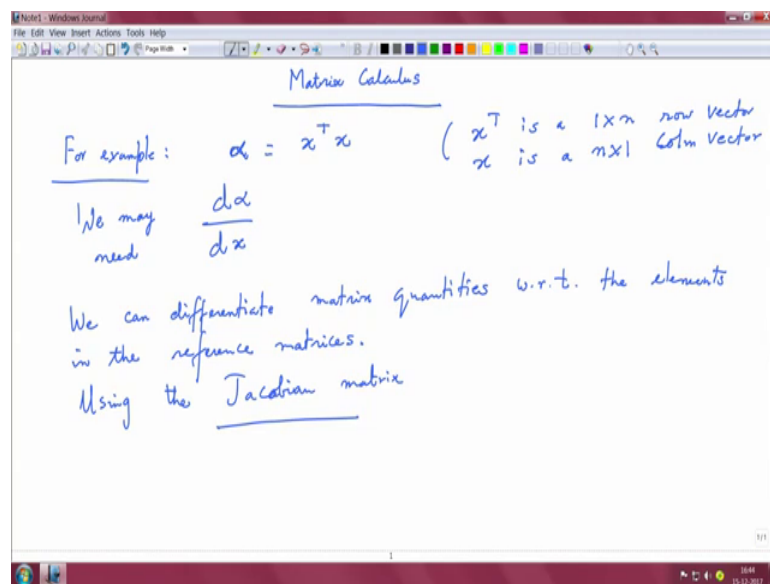


Mathematical Methods and Techniques in Signal Processing – I
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Lecture – 74
Matrix Calculus

So, we have seen cases, where it is required for us to differentiate with respect to vectors, with respect to matrices etcetera. So, this is often encountered in signal processing.

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For example, a simple case would be a form of a scalar which is x transpose x , right. Imagine x is a column vector. So, therefore, x transpose is a 1 by n row matrix and x is n by 1 column I would say row vector, this is a row vector this is a column vector and we may want for some instance different take the derivative of α with respect to x . So, we may need the α by $\text{del } x$.

So, how to go about problems of this form and this is particularly useful when we deal with representing problems vectorially or in the form of matrices and then we have to take derivative of some function of vectors and matrices and compute these quantities and this becomes a nontrivial task.

So, unless you know how to play around with the algebra we will often get stuck and if you do in a routine way we will have to really do this as scalar derivatives over each element by element computation.

So, we will figure out some intuition behind how to go about doing this matrix calculus and then this will be useful when we discuss for example, in k l transforms we will find this often helpful this is an old concept nothing really new, but I would like to give you some idea here.

So, we can differentiate matrix quantities with respect to the elements in the reference matrices and often this is done using the Jacobian matrix. So, there are certain conventions I will present to you an intuition how this works and then we can discuss certain properties, ok.

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Let us start with an example.

Consider $y = Ax$; Suppose A is a 2×2 matrix
 x is a column vector 2×1 .

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + a_{12}x_2 \\ a_{21}x_1 + a_{22}x_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$\frac{\partial y}{\partial x} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = A^T$$

(Denominator layout) $\frac{d(Ax)}{dx} = A^T$

So, let us just start with an example. So, consider A times x. So, y is some A times x suppose A is a 2 by 2 matrix and x is a column vector and this is say suppose 2 by 1 right.

So, let us just compute these quantities a is a 1 1, a 1 2 a 2 1, a 2 2 this is our standard notation right the first row first column, the first row second column, second row first column and the second row second column and then we have x 1, x 2 these are the

elements of this vector x right. So, I just put this bar underneath y index indicated that they are vectors ok.

Now, if you compute this is a 1×1 plus a 1×2 this is a 2×1 plus a 2×2 time x and this is the vector y composed of elements y_1 and y_2 . Now, let us adopt one convention which is basically the hessian rule.

So, if I want to take the derivative of y with respect to x , so that means, I am trying to differentiate I am I am differentiating the vector y with respect to x and this is given in this format this is $\frac{\partial y_1}{\partial x_1}$ then $\frac{\partial y_2}{\partial x_1}$ that is I vary in the row I vary the coordinates of y that is I choose y_1, y_2 and then I take y_1 ; I differentiate with respect to x_1 ; I choose y_2 differentiate with respect to x_1 so on and so forth.

