

Lecture 2: Convex optimization

Optimization for data sciences



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Course organization

What can we optimize?

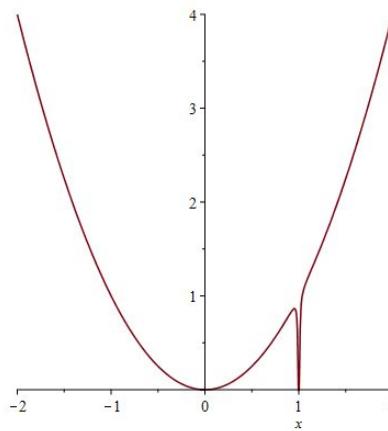
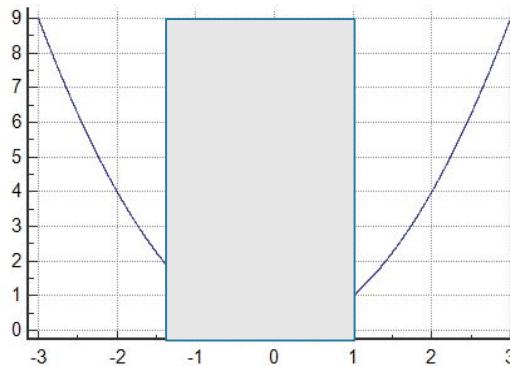
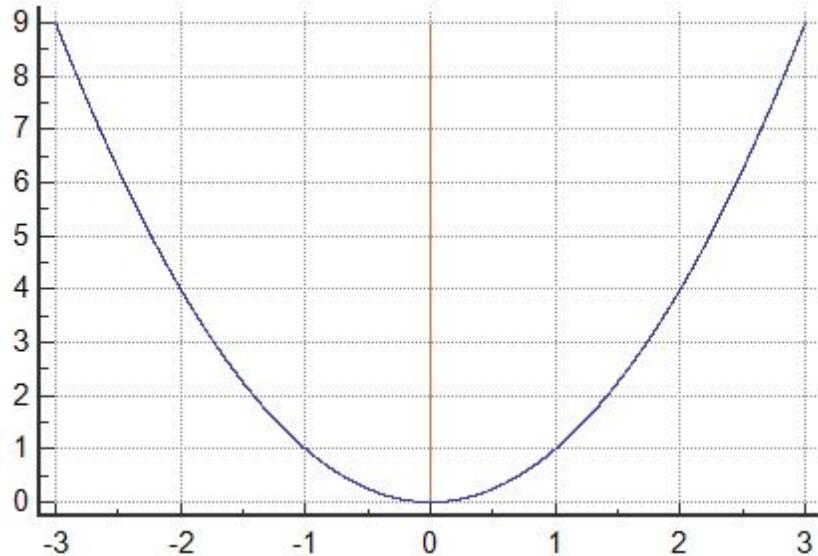
- Reduce the complexity/overhead of a problem
 - E.g. Network quantization
 - E.g. Computational optimization
- **Find the best solution to a problem**
 - **Numerical optimization**
 - **Evaluate solutions according to a criterion**
 - **Look at solutions from some given space of possible solutions to consider**

Defining an optimization problem

- Minimize a quantity $f_0(x)$
 - Under inequality and equality constraints
 - Constraints define a domain D
 - Could have no constraint except $x \in D$

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && g_i(x) = 0, \quad i = 1, \dots, p \end{aligned}$$

Can you formalize these problems?



Course organization

- Introduction to optimization
 - A few problems of interest
 - Quick mathematical refresher
- **Convex problems (Following Stephen Boyd)**
 - **Quick refresher on last week**
 - **Convex sets**
 - **Convex functions**
 - **Convex problems**
 - **Simplex algorithm for Linear Programming**

Course organization

- Duality (for convex problems)
- Newton's Descent and Barrier methods for convex case
- (First order) descent methods for the general case
- Backpropagation
- Some more properties on stochastic gradient descent

- Reports on lab sessions
 - Labs on jupyter notebooks
 - Not every session
 - Explain the code done in the session
 - Summarize what is done in the practical
- Written Exam
 - Theoretical questions
 - We will do exercises in class

Refresher on last week

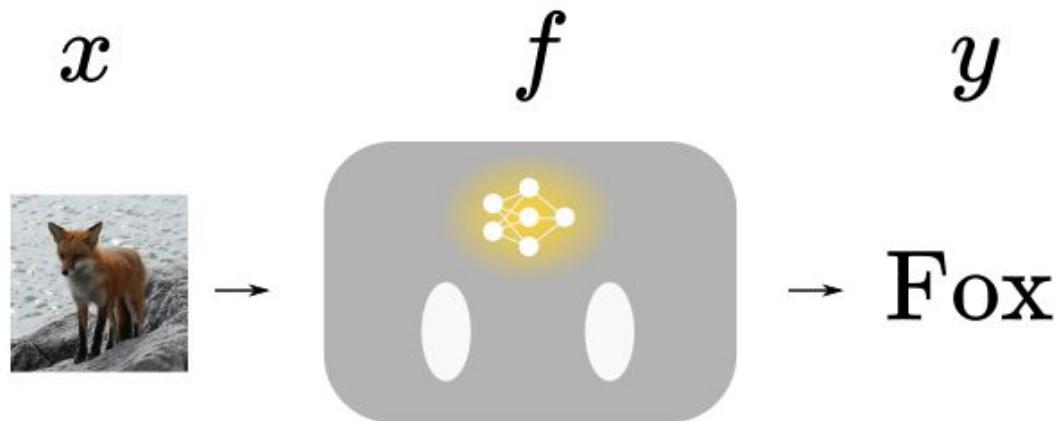
Optimization problem

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && g_i(x) = 0, \quad i = 1, \dots, p \end{aligned}$$

- ▶ $x \in \mathbf{R}^n$ is (vector) variable to be chosen (n scalar variables x_1, \dots, x_n)
- ▶ f_0 is the **objective function**, to be minimized
- ▶ f_1, \dots, f_m are the **inequality constraint functions**
- ▶ g_1, \dots, g_p are the **equality constraint functions**

- ▶ variations: maximize objective, multiple objectives, ...

Problem statement: Ideal case



- Find (robot) f that classifies images well
 - Often based on neural networks

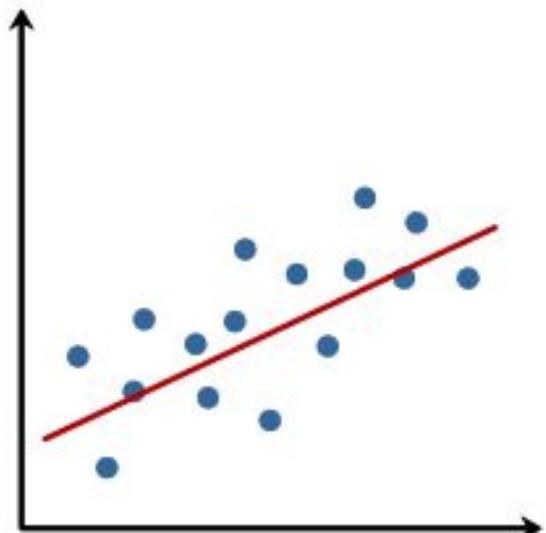
$$\forall (x, y) \in \mathcal{D}, f(x) = y$$

Minimizing Risk

- Problem: we do not know \mathcal{D} !
 - Solved problem otherwise...
 - Evaluating the risk requires this distribution
- Solution: Use a dataset D of (x,y) sampled from \mathcal{D}
 - **Empirical Risk Minimization**
 - If the (x,y) are i.i.d drawn from \mathcal{D} can be expressed as a mean over the dataset

$$\min_{\theta} \hat{\mathcal{R}}_{\theta} = \frac{1}{N} \sum_{i=0, \dots, N-1} l(f_{\theta}(x_i), y_i)$$

