

Submodular Function Minimization

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Outline

- Submodular Functions
 - Examples
 - Discrete Convexity
- Submodular Function Minimization
 - Min-Max Theorem
 - Combinatorial Algorithms
- Applications
- Approximation Algorithms
- Conclusion

Submodular Functions

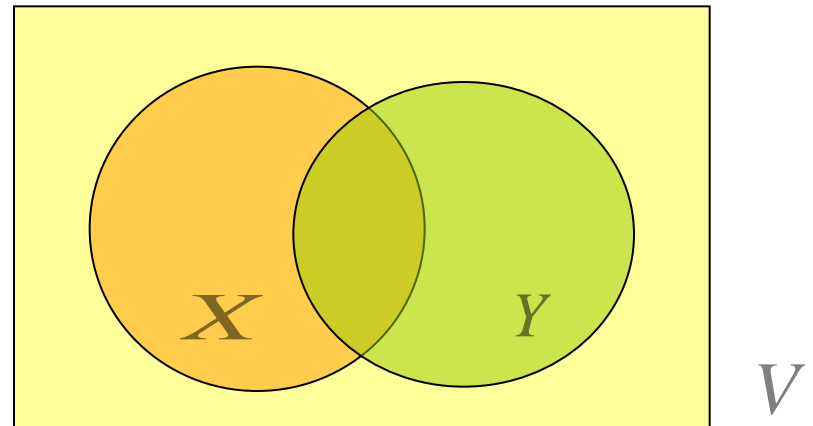
V : Finite Set

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

$\forall X, Y \subseteq V$

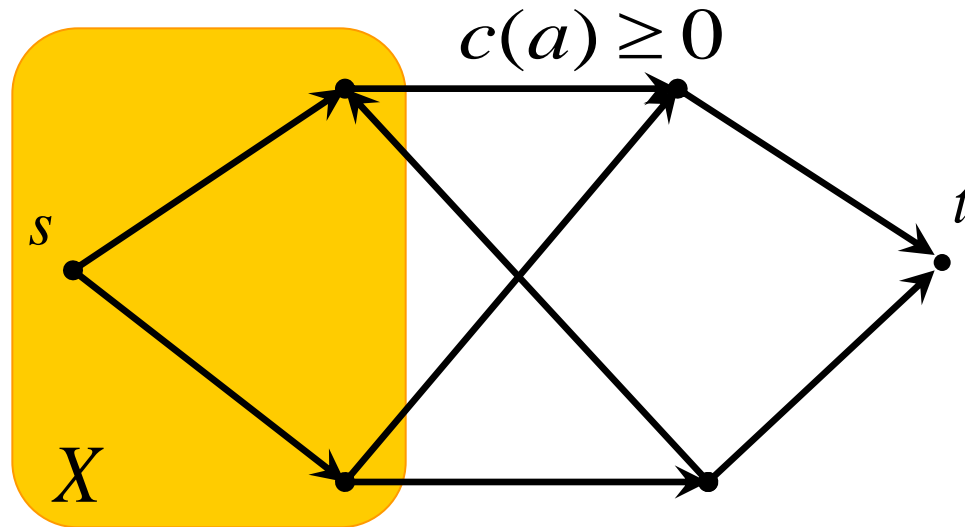
$$f(X) + f(Y) \geq f(X \cap Y) + f(X \cup Y)$$

- Cut Capacity Functions
- Matroid Rank Functions
- Entropy Functions



Cut Capacity Function

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



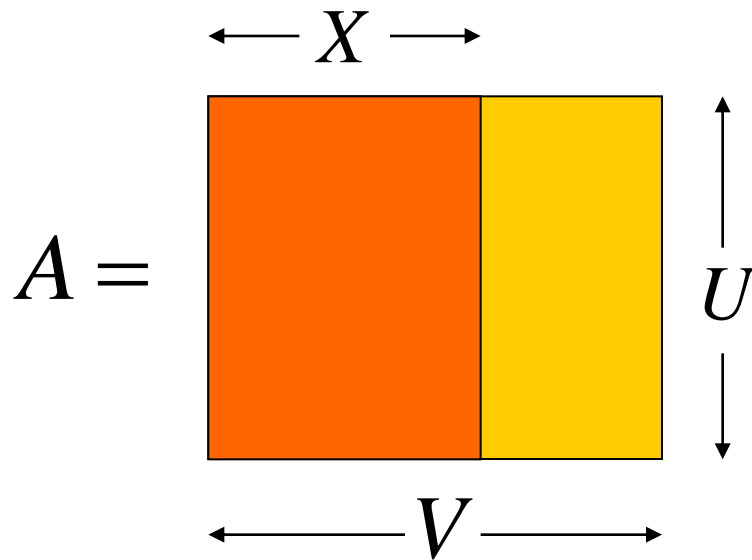
Max Flow Value = Min Cut Capacity

Matroid Rank Functions

Matrix Rank Function

Whitney (1935)

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



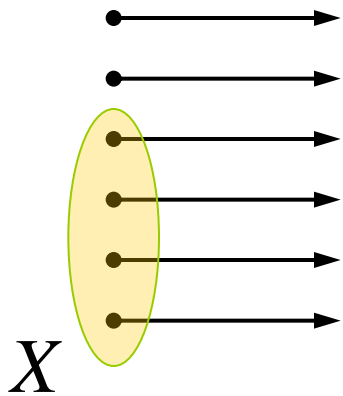
$$\forall X \subseteq V, \rho(X) \leq |X|$$

