

RIMS Summer School (COSS 2018), Kyoto, July 2018

# **Discrete Convex Analysis III: Algorithms for Discrete Convex Functions**

**Kazuo Murota**  
**(Tokyo Metropolitan University)**

# Contents of Part III

## **A** Algorithms for Discrete Convex Functions

**A1.** Minimization (General)

**A2.** M-convex Minimization

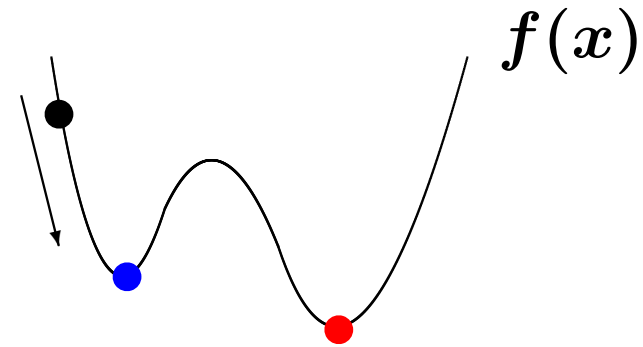
**A3.** L-convex Minimization

**A4.** M-convex Intersection

# A1.

## Minimization (General)

# Descent Method



**S0:** Initial sol  $x^*$

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

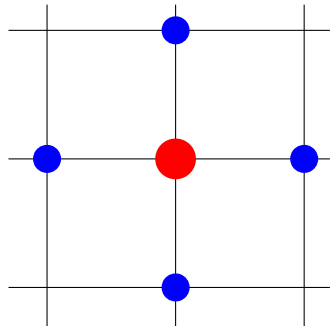
**S2:** If  $f(x^*) \leq f(x^\bullet)$ , return  $x^*$  (**local opt**)

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

What is **neighborhood**?