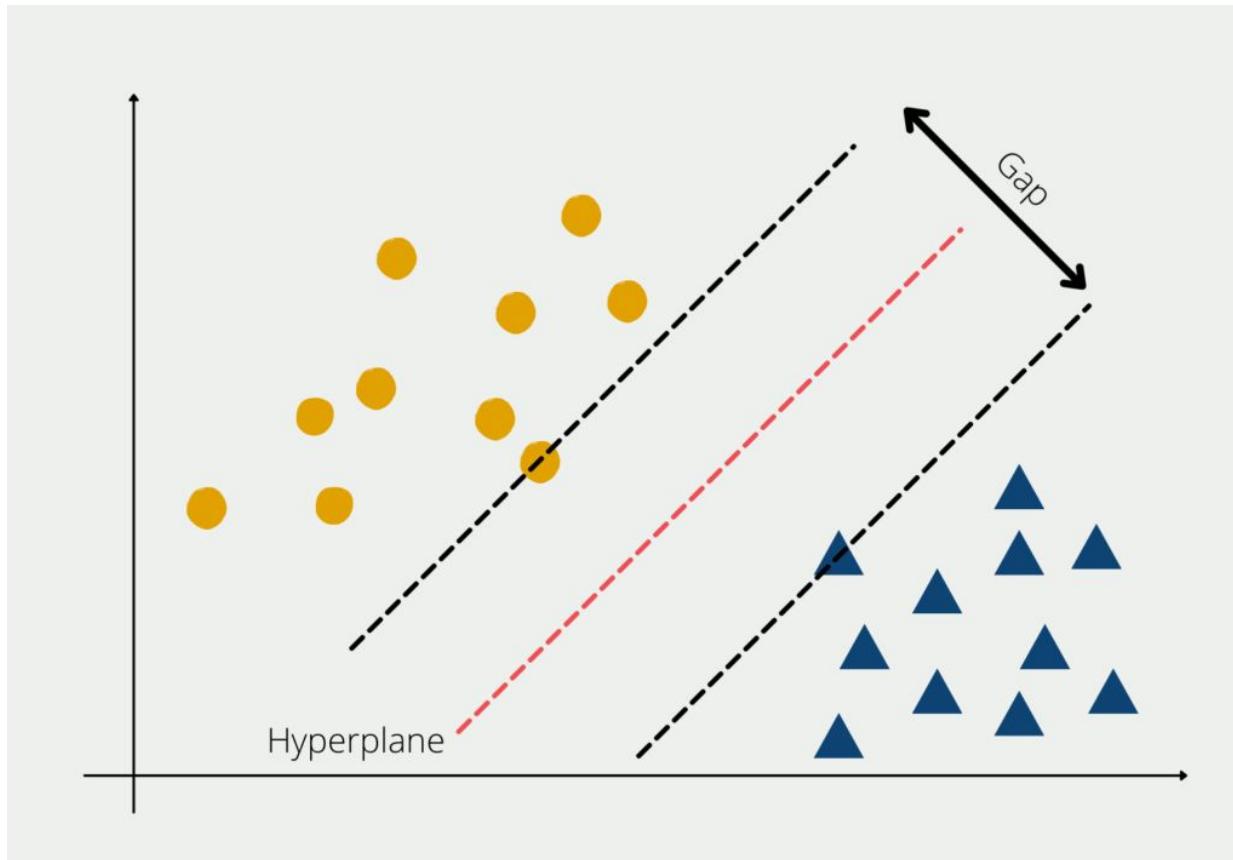
Linear regression



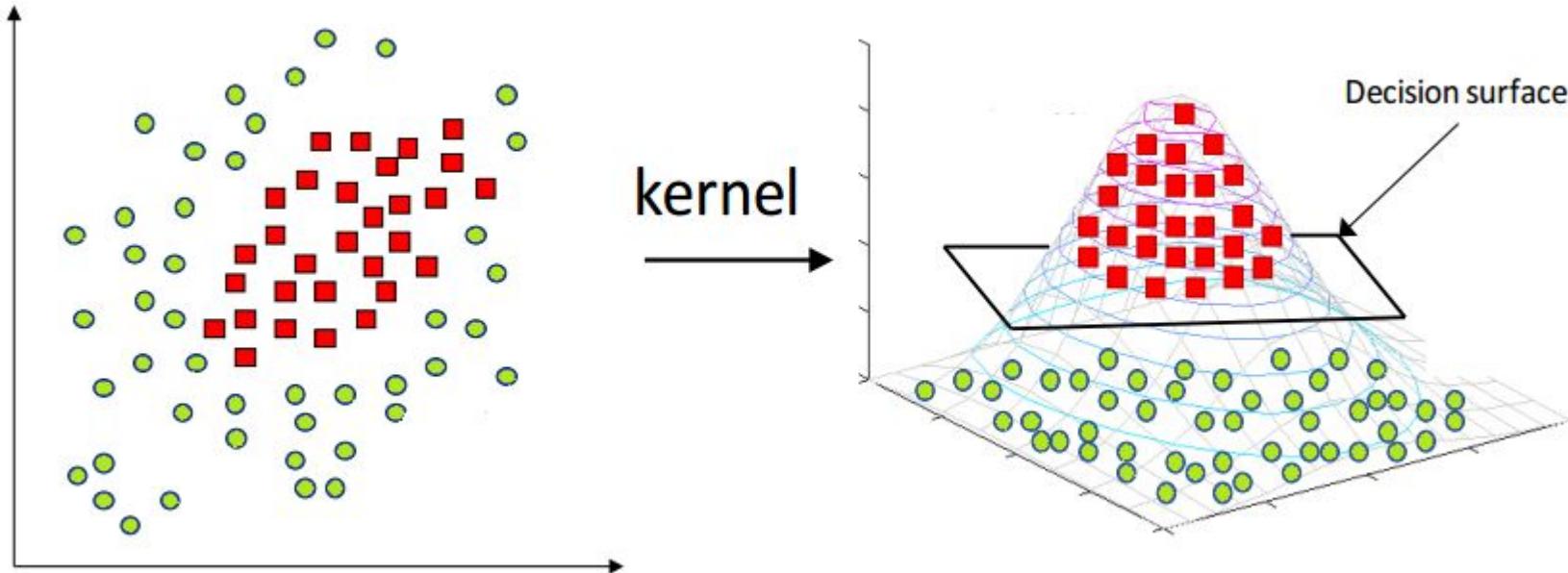
- Linearly correlated data
 - Input x (e.g. Voltage)
 - Output y (e.g. Intensity)
- Simple family of linear functions
 - Find linear coefficient

$$f_{\theta}(x) = \theta x$$

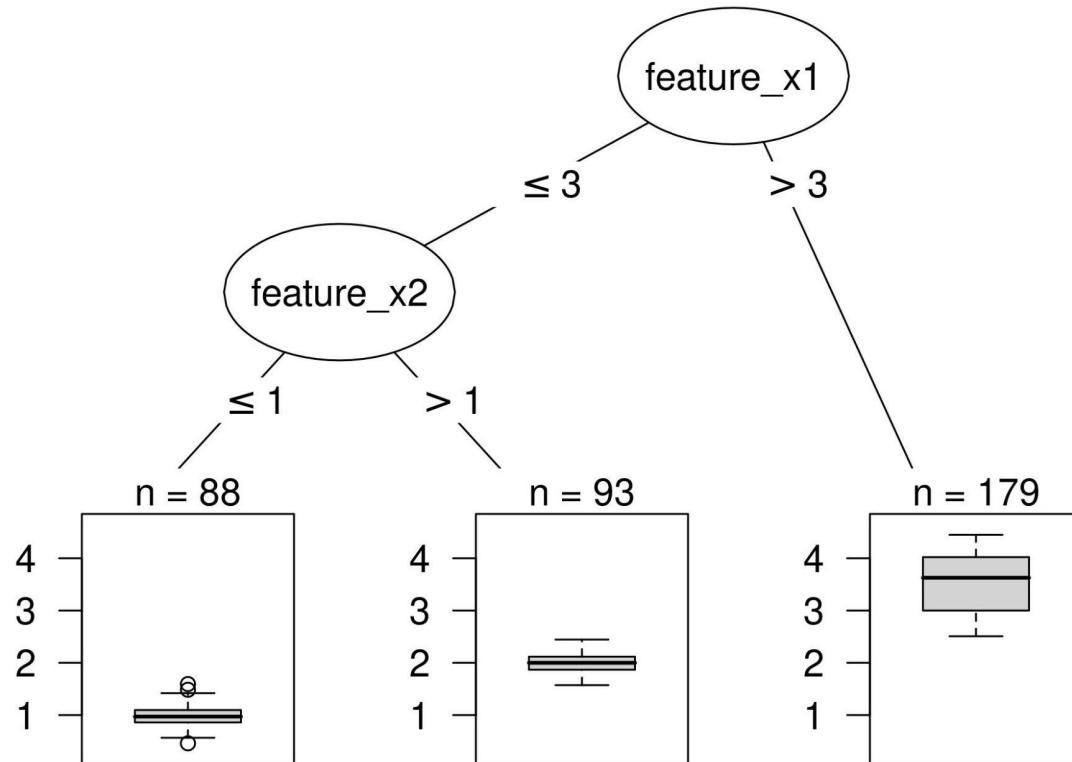
Separating hyperplane (SVM)



