

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

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 $x = 1.7$?

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

$$\approx -3.375 - 0.45 \quad (3)$$

$$\approx -3.825 \quad (4)$$

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?

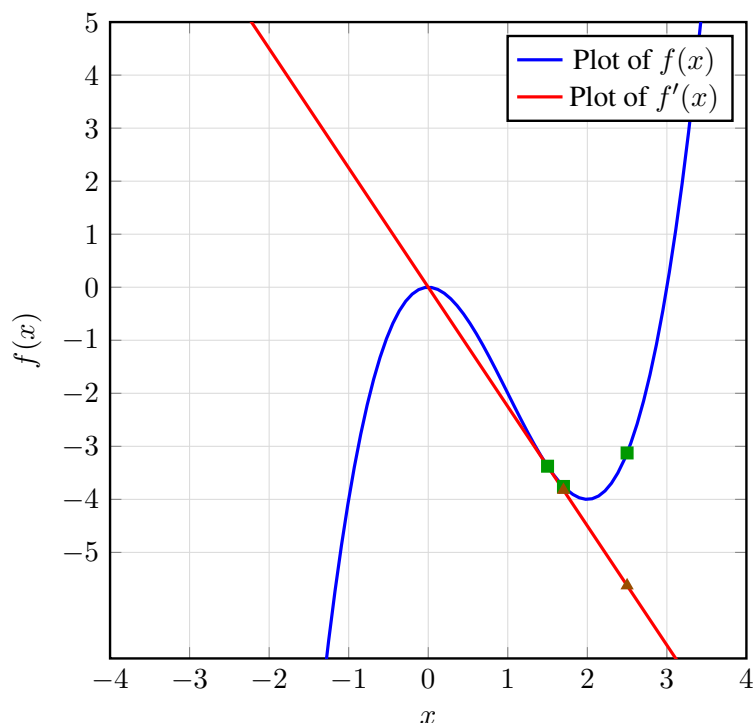
$$f(2.5) \approx -3.375 + (-2.25) \cdot (2.5 - 1.5) \quad (5)$$

$$\approx -3.375 - 2.25 \quad (6)$$

$$\approx -5.625 \quad (7)$$

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 $x_* = 1.5$ 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_*, y_*) is given by

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

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

- (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 $\frac{\partial f(x, y)}{\partial y}$.**

- (c) **Write out the linear approximation of f near (x_*, y_*) .**

- (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 $(x_*, y_*) = (2, 3)$. Next, compare the result to $f(2.01, 3.01)$.**

- (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.

- (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 $\mathbb{R}^n \times \mathbb{R}^k \rightarrow \mathbb{R}$. 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 $\vec{x} = [x_1 \ x_2 \ \dots \ x_n]^\top$ and $\vec{y} = [y_1 \ y_2 \ \dots \ y_k]^\top$. Then, when we are looking at x_i or y_j , we fix everything else as constant. This would give us the linear approximation

$$f(\vec{x}, \vec{y}) \approx f(\vec{x}_*, \vec{y}_*) + \sum_{i=1}^n \frac{\partial f(\vec{x}, \vec{y})}{\partial x_i} (x_i - x_{i,*}) + \sum_{j=1}^k \frac{\partial f(\vec{x}, \vec{y})}{\partial y_j} (y_j - y_{j,*}). \quad (9)$$

In order to simplify this equation, we can define the rows $D_{\vec{x}}$ and $D_{\vec{y}}$ as

$$D_{\vec{x}}f = \left[\frac{\partial f}{\partial x_1} \quad \dots \quad \frac{\partial f}{\partial x_n} \right], \quad (10)$$

$$D_{\vec{y}}f = \left[\frac{\partial f}{\partial y_1} \quad \dots \quad \frac{\partial f}{\partial y_k} \right]. \quad (11)$$

Then, eq. (9) can be rewritten as

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

Assume that $n = k$ and we define the function $f(\vec{x}, \vec{y}) = \vec{x}^\top \vec{y} = \sum_{i=1}^k x_i y_i$. 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.

- (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 $f(\vec{x}, \vec{y}) = \vec{x}^\top \vec{y} = \sum_{i=1}^k x_i y_i$.**

These linearizations are important for us because we can do many easy computations using linear functions.

Contributors:

- Neelesh Ramachandran.
- Kuan-Yun Lee.