

劣モジュラ最適化

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Outline

- Submodular Functions

Examples

Discrete Convexity

- Minimizing Submodular Functions
- Symmetric Submodular Functions
- Maximizing Submodular Functions
- Approximating Submodular Functions

Submodular Functions

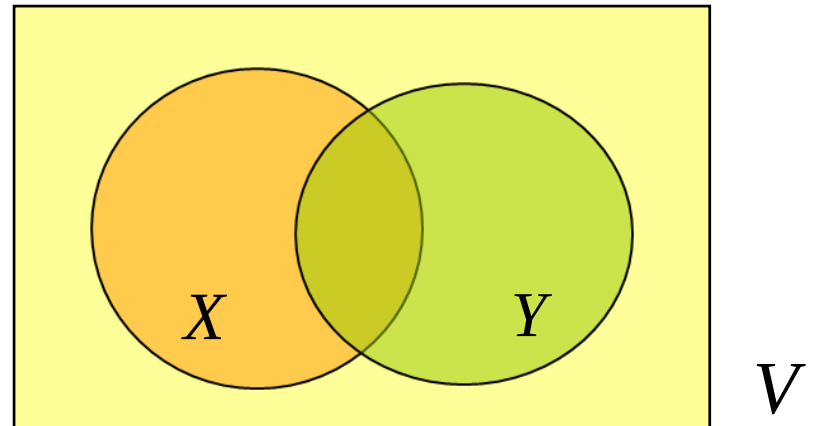
V : Finite Set

$$f : 2^V \rightarrow \mathbb{R}$$

$$\forall X, Y \subseteq V$$

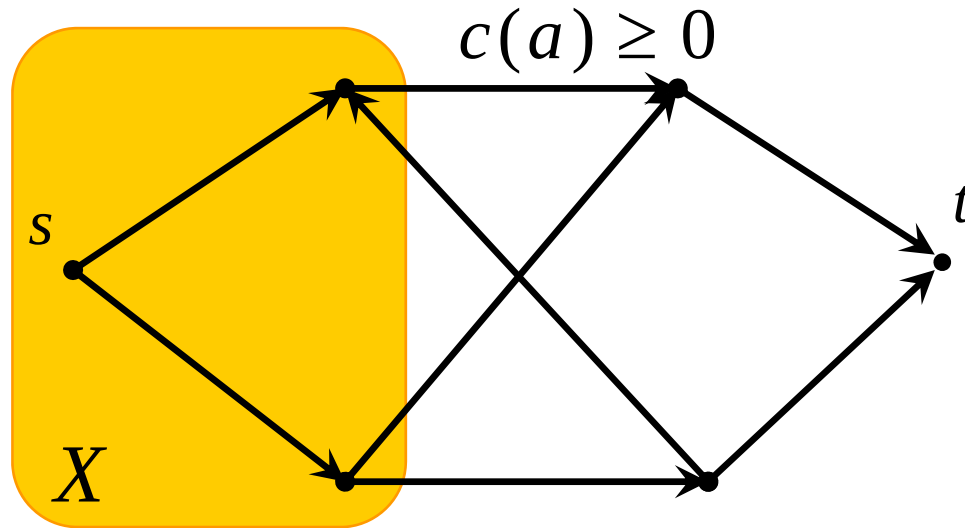
$$f(X) + f(Y) \geq f(X \cap Y) + f(X \cup Y)$$

- Cut Capacity Functions
- Matroid Rank Functions
- Entropy Functions



Cut Capacity Function

Cut Capacity $\kappa(X) = \sum \{c(a) \mid a : \text{leaving } X\}$



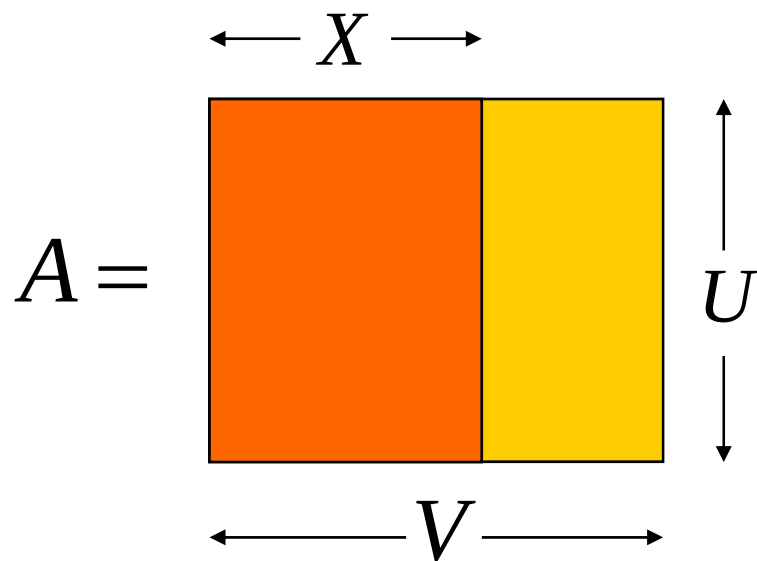
Max Flow Value = Min Cut Capacity

Matroid Rank Functions

Matrix Rank Function

Whitney (1935)

$$\rho(X) = \text{rank } A[U, X]$$



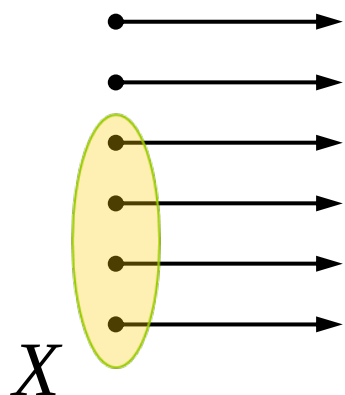
$$\forall X \subseteq V, \rho(X) \leq |X|$$