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

ρ : Submodular

Entropy Functions

Information Sources



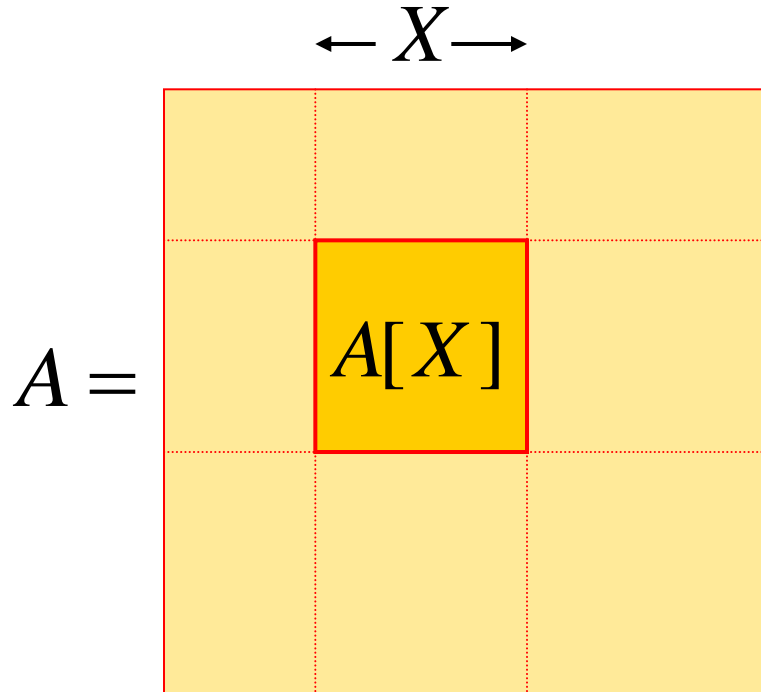
$$h(\phi) = 0$$

$h(X)$: 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



$$f(\phi) = 0$$

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

Ky Fan's Inequality

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

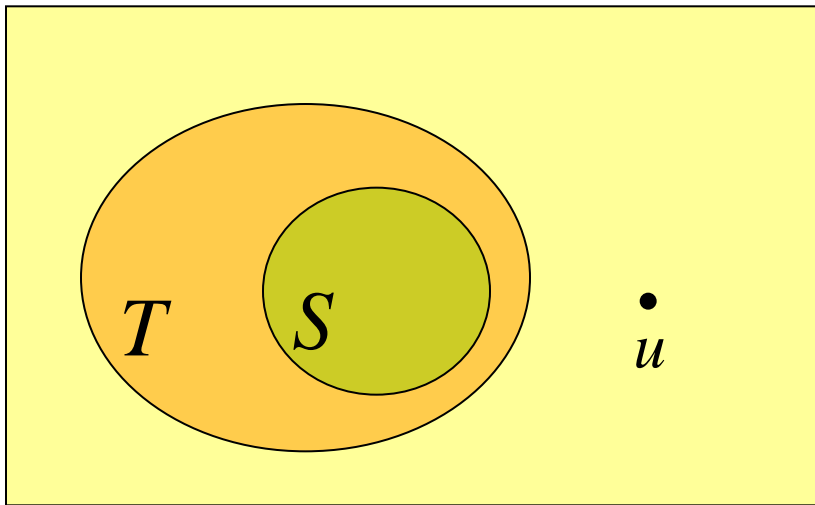
Extension of the Hadamard Inequality

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

Discrete Concavity

$$S \subseteq T \Rightarrow$$

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



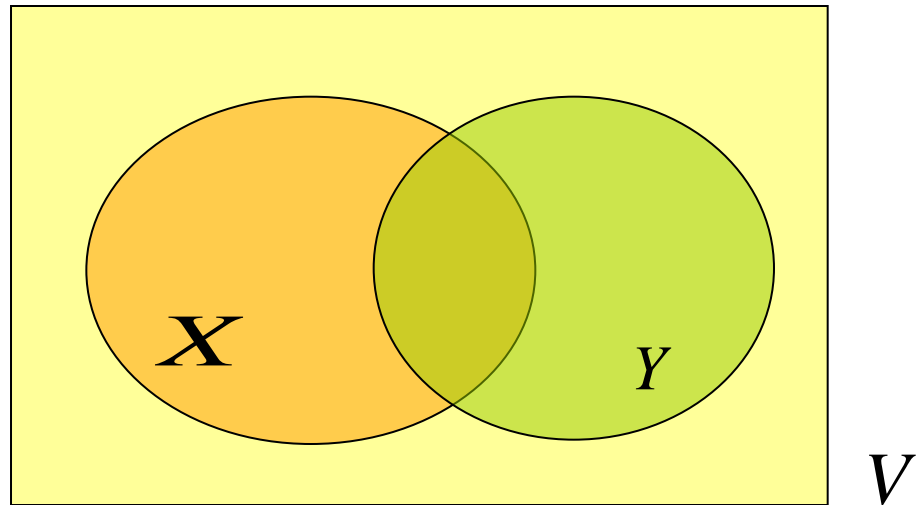
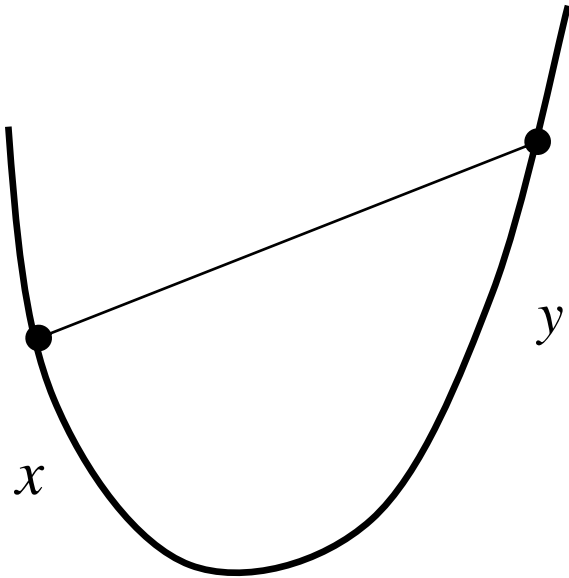
V