Similarly, second row I look at y_1 take the derivative with respect to x_2 then look at y_2 take the derivative with respect to x_2 and you may really question I mean should I go this way you do not have to for example, if you look at a different format then you can take $\frac{\partial y_1}{\partial x_2}$ by $\frac{\partial y_1}{\partial x_1}$ you can choose $\frac{\partial y_1}{\partial x_2}$ and so on and so forth.

So, this is a different convention. So, there are two different conventions one convention basically keeps the first coordinate of the vector constant in the row and then take the derivative we can follow this convention here which is basically the denominator layout and I mentioned this sort of carefully as long as you are consistent it is fine.

So, you basically keep the y coordinate fixed in there I mean the x coordinate fixed in the denominator and you let the y coordinate basically vary you know within the row that is across the columns. So, this is this is the convention that we will follow. So, now, if you take the derivative $\frac{\partial y_1}{\partial x_1}$ this is basically a 1×1 and $\frac{\partial y_2}{\partial x_1}$ if you take the derivative of y_2 with respect to x_1 you get a 2×1 and similarly if you populate the rest of the entries you get a 1×2 here you get a 2×2 here and observe that this matrix is basically the transpose of A right.

So, we can formulate a rule here that is if I want to differentiate the quantity $A \cdot x$ with respect to x . So, x is a vector I get A transpose, but of course, you should remember the convention which is basically we are following denominator layout and your calculus

has to be sort of consistent I mean if you are basically varying y in the row and keeping x fixed then you should be consistent with respect to that you do not want to mix once when you differentiate you want to have y varying other time, x varying I think that should not really happen, ok.

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Consider $\underline{x}^T A \underline{x}$; Let \underline{x} be a 2×1 column vector
 \underline{x}^T is a 1×2 row vector
 A is a 2×2 matrix

Suppose we are interested in $\frac{d}{d\underline{x}} (\underline{x}^T A \underline{x})$

$$\begin{pmatrix} x_1 & x_2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

A

$$= \begin{pmatrix} x_1 & x_2 \end{pmatrix} \begin{bmatrix} a_{11}x_1 + a_{12}x_2 \\ a_{21}x_1 + a_{22}x_2 \end{bmatrix} = x_1 (a_{11}x_1 + a_{12}x_2) + x_2 (a_{21}x_1 + a_{22}x_2)$$

Now, let us take another example this would be a good example for us consider x transpose A x you will see this form in many many cases, ok. Now, let us look at the math for working out this example. Now, let x be a 2 by 1 column vector, ok. Now, x transpose is a 1 by 2 row vector and a is our 2 by 2 matrix like in the last example.

So, again this is a scalar x transpose a x is a scalar like possibly you think about x transpose x is a scalar I mean if you just multiply you know what makes instead of x transpose x I have x transpose a x and this is a scalar we will find this form this quadratic form in many signal processing applications. So, let us just get an intuitive feel how this works.

So, suppose we are interested in taking derivative with respect to x of the quantity x transpose A x ok. Let us work out the math this is routine computations to get a feel an intuitive feel how this works, right. I have x 1 x 2 this is my x transpose right. So, this is my x transpose now my a is a 1 1, a 1 2 a 2 1 a 2 2 right. This is my A and my x is basically x 1 x 2. Now, if I compute this quantity right I get basically x 1 x 2 let us do an interim step.

So, $x^T A x$ is basically what we had earlier which is a 1×1 plus a 1×2 plus a 2×1 plus a 2×2 , right. When we simplify this is basically x_1 times a 1×1 plus a 1×2 plus x_2 times a 2×1 plus a 2×2 right. Now, we will adopt the same convention let us differentiate the scalar with respect to x_1 and x_2 right. So, earlier case we had a vector and we were differentiating that vector with respect to the with respect to another vector, now we are differentiating a scalar with respect to a vector.

