

Taylor Polynomials

Recall: Taylor's theorem for $f: \mathbb{R} \rightarrow \mathbb{R}$:

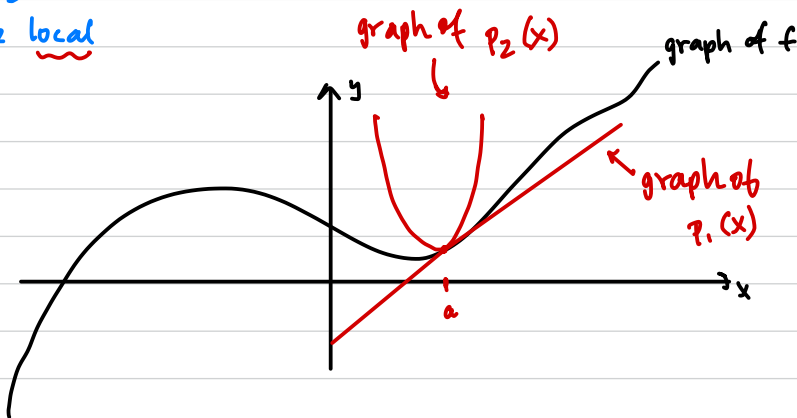
Near a ,

tangent line ... recall defn of DF(\bar{a})

$$f(x) \approx f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \dots + \frac{f^{(k)}(a)}{k!}(x-a)^k$$

$p_2(x)$... fows here now.

can use $p_2(x)$ to determine local max/min



By design, i^{th} derivative of $p_k(x)$ matches i^{th} derivative of f ,
 $i=1, \dots, k$.

Goal: Do similar for $f: \mathbb{R}^n \rightarrow \mathbb{R}$... figure out $p_2(\bar{x})$.

Recall: we've already done a 1st order approximation:

$$\text{Near } \bar{a}, f(\bar{x}) \approx f(\bar{a}) + \underbrace{Df(\bar{a})}_{\substack{\text{matrix of 1st} \\ \text{partials} \\ (1 \times n \text{ matrix})}} (\bar{x} - \bar{a})$$

called this $h(\bar{x})$: Now, call it $p_1(\bar{x})$.

For 2nd order approximation $p_2(\bar{x})$, need to keep track of

2nd order partials:

Defn Spc $f: \mathbb{R}^n \rightarrow \mathbb{R}$. The Hessian of f at \bar{a} is the $n \times n$ matrix:

$$Hf(\bar{a}) = \begin{bmatrix} f_{x_1 x_1} & f_{x_1 x_2} & \dots & f_{x_1 x_n} \\ f_{x_2 x_1} & f_{x_2 x_2} & & f_{x_2 x_n} \\ & & & \\ f_{x_n x_1} & f_{x_n x_2} & & f_{x_n x_n} \end{bmatrix} \quad \leftarrow \text{all eval. at } \bar{a}$$

Note: if second order partials are cts, then mixed partials are equal so $Hf(\bar{a})$ is symmetric

$$\uparrow (Hf(\bar{a}))^T = Hf(\bar{a})$$

Consider $\bar{x} - \bar{a}$: an n -vector $\begin{bmatrix} x_1 - a_1 \\ x_2 - a_2 \\ \vdots \\ x_n - a_n \end{bmatrix}$

Then $\frac{1}{2} (\bar{x} - \bar{a})^T Hf(\bar{a}) (\bar{x} - \bar{a})$ is:

$$f: \mathbb{R} \rightarrow \mathbb{R} \quad \begin{aligned} & f(\bar{x}) + f'(\bar{a})(x-a) + \frac{f''(\bar{a})(x-a)^2}{2!} \end{aligned} \quad *$$

$$\frac{1}{2} \begin{matrix} 1 \times n \\ \left[(\bar{x} - \bar{a})^T \right] \end{matrix} \begin{matrix} n \times n \\ \left[Hf(\bar{a}) \right] \end{matrix} \begin{matrix} n \times 1 \\ \left[\bar{x} - \bar{a} \right] \end{matrix} = \text{a scalar}$$

Defn The second order Taylor polynomial of $f: \mathbb{R}^n \rightarrow \mathbb{R}$ at \bar{a} is:

$$p_2(\bar{x}) = f(\bar{a}) + Df(\bar{a})(\bar{x} - \bar{a}) + \frac{1}{2} (\bar{x} - \bar{a})^T Hf(\bar{a})(\bar{x} - \bar{a}).$$

gives sum of all 2nd partial information.

It's a better approximation of f than $p_1(\bar{x}) = f(\bar{a}) + Df(\bar{a})(\bar{x} - \bar{a})$.

↳ best quadratic (as opp. to linear) approx. of f .