EECSIB DISIIB remote

learning objectives

- I Writing linearizations of a function at an operating point for functions of one variable
- 2 Extending linearizations to functions of multiple variables

Linearization: Coming up with a linear model for a nonlinear system that is "true" for states close to some state (operating point)

Q: Why do we want to look at a nonlinear system as if it were linear?

A: Use all of our tools we have developed up until now!

Control system

We've seen

$$\dot{x}(it1) = \dot{A}\dot{x}(i) + \dot{B}\dot{u}(i)$$
(Inear system)

 $\dot{d}\dot{x}(t) = \dot{A}\dot{x}(t) + \dot{B}\dot{u}(t)$
(continuous time)

 $\dot{d}\dot{x}(t) = \dot{A}\dot{x}(t) + \dot{B}\dot{u}(t)$
(linear system)

Mot systems in real life are nothinear

EECS 16B Designing Information Devices and Systems II
Fall 2021 Discussion Worksheet Discussion 11B

The following notes are useful for this discussion: Note 19

1. Linear Approximation

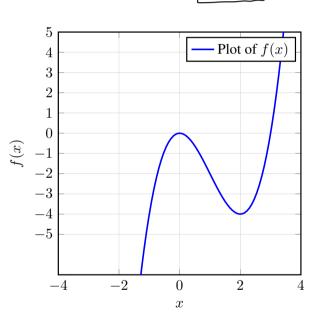
A common way to approximate a nonlinear function is to perform linearization near a point. In the case of a one-dimensional function f(x), the linear approximation of f(x) at a point x_* is given by

$$f(x) \approx f(x_{\star}) + f'(x_{\star}) \cdot (x - x_{\star}), \tag{1}$$

where $f'(x_{\star}) := \frac{\mathrm{d}f}{\mathrm{d}x}(x_{\star})$ is the derivative of f(x) at $x = x_{\star}$.

Keep in mind that wherever we see x_{\star} , this denotes a *constant value* or operating point.

(a) Suppose we have the single-variable function $f(x) = x^3 - 3x^2$. We can plot the function f(x) as follows:



To linearize a function of one variable Compute $f(X_{A})$

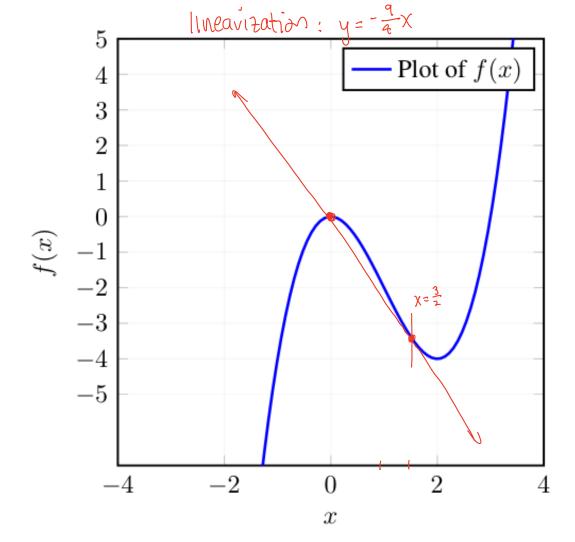
1

i. Write the linear approximation of the function around an arbitrary point x_{\star} .

$$f(x_{A}) = \chi_{A}^{3} - 3\chi_{A}^{2}$$

$$f'(x) = \frac{1}{4x} \left(\frac{x^{3} - 3x^{2}}{f(x)} \right) = 3x^{2} - 6x \qquad f'(x_{A}) = 3x_{A}^{2} - 6x_{A}$$

$$f(x) \approx \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{3x_{A}^{2} - 6x_{A}}{f(x)} \right) \left(\frac{x^{3} - 3x_{A}^{2}}{f(x)} \right) + \left(\frac{x^{$$



ii. Using the expression above, linearize the function around the point x=1.5. Draw the linearization into the plot of part i).