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$$\frac{d(x^T A x)}{dx} = \begin{bmatrix} \frac{\partial \eta}{\partial x_1} \\ \frac{\partial \eta}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 2a_{11}x_1 + a_{12}x_2 + a_{21}x_2 \\ a_{12}x_1 + a_{21}x_1 + 2a_{22}x_2 \end{bmatrix}$$

← Rearranging slightly

$$= \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

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

(If A is symmetric i.e. $A = A^T$)
 Then $\frac{d}{dx}(x^T A x) = 2Ax$

Now, derivative of $x^T A x$ by dx . So, this can be done as follows this is basically derivative of. So, let me call this quantity here you know the scalar as eta just for convention. So, this is basically eta here ok. So, now, we have $\frac{\partial \eta}{\partial x_1}$ and then you have $\frac{\partial \eta}{\partial x_2}$. If you work out this carefully you will end up with the following this is going to be 2 times a 1×1 plus a 1×2 plus a 2×1 and then you have the other term which is a 1×2 plus a 2×1 plus 2 a 2×2 .

Now, let us try to rearrange this right. We will end up as follows where a 1×1 , a 1×2 , a 2×1 , a 2×2 you can just verify this that it is going to be of this form. So, you will have to have 2 times a 1×1 that has to appear and you have one term here and here another term here right I think this is straightforward to verify.

So, now this can be written as $Ax + A^T x$ which is basically $(A + A^T)x$. So, if A is symmetric that is $A = A^T$ right then derivative

of $x^T A x$ with respect to x is going to be $2 A x$. So, I think is a standard result.

Now, you will find this form very very helpful when you when you deal with calculus I mean I just gave you an intuitive feel how you can do this for a 2 by 2 matrix and 1 by 2 vector and you can sort of generalize this to A which is an n by n matrix x being n by 1 column vector and x^T being a 1 by n row vector and the results are pretty straightforward ok. So, let us see one other case will give you an example again.

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Consider another example

$$\frac{\partial}{\partial x} (u^T \cdot v)$$

$$\eta = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$$

$$\eta = u_1 v_1 + u_2 v_2$$

$$\frac{\partial \eta}{\partial x} = \begin{bmatrix} u_1 \frac{\partial v_1}{\partial x_1} + v_1 \frac{\partial u_1}{\partial x_1} + u_2 \frac{\partial v_2}{\partial x_1} + v_2 \frac{\partial u_2}{\partial x_1} \\ u_1 \frac{\partial v_1}{\partial x_2} + v_1 \frac{\partial u_1}{\partial x_2} + u_2 \frac{\partial v_2}{\partial x_2} + v_2 \frac{\partial u_2}{\partial x_2} \end{bmatrix}$$

Consider another example where I want to take the derivative with respect to x of some product of 2 vectors u and v right. So, let us form this scalar which is u_1, u_2 times v_1, v_2 now that you could call this possibly $u^T v$ following the same convention that we followed right.

Now, η in general is say $u_1 v_1$ plus $u_2 v_2$ they are two different vectors. Now, if you are interested in taking the derivative with respect to x of the scalar η then you will end up with the chain rule as follows, right. So, it is $u_1 \frac{\partial v_1}{\partial x_1} + v_1 \frac{\partial u_1}{\partial x_1} + u_2 \frac{\partial v_2}{\partial x_1} + v_2 \frac{\partial u_2}{\partial x_1}$ plus $u_1 \frac{\partial v_1}{\partial x_2} + v_1 \frac{\partial u_1}{\partial x_2} + u_2 \frac{\partial v_2}{\partial x_2} + v_2 \frac{\partial u_2}{\partial x_2}$.

So, just carefully observe that I kept this x_1 fixed throughout in the in the in the in the derivative I assumed this form. So, this is basically the denominator layout. Now, the

second term of course, would be $u_1 \frac{\partial}{\partial x_2} v_1 + v_1 \frac{\partial}{\partial x_2} u_1 + u_2 \frac{\partial}{\partial x_2} v_2 + v_2 \frac{\partial}{\partial x_2} u_2$. So, if you rearrange the terms carefully, right.