# Neighborhood for Local Optimality

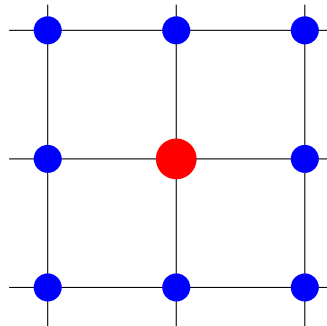
separable  
convex



$$2n + 1$$

$$\{\pm e_1, \dots, \pm e_n\}$$

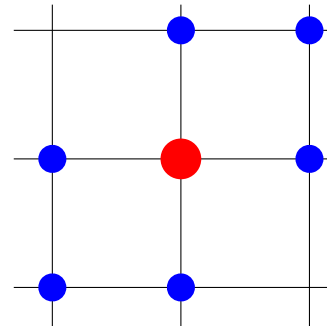
integrally  
convex



$$3^n$$

$$\{\chi_X - \chi_Y\}$$

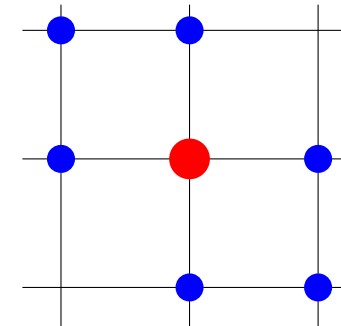
$L_{\square}$ -  
convex



$$2^{n+1} - 1$$

$$\{\pm \chi_X\}$$

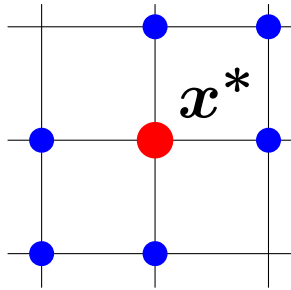
$M_{\square}$ -  
convex



$$n(n + 1) + 1$$

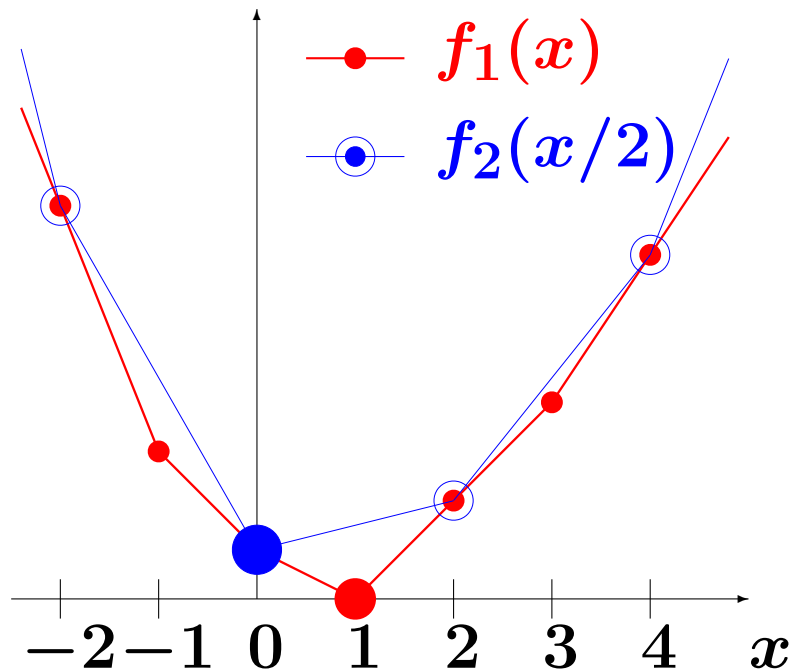
$$\{e_i - e_j\}$$

# Local Optimality



	#neigh -bors	poly-time local opt	algorithm global opt
submodular (set fn)	$2^n$	Y	
separable-conv	$2n$	Y	
integrally-conv	$3^n$	N	
$L^{\natural}$ -conv ( $\mathbb{Z}^n$ )	$2^n$	Y	
$M^{\natural}$ -conv ( $\mathbb{Z}^n$ )	$n^2$	Y	

# Scaling and Proximity



## Proximity theorem:

True minimum ● exists

in a neighborhood of

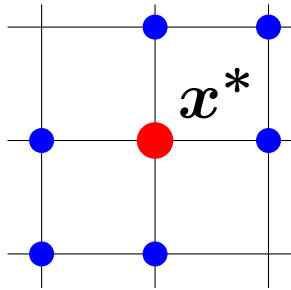
a scaled local minimum ●

⇒ efficient algorithm

## Facts in DCA:

- Scaling preserves L-convexity
- Scaling does NOT preserve M-convexity
- Proximity thms known for L-conv and M-conv

# Minimization



	#neigh -bors	poly-time local opt	algorithm global opt
submodular (set fn)	$2^n$	Y	Y
separable-conv	$2n$	Y	Y
integrally-conv	$3^n$	N	N
$L^{\natural}$ -conv ( $\mathbb{Z}^n$ )	$2^n$	Y	Y
$M^{\natural}$ -conv ( $\mathbb{Z}^n$ )	$n^2$	Y	Y



# A2.

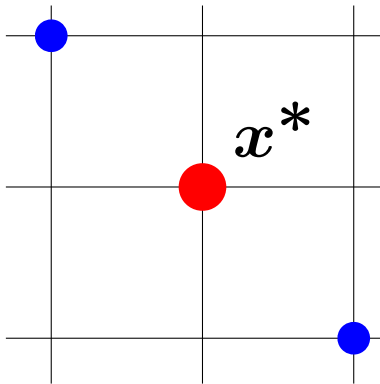
## M-convex Minimization

# Local vs Global Opt (M-conv)

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

$x^*$ : global opt

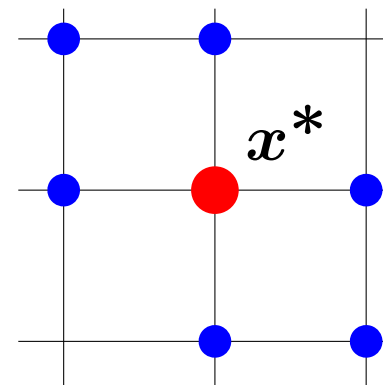
$\iff$  local opt     $f(x^*) \leq f(x^* - e_i + e_j)$      $(\forall i, j)$



