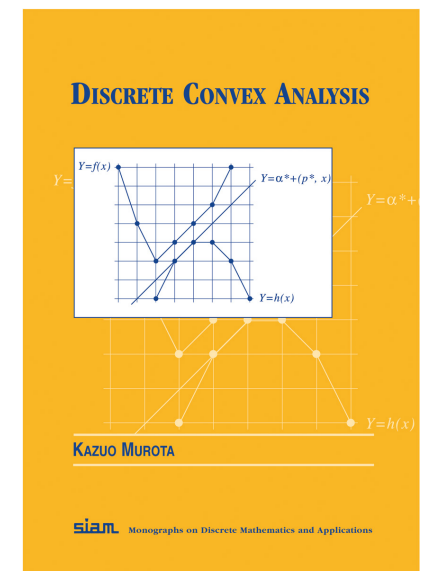
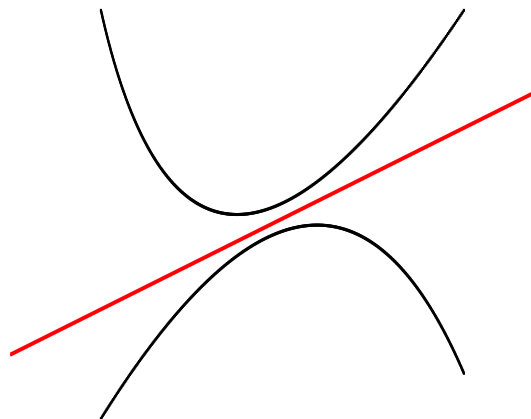


RIMS, August 30, 2012

Introduction to Discrete Convex Analysis

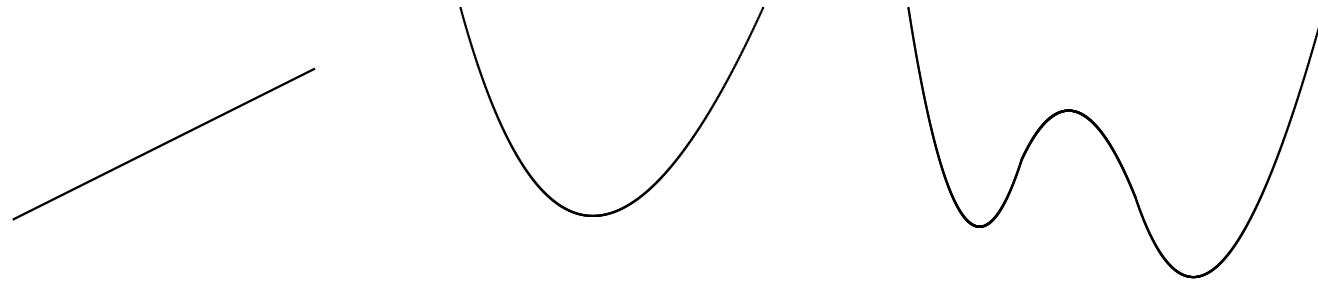
Kazuo Murota (Univ. Tokyo)



120830rims

Convexity Paradigm

NOT Linear vs Nonlinear



BUT Convex vs Nonconvex

Convexity in discrete optimization?

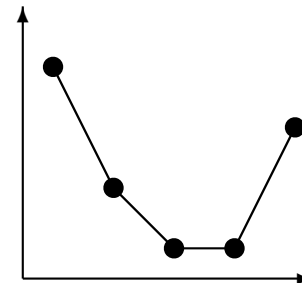
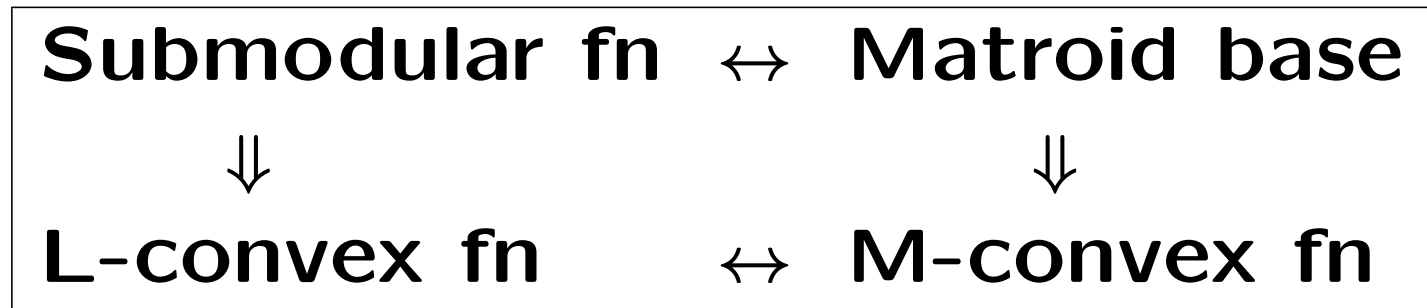
\implies Convexity + Combinatorics

$$f : \mathbb{Z}^n \rightarrow \mathbb{Z}, \quad \mathbb{Z}^n \rightarrow \mathbb{R}, \quad \mathbb{R}^n \rightarrow \mathbb{R}$$

Discrete Convex Analysis

Convexity Paradigm in Discrete Optimization

Matroid Theory + Convex Analysis



- Global optimality \iff local optimality
- Conjugacy: Legendre–Fenchel transform
- Duality (Fenchel min-max, discrete separation)
- Minimization algorithms
- Applications: OR, game, economics, matrices

Some History

1935	Matroid	Whitney
1965	Submodular function	Edmonds
1975	Engrg application of matroid	Iri, Recski
1983	Submodularity and convexity	
		Lovász, Frank, Fujishige
1990	Valuated matroid	Dress–Wenzel
	Integrally convex fn	Favati–Tardella
1996	Discrete convex analysis	Murota
2000	Submod. fn minimization algorithm	
		Iwata–Fleischer–Fujishige, Schrijver

Contents

B1. Submodularity and Convexity

B2. L-convex and M-convex Functions

B3. Conjugacy and Duality

A1. M-convex Minimization

A2. L-convex Minimization

C1. Electric Circuit

C2. L-/M-convexity in Continuous Variables

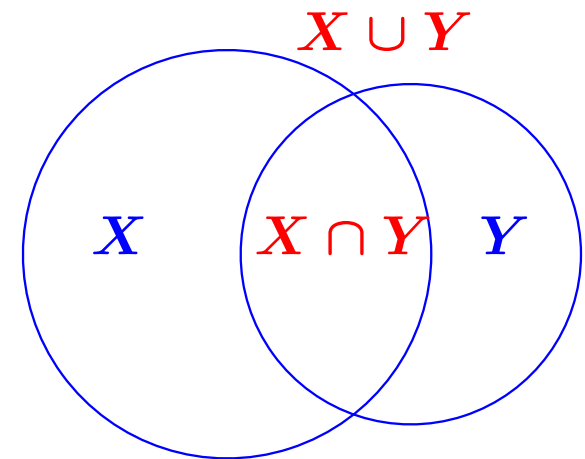
B1.

**Submodularity and Convexity
(1980's)**

Submodular Function

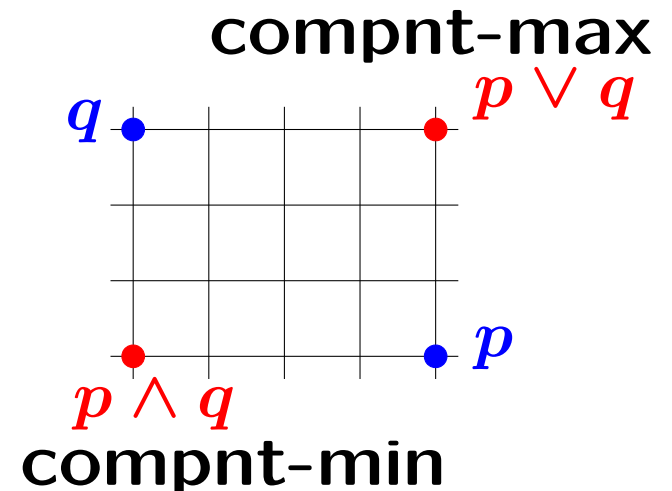
Set function ρ is submodular:

$$\rho(X) + \rho(Y) \geq \rho(X \cup Y) + \rho(X \cap Y)$$



$g : \mathbb{Z}^n \rightarrow \mathbb{R}$ is submodular:

$$g(p) + g(q) \geq g(p \vee q) + g(p \wedge q)$$



Submodularity & Convexity in 1980's

$$\rho(X) + \rho(Y) \geq \rho(X \cup Y) + \rho(X \cap Y)$$

- **min/max algorithms** (Grötschel–Lovász–Schrijver/
Jensen–Korte, Lovász)

min \Rightarrow polynomial, max \Rightarrow NP-hard

- **Convex extension** (Lovász)

set fn is submod \Leftrightarrow Lovász ext is convex

- **Duality theorems** (Edmonds, Frank, Fujishige)

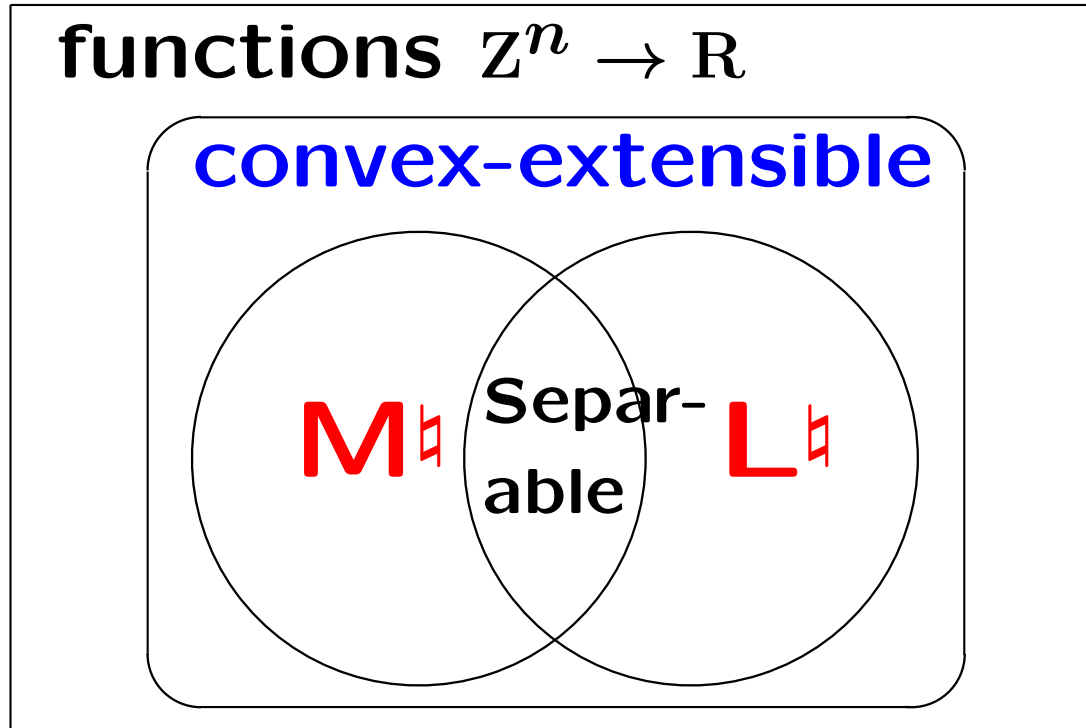
discrete separation, Fenchel min-max

**Duality for submodular set functions
= Convexity + Discreteness**

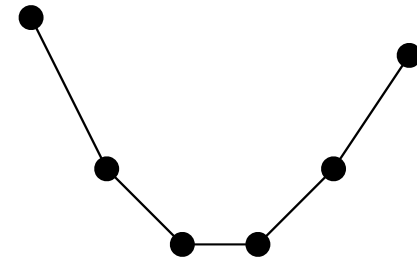
B2.