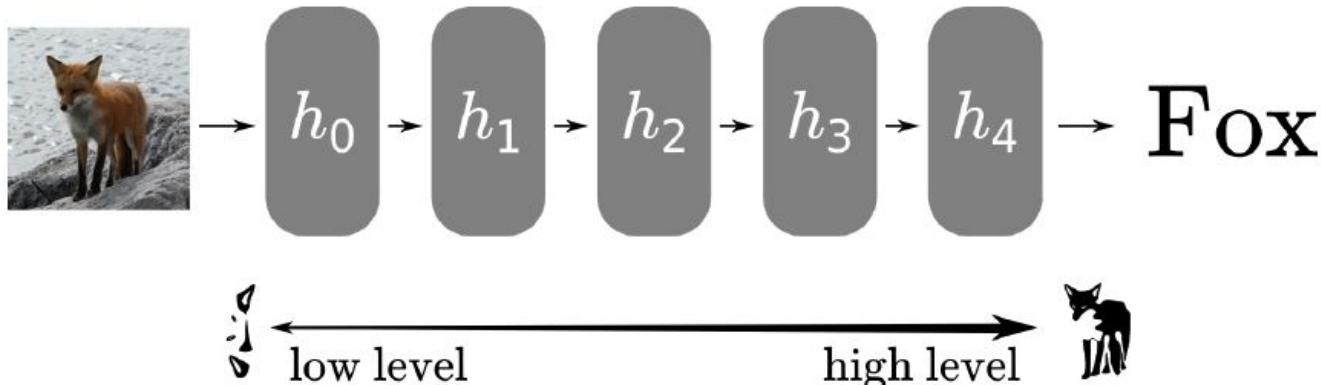
Separating hyperplane (SVM with kernel)



Decision trees



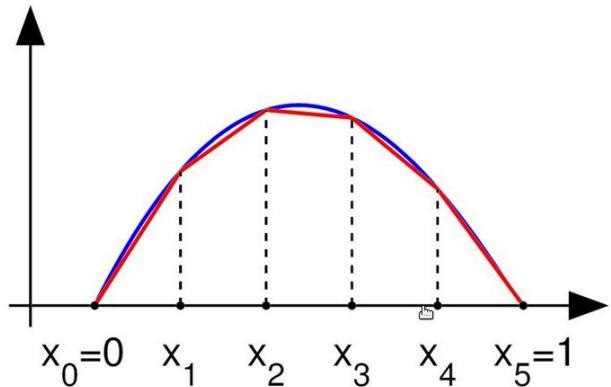
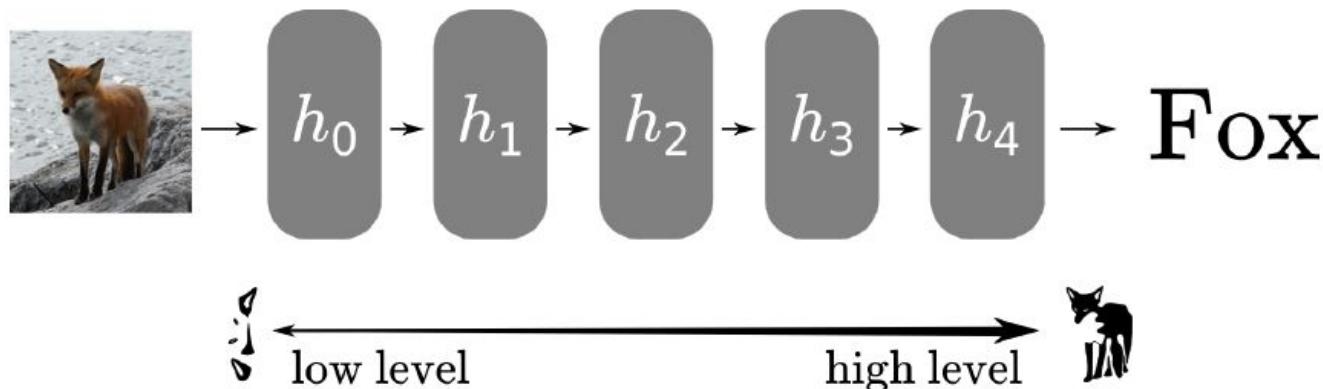
Neural network functions



- Neural networks are sequences of simple functions

$$f_\theta = h_\theta^0 \circ h_\theta^1 \circ \cdots \circ h_\theta^{L-1}$$

Interlude: Formalization of dense networks



- Highly expressive
 - Can fit many types of distributions

0. Convex problem?

Convex problem

convex optimization problem:

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && Ax = b \end{aligned}$$

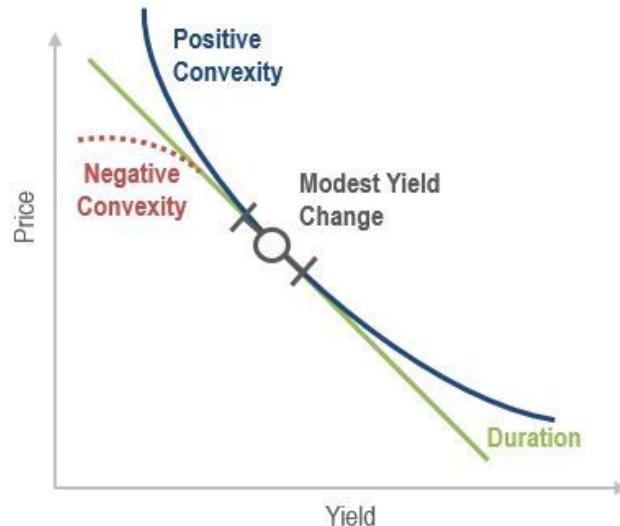
- ▶ variable $x \in \mathbf{R}^n$
- ▶ equality constraints are linear
- ▶ f_0, \dots, f_m are **convex**: for $\theta \in [0, 1]$,

$$f_i(\theta x + (1 - \theta)y) \leq \theta f_i(x) + (1 - \theta)f_i(y)$$

i.e., f_i have nonnegative (upward) curvature

Easy problem

- ▶ classical view:
 - linear (zero curvature) is easy
 - nonlinear (nonzero curvature) is hard
- ▶ the classical view is **wrong**
- ▶ the correct view:
 - convex (nonnegative curvature) is easy
 - nonconvex (negative curvature) is hard



Easy to solve!

