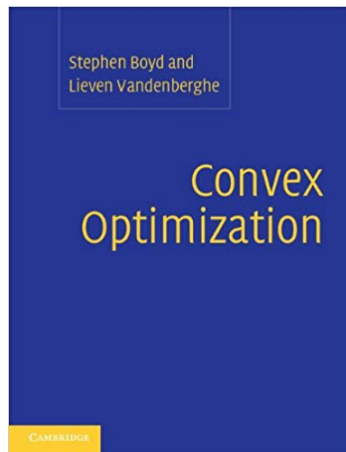# CS495
Optimiztaion

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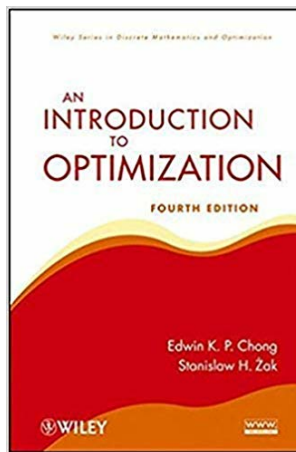April 8, 2019

Lectures follow:
Boyd and Vandenberghe (2004)

Some examples from:
Chong and Zak (2013)

Other complementary rigorous books for optimization/convex analysis are:
Bagirov (2014)
Bertsekas (2003)
Borwein (2006)
Dattorro (2009)
Hiriart (2001)
Rockafellar (1997)

Boyd, S., & Vandenberghe, L. (2004). Convex Optimization. Cambridge: Cambridge University Press.

Chong, E. K., & Zak, S. (2001). An introduction to optimization: Wiley-Interscience.

Book and Stanford course:
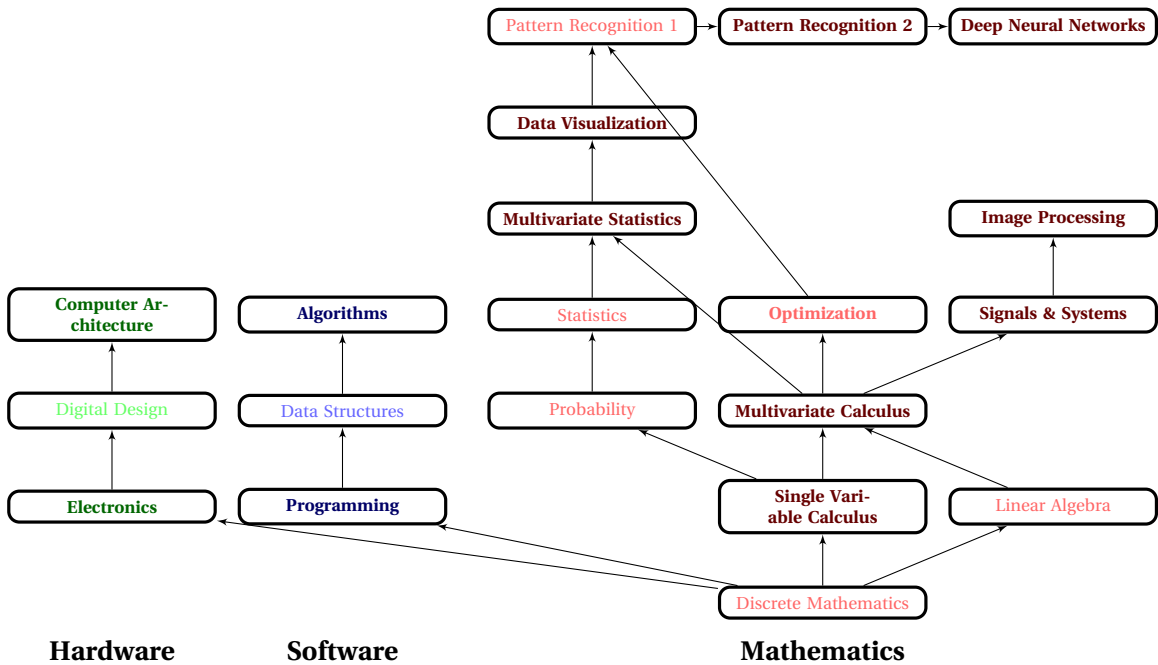http://web.stanford.edu/~boyd/cvxbook/

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Course Objectives

- Developing rigorous mathematical treatment for mathematical optimization.
- Building intuition, in particular to practical problems.
- Developing computer practice to using optimization SW.

Prerequisites

1. Discrete Mathematics
2. Calculus (single variable)
3. Calculus (multi variable)
4. Linear Algebra

5. Some Real Analysis and some Topology: Wade (2000); Kreyszig (1978) are rigorous and wonderfully lucid; Rudin (1976) is the reference of references but very terse.

Pattern Recognition 1	→	Pattern Recognition 2	→ Deep Neural Networks

Data Visualization

Multivariate Statistics

Image Processing

Statistics — Optimization — Signals & Systems

Probability — Multivariate Calculus

Computer Architecture

Algorithms

Digital Design

Data Structures

Electronics

Programming

Single Variable Calculus

Linear Algebra

Discrete Mathematics

Hardware   **Software**   **Mathematics**

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Chapter 1
Introduction
Snapshot on Optimization

Contents

Chapter 1

Introduction

1.1 Mathematical Optimization

Definition 1 *A mathematical optimization problem or just optimization problem, has the form ([Boyd and Vandenberghe, 2004](#)):*

$$\underset{x}{\text{minimize}} \quad f_0(x)$$

$$\text{subject to:} \quad f_i(x) \leq 0, \quad \quad i = 1, \ldots, m$$

$$\quad \quad \quad \quad \quad h_i(x) = 0, \quad \quad i = 1, \ldots, p,$$

$x = (x_1, \ldots, x_n) \in \mathbf{R}^n,$ (*optimization variable*)

$f_0 : \mathbf{R}^n \mapsto \mathbf{R},$ (*objective (cost/utility) function*)

$f_i : \mathbf{R}^n \mapsto \mathbf{R},$ (*inequality constraints (functions)*)

$h_i : \mathbf{R}^n \mapsto \mathbf{R},$ (*equality constraints (functions)*)

$\mathcal{D} : \bigcap\limits_{i=1}^{m} \mathbf{dom}\, f_i \cap \bigcap\limits_{i=1}^{p} \mathbf{dom}\, h_i$ (*feasible set*)

$\quad = \left\{ x \mid x \in \mathbf{R}^n \wedge f_i(x) \leq 0 \wedge h_i(x) = 0 \right\}$

$x^* : \left\{ x \mid x \in \mathcal{D} \wedge f_0(x) \leq f_0(z) \ \forall z \in \mathcal{D} \right\}$ (*solution*)

- minimize $f_0 \equiv$ maximize $-f_0$.
- $f_i \leq 0 \equiv -f_i \geq 0$.
- 0s can be replaced of course by constants b_i, c_i
- unconstrained problem when $m = p = 0$.

