

Discrete Convex Optimization for Left-Right Action (nc-rank & det)

Part I

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Based on joint work with
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M. Hamada & H. Hirai: Computing the nc-rank via discrete convex optimization on CAT(0) spaces, *SIAM Journal on Applied Geometry and Algebra*, 2021.

H. Hirai & M. Ikeda: A cost-scaling algorithm for computing the degree of determinants, 2020, arXiv.

H. Hirai: Computing the degree of determinants via discrete convex optimization on Euclidean buildings, *SIAM Journal on Applied Geometry and Algebra*, 2019.

0. Edmonds problem, ncrank, left-right action

~ summarize basic facts

& explain how *submodularity* arises in this context

Edmonds Problem Edmonds 1967

Can we compute the rank of

$$A = A_1x_1 + A_2x_2 + \cdots + A_mx_m$$

in polynomial time ?

x_i : variables, A_i : $n \times n$ matrices over field \mathbb{K}

A : matrix over $\mathbb{K}[x_1, x_2, \dots, x_m] \subset \mathbb{K}(x_1, x_2, \dots, x_m)$

- RP, but P ? (for large field)
- Related to fundamental problems in diverse areas
~ combinatorial optimization, rigidity theory, TCS,...

Non-commutative Edmonds Problem

Ivanyos-Qiao-Subrahmanyam 2017

Can we compute the rank (*ncrank*) of

$$A = A_1x_1 + A_2x_2 + \cdots + A_mx_m$$

in polynomial time ?

x_i : noncommutative variables, A_i : matrices over field \mathbb{K}

A : matrix over free ring $\mathbb{K}\langle x_1, x_2, \dots, x_m \rangle$

\cap

free skew field $\mathbb{K}(\langle x_1, x_2, \dots, x_m \rangle)$

- Broaden the literature:
Noncommutative algebra, Invariant theory, ...

Connection to invariant theory

$$\mathbb{K} = \mathbb{C}$$

Left-right action: $SL_n \times SL_n \ni (S, T) \mapsto (SA_k T)_{k=1,2,\dots,m}$

- $(A_k)_{k=1,2,\dots,m}$ belongs to the null cone of this action
- $\mathbf{0} \in$ The closure of the orbit of $(A_k)_{k=1,2,\dots,m}$ of this action
- $0 =$ The infimum of norm of $(SA_k T)_{k=1,2,\dots,m}$ over (S, T)
- $\text{ncrank } \sum_k A_k x_k < n$

nc-rank in \mathbf{P}

- Garg-Gurvits-Oliveira-Wigderson 2019 : $\mathbb{K} = \mathbb{Q}, \mathbb{R}, \mathbb{C}$

Gurvits' operator scaling \approx alternating minimization for
a *geodesically convex* function

on symmetric space GL_n/U_n

$$\text{nc-nonsingularity} \Leftrightarrow \inf \left\{ \log \frac{\det \sum A_i X A_i^T}{\det X} : X \succ 0 \right\} > -\infty$$

→ *Noncommutative optimization* (Bürgisser et al.)

- Ivanyos-Qiao-Subrahmanyam 2018: \mathbb{K} arbitrary

Wong sequence --- vector-space analogue of augmenting path

Matrix completion by cyclic division algebra

The contribution of [Hamada-H. 21]

~ a different polytime algorithm to compute nc-rank

Features / techniques:

- Submodular function optimization on modular lattice
- Geodesically convex optimization on (non-manifold) CAT(0) space

For nc-rank over \mathbb{Q} (to avoid bit-complexity issue):

- reduction to nc-rank over $\text{GF}(p)$ by p -adic valuation
→ discrete convex optimization on Euclidean building for $GL_n(\mathbb{Q})$

Submodularity in ncrank

Thm (Fortin-Reutenauer 2004)

$$\text{ncrank } \sum_k A_k x_k = 2n - \text{Max. } r + s$$

$$\text{s.t. } PA_k Q = \begin{matrix} & \begin{matrix} * & & * \\ & * & & \\ \hline \mathbf{0} & & & * \\ & & & \end{matrix} & \\ r & & & & \\ & & s & & \end{matrix} \quad (\forall k)$$

$$P, Q \in GL_n(\mathbb{K})$$

$$\text{Min. } 2n - \dim X - \dim Y \quad \text{s.t. } A_k(X, Y) = \{0\} \quad (\forall k)$$

$$X, Y \subseteq \mathbb{K}^n \text{ vector subspaces}$$

$$\text{where } A_k(x, y) := x^T A_k y$$

$$Y \leftarrow \bigcap_k (A_k X)^\perp = \left(\sum_k A_k X \right)^\perp$$

$$\dim(\sum_k A_k X)^\perp = n - \dim \sum_k A_k X$$

Min. $n - \dim X + \dim \sum_k A_k X$ s.t. $X \subseteq \mathbb{K}^n$ vector subspaces

Obs. $X \mapsto f(X) := n - \dim X + \dim \sum_k A_k X$ is *submodular*:

$$f(X) + f(X') \geq f(X \cap X') + f(X + X')$$

$$\because \dim X + \dim X' = \dim X \cap X' + \dim X + X'$$

$$\dim \sum_k A_k X + \dim \sum_k A_k X'$$

$$= \dim(\sum_k A_k X) \cap (\sum_k A_k X') + \dim(\sum_k A_k X) + (\sum_k A_k X')$$

\cup

\parallel

$$\geq \dim \sum_k A_k (X \cap X') + \dim \sum_k A_k (X + X')$$

1. Background: Submodular function

- ~ explain basic facts of (classical) submodular functions
& some results of submodular functions on *lattices*