**L-convex and M-convex
Functions**

Discrete Convex Functions



$$f : \mathbb{Z}^n \rightarrow \mathbb{R}$$



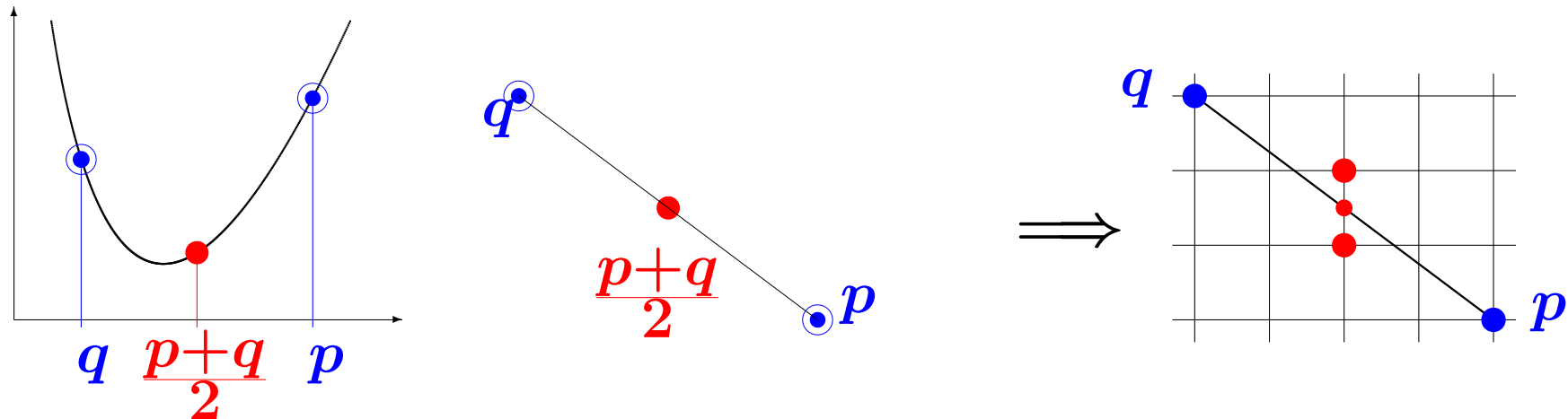
f is convex-extensible

$$\Leftrightarrow \exists \text{ convex } \bar{f}: \\ f(x) = \bar{f}(x)$$

Convex-extensibility does not help much

L -convexity from Mid-pt-convexity

(Murota 98, Fujishige–Murota 00)



Mid-point convex ($g : \mathbb{R}^n \rightarrow \mathbb{R}$):

$$g(p) + g(q) \geq 2g\left(\frac{p+q}{2}\right)$$

\Rightarrow **Discrete mid-point convex ($g : \mathbb{Z}^n \rightarrow \mathbb{R}$)**

$$g(p) + g(q) \geq g\left(\left\lceil \frac{p+q}{2} \right\rceil\right) + g\left(\left\lfloor \frac{p+q}{2} \right\rfloor\right)$$

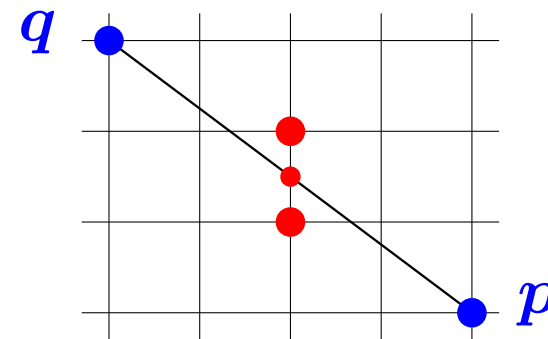
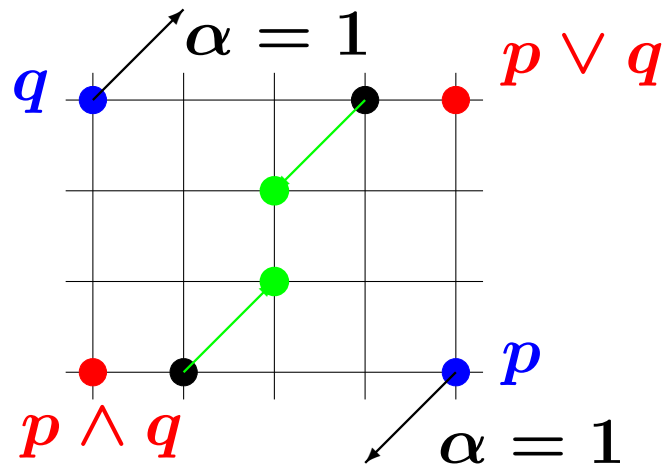
L -convex function

($L = \text{Lattice}$)

Translation Submodularity ($L_{\mathbb{H}}$)

$$g(p) + g(q) \geq g((p - \alpha 1) \vee q) + g(p \wedge (q + \alpha 1))$$

$$(\alpha \geq 0)$$



discrete mid-pt convex

$\tilde{g}(p_0, p) = g(p - p_0 1)$ is submodular in (p_0, p)

\Leftrightarrow translation submodular (Fujishige-Murota 00)

\Leftrightarrow discrete mid-pt convex (Fujishige-Murota 00)

\Leftrightarrow submod. integ. convex (Favati-Tardella 90)

L[♯]-convex Function: Examples

Quadratic: $g(p) = \sum_{i=1}^n \sum_{j=1}^n a_{ij} p_i p_j$ is L[♯]-convex

$$\Leftrightarrow a_{ij} \leq 0 \quad (i \neq j), \quad \sum_{j=1}^n a_{ij} \geq 0 \quad (\forall i)$$

Separable convex: For univariate convex ψ_i and ψ_{ij}

$$g(p) = \sum_{i=1}^n \psi_i(p_i) + \sum_{i \neq j} \psi_{ij}(p_i - p_j)$$

Range: $g(p) = \max\{p_1, p_2, \dots, p_n\} - \min\{p_1, p_2, \dots, p_n\}$

Submodular set function: $\rho : 2^V \rightarrow \bar{\mathbb{R}}$

$$\Leftrightarrow \rho(X) = g(\chi_X) \text{ for L}^{\sharp}\text{-convex } g$$

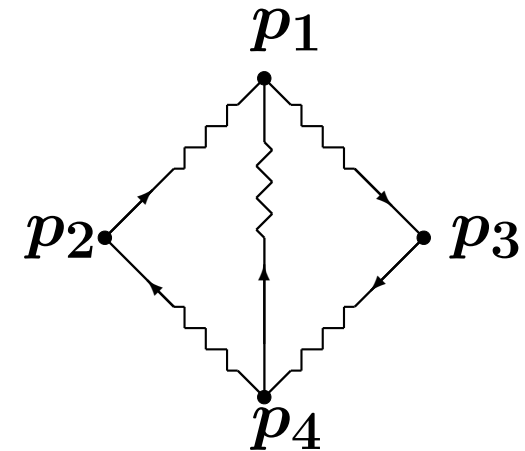
Multimodular: $h : \mathbb{Z}^n \rightarrow \bar{\mathbb{R}}$ is multimodular \Leftrightarrow

$h(p) = g(p_1, p_1 + p_2, \dots, p_1 + \dots + p_n)$ for L[♯]-convex g

Node-branch incidence

$$A = \begin{bmatrix} -1 & 1 & 0 & 0 & -1 \\ 1 & 0 & 0 & -1 & 0 \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 1 \end{bmatrix}$$

(graph structure)



Node admittance

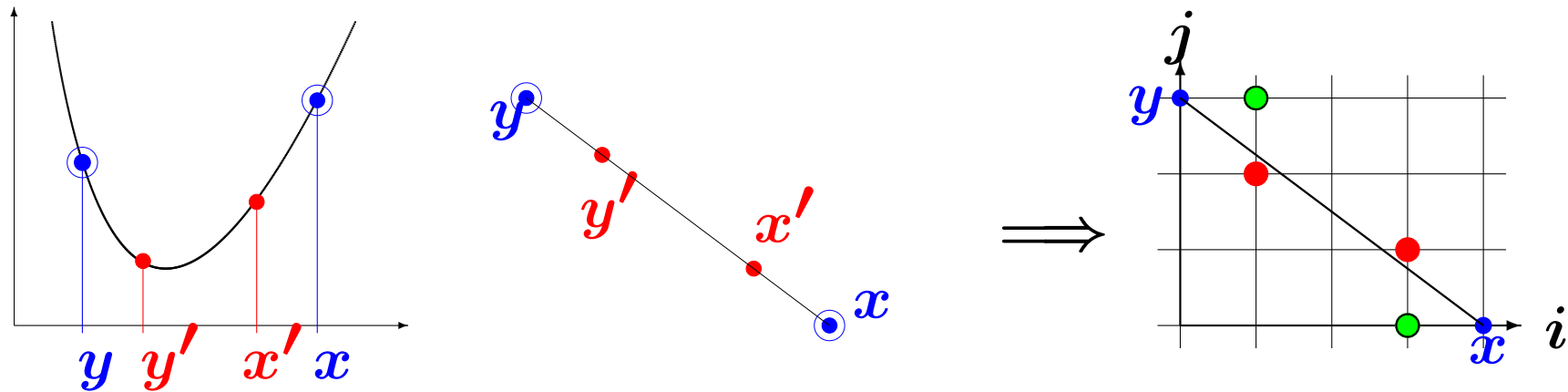
$$L = A \text{diag}(g_j) A^T =$$

$$\begin{bmatrix} g_1 + g_2 + g_5 & -g_1 & -g_2 & -g_5 \\ -g_1 & g_1 + g_4 & 0 & -g_4 \\ -g_2 & 0 & g_2 + g_3 & -g_3 \\ -g_5 & -g_4 & -g_3 & g_3 + g_4 + g_5 \end{bmatrix}$$

(off-diag ≤ 0 , row sum = 0)

M[‡]-convexity from Equi-dist-convexity

(Murota 96, Murota–Shioura 99)