$$X \subseteq Y \Rightarrow \rho(X) \leq \rho(Y)$$

ρ : Submodular

Entropy Functions

Information
Sources



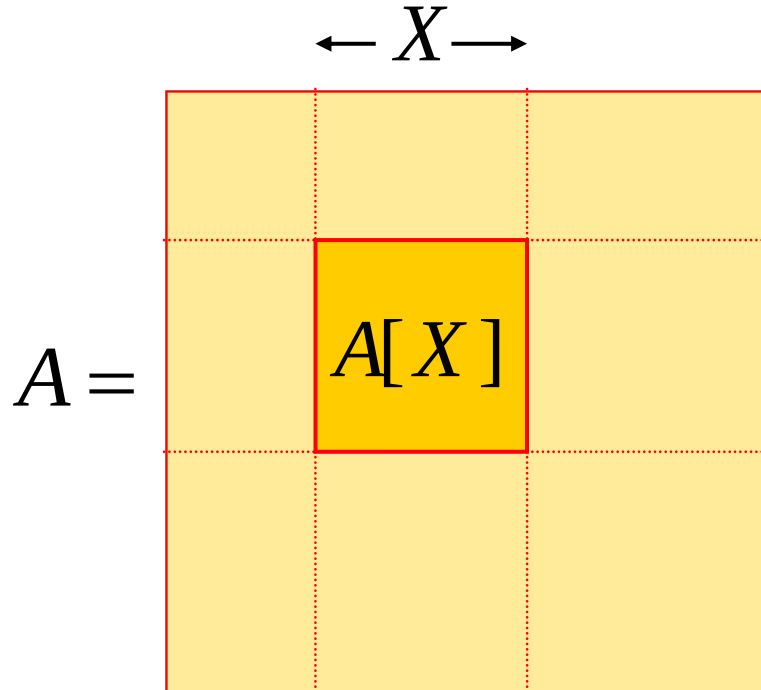
$$h(\phi) = 0$$

$h(X)$: Entropy of the Joint Distribution

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

Conditional Mutual Information ≥ 0

Positive Definite Symmetric Matrices



$$f(\emptyset) = 0$$

$$f(X) = \log \det A[X]$$

Ky Fan's Inequality

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

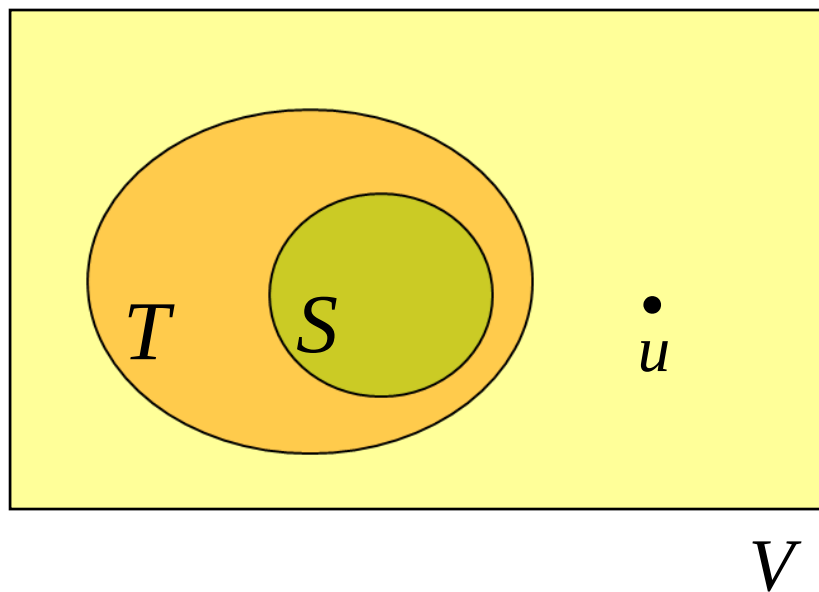
Extension of the Hadamard Inequality

$$\det A \leq \prod_{i \in V} A_{ii}$$

Discrete Concavity

$$S \subseteq T \Rightarrow$$

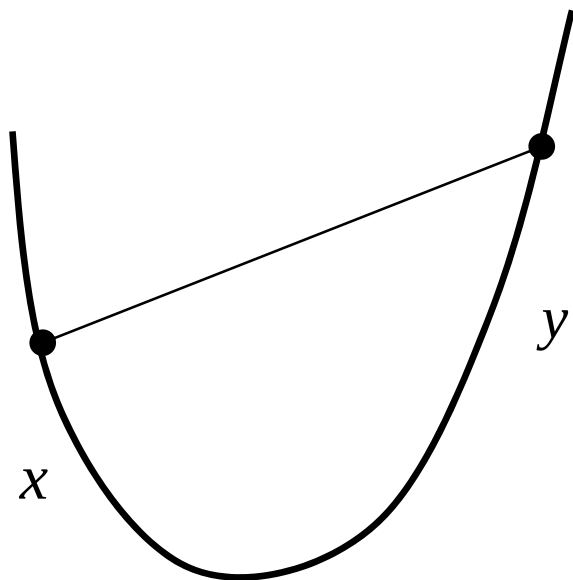
$$f(S \cup \{u\}) - f(S) \geq f(T \cup \{u\}) - f(\{u\})$$



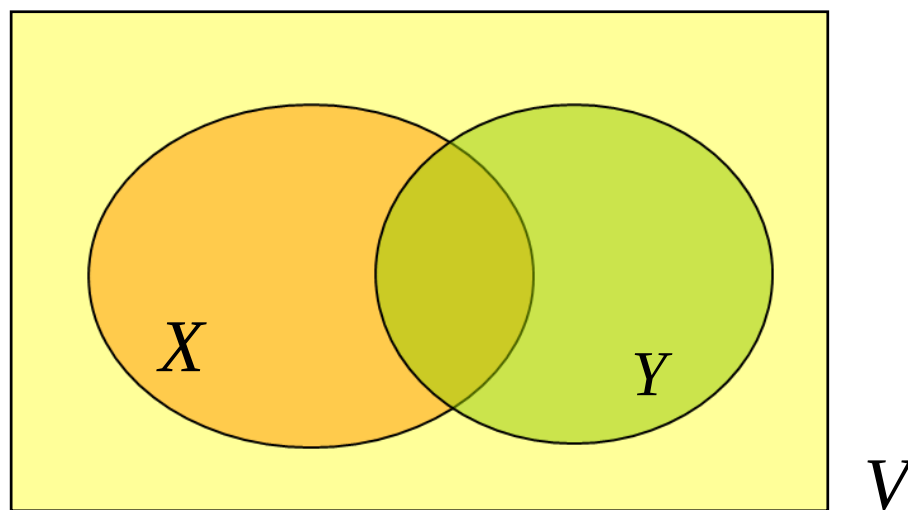
Diminishing Returns

Discrete Convexity

Convex Function

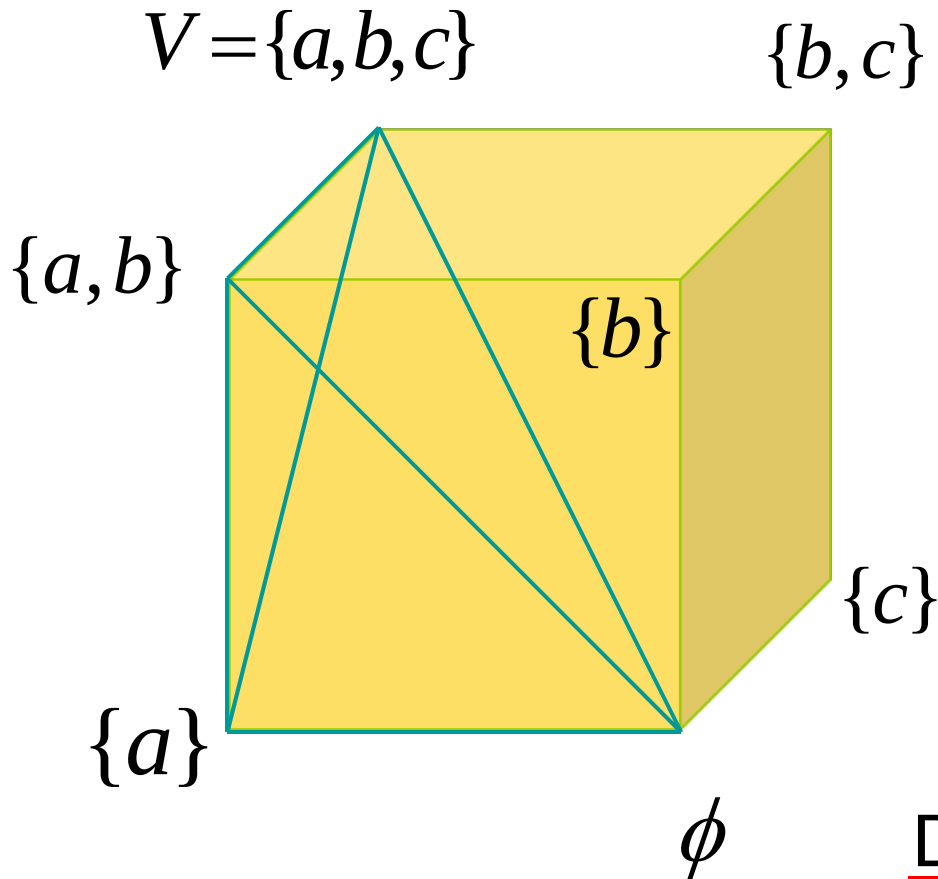


$$f(X) + f(Y) \geq f(X \cap Y) + f(X \cup Y)$$



Discrete Convexity

Lovász (1983)