Submodular function

$$[n] := \{1, 2, \dots, n\}, \quad \bar{\mathbb{R}} := \mathbb{R} \cup \{\infty\}$$

Def: $f: 2^{[n]} \rightarrow \bar{\mathbb{R}}$ is submodular \Leftrightarrow

$$f(X) + f(Y) \geq f(X \cap Y) + f(X \cup Y) \quad (X, Y \subseteq [n])$$

Usually assume $f(\emptyset) = 0$

- Fundamental importance in combinatorial optimization from 60' (Edmonds)
- Generalize matroid (rank function) & greedy algorithm

$$\text{Max. } w^T x$$

$$\text{s.t. } x(X) \leq f(X) \quad (\forall X)$$

$$x(V) = f(V)$$

$$x \in \mathbb{R}^n$$

Linear optimization over “base polytope” of f

solved by: $w_1 \geq w_2 \geq \dots \geq w_n$

$$x_i := f([i]) - f([i - 1])$$

This generalizes matroid greedy algorithm

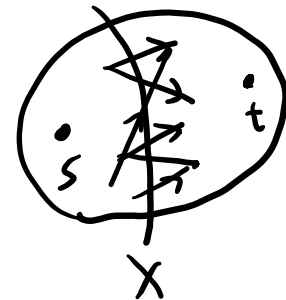
$$x(X) := \sum_{i \in X} x_i$$

Min-max theorems in combinatorial optimization
are often written by submodular functions

Max-flow min-cut theorem (Ford-Fulkerson)

$$\text{Max. flow-value of } f = \text{Min } c(\delta X) := \sum_{e \in \delta X} c(e)$$

$$\text{s.t. } s \in X \not\ni t$$

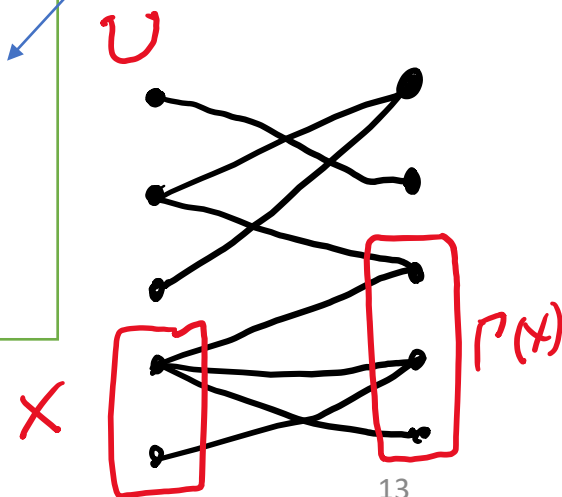


submodular

Bipartite matching (Hall, Konig-Egervary)

$$\text{Max. } |M| = \text{Min. } |U| - |X| + \Gamma(X)$$

$$\text{s.t. } M:\text{matching} \quad \text{s.t. } X \subseteq U$$



Submodular Function Minimization (SFM)

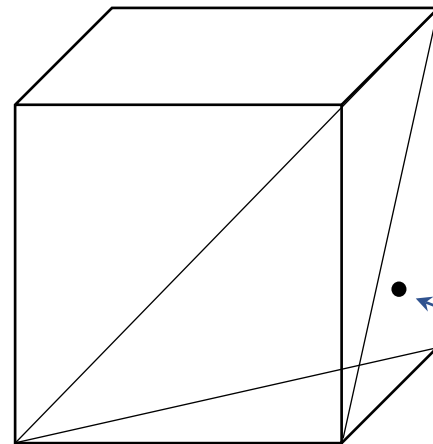
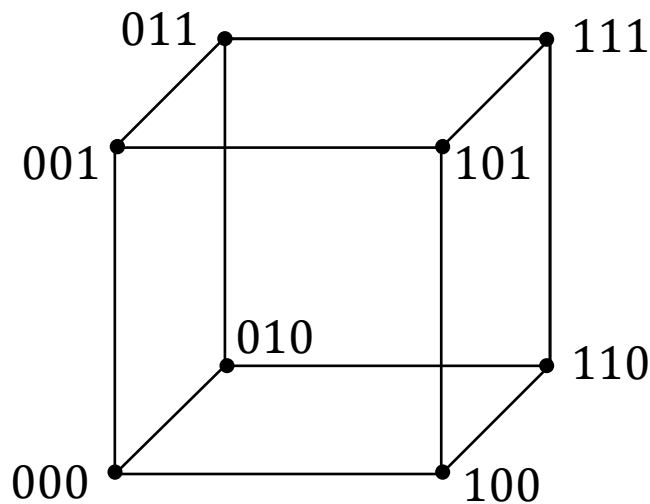
$$\text{Min. } f(X) \text{ s.t. } X \subseteq [n]$$

$$f: 2^{[n]} \rightarrow \bar{\mathbb{R}}: f(X) + f(Y) \geq f(X \cap Y) + f(X \cup Y)$$

$$f: \{0,1\}^n \rightarrow \bar{\mathbb{R}}: f(x) + f(y) \geq f(\min(x,y)) + f(\max(x,y))$$

$$\bar{f}: [0,1]^n \rightarrow \bar{\mathbb{R}} \text{ Lovász extension, convex}$$

$$X \leftrightarrow \mathbf{1}_X := \sum_{i \in X} e_i$$



$$\bar{f}(x) = \lambda_0 f(000) + \lambda_1 f(100) + \lambda_2 f(110) + \lambda_3 f(111)$$