- ▶ many different algorithms (that run on many platforms)
 - interior-point methods for up to 10000s of variables
 - first-order methods for larger problems
 - do not require initial point, babysitting, or tuning
- ▶ can develop and deploy quickly using modeling languages such as CVXPY
- ▶ solvers are reliable, so can be embedded
- ▶ code generation yields real-time solvers that execute in milliseconds (e.g., on Falcon 9 and Heavy for landing)

Brief history

► **theory (convex analysis): 1900–1970**

► **algorithms**

- 1947: simplex algorithm for linear programming (Dantzig)
- 1960s: early interior-point methods (Fiacco & McCormick, Dikin, ...)
- 1970s: ellipsoid method and other subgradient methods
- 1980s & 90s: interior-point methods (Karmarkar, Nesterov & Nemirovski)
- since 2000s: many methods for large-scale convex optimization

► **applications**

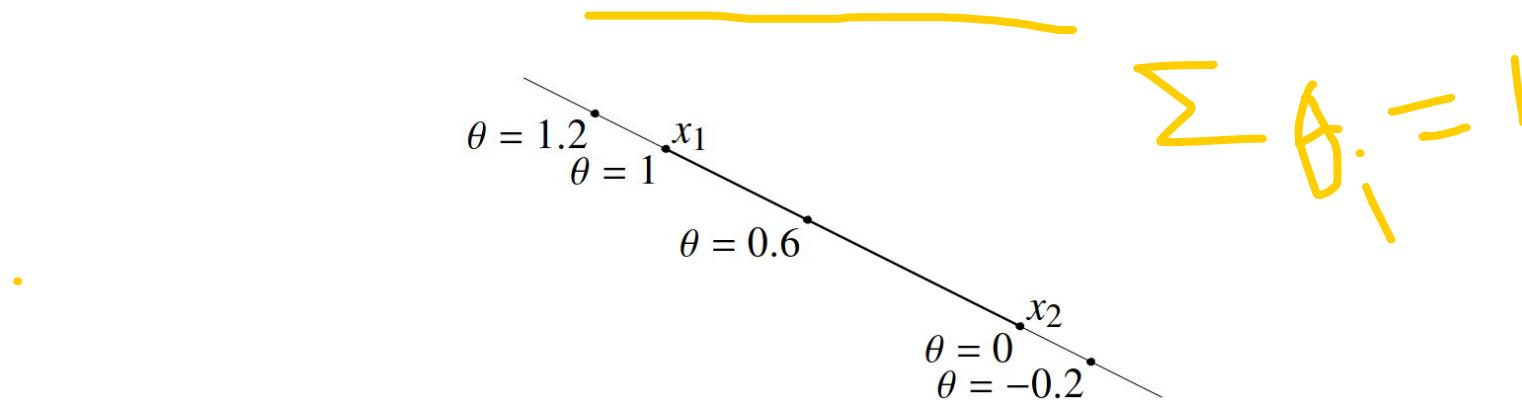
- before 1990: mostly in operations research, a few in engineering
- since 1990: many applications in engineering (control, signal processing, communications, circuit design, ...)
- since 2000s: machine learning and statistics, finance



1. Convex sets

Affine sets

line through x_1, x_2 : all points of form $x = \theta x_1 + (1 - \theta)x_2$, with $\theta \in \mathbf{R}$



affine set: contains the line through any two distinct points in the set

example: solution set of linear equations $\{x \mid Ax = b\}$
(conversely, every affine set can be expressed as solution set of system of linear equations)

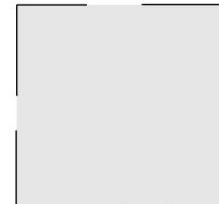
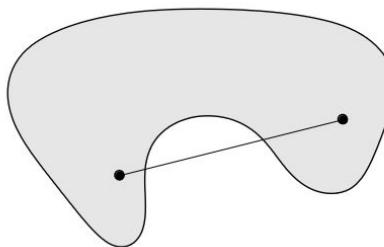
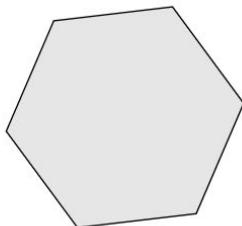
line segment between x_1 and x_2 : all points of form $x = \theta x_1 + (1 - \theta)x_2$, with $0 \leq \theta \leq 1$



convex set: contains line segment between any two points in the set

$$x_1, x_2 \in C, \quad 0 \leq \theta \leq 1 \quad \implies \quad \theta x_1 + (1 - \theta)x_2 \in C$$

examples (one convex, two nonconvex sets)



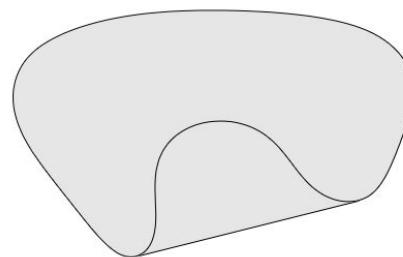
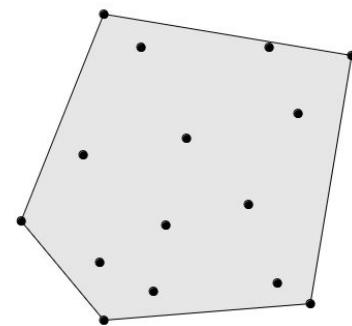
Convex combination and hull

convex combination of x_1, \dots, x_k : any point x of the form

$$x = \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_k x_k$$

with $\theta_1 + \cdots + \theta_k = 1$, $\theta_i \geq 0$

convex hull $\text{conv } S$: set of all convex combinations of points in S

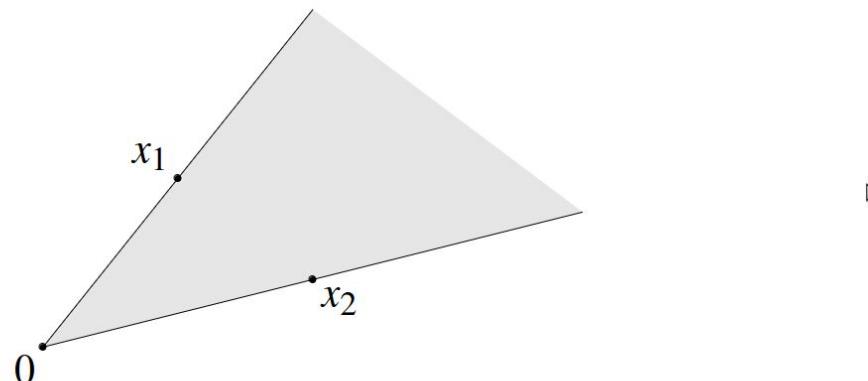


Convex cone

conic (nonnegative) combination of x_1 and x_2 : any point of the form

$$x = \theta_1 x_1 + \theta_2 x_2$$

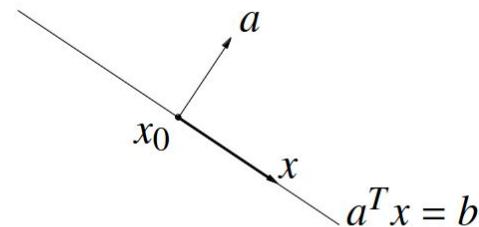
with $\theta_1 \geq 0, \theta_2 \geq 0$



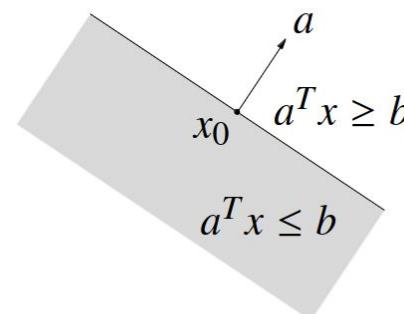
convex cone: set that contains all conic combinations of points in the set

Hyperplanes and halfspaces

hyperplane: set of the form $\{x \mid a^T x = b\}$, with $a \neq 0$



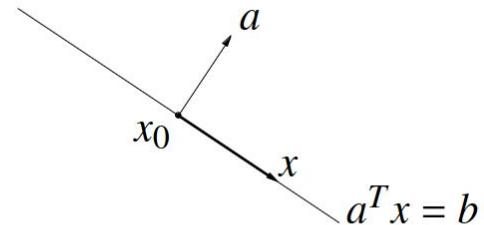
halfspace: set of the form $\{x \mid a^T x \leq b\}$, with $a \neq 0$