$\hat{f}$: Linear Interpolation

$\hat{f}$: Convex



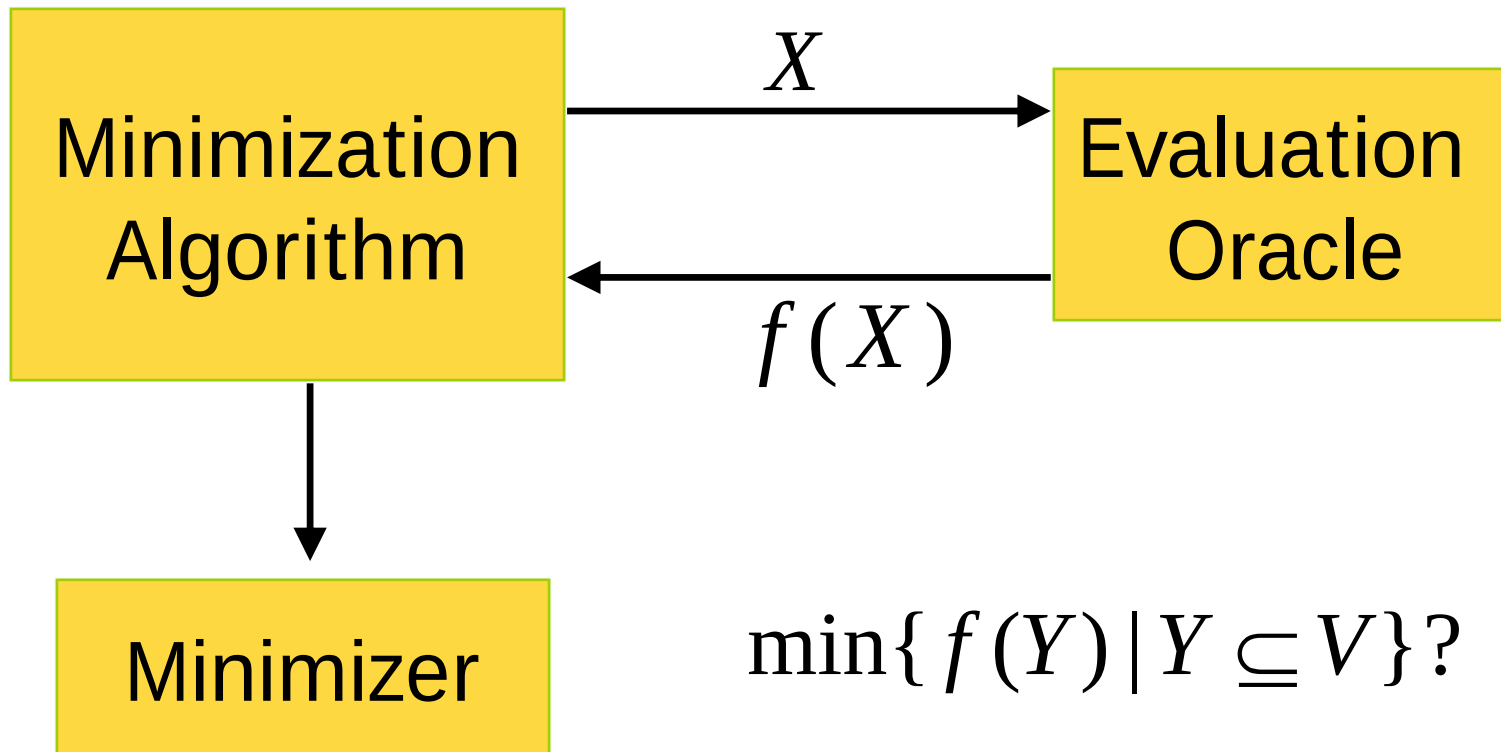
f : Submodular

Discrete Convex Analysis

Murota (2003)

Submodular Function Minimization

Assumption: $f(\emptyset) = 0$



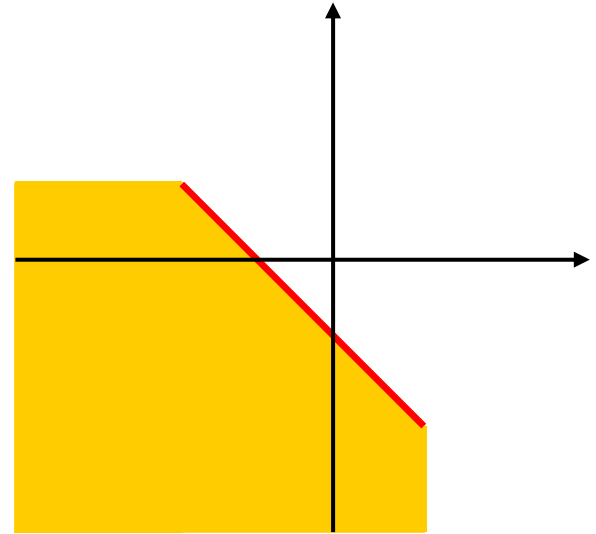
Ellipsoid Method

Grötschel, Lovász, Schrijver (1981)

Base Polyhedra

$$\mathbf{R}^V = \{x \mid V \rightarrow \mathbf{R}\}$$

$$x(Y) = \sum_{v \in Y} x(v)$$



Submodular Polyhedron

$$P(f) = \{x \mid x \in \mathbf{R}^V, \forall Y \subseteq V, x(Y) \leq f(Y)\}$$

Base Polyhedron

$$B(f) = \{x \mid x \in P(f), x(V) = f(V)\}$$

Greedy Algorithm

Edmonds (1970)
Shapley (1971)

$\longleftrightarrow L(v) \longrightarrow$



$$y(v) = f(L(v)) - f(L(v) - \{v\}) \quad (v \in V)$$

y : Extreme Base

$$\begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} y(v_1) \\ y(v_2) \\ \vdots \\ y(v_n) \end{bmatrix} = \begin{bmatrix} f(L(v_1)) \\ f(L(v_2)) \\ \vdots \\ f(L(v_n)) \end{bmatrix}$$

Min-Max Theorem

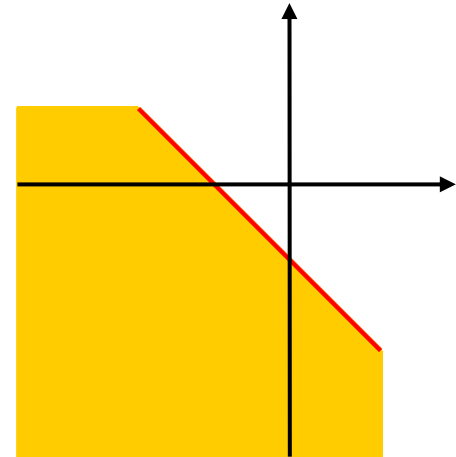
Theorem

Edmonds (1970)

$$\min_{Y \subseteq V} f(Y) = \max \{x^-(V) \mid x \in B(f)\}$$

$$x^-(v) := \min\{0, x(v)\}$$

$$x^-(V) \leq x(Y) \leq f(Y)$$



Combinatorial Approach

Extreme Base $y_L \in B(f)$

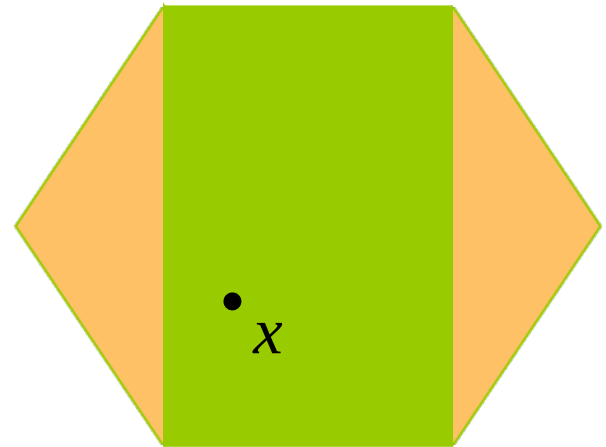
Convex Combination

$$x = \sum_{L \in \Lambda} \lambda_L y_L$$

Cunningham (1985)

$$O(n^6 M \gamma \log n M)$$

$$M = \max_{X \subseteq V} |f(X)|$$



Submodular Function Minimization

Grötschel, Lovász, Schrijver (1981, 1988)