Diminishing Returns

Discrete Convexity

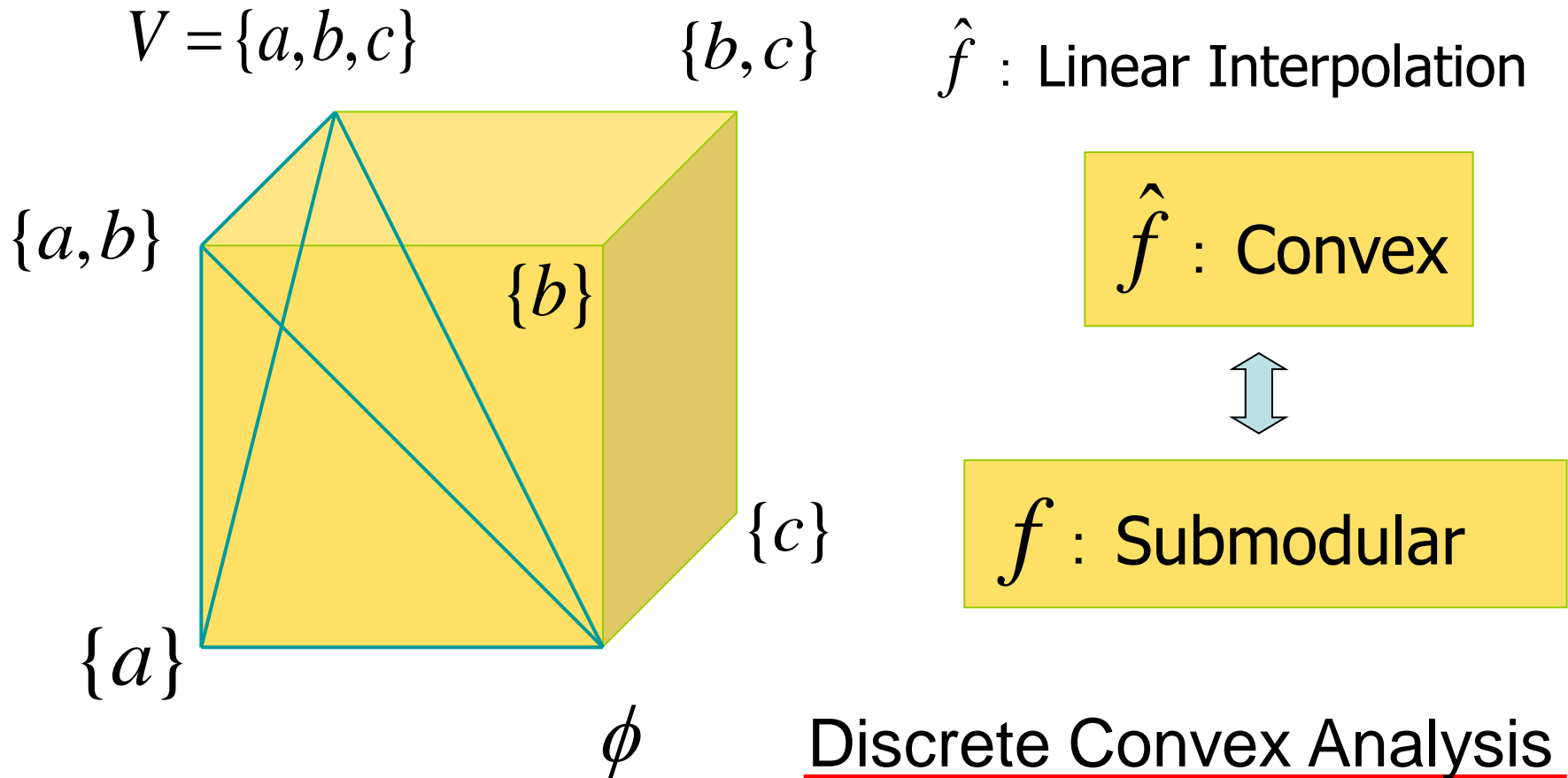
Convex Function

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



Discrete Convexity

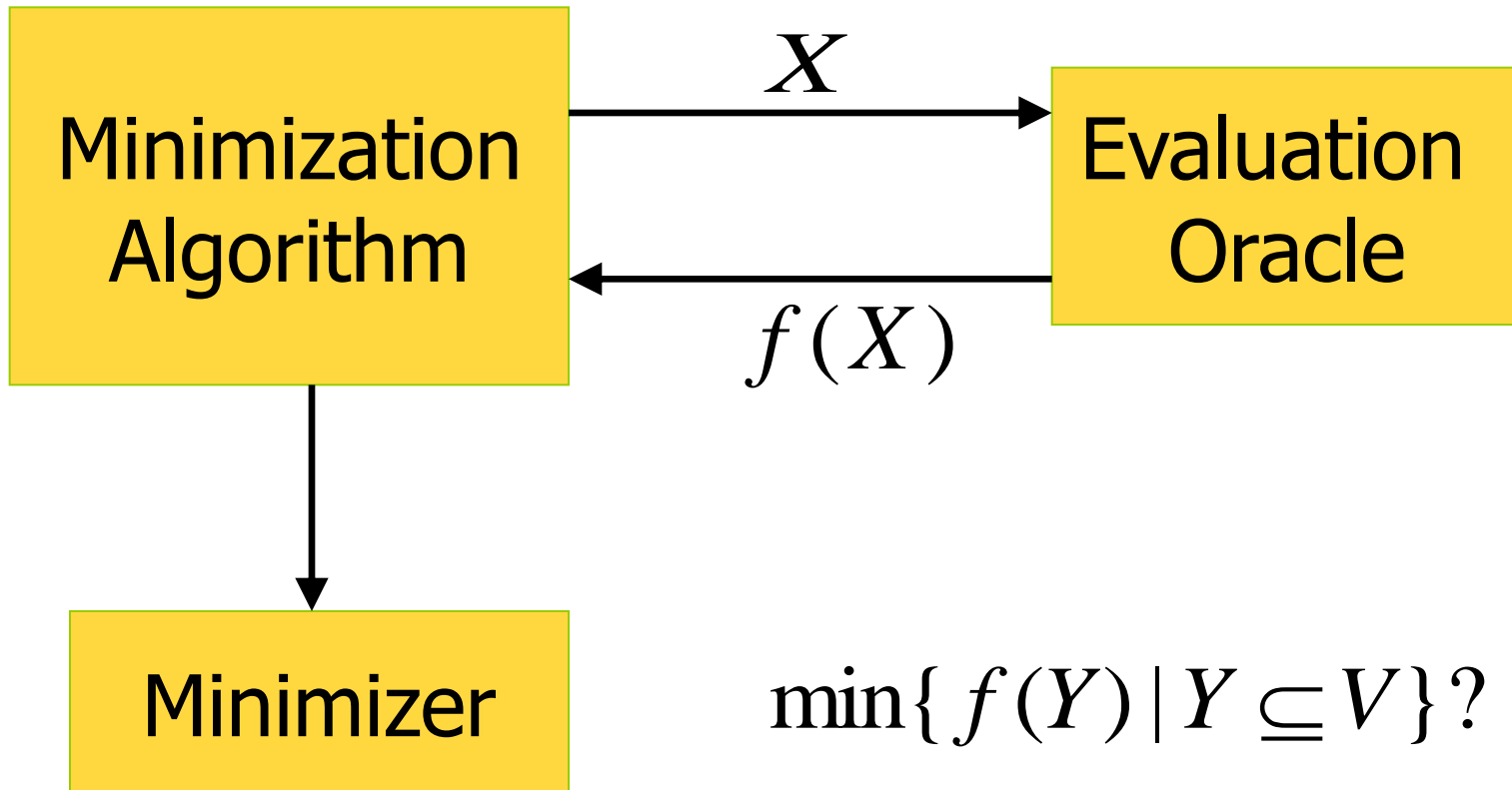
Lovász (1983)



Murota (2003)

Submodular Function Minimization

Assumption: $f(\emptyset) = 0$



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)

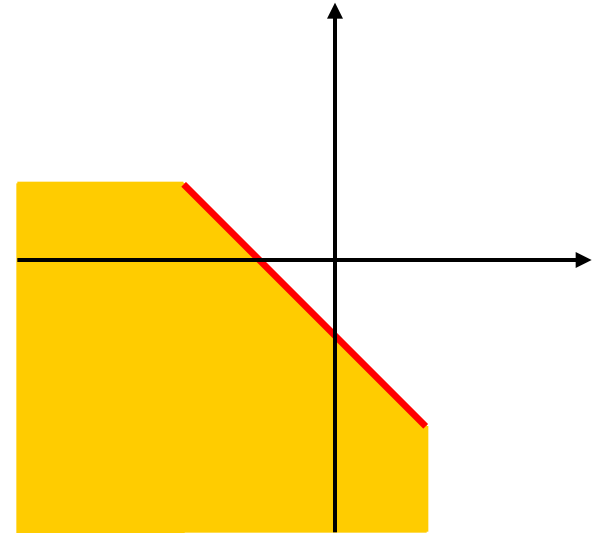
γ : Time for Function Evaluation

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

Base Polyhedra

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

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