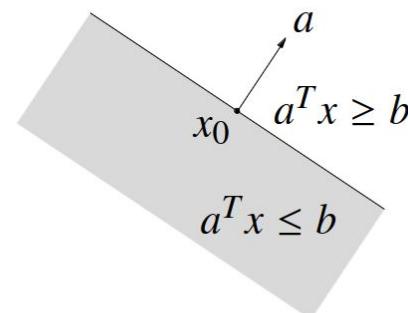
- ▶ a is the normal vector
- ▶ hyperplanes are affine and convex; halfspaces are convex

Hyperplanes and halfspaces

hyperplane: set of the form $\{x \mid a^T x = b\}$, with $a \neq 0$



halfspace: set of the form $\{x \mid a^T x \leq b\}$, with $a \neq 0$



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Hyperplanes and halfspaces

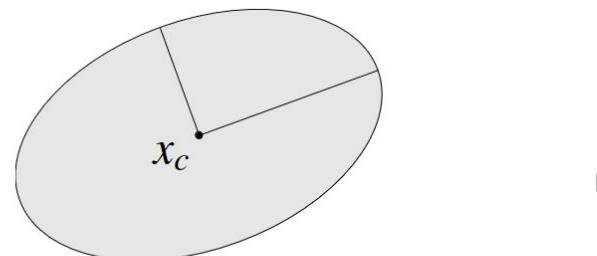
(Euclidean) ball with center x_c and radius r :

$$B(x_c, r) = \{x \mid \|x - x_c\|_2 \leq r\} = \{x_c + ru \mid \|u\|_2 \leq 1\}$$

ellipsoid: set of the form

$$\{x \mid (x - x_c)^T P^{-1}(x - x_c) \leq 1\}$$

with $P \in \mathbf{S}_{++}^n$ (i.e., P symmetric positive definite)



another representation: $\{x_c + Au \mid \|u\|_2 \leq 1\}$ with A square and nonsingular

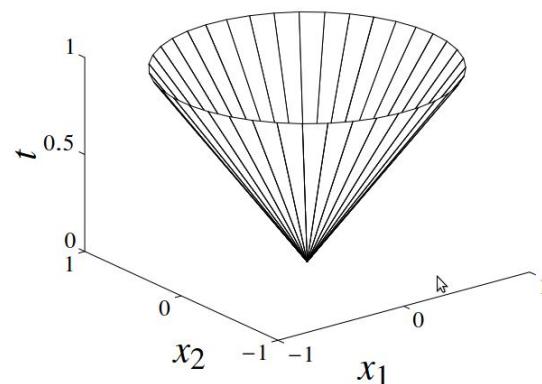
Norm balls and norm cones

- ▶ **norm:** a function $\|\cdot\|$ that satisfies
 - $\|x\| \geq 0$; $\|x\| = 0$ if and only if $x = 0$
 - $\|tx\| = |t| \|x\|$ for $t \in \mathbf{R}$
 - $\|x + y\| \leq \|x\| + \|y\|$
- ▶ notation: $\|\cdot\|$ is general (unspecified) norm; $\|\cdot\|_{\text{symb}}$ is particular norm
- ▶ **norm ball** with center x_c and radius r : $\{x \mid \|x - x_c\| \leq r\}$
- ▶ **norm cone:** $\{(x, t) \mid \|x\| \leq t\}$
- ▶ norm balls and cones are convex

Euclidean norm cone

$$\{(x, t) \mid \|x\|_2 \leq t\} \subset \mathbf{R}^{n+1}$$

is called **second-order cone**

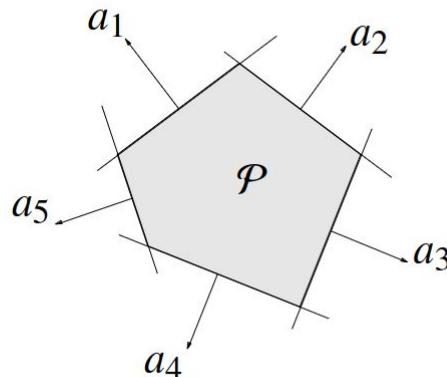


- ▶ **Polyhedron** is solution set of finitely many linear inequalities and equalities

$$\{x \mid Ax \leq b, Cx = d\}$$

($A \in \mathbf{R}^{m \times n}$, $C \in \mathbf{R}^{p \times n}$, \leq is componentwise inequality)

- ▶ intersection of finite number of halfspaces and hyperplanes
- ▶ example with no equality constraints; a_i^T are rows of A



Positive semidefinite cone

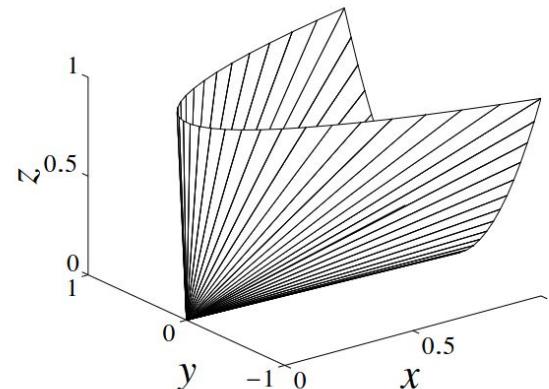
notation:

- ▶ \mathbf{S}^n is set of symmetric $n \times n$ matrices
- ▶ $\mathbf{S}_+^n = \{X \in \mathbf{S}^n \mid X \succeq 0\}$: positive semidefinite (symmetric) $n \times n$ matrices

$$X \in \mathbf{S}_+^n \iff z^T X z \geq 0 \text{ for all } z$$

- ▶ \mathbf{S}_+^n is a convex cone, the **positive semidefinite cone**
- ▶ $\mathbf{S}_{++}^n = \{X \in \mathbf{S}^n \mid X > 0\}$: positive definite (symmetric) $n \times n$ matrices

example: $\begin{bmatrix} x & y \\ y & z \end{bmatrix} \in \mathbf{S}_+^2$



Showing a set is convex

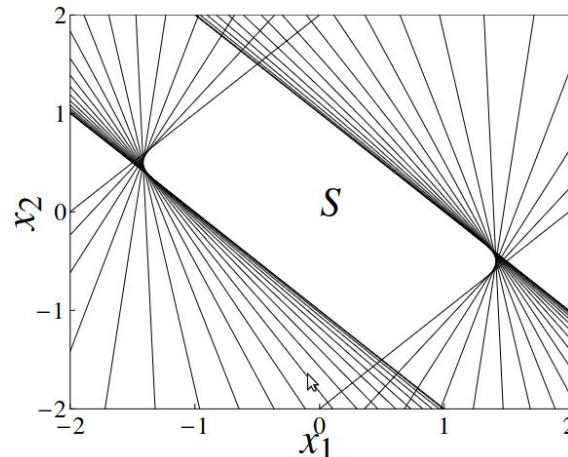
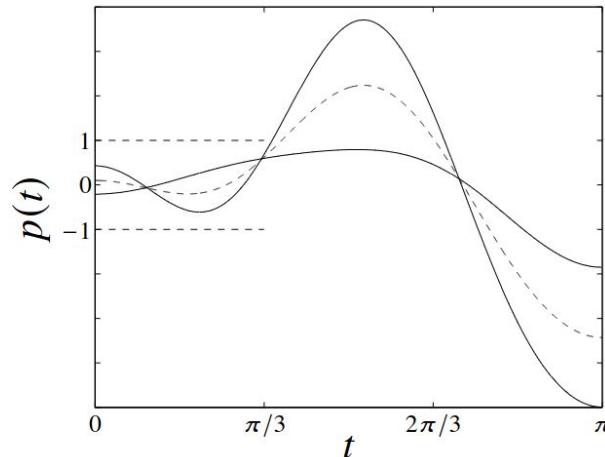
methods for establishing convexity of a set C