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Let us rearrange the terms

$$\begin{bmatrix} \frac{\partial u_1}{\partial x_1} & \frac{\partial u_2}{\partial x_1} \\ \frac{\partial u_1}{\partial x_2} & \frac{\partial u_2}{\partial x_2} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} + \begin{bmatrix} \frac{\partial v_1}{\partial x_1} & \frac{\partial v_2}{\partial x_1} \\ \frac{\partial v_1}{\partial x_2} & \frac{\partial v_2}{\partial x_2} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$= \frac{\partial u}{\partial x} \cdot v + \frac{\partial v}{\partial x} \cdot u$$

Let us try to do that you will get $\frac{\partial}{\partial x_1} u_1 v_1 + \frac{\partial}{\partial x_1} u_2 v_2 + \frac{\partial}{\partial x_2} u_1 v_1 + \frac{\partial}{\partial x_2} u_2 v_2$ and then you will have a vector $v_1 v_2$ here. Similarly, you will have one more matrix as you can similarly imagine this is going to be the vector u_1 the vector u comprised of u_1 and u_2 and you can think of $\frac{\partial}{\partial x_1} v_1 + \frac{\partial}{\partial x_1} v_2$ upon $\frac{\partial}{\partial x_1}$ and $\frac{\partial}{\partial x_2} v_1 + \frac{\partial}{\partial x_2} v_2$ upon $\frac{\partial}{\partial x_2}$ this is a this is v_1 here $\frac{\partial}{\partial x_1} v_1 + \frac{\partial}{\partial x_2} v_1$ upon $\frac{\partial}{\partial x_1}$ and $\frac{\partial}{\partial x_2}$, ok.

So, this is basically written in the form $\frac{\partial u}{\partial x} \cdot v + \frac{\partial v}{\partial x} \cdot u$ the in dot product with the times v plus $\frac{\partial v}{\partial x} \cdot u$.

Of course, we have to see that this is not the dot product it is just a normal multiplication you will find is very very useful. So, I think now since you have gotten a feel an intuitive feel how to go about doing the calculus I will give you some quantity of a table comprising of these derivatives you can just directly verify those as a part of a homework exercise and basically you can convince yourself that these results are correct, ok.

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Summarize some rules of matrix differentiation

Quantity	Result
1) a is not a function of x $\frac{\partial a}{\partial x}$	0
2) $\frac{\partial (Ax)}{\partial x}$	A^T
3) $\frac{\partial (x^T A)}{\partial x}$	A
4) $\frac{\partial (Ax)}{\partial x}$	$\frac{\partial u}{\partial x} \cdot A^T$
5) $\frac{\partial (x^T A x)}{\partial x}$	$(A + A^T)x = 2Ax$ if $A = A^T$ (i.e., for symmetric matrices)

So, let me summarize some rules of matrix differentiation [noise]. Now, let us see the quantity and then the result right. First is a is a constant that is not a function of x and if I am interested in $\frac{\partial a}{\partial x}$ the result should be 0.

Then, we saw that $\frac{\partial (Ax)}{\partial x}$ is a vector upon $\frac{\partial}{\partial x}$ and this is A^T transpose and you could do the other way around you could take x^T transpose here right, that is another possibility if you did $\frac{\partial (x^T A)}{\partial x}$ with respect to $\frac{\partial}{\partial x}$ you should get A here ok, two different variations A and B then $\frac{\partial (Ax)}{\partial x} = A^T x$, where u is some function of x and A is a constant matrix you get $\frac{\partial (u^T A)}{\partial x} = A$ times $\frac{\partial u}{\partial x}$ then we have this important result $\frac{\partial (x^T A x)}{\partial x} = (A + A^T)x$ this is A plus A transpose times x and when A is symmetric which is equal to $2Ax$ if $A = A^T$ that is for symmetric matrices.

So, I think using these basic rules for doing matrix calculus. It is very easy for you to take a derivative of a scalar with respect to a vector or scalar with respect to a matrix and so on and so forth and we will explore these results when we discuss you know some optimization that requires taking derivatives of certain quantities with respect to vectors.

So, with this we conclude some basics on Matrix Calculus that is required for your mathematical methods.