Submodular Polyhedron

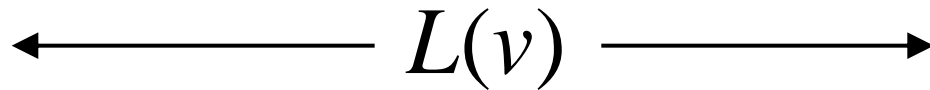
$$P(f) = \{x \mid x \in \mathbf{R}^V, \forall Y \subseteq V, x(Y) \leq f(Y)\}$$

Base Polyhedron

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

Greedy Algorithm

Edmonds (1970)
Shapley (1971)



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

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

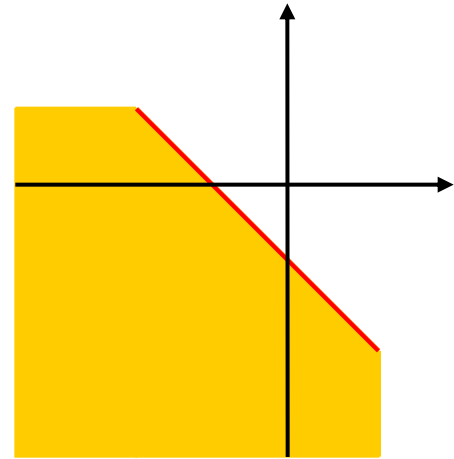
Theorem

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 $y_L \in B(f)$

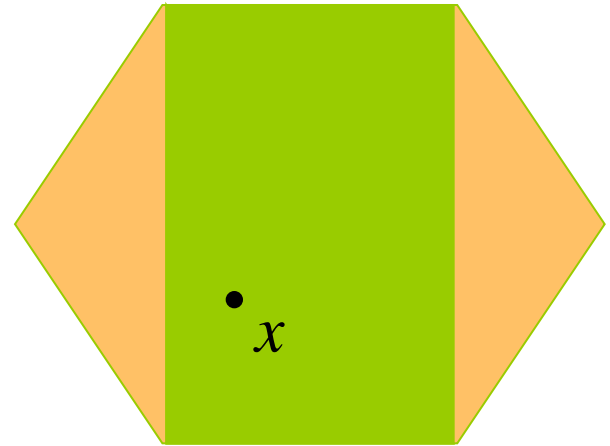
Convex Combination

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

Cunningham (1985)

