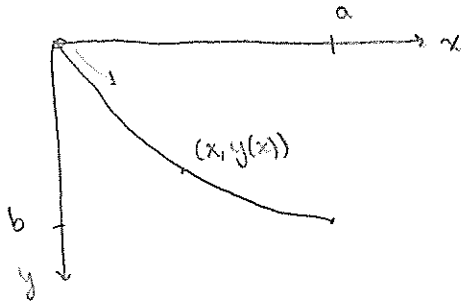


Optimization for unknown functions

Newton (1687) profile of minimum drag

Bernoulli (1696/7) Brachistochrone, shortest time curve



m = mass of the bead

initial point: $(0,0)$

final point: (a,b)

$a, b > 0$

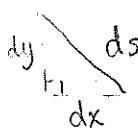
Conservation of energy:

$$\frac{1}{2}mv^2 - mgy = \text{const.} = 0$$

start from rest, no friction

$$\rightarrow v^2 = 2gy \rightarrow v = \sqrt{2gy}$$

velocity: $v = \frac{ds}{dt}$, $ds = \sqrt{(dx)^2 + (dy)^2}$



$$\frac{ds}{dx} = \sqrt{1 + \left(\frac{dy}{dx}\right)^2}$$

$$\frac{dt}{ds} = \frac{1}{\frac{ds}{dt}} = \frac{1}{\sqrt{2gy}}$$

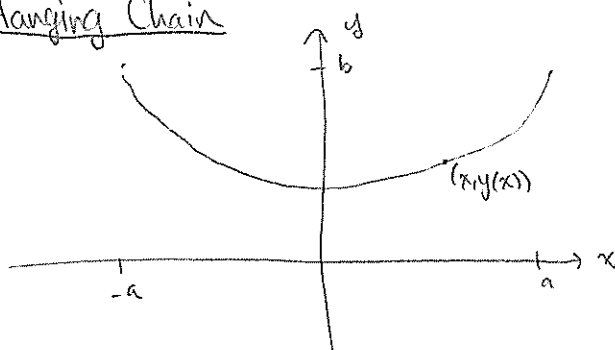
time of descent:

$$T[y] = \int dt = \int_0^a \frac{dt}{ds} \frac{ds}{dx} dx = \int_0^a \frac{\sqrt{1 + \left(\frac{dy}{dx}\right)^2}}{\sqrt{2gy}} dx$$

Problem: minimize $T[y] = \int_0^a \sqrt{\frac{1 + y'(x)^2}{2gy(x)}} dx$

subject to $y(0) = 0, y(a) = b$

Hanging Chain



ρ = density, mass per unit length

Minimize

$$E[y] = \int \rho g y ds = \int \rho g y(x) \sqrt{1 + y'(x)^2} dx$$

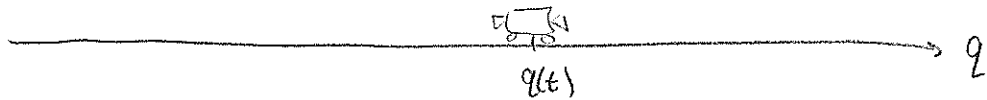
subject to $y(\pm a) = b$, $a, b > 0$

$$\int ds = \int_{-a}^a \frac{ds}{dx} dx = \int_{-a}^a \sqrt{1 + y'(x)^2} dx = L.$$

$L =$ length of chain

$$L \geq 2a$$

Rocket Car



$m =$ mass of the car
 $m\ddot{q}(t) = u(t)$, $|u(t)| \leq M$

assume frictionless, mass doesn't change

Let $p(t) = m\dot{q}(t)$,

$$\begin{cases} \dot{q} = \frac{1}{m} p \\ \dot{p} = u \end{cases}$$

$(q_0, p_0) = (q(0), p(0))$ is given

Target: $(q(t_1), p(t_1)) = (0, 0)$, $t_1 > 0$

(i) Minimize $t_1 = \int_0^{t_1} dt$

or (ii) Minimize $\int_0^{t_1} |u(t)| dt$ expenditure of fuel

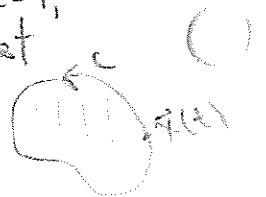
or (iii) Minimize $\frac{1}{2m} \int_0^{t_1} p(t)^2 dt$ kinetic energy

$u(t) = \pm M$ bang-bang control

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Isoperimetric Problem

Find the simplest closed curve C , $\vec{x}(t) = (x(t), y(t))$, $0 \leq t \leq 1$,
 $\vec{x}(0) = \vec{x}(1)$ of given length L which encloses the largest area A .



