EE595A – Submodular functions, their optimization and applications – Spring 2011

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Announcements

- Weekly Office Hours: Wednesdays, 12:30-1:30pm, 10 minutes after class on Wednesdays.

Scratch Paper

Scratch Paper

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Submodular Definitions

Definition (submodular)

A function $f : 2^V \to \mathbb{R}$ is submodular if for any $A, B \subseteq V$, we have that:

$$f(A) + f(B) \geq f(A \cup B) + f(A \cap B) \tag{1}$$

An alternate and equivalent definition is:

Definition (diminishing returns)

A function $f : 2^V \to \mathbb{R}$ is submodular if for any $A \subseteq B \subset V$, and $v \in V \setminus B$, we have that:

$$f(A \cup \{v\}) - f(A) \geq f(B \cup \{v\}) - f(B) \tag{2}$$

This means that the incremental "value", "gain", or "cost" of v decreases (diminishes) as the context in which v is considered grows from A to B.

Ground set: E or V?

Submodular functions are functions defined on subsets of some finite set, called the ground set .

- It is common in the literature to use either E or V as the ground set.

Ground set: E or V?

Submodular functions are functions defined on subsets of some finite set, called the ground set .

- It is common in the literature to use either E or V as the ground set.
- We will follow this inconsistency in the literature and will inconsistently use either E or V as our ground set (hopefully not in the same equation, if so, please point this out).

Notation $\mathbb{R}^E$

$$\mathbb{R}^E = \{x = (x_j \in \mathbb{R} : j \in E)\} \tag{3}$$

$$\mathbb{R}^E_+ = \{x = (x_j : j \in E) : x \geq 0\} \tag{4}$$

Any vector $x \in \mathbb{R}^E$ can be treated as a normalized modular function, and vice versa. That is

$$x(A) = \sum_{a \in A} x_a \tag{5}$$

Note that x is said to be normalized since $x(\emptyset) = 0$.

Other Notation: indicator vectors of sets

Given an $A \subseteq E$, define the vector $\mathbf{1}_A \in \mathbb{R}_+^E$ to be

$$\mathbf{1}_A(j) = \begin{cases} 1 & \text{if } j \in A; \\ 0 & \text{if } j \notin A \end{cases} \tag{6}$$

Sometimes this will be written as $\chi_A \equiv \mathbf{1}_A$.

Other Notation: indicator vectors of sets

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$$\mathbf{1}_A(j) = \begin{cases} 1 & \text{if } j \in A; \\ 0 & \text{if } j \notin A \end{cases} \tag{6}$$

Sometimes this will be written as $\chi_A \equiv \mathbf{1}_A$.
Thus, given modular function $x \in \mathbb{R}^E$, we can write $x(A)$ in a variety of ways, i.e.,

$$x(A) = x \cdot \mathbf{1}_A = \sum_{i \in A} x(i) \tag{7}$$

Other Notation: singletons and sets

When A is a set and k is a singleton (i.e., a single item), the union is properly written as $A \cup \{k\}$, but sometimes I will write just $A + k$.

Summing Submodular Functions

Given E, let $f_1, f_2 : 2^E \to \mathbb{R}$ be two submodular functions. Then

$$f : 2^E \to \mathbb{R} \text{ with } f(A) = f_1(A) + f_2(A) \tag{8}$$

is submodular. This follows easily since

$$\begin{aligned} f(A) + f(B) &= f_1(A) + f_2(A) + f_1(B) + f_2(B) && (9)\\ &\geq f_1(A \cup B) + f_2(A \cup B) + f_1(A \cap B) + f_2(A \cap B) && (10)\\ &= f(A \cup B) + f(A \cap B). && (11) \end{aligned}$$

I.e., it holds for each component of f in each term in the inequality. In fact, any conic combination (i.e., non-negative linear combination) of submodular functions is submodular, as in $f(A) = \alpha_1 f_1(A) + \alpha_2 f_2(A)$ for $\alpha_1, \alpha_2 \geq 0$.

Summing Submodular and Modular Functions

Given E, let $f_1, m : 2^E \to \mathbb{R}$ be a submodular and a modular function. Then

$$f : 2^E \to \mathbb{R} \text{ with } f(A) = f_1(A) - m(A) \tag{12}$$

is submodular (as is $f(A) = f_1(A) + m(A)$). This follows easily since

$$\begin{aligned} f(A) + f(B) &= f_1(A) - m(A) + f_1(B) - m(B) & (13)\\ &\geq f_1(A \cup B) - m(A \cup B) + f_1(A \cap B) - m(A \cap B) & (14)\\ &= f(A \cup B) + f(A \cap B). & (15) \end{aligned}$$

That is, the modular component with $m(A) + m(B) = m(A \cup B) + m(A \cap B)$ never destroys the inequality. Note of course that if m is modular than so is $-m$.