$$f(x) \approx (x_{A}^{3} - 3x_{A}^{2}) + (3x_{A}^{2} - 6x_{A})(x - x_{A})$$

$$x_{A} = 1.5 = \frac{3}{2}$$

$$f(x) \approx ((\frac{3}{2})^{2} - 3(\frac{3}{2})^{2}) + (3(\frac{3}{2})^{2} - 6(\frac{3}{2}))(x - \frac{3}{2})$$

$$= \frac{27}{8} - \frac{27}{4} + (\frac{27}{4} - \frac{18}{2})(x - \frac{3}{2})$$

$$= -\frac{27}{8} + (\frac{27 - 36}{4})(x - \frac{3}{2})$$

$$= -\frac{27}{8} + (-\frac{9}{4})(x - \frac{3}{2})$$

$$= -\frac{27}{8} - \frac{9}{4} \times |$$

$$= -\frac{9}{4} \times |$$

ii. Using the expression above, linearize the function around the point x=1.5. Draw the linearization into the plot of part i). Dove above.

> Now that we have this specific point's linearization, we understand how the function behaves around the point. Let's use this linearization to evaluate the function's approximation at x = 1.7(based on our approximation at x = 1.5, we want to see how a $\delta = +0.2$ shift in the x value changes the corresponding f(x) value). How does this approximation compare to the exact value of the function at x = 1.7?

$$f(1.7) \approx -3.375 + (-2.25) \cdot (1.7 - 1.5)$$
 (2)

$$\approx -3.375 - 0.45 \tag{3}$$

$$f(1.7) \approx -3.375 + (-2.25) \cdot (1.7 - 1.5)$$
 (2)
 $\approx -3.375 - 0.45$ (3)
 ≈ -3.825 close because 1.7 is (4) point close to 1.5 (operating point)

Comparing to the exact value $f(1.7) = 1.7^3 - 3 \cdot 1.7^2 = -3.757$, we find that the difference is 0.068. Not too bad! What if we repeat with $\delta = 1$? To do so, we must use the approximation around x = 1.5 to compute x = 2.5, and compare to the exact value f(2.5). How does our new approximation compare to the exact result?

$$f(2.5) \approx -3.375 + (-2.25) \cdot (2.5 - 1.5) \tag{5}$$

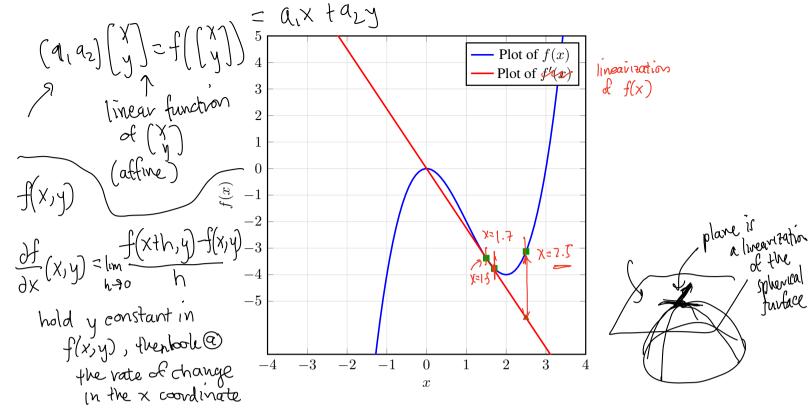
$$\approx -3.375 - 2.25 \tag{6}$$

$$\approx -3.375 - 2.25$$

$$\approx -5.625 \iff \text{very different} \tag{6}$$

Comparing to the exact value $f(2.5) = 2.5^3 - 3 \cdot 2.5^2 = -3.125$, we find that the difference is much larger; the error jumped to 2.5! This is an error multiplication of $\frac{2.5}{0.068} \approx 37$, even though our δ only multiplied by 5. What happened?

Looking at the actual function, we see that the function has a significant curvature between our "anchor point" of $x_{\star} = 1.5$ and x = 2.5. Our linear model is unable to capture this curvature, and so we estimated f(2.5) as if the function kept decreasing, as it did around x = 1.5 (where the slope was -2.25).



