeoung Apr 15 '15 at 23:37



Here is relationship between directional derivative whenever f is differentiable.



$f'(p : v)$ denotes the derivative of f at p in the direction of v .



Let $f : U \subset \mathbb{R}^n \rightarrow \mathbb{R}$ and $p \in U, v \in \mathbb{R}^n$. Suppose that f is differentiable at p . Then we have



$$df_p(v) = f(p; v) = \lim_{t \rightarrow 0} \frac{f(\sigma(t)) - f(p)}{t}$$

for any differentiable curve $\sigma : (-\epsilon, \epsilon) \rightarrow U$ such that $\sigma(0) = p$ and $\sigma'(0) = v$.

In our case $f(x) = x^T A x$ and $\sigma(t) = x + th$,

$$f'(x; h) = \lim_{t \rightarrow 0} \frac{(x + th)^T A (x + th) - x^T A x}{t}$$

$$f'(x; h) = x^T A h + h^T A x$$

Since A is symmetric and we have the following:

$$f'(x; h) = x^T A h + h^T A x = x^T A h + x^T A^T h$$

$$f'(x; h) = x^T (A + A^T) h$$

So the differential/gradient is simply $2x^T A$.

$$f'(x; h) = 2x^T A h$$

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answered Jul 19 at 8:38



Tutankhamun

356 1 3 12