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

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



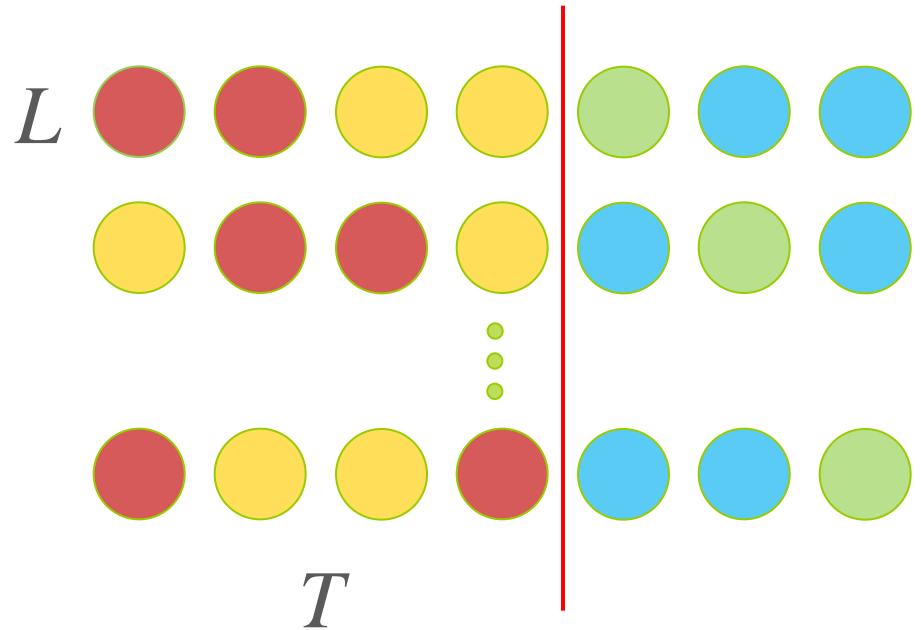
Combinatorial Approach

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

y_L : Extreme Base

$$x(v) \leq 0, \quad \forall v \in T$$

$$x(v) \geq 0, \quad \forall v \notin T$$



$$y_L(T) = f(T), \quad \forall L \in \Lambda. \quad \therefore x(T) = f(T).$$

$$\underline{x^-(V) = x(T) = f(T)}$$

→ T : Minimizer

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)

Iwata (2002)

Fleischer, Iwata (2000)

Fully Combinatorial

Iwata (2003)

Orlin (2007)

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

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

Iwata, Orlin (2009)

The Fujishige-Wolfe Algorithm

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

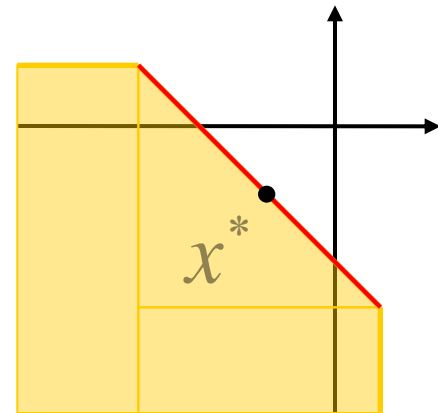
x^* : opt.sol.

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

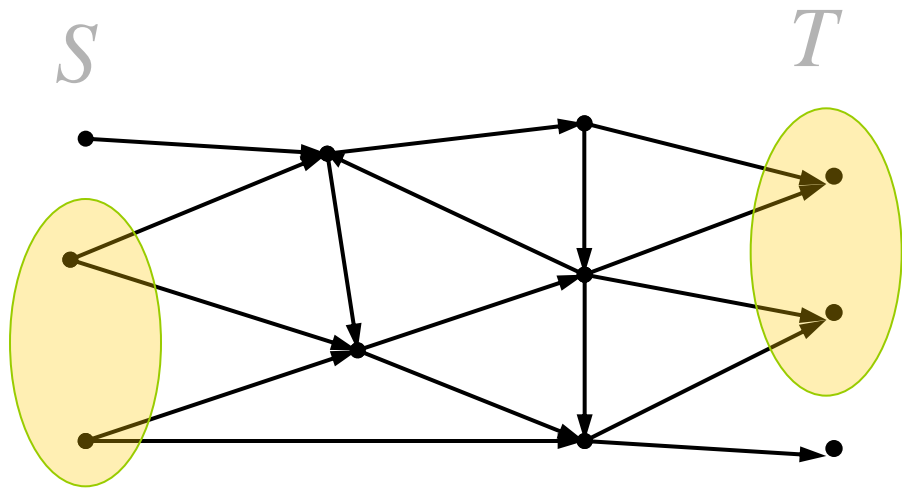
$T := \{v \mid x^*(v) \leq 0\} \longrightarrow$ Maximal Minimizer

$$f(S) = f(T) = \min_{X \subseteq V} f(X)$$

Fujishige (1984)



Evacuation Problem (Dynamic Flow)



Hoppe, Tardos (2000)

$c(a)$: Capacity

$\tau(a)$: Transit Time

$b(v)$: Supply/Demand

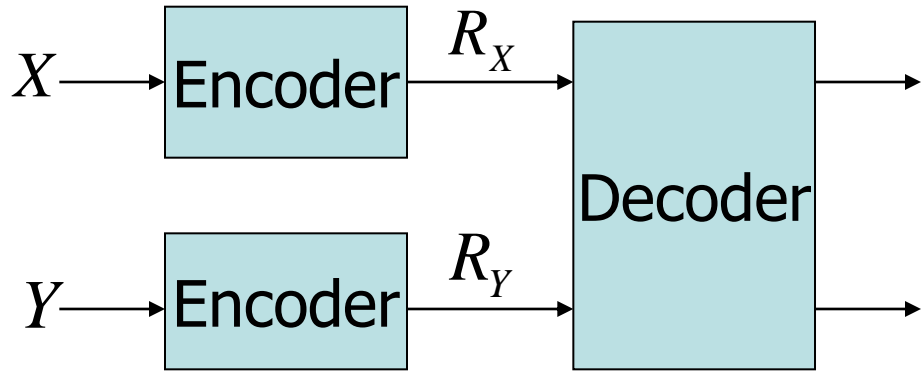
$o(X)$: Maximum Amount of Flow from $X \cap S$ to $T \setminus X$.