Equi-distance convex ($f : \mathbb{R}^n \rightarrow \mathbb{R}$):

$$f(x) + f(y) \geq f(x - \alpha(x - y)) + f(y + \alpha(x - y))$$

\implies Exchange ($f : \mathbb{Z}^n \rightarrow \mathbb{R}$) $\forall x, y, \forall i : x_i > y_i$

$$f(x) + f(y) \geq \min \left[f(x - e_i) + f(y + e_i), \right.$$

$$\left. \min_{x_j < y_j} \{ f(x - e_i + e_j) + f(y + e_i - e_j) \} \right]$$

M[‡]-convex function

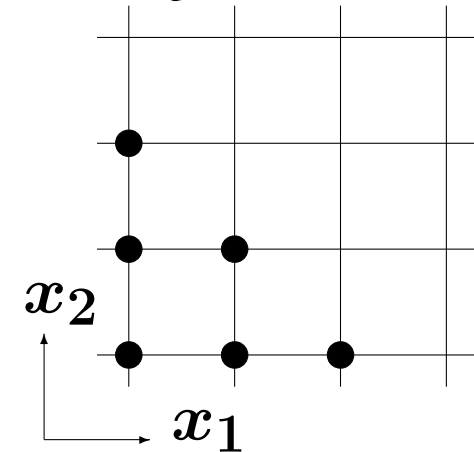
(M = Matroid)

Discrete Hessian for M^{\natural} -convexity

$$H_{ij}(x) = f(x + e_i + e_j) - f(x + e_i) - f(x + e_j) + f(x)$$

$$H_{11}(0, 0) = f(2, 0) - 2f(1, 0) + f(0, 0)$$

$$H_{12}(0, 0) = f(1, 1) - f(1, 0) - f(0, 1) + f(0, 0)$$



M^{\natural} -convexity: (Hirai-M. 04, M. 07)

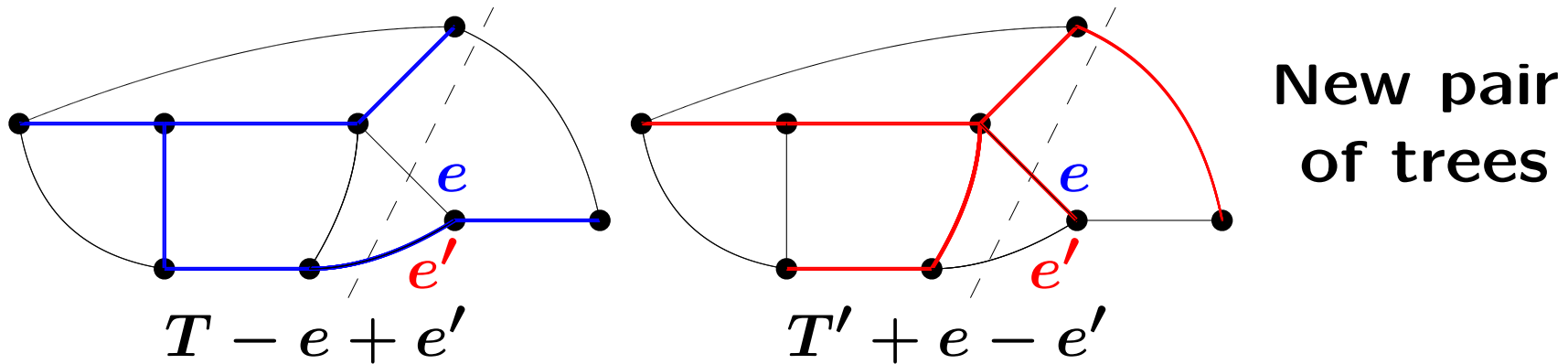
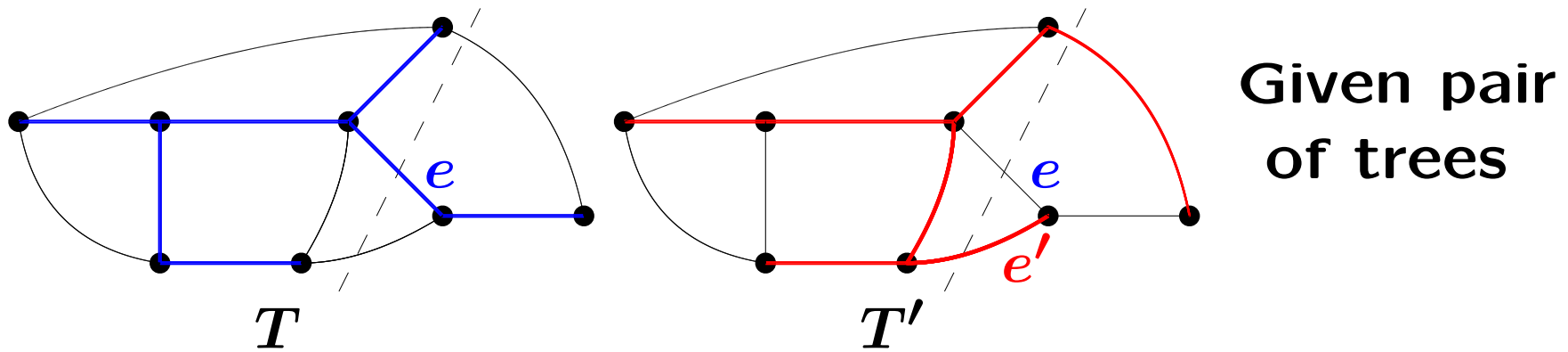
$f : \mathbb{Z}^n \rightarrow \mathbb{R}$ is M^{\natural} -convex

\iff For each $x \in \mathbb{Z}^n$:

- $H_{ij}(x) \geq \min(H_{ik}(x), H_{jk}(x))$ if $\{i, j\} \cap \{k\} = \emptyset$
- $H_{ij}(x) \geq 0$ for any (i, j)

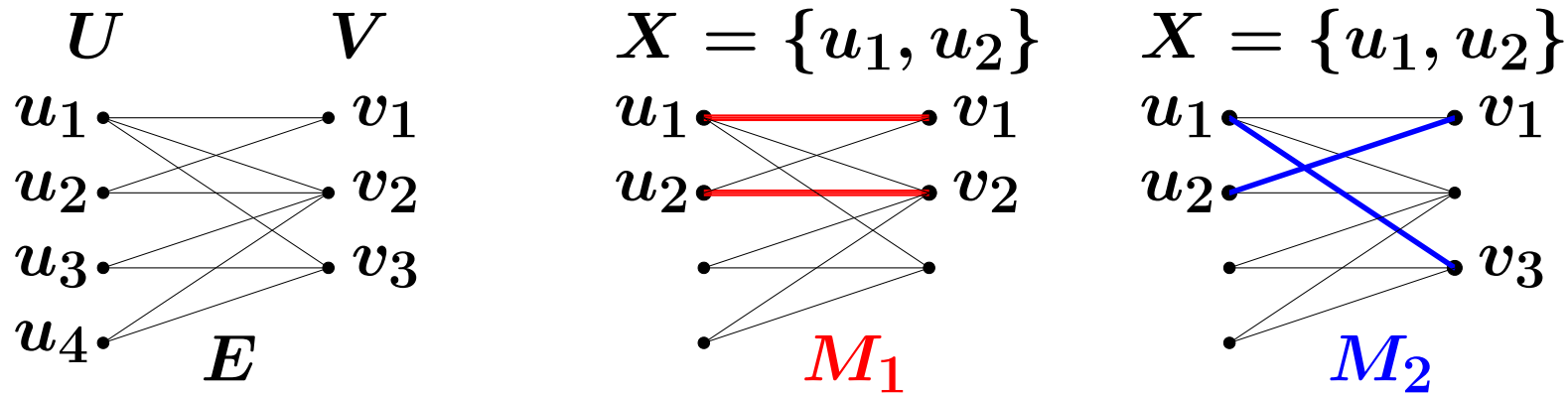
cf. “ultra metric” in finite metric space

Tree: Exchange Property



Exchange property: For any $T, T' \in \mathcal{T}$, $e \in T \setminus T'$ there exists $e' \in T' \setminus T$ s.t. $T - e + e' \in \mathcal{T}$, $T' + e - e' \in \mathcal{T}$

Matching / Assignment



Max weight for $X \subseteq U$ (w : given weight)

$$f(X) = \max \left\{ \sum_{e \in M} w(e) \mid M: \text{matching}, U \cap \partial M = X \right\}$$

Max-weight function f is M^{\sharp} -concave (Murota 96)

- Proof by augmenting path
- Extension to min-cost network flow

Gross Substitutes

$f : 2^V \rightarrow \mathbb{R}$ utility (reservation value) function

p price vector

$D(p) = \arg \max(f - p) = \{X \mid f(X) - p(X) \text{ is maximum}\}$
demand correspondence

Gross substitutes property: (Kelso–Crawford 82)

$$X \in D(p), \quad p \leq q$$

$$\Rightarrow \exists Y \in D(q) : \{i \in X \mid p_i = q_i\} \subseteq Y$$

Equiv. cond. for $D(p)$ (Gul–Stacchetti 99)

Equiv. cond. for f (Reijnierse–van Gallekom–Potters 02)

& equivalence to M^\natural -concavity (Fujishige–Yang 03)

\implies To be extended for $f : Z^n \rightarrow \mathbb{R}$

Gross Substitutes for f (not for $D(p)$)

$f : 2^V \rightarrow \mathbb{R}$ (set function)

f : **gross substitutes** \iff

(i) $f(S \cup \{i, j\}) + f(S) \leq f(S \cup \{i\}) + f(S \cup \{j\})$

(submodular)

(ii) $f(S \cup \{i, j\}) + f(S \cup \{k\}) \leq$

$\max[f(S \cup \{i, k\}) + f(S \cup \{j\}), f(S \cup \{j, k\}) + f(S \cup \{i\})]$

(Reijnierse–van Gallekom–Potters 02)

cf. Local exchange axiom of M^{\natural} -concave functions

Polynomial Matrix

(Dress-Wenzel 90)

$$A = \begin{array}{|c|c|c|c|} \hline s+1 & s & 1 & 0 \\ \hline 1 & 1 & 1 & 1 \\ \hline \end{array} \quad \omega(J) = \deg \det A[J]$$

$\mathcal{B} = \{J \mid J \text{ is a base of column vectors}\}$

Grassman-Plücker \Rightarrow Exchange (M-concave)

