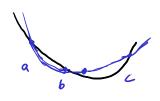
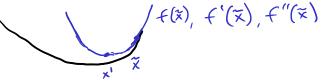
- Golden Section Search linear convergence
- Schubert Pyavskii
- Quadratic Fit Search

Newton's Method





$$q(x) = f(\tilde{x}) + f(\tilde{x})(x - \tilde{x}) + f''(\tilde{x})\frac{(x - \tilde{x})^2}{2}$$

$$\frac{\partial q}{\partial x} = 0 = f'(\tilde{x}) + (x' - \tilde{x}) f''(\tilde{x})$$

$$x' = \tilde{x} - \frac{f'(\tilde{x})}{f''(\tilde{x})}$$

Informally, Newton's method converges quadratically near a smooth local minimum.

For an interval $\Gamma = [x^* - \delta, x^* + \delta]$ where $f''(x) \neq 0$ $\forall x \in T$

 $f''(x) \neq 0$ $f \times \in \mathbb{T}$

 $\exists \ C \ \text{s.t.} \ \frac{1}{2} \left| \frac{f'''(x^{(i)})}{f''(x^{(i)})} \right| \ \leq \ C \left| \frac{f'''(x^*)}{f''(x^*)} \right|$

Then 7 y>0 s.t. (x*-x(k·1)) = y (x*-x(k))2

Review of vector Calculus

Derivative

$$\frac{d}{dx}f(x) = f'(x) \equiv \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$



Partial Derivetive Luit vector in direction i

$$\frac{\partial}{\partial x_i} f(\vec{x}) = \lim_{h \to 0} \frac{f(\vec{x} + h\hat{e}_i) - f(\vec{x})}{h}$$

Gradient firm R

$$\nabla f(\vec{x}) = g = \int_{\delta x_1}^{\delta f} dx$$

×₂

 $\frac{\int a \cos \cos \alpha}{f \cdot R^n \rightarrow R^n}$ $\frac{\partial f_1}{\partial x_1} \qquad \frac{\partial f_2}{\partial x_n}$ $\frac{\partial f_n}{\partial x_n} \qquad \frac{\partial f_n}{\partial x_n}$

Hessian

$$\nabla^2 f(x) = H = \begin{bmatrix} \frac{\partial^2 f}{\partial x_i^2} & \frac{\partial^2 f}{\partial x_i \partial x_2} & \dots & \frac{\partial^2 f}{\partial x_n \partial x_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_i} & \frac{\partial^2 f}{\partial x_n \partial x_n} & \frac{\partial^2 f}{\partial x_n \partial x_n} \end{bmatrix}$$

symmetric if second derivatives are all continuous in a neighborhood

Directional Derivative

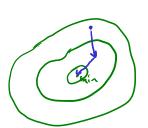
direction 3 (often a unit vector)

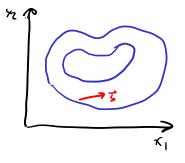
$$\nabla_{\vec{s}} f(\vec{x}) = \lim_{h \to 0} \frac{f(\vec{x} + h\vec{s}) - f(\vec{x})}{h}$$

"instantaneous rate of change in f when moving at velocity s.

Naw: Da

$$\nabla_{\vec{s}} f(\vec{x}) = \nabla f(\vec{x}) \cdot \vec{s}$$





Calculating Derivatives

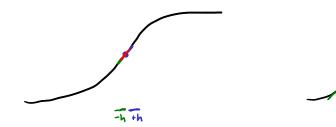
- 1. Symbolic 2. Numerical
- 3. Automatic

Numerical

Finite Difference

forward $f'(x) \stackrel{\sim}{\sim} f(x+h) - f(x) \stackrel{\sim}{\sim} f(x) - f(x-h) \stackrel{\sim}{\sim} f(x-h) \stackrel{\sim}{\sim} f(x-h) \stackrel{\sim}{\sim} h$ central

h



Errors

$$f(x+h) = f(x) + \frac{f'(x)h}{1!} + \frac{f''(x)h^{2} + \dots}{2!} + \dots$$

$$-f(x)h = f(x)-f(x+h) - \frac{f''(x)}{2!}h^{2} + \dots$$

$$f'(x) = \frac{f(x+h)-f(x)}{h} + \frac{f''(x)}{2!}h + \dots$$

$$f(x+\frac{h}{2}) = f(x) + f'(x)\frac{h}{2} + \frac{f''(x)(\frac{h}{2})^{2}}{2!} + \frac{f''(x)(\frac{h}{2})^{3}}{3!} + \dots$$