Example 2 *:*

$$\underset{x}{\text{minimize}} \quad x^2$$

$$\text{subject to:} \quad x \leq 2 \ \wedge \ x \geq 1.$$
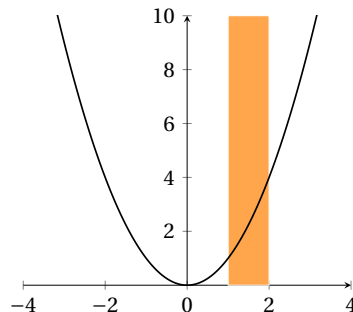
$x^* = 1.$

If the constraints are relaxed, then $x^* = 0$.

$$\underset{x}{\text{minimize}} \quad f_0(x)$$

$$\text{subject to:} \quad f_i(x) \le 0, \qquad i = 1, \ldots, m$$

$$\quad h_i(x) = 0, \qquad i = 1, \ldots, p,$$

$x = (x_1, \ldots, x_n) \in \mathbf{R}^n,$ (*optimization variable*)

$f_0 : \mathbf{R}^n \mapsto \mathbf{R},$ (*objective (cost/utility) function*)

$f_i : \mathbf{R}^n \mapsto \mathbf{R},$ (*inequality constraints (functions)*)

$h_i : \mathbf{R}^n \mapsto \mathbf{R},$ (*equality constraints (functions)*)

$\mathcal{D} : \bigcap_{i=1}^{m} \mathbf{dom} f_i \cap \bigcap_{i=1}^{p} \mathbf{dom} h_i$ (*feasible set*)

$\quad = \left\{ x \mid x \in \mathbf{R}^n \wedge f_i(x) \le 0 \wedge h_i(x) = 0 \right\}$

$x^* : \left\{ x \mid x \in \mathcal{D} \wedge f_0(x) \le f_0(z) \; \forall z \in \mathcal{D} \right\}$ (*solution*)

Example 3 *(Chong and Zak, 2013, Ex. 20.1, P. 454):*

$$\underset{x}{\text{minimize}} \quad (x_1 - 1)^2 + x_2 - 2$$

$$\text{subject to:} \quad x_2 - x_1 = 1$$

$$\quad x_1 + x_2 \le 2.$$

No global minimizer: $\partial z / \partial x_2 = 1 \ne 0$. However, $z|_{(x_2 - x_1 = 1)} = (x_1 - 1)^2 + (x_1 - 1)$, which attains a minima at $x_1 = 1/2$.
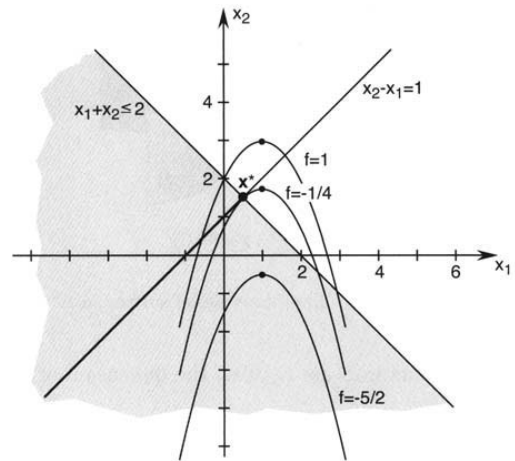
$x* = (1/2, 3/2)'$. (Let's see animation)

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1.1.1 Motivation and Applications

- *optimization problem* is an abstraction of how to make "best" possible choice of $x \in \mathbf{R}^n$.

- *constrains* represent trim requirements or specifications that limit the possible choices.

- *objective function* represents the *cost* to minimize or the *utility* to maximize for each x.

Examples:

	Any problem	*Portfolio Optimization*	*Device Sizing*	*Data Science*
$x \in \mathbf{R}^n$	choice made	investment in capitals	dimensions	parameters
f_i, h_i	firm requirements /conditions	overall budget	engineering constraints	regularizer
f_0	cost (or utility)	overall risk	power consumption	error

- Amazing variety of practical problems. In particular, data science: two sub-fields: construction and assessment.

- The construction of: Least Mean Square (LMS), Logistic Regression (LR), Support Vector Machines (SVM), Neural Networks(NN), Deep Neural Networks (DNN), etc.

- Many techniques are for solving the optimization problem:
  - Closed form solutions: convex optimization problems

  - Numerical solutions: Newton's methods, Gradient methods, Gradient descent, etc.

  - "Intelligent" methods: particle swarm optimization, genetic algorithms, etc.

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Example 4 (Machine Learning: construction) :
Let's suppose that the best regression function is
$Y = \beta_0 + \beta_1 X$, *then for the training dataset* (x_i, y_i)
we need to minimize the MSE.
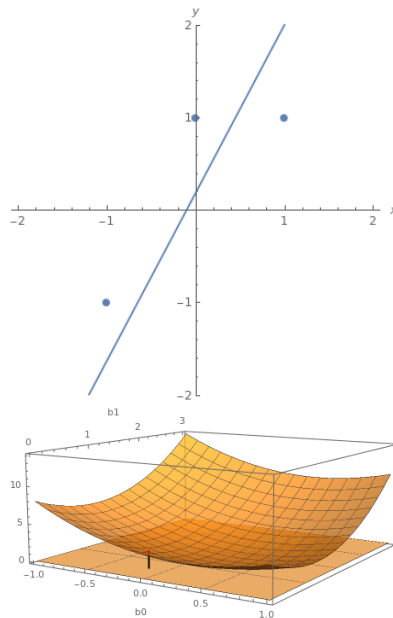
- Half of ML field is construction: NN, SVM, etc.

- In DNN it is an optimization problem of millions of parameters.

- Let's see animation.

- Where are Probability, Statistics, and Linear Algebra here? Let's re-visit the chart.

- Is the optimization problem solvable:
  - closed form? (LSM)
  - numerically and guaranteed? (convex and linear)
  - numerically but not guaranteed? (non-convex):
    * numerical algorithms, e.g., GD,
    * local optimization,
    * heuristics, swarm, and genetics,
    * brute-force with exhaustive search

$$\underset{\beta_o, \beta_1}{\text{minimize}} \sum_i (\beta_o + \beta_1 x_i - y_i)^2$$

1.1.2 Solving Optimization Problems

- A *solution method* for a class of optimization problems is an algorithm that computes a solution.

- Even when the *objective function* and constraints are smooth, e.g., polynomials, the solution is very difficult.

- There are three classes where solutions exist, theory is very well developed, and amazingly found in many practical problems:

  Linear $\subset$ Quadratic $\subset$ Convex $\subset$ Non-linear (not linear and not known to be convex!)

- For the first three classes, the problem can be solved very reliably in hundreds or thousands of variables!