Restricting Submodular Functions

Given E, let $f : 2^E \to \mathbb{R}$ be a submodular functions. And let $S \subseteq E$ be an arbitrary fixed set. then

$$f' : 2^E \to \mathbb{R} \text{ with } f(A) = f(A \cap S) \tag{16}$$

is submodular.

Proof.

Given $A \subseteq B \subseteq E \setminus v$, consider

$$f((A+v) \cap S) - f(A \cap S) \geq f((B+v) \cap S) - f(B \cap S) \tag{17}$$

If $v \notin S$, then both differences on each size are zero. If $v \in S$, then we can consider this

$$f(A'+v) - f(A') \geq f(B'+v) - f(B') \tag{18}$$

with $A' = A \cap S$ and $B' = B \cap S$. Since $A' \subseteq B'$, this holds due to submodularity of f. $\square$

Summing Restricted Submodular Functions

Given V, let $f_1, f_2 : 2^V \to \mathbb{R}$ be two submodular functions and let S_1, S_2 be two arbitrary fixed sets. Then

$$f : 2^V \to \mathbb{R} \text{ with } f(A) = f_1(A \cap S_1) + f_2(A \cap S_2) \tag{19}$$

is submodular. This follows easily from the preceding two results.

Summing Restricted Submodular Functions

Given V, let $\mathcal{C} = \{C_1, C_2, \dots, C_k\}$ be a set of subsets of V, and for each $C \in \mathcal{C}$, let $f_C : 2^V \to \mathbb{R}$ be a submodular function. Then

$$f : 2^V \to \mathbb{R} \text{ with } f(A) = \sum_{C \in \mathcal{C}} f_C(A \cap C) \tag{19}$$

is submodular. This property is critical for image processing and graphical models. For example, let $\mathcal{C}$ be all pairs of the form $\{\{u, v\} : u, v \in V\}$, or let it be all pairs corresponding to the edges of some undirected graphical model. We plan to revisit this topic later in the term.

Max - normalized

Given V, let $c \in \mathbb{R}_+^V$ be a given fixed vector. Then $f : 2^V \to \mathbb{R}_+$, where

$$f(A) = \max_{j \in A} c_j \tag{20}$$

is submodular and normalized (we take $f(\emptyset) = 0$).

Proof.

Consider

$$\max_{j \in A} c_j + \max_{j \in B} c_j \geq \max_{j \in A \cup B} c_j + \max_{j \in A \cap B} c_j \tag{21}$$

which follows since we have that

$$\max(\max_{j \in A} c_j, \max_{j \in B} c_j) = \max_{j \in A \cup B} c_j \tag{22}$$

and

$$\min(\max_{j \in A} c_j, \max_{j \in B} c_j) \geq \max_{j \in A \cap B} c_j \tag{23}$$

$\square$

Max

Given V, let $c \in \mathbb{R}^V$ be a given fixed vector (not necessarily non-negative). Then $f : 2^V \to \mathbb{R}$, where

$$f(A) = \max_{j \in A} c_j \tag{24}$$

is submodular, where we take $f(\emptyset) \leq \min_j c_j$ (so the function is not normalized).

Proof.

The proof is identical to the normalized case. □

Facility Location

Given V, E, let $c \in \mathbb{R}^{V \times E}$ be a given $|V| \times |E|$ matrix. Then

$$f : 2^E \to \mathbb{R}, \text{ where } f(A) = \sum_{i \in V} \max_{j \in A} c_{ij} \tag{25}$$

is submodular. This is a facility location function.

Proof.

We can write $f(A)$ as $f(A) = \sum_{i \in V} f_i(A)$ where $f_i(A) = \max_{j \in A} c_{ij}$ is submodular (max of a i^{th} row vector), so f can be written as a sum of submodular functions. □

Facility/Plant Location (uncapacitated)

- Facility Location is a core problem in operations research and a strong motivation for submodular functions. Key goal is to place "facilities" to supply demand sites as efficiently as possible.
- Let E be a set of possible factory/plant locations, and V is a set of sites needing to be serviced (e.g., cities).
- Let c_{ij} be the "benefit" (e.g., $1/c_{ij}$ is the cost) of servicing city i with plant j.
- Let $m : 2^E \to \mathbb{R}_+^E$ be a plant construction modular function (vector). E.g., $1/m_j$ is the cost to build a plant at location j.
- Each city needs to be serviced by only one plant but no less than one.
- Define $f(A)$ as the "delivery benefit" plus "construction benefit" when the plants in set A are considered to be constructed.
- We can define $f(A) = m(A) + \sum_{i \in V} \max_{j \in A} c_{ij}$.
- Goal is to find a set A that maximizes $f(A)$ (the benefit) placing a bound on the number of plants A (e.g., $|A| \leq k$).

Log Determinant

Let $\mathbf{\Sigma}$ be an $n \times n$ positive definite matrix. Let $V = \{1, 2, \ldots, n\} \equiv [n]$ be an index set, and for $A \subseteq V$, let $\mathbf{\Sigma}_A$ be the (square) submatrix of $\mathbf{\Sigma}$