Now, we can extend this to higher dimensional functions. In the case of a two-dimensional function

f(x, y), the linear approximation of
$$f(x, y)$$
 at a point (x_{\star}, y_{\star}) is given by

$$f(x, y) \approx f(x_{\star}, y_{\star}) + \frac{\partial f}{\partial x}(x_{\star}, y_{\star}) \cdot (x - x_{\star}) + \frac{\partial f}{\partial y}(x_{\star}, y_{\star}) \cdot (y - y_{\star}). \tag{8}$$

where $\frac{\partial f}{\partial x}(x_\star,y_\star)$ is the partial derivative of f(x,y) with respect to x at the point (x_\star,y_\star) , and similarly for $\frac{\partial f}{\partial u}(x_{\star}, y_{\star})$

(b) Now, let's see how we can find partial derivatives. When we are given a function f(x, y), we calculate the partial derivative of f with respect to x by fixing y and taking the derivative with respect to x. Given the function $f(x,y)=x^2y$, find the partial derivatives $\frac{\partial f(x,y)}{\partial x}$ and $\frac{\partial f(x,y)}{\partial y}$.

$$\frac{\partial f}{\partial x} = \frac{\partial}{\partial x}(x^2y) = y\frac{\partial}{\partial x}(x^2) = 2xy, \quad \text{if } z = \frac{\partial}{\partial y}(x^2y) = x^2\frac{\partial}{\partial y}y = x^2(1)$$

(c) Write out the linear approximation of f near (x_{\star}, y_{\star}) .

$$f(x,y) \approx f(x_{A},y_{A}) + 2x_{A}y_{A}(x-x_{A}) + x_{A}^{2}(y-y_{A})$$

(d) We want to see if the approximation arising from linearization of this function is reasonable for a point close to our point of evaluation. First, approximate f(x,y) at the point (2.01,3.01) using $(x_{\star}, y_{\star}) = (2, 3)$. Next, compare the result to f(2.01, 3.01).

$$f(x,y) = x^{2}y \qquad f(2,3) = 4 \cdot 3 = 12$$

$$f(x,y) \approx 12 + 2(2)(3)(x-2) + (2)^{2}(y-3)$$

$$= 1/2 + 1/2 \times -24 + 4y - 1/2$$

$$= 1/2 \times 4y - 24$$

$$f(2.01, 3.01) = (1.01)^{2}(3.01) \stackrel{?}{>} 1^{2}(2.01) + 4(3.01) - 24$$

$$= (2+h)^{2}(3+h)$$

$$= (2+h)^{2}(3+h)$$

$$= (4+4h+h^{2})(3+h)$$

$$= (2+1/2h+3h^{2} + 4h+4h^{2}+h^{3})$$

$$h = \frac{1}{100}$$

$$h^{2} = \frac{100^{2}}{100^{4}}$$

$$\frac{1}{100^{4}}$$

If h small, how does h2 & h3 campare to h? $h = \frac{1}{100}$ $h^{2} = \frac{1}{100^{3}}$ $h^{3} = \frac{1}{100^{3}}$ $h^{3} = \frac{1}{100^{3}}$

approximatory

My pant here is just "do linearizations only north for small values away from the operating point? A: No depends on what small means!

- (e) We will now define the notion of a derivative as a function, and take a look at one possible representation of that function.
 - Given the representation of the derivative as a row-vector, describe a function that can take this representation, along with some column vector defining a change in direction, to return a scalar value (which is the change in the real-valued output). Don't worry if this seems abstract for now,

the next subpart will clarify.

From & d T Derivative - From vector Single humbre? (Hope: that this # clumn vector)

count of direction - column vector this is the matrix of change along the direction.

(f) Suppose we have now a scalar-valued function $f(\vec{x}, \vec{y})$, which takes in vector-valued arguments $\vec{x} \in \mathbb{R}^n$, $\vec{y} \in \mathbb{R}^k$ and outputs a scalar $\in \mathbb{R}$. That is, $f(\vec{x})(\vec{y})$ is $\mathbb{R}^n \times \mathbb{R}^k \to \mathbb{R}$. For this new model involving a vector-valued function, how can we adapt our previous linearization method?