Feasible

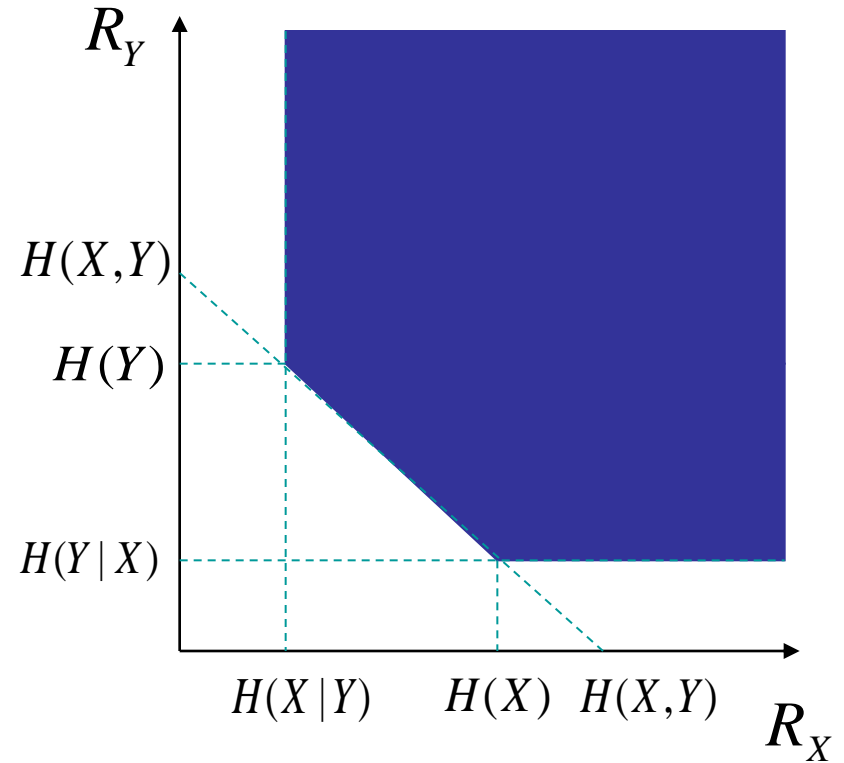


$$b(X) \leq o(X), \forall X \subseteq S \cup T$$

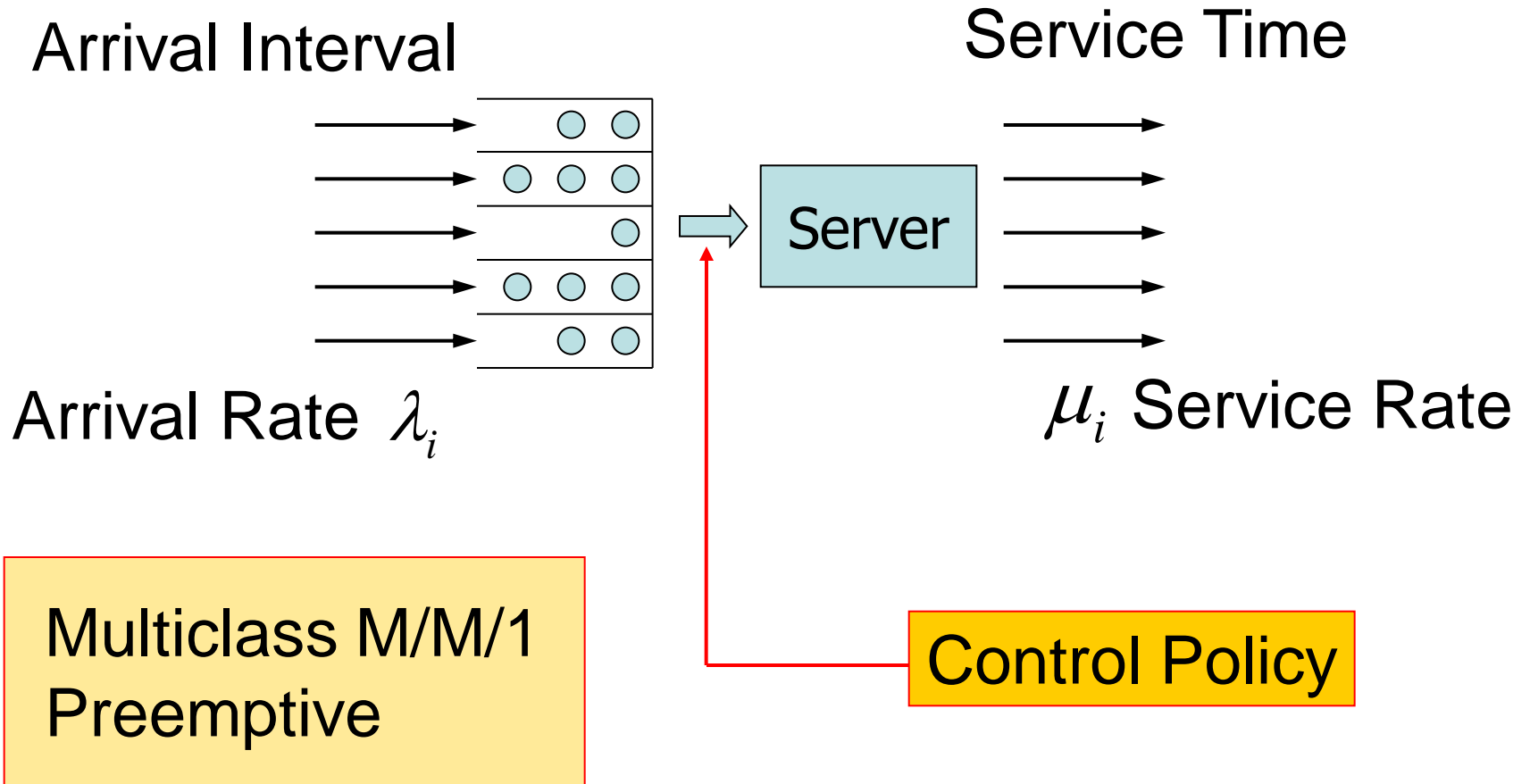
Multiterminal Source Coding



Slepian, Wolf (1973)