1.2 Least-Squares and Linear Programming

1.2.1 Least-Squares Problems

A *least-squares* problem is an optimization problem with no constraints (i.e., $m = p = 0$), and an objective in the form:

$$\underset{x}{\text{minimize}}\, f_0(x) = \sum_{i=1}^{k} (a_i'x - b_i)^2 = \|A_{k \times n} x_{n \times 1} - b_{k \times 1}\|^2.$$

The solution is given in **closed form** by:

$$x = (A'A)^{-1} A'b$$

- Good algorithms in many SC SW exist; it is a very mature technology.
- Solution time is $O(n^2 k)$.
- Easily solvable even for hundreds or thousands of variables.
- More on that in the Linear Algebra course.
- Many other problems reduce to typical LS problem:
  - Weighted LS (to emphasize some observations)

$$\underset{x}{\text{minimize}}\, f_0(x) = \sum_{i=1}^{k} w_i(a_i'x - b_i)^2.$$

  - Regularization (to penalize for over-fitting)

$$\underset{x}{\text{minimize}}\, f_0(x) = \sum_{i=1}^{k} (a_i'x - b_i)^2 + \rho \sum_{j=1}^{n} x_j^2.$$

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1.2.2 Linear Programming

A *linear programming* problem is an optimization problem with objective and all constraint functions are linear:

$$\begin{aligned}
\underset{x}{\text{minimize}} \quad & f_0(x) = C'x \\
\text{subject to:} \quad & a_i'x \le b_i, \quad & i = 1, \dots, m \\
& h_i'x = g_i, \quad & i = 1, \dots, p,
\end{aligned}$$

- **No** closed form solution as opposed to LS.
- Very robust, reliable, and effective set of methods for numerical solution; e.g., Dantzig's simplex, and interior point.
- Complexity is $\simeq O(n^2 m)$.
- Similar to LS, we can solve a problem of thousands of variables.
- Example is *Chebyshev minimization* problem:

$$\underset{x}{\text{minimize}} f_0(x) = \max_{i=1,\dots,k} |a_i'x - b_i|,$$

- The objective is different from the LS: minimize the maximum error. **Ex:**
- After some tricks, requiring familiarity with optimization, it is equivalent to a LP:

$$\begin{aligned}
\underset{x}{\text{minimize}} \quad & t \\
\text{subject to:} \quad & a_i'x - t \le b_i, \quad & i = 1, \dots, k \\
& -a_i'x - t \le -b_i, \quad & i = 1, \dots, k
\end{aligned}$$

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1.3 Convex Optimization

A *convex optimization* problem is an optimization problem with objective and all constraint function are convex:

$$
\begin{aligned}
\underset{x}{\text{minimize}} \quad & f_0(x) \\
\text{subject to:} \quad & f_i(x) \le 0, & i = 1, \ldots, m \\
& h_i(x) = 0, & i = 1, \ldots, p, \\
& f_i(\alpha x + \beta y) \le \alpha f_i(x) + \beta f_i(y), \quad \alpha + \beta = 1, & 0 \le \alpha,\ 0 \le \beta, & \quad 0 \le i \le m \\
& h_i(x) = a_i' x + b_i & 0 \le i \le p
\end{aligned}
$$

- The LP and LS are special cases; however, only LS has closed-form solution.
- Very robust, reliable, and effective set of methods, including *interior point methods*.
- Complexity is almost: $O\big(\max(n^3, n^2 m, F)\big)$, where F is the cost of evaluating 1st and 2nd derivatives of f_i and h_i.
- Similar to LS and LP, we can solve a problem of thousands of variables.
- However, it is not as very mature technology as the LP and LS yet.
- There are many practical problems that can be re-formulated as convex problem **BUT** requires mathematical skills; but once done the problem is solved. **Hint:** realizing that the problem is convex requires more mathematical maturity than those required for LP and LS.

1.4 Nonlinear Optimization

A *non-linear optimization* problem is an optimization problem with objective and constraint functions are non-linear **BUT** not known to be convex (**so far**). Even simple-looking problems in 10 variables can be extremely challenging. Several approaches for solutions:

Local Optimization : starting at initial point in space, using differentiablity, then navigate

- does not guarantee global optimal.
- affected heavily by initial point.
- depends heavily on numerical algorithm and their parameters.
- More art than technology.
- In contrast to convex optimization, where a lot of art and mathematical skills are required to formulate the problem as convex; then numerical solution is straightforward.

Global Optimization : the true global solution is found; the compromise is complexity.

- The complexity goes exponential with dimensions.
- Sometimes it is worth it when: the cost is huge, not in real time, and dimensionality is low.

Role of Convex Optimization :

- Approximate the non-linear function to a convex one, finding the exact solution, then using it as a starting point for the original problem. (Also does not guarantee optimality)
- Setting bounds on the global solution.

Evolutionary Computations : Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), etc.

Example 5 (Nonlinear Objective Function) : *([Chong and Zak, 2013](), Ex. 14.3, P.290)*

$$f(x,y) = 3(1-x)^2 e^{-x^2-(y+1)^2} - 10 e^{-x^2-y^2}\left(-x^3 + \frac{x}{5} - y^5\right) - \frac{1}{3}e^{-(x+1)^2-y^2}$$
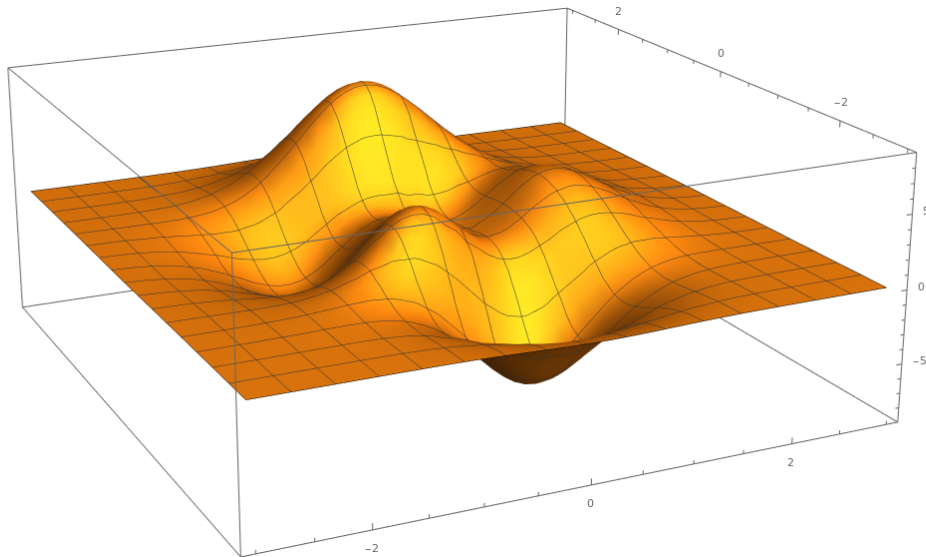
Part I

Theory

Chapter 2

Convex sets

2.1 Affine and convex sets

2.1.1 Lines and line segments

Definition 6 (line and line segment) *Suppose* $x_1 \neq x_2 \in \mathbf{R}^n$. *Points of the form*

$$y = \theta x_1 + (1 - \theta)x_2$$
$$= x_2 + \theta(x_1 - x_2),$$

where $\theta \in \mathbf{R}$, *form the line passing through* x_1 *and* x_2.