Ellipsoid Method

Cunningham (1985)

$O(n^5 \gamma \log M)$
 $O(n^7 \gamma \log n)$

$O(n^7 \gamma + n^8)$

Iwata, Fleischer, Fujishige (2000)

Schrijver (2000)

Fleischer, Iwata (2000)

Iwata (2002)

Fully Combinatorial

Iwata (2003)

Orlin (2007)

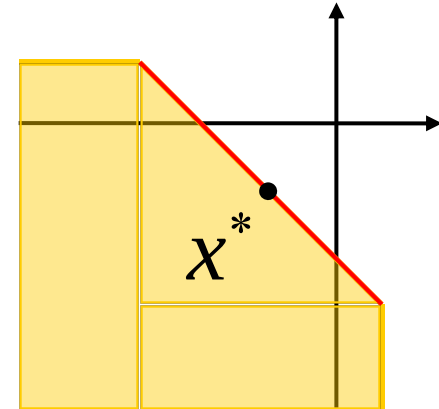
$O((n^4 \gamma + n^5) \log M)$

$O(n^5 \gamma + n^6)$

Iwata, Orlin (2009)

The Minimum-Norm Base

Minimize $\|x\|^2$
subject to $x \in B(f)$



Theorem

Fujishige (1984)

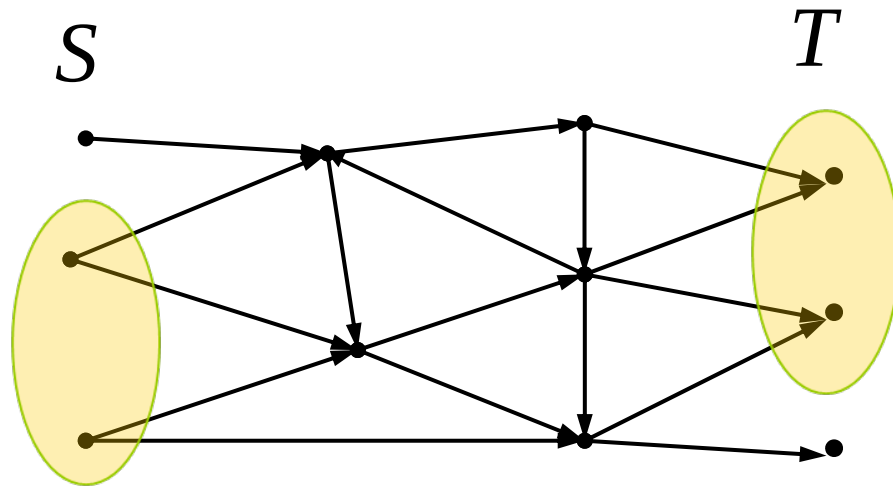
x^* : opt.sol.

$X_- := \{v \mid x^*(v) < 0\} \longrightarrow$ Minimal Minimizer

$X_0 := \{v \mid x^*(v) \leq 0\} \longrightarrow$ Maximal Minimizer

Wolfe's Algorithm $\longrightarrow$ Practically Efficient

Evacuation Problem (Dynamic Flow)



Hoppe, Tardos (2000)

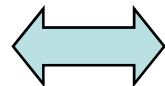
$c(a)$: Capacity

$\tau(a)$: Transit Time

$b(v)$: Supply/Demand

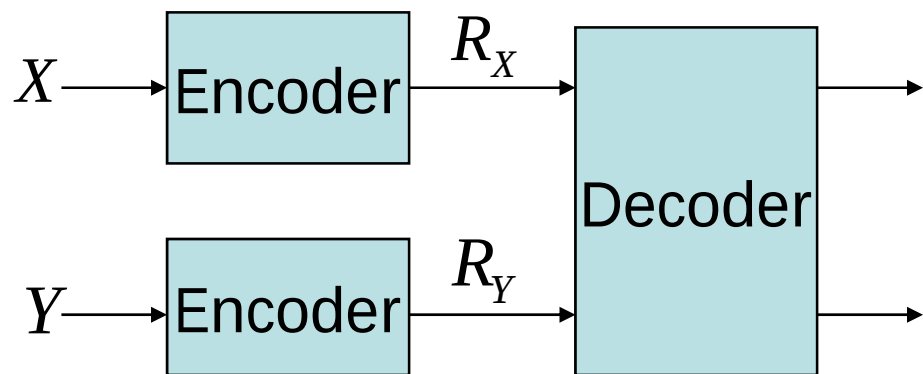
$o(X)$: Maximum Amount of Flow from $X \cap S$ to $T \setminus X$.