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

Can check with  $n^2$  fn evals

For M-convex fn  $\Rightarrow$



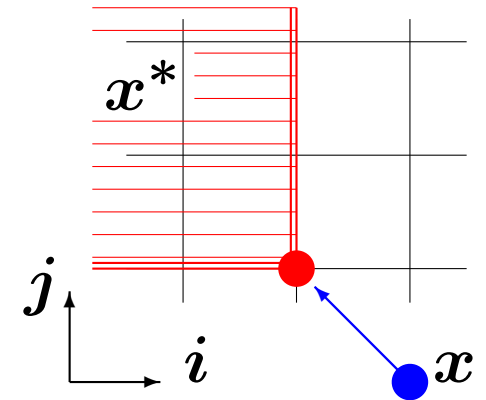
# Steepest Descent for M-convex Fn

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

S1: Find  $(i, j)$  that minimizes  $f(x - e_i + e_j)$

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

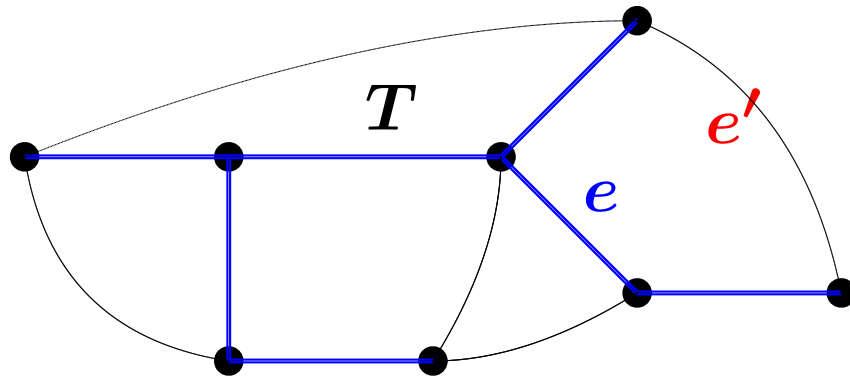
(Shioura 98)

$\exists$  minimizer  $x^*$  with  $x^*(i) \leq x(i) - 1$ ,  $x^*(j) \geq x(j) + 1$

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

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

# Min Spanning Tree Problem



edge length  $d : E \rightarrow \mathbb{R}$   
total length of  $T$

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

**Thm**

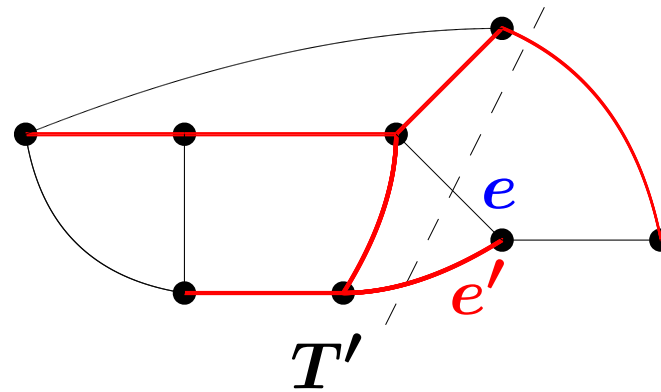
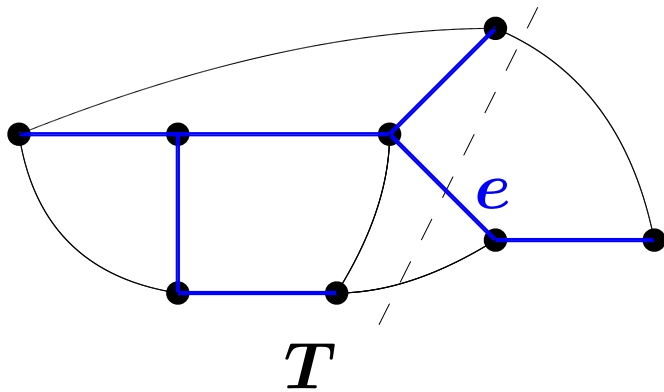
$$\begin{aligned} T: \text{MST} &\iff \tilde{d}(T) \leq \tilde{d}(T - e + e') \\ &\iff d(e) \leq d(e') \quad \text{if } T - e + e' \text{ is tree} \end{aligned}$$