One way to linearize the function f is to do it for every single element in $\vec{x} = (x_1)(x_2) \dots x_n$ and $\vec{y} = \begin{bmatrix} y_1 & y_2 & \dots & y_k \end{bmatrix}^{\top}$. Then, when we are looking at x_i or y_j , we fix everything else as constant. This would give us the linear approximation

Derivative of f with respect to χ $D_{\vec{x}}f = \begin{bmatrix} \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_n} \end{bmatrix}$, with respect to χ $D_{\vec{y}}f = \begin{bmatrix} \frac{\partial f}{\partial y_1} & \dots & \frac{\partial f}{\partial y_k} \end{bmatrix}$. (11) Then, eq. (9) can be rewritten as

$$f(\vec{x}, \vec{y}) \approx f(\vec{x}_{\star}, \vec{y}_{\star}) + (D_{\vec{x}}f)\Big|_{(\vec{x}_{\star}, \vec{y}_{\star})} \cdot (\vec{x} - \vec{x}_{\star}) + (D_{\vec{y}}f)\Big|_{(\vec{x}_{\star}, \vec{y}_{\star})} \cdot (\vec{y} - \vec{y}_{\star}). \tag{12}$$

Assume that $\underline{n=k}$ and we define the function $\underline{f(\vec{x},\vec{y})} = \vec{x}^\top \vec{y} = \sum_{i=1}^k x_i y_i$. Find $D_{\vec{x}}f$ and $D_{\vec{y}}f$. [Practice] Next, suppose $g(\vec{x},\vec{y}) = x_1 x_2^2 y_1 + x_1 y_2^3 + x_2 x_1 y_2 y_1 + \frac{x_1^2}{x_2^3 y_1}$. Find $D_{\vec{x}}g$ and $D_{\vec{y}}g$

Hint: it can help to look at eq. (8), and match the terms in eq. (9) to that formulation.

annyo IN IZV

 $f(\vec{x}, \vec{y}) = \vec{x}^T \vec{y} = \sum_{i=1}^{n} x_i y_i$ $\frac{\partial f}{\partial x_i} = y_i$ $\frac{\partial f}{\partial x_i} = y_i$ $\begin{array}{c|c}
\overrightarrow{X} - \overrightarrow{X}_{A} = \begin{vmatrix} x_{1} \\ x_{2} \\ \vdots \\ x_{n} \end{vmatrix} - \begin{vmatrix} x_{2} \\ x_{2} \\ \vdots \\ x_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix} y_{1} \\ y_{2} \\ \vdots \\ y_{n} \end{vmatrix} = \begin{vmatrix}$ Dyf=[x, x2 -- · xn] = = +

Derivatives are now rectors

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(g) Following the above part, find the linear approximation of
$$f(\vec{x}, \vec{y})$$
 near $\vec{x}_{\star} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and $\vec{y}_{\star} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$.

Recall that $f(\vec{x}, \vec{y}) = \vec{x}^{\top} \vec{y} = \sum_{i=1}^{k} x_{i} y_{i} = x_{i} y_{i} + x_{i} y_{i}$

$$\begin{aligned}
& \vec{y} = \begin{bmatrix} y_{1} & y_{2} \end{bmatrix} = \vec{y}^{\top} & \vec{y} + \vec{y} = \begin{bmatrix} -1 & 2 \end{bmatrix} \\
& \vec{y} = \begin{bmatrix} x_{1} & x_{2} \end{bmatrix} = \vec{x}^{\top} & \vec{y} + \vec{y} = \begin{bmatrix} -1 & 2 \end{bmatrix} \\
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These linearizations are important for us because we can do many easy computations using linear functions.