Feasible

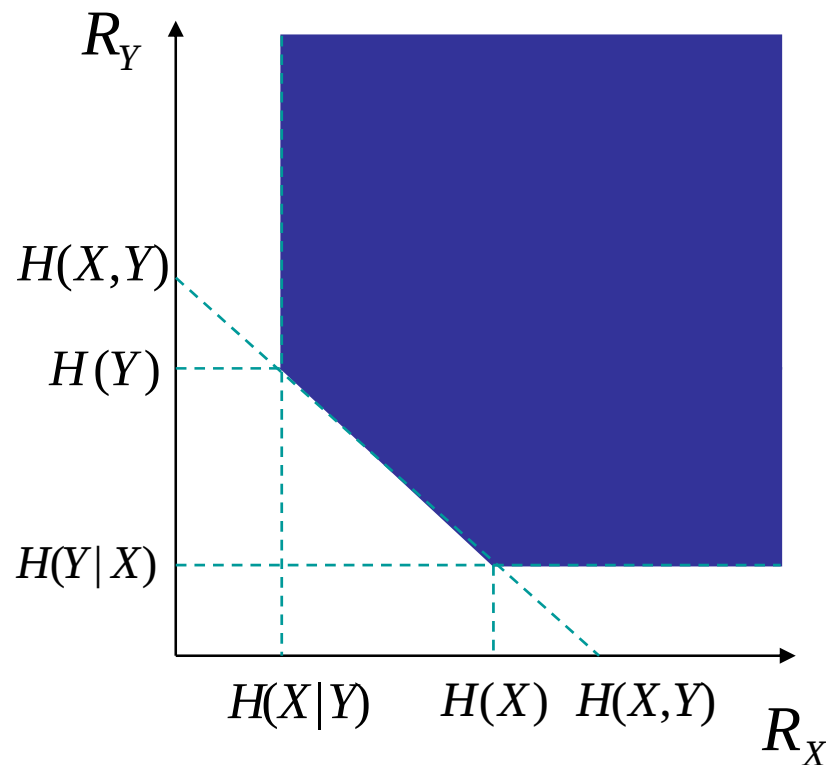


$$b(X) \leq o(X), \forall X \subseteq S \cup T$$

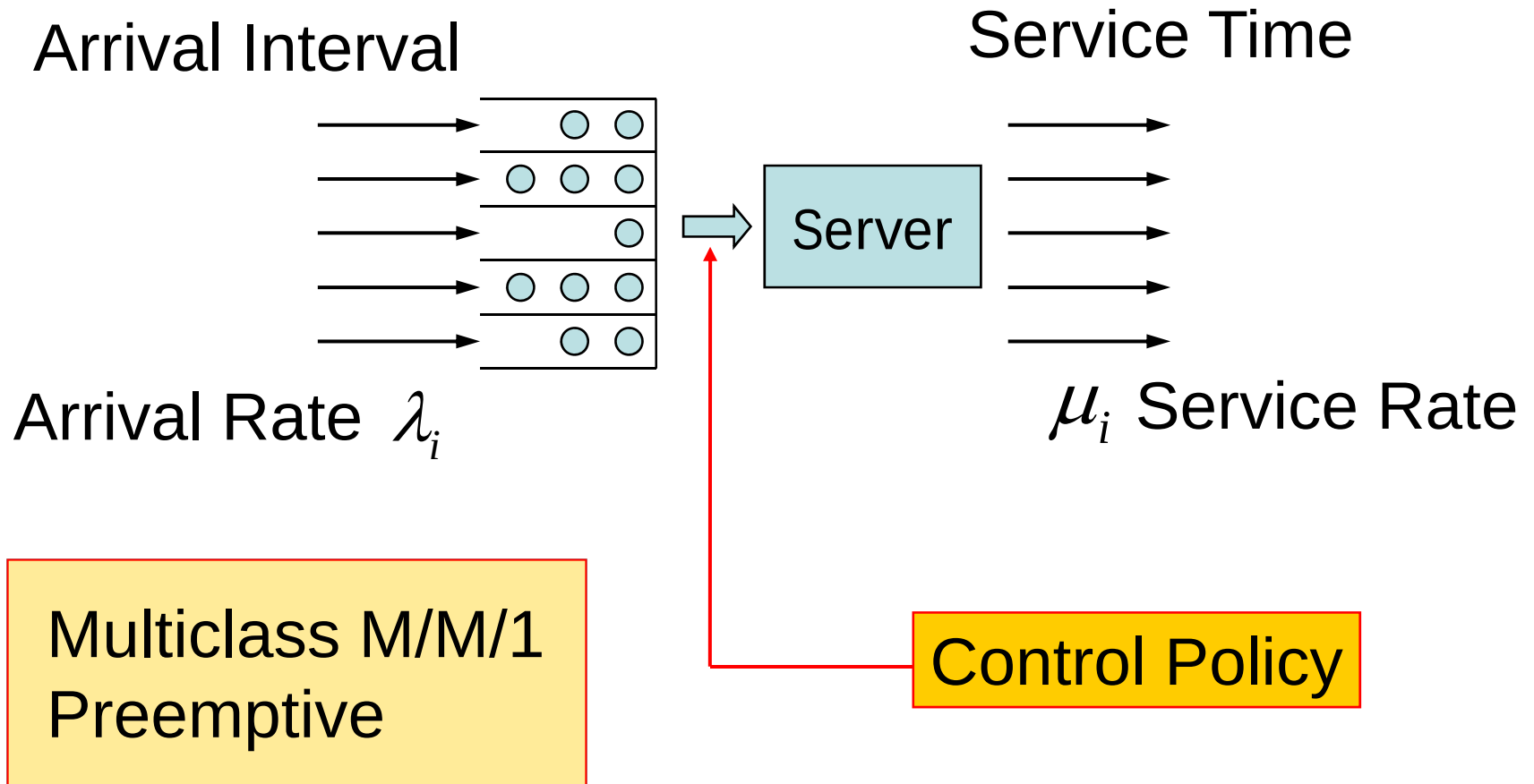
Multiterminal Source Coding



Slepian, Wolf (1973)



Multiclass Queueing Systems



Performance Region

S_j : Expected Staying Time of a Job in j

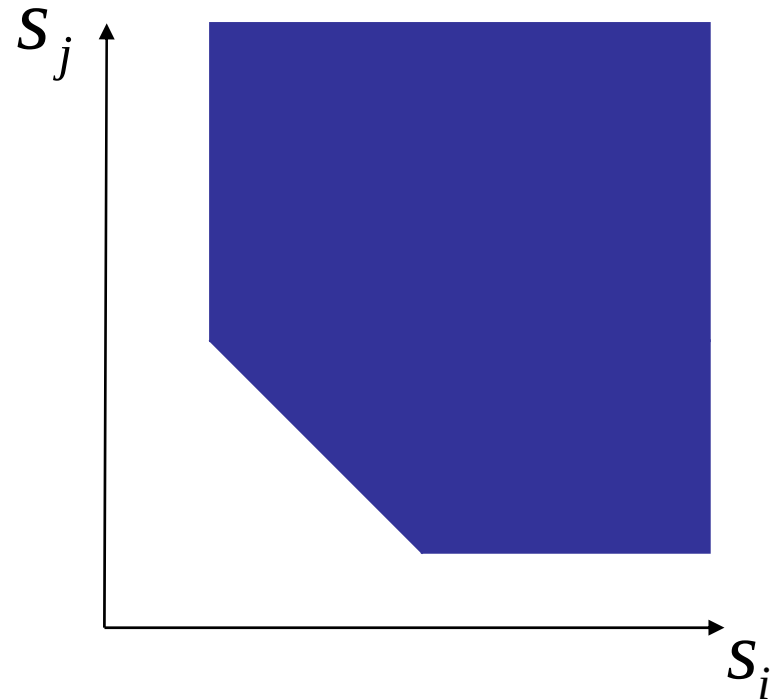
S : Achievable



$$\sum_{i \in X} \rho_i S_i \geq \frac{\sum_{i \in X} \rho_i / \mu_i}{1 - \sum_{i \in X} \rho_i}, \forall X \subseteq V$$

Coffman, Mitrani (1980)

$$\rho_i := \lambda_i / \mu_i, \quad \sum_{i \in V} \rho_i < 1$$



A Class of Submodular Functions

$$x, y, z \in \mathbb{R}_+^V$$

Itoko & Iwata (2005)

h : Nonnegative, Nondecreasing, Convex

$$f(X) = z(X) - y(X)h(x(X)) \quad (X \subseteq V)$$

Submodular

$$\sum_{i \in X} \rho_i S_i \geq \frac{\sum_{i \in X} \rho_i / \mu_i}{1 - \sum_{i \in X} \rho_i}, \forall X \subseteq V$$

$$\begin{aligned} z_i &:= \rho_i S_i & y_i &:= \frac{\rho_i}{\mu_i} \\ x_i &:= \rho_i & h(x) &:= \frac{1}{1 - x} \end{aligned}$$