1. apply definition: show $x_1, x_2 \in C, 0 \leq \theta \leq 1 \implies \theta x_1 + (1 - \theta)x_2 \in C$
 - recommended only for **very simple** sets
2. use convex functions (next lecture)
3. show that C is obtained from simple convex sets (hyperplanes, halfspaces, norm balls, ...) by operations that preserve convexity
 - intersection
 - affine mapping
 - perspective mapping
 - linear-fractional mapping

you'll mostly use methods 2 and 3

Showing a set is convex

- ▶ the intersection of (any number of) convex sets is convex
- ▶ **example:**
 - $S = \{x \in \mathbf{R}^m \mid |p(t)| \leq 1 \text{ for } |t| \leq \pi/3\}$, with $p(t) = x_1 \cos t + \cdots + x_m \cos mt$
 - write $S = \bigcap_{|t| \leq \pi/3} \{x \mid |p(t)| \leq 1\}$, i.e., an intersection of (convex) slabs
- ▶ picture for $m = 2$:



Showing a set is convex

- ▶ suppose $f : \mathbf{R}^n \rightarrow \mathbf{R}^m$ is affine, i.e., $f(x) = Ax + b$ with $A \in \mathbf{R}^{m \times n}$, $b \in \mathbf{R}^m$
- ▶ the **image** of a convex set under f is convex

$$S \subseteq \mathbf{R}^n \text{ convex} \implies f(S) = \{f(x) \mid x \in S\} \text{ convex}$$

- ▶ the **inverse image** $f^{-1}(C)$ of a convex set under f is convex

$$C \subseteq \mathbf{R}^m \text{ convex} \implies f^{-1}(C) = \{x \in \mathbf{R}^n \mid f(x) \in C\} \text{ convex}$$

Showing a set is convex

- ▶ **perspective function** $P : \mathbf{R}^{n+1} \rightarrow \mathbf{R}^n$:

$$P(x, t) = x/t, \quad \text{dom } P = \{(x, t) \mid t > 0\}$$

- ▶ images and inverse images of convex sets under perspective are convex
 - ▶ **linear-fractional function** $f : \mathbf{R}^n \rightarrow \mathbf{R}^m$:
- $$f(x) = \frac{Ax + b}{c^T x + d}, \quad \text{dom } f = \{x \mid c^T x + d > 0\}$$
- ▶ images and inverse images of convex sets under linear-fractional functions are convex

Proper cones

a convex cone $K \subseteq \mathbf{R}^n$ is a **proper cone** if



- ▶ K is closed (contains its boundary)
- ▶ K is solid (has nonempty interior)
- ▶ K is pointed (contains no line)

examples

- ▶ nonnegative orthant $K = \mathbf{R}_+^n = \{x \in \mathbf{R}^n \mid x_i \geq 0, i = 1, \dots, n\}$
- ▶ positive semidefinite cone $K = \mathbf{S}_+^n$
- ▶ nonnegative polynomials on $[0, 1]$:

$$K = \{x \in \mathbf{R}^n \mid x_1 + x_2 t + x_3 t^2 + \cdots + x_n t^{n-1} \geq 0 \text{ for } t \in [0, 1]\}$$

Generalized inequality

- ▶ (nonstrict and strict) **generalized inequality** defined by a proper cone K :

$$x \leq_K y \iff y - x \in K, \quad x <_K y \iff y - x \in \text{int } K$$

- ▶ **examples**

- componentwise inequality ($K = \mathbf{R}_+^n$): $x \leq_{\mathbf{R}_+^n} y \iff x_i \leq y_i, \quad i = 1, \dots, n$
- matrix inequality ($K = \mathbf{S}_+^n$): $X \leq_{\mathbf{S}_+^n} Y \iff Y - X \text{ positive semidefinite}$

these two types are so common that we drop the subscript in \leq_K

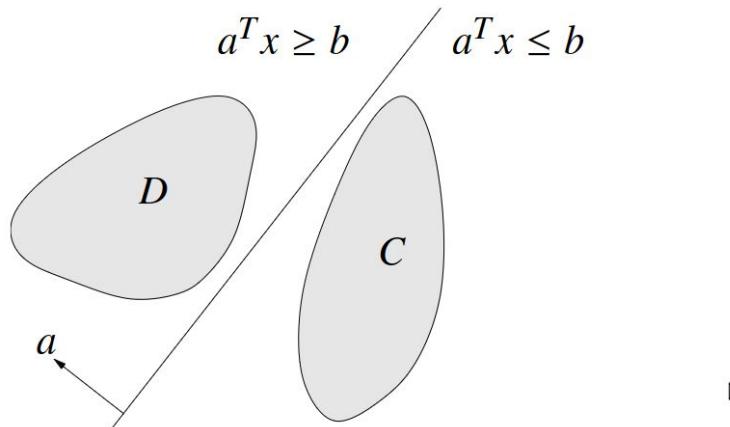
- ▶ many properties of \leq_K are similar to \leq on \mathbf{R} , e.g.,

$$x \leq_K y, \quad u \leq_K v \implies x + u \leq_K y + v$$

Separating hyperplane

- if C and D are nonempty disjoint (i.e., $C \cap D = \emptyset$) convex sets, there exist $a \neq 0, b$ s.t.

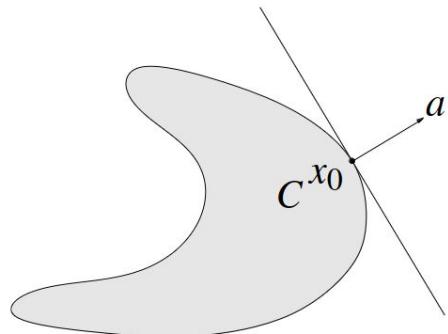
$$a^T x \leq b \text{ for } x \in C, \quad a^T x \geq b \text{ for } x \in D$$



- the hyperplane $\{x \mid a^T x = b\}$ **separates** C and D
- strict separation requires additional assumptions (e.g., C is closed, D is a singleton)

Separating hyperplane

- ▶ suppose x_0 is a boundary point of set $C \subset \mathbf{R}^n$
- ▶ **supporting hyperplane** to C at x_0 has form $\{x \mid a^T x = a^T x_0\}$, where $a \neq 0$ and $a^T x \leq a^T x_0$ for all $x \in C$



- ▶ **supporting hyperplane theorem:** if C is convex, then there exists a supporting hyperplane at every boundary point of C

Takeaway

$$x_1, x_2 \in C, \quad 0 \leq \theta \leq 1 \quad \implies \quad \theta x_1 + (1 - \theta)x_2 \in C$$

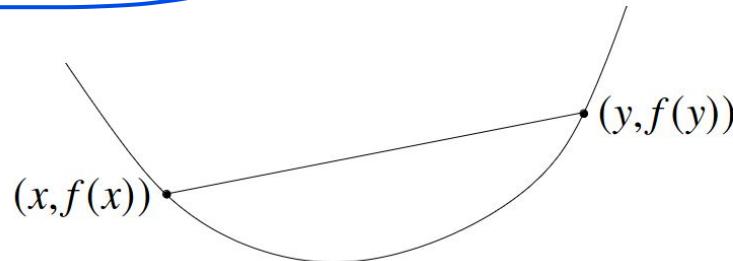
- Classic convex sets
 - Affine sets, hyperplanes, cones, balls, polyhedrons
- Convexity preserving operations
 - Intersection
 - Affine mapping
 - Perspective
 - Linear Fractional mapping

2. Convex functions

Convex functions

- $f : \mathbf{R}^n \rightarrow \mathbf{R}$ is convex if $\text{dom } f$ is a convex set and for all $x, y \in \text{dom } f$, $0 \leq \theta \leq 1$,

$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$



- f is concave if $-f$ is convex
- f is strictly convex if $\text{dom } f$ is convex and for $x, y \in \text{dom } f$, $x \neq y$, $0 < \theta < 1$,

$$f(\theta x + (1 - \theta)y) < \theta f(x) + (1 - \theta)f(y)$$



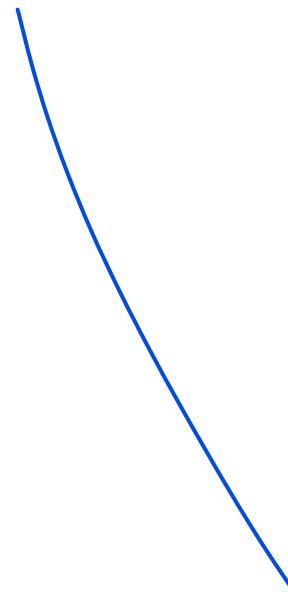
Convex functions (Examples)

convex functions:

