## Optimization (Introduction)

## Optimization

Goal: Find the minimizer $\boldsymbol{x}^{*}$ that minimizes the objective (cost) function $f(\boldsymbol{x}): \mathcal{R}^{n} \rightarrow \mathcal{R}$

## Unconstrained Optimization

## Optimization

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## Constrained Optimization

## Unconstrained Optimization

- What if we are looking for a maximizer $\boldsymbol{x}^{*}$ ?

$$
f\left(\boldsymbol{x}^{*}\right)=\max _{\boldsymbol{x}} f(\boldsymbol{x})
$$

## Calculus problem: maximize the rectangle area subject to perimeter constraint

$$
\max _{\boldsymbol{d} \in \mathcal{R}^{2}} \quad f\left(d_{1}, d_{2}\right)=d_{1} \times d_{2}
$$

such that $\quad g\left(d_{1}, d_{2}\right)=2\left(d_{1}+d_{2}\right)-20 \leq 0$




## Unconstrained Optimization 1D

## What is the optimal solution? (1D)

$$
f\left(x^{*}\right)=\min _{x} f(x)
$$

(First-order) Necessary condition
(Second-order) Sufficient condition

## Types of optimization problems

$$
f\left(x^{*}\right)=\min _{x} f(x)
$$

$f$ : nonlinear, continuous and smooth

Gradient-free methods
Evaluate $f(x)$
Gradient (first-derivative) methods
Evaluate $f(x), f^{\prime}(x)$

Second-derivative methods
Evaluate $f(x), f^{\prime}(x), f^{\prime \prime}(x)$

## Does the solution exists? Local or global

 solution?
## Example (1D)

Consider the function $f(\boldsymbol{x})=\frac{x^{4}}{4}-\frac{x^{3}}{3}-11 x^{2}+40 x$. Find the stationary point and check the sufficient condition


## Optimization in 1D: <br> Golden Section Search

- Similar idea of bisection method for root finding
- Needs to bracket the minimum inside an interval
- Required the function to be unimodal

A function $f: \mathcal{R} \rightarrow \mathcal{R}$ is unimodal on an interval $[a, b]$
$\checkmark$ There is a unique $\boldsymbol{x}^{*} \in[a, b]$ such that $f\left(\boldsymbol{x}^{*}\right)$ is the minimum in [ $a, b$ ]
$\checkmark$ For any $x_{1}, x_{2} \in[a, b]$ with $x_{1}<x_{2}$

- $x_{2}<x^{*} \Rightarrow f\left(x_{1}\right)>f\left(x_{2}\right)$
- $x_{1}>x^{*} \Longrightarrow f\left(x_{1}\right)<f\left(x_{2}\right)$





Golden Section Search


Propose:

$$
\begin{aligned}
& x_{1}=a+(1-\tau) h_{0} \\
& x_{2}=a+\tau h_{0}
\end{aligned}
$$

Evaluate $f_{1}=f\left(x_{1}\right)$

$$
f_{2}=f\left(x_{2}\right)
$$

if $\left(f_{1}>f_{2}\right)$ :

$$
a=x_{1}
$$

$x_{1}=x_{2} \rightarrow$ already have funk.
$h_{1}=b-a$ value!
$x_{2}=a+\tau h_{1}$
$f_{2}=f\left(x_{2}\right) \rightarrow$ onlu one
if $\left(f_{1}<f_{2}\right)$ :

$$
\begin{aligned}
& b=x_{2} \\
& x_{2}=x_{1} \\
& x_{1}=a+(1-\tau) h_{1} \\
& f_{1}=f\left(x_{1}\right)
\end{aligned}
$$

## Golden Section Search

What happens with the length of the interval after one iteration?

$$
h_{1}=\tau h_{o}
$$

Or in general: $h_{k+1}=\tau h_{k}$

## Hence the interval gets reduced by $\tau$

(for bisection method to solve nonlinear equations, $\tau=0.5$ )
For recursion:

$$
\begin{aligned}
\tau h_{1} & =(1-\tau) h_{o} \\
\tau \tau h_{o} & =(1-\tau) h_{o} \\
\tau^{2} & =(1-\tau) \\
\boldsymbol{\tau} & =\mathbf{0 . 6 1 8}
\end{aligned}
$$

## Golden Section Search

- Derivative free method!
- Slow convergence:

$$
\lim _{k \rightarrow \infty} \frac{\left|e_{k+1}\right|}{\left|e_{k}\right|}=0.618 \quad r=1 \text { (linear convergence) }
$$

- Only one function evaluation per iteration


## Example

Consider running golden section search on a function that is unimodal. If golden section search is started with an initial brakcet of $[-10,10]$, what is the length of the new bracket after 1 iteration?
A) 20
B) 10
C) 12.36
D) 7.64

## Newton's Method

Using Taylor Expansion, we can approximate the function $f$ with a quadratic function about $x_{0}$

$$
f(x) \approx f\left(x_{0}\right)+f^{\prime}\left(x_{0}\right)\left(x-x_{0}\right)+\frac{1}{2} f^{\prime \prime}\left(x_{0}\right)\left(x-x_{0}\right)^{2}
$$

And we want to find the minimum of the quadratic function using the first-order necessary condition

## Newton's Method

- Algorithm:
$x_{0}=$ starting guess
$x_{k+1}=x_{k}-f^{\prime}\left(x_{k}\right) / f^{\prime \prime}\left(x_{k}\right)$
- Convergence:
- Typical quadratic convergence
- Local convergence (start guess close to solution)
- May fail to converge, or converge to a maximum or point of inflection

Newton's Method (Graphical Representation)

## Example

Consider the function $f(x)=4 x^{3}+2 x^{2}+5 x+40$

If we use the initial guess $x_{0}=2$, what would be the value of $x$ after one iteration of the Newton's method?