For any $J, J' \in \mathcal{B}$, $i \in J \setminus J'$, there exists $j \in J' \setminus J$
s.t. $J - i + j \in \mathcal{B}$, $J' + i - j \in \mathcal{B}$,

$$\omega(J) + \omega(J') \leq \omega(J - i + j) + \omega(J' + i - j)$$

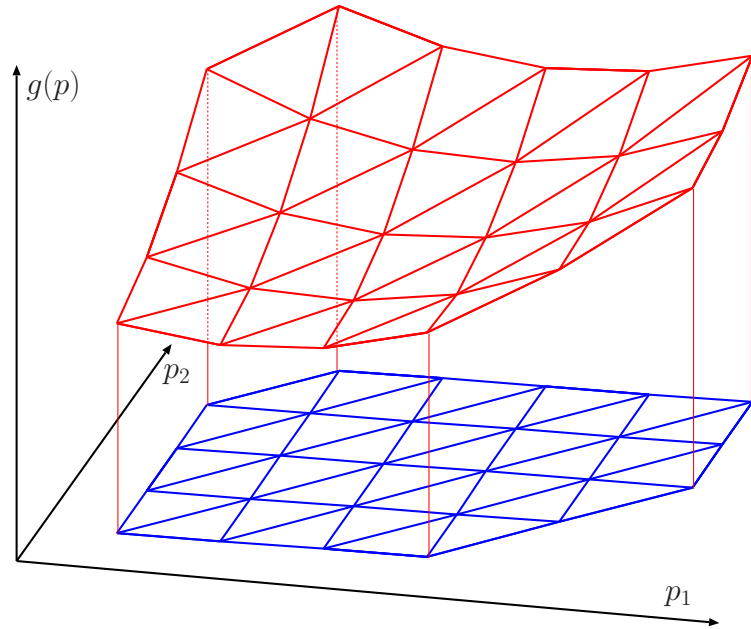
Ex. $J = \{1, 2\}$, $J' = \{3, 4\}$, $i = 1$

$$\det A[\{1, 2\}] = \det A[\{3, 4\}] = 1, \quad \omega(J) = \omega(J') = 0$$

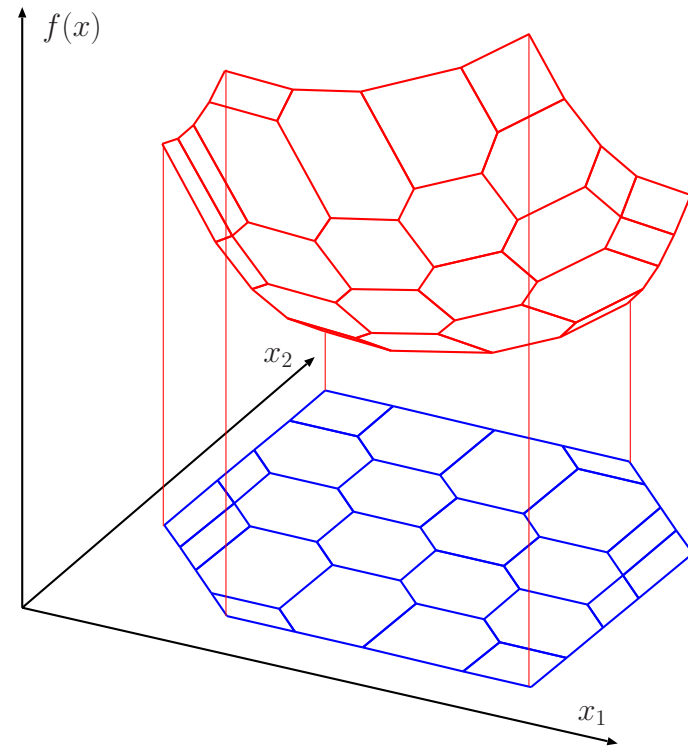
Can take $j = 3$: $J - i + j = \{3, 2\}$, $J' + i - j = \{1, 4\}$

$$\omega(J - i + j) = 1, \quad \omega(J' + i - j) = 1$$

Discrete Convex Functions



L_1 -convex fn



M_1 -convex fn

B3.

Conjugacy and Duality

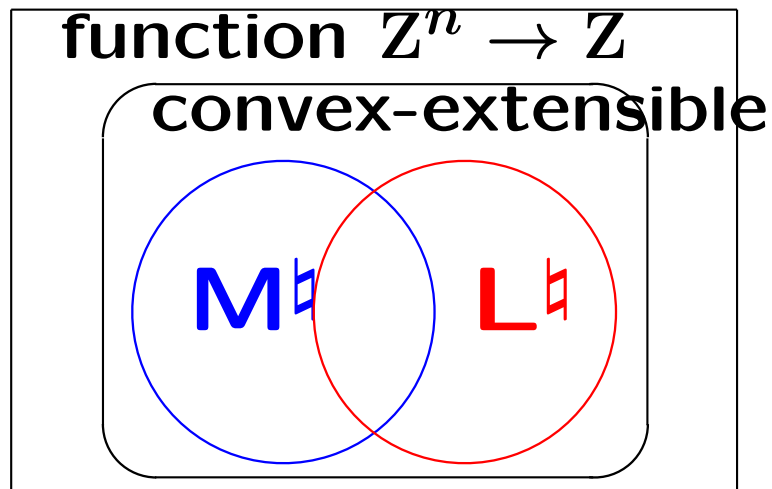
M-L Conjugacy Theorem

Integer-valued discrete fn $f : \mathbb{Z}^n \rightarrow \bar{\mathbb{Z}}$

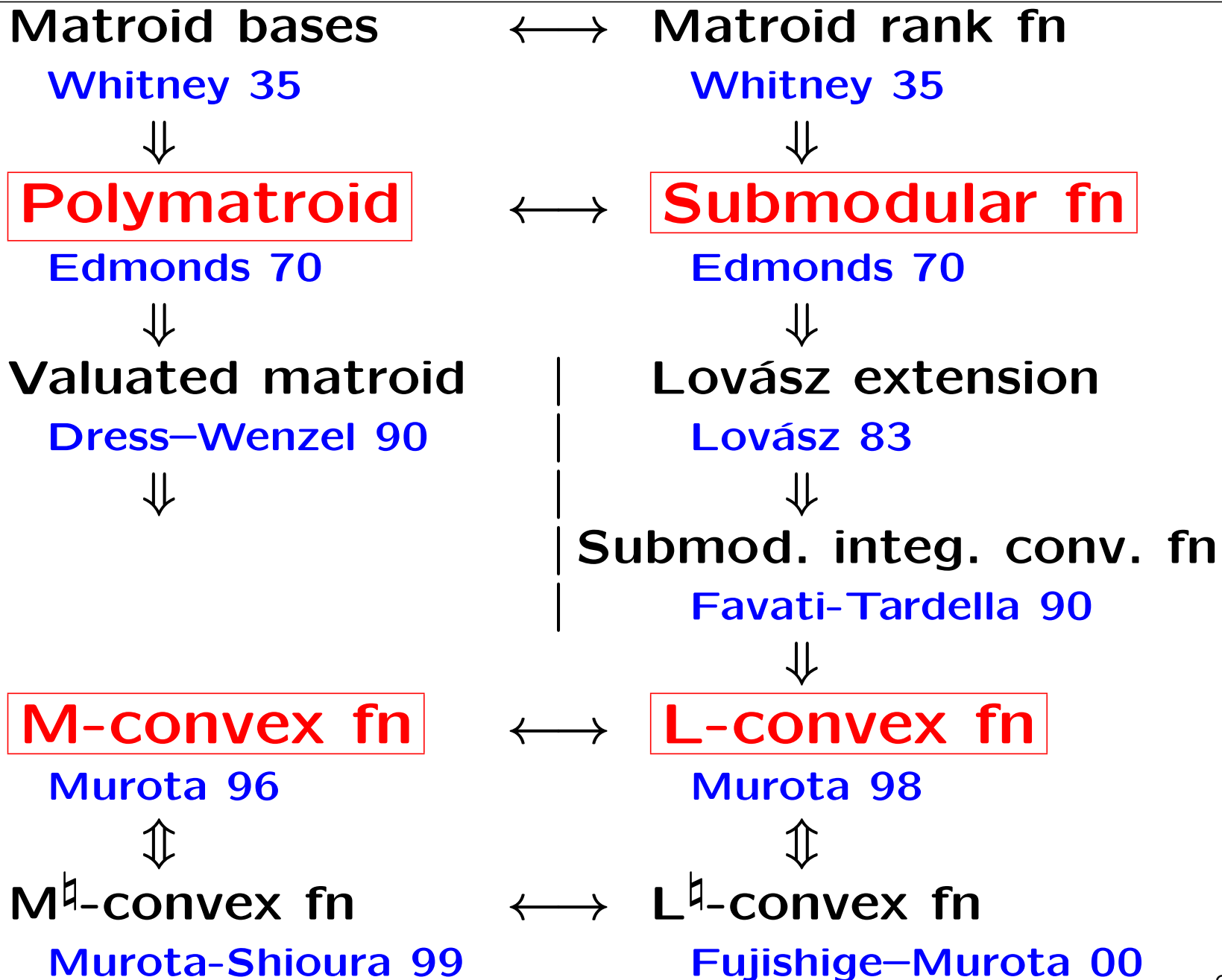
Legendre transform: $f^\bullet(p) = \sup_{x \in \mathbb{Z}^n} [\langle p, x \rangle - f(x)]$

M[♯]-convex and L[♯]-convex are conjugate

$$f \mapsto f^\bullet = g \mapsto g^\bullet = f \quad (\text{Murota 98})$$

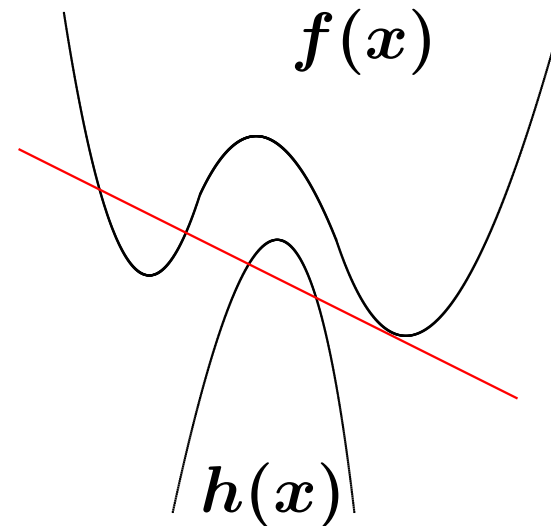
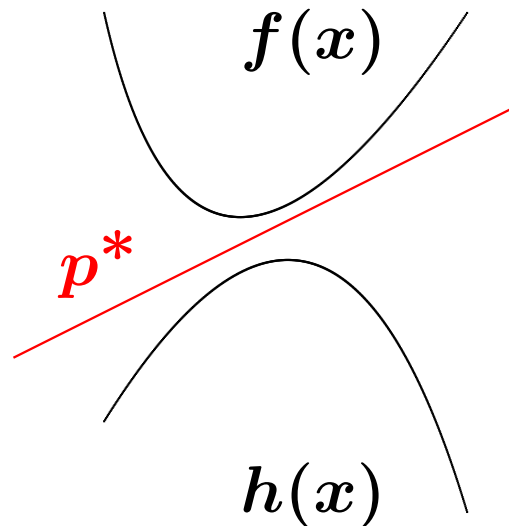