$$x = \lambda_0(000) + \lambda_1(100) + \lambda_2(110) + \lambda_3(111)$$

Min f over $\{0,1\}^n$

\equiv

Min \bar{f} over $[0,1]^n$

Polynomial time algorithm

\Leftarrow

Ellipsoid method

Subgradient of \bar{f}

\uparrow

greedy algorithm

Lovász extension ~ submodular function and convexity

$$f: \{0,1\}^n \rightarrow \overline{\mathbb{R}}$$

Def. Lovász extension $\bar{f}: [0,1]^n \rightarrow \overline{\mathbb{R}}$

$$\bar{f}(x) := \sum_i \lambda_i f(\mathbf{1}_{X_i}) \quad (x \in [0,1]^n)$$

$$\text{where } x = \sum_i \lambda_i \mathbf{1}_{X_i}$$

$$X_1 \subset X_2 \subset \dots \subset X_n = [n]$$

$$(0.8 \ 0.2 \ 0.5 \ 0.3) = 0.2 (0100) + 0.1 (0101) + 0.2 (0111) + 0.3 (1111)$$

$$\bar{f}(0.8 \ 0.2 \ 0.5 \ 0.3) = 0.2f(0100) + 0.1f(0101) + 0.2f(0111) + 0.3f(1111)$$

Thm. [Lovász]

$$f: \{0,1\}^n \rightarrow \overline{\mathbb{R}} \text{ is submodular} \Leftrightarrow \bar{f}: [0,1]^n \rightarrow \overline{\mathbb{R}} \text{ is convex}$$

Variants of submodular functions extensible to convex functions

Bisubmodular function $f: \{-1,0,1\}^n \rightarrow \mathbb{R}$

$$f(x) + f(y) \geq f(x \sqcap y) + f(x \sqcup y)$$

\exists convex extension on $[-1,1]^n$, minimizable in polytime

L-convex function $f: \mathbb{Z}^n \rightarrow \mathbb{R}$

$$f(x) + f(y) \geq f(\min(x, y)) + f(\max(x, y))$$

$$f(x + \mathbf{1}) = f(x)$$

\exists convex extension on \mathbb{R}^n , successive descent by SFM

\rightarrow Discrete Convex Analysis (Murota 90'~)

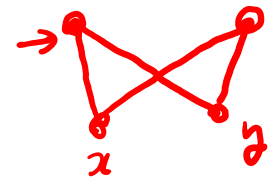
Submodular functions on lattices

Def. Lattice := partially ordered set (poset) (\mathcal{L}, \preceq) s.t.

join $x \vee y = \min \{z \in \mathcal{L} \mid x \preceq z \succeq y\}$ &
meet $x \wedge y = \max \{z \in \mathcal{L} \mid x \succeq z \preceq y\}$ exist

Ex. $(2^{[n]}, \subseteq)$, $X \wedge Y = X \cap Y$, $X \vee Y = X \cup Y$

Ex. $(\mathcal{S}(\mathbb{K}^n), \subseteq)$, $X \wedge Y = X \cap Y$, $X \vee Y = X + Y$



family of all vector subspaces of \mathbb{K}^n

Def. Submodular function on lattice \mathcal{L}

$$\Leftrightarrow f: \mathcal{L} \rightarrow \overline{\mathbb{R}}, f(x) + f(y) \geq f(x \wedge y) + f(x \vee y)$$

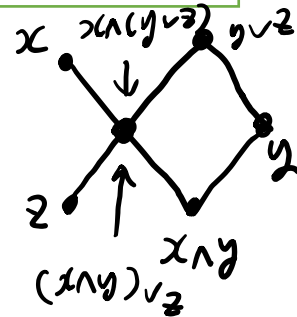
In this view, the original submodular function $f: 2^{[n]} \rightarrow \overline{\mathbb{R}}$
is submodular function on Boolean / distributive lattice

Submodular functions on modular lattices

Modular lattice := lattice \mathcal{L} s.t. $x \succcurlyeq z \Rightarrow (x \wedge y) \vee z = x \wedge (y \vee z)$

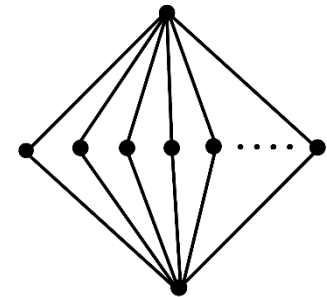
Ex. $\mathcal{S}(\mathbb{K}^n)$ lattice of all vector subspaces of \mathbb{K}^n

ncrank $\sum_k A_k x_k = \text{Min. } n - \dim X + \dim \sum_k A_k X$
 s.t. $X \subseteq \mathbb{K}^n$ vector subspaces
 is SFM on modular lattice $\mathcal{S}(\mathbb{K}^n)$



Currently, little is known on tractability of SFM on modular lattices. So, ncrank is interesting from submodular function theory.

One positive result [Fujishige et al. 14]
 SFM on \mathcal{L}^n for finite rank-2 modular lattice \mathcal{L}
 is solvable in $\text{poly}(n, |\mathcal{L}|)$ - time



- For SFM on modular lattice, nice convex relaxation on \mathbb{R}^n , i.e., Lovász extension, is not known.
- Recent study [H. 18] showed SFM on modular lattice admits convex relaxation on a CAT(0)-space.
- [Hamada-H 21] applied this relaxation to SFM of ncrank.