- ▶ affine: $ax + b$ on \mathbf{R} , for any $a, b \in \mathbf{R}$
- ▶ exponential: e^{ax} , for any $a \in \mathbf{R}$
- ▶ powers: x^α on \mathbf{R}_{++} , for $\alpha \geq 1$ or $\alpha \leq 0$
- ▶ powers of absolute value: $|x|^p$ on \mathbf{R} , for $p \geq 1$
- ▶ positive part (relu): $\max\{0, x\}$

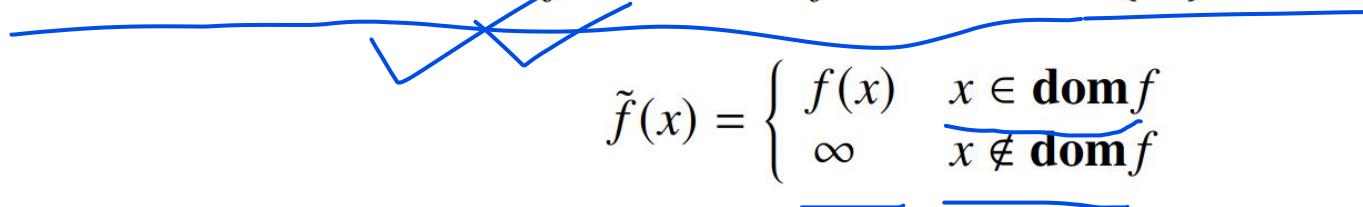
concave functions:

- ▶ affine: $ax + b$ on \mathbf{R} , for any $a, b \in \mathbf{R}$
- ▶ powers: x^α on \mathbf{R}_{++} , for $0 \leq \alpha \leq 1$
- ▶ logarithm: $\log x$ on \mathbf{R}_{++}
- ▶ entropy: $-x \log x$ on \mathbf{R}_{++}
- ▶ negative part: $\min\{0, x\}$



Extended value

- ▶ suppose f is convex on \mathbf{R}^n , with domain $\mathbf{dom} f$
- ▶ its extended-value extension \tilde{f} is function $\tilde{f} : \mathbf{R}^n \rightarrow \mathbf{R} \cup \{\infty\}$



$$\tilde{f}(x) = \begin{cases} f(x) & x \in \mathbf{dom} f \\ \infty & x \notin \mathbf{dom} f \end{cases}$$

- ▶ often simplifies notation; for example, the condition

$$0 \leq \theta \leq 1 \implies \tilde{f}(\theta x + (1 - \theta)y) \leq \theta \tilde{f}(x) + (1 - \theta) \tilde{f}(y)$$

(as an inequality in $\mathbf{R} \cup \{\infty\}$), means the same as the two conditions

- $\mathbf{dom} f$ is convex
- $x, y \in \mathbf{dom} f, 0 \leq \theta \leq 1 \implies f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$

Line restriction

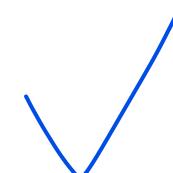
- ▶ $f : \mathbf{R}^n \rightarrow \mathbf{R}$ is convex if and only if the function $g : \mathbf{R} \rightarrow \mathbf{R}$,

$$g(t) = f(x + tv),$$

$$\mathbf{dom} g = \{t \mid x + tv \in \mathbf{dom} f\}$$

is convex (in t) for any $x \in \mathbf{dom} f$, $v \in \mathbf{R}^n$

- ▶ can check convexity of f by checking convexity of functions of one variable



First order condition

- f is **differentiable** if $\text{dom } f$ is open and the gradient



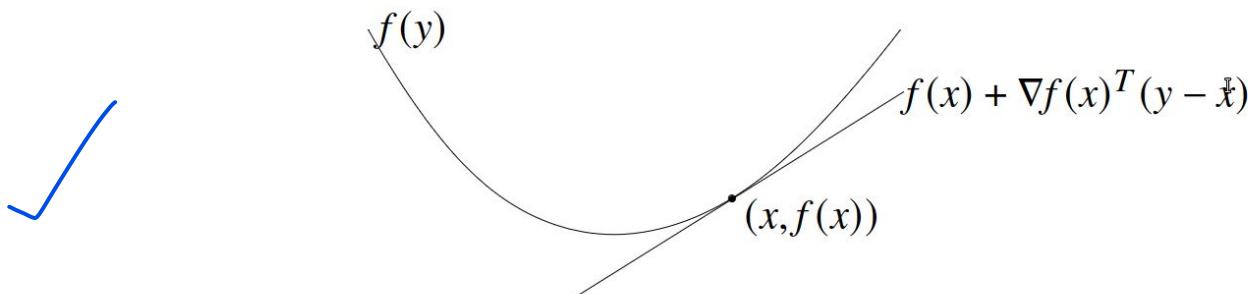
$$\nabla f(x) = \left(\frac{\partial f(x)}{\partial x_1}, \frac{\partial f(x)}{\partial x_2}, \dots, \frac{\partial f(x)}{\partial x_n} \right) \in \mathbf{R}^n$$

exists at each $x \in \text{dom } f$

- **1st-order condition:** differentiable f with convex domain is convex if and only if

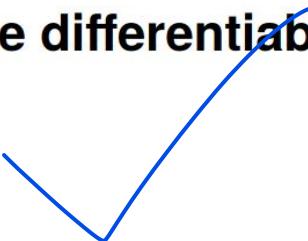
$$f(y) \geq f(x) + \nabla f(x)^T (y - x) \quad \text{for all } x, y \in \text{dom } f$$

- first order Taylor approximation of convex f is a **global underestimator** of f



Second order condition

- ▶ f is **twice differentiable** if $\text{dom } f$ is open and the Hessian $\nabla^2 f(x) \in \mathbf{S}^n$,

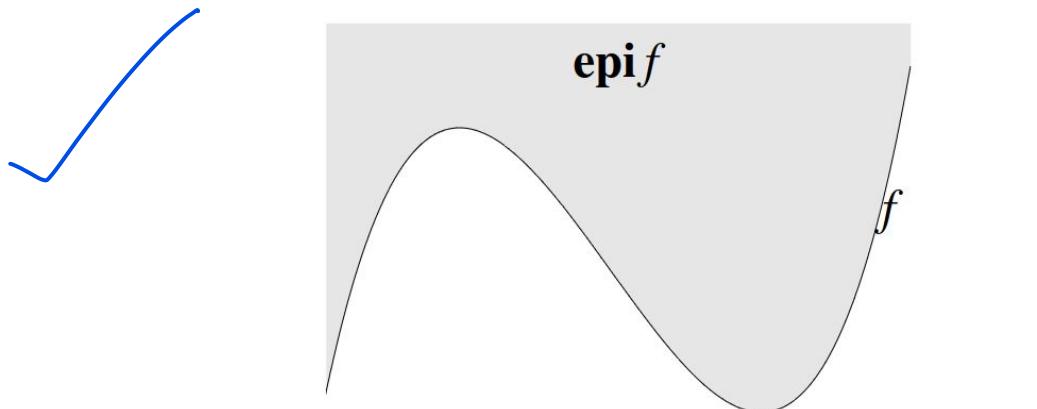

$$\nabla^2 f(x)_{ij} = \frac{\partial^2 f(x)}{\partial x_i \partial x_j}, \quad i, j = 1, \dots, n,$$

exists at each $x \in \text{dom } f$

- ▶ **2nd-order conditions:** for twice differentiable f with convex domain
 - f is convex if and only if $\nabla^2 f(x) \geq 0$ for all $x \in \text{dom } f$
 - if $\nabla^2 f(x) > 0$ for all $x \in \text{dom } f$, then f is strictly convex