Samething that might help clavify for
$$f(\vec{x}, \vec{y}) = \vec{x}^T \vec{y}$$

$$f(\vec{x}, \vec{y}) = x_1 y_1 + x_2 y_2 + \cdots + x_n y_n$$

$$\frac{\partial}{\partial x_2} f(\vec{x}, \vec{y}) = \frac{\partial}{\partial x_2} (x_1 y_1) + \frac{\partial}{\partial x_2} (x_2 y_2) + \cdots + \frac{\partial}{\partial x_n} (x_n y_n)$$

$$= 0 + y_2 + \frac{\partial}{\partial x_n} (x_n y_n) + \frac{\partial}{\partial x_n} (x_n y_n)$$

$$= 0 + y_2 + \frac{\partial}{\partial x_n} (x_n y_n) + \frac{\partial}{\partial x_n} (x_n y_n)$$

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Contributors:

- · Neelesh Ramachandran.
- · Kuan-Yun Lee.

Practice:
$$g(\vec{x}_1\vec{y}) = x_1x_2^2y_1 + x_1y_2^3 + x_2x_1y_2y_1 + \frac{x_1^2}{x_2^3y_1}$$
 $D_{\vec{x}} g = \begin{bmatrix} \frac{\partial g}{\partial x_1} & \frac{\partial g}{\partial x_2} \end{bmatrix}$
 $D_{\vec{y}} g = \begin{bmatrix} \frac{\partial g}{\partial y_1} & \frac{\partial g}{\partial y_2} \end{bmatrix}$
 $\frac{\partial g}{\partial x_1} = \frac{\partial}{\partial x_1} \begin{pmatrix} x_1x_2^2y_1 + x_1y_2^3 + x_2x_1y_2y_1 + \frac{x_1^2}{x_2^3y_1} \\ x_2^3y_1 + y_2^3 + x_2y_2y_1 + \frac{1}{x_2^3y_1} \frac{\partial}{\partial x_1}(x_1^2) \\ = x_2^2y_1 + y_2^3 + x_2y_2y_1 + \frac{1}{x_2^3y_1} \frac{\partial}{\partial x_1}(x_1^2)$
 $= x_1y_1 \frac{\partial}{\partial x_2}(x_1^2) + x_1y_2^3 + x_1x_2y_1 + \frac{x_1^2}{x_2^3y_1} \frac{\partial}{\partial x_2}(\frac{1}{x_2^3})$
 $= 2x_1x_1y_1 + x_1y_2y_1 + \frac{x_1^2}{y_1} \begin{pmatrix} -3x_1^4 \end{pmatrix}$
 $= 2x_1x_1y_1 + x_1y_2 + x_1y_2 + \frac{x_1^2}{x_2^3} \frac{\partial}{\partial y_1} \begin{pmatrix} x_1x_2^2y_1 + x_1y_2 + \frac{x_1^2}{x_2^3} \frac{\partial}{\partial y_1} \begin{pmatrix} -y_1 \end{pmatrix}$
 $= x_1x_2^2 + x_1x_1y_2 + \frac{x_1^2}{x_2^3} \begin{pmatrix} -y_1^2 \end{pmatrix}$
 $\frac{\partial g}{\partial y_1} = \frac{\partial}{\partial y_2} \begin{pmatrix} x_1x_2^2y_1 + x_1y_2 + \frac{x_1^2}{x_2^3} \frac{\partial}{\partial y_1} \begin{pmatrix} -y_1^2 \end{pmatrix}$
 $\frac{\partial g}{\partial y_1} = \frac{\partial}{\partial y_2} \begin{pmatrix} x_1x_2^2y_1 + x_1y_2 + \frac{x_1^2}{x_2^3} \frac{\partial}{\partial y_1} \begin{pmatrix} -y_1^2 \end{pmatrix}$
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 $\frac{\partial g}{\partial y_1} = \frac{\partial}{\partial y_2} \begin{pmatrix} x_1x_2^2y_1 + x_1y_2 + \frac{x_1^2}{x_2^3} \frac{\partial}{\partial y_1} \begin{pmatrix} -y_1^2 \end{pmatrix} \begin{pmatrix} -y_$