2. Background: CAT(0) space / Hadamard space

- definition & examples of CAT(0) spaces
- CAT(0) complexes associated with lattices
- convex relaxation of SFM on modular lattice

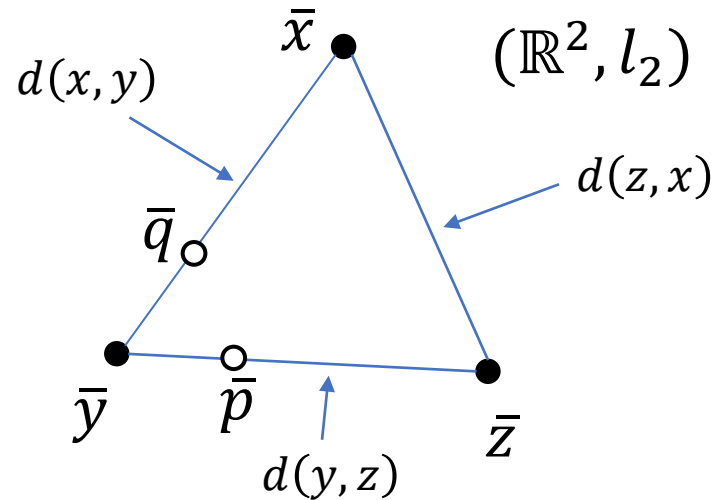
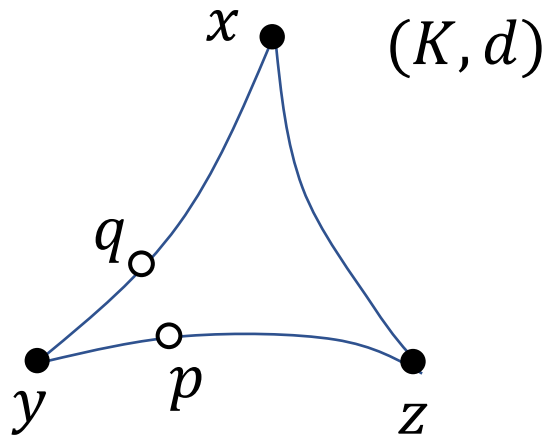
(K, d) : metric space

Geodesic := path $\gamma: [0,1] \rightarrow K$ with $d(\gamma(s), \gamma(t)) = |s - t|d(\gamma(0), \gamma(1))$

(K, d) : geodesic \Leftrightarrow any of two points can be joined by a geodesic

CAT(0) space (Gromov 1987)

A geodesic metric space (K, d) s.t. every triangle is “slimmer”



$$\text{CAT}(0)\text{-inequality: } d(p, q) \leq \|\bar{p} - \bar{q}\|_2$$

Def: Hadamard space := complete CAT(0) space

Textbook:

B.R. Bridson & A. Haefliger: *Metric Spaces of Non-Positive Curvature*, Springer, 1999.

Examples

\mathbb{R}^n , hyperbolic space,...

Symmetric space of nonpositive curvature / noncompact type

$$\mathbb{R}^k \times G/K \quad (G: \text{semisimple Lie group}, K: \text{maximal compact})$$

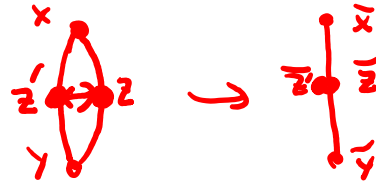
$$\text{Ex. } GL_n(\mathbb{C})/U_n = P_n$$

Hadamard manifold = simply-connected complete Riemannian manifold
of nonpositive sectional curvature

Tree, Euclidean building,...

$$\text{Ex. } GL_n(\mathbb{K}(t))/GL_n(\mathbb{K}(t)^-)$$

Thm. A CAT(0) space is uniquely geodesic, i.e.,
any of two points can be joined by a unique geodesic.



Def. $f: K \rightarrow \mathbb{R}$ is (geodesically) convex \Leftrightarrow

$$(1 - t)f(x) + tf(y) \geq f(\gamma(t)) \quad (x, y \in K, t \in [0,1])$$

γ : unique geodesic connecting x, y

*Convex optimization theory on CAT(0) space / Hadamard space
is now developing but still undeveloped.*

M. Bačák: *Convex Analysis and Optimization in Hadamard Spaces*, De Gruyter, 2014

Modeling & Algorithm & Optimization on CAT(0) spaces

- The space of phylogenetic trees (BHV-tree space) [Billera et al 2001]
- Configuration spaces of robots [Abram & Ghrist 2004]
- Polynomial-time geodesic computation
 - for BHV-tree space [Owen 2011]
 - for CAT(0) cubical complex [Hayashi 2021]
- Proximal point algorithm for convex optimization [Bačák 2014]
- Combinatorially-defined CAT(0) spaces:
 - median graph \rightarrow CAT(0) cubical complex [Chepoi 2000]
 - poset / lattice \rightarrow orthoscheme complex [Brady-McCammond 2012]