**Algorithm** Kruskal's, Kalaba's

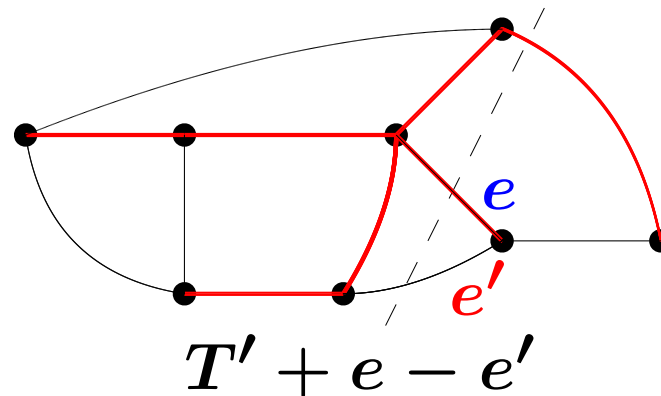
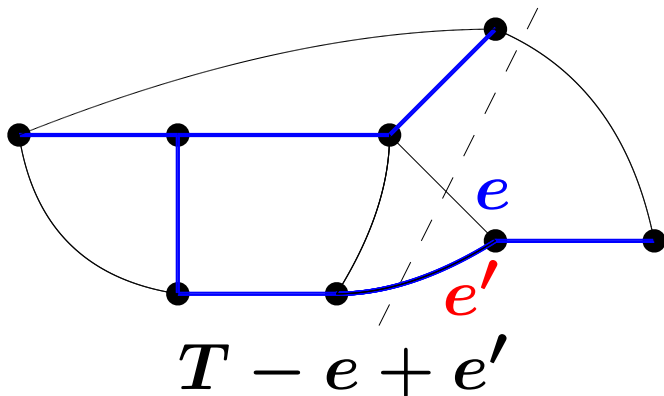
**DCA view**

- 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.  $T - e + e' \in \mathcal{T}$ ,  $T' + e - e' \in \mathcal{T}$

# Kruskal's Greedy Algorithm for MST

Kruskal (1959)

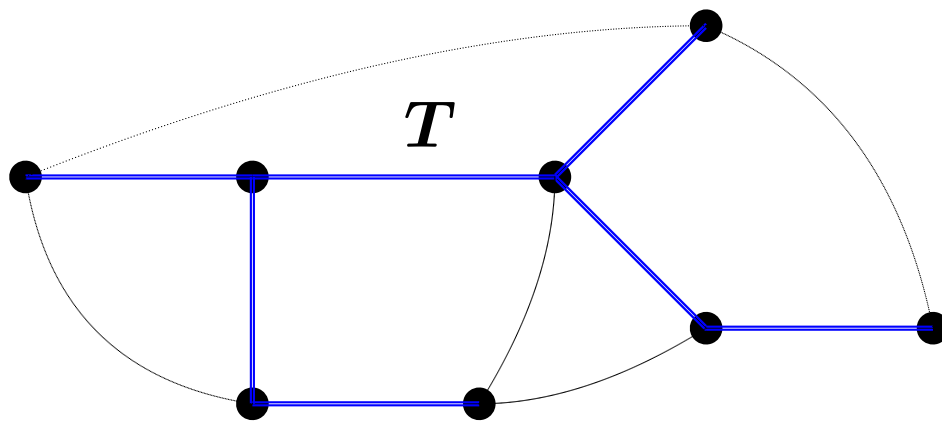
**S0:** Order edges by length:  $d(e_1) \leq d(e_2) \leq \dots$

**S1:**  $T = \emptyset$ ;  $i = 1$

**S2:** Pick edge  $e_i$

**S3:** If  $T + e_i$  contains a cycle, discard  $e_i$

**S4:** Update  $T = T + e_i$ ;  $i = i + 1$ ; go to S2



# Kalaba's Algorithm for MST

Kalaba (1960), Dijkstra (1960)