History of Discrete Conjugacy



Duality: Separation Theorem

main issue in convexity paradigm



$f : \mathbb{R}^n \rightarrow \mathbb{R}$ **convex**

$h : \mathbb{R}^n \rightarrow \mathbb{R}$ **concave**

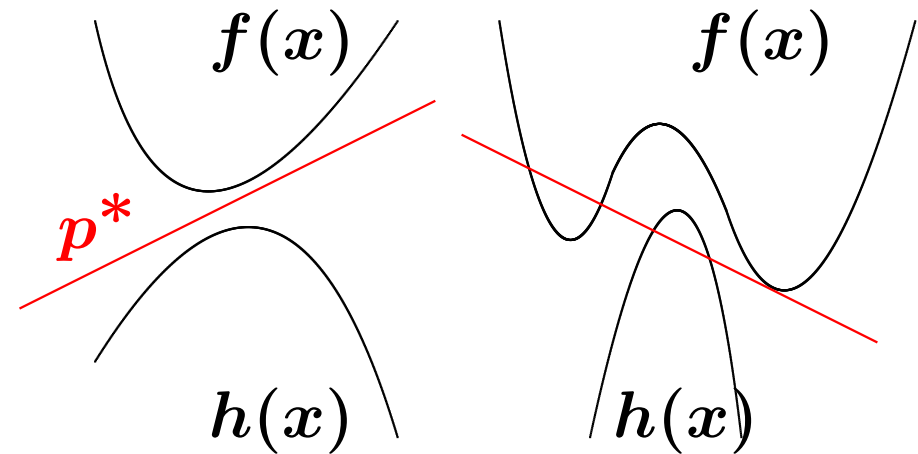
$$f(x) \geq h(x) \quad (\forall x) \Rightarrow \exists \alpha^* \in \mathbb{R}, \quad \exists p^* \in \mathbb{R}^n:$$

$$f(x) \geq \alpha^* + \langle p^*, x \rangle \geq h(x) \quad (x \in \mathbb{R}^n)$$

Discrete Separation Theorem

$f : \mathbb{Z}^n \rightarrow \mathbb{R}$ “convex”

$h : \mathbb{Z}^n \rightarrow \mathbb{R}$ “concave”



$$f(x) \geq h(x) \quad (\forall x \in \mathbb{Z}^n) \Rightarrow \exists \alpha^* \in \mathbb{R}, \exists p^* \in \mathbb{R}^n:$$

$$f(x) \geq \alpha^* + \langle p^*, x \rangle \geq h(x) \quad (x \in \mathbb{Z}^n)$$

$$f, h: \text{integer-valued} \Rightarrow \alpha^* \in \mathbb{Z}, p^* \in \mathbb{Z}^n$$

Frank's Discrete Separation

Equivalent to Edmonds' polymatroid intersection

$$\rho : 2^V \rightarrow \mathbb{R}: \text{ submodular} \quad (\rho(\emptyset) = 0)$$

$$\mu : 2^V \rightarrow \mathbb{R}: \text{ supermodular} \quad (\mu(\emptyset) = 0)$$

$$\rho(X) \geq \mu(X) \quad (\forall X \subseteq V) \Rightarrow \exists x^* \in \mathbb{R}^V:$$

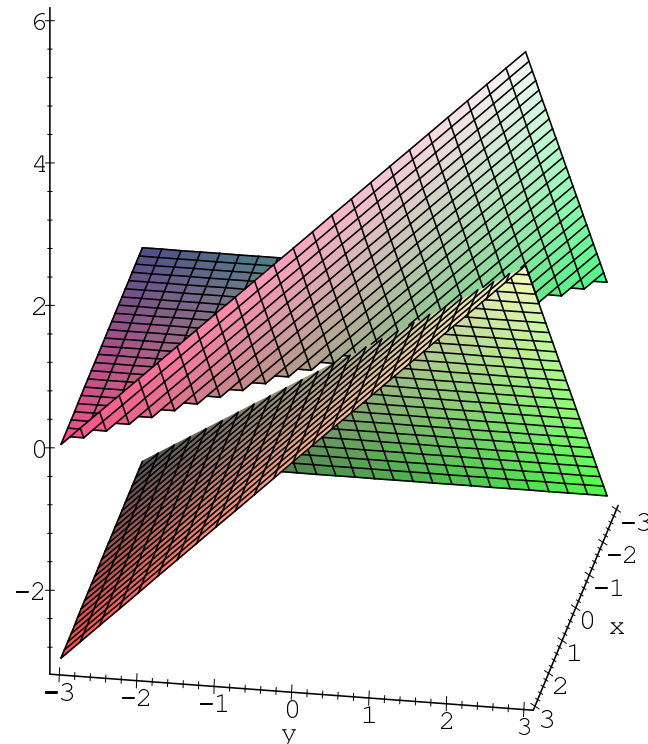
$$\rho(X) \geq x^*(X) \geq \mu(X) \quad (\forall X \subseteq V)$$

$$\rho, \mu: \text{ integer-valued} \Rightarrow x^* \in \mathbb{Z}^V$$

Difficulty of Discrete Separation (1)

$$f(x, y) = \max(0, x + y) \quad \text{convex}$$

$$h(x, y) = \min(x, y) \quad \text{concave}$$



**separable
but
nonintegral**

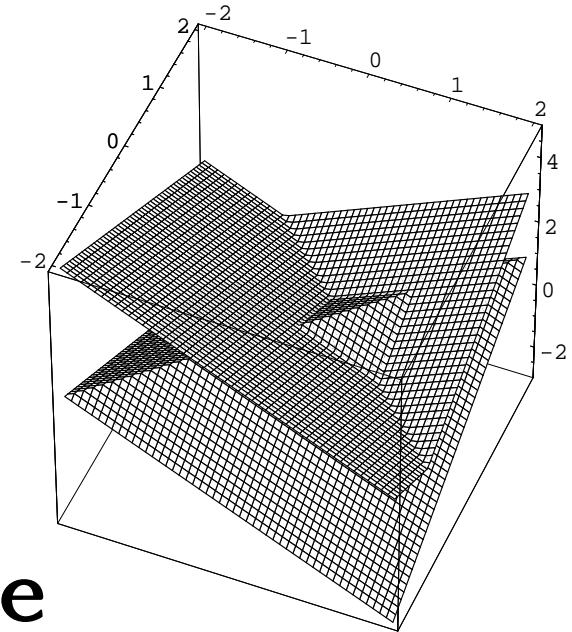
$p^* = (1/2, 1/2), \alpha^* = 0$ unique separating plane

Difficulty of Discrete Separation (2)

Even real-separation is nontrivial

$$f(x, y) = |x + y - 1| \quad \text{convex}$$

$$h(x, y) = 1 - |x - y| \quad \text{concave}$$



- $f(x, y) \geq h(x, y) \quad (\forall (x, y) \in \mathbb{Z}^2) \quad \text{true}$
- $f(x, y) \geq h(x, y) \quad (\forall (x, y) \in \mathbb{R}^2) \quad \text{not true}$

since $f = 0 < h = 1$ at $(x, y) = (1/2, 1/2)$

\implies **No** $\alpha^* \in \mathbb{R}, p^* \in \mathbb{R}^2$ satisfies

$$f(x) \geq \alpha^* + \langle p^*, x \rangle \geq h(x)$$

Discrete Separation Theorems

(Murota 96/98)

M-separation Thm: M^{\natural} -convex fn

▷ Weight splitting for weighted matroid intersection

(Iri-Tomizawa 76, Frank 81)

(linear fn, indicator fn = M^{\natural} -convex fn)

L-separation Thm: L^{\natural} -convex fn

▷ Discrete separation for submod. set function

(Frank 82)

(submod. set fn = L^{\natural} -convex fn on 0–1 vectors)

Min-Max Duality

Legendre–Fenchel transform

$$f^\bullet(p) = \sup\{\langle p, x \rangle - f(x) \mid x \in Z^n\}$$

$$h^\circ(p) = \inf\{\langle p, x \rangle - h(x) \mid x \in Z^n\}$$

Fenchel-type duality thm

$$f: M^\natural\text{-convex} \quad h: M^\natural\text{-concave} \quad (Z^n \rightarrow Z)$$

$$\inf_{x \in Z^n} \{f(x) - h(x)\} = \sup_{p \in Z^n} \{h^\circ(p) - f^\bullet(p)\}$$

self-conjugate $(f^\bullet: L^\natural\text{-conv} \quad h^\circ: L^\natural\text{-conv})$

\implies Edmonds' matroid intersection thm

Relation among Duality Thms

Discrete Convex

Combinatorial Opt.

M-separation

$$f(x) \geq \boxed{\text{Lin}} \geq h(x)$$



Fenchel duality

$$\inf\{f - h\} = \sup\{h^\circ - f^\bullet\}$$



L-separation

$$f^\bullet(p) \geq \boxed{\text{Lin}} \geq h^\circ(p)$$

Fenchel duality (Fujishige 84)
matroid intersect. (Edmonds 70)



⇒ **discrete separ. for submod**
 (Frank 82)

⇒ **valuated matroid intersect.**
 (M. 96)



weighted matroid intersect.

(Edmonds 79, Iri-Tomizawa 76,
 Frank 81)

A.

Minimization (General)

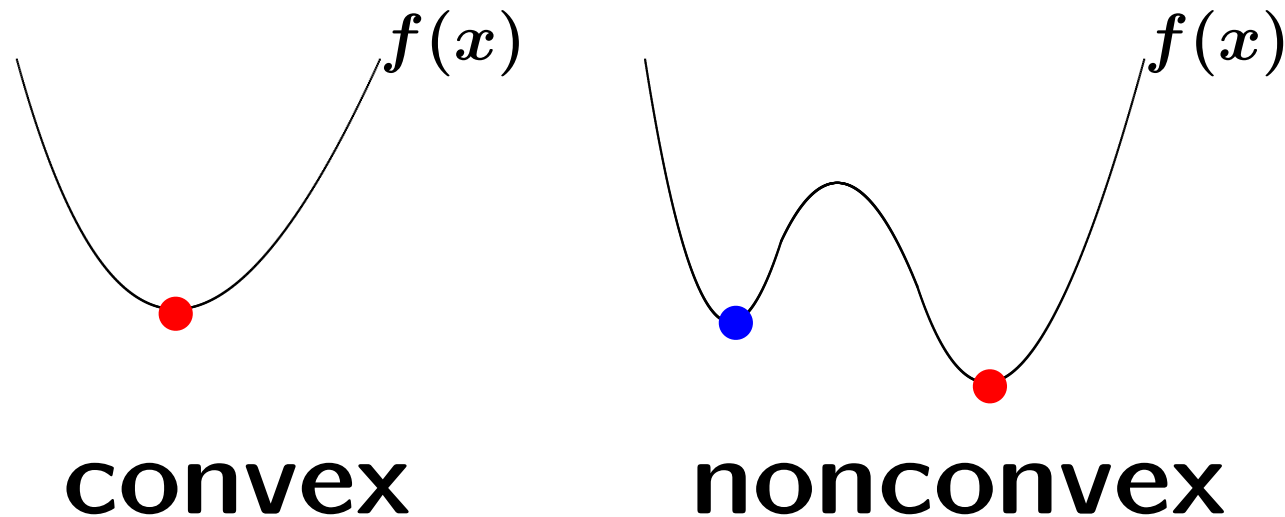
Optimality Criterion

Descent Method

Scaling and Proximity

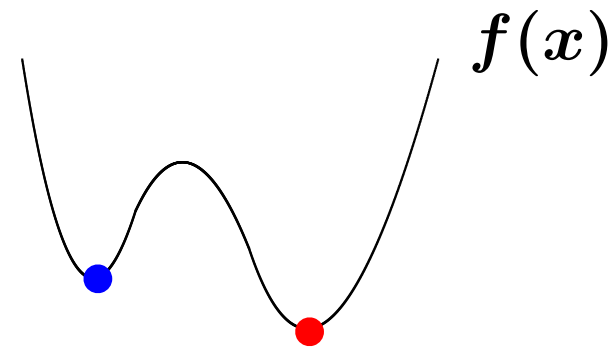
Optimality Criterion

Global opt vs **Local opt**



Local opt wrt neighborhood

Descent Method



S0: Initial sol x^*

S1: Minimize $f(x)$ in **nbhd** of x^* to obtain x^\bullet

S2: If $f(x^*) \leq f(x^\bullet)$, return x^* (**local opt**)