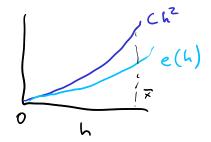
$$f(x-\frac{h}{2}) = f(x) - f'(x)\frac{h}{2} + \frac{f''(x)(\frac{h}{2})^{2}}{2!} - \frac{f'''(x)(\frac{h}{2})^{3} + \dots}{3!} + \dots$$

$$f(x+\frac{h}{2})-f(x-\frac{h}{2}) = 2f(x)\frac{h}{2} + \frac{2}{3!}f'''(x)(\frac{h}{2})^{3} + \dots$$

$$f'(x) = f(x+\frac{h}{2})-f(x-\frac{h}{2}) - f(x-\frac{h}{2}) - f(x-\frac{h}{2}) - f(x-\frac{h}{2}) + \dots$$

$$f'(x) = f(x+\frac{h}{2})-f(x-\frac{h}{2}) - f(x-\frac{h}{2}) -$$

$$e(h) \in O(h^2)$$
 as $h \to 0$



estimate f'(x) by evaluating f(x+hi)

Complex - Step

$$f(x+hi) = f(x) + ihf'(x) - h^2 \frac{f''(x)}{2!} - ih^3 f''(x)$$

$$Im(f(x+ih)) = hf'(x) - h^3 f''(x)$$

$$f'(x) = \frac{Im(f(x+ih))^3!}{h} + h^2 f'''(x)$$

$$f'(x) \approx \lim(f(x+ih))$$

$$f(x) \approx \operatorname{Re}(f(x+ih))$$

Automatic Differentiation

Dual Numbers

a+bE

$$f(a+b\epsilon) = \sum_{k=0}^{\infty} \frac{f^{(k)}(a)}{k!} (a+b\epsilon-a)^{k}$$

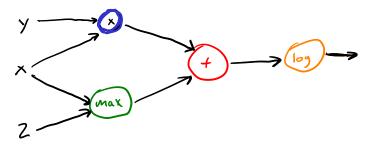
$$= \sum_{k=0}^{\infty} \frac{f^{(k)}(a)}{k!} \frac{b^{k}\epsilon^{k}}{k!}$$

$$= f(a) + bf'(a) \epsilon + \epsilon^{2} \sum_{k=2}^{\infty} \frac{f^{(k)}(a+b\epsilon-a)^{k}}{k!}$$

Du = dual part everything multiplied by E

Computational Graphs + Chain Rule.

$$f(x,y) = \log(xy + \max(x,2))$$



$$\frac{\text{Chain Rule }}{\frac{\partial}{\partial x} f(g(x))} = \frac{\partial f}{\partial g} \frac{\partial g}{\partial x}$$

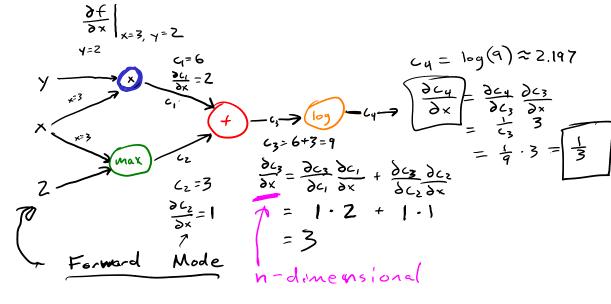
$$f(x,y) = \frac{\log(xy + \max(x,2))}{f}$$

$$\frac{\partial f}{\partial x} = \frac{\partial \log(g)}{\partial g} \frac{\partial g}{\partial g}$$

$$= \frac{1}{xy + \max(a,2)} \frac{\partial}{\partial x} (xy + \max(x,2))$$

$$= (1) \left(\frac{9\times}{9(\times)} + \frac{9\times}{9(\times)} \right)$$

$$= \frac{11}{\frac{y + (x \ge 2)}{xy + max(a, 2)}} + O(x \le 2)$$



Reverse Mode

$$\begin{array}{c}
y = 7 \\
x = 3
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f: R" -> R"

n 77 m Reverse Mode more efficient

For optimization, usually the case

nam roughly same efficiency