- As usual, this is a definition for high dimensions taken from a proof for $n \leq 3$.

- We have done it many times: angle, norm, cardinality of sets, etc.

- if $0 \leq \theta \leq 1$ this forms a line segment.

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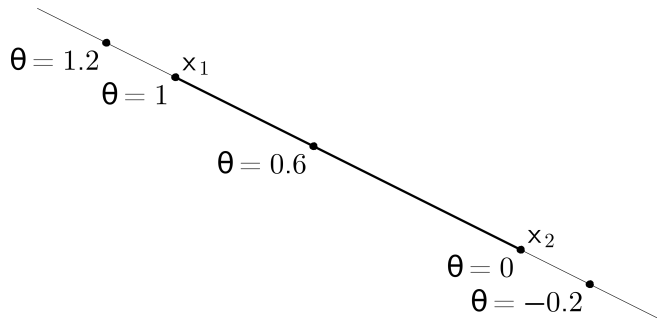
2.1.2 Affine sets

Definition 7 (Affine sets) *A set $C \subset \mathbf{R}^n$ is affine if the line through any two distinct points in C lies in C. I.e., $\forall x_1, x_2 \in C$ and $\theta \in \mathbf{R}$, we have $\theta x_1 + (1 - \theta)x_2 \in C$. In other words, C contains any linear combination (summing to one) of any two points in C.*

Examples: what about line, line segment, circle, disk, strip, first quadrant?

Corollary 8 *Suppose C is an affine set, and $x_1, \ldots, x_k \in C$, then C contains every general affine combination of the form $\theta_1 x_1 + \ldots + \theta_k x_k$, where $\theta_1 + \ldots + \theta_k = 1$.*

Wrong Proof. Suppose $y_1, y_2 \in C$, then

$$x = \sum_{i=1}^{k} \theta_i x_i = \sum_{i=1}^{k} \theta_i (\alpha_i y_1 + (1 - \alpha_i) y_2);$$

and the summation of the coefficients will be

$$\sum_{i=1}^{k} \theta_i \alpha_i + \sum_{i=1}^{k} \theta_i (1 - \alpha_i) = \sum_{i=1}^{k} \theta_i (\alpha_i + 1 - \alpha_i) = \sum_{i=1}^{k} \theta_i = 1.$$

Where is the bug? ∎

Correct Proof. **base:** $k = 3$.

$$x = \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3$$
$$= (1 - \theta_3)\left(\frac{\theta_1}{1 - \theta_3} x_1 + \frac{\theta_2}{1 - \theta_3} x_2\right) + \theta_3 x_3.$$
$$= (1 - \theta_3)(\cdot \in C) + \theta_3 (\cdot \in C).$$

induction: suppose it is true for some $k \geq 3$; i.e., $\sum_{i=1}^{k} \theta_i x_i \in C$ when $\sum_{i=1}^{k} \theta_i = 1$. Then

$$x = \sum_{i=1}^{k+1} \theta_i x_i$$
$$= \sum_{i=1}^{k} \theta_i x_i + \theta_{k+1} x_{k+1}$$
$$= (1 - \theta_{k+1}) \sum_{i=1}^{k} \theta_i / (1 - \theta_{k+1}) x_i + \theta_{k+1} x_{k+1}$$
$$= (1 - \theta_{k+1})(\cdot \in C) + \theta_{k+1}(\cdot \in C),$$
$$\text{(from the induction hypothesis)}$$

which completes the proof. ∎

Definition 9 (Subspace from Linear Algebra) *a set $V \subset \mathbf{R}^n$ of vector (here points) is a subspace if it is closed under sums and scalar multiplication. I.e., $\forall v_1, v_2 \in V$ and $\forall \alpha, \beta \in \mathbf{R}$ we have $\alpha v_1 + \beta v_2 \in V$.*

Remember:

- $\alpha + \beta$ not necessarily equals 1
- $\alpha = 0, \beta = 0 \rightarrow \mathbf{0} \in V$.
- Any subspace V is the solution set of $A_{m \times n} x_{n \times 1} = 0$, which is $\mathcal{N}(A)$ (the null space of A). Geometry? I.e., $V = \{x \mid Ax = 0\}$
- **rank**$(A) = n - \dim(V)$.

Corollary 10 .

1. *If C is affine, then $V = C - x_0 = \{x - x_0 \mid x, x_0 \in C\}$ is a subspace.*
2. *If V is a subspace, then $C = V + x_0 = \{x + x_0 \mid x \in V\}$ is affine $\forall x_0$.*
3. *An affine set C can be represented as the solution set of a nonhomogeneous linear system $Ax = b$, where $V = C - x_0$ is $\mathcal{N}(A)$.*
4. *The solution set of any nonhomogeneous system is an affine set. (Ex. 2.1)*

Proof.

1. Suppose $x_1, x_2, x_0 \in C$, an affine set. Both $x_1 - x_0$ and $x_2 - x_0$, by construction, $\in V$; then

$$x = \alpha(x_1 - x_0) + \beta(x_2 - x_0) + x_0$$
$$= \alpha x_1 + \beta x_2 + (1 - \alpha - \beta)x_0 \in C$$

Then $x - x_0 = \alpha(x_1 - x_0) + \beta(x_2 - x_0) \in V$; hence V is a subspace.

2. Suppose $x_1, x_2 \in V$, a subspace. Both $x_1 + x_0$ and $x_2 + x_0$, by construction, $\in C$; then

$$x = \theta(x_1 + x_0) + (1 - \theta)(x_2 + x_0)$$
$$= \theta x_1 + (1 - \theta)x_2 + x_0 = (\cdot \in V) + x_0 \in C$$

3. If C is affine and $x_0 \in C$, then

$$C - x_0 = \{x \mid Ax = 0\} \quad \text{(since it is a subspace)}$$
$$C = \{x + x_0 \mid A(x + x_0) = Ax_0\}$$
$$C = \{c \mid Ac = b\}.$$

4. $C = \{x \mid Ax = b\}$; if $x_0 \in C$ then $Ax_0 = b$ and

$$C - x_0 = \{x - x_0 \mid A(x - x_0) = b - Ax_0 = 0\}.$$

Hence, $C - x_0$ is a subspace and C is affine.