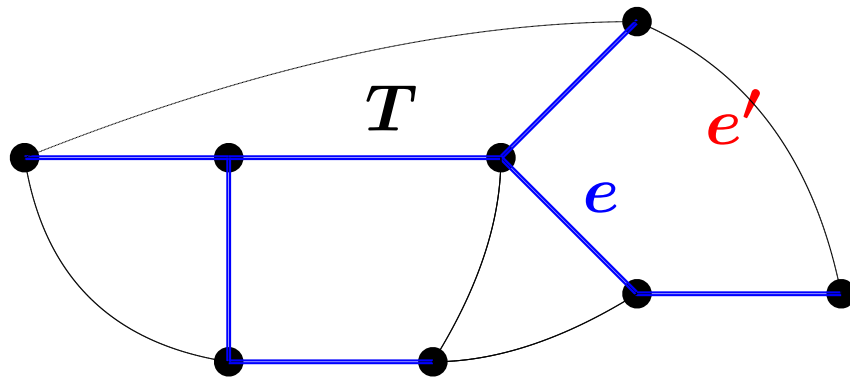
S3: Update $x^* = x^\bullet$; go to S1

.....What is **nbhd** ?

A1.

M-convex Minimization

Min Spanning Tree Problem



length $d : E \rightarrow \mathbb{R}$

total length of T

$$\tilde{d}(T) = \sum_{e \in T} d(e)$$

Thm

$$T: \text{MST} \iff \tilde{d}(T) \leq \tilde{d}(T - e + e')$$

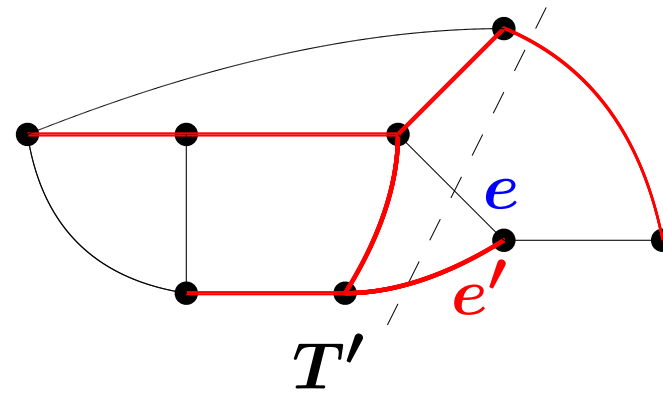
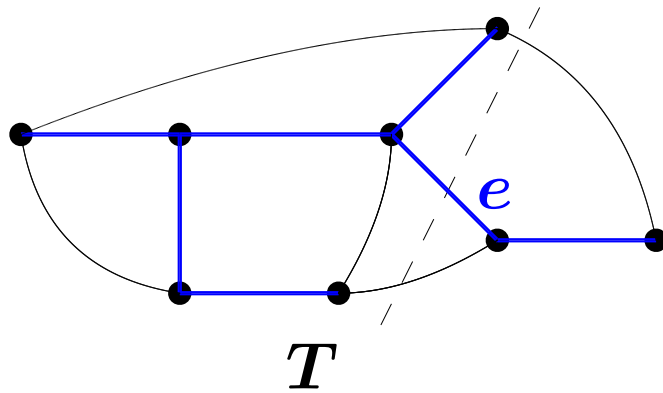
$$\iff d(e) \leq d(e') \quad \text{if } T - e + e' \text{ is tree}$$

Algorithm Kruskal's, Kalaba's

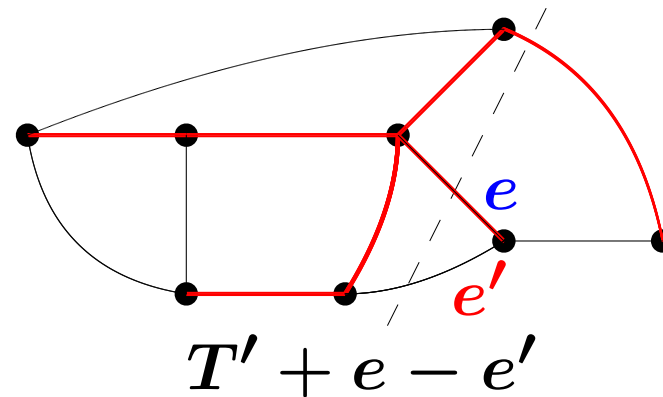
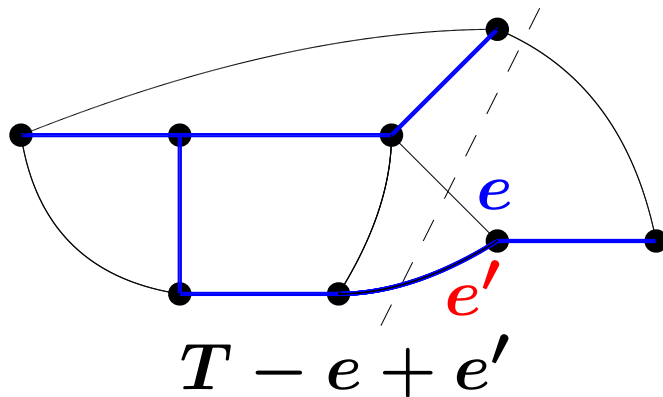
DCA view

- linear optimization on an M-convex set
- M-optimality: $f(x^*) \leq f(x^* - e_i + e_j)$

Tree: Exchange Property



Given pair
of trees



New pair
of trees

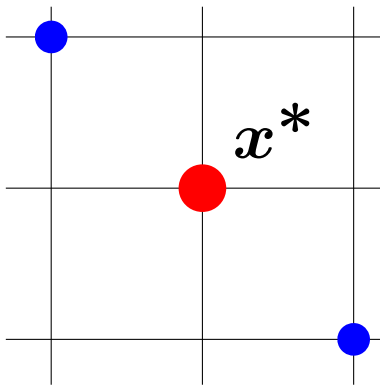
Exchange property: For any $T, T' \in \mathcal{T}$, $e \in T \setminus T'$
there exists $e' \in T' \setminus T$ s.t. $T - e + e' \in \mathcal{T}$, $T' + e - e' \in \mathcal{T}$

Local vs Global Opt (M-conv)

Thm : $f : \mathbb{Z}^n \rightarrow \mathbb{R}$ M-convex (Murota 96)

x^* : global opt

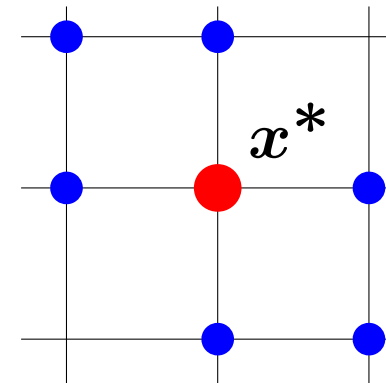
\iff local opt $f(x^*) \leq f(x^* - e_i + e_j) \quad (\forall i, j)$



Ex: $x^* + (0, 1, 0, 0, -1, 0, 0, 0)$

Can check with n^2 fn evals

For M ∇ -convex fn \Rightarrow



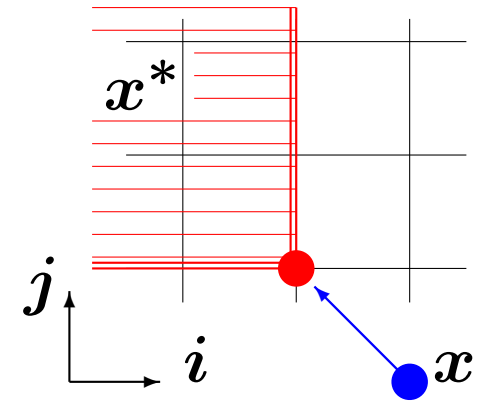
Steepest Descent for M-convex Fn

S0: Find a vector $x \in \text{dom} f$

S1: Find $i \neq j$ that **minimize $f(x - e_i + e_j)$**

S2: If $f(x) \leq f(x - e_i + e_j)$, stop
(x : minimizer)

S3: Set $x := x - e_i + e_j$
and go to S1



Minimizer Cut Thm

(Shioura 98)

\exists minimizer x^* with $x_i^* \leq x_i - 1$, $x_j^* \geq x_j + 1$

\Rightarrow Murota 03, Shioura 98, 03, Tamura 05

- Kalaba's for min spanning tree
- Dress–Wenzel's for valuated matroid

A2.

L-convex Minimization

Shortest Path Problem (one-to-all)

one vertex (s) to all vertices, length $\ell \geq 0$, integer

Dual LP

$$\begin{aligned} & \text{Maximize } \sum p(v) \\ & \text{subject to } p(v) - p(u) \leq \ell(u, v) \quad \forall (u, v) \\ & \qquad \qquad p(s) = 0 \end{aligned}$$

Algorithm

Dijkstra's

DCA view

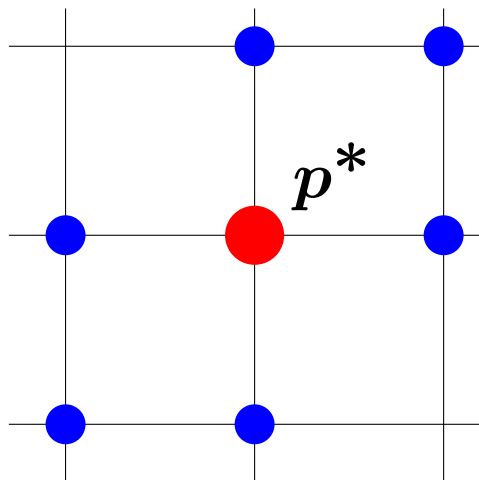
- linear optimization on an L^{\natural} -convex set (in polyhedral description)
- Dijkstra's algorithm (M.-Shioura 12)
= steepest ascent for L^{\natural} -concave maximization
with uniform linear objective $(1, 1, \dots, 1)$

Local vs Global Opt (L_{\square} -conv)

Thm : $g : \mathbb{Z}^n \rightarrow \mathbb{R}$ L_{\square} -convex (Murota 98,03)

p^* : global opt

\iff local opt $g(p^*) \leq g(p^* \pm q)$ ($\forall q \in \{0, 1\}^n$)



Ex: $p^* + (0, 1, 0, 1, 1, 1, 0, 0)$

$\iff \rho_{\pm}(X) = g(p^* \pm \chi_X) - g(p^*)$

takes min at $X = \emptyset$

Can check with n^5 (or less) fn evals
using submodular fn min algorithm
(Iwata-Fleischer-Fujishige, Schrijver, Orlin)

Steepest Descent for L^1 -convex F_n

(Iwata 99, Murota 00, 03, Kolmogorov-Shioura 09)

S0: Find a vector $p \in \text{dom}g$

S1: Find $\varepsilon = \pm 1$ and X that minimize $g(p + \varepsilon\chi_X)$

S2: If $g(p) \leq g(p + \varepsilon\chi_X)$, stop (p : minimizer)

S3: Set $p := p + \varepsilon\chi_X$ and go to S1

- Dijkstra's algorithm for shortest path (M.-Shioura 12)

π : potential, $V \setminus U$: permanent labeled

Special case with $g(p) = -1^\top p$:

$$\pi(v) = \min\{p(u) + \ell(u, v) \mid u \notin U\} \quad (v \in U \setminus \{s\})$$

C1.