Answer: C is a circle of radius $\frac{L}{2\pi}$.
 Hurwitz⁽¹⁹⁰²⁾ gave a proof based on Fourier series.

Green's Theorem.



$$\oint_C P dx + Q dy = \iint_D [Q_x - P_y] dA$$

$$\rightarrow \oint_C x dy - y dx = \iint_D [1 - (-1)] dA = 2A$$

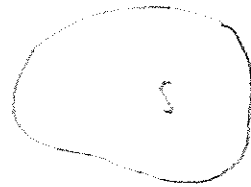
$A = \text{area of } D$

Minimize $A[\vec{x}] = \frac{1}{2} \oint_C x dy - y dx = \frac{1}{2} \int_0^1 [x(t)y'(t) - y(t)x'(t)] dt$

Subject to $\int_0^1 \sqrt{x'(t)^2 + y'(t)^2} dt = L, \quad \vec{x}(0) = \vec{x}(1)$

Optimization in Calculus

$$f: S \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$$



Ball of radius ϵ about x^* :

$$B_\epsilon(x^*) = \{x \in \mathbb{R}^n; \|x - x^*\| < \epsilon\}$$

x^* is an interior point of S if $B_\epsilon(x^*) \subseteq S$

x^* is a boundary point of S if $B_\epsilon(x^*) \cap S \neq \emptyset$ & $B_\epsilon(x^*) \cap S^c \neq \emptyset$
 $\forall \epsilon > 0$

$f \in C^1$ means $\frac{\partial f}{\partial x_i}$ is continuous on $S \quad \forall i$

& f is continuous on S

S° is the set of interior points of S

∂S is the set of boundary points of S

Def) The variation of f in the direction of $v \in \mathbb{R}^n$ at $x^* \in \mathcal{D}^0$ is

$$\delta f(x^*; v) = \lim_{s \rightarrow 0} \frac{f(x^* + sv) - f(x^*)}{s}$$

This is the directional derivative if $\|v\|=1$.

Theorem: If $f \in C^1$ then $\delta f(x^*; v) = \nabla f(x^*) \cdot v$.

Proof

$$\begin{aligned} \delta f(x^*; v) &= \left. \frac{d}{ds} f(x^* + sv) \right|_{s=0} \\ &= \nabla f(x^* + sv) \cdot \left. \frac{d}{ds} (x^* + sv) \right|_{s=0} \\ &= \nabla f(x^* + 0v) \cdot v \\ &= \nabla f(x^*) \cdot v \quad \square \end{aligned}$$

Theorem: If $f \in C^1$ & f has a local max or min at $x^* \in \mathcal{D}^0$ then

$$\frac{\partial f}{\partial x_i}(x^*) = 0, \quad 1 \leq i \leq n$$

(x^* is a critical point)

Proof: For $v \in \mathbb{R}^n$ consider

$$g(s) = f(x^* + sv), \quad g: \mathbb{R} \rightarrow \mathbb{R}$$

f has local max or min at $x^* \Rightarrow g$ has a local max or min at $s=0$.

$$\Rightarrow g'(0) = 0 \Rightarrow \delta f(x^*; v) = \nabla f(x^*) \cdot v = 0$$

Let $v = e_i \Rightarrow$

$$\frac{\partial f}{\partial x_i}(x^*) = 0, \quad 1 \leq i \leq n. \quad \square$$

Consider

$$g(s) = f(x^* + sv), \quad 0 \leq s \leq 1$$

Taylor's Thm \Rightarrow

$$g(1) = g(0) + g'(0)(1-0) + \frac{1}{2} g''(c)(1-0)^2$$

for some $c, 0 < c < 1$,

$$f(x^* + v) = f(x^*) + \nabla f(x^*) \cdot v + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j}(x^* + cv) v_i v_j$$

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$$g'(s) = \nabla f(x^* + sv) \cdot v = \sum_{i=1}^n \frac{\partial f}{\partial x_i}(x^* + sv) \cdot v_i$$

$$g''(s) = \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j}(x^* + sv) v_i v_j$$