$\blacksquare$

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Proof of the book. Suppose $x_1, x_2 \in C$, where $C = \{x \mid Ax = b\}$. Then

$$A(\theta x_1 + (1 - \theta)x_2) = \theta Ax_1 + (1 - \theta)Ax_2 = \theta b + (1 - \theta)b = b,$$

which means $\theta x_1 + (1 - \theta)x_2 \in C$ as well. ∎

Remark 1 *:*
- *The dimension of affine is defined to be the dimension of the associate subspace.*
- *affine is a subspace plus offset.*
- *every subspace is affine but not the vice versa; i.e., subspace is a special case of affine.*

Definition 11 (affine hull) *The "smallest" set of all affine combinations of some set C (not necessarily affine) is called the affine hull (**aff** C):*

$$\textbf{aff } C = \Big\{\sum_{i=1}^{k} \theta_i x_i \mid x_i \in C, \ \sum_i \theta_i = 1\Big\}.$$

Corollary 12 **aff** C *is affine.*

Proof. For $x_1 = \sum_i \alpha_i x_i$, $\sum_i \alpha_i = 1$, and $x_2 = \sum_i \beta_i x_i$, $\sum_i \beta_i = 1$, we have

$$\theta x_1 + (1-\theta)x_2 = \theta \sum_i \alpha_i x_i + (1-\theta)\sum_i \beta_i x_i = \sum_i (\theta\alpha_i + (1-\theta)\beta_i)x_i$$

$$\sum_i (\theta\alpha_i + (1-\theta)\beta_i) = \theta \sum_i \alpha_i + (1-\theta)\sum_i \beta_i = \theta + (1-\theta) = 1.$$

Hence, **aff** C is affine as well. ∎

Example 13 *Construct the affine hull of the set* $C = \big\{(-1,0),(1,0),(0,1)\big\}$

$$\begin{aligned}
\theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 &= (1-\theta_3)\Big(\frac{\theta_1}{1-\theta_3}x_1 + \frac{\theta_2}{1-\theta_3}x_2\Big) + \theta_3 x_3 \\
&= (1-\alpha_3)\big((1-\alpha_2)x_1 + \alpha_2 x_2\big) + \alpha_3 x_3 \qquad = (1-\alpha_2)(1-\alpha_3)x_1 + \alpha_2(1-\alpha_3)x_2 + \alpha_3 x_3,
\end{aligned}$$

$$\begin{array}{lll}
\theta_3 = \alpha_3 & \theta_2 = \alpha_2(1-\alpha_3) & \theta_1 = 1 - \theta_2 - \theta_3 = (1-\alpha_2)(1-\alpha_3) \\
\alpha_3 = \theta_3 & \alpha_2 = \theta_2/(1-\theta_3) & \alpha_1 = 1 - \alpha_2 = \theta_1/(1-\theta_3).
\end{array}$$

HW: Derive expressions for α_i and θ_i for n-point combination.

2.1.3 Affine dimension and relative interior

Definition 14 (some basic topology in $\mathbf{R}^n$) :

1. *The ball of radious r and center x in the norm $\|\cdot\|$.*

$$B(x,r) = \{y \mid \|y - x\| \le r\}.$$

2. *An element $x \in C \subseteq \mathbf{R}^n$ is called an interior point of C if $\exists\, \varepsilon > 0$ for which*

$$B(x,\epsilon) = \{y \mid \|y - x\|_2 \le \varepsilon\} \subseteq C.$$

   I.e., $\exists$ a ball centered at x that lies entirely in C.

3. *The set of all points interior to C is called the interior of C and is denoted $\mathbf{int}\, C$.*

4. *A set C is open if $\mathbf{int}\, C = C$. I.e., every point in C is an interior point.*

5. *A set C is closed if its complement is open*

$$\mathbf{R}^n \setminus C = \{x \in \mathbf{R}^n \mid x \notin C\}$$

6. *The closure of a set C is defined as*

$$\mathbf{cl}\, C = \mathbf{R}^n \setminus \mathbf{int}(\mathbf{R}^n \setminus C).$$

7. *The boundary C is defined as*

$$\mathbf{bd}\, C = \mathbf{cl}\, C \setminus \mathbf{int}\, C.$$

Corollary 15 *A boundary point (a point $x \in \mathbf{bd}\, C$) satisfies: $\forall \epsilon > 0, \exists\, y \in C$ and $z \notin C$ s.t. $y, z \in B(x, \epsilon)$.*
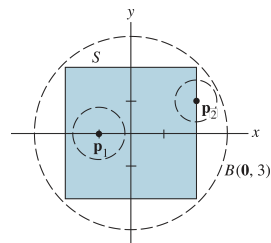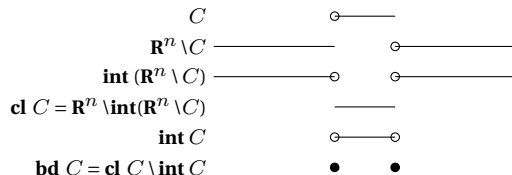
Definition 16 (alter. equiv. def.) :

- $\mathbf{int}\, C$ *and* $\mathbf{bd}\, C$ *are defined as 2,3, corollary. (It is obvious that: $\mathbf{int}\, C \cap \mathbf{bd}\, C = \phi$.)*
- C *is open if* $\mathbf{int}\, C = C$ $\equiv$ $C \cap \mathbf{bd}\, C = \phi$.
- C *is closed if* $\mathbf{bd}\, C \subseteq C$.
- $\mathbf{cl}\, C = \mathbf{bd}\, C \cup \mathbf{int}\, C$.

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Definition 17 *We define the affine dimension of a set C as the dimension of its affine hull.*

Example 18 *The unit circle in $\mathbf{R}^2$, i.e., $\{x \mid x_1^2 + x_2^2 = 1\}$ has affine hull of whole $\mathbf{R}^2$. So its affine dimension is 2. However, it has a dimensionality of 1 since it is parametric in just one parameter (manifold).*

Definition 19 *We define the relative interior of the set C, denoted **relint** C, as its interior relative to **aff** C*

$$\text{relint } C = \left\{ x \in C \mid B(x,r) \cap \text{aff } C \subseteq C \text{ for some } r > 0 \right\},$$

*and its relative boundary, denoted **relbd** C is defined as*

$$\text{relbd } C = \text{cl } C \setminus \text{relint } C.$$

Example 20 *Consider a square in the (x_1, x_2)-plane in $\mathbf{R}^3$, defined as:*

$$C = \left\{ x \in \mathbf{R}^3 \mid -1 \le x_1 \le 1,\ -1 \le x_2 \le 1,\ x_3 = 0 \right\}.$$

Then:

$$\textbf{int } C = \Phi$$
$$\textbf{cl } C = \mathbf{R}^n \setminus \textbf{int}\left(\mathbf{R}^n \setminus C\right) = C$$
$$\textbf{bd } C = \textbf{cl } C \setminus \textbf{int } C = C$$
$$\textbf{aff } C = \left\{ x \in \mathbf{R}^3 \mid x_3 = 0 \right\}$$
$$\textbf{relint } C = \left\{ x \in \mathbf{R}^3 \mid -1 < x_1 < 1,\ -1 < x_2 < 1,\ x_3 = 0 \right\}$$
$$\textbf{relbd } C = \left\{ x \in \mathbf{R}^3 \mid \max\{|x_1|, |x_2|\} = 1,\ x_3 = 0 \right\}$$