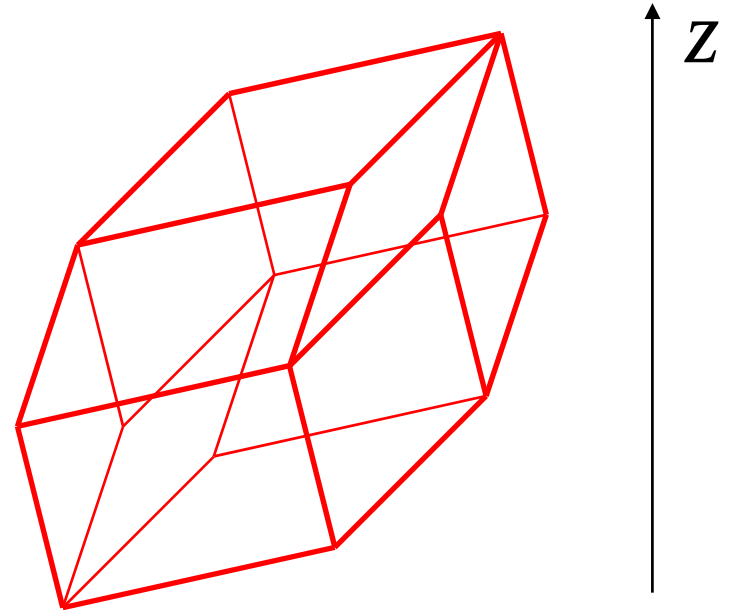
Zonotope in 3D

$$w(X) = (x(X), y(X), z(X))$$

$$Z = \text{conv}\{w(X) \mid X \subseteq V\}$$

Zonotope

$$\tilde{f}(x, y, z) = z - yh(x)$$

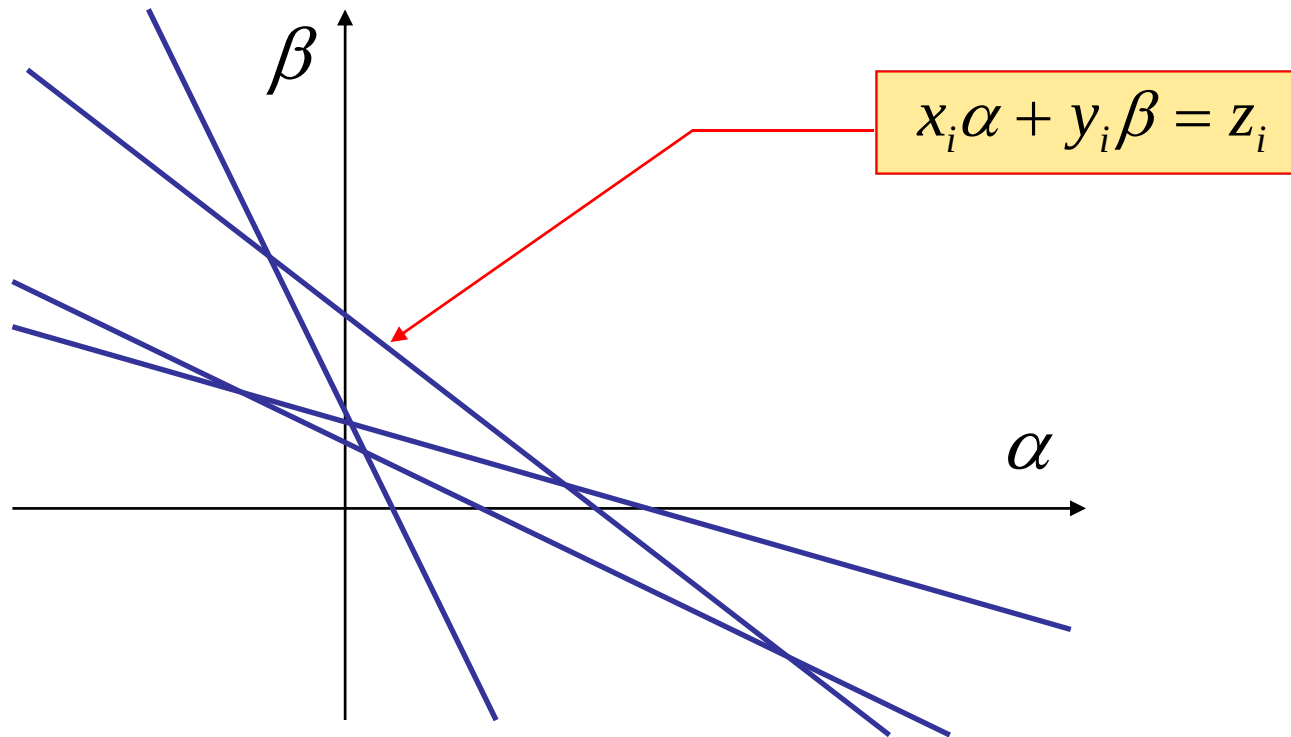


$$\min\{f(X) \mid X \subseteq V\}$$

$$= \min\{\tilde{f}(x, y, z) \mid (x, y, z) : \text{Lower Extreme Point of } Z\}$$

Remark: $\tilde{f}(x, y, z)$ is NOT concave!

Line Arrangement



Enumerating All the Cells

Topological Sweeping Method
Edelsbrunner, Guibas (1989)

→ $O(n^2)$

Symmetric Submodular Functions

$$f : 2^V \rightarrow \mathbf{R}$$

$$\text{Symmetric } f(X) = f(V \setminus X), \quad \forall X \subseteq V.$$

Crossing Submodular

$$X \cap Y \neq \emptyset, X \cup Y \neq V \Rightarrow$$

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

Symmetric Submodular Function Minimization

$$\min\{f(X) \mid \emptyset \neq X \subset V, X \neq V\}?$$

Maximum Adjacency Ordering

- Minimum Cut Algorithm by MA-ordering
Nagamochi & Ibaraki (1992)
- Simpler Proofs
Frank (1994), Stoer & Wagner (1997)
- Symmetric Submodular Functions
Queyranne (1998)
- Alternative Proofs
Fujishige (1998), Rizzi (2000)

Minimum Degree Ordering

Nagamochi (2007)

ISAAC'07, Sendai, Japan

Finding the family of all extreme sets for symmetric crossing submodular functions in $O(n^3\gamma)$ time.



Symmetric Submodular Function Minimization

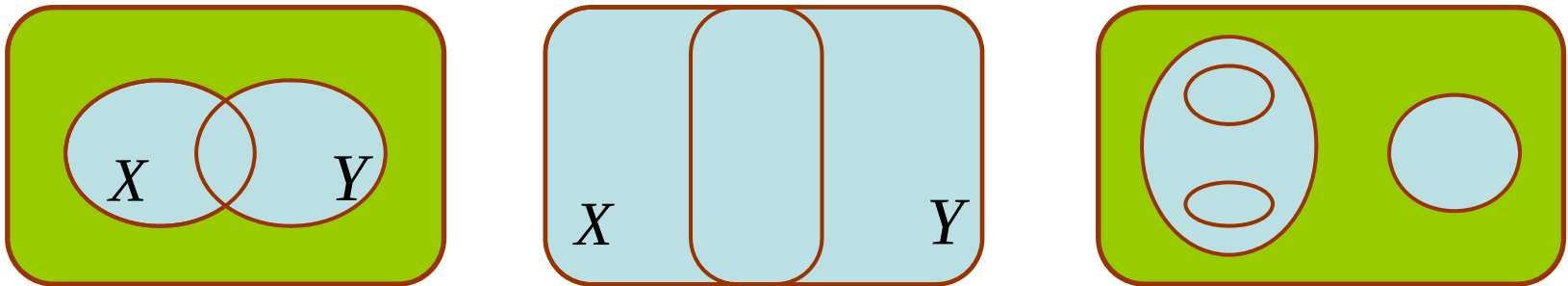
Extreme Sets

f : Symmetric Crossing Submodular Function

X : Extreme Set

$$f(Z) > f(X), \quad \forall Z \subset X : \emptyset \neq Z \neq X.$$

The family of all extreme sets forms a laminar.



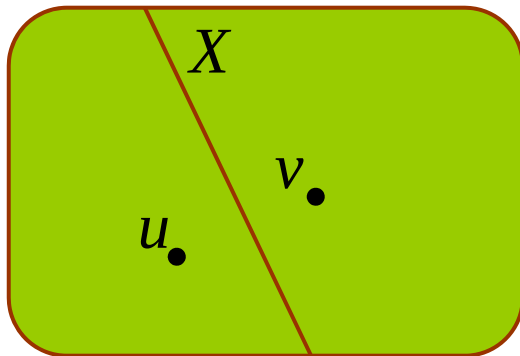
$$f(X) + f(Y) \geq f(X \setminus Y) + f(Y \setminus X)$$

Flat Pair for Symmetric Submodular Functions

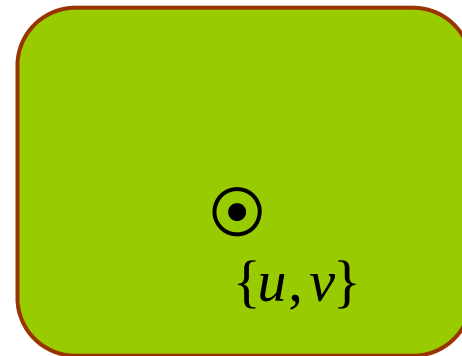
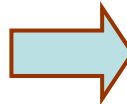
Flat Pair $\{u, v\} \subseteq V$ ($u \neq v$)

$$f(X) \geq \min\{f(x) \mid x \in X\},$$

$$\forall X \subseteq V \text{ s.t. } |X \cap \{u, v\}| = 1.$$



No Extreme Sets
Separate u and v .