Electric Circuit

Combinatorics on top of convexity

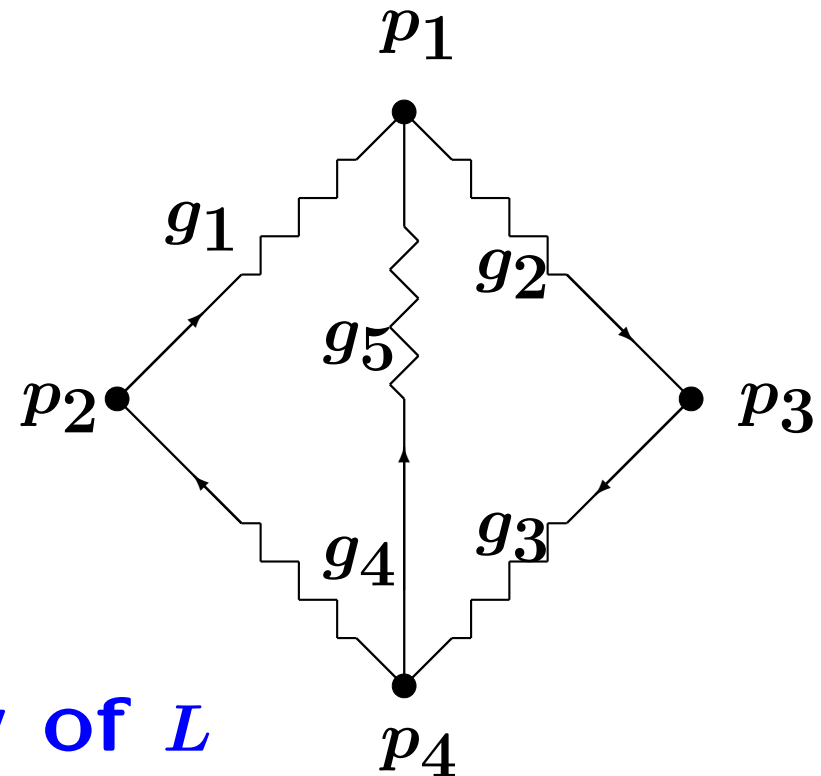
Linear Resistor Circuit

g_j : conductance

p : potential at nodes

Consumed power:

$$g(p) = \frac{1}{2} p^\top L p$$



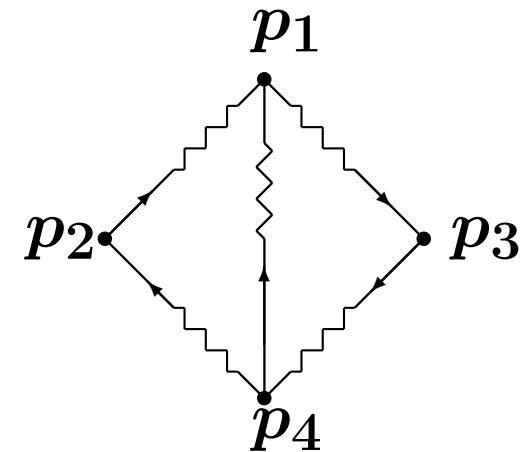
Combinatorial property of L

- off-diagonal $l_{ij} \leq 0 \quad (i \neq j; 1 \leq i, j \leq n)$
- row-sum $\sum_{j=1}^n l_{ij} \geq 0 \quad (1 \leq i \leq n)$

Node-branch incidence

$$A = \begin{bmatrix} -1 & 1 & 0 & 0 & -1 \\ 1 & 0 & 0 & -1 & 0 \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 1 \end{bmatrix}$$

(graph structure)



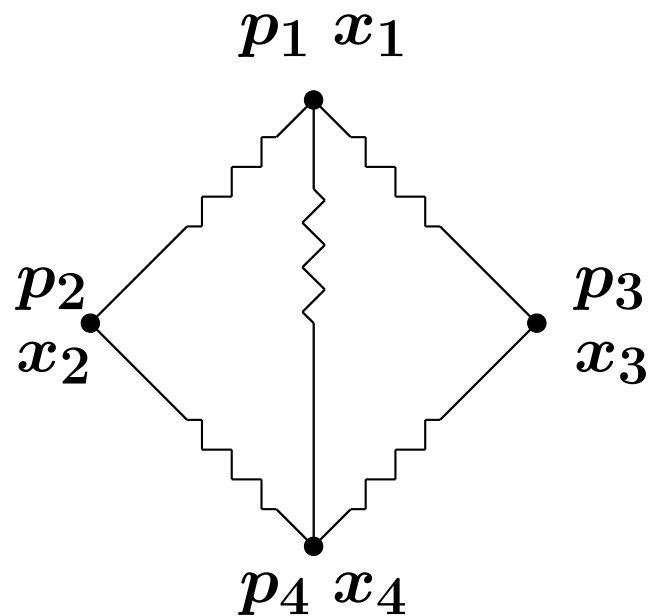
Node admittance

$$L = A \text{diag}(g_j) A^T =$$

$$\begin{bmatrix} g_1 + g_2 + g_5 & -g_1 & -g_2 & -g_5 \\ -g_1 & g_1 + g_4 & 0 & -g_4 \\ -g_2 & 0 & g_2 + g_3 & -g_3 \\ -g_5 & -g_4 & -g_3 & g_3 + g_4 + g_5 \end{bmatrix}$$

(off-diag ≤ 0 , row sum = 0)

Nonlinear Resistor Circuit



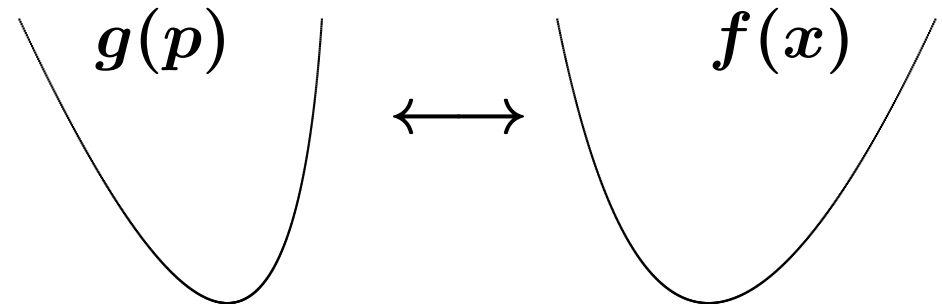
discrete structure + convex fn
electric circuit + power

voltage source p

$g(p)$: voltage potential (power)

current source x

$f(x)$: current potential (power)



- $g(p)$ and $f(x)$ are convex
- $g(p)$ and $f(x)$ are conjugate (Legendre transform)

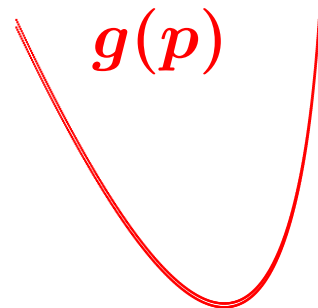
⇒ **What is their difference?**

Distinction btw Voltage and Current

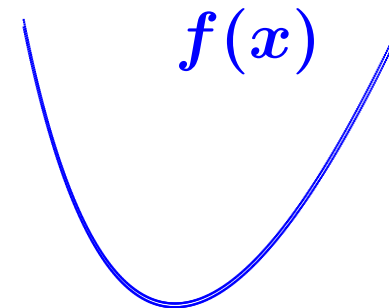
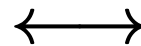
discrete structure + **convexity**

voltage p , power $g(p)$

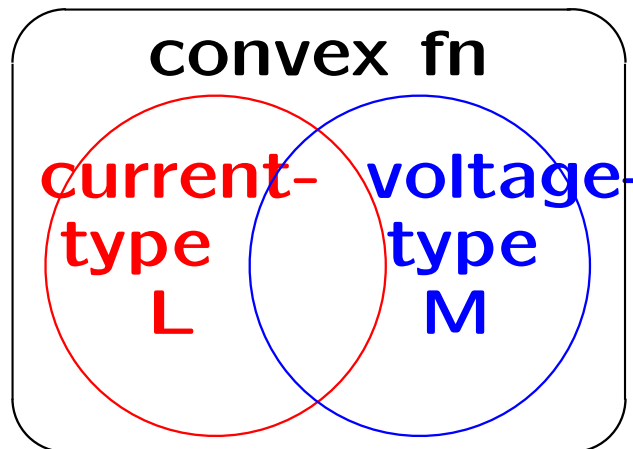
current x , power $f(x)$



L-convex



M-convex



C2.

L-/M-convexity

in Continuous Variables

L^{\sharp} -convex Fn in Continuous Vars

(Murota–Shioura 00, 03)

Continuous $\mathbb{R}^n \rightarrow \mathbb{R}$

Discrete $\mathbb{Z}^n \rightarrow \mathbb{R}$

convexity

\Updownarrow (convex fn)

discr

mid-pt convexity

\longrightarrow

discr mid-pt convexity

\Updownarrow (L^{\sharp} -convex fn)

transl. submodular

\longleftarrow

transl. submodular

(L^{\sharp} -convex fn)

conti

mid-pt conv: $f(x) + f(y) \geq f\left(\frac{x+y}{2}\right) + f\left(\frac{x+y}{2}\right)$

discr mid-pt conv: $f(x) + f(y) \geq f\left(\left\lceil \frac{x+y}{2} \right\rceil\right) + f\left(\left\lfloor \frac{x+y}{2} \right\rfloor\right)$

transl. sbm: $f(x) + f(y) \geq f((x - \alpha 1) \vee y) + f(x \wedge (y + \alpha 1))$

continuous $\alpha \in \mathbb{R}_+$ \longleftarrow discrete $\alpha \in \mathbb{Z}_+$

M[‡]-convex Fn in Continuous Vars

(Murota–Shioura 00, 03)

Continuous $\mathbb{R}^n \rightarrow \mathbb{R}$		Discrete $\mathbb{Z}^n \rightarrow \mathbb{R}$
convexity		
\Updownarrow (convex fn)	discr	
equi-dist convexity	\longrightarrow	
		exchange property
exchange property	\longleftarrow	
(M [‡] -convex fn)	conti	(M [‡] -convex fn)

equi-distance convex:

$$f(x) + f(y) \geq f(x - \alpha(x - y)) + f(y + \alpha(x - y))$$

exchange: $f(x) + f(y) \geq \min \left[f(x - \alpha e_i) + f(y + \alpha e_i) \right.$

$$\left. \min_{x_j < y_j} \{ f(x - \alpha(e_i - e_j)) + f(y + \alpha(e_i - e_j)) \} \right]$$

continuous $\alpha \in \mathbb{R}_+$ \longleftarrow discrete $\alpha \in \mathbb{Z}_+$