2.1.4 Convex sets

Definition 21 (convex set) *A set C is convex if the line segment between any two points in C lies in C; i.e., if for any x_1, $x_2 \in C$ and any θ with $0 \le \theta \le 1$, we have*

$$\theta x_1 + (1-\theta)x_2 \in C.$$

Corollary 22 *Suppose C is convex set, and $x_1, \ldots, x_k \in C$, then C contains every general convex combination (also called mixture); i.e.,*

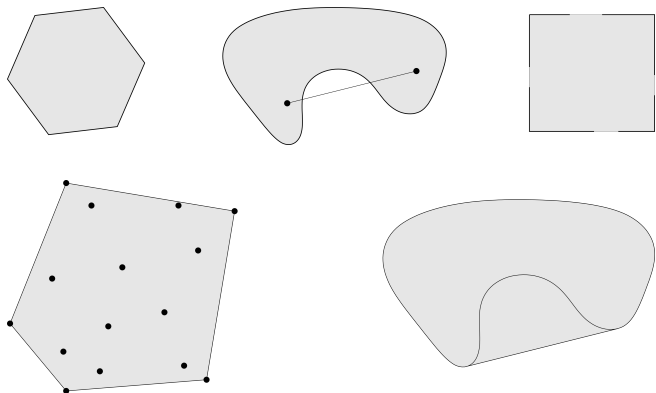$$\sum_i \theta_i x_i \in C, \ \sum_i \theta_i = 1, \ \theta_i \ge 0.$$

Proof. identical to proof of corollary 8. ∎

Definition 23 (convex hull) *The "smallest" set of all convex combinations of some set C (not necessarily convex) is called the convex hull (**conv** C)*

$$\mathbf{conv}\,C = \Big\{ \sum_{i=1}^{k} \theta_i x_i \mid x_i \in C, \ \sum_i \theta_i = 1, \ \theta_i \ge 0 \Big\}.$$

Corollary 24 **conv** C *is convex.*

Proof. identical to proof of corollary 12. ∎

Example 25 *Revisit example 13.*

Example 26 (Applications) *: Suppose $X \in C$ is a r.v., C is convex. Then $\mathrm{E}\,X \in C$ if it exists:*

$$\mathrm{E}\,X = \sum_{i=1}^{n} p_i x_i$$

$$\mathrm{E}\,X = \sum_{i=1}^{\infty} p_i x_i$$

$$\mathrm{E}\,X = \int_C f_X(x)x \, dx \qquad \text{(Riemann sum)}$$

2.1.5 Cones

Definition 27 *A set C is called a cone (or nonnegative homogeneous) if $\forall\, x \in C$, $\theta \geq 0$ we have $\theta x \in C$; and it is a convex cone if it is convex in addition to being a cone.*

Definition 28 *A point of the form $\sum_{i=1}^{k} \theta_i x_i$, $\theta_i \geq 0$ is called a conic combination.*

Corollary 29 *A set C is a convex cone if and only if it contains all conic combinations of its elements; i.e.,*

$$\sum_i \theta_i x_i \in C \;\; \forall x_i \in C \; and \; \theta_i \geq 0.$$

Proof.
Sufficiency: is obvious. Choosing $\sum_i \theta_i = 1$ implies C is convex; and setting $\theta_i = 0 \;\forall i > 1$ implies C is cone.
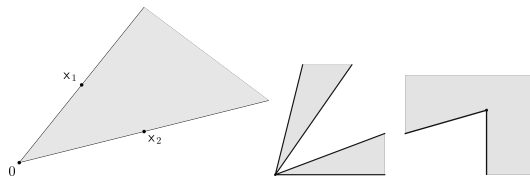**Necessity:** Since C is convex cone, then $\forall x_i \in C, \theta_i \geq 0$ we have:

$$\theta_i x_i \in C \qquad \text{(cone)}$$

$$\sum_i (1/n)(\theta_i x_i) \in C \qquad \text{(convex)}$$

$$n \sum_i (1/n)(\theta_i x_i) = \sum_i \theta_i x_i \in C \qquad \text{(cone)}$$

$\blacksquare$

Definition 30 *A conic hull of a set C is the minimum set of all conic combination:*

$$\textbf{cone } C = \{\sum_i \theta_i x_i \mid x_i \in C, \; \theta_i \geq 0, \; i = 1, \dots, n\}.$$

Corollary 31 **cone** C *is convex cone.*

Proof. If $y \in$ **cone** $C, \alpha \geq 0$, then $\alpha y = \alpha \sum_i \theta_i x_i = \sum_i (\alpha \theta_i) x_i \in$ **cone** C. And if $y_1, y_2 \in$ **cone** C then $\alpha y_1 + (1-\alpha) y_2 = \alpha \sum_i \theta_i x_i + (1-\alpha) \sum_i \mu_i x_i = \sum_i (\alpha \theta_i + (1-\alpha) \mu_i) x_i \in$ **cone** C $\blacksquare$
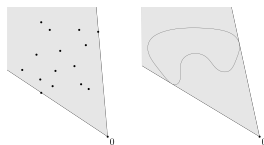
2.2 Some important examples

Fast Revision

- Each of the sets: ϕ, x_0 (a singleton), $\mathbf{R}^n$ are affine and convex.

- Any line is affine. If it passes through zero, it is a subspace and a convex cone.

- Any subspace is convex cone but not vise versa.

- A line segment is convex, but not affine (unless it reduces to a singleton).

- A *ray*, $\{x_0 + \theta v \mid \theta \geq 0, v \neq 0\}$ is convex but not affine. It is convex cone if $x_0 = 0$.

2.2.1 Hyperplanes and halfspaces

Definition 32 *A hyperplane is a set of the form*

$$\mathcal{S} = \{x \mid a'x = b\}, \qquad a, b \in \mathbf{R}^n, \ a \neq 0$$
$$\equiv \{x \mid a'(x - x_0) = 0\}, \qquad a'x_0 = b.$$

- Vectors with inner product with a is b: $\frac{a'}{\|a\|}x = \frac{b}{\|a\|}$.
  I.e., from **0**, walk a distance $\frac{b}{\|a\|}$ (either + or -) in the direction of a, then draw perpendicular line.