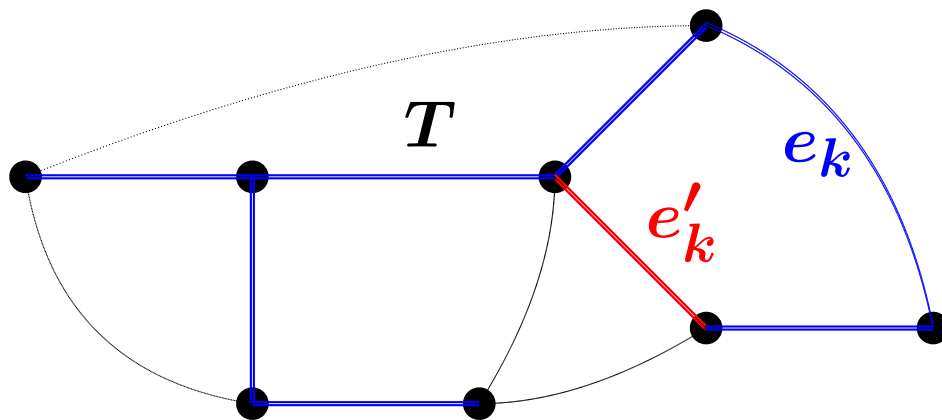
S0:  $T =$  any spanning tree

S1: Order  $e' \notin T$  by length:  $d(e'_1) \leq d(e'_2) \leq \dots$

$k = 1$

S2:  $e_k =$  longest edge s.t.  $T - e_k + e'_k$  is tree

S3:  $T = T - e_k + e'_k$ ;  $k = k + 1$ ; go to S2



# A3.

## L-convex Minimization

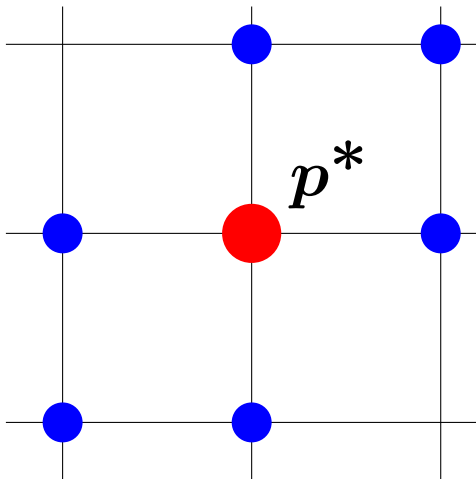


# Local vs Global Opt ( $L^{\natural}$ -conv)

**Thm** :  $g : \mathbb{Z}^n \rightarrow \mathbb{R}$   $L^{\natural}$ -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,  
Lee-Sidford-Wong)

# Steepest Descent for $L^1$ -convex Fn

(Murota 00, 03, Kolmogorov-Shioura 09, Murota-Shioura 14)

**S0:** Find a vector  $p^\circ \in \text{dom } g$  and set  $p := p^\circ$

**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

**Thm:** (Murota-Shioura 14)

Termination exactly in  $\mu(p^\circ) + 1$  iterations, where

$$\mu(p^\circ) = \min\{\|p^* - p^\circ\|_\infty^+ + \|p^* - p^\circ\|_\infty^- \mid p^* \in \arg \min g\}$$

$$\|q\|_\infty^+ = \max_i \max(0, q(i)), \quad \|q\|_\infty^- = \max_i \max(0, -q(i))$$

# Monotone Steepest Descent for $L^1$ -convex Fn

S0: Find a vector  $p^\circ \in \text{dom } g$  s.t

$\{q \mid q \geq p^\circ\} \cap \text{argmin } g \neq \emptyset$  and set  $p := p^\circ$

S1: Find  $X$  that minimizes  $g(p + \chi_X)$

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

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

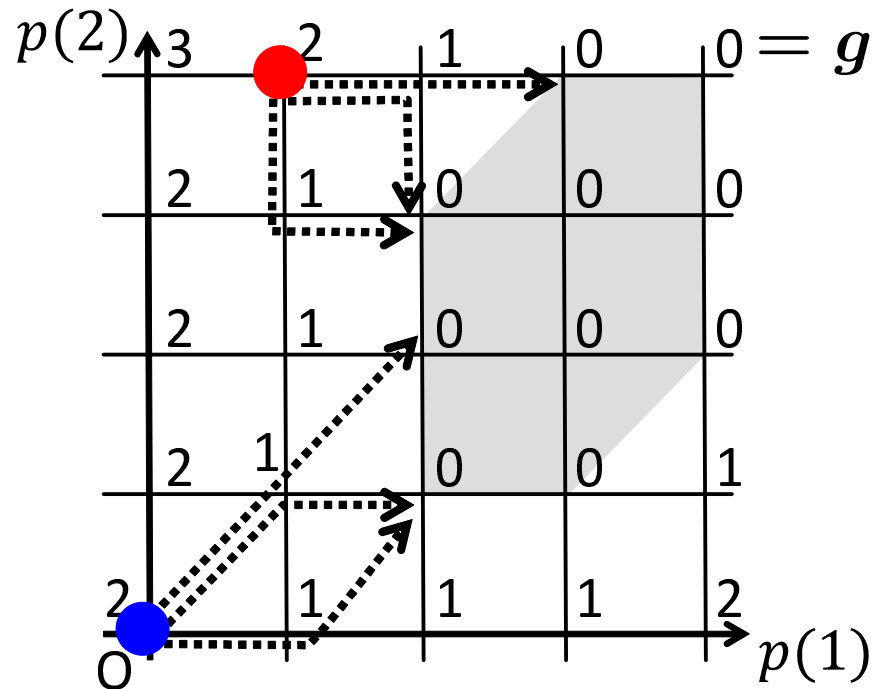
**Thm:** (Murota-Shioura 14)