Multiclass Queueing Systems



Performance Region

S_j : Expected Staying Time of a Job in j

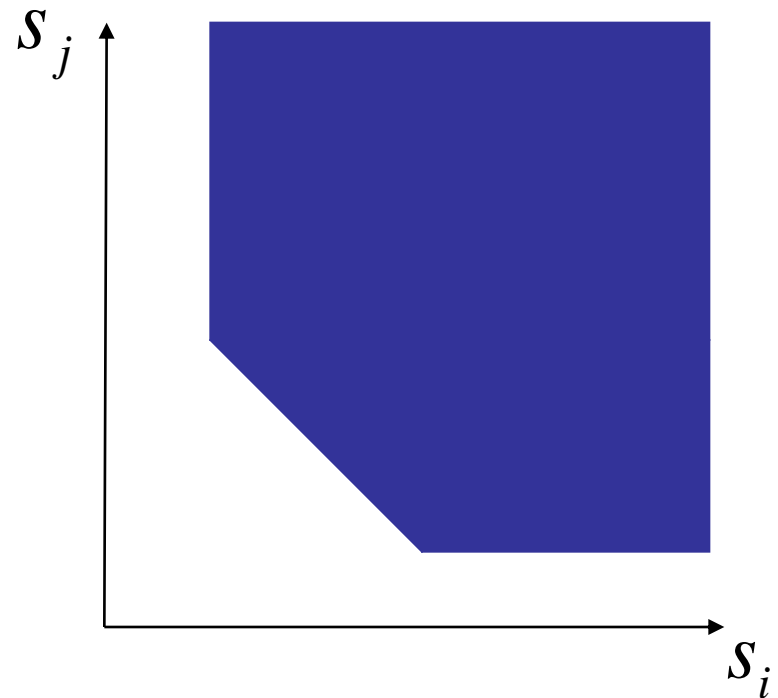
S : Achievable



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

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 (2007)

h : Nonnegative, Nondecreasing, Convex

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

Submodular

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

$$z_i := \rho_i S_i \quad y_i := \frac{\rho_i}{\mu_i}$$
$$x_i := \rho_i \quad h(x) := \frac{1}{1 - x}$$