Definition 33 *A closed halfspace is the region generated by the hyperplane and defined as:*

$$\mathcal{H} = \{x \mid a'x \leq b\}, \qquad a, b \in \mathbf{R}^n, \ a \neq 0$$
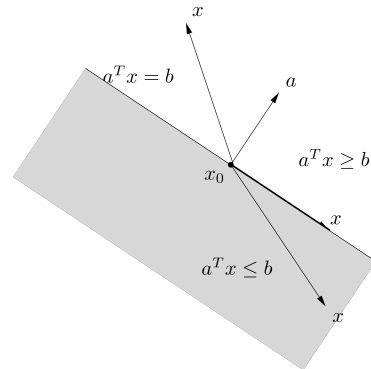$$\equiv \{x \mid a'(x - x_0) \leq 0\}, \qquad a'x_0 = b.$$

- region of all vectors with projection $< b/\|a\|$.
- Vectors with obtuse angle with a: $(\cos\theta = \frac{a'x}{\|a\|\|x\|})$.
- Line passing with p_0 and $\perp$ on $\mathcal{S}$:

$$x = p_0 + \theta\bar{a} \qquad \text{(parametric eq.)}$$
$$a'x_0 = a'p_0 + \theta_0\|a\|$$
$$\theta_0 = (b - a'p_0)/\|a\| \qquad (x_0 \text{ pt. of intersection.})$$
$$x_0 - p_0 = \frac{(b - a'p_0)}{\|a\|}\bar{a}.$$

Corollary 34 *$\mathcal{S}$ is affine, $\mathcal{H}$ is convex and not affine,* **int** *$\mathcal{H} = \mathcal{H} \setminus \mathcal{S}$, and* **bd** *$\mathcal{H} = \mathcal{S}$.*

Proof. $\mathcal{S}$ is affine done. $\mathcal{H}$ is convex: take $0 \leq \theta \leq 1$
$\theta a'x_1 + (1-\theta)a'x_2 \leq \theta b + (1-\theta)b = b$. (why not affine?!)

$$y = x + ru, \quad 0 \leq \|u\| \leq 1 \qquad (y \in B(x, r))$$
$$a'y = a'x + ra'u = b - (b - a'x) + r\|a\|\|u\|\cos(a, u)$$

If $b = a'x$, i.e., $x \in \mathcal{S}$, $a'u > 0$ or < 0 (depending on the angle) and hence $a'y > b$ or $< b$. Then $\mathcal{S} \subseteq$ **bd** $\mathcal{H}$.

If $a'x < b$, i.e., $x \in \mathcal{H} \setminus \mathcal{S}$, $\exists r < \frac{b - a'x}{\|a\|}$, s.t. $a'y < b$. Hence: **int** $\mathcal{H} = \mathcal{H} \setminus \mathcal{S}$ and **bd** $\mathcal{H} = \mathcal{S}$. ∎

24

2.2.2 Euclidean balls and ellipsoids

Definition 35 *A Euclidean ball in* $\mathbf{R}^n$ *is the set:*

$$
\begin{aligned}
B(x_c, r) &= \{ x = x_c + ru \mid \|u\|_2 \le 1 \} \\
&= \{ x \mid \|x - x_c\|_2 / r \le 1 \} \\
&= \{ x \mid (x - x_c)'(x - x_c)/r^2 \le 1 \}.
\end{aligned}
$$

Definition 36 *Ellipsoid in* $\mathbf{R}^n$ *is the set:*

$$
\begin{aligned}
\mathcal{E} &= \{ x = x_c + Au \mid \|u\|_2 \le 1, \ A \succ 0 \} \\
&= \{ x \mid \|A^{-1}(x - x_c)\|_2 \le 1, A \succ 0 \} \\
&= \{ x \mid (x - x_c)'(A^{-1})'A^{-1}(x - x_c) \le 1 \}
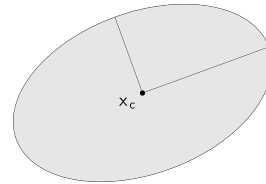\end{aligned}
$$

Spectral decomposition for $A = A'$.

$$
\begin{aligned}
Au &= (\lambda_1 v_1 v_1' + \lambda_2 v_2 v_2' + \cdots + \lambda_n v_n v_n')u \\
&= \lambda_1 v_1 (v_1' u) + \lambda_2 v_2 (v_2' u) + \cdots + \lambda_n v_n (v_n' u),
\end{aligned}
$$

which reduces to a Ball when $\lambda_i = r$.

Remark 2 *A does not have to be symmetric; put:*

$$
P^{-1} = (A^{-1})'A^{-1} = V\Sigma^{-1/2}\Sigma^{-1/2}V' \quad \textit{symmetric}
$$
$$
P^{1/2} u_2 = A u_1 \qquad\qquad\qquad \textit{is bijection}
$$
$$
\|u_2\|^2 = u_1' A' P^{-1/2} P^{-1/2} A u_1 = \|u_1\|^2
$$

Remark 3 (Contours of $\mathcal{N}(\mu, \Sigma)$**)** :

$$
f_X(x) = \frac{1}{((2\pi)^p \, |\Sigma|)^{1/2}} e^{-\frac{1}{2}(x-\mu)'\Sigma^{-1}(x-\mu)}
$$

Corollary 37 *An ellipsoid, hence a ball, is convex*

Proof. For $x_1, x_2 \in \mathcal{E}, 0 \le \theta \le 1$,

$$
\begin{aligned}
x_1 &= x_c + Au_1, \|u_1\| \le 1 \\
x_2 &= x_c + Au_2, \|u_2\| \le 1 \\
x &= \theta(x_c + Au_1) + (1-\theta)(x_c + Au_2) \\
&= x_c + A(\theta u_1 + (1-\theta)u_2) \\
\|u\| &= \|(\theta u_1 + (1-\theta)u_2)\| \\
&\le \theta\|u_1\| + (1-\theta)\|u_2\| \\
&\le \theta + (1-\theta) = 1.
\end{aligned}
$$

∎

2.2.3 Norm balls and norm cones

Introduction: norm, metric, and loss

Definition 38 (Norm) *Let $x, y \in \mathbf{R}^n$, $t \in \mathbf{R}$; a function $f : \mathbf{R}^n \mapsto \mathbf{R}_+$ with **dom** $f = \mathbf{R}^n$ is called a norm if*

1. $f(x) = 0 \to x = 0$ (definite)
2. $f(tx) = |t| f(x)$ (homogeneous)
3. $f(x + y) \le f(x) + f(y)$ (triangle inequality)
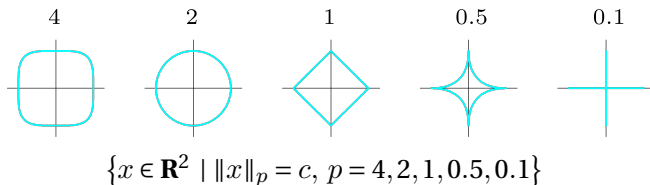*$f(0) = 0$ is implied from (2)   (positive definite)*

Definition 39 (L^p-norm ($\|\cdot\|_p$)) *is defined as*

$$\|x\|_p = \Big(\sum_{i=1}^{n} |x_i|^p\Big)^{1/p} = \big(|x_1|^p + \cdots + |x_2|^p\big)^{1/p}.$$

$\|\cdot\|_p$ **is a norm.** :

1. $\Big(\sum_{i=1}^{n} |x_i|^p\Big)^{1/p} = 0 \to \sum_{i=1}^{n} |x_i|^p = 0 \to x_i = 0.$

2. $\|tx\|_p = \Big(\sum_{i=1}^{n} |tx_i|^p\Big)^{1/p} = |t| \Big(\sum_{i=1}^{n} |x_i|^p\Big)^{1/p} = |t| \|x\|_p$