Orthoscheme Complex Brady-McCammond 2012

\mathcal{L} : graded poset of finite rank

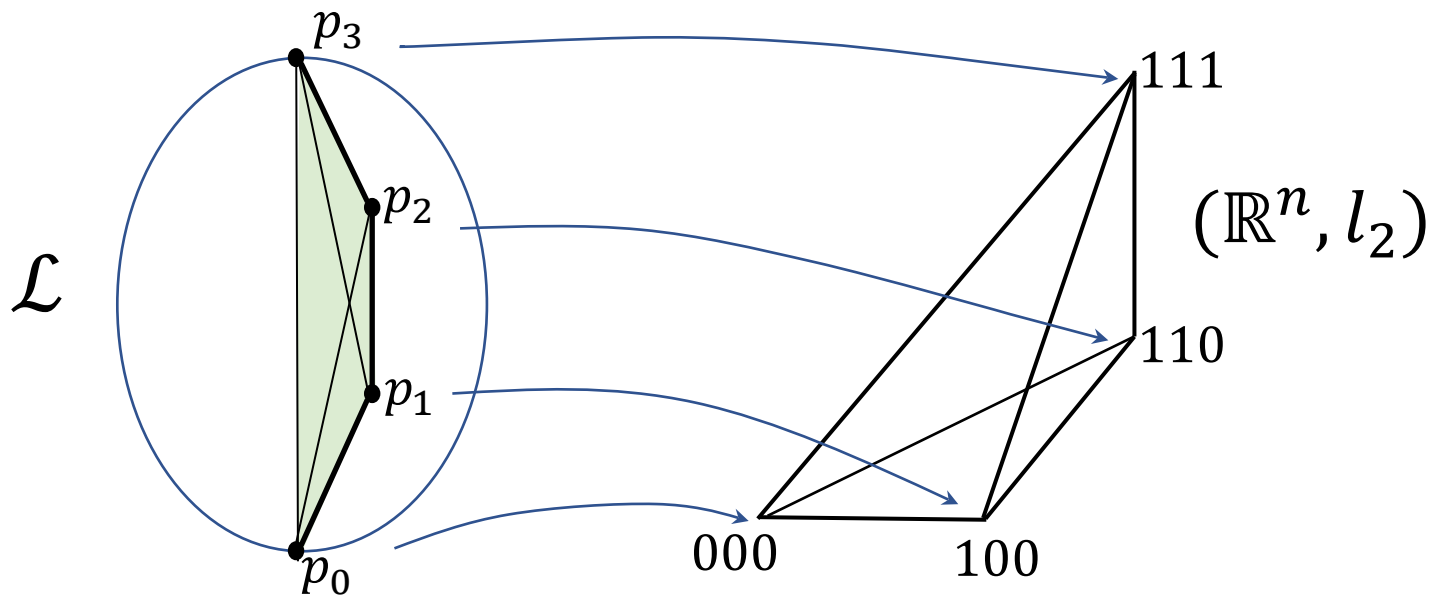
formal convex combination $\sum_i \mu_i = 1, \mu_i \geq 0$

$$K(\mathcal{L}) := \left\{ \sum_i \mu_i p_i \mid p_0 < p_1 < \dots < p_n, p_i \in \mathcal{L} \right\}$$

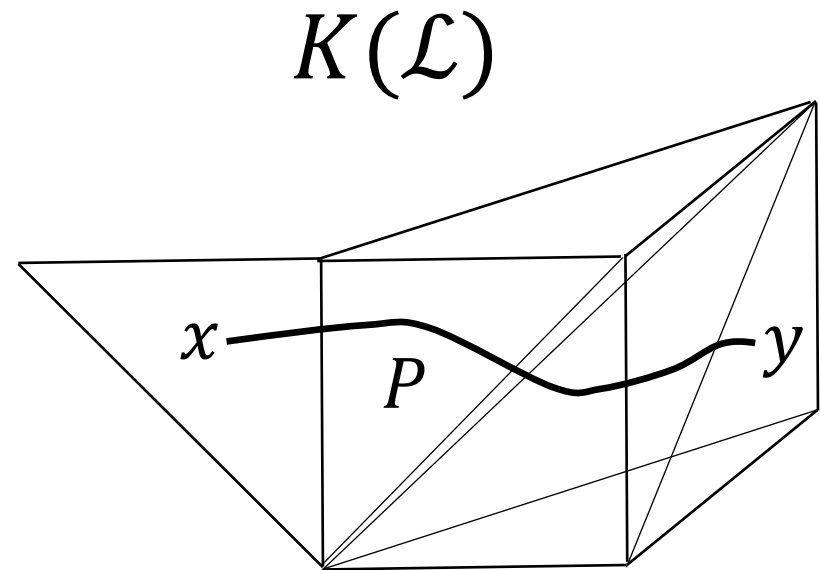
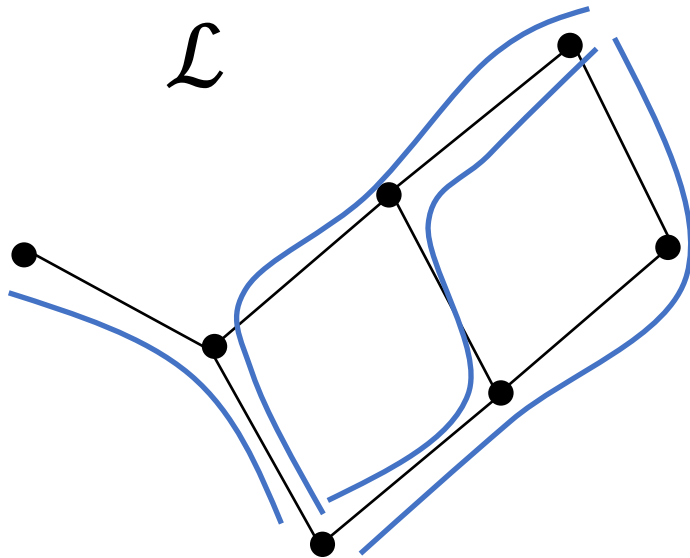
= the order complex
of \mathcal{L}

metrized by filling *orthoscheme* to each simplex:

$$\sum_i \mu_i p_i \mapsto \sum_i \mu_i (\overbrace{1, \dots, 1}^i, 0, \dots, 0)$$



Orthoscheme = $\text{conv} \{(0,0, \dots, 0), (1,0, \dots, 0), (1,1,0, \dots, 0), \dots, (1,1,1, \dots, 1)\}$ 25



The length $d(P)$ of a path $P: [0,1] \rightarrow K(\mathcal{L})$ is well-defined