Shrink $\{u, v\}$ into
a single vertex.

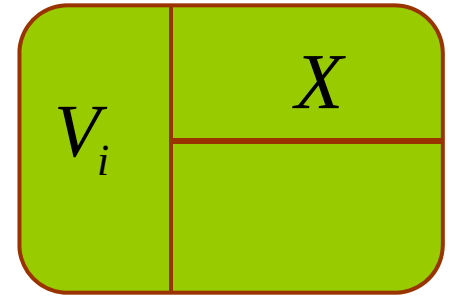
MD-Ordering for Symmetric Submodular Functions

MD-ordering

$$v_1, v_2, \dots, v_{n-1}, v_n \in V$$

Each v_j has minimum value of $f_{j-1}(v)$ among $v \in V \setminus V_{j-1}$.

$$V_i := \{v_1, \dots, v_i\}$$



$$f_i(X) := f(X) + f(V_i \cup X) \quad (X \subseteq V \setminus V_i)$$

Symmetric, Crossing Submodular

MD-Ordering for Symmetric Submodular Functions

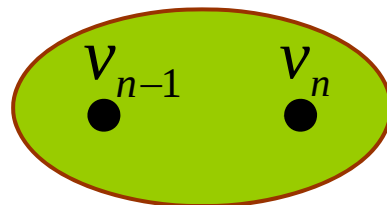
The last two vertices v_{n-1}, v_n of an MD-ordering form a flat pair.

Proof by Induction:

$\{v_{n-1}, v_n\}$: Flat Pair for f_i on $V \setminus V_i$

$i = n-2, \dots, 1, 0.$

$i = n-2$



Time Complexity

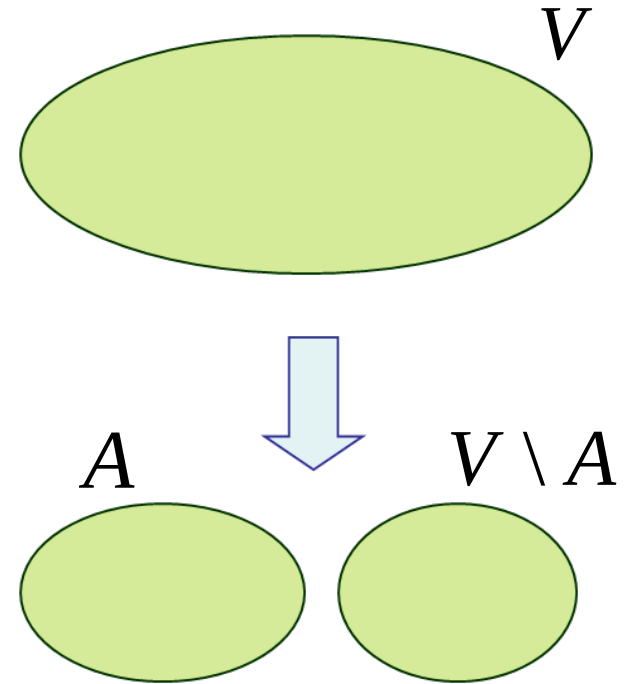
- Finding an MD-ordering in $O(n^2\gamma)$ time.
- Finding all the extreme sets in $O(n^3\gamma)$ time.
- Minimizing symmetric submodular functions in $O(n^3\gamma)$ time.

Application to Clustering

Random variables $X_1, \dots, X_n$

Partition V into A and $V \setminus A$
as independent as possible

Minimize $I(X_A; X_{V \setminus A})$
subject to $\phi \neq A \neq V$



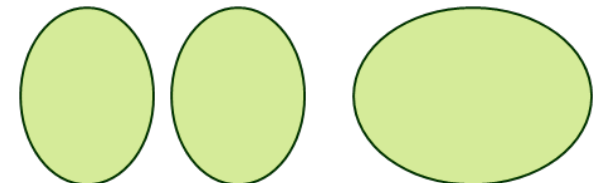
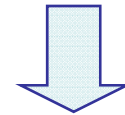
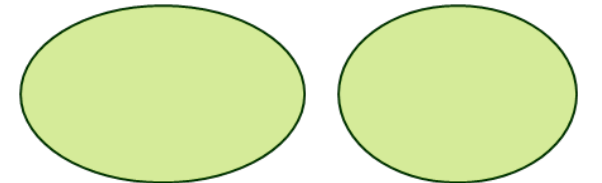
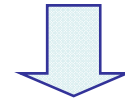
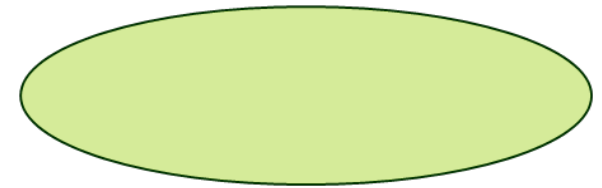
$$\begin{aligned} I(X_A; X_B) &= H(X_B) - H(X_B | X_A) \\ &= H(X_A) + H(X_B) - H(X_A, X_B) \end{aligned}$$

Application to Clustering

$$\begin{array}{ll} \text{Minimize} & \sum_{i=1}^k f(V_i) \\ \text{subject to} & V = V_1 \cup \dots \cup V_k \\ & V_i \cap V_j = \phi \quad (i \neq j) \end{array}$$

$(2 - 1/k)$ -Approximation

Greedy Split



Submodular Function Maximization

Approximation Algorithms

Nemhauser, Wolsey, Fisher (1978)

Monotone SF / Cardinality Constraint

$(1-1/e)$ -Approximation

Feige, Mirrokni, Vondrák (FOCS 2007)

Nonnegative SF

$2/5$ -Approximation

Vondrák (STOC 2008)

Monotone SF / Matroid Constraint

$(1-1/e)$ -Approximation

Approximate Maximization

Maximize $f(S)$ subject to $|S| \leq k$

Greedy Algorithm



$$T_0 := \phi$$

$$v_j := \arg \max f(T_{j-1} \cup \{v\})$$

$$T_j := T_{j-1} \cup \{v_j\}$$

$$\rho_j := f(T_j) - f(T_{j-1})$$

$$\left. \begin{array}{l} v_j := \arg \max f(T_{j-1} \cup \{v\}) \\ T_j := T_{j-1} \cup \{v_j\} \\ \rho_j := f(T_j) - f(T_{j-1}) \end{array} \right\} j = 1, \dots, k$$

$$f(T_k) \geq (1 - 1/e) f(S), \quad \forall S : |S| \leq k$$

Approximate Maximization

S^* : Optimal Solution $\eta := f(S^*)$

$$\eta \leq k\rho_j + \sum_{i=1}^{j-1} \rho_i \quad (j = 1, \dots, k) \quad f(T_k) = \sum_{i=1}^k \rho_i$$

$$\begin{aligned} \because) \quad f(S^*) &\leq f(S^* \cup T_{j-1}) \\ &\leq f(T_{j-1}) + \sum_{u \in S^* \setminus T_{j-1}} [f(T_{j-1} \cup \{u\}) - f(T_{j-1})] \\ &\leq \underbrace{f(T_{j-1})}_{\sum_{i=1}^{j-1} \rho_i} + k\rho_j \end{aligned}$$

Approximate Maximization

$$\begin{array}{ll}
 \text{Minimize} & \sum_{i=1}^k \rho_i \\
 \text{subject to} & \begin{bmatrix} k & 0 & \cdots & 0 \\ 1 & k & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & \cdots & 1 & k \end{bmatrix} \begin{bmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \rho_k \end{bmatrix} \geq \begin{bmatrix} \eta \\ \eta \\ \vdots \\ \eta \end{bmatrix} \\
 & \rho_j \geq 0 \quad (j = 1, \dots, k)
 \end{array}$$

$$\sum_{i=1}^k \rho_i = f(T_k)$$

$$\eta := f(S^*)$$

$$\begin{aligned}
 \hat{\rho}_j &:= \frac{\eta}{k} \left(1 - \frac{1}{k} \right)^{j-1} \\
 &\quad (j = 1, \dots, k)
 \end{aligned}$$