Termination exactly in  $\hat{\mu}(p^\circ) + 1$  iterations, where

$$\hat{\mu}(p^\circ) = \min\{\|p^* - p^\circ\|_\infty \mid p^* \in \text{argmin } g, p^* \geq p^\circ\}$$

$\Rightarrow$  Application to ascending auction

# Steepest Descent Path for $L_1$ -convex Fn



$$\mu(\mathbf{p}^\circ) = \hat{\mu}(\mathbf{p}^\circ) = 2$$

$$\|\mathbf{p}^\circ, \operatorname{argmin} g\|_\infty = 1$$

$$\mu(\mathbf{p}^\circ) = \hat{\mu}(\mathbf{p}^\circ) = 2$$

$$\|\mathbf{p}^\circ, \operatorname{argmin} g\|_\infty = 2$$

# 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 (Murota-Shioura 12)  
= steepest ascent for  $L^{\natural}$ -concave maximization  
with uniform linear objective  $(1, 1, \dots, 1)$

# Optimality & Proximity Theorems

Func Class	Optimality	Proximity
L-convex	$f(x^*) \leq f(x^* + \chi_S) \quad (\forall S)$ $f(x^* + 1) = f(x^*) \quad (\text{M. 01})$	$\ x^* - x^\alpha\  \leq (n-1)(\alpha-1)$ (Iwata-Shigeno 03)
M-convex	$f(x^*) \leq f(x^* - \chi_u + \chi_v)$ $(\forall u, v \in V) \quad (\text{M. 96})$	$\ x^* - x^\alpha\  \leq (n-1)(\alpha-1)$ (Moriguchi-M.-Shioura 02)
L2-convex (L $\square$ L convol)	$f(x^*) \leq f(x^* + \chi_S) \quad (\forall S)$ $f(x^* + 1) = f(x^*)$	$\ x^* - x^\alpha\  \leq 2(n-1)(\alpha-1)$ (M.-Tamura 04)
M2-convex (M $\dagger$ M)	$f(x^*) \leq f(x^* - \chi_U + \chi_W)$ $(\forall U, W;  U  =  W ) \quad (\text{M. 01})$	$\ x^* - x^\alpha\  \leq \frac{n^2}{2}(\alpha-1)$ (M.-Tamura 04)
integrally convex	$f(x^*) \leq f(x^* - \chi_U + \chi_W)$ $(\forall U, W) \quad (\text{Favati-Tardella 90})$	$\ x^* - x^\alpha\  \leq \frac{(n+1)!}{2^{n-1}}(\alpha-1)$ (Moriguchi-M.-Tamura -Tardella 16)

$$\| \cdot \| = \| \cdot \|_\infty$$

**A4.**

**M-convex Intersection**

**(Fenchel Duality)**

# Intersection Problem $(f_1 + f_2)$

Recall:  $L^{\natural} + L^{\natural} \Rightarrow L^{\natural}, \quad M^{\natural} + M^{\natural} \not\Rightarrow M^{\natural}$

## **M-convex Intersection Algorithm:**

Minimizes  $f_1 + f_2$  for  $M^{\natural}$ -convex  $f_1, f_2$

$\Leftrightarrow$  Maximizes  $f_1 + f_2$  for  $M^{\natural}$ -concave  $f_1, f_2$   
(submodular function maximization)

$\Leftrightarrow$  Fenchel duality (min = max)

$\Rightarrow$  Valuated matroid intersection (Murota 96)

$\Rightarrow$  Weighted matroid intersection

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



# M-convex Intersection: Min $[M^\natural + M^\natural]$

$M^\natural + M^\natural$  is NOT  $M^\natural$

$f_1, f_2 : M^\natural$ -convex  $(\mathbb{Z}^n \rightarrow \mathbb{R})$ ,  $x^* \in \text{dom } f_1 \cap \text{dom } f_2$

(1)  $x^*$  minimizes  $f_1 + f_2$  (Murota 96)

$\iff \exists p$  (certificate of optimality)