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$$\begin{aligned} f(x^* + v) &= f(x^*) + \sum_{i=1}^n \frac{\partial f}{\partial x_i}(x^*) v_i + \frac{1}{2} \sum_{i,j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j}(x^* + cv) v_i v_j \\ &\stackrel{(*)}{=} f(x^*) + \frac{1}{2} \sum_{i,j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j}(x^* + cv) v_i v_j \end{aligned}$$

Let

$$\nabla^2 f = \left(\frac{\partial^2 f}{\partial x_i \partial x_j} \right)_{i,j=1}^n$$

the Hessian matrix.

Theorem: Suppose $f \in C^2$, $\nabla f(x^*) = 0$, $x^* \in S^\circ$.

- (1) If $\nabla^2 f(x^*)$ is positive definite then f has a local min at x^* .
- (2) If $\nabla^2 f(x^*)$ is negative definite then f has a local max at x^* .
- (3) If $\nabla^2 f(x^*)$ indefinite then f has neither max nor min at x^* .

$$n=1: \nabla^2 f(x^*) = f''(x^*)$$

Theorem: Let $f \in C^2$, $\nabla f(x^*) = 0$, $x^* \in S^\circ$.

- (1) If f has a local min at x^* then $\nabla^2 f(x^*)$ is positive semi-definite.
- (2) If f has a local max at x^* then $\nabla^2 f(x^*)$ is negative semi-definite.

Proof (of (1)): $g(s) = f(x^* + sv)$

$$\rightarrow g'(0) = 0 \quad \& \quad g''(0) \geq 0$$

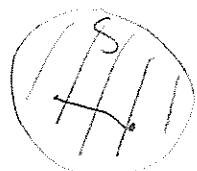
$$\Rightarrow \sum_{i,j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j}(x^*) v_i v_j \geq 0$$

$$\Rightarrow v^T \nabla^2 f(x^*) v \geq 0$$

Convex Functions

$S \subseteq \mathbb{R}^n$ is convex if $\forall x, y \in S, x \neq y, \alpha x + (1-\alpha)y \in S$ for $0 < \alpha < 1$.

For $0 \leq \alpha \leq 1$, $\alpha x + (1-\alpha)y = y + \alpha(x-y)$
gives the line segment between x and y .

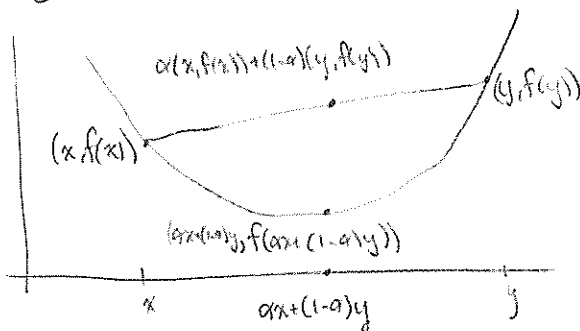


convex



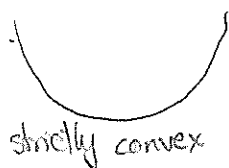
not convex

Let $f: S \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$, S is convex, f is convex if $\forall x, y \in S, x \neq y$,
 $f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y)$
for all $\alpha, 0 < \alpha < 1$.



Any chord lies above the graph

f is strictly convex if $\forall x, y \in S, x \neq y, f(\alpha x + (1-\alpha)y) < \alpha f(x) + (1-\alpha)f(y)$
 $\forall \alpha, 0 < \alpha < 1$



strictly convex



convex but not strictly convex

The epigraph of f is $\text{epi}(f)$:

$$\{(x, z); z \geq f(x), x \in S\}$$

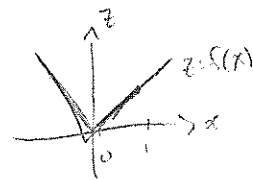
f is convex if and only if $\text{epi}(f)$ is convex