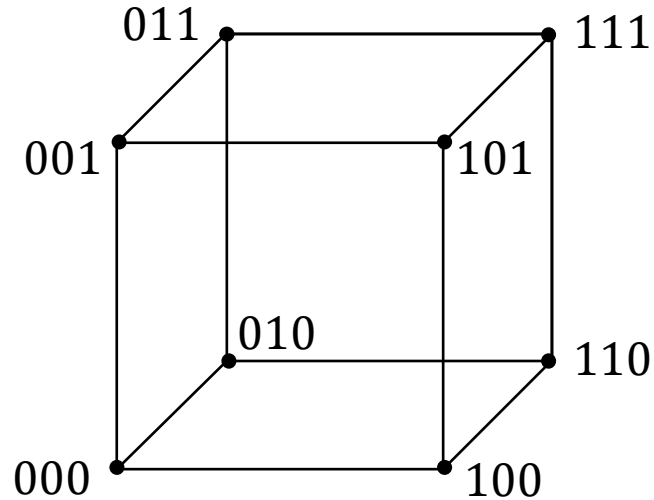
$$d(x, y) := \inf \{d(P) \mid P: (x, y)\text{-path}\}$$

$\rightarrow (K(\mathcal{L}), d)$ is a complete geodesic metric space

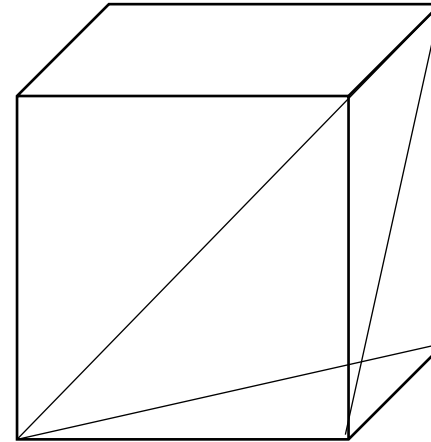
Question [Brady-McCammond 2012]:

Which is the class of posets \mathcal{L} having $CAT(0) K(\mathcal{L})$?

Boolean Lattice



$$\mathcal{L} = \{0,1\}^n = 2^{[n]}$$



$$K(\mathcal{L}) \simeq [0,1]^n$$

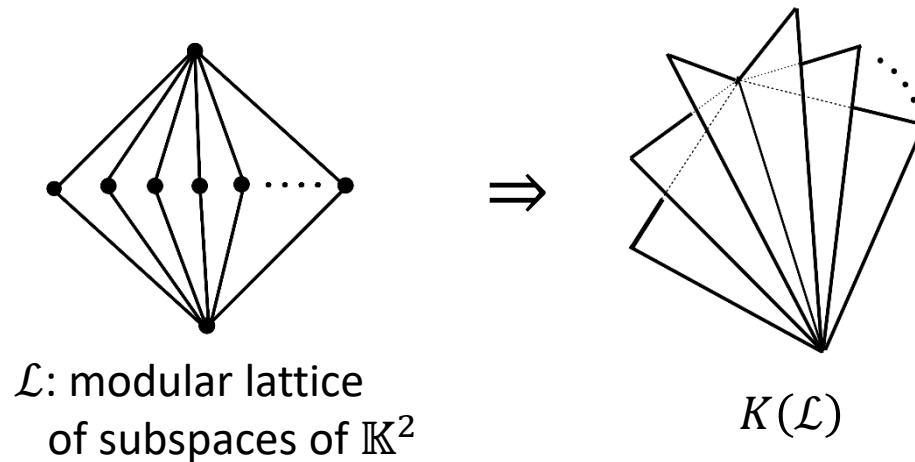
→ CAT(0)

\mathcal{L} : distributive lattice → $K(\mathcal{L})$: order polytope, CAT(0)

Thm [Haettel-Kielak-Schwer 2015, Chalopin-Chepoi-H-Osajda 2020]

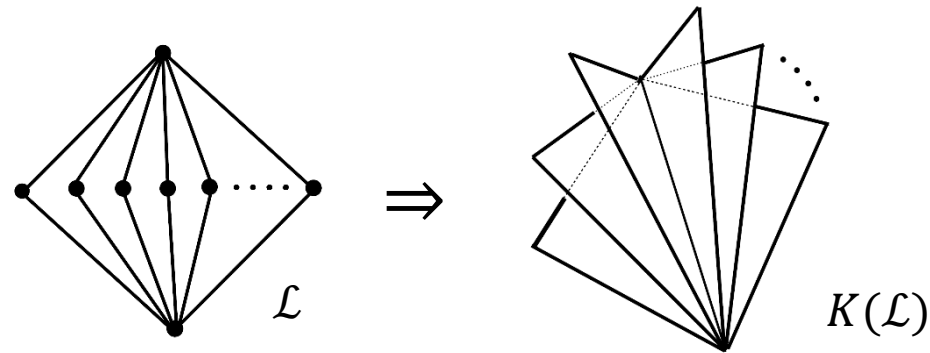
\mathcal{L} : modular lattice of finite rank

$\Rightarrow K(\mathcal{L})$ is CAT(0) (\rightarrow Hadamard space)



\rightarrow *We can consider convexity on $K(\mathcal{L})$*

Submodularity and convexity



$$f: \mathcal{L} \rightarrow \mathbb{R}$$

Def. Lovász extension $\bar{f}: K(\mathcal{L}) \rightarrow \mathbb{R}$

$$\bar{f}(x) := \sum_i \mu_i f(p_i) \quad \left(x = \sum_i \mu_i p_i ; p_0 < p_1 < \dots < p_n \right)$$

Thm [H.18] \mathcal{L} : modular lattice

$f: \mathcal{L} \rightarrow \mathbb{R}$ is submodular $\Leftrightarrow \bar{f}: K(\mathcal{L}) \rightarrow \mathbb{R}$ is convex

Classical Lovász extension: $f: \{0,1\}^n \rightarrow \mathbb{R}$ is submodular $\Leftrightarrow \bar{f}: [0,1]^n \rightarrow \mathbb{R}$ is convex