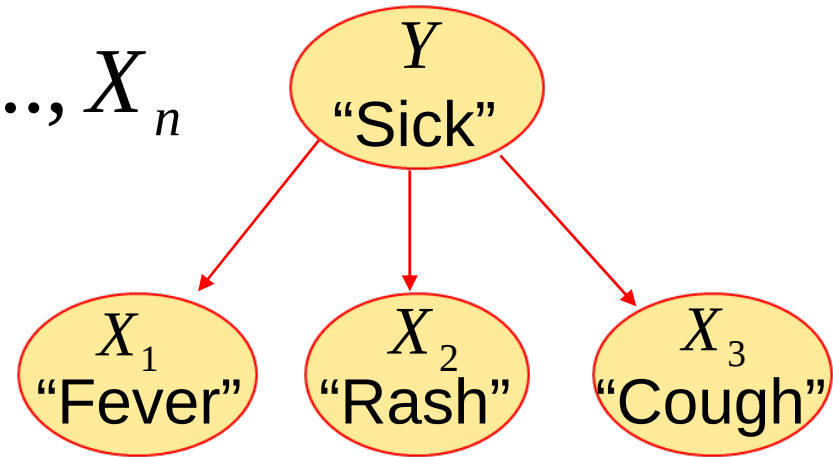
$$\sum_{i=1}^k \hat{\rho}_i = \eta \left[1 - \left(1 - \frac{1}{k} \right)^k \right] \geq \eta \left(1 - \frac{1}{e} \right)$$

Feature Selection

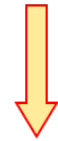
Random Variables $Y, X_1, \dots, X_n$

Predict Y from subset X_A

Maximize $I(X_A; Y)$
subject to $|A| \leq k$



X : Conditionally
Independent



Submodular

$$I(X_A; Y) := H(Y) - H(Y | X_A)$$

$$= H(X_A) - H(X_A | Y)$$

Krause & Guestrin (2005)

Submodular Welfare Problem

Utility Functions $f_1, \dots, f_k$

(Monotone, Submodular)

$$\text{Maximize} \quad \sum_{i=1}^k f(V_i)$$

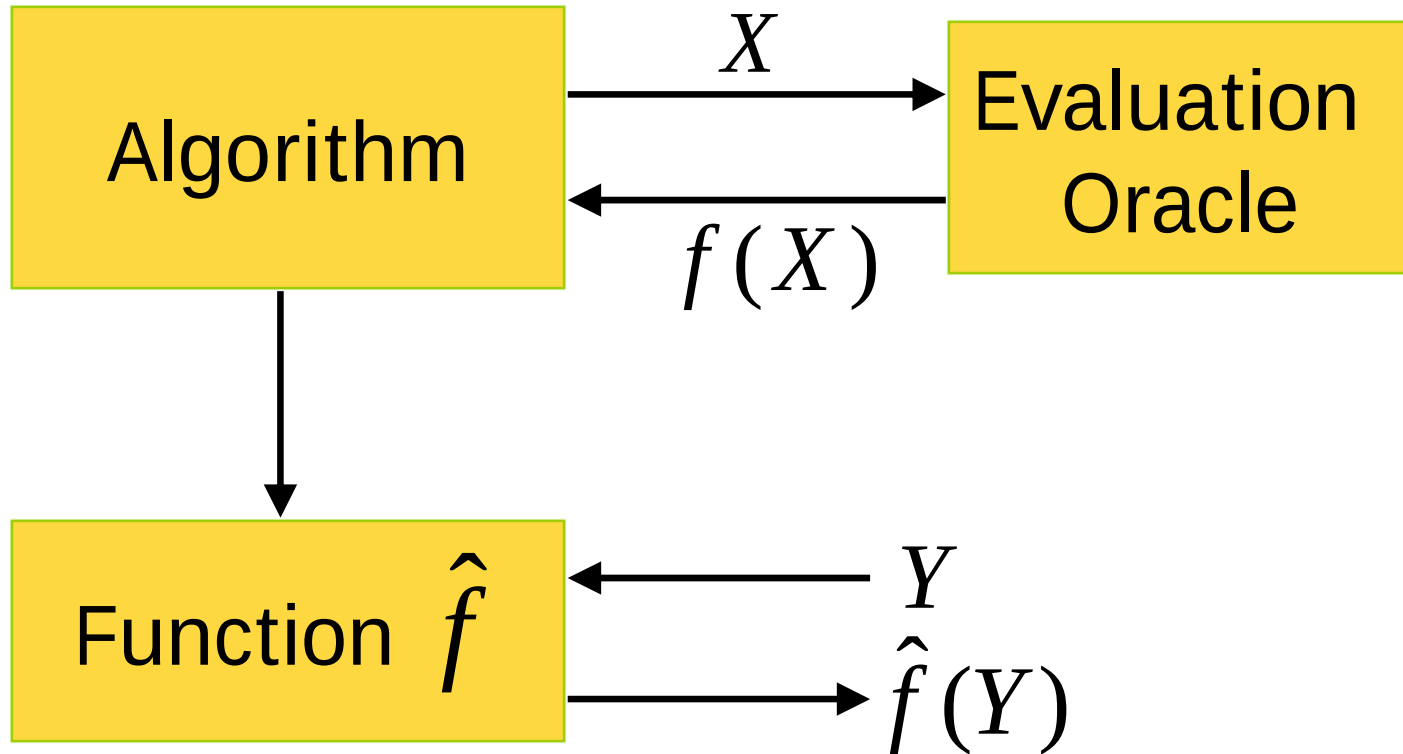
$$\text{subject to} \quad V = V_1 \cup \dots \cup V_k$$

$$V_i \cap V_j = \emptyset \quad (i \neq j)$$

$(1 - 1/e)$ -Approximation

Vondrák (2008)

Approximating Submodular Functions



Approximating Submodular Functions

Assumption $f(\emptyset) = 0$, $f(X) \geq 0$, $\forall X \subseteq V$.

Problem

Construct a set function $\hat{f}$ such that

$$\hat{f}(X) \leq f(X) \leq \alpha(n) \hat{f}(X), \quad \forall X \subseteq V.$$

For what function α is this possible?

Remarks

$\alpha(n) = 1$ for cut capacity functions

$\alpha(n) = n$ for general monotone
submodular functions

Approximating Submodular Functions

Goemans, Harvey, Iwata, Mirrokni (2009)

- Algorithm with $\alpha(n) = \sqrt{n+1}$ for matroid rank functions.
- Algorithm with $\alpha(n) = O(\sqrt{n} \log n)$ for monotone submodular functions.
- No polynomial algorithm can achieve a factor better than $\alpha(n) = \Omega(\sqrt{n}/\log n)$ even for matroid rank functions.

Submodular Load Balancing

Svitkina & Fleischer (2008)

$f_1, \dots, f_m$: Monotone Submodular Functions

$$\min_{\{V_1, \dots, V_m\}} \max_j f_j(V_j)?$$

$$f_j(X) := \sum_{v \in X} p_{jv} \longrightarrow \text{Scheduling}$$

2-Approximation Algorithm

Lenstra, Shmoys, Tardos (1990)

$O(\sqrt{n} \log n)$ -Approximation Algorithm

Pointers

- S. Fujishige: *Submodular Functions and Optimization*, Elsevier, 2005.
- ICML 2008 Tutorial Session
<http://www.submodularity.org>
- 永野清仁, 河原吉伸, 岡本吉央: 離散凸最適化手法による機械学習の諸問題へのアプローチ, 回路とシステム軽井沢ワークショップ, 2009.