M-L Conjugacy Theorem

$$f : \mathbb{Z}^n \rightarrow \bar{\mathbb{Z}}, \quad f : \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$$

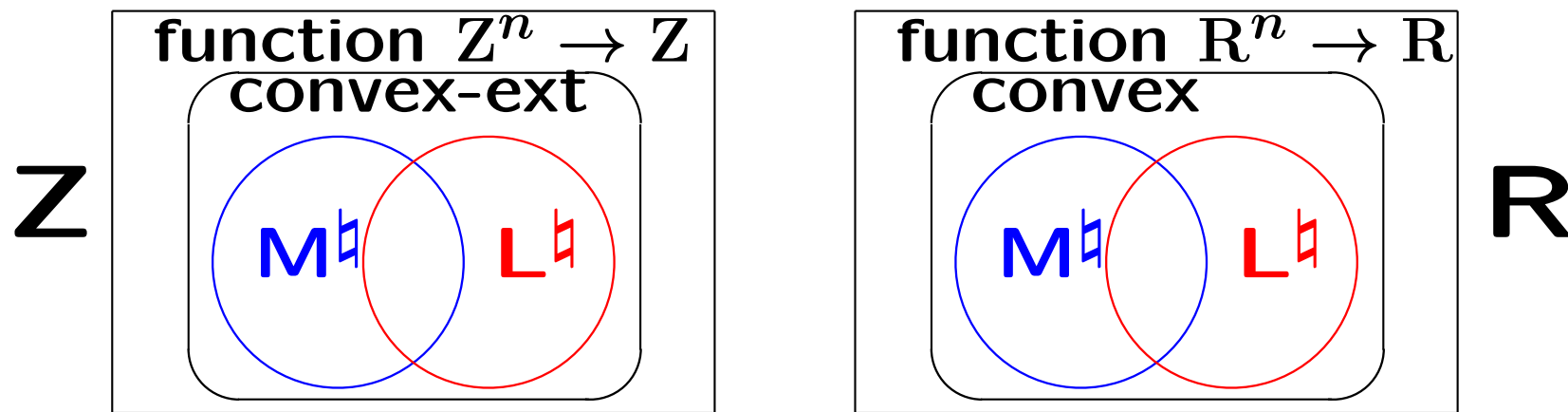
Legendre transform: $f^\bullet(p) = \sup_x [\langle p, x \rangle - f(x)]$

M[‡]-convex and L[‡]-convex are conjugate

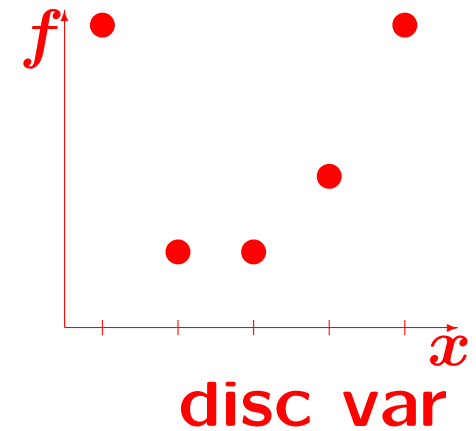
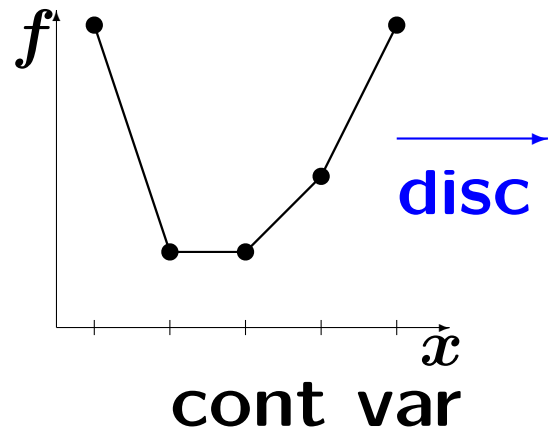
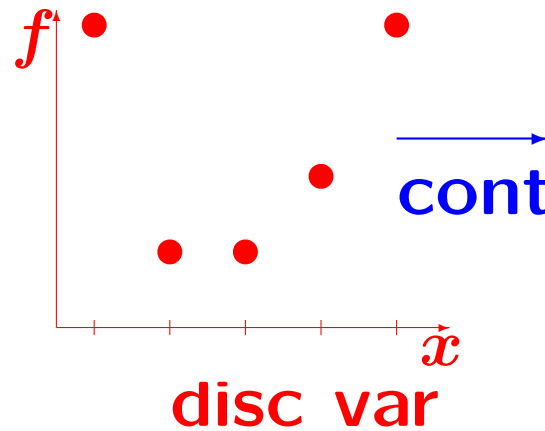
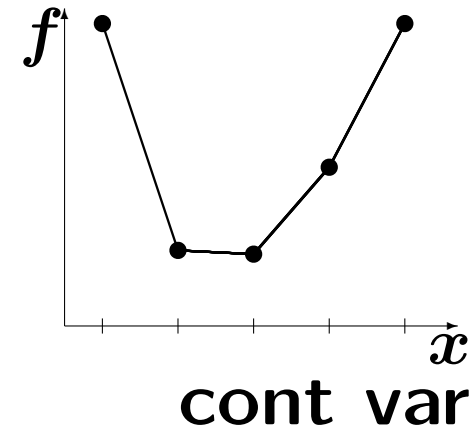
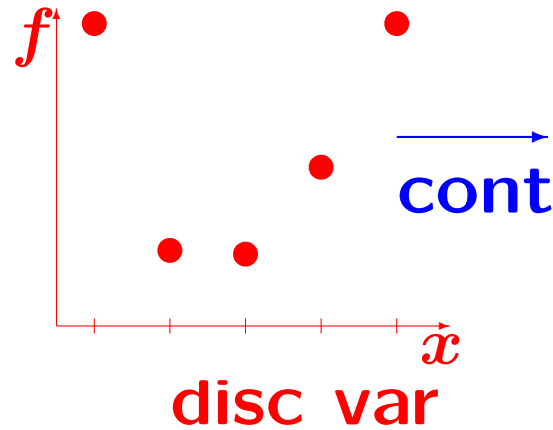
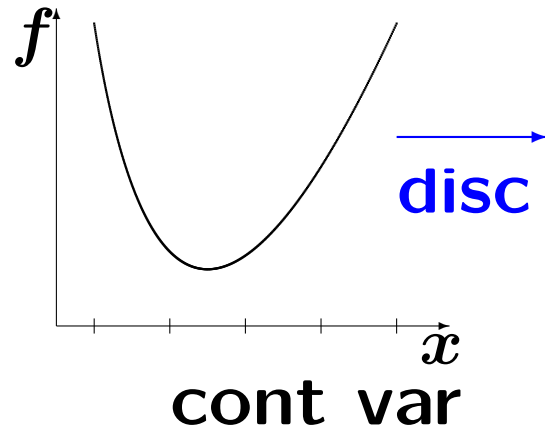
(1) $\mathbb{Z}^n \rightarrow \mathbb{Z}$ (Murota 98)

(2) $\mathbb{R}^n \rightarrow \mathbb{R}$, polyhedral (Murota–Shioura 00)

(3) $\mathbb{R}^n \rightarrow \mathbb{R}$, closed proper (Murota–Shioura 03)



Discretization vs Prolongation



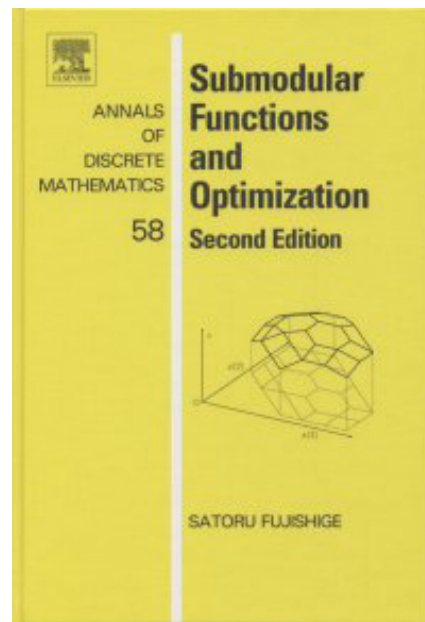
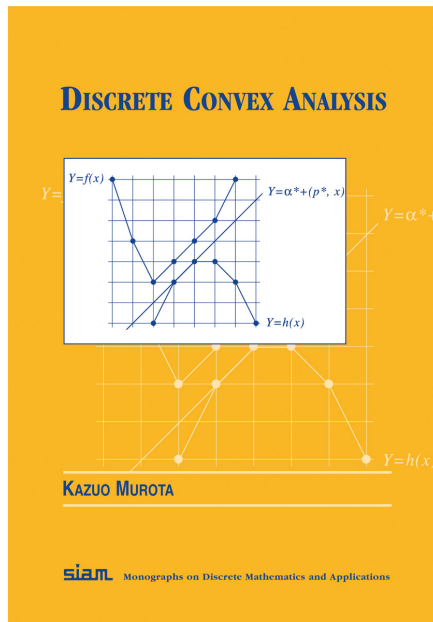
Prolongation, Discretization, Scaling

	Prolong. $Z^n \Rightarrow R^n$	Discret. $R^n \Rightarrow Z^n$	Scaling $Z^n \Rightarrow (2Z)^n$
L¹-conv	OK	OK	OK
M¹-conv	OK	NG	NG
(quadratic)	OK'	NG	OK
(laminar)	OK	OK	OK

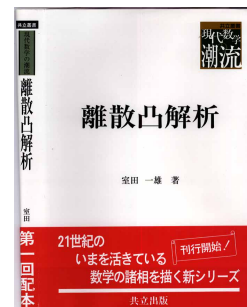
Books/Surveys

Murota: Discrete Convex Analysis, SIAM, 2003

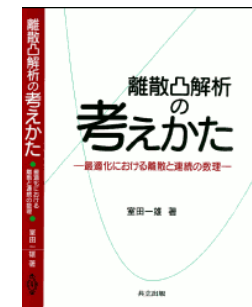
Fujishige: Submodular Functions and Optimization, 2nd ed., Elsevier, 2005 (Chap. VII)



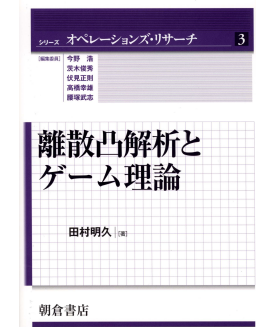
M. 01



M. 07



Tamura 09



Murota: Recent developments in discrete convex analysis, in: Research Trends in Combinatorial Optimization, Bonn 2008, Springer, 2009, Chap. 11, 219–260.

E N D