Lattice theory behind this

The product of lattices of vector subspaces

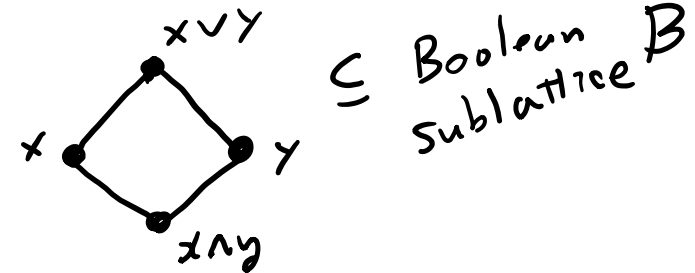
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Lem. (Birkhoff-Dedekind) \mathcal{L} : "complemented" modular lattice of rank n

- For two chains C, D , there is a Boolean sublattice $\mathcal{B} \supseteq C, D$.
- There is a rank & order-preserving retraction $\mathcal{L} \rightarrow \mathcal{B}$

- nonexpansive retraction $K(\mathcal{L}) \rightarrow K(\mathcal{B}) \simeq [0,1]^n$
- $K(\mathcal{B})$ is a convex subspace of $K(\mathcal{L})$

- $f: \mathcal{L} \rightarrow \mathbb{R}$ is submodular
- $\Leftrightarrow f: \mathcal{B} \rightarrow \mathbb{R}$ is submodular for $\forall \mathcal{B}$
- $\Leftrightarrow \bar{f}: K(\mathcal{B}) \rightarrow \mathbb{R}$ is convex for $\forall \mathcal{B}$
- $\Leftrightarrow \bar{f}: K(\mathcal{L}) \rightarrow \mathbb{R}$ is convex



Rem. The lemma is part of the axiom of *building*

Thm (Birkhoff, Tits) complemented modular lattice
 \equiv spherical building of type A

Nc-rank is convex optimization on CAT(0) space

$$\begin{aligned} \text{ncrank } \sum_k A_k x_k &= \text{Min. } n - \dim X + \dim \sum_k A_k X \\ \text{s.t. } X &\in \mathcal{S}(\mathbb{K}^n) \end{aligned}$$

⇓ Lovász extension

$$\begin{aligned} \text{ncrank } \sum_k A_k x_k &= \text{Min. } n - \overline{\dim}(x) + \overline{\dim} \sum_k A_k (x) \\ \text{s.t. } x &\in K(\mathcal{S}(\mathbb{K}^n)) \end{aligned}$$

→ Convex optimization on CAT(0) space (Hadamard space)

*But, convex optimization on CAT(0) space is undeveloped.
We have no powerful method such as ellipsoid method.*

3. Discrete convex optimization for nc-rank

- Splitting Proximal Point Algorithm (SPPA)
- Its convergence
- Application to ncrank
- Application to other problems

Terminology for convex optimization

(K, d) : Hadamard space, $f: K \rightarrow \mathbb{R}$

$$L\text{-Lipschitz: } |f(x) - f(y)| \leq L d(x, y)$$

ε -strongly convex for $\varepsilon > 0$:

$$(1 - t)f(x) + tf(y) \geq f(\gamma(t)) + \frac{\varepsilon}{2} t(1 - t)d(x, y)^2$$

Lem [see Bačák's book]

- \exists unique minimizer for a strongly convex function
 - $x \rightarrow d(x, z)^2$ is 2-strongly convex & $2\text{diam } K$ -Lipschitz
- \Downarrow

CAT(0)-inequality

Splitting Proximal Point Algorithm Bačák 2014

(K, d) : Hadamard space, f_1, f_2, \dots, f_N : convex functions on K

Goal: Minimize $f = \sum_{i=1}^N f_i$

$$\text{SPPA: } x_{k+1} \leftarrow \operatorname{argmin}_{z \in K} f_{k \bmod N}(z) + \frac{1}{2\lambda_k} d(z, x_k)^2$$

Thm (Ohta-Pálfi 2015)

$$f_i: L\text{-Lipschitz, } f: \varepsilon\text{-strongly convex, } \lambda_k := \frac{1}{\varepsilon(k+1)}$$

$$\Rightarrow d(x_{kN}, x^*)^2 \leq \operatorname{poly}(L, N, \varepsilon^{-1}) \frac{\log k}{k}$$

$$\Rightarrow f(x_{kN}) - \min f \leq \operatorname{poly}(L, N, \varepsilon^{-1}) \sqrt{\frac{\log k}{k}}$$

We do not know whether SPPA is applicable to

$$\text{ncrank } \sum_k A_k x_k = n + \text{Min. } - \overline{\dim}(x) + \overline{\dim} \sum_k A_k (x)$$

$$\text{s.t. } x \in K(\mathcal{S}(\mathbb{K}^n))$$

Instead, we consider Lovász extension of

$$\text{Min. } - \dim X - \dim Y \quad \text{s.t. } A_k(X, Y) = \{0\} \quad (\forall k)$$

$$X, Y \in \mathcal{S}(\mathbb{K}^n)$$

III

$$\text{Min. } -\dim X - \dim Y + (2n + 1) \sum_k \text{rank } A_k|_{X \times Y}$$

$$\text{s.t. } (X, Y) \in \mathcal{L} \times \mathcal{L}, \quad \mathcal{L} := \mathcal{S}(\mathbb{K}^n)$$

partial order reversed

Lem: The objective function is submodular in $\mathcal{L} \times \mathcal{L}^*$

$$f(X, Y) + f(X', Y') \geq f(X + X', Y \cap Y') + f(X \cap X', Y + Y')$$

$$\wedge = (+, \cap), \vee = (\cap, +)$$

$$\text{Min. } -\dim X - \dim Y + (2n + 1) \sum_i \text{rank } A_i|_{X \times Y}$$