Epigraph and sublevel set

- ▶ **α -sublevel set** of $f : \mathbf{R}^n \rightarrow \mathbf{R}$ is $C_\alpha = \{x \in \text{dom } f \mid f(x) \leq \alpha\}$
- ▶ sublevel sets of convex functions are convex sets (but converse is false)
- ▶ **epigraph** of $f : \mathbf{R}^n \rightarrow \mathbf{R}$ is $\text{epi } f = \{(x, t) \in \mathbf{R}^{n+1} \mid x \in \text{dom } f, f(x) \leq t\}$



- ▶ f is convex if and only if $\text{epi } f$ is a convex set

Jensen's inequality

basic inequality: if f is convex, then for $x, y \in \text{dom}f$, $0 \leq \theta \leq 1$,

$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$

- **extension:** if f is convex and z is a random variable on $\text{dom}f$,

$$f(\mathbf{E} z) \leq \mathbf{E} f(z)$$

- basic inequality is special case with discrete distribution

$$\mathbf{prob}(z = x) = \theta, \quad \mathbf{prob}(z = y) = 1 - \theta$$



Showing a function is convex

methods for establishing convexity of a function f

1. verify definition (often simplified by restricting to a line)
2. for twice differentiable functions, show $\nabla^2 f(x) \geq 0$
 - recommended only for **very simple** functions
3. show that f is obtained from simple convex functions by operations that preserve convexity
 - nonnegative weighted sum
 - composition with affine function
 - pointwise maximum and supremum
 - composition
 - minimization
 - perspective

you'll mostly use methods 2 and 3



Showing a function is convex

- ▶ **nonnegative multiple:** αf is convex if f is convex, $\alpha \geq 0$
 - ▶ **sum:** $f_1 + f_2$ convex if f_1, f_2 convex
 - ▶ **infinite sum:** if f_1, f_2, \dots are convex functions, infinite sum $\sum_{i=1}^{\infty} f_i$ is convex
 - ▶ **integral:** if $f(x, \alpha)$ is convex in x for each $\alpha \in \mathcal{A}$, then $\int_{\alpha \in \mathcal{A}} f(x, \alpha) d\alpha$ is convex
- ↗
- ▶ there are analogous rules for concave functions

Showing a function is convex

(pre-)composition with affine function: $f(Ax + b)$ is convex if f is convex

examples

- ▶ log barrier for linear inequalities

$$f(x) = - \sum_{i=1}^m \log(b_i - a_i^T x), \quad \text{dom } f = \{x \mid a_i^T x < b_i, i = 1, \dots, m\}$$

- ▶ norm approximation error: $f(x) = \|Ax - b\|$ (any norm)

Showing a function is convex

if f_1, \dots, f_m are convex, then $f(x) = \max\{f_1(x), \dots, f_m(x)\}$ is convex

examples

- ▶ piecewise-linear function: $f(x) = \max_{i=1,\dots,m}(a_i^T x + b_i)$
- ▶ sum of r largest components of $x \in \mathbf{R}^n$:

$$f(x) = x_{[1]} + x_{[2]} + \cdots + x_{[r]}$$

($x_{[i]}$ is i th largest component of x)

proof:
$$f(x) = \max\{x_{i_1} + x_{i_2} + \cdots + x_{i_r} \mid 1 \leq i_1 < i_2 < \cdots < i_r \leq n\}$$

Showing a function is convex

if $f(x, y)$ is convex in x for each $y \in \mathcal{A}$, then $g(x) = \sup_{y \in \mathcal{A}} f(x, y)$ is convex

examples

- ▶ distance to farthest point in a set C : $f(x) = \sup_{y \in C} \|x - y\|$
- ▶ maximum eigenvalue of symmetric matrix: for $X \in \mathbf{S}^n$, $\lambda_{\max}(X) = \sup_{\|y\|_2=1} y^T X y$ is convex
- ▶ support function of a set C : $S_C(x) = \sup_{y \in C} y^T x$ is convex

Showing a function is convex

- ▶ the function $g(x) = \inf_{y \in C} f(x, y)$ is called the **partial minimization** of f (w.r.t. y)
- ▶ if $f(x, y)$ is convex in (x, y) and C is a convex set, then partial minimization g is convex

examples

- ▶ $f(x, y) = x^T A x + 2x^T B y + y^T C y$ with

$$\begin{bmatrix} A & B \\ B^T & C \end{bmatrix} \succeq 0, \quad C > 0$$



minimizing over y gives $g(x) = \inf_y f(x, y) = x^T (A - BC^{-1}B^T)x$
 g is convex, hence Schur complement $A - BC^{-1}B^T \succeq 0$

- ▶ distance to a set: $\text{dist}(x, S) = \inf_{y \in S} \|x - y\|$ is convex if S is convex

Showing a function is convex

- ▶ composition of $g : \mathbf{R}^n \rightarrow \mathbf{R}$ and $h : \mathbf{R} \rightarrow \mathbf{R}$ is $f(x) = h(g(x))$ (written as $f = h \circ g$)
- ▶ composition f is convex if
 - g convex, h convex, \tilde{h} nondecreasing
 - or g concave, h convex, \tilde{h} nonincreasing(monotonicity must hold for extended-value extension \tilde{h})
- ▶ proof (for $n = 1$, differentiable g, h)

$$f''(x) = h''(g(x))g'(x)^2 + h'(g(x))g''(x)$$

examples

- ▶ $f(x) = \exp g(x)$ is convex if g is convex
- ▶ $f(x) = 1/g(x)$ is convex if g is concave and positive

↳

Showing a function is convex

- ▶ composition of $g : \mathbf{R}^n \rightarrow \mathbf{R}^k$ and $h : \mathbf{R}^k \rightarrow \mathbf{R}$ is $f(x) = h(g(x)) = h(g_1(x), g_2(x), \dots, g_k(x))$
- ▶ f is convex if h is convex and for each i one of the following holds
 - g_i convex, \tilde{h} nondecreasing in its i th argument
 - g_i concave, \tilde{h} nonincreasing in its i th argument
 - g_i affine
- ▶ you will use this composition rule **constantly** throughout this course
- ▶ you need to commit this rule to memory



- ▶ the **perspective** of a function $f : \mathbf{R}^n \rightarrow \mathbf{R}$ is the function $g : \mathbf{R}^n \times \mathbf{R} \rightarrow \mathbf{R}$,

$$g(x, t) = tf(x/t), \quad \text{dom } g = \{(x, t) \mid x/t \in \text{dom } f, t > 0\}$$

- ▶ g is convex if f is convex

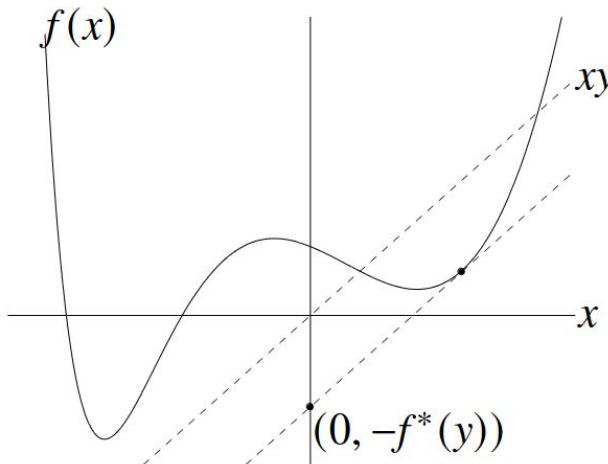


examples

- ▶ $f(x) = x^T x$ is convex; so $g(x, t) = x^T x/t$ is convex for $t > 0$
- ▶ $f(x) = -\log x$ is convex; so relative entropy $g(x, t) = t \log t - t \log x$ is convex on \mathbf{R}_{++}^2

Conjugate

- ▶ the **conjugate** of a function f is $f^*(y) = \sup_{x \in \text{dom } f} (y^T x - f(x))$



↳

- ▶ f^* is convex (even if f is not)
- ▶ will be useful in chapter 5

Takeaway

$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$

- Classic convex functions
 - Affine, exponential, norms, max, ...
- Convexity preserving operations
 - Non negative weighted sum, composition with affine
 - Pointwise maximum and supremum
 - Composition
 - Minimization
 - Perspective