3. $\|x + y\|_p \le \|x\|_p + \|y\|_p$:
   (Minkowski's inequality proof (Kreyszig, 1978))

counter example for $p < 1$: $\|(0,1)\|_{1/2} + \|(1,0)\|_{1/2} = 1 + 1 = 2$, whereas $\|(1,1)\|_{1/2} = (1 + 1)^{1/(1/2)} = 4$. ∎

$$\{x \in \mathbf{R}^2 \mid \|x\|_p = c, \; p = 4, 2, 1, 0.5, 0.1\}$$

- L_1-norm, Manhatan dist., Taxicab, abs. value

$$\|x\|_1 = \Big(\sum_{i=1}^{n} |x_i|\Big).$$

- L_2-norm, Euclidean distance (most meaningful)

$$\|x\|_2 = \Big(\sum_{i=1}^{n} |x_i|^2\Big)^{1/2}.$$

- L_∞-norm

$$\|x\|_\infty = \lim_{p \to \infty} \Big(\sum_{i=1}^{n} |x_i|^p\Big)^{1/p} = \max_i |x_i|$$

Definition 40 (Metric) *Let $x, y, z \in S$, a function $\delta :$ $S \times S \mapsto \mathbf{R}_+$ is called a metric on S if:*

1. $\delta(x,y) = 0 \leftrightarrow x = y$ (positive definite)

2. $\delta(x,y) = \delta(y,x)$ (symmetric)

3. $\delta(x,y) \leq \delta(x,z) + \delta(z,y)$ (triangle inequality)

Lemma 41 *: $\delta(x,y) = f(x-y)$ is a metric ($\delta(x,0) = f(x)$):*

$$\delta(x,y) = f(x-y) = 0 \leftrightarrow x - y = 0 \leftrightarrow x = y$$

$$\delta(x,y) = f(x-y) = f(-1(y-x)) = f(y,x) = \delta(y,x)$$

$$\delta(x,y) = f(x-y) = f((x-z) + (z-y))$$

$$\leq f(x-z) + f(z-y) = \delta(x,z) + \delta(y,z)$$

Definition 42 (Loss) *Let $x \in S_1$ (called set of nature), and $y \in S_2$ (called set of actions); then a function $L :$ $S_1 \times S_2 \mapsto \mathbf{R}_+$ is called a loss incurred from assigning the action y based on the truth of nature x. For details on loss and utility theory see Berger (1993).*

Remark 4 *:*

- *Not any metric defines a norm; e.g., $\delta(x,y) = I_{x=y}$*
  $\delta(x,0) = f(x) = 1 \neq 10 = f(10x) = \delta(10x, 0) \quad \forall x \neq 0$.
- *Why? metric suites any set even categorical.*
- *Loss do not have to follow metric properties at all; e.g., $L(P,N) \neq L(N,P)$ in medical classification prediction.*

Norm balls and norm cones

Corollary 43 *A norm ball, for any norm $\|\cdot\|$, of radius r and center x_c is convex.*

Definition 44 *The norm cone associated with any norm $\|\cdot\|$ is the set*

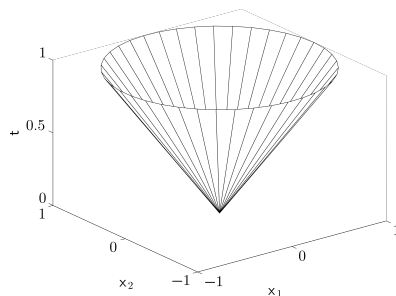$$C = \left\{(x,t) \in \mathbf{R}^{n+1} \mid \|x\| \le t, \ t > 0\right\}$$

Example 45 *The second-order cone is the norm cone for the Euclidean norm; i.e.,*

$$C = \left\{(x,t) \in \mathbf{R}^{n+1} \mid \|x\|_2 \le t\right\}$$
$$= \left\{(x,t) \mid x'x \le t, t > 0\right\}$$

Corollary 46 *The norm cone is convex.*

Proof.

$\blacksquare$

2.2.4 Polyhedra

Definition 47 *A polyhedron is defined as the solution set of a finite number of linear qualities and inequalities:*

$$\mathcal{P} = \left\{ x \mid a_j' x \le b_j,\ j = 1, \cdots, m, \quad c_j' x = d_j,\ j = 1, \cdots, p \right\}.$$
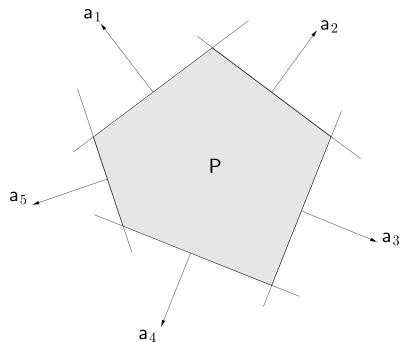
For short notation, we write

$$\mathcal{P} = \left\{ x \mid Ax \le b,\ Cx = d \right\}, \quad A = \begin{pmatrix} a_1' \\ \vdots \\ a_m' \end{pmatrix}, \quad C = \begin{pmatrix} c_1' \\ \vdots \\ c_m' \end{pmatrix}.$$

The polyhedron is called polytope if it is bounded.

Example 48 *The nonnegative orthant*

$$\mathbf{R}_+^n = \left\{ x \in \mathbf{R}^n \mid x_i \ge 0,\ i = 1, \cdots, n \right\} = \left\{ x \in \mathbf{R}^n \mid x \ge 0 \right\}$$
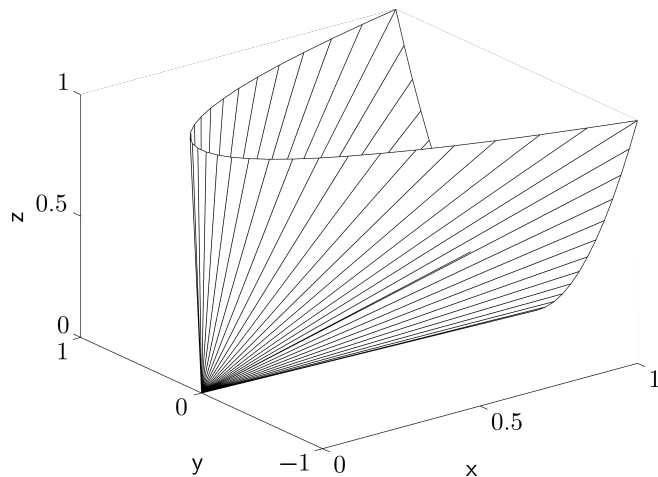

Corollary 49 *The polyhedron is convex*

Proof.

∎

2.2.5 The positive semidefinite cone

2.3 Operations that preserve convexity

2.4   Generalized inequalities

2.5 Separating and supporting hyperplanes

2.6   Dual cones and generalized inequalities

Part II

Applications

Part III

Algorithms

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