$$\text{s. t. } (X, Y) \in \mathcal{L} \times \mathcal{L}^*$$

⇓ Lovász extension

$$\text{Min. } -\overline{\dim}(x) - \overline{\dim}(y) + (2n + 1) \sum_i \overline{\text{rank}} A_i(x, y)$$

$$\text{s. t. } (x, y) \in K(\mathcal{L} \times \mathcal{L}^*) = K(\mathcal{L}) \times K(\mathcal{L}^*)$$

$$+ \frac{1}{4n} (d(0, x)^2 + d(0, y)^2)$$

$$\text{Min. } -\overline{\dim}(x) - \overline{\dim}(y) + (2n + 1) \sum_i \overline{\text{rank } A_i}(x, y)$$

$$\text{s. t. } (x, y) \in K(\mathcal{L} \times \mathcal{L}^*) = K(\mathcal{L}) \times K(\mathcal{L}^*)$$

- Apply SPPA with: $\text{diam } K(\mathcal{L}) = \sqrt{n}$

$$f_0(x, y) := -\overline{\dim}(x) - \overline{\dim}(y) + \frac{1}{4n} (d(0, x)^2 + d(0, y)^2) \quad L = \text{poly}(n, m)$$

$$f_i(x, y) := (2n + 1) \overline{\text{rank } A_i}(x, y) \quad (i = 1, 2, \dots, m) \quad \varepsilon = \frac{1}{2n}$$

- After $k = \text{poly}(n, m)$ iterations, we have $\tilde{f}(x_k, y_k) - \min \tilde{f} < 1/2$

$$\rightarrow \bar{f}(x_k, y_k) - \min f < 1$$

$$f(x_k, y_k) - \min f \leq \tilde{f}(x_k, y_k) - \min \tilde{f} + \min \tilde{f} - \tilde{f}(x^*, y^*) + \frac{1}{4n} (d(0, x^*)^2 + d(0, y^*)^2) < 1$$

- By integrality of f , an optimum (X^*, Y^*) exists

$$\text{in the support of } (x_k, y_k) = \sum_i \lambda_i (X_i, Y_i)$$

Main technical contribution of [Hamada-H. 21]

Thm: SPPA is implementable in polytime, i.e.,

$$\text{Min. } f_i(x, y) + \frac{1}{2\lambda} (d(x, x_0)^2 + d(y, y_0)^2)$$

$$\text{s. t. } (x, y) \in K(\mathcal{L} \times \mathcal{L}^*) = K(\mathcal{L}) \times K(\mathcal{L}^*)$$

$$\text{where } f_i(x, y) = -\overline{\dim}(x) - \overline{\dim}(y) + C(d(0, x)^2 + d(0, y)^2)$$

$$\text{or } f_i(x, y) = C \overline{\text{rank } A_i}(x, y)$$

is solvable in polytime.

Proof: Lattice theoretic / building theoretic argument

- An optimum exists in an *apartment* = the subcomplex of a Boolean sublattice including the supports of $x_0, y_0, x_0^{\perp A_i}, y_0^{\perp A_i}$
- In the apartment $\approx [0, 1]^{2n}$, the problem is an easy convex quadratic program

Good / bad points

- Conceptually simple, described uniformly in an arbitrary field
- Applications to other problems ?
- Polytime, but very slow:
 - ← Less use of characteristics of the objective function
 - ← Undevelopment of optimization theory in CAT(0) spaces
- Bit complexity problem for $\mathbb{K} = \mathbb{Q}$:
 - ← Polynomial number of vector-space operations $X \cap X', X + X'$
can cause exponential bit explosion of bases

Application to related problems

(p, q) -scalability of $\{A_k\}$ by triangular matrices [Franks 2018]

$$\begin{aligned} \text{Max.} \quad & \sum_i (p_i - p_{i+1}) \dim E_i \cap X + \sum_i (q_i - q_{i+1}) \dim F_i \cap Y \\ & E_i, F_i: \text{standard flags} \\ \text{s. t.} \quad & A_k(X, Y) = \{0\} \quad (\forall k) \\ & X, Y: \text{vector subspaces} \end{aligned}$$

Brascamp-Lieb separation for BL-data (B, p) [Garg et al. 2018]

$$\begin{aligned} \text{Max.} \quad & \dim X + \sum_i p_i \dim Y_i \\ \text{s. t.} \quad & B_i(X, Y_i) = \{0\} \quad (\forall i) \\ & X, Y_i: \text{vector subspaces} \end{aligned}$$

The objectives are sum of supermodular functions.

SPPA approach is applicable, but it only gives pseudo-polynomial complexity

G : connected reductive algebraic group over \mathbb{C} ,
 $K \subseteq G$: maximal compact

$\pi: G \rightarrow GL(N, \mathbb{C})$: rational representation

Null-cone membership: $0 \notin \overline{\pi(G)v}$

Symmetric space
of nonpositive curvature

$$\begin{array}{c}
 \updownarrow \\
 -\infty < \overset{?}{\inf} \log \|\pi(g)v\| \text{ s.t. } gK \in G/K \\
 \text{geodesically convex}
 \end{array}$$

I found:

Unboundedness \leftarrow geodesically convex optimization on
 another CAT(0) space obtained from the boundary of G/K at infinity

Ex: Boundary of $GL_n/U_n \approx \{\sum_i \alpha_i X_i \mid X_1 \subset X_2 \subset \dots \subset X_n = \mathbb{C}^n, \alpha_i \geq 0\} \cong K(\mathcal{L})$

I am now writing a note explaining this fact.

Still, I don't know whether SPPA approach is applicable.

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