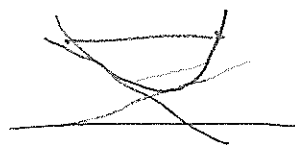
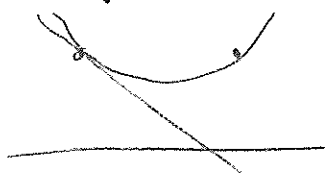
Ex. $f(x) = |x|, f: \mathbb{R} \rightarrow \mathbb{R}$

f is convex. for $0 < \alpha < 1$

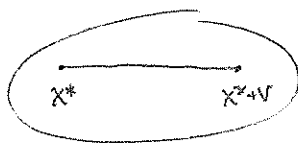
$$f(\alpha x + (1-\alpha)y) = |\alpha x + (1-\alpha)y| \leq (\alpha|x| + (1-\alpha)|y|) = \alpha|x| + (1-\alpha)|y| = \alpha f(x) + (1-\alpha)f(y)$$

$$x=0, y=1, \alpha = \frac{1}{2} : \alpha x + (1-\alpha)y = \frac{1}{2}x + \frac{1}{2}y = \frac{1}{2} \quad f(\frac{1}{2}) = \frac{1}{2} \quad \text{not strictly convex}$$



$f \in C^0$ $\forall x, y \in S, x \neq y, 0 < \alpha < 1$ f is convex: $f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y)$ f is strictly convex: $f(\alpha x + (1-\alpha)y) < \alpha f(x) + (1-\alpha)f(y)$ $f \in C^1$ f is convex if and only if $\forall x, x+v \in S, v \neq 0$
 $f(x+v) \geq f(x) + \nabla f(x) \cdot v$ f is strictly convex if and only if $\forall x, x+v \in S, v \neq 0$
 $f(x+v) > f(x) + \nabla f(x) \cdot v$ (the right hand side is linear approximation to f at x) $\nabla^2 f$ = Hessian matrix $f \in C^2$ f is convex if and only if $\nabla^2 f$ is positive semi-definite f is strictly convex if $\nabla^2 f$ is positive definiteTheorem: If $f \in C^1$ is strictly convex and $\nabla f(x^*) = 0, x^* \in S$, then x^* is the unique minimum point of f .Proof: If $x^* + v \in S, v \neq 0$

$$f(x^* + v) > f(x^*) + \nabla f(x^*) \cdot v = f(x^*)$$

 $f \in C^2$: let $g(s) = f(x+sv), 0 \leq s \leq 1$

$$g'(s) = \nabla f(x+sv) \cdot v$$

$$g''(s) = \sum_{i,j=1}^n \frac{\partial^2 f}{\partial x_i \partial x_j} v_i v_j = v^T \nabla^2 f(x+sv) v$$

By Taylor's theorem \Rightarrow

$$\begin{aligned}
 g(1) &= g(0) + g'(0)(1-0) + \frac{1}{2}g''(c)(1-0)^2 \\
 &= g(0) + g'(0) + \frac{1}{2}g''(c) \text{ for some } c, 0 < c < 1 \\
 &\geq g(0) + g'(0) \\
 &= f(x) + \nabla f(x) \cdot v \\
 &= f(x) + \delta f(x; v)
 \end{aligned}$$

If $\nabla^2 f$ is pos. def. then $f(x) > f(x) + \delta f(x; v)$

Ex. $f: \mathbb{R}^2 \rightarrow \mathbb{R}, f(x, y) = x^2 + 2xy + 2y^2 + 2x + 5$

$$f_x = 2x + 2y + 2$$

$$f_y = 2x + 4y$$

$$\nabla^2 f = \begin{pmatrix} 2 & 2 \\ 2 & 4 \end{pmatrix}$$

$$f_{xx} = 2, f_{xy} = 2, f_{yy} = 4$$

$$a_{11} = 2 > 0, a_{11}a_{22} - a_{12}^2 = 2 \cdot 4 - 2^2 = 4 > 0$$

$\therefore f$ is strictly convex on \mathbb{R}^2

Let $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{12} & a_{22} \end{pmatrix}$:

A is positive definite if and only if $a_{11} > 0$ and $a_{11}a_{22} - a_{12}^2 > 0$

A is positive semidefinite if and only if $a_{11} \geq 0, a_{11}a_{22} - a_{12}^2 \geq 0, a_{22} \geq 0$