•  $x^*$  minimizes  $f_1(x) - \langle p, x \rangle$  (M-opt thm)

•  $x^*$  minimizes  $f_2(x) + \langle p, x \rangle$  (M-opt thm)

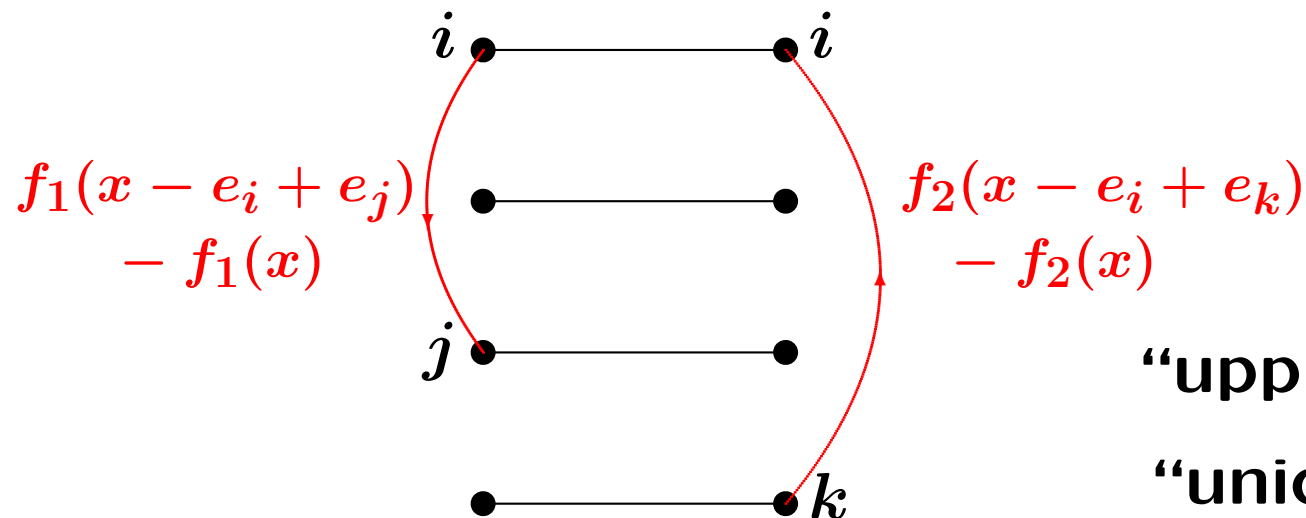
(2)  $\text{argmin}(f_1 + f_2) = \text{argmin}(f_1 - p) \cap \text{argmin}(f_2 + p)$

(3)  $f_1, f_2$  are integer-valued  $\Rightarrow$  integral  $p$

# M-convex Intersection Algorithms

Natural extensions of  
weighted (poly)matroid intersection algorithms

Exchange arcs are weighted



“upper-bound lemma”

“unique-max lemma”

- cycle-canceling (Murota 96, 99)
- successive shortest path (Murota-Tamura 03)
- scaling (Iwata-Shigeno 03, Iwata-Moriguchi-Murota 05)

# Convolution

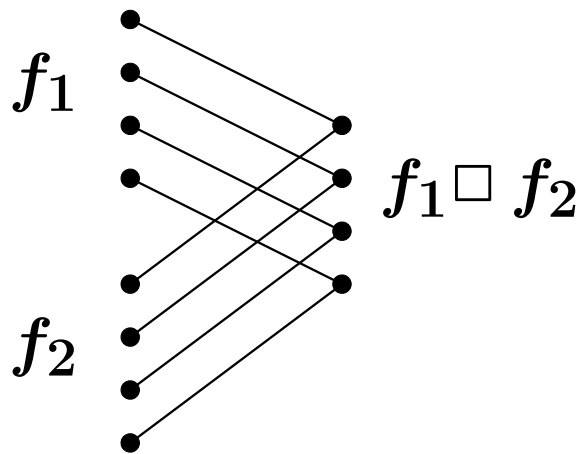
Convolutions of  $M^{\natural}$ -convex functions:

$$(f_1 \square f_2)(x) = \min_y (f_1(y) + f_2(x - y))$$

$$(f_1 \square f_2 \square f_3)(x), \quad (f_1 \square f_2 \square \cdots \square f_k)(x)$$

can be computed by **M-convex intersection algorithms**

cf. aggregated utility function



**E N D**