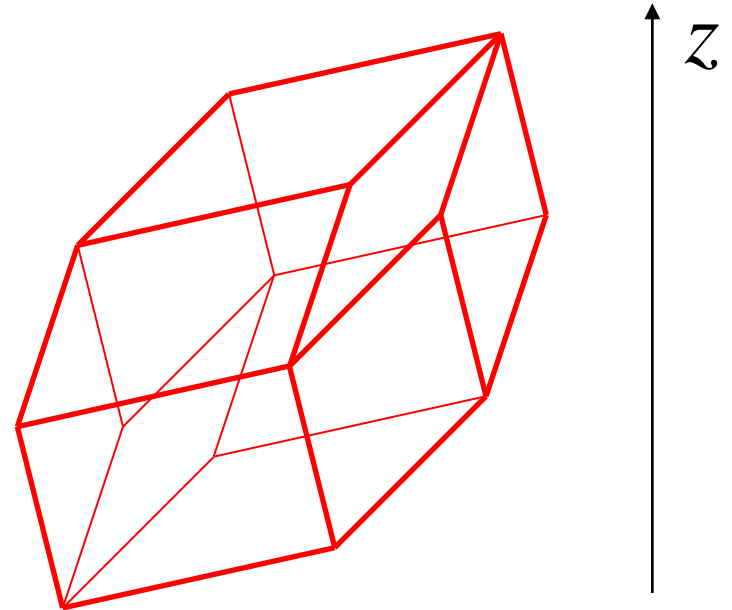
Zonotope in 3D

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

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

Zonotope

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

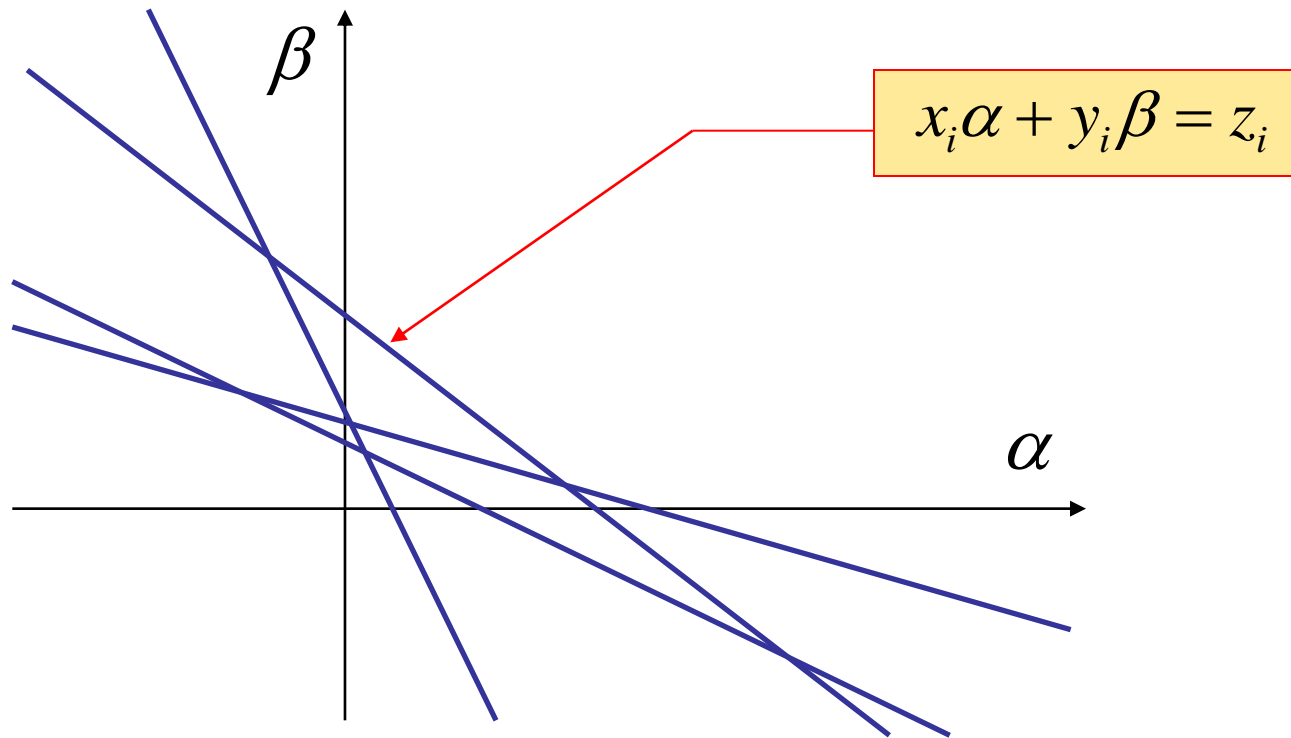


$$\min\{f(X) \mid X \subseteq V\}$$

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

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

Line Arrangement



Enumerating All the Cells

Topological Sweeping Method
Edelsbrunner, Guibas (1989)

→ $O(n^2)$

Questions

What Kind of Approximation Algorithms
Can Be Extended to Optimization Problems
with Submodular Cost or Constraints ?

Cf. Submodular Flow (Edmonds & Giles, 1977)

Svitkina & Fleischer (FOCS 2008)

Randomized Sampling / Lower Bounds

Submodular Load Balancing

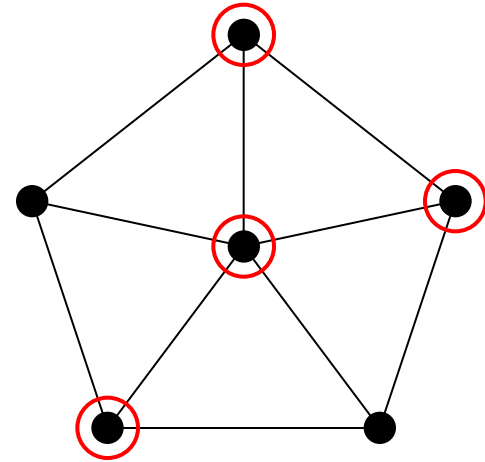
Submodular Sparsest Cut

Submodular Vertex Cover

Graph $G = (V, E)$

Submodular Function

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



Find a Vertex Cover $S \subseteq V$ Minimizing $f(S)$

2-Approximation Algorithm

Goel, Karande, Tripathi, Wang (FOCS 2009)

Iwata & Nagano (FOCS 2009)

Relaxation Problem

Convex Programming Relaxation (CPR)

Minimize $\hat{f}(x)$

subject to $x(u) + x(v) \geq 1 \quad (\forall e = (u, v) \in E)$

$x(v) \geq 0 \quad (\forall v \in V)$

CPR has a half-integral optimal solution.

→ 2-Approximation Algorithm

Submodular Cost Set Cover

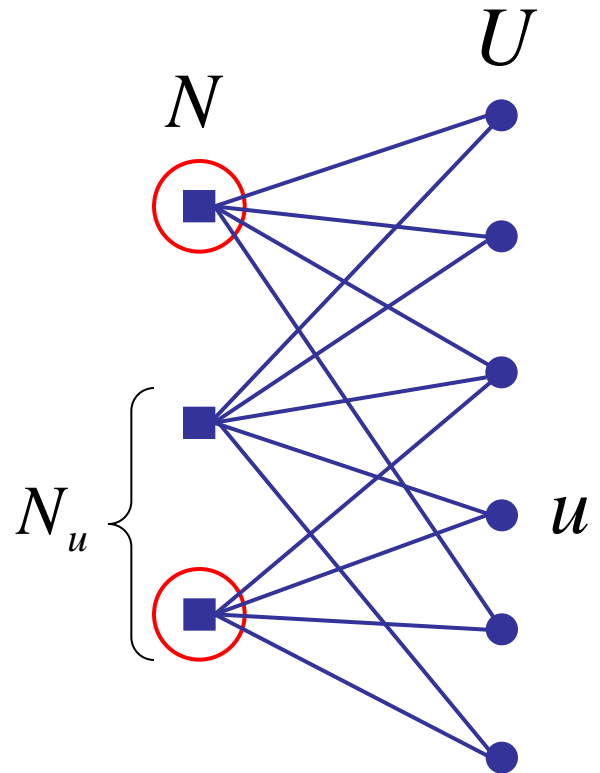
Find $X \subseteq N$ Covering U
with Minimum $f(X)$.

$$\eta := \max_{u \in U} |N_u|$$

η -Approximation

Rounding Algorithm

Primal-Dual Algorithm



Summary

- Submodular Functions Arise Everywhere.
- Discrete Analogue of Convexity.
- General SFM Algorithms Available.
- Exploit Special Structures of Problems.
- Approx. Algorithms for Constrained SFM.