Crit pt: $\begin{cases} f_x = 0 \rightarrow x + y + 1 = 0 \\ f_y = 0 \rightarrow x + 2y = 0 \end{cases}$

$$\rightarrow x = -2y \rightarrow -y + 1 = 0 \rightarrow y = 1, x = -2$$

$\therefore f(x, y) > f(-2, 1) = 3$ for $(x, y) \neq (-2, 1)$

$f \in C^1, x, x+v \in S, v \neq 0$

let $g(s) = f(x+sv), 0 \leq s \leq 1$

f is convex $\Rightarrow g$ is convex $\Rightarrow g'(s)$ is increasing $\Rightarrow f(x+v) \geq f(x) + \delta f(x; v)$

For $s_1 < s_2$,

$$\frac{g(s_1 + \epsilon_1) - g(s_1)}{\epsilon_1} \leq \frac{g(s_2) - g(s_1)}{\epsilon_2 - \epsilon_1} \leq \frac{g(s_2) - g(s_2 - \epsilon_2)}{\epsilon_2}$$

let $\epsilon_1 \rightarrow 0^+, \epsilon_2 \rightarrow 0^+ : g'(s_1) \leq g'(s_2)$

By Taylor's theorem:

$$g(1) = g(0) + g'(c) \text{ some } c, 0 < c < 1$$

$$\geq g(0) + g'(0)$$

$$\Rightarrow f(x+v) \geq f(x) + \delta f(x; v)$$

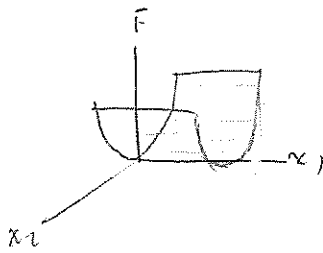
Let $x \neq y, x, y \in S$ Let $z = \alpha x + (1-\alpha)y$

$$f(x) = f(z + (x-z)) \geq f(z) + \nabla f(z) \cdot (x-z)$$

$$f(y) = f(z + (y-z)) \geq f(z) + \nabla f(z) \cdot (y-z)$$

$$\Rightarrow \alpha f(x) + (1-\alpha)f(y) \geq \alpha f(z) + (1-\alpha)f(z) + \nabla f(z) \cdot (\alpha(x-z) + (1-\alpha)(y-z))$$

(2) $F(x_1, x_2) = x_1^2$ on \mathbb{R}^2



$\nabla^2 F = \begin{pmatrix} 2 & 0 \\ 0 & 0 \end{pmatrix}$

$\nabla^2 F$ is pos. semi-def. $\forall x$
 $\Rightarrow F$ is convex

However, F is not strictly convex on \mathbb{R}^2 :

Let $x = (0, 1)$, $y = (1, 0)$, $\alpha = \frac{1}{2}$
 $F(0, 1) = 0 = \frac{1}{2} F(1, 0) + \frac{1}{2} F(0, 2)$
 shows F is not strictly convex

Functionals

Let \mathcal{Y} is a linear space (vector space) of functions.

If $y_1, y_2 \in \mathcal{Y}$ then $y_1 + y_2, cy_1 \in \mathcal{Y}, \forall c \in \mathbb{R}$

$C^m[a, b] = \{f: [a, b] \rightarrow \mathbb{R}; f, f', \dots, f^{(m)} \text{ are continuous on } [a, b]\}$, $m \geq 0$

$(C^m[a, b])^d = \underbrace{C^m[a, b] \times \dots \times C^m[a, b]}_{d \text{ factors}}$

$= \{(f_1, \dots, f_d); f_j \in C^m[a, b], 1 \leq j \leq d\}$

A functional is a real-valued function defined on \mathcal{D} a subset of a linear space of functions \mathcal{Y} .

Ex 1 $J(y) = \int_a^b \frac{1}{y(x)} dx$ $\mathcal{Y} = C^0[a, b] = C[a, b]$

$\mathcal{D} = \{y \in \mathcal{Y}; y(x) > 0 \text{ on } [a, b]\}$
 $\mathcal{D} \subset \mathcal{Y}$

Ex 2 $J(y) = \int_a^b \sqrt{1 + y'(x)^2} dx$ $J(y)$ is the length of the curve $y=y(x)$

$\mathcal{D} = \mathcal{Y} = C^1[a, b]$

Ex (2) $J(\vec{x}) = \int_a^b \sqrt{x'(t)^2 + y'(t)^2} dt$
 $\forall \vec{x} = (x, y) \in C^1[a, b] \times C^1[a, b] = (C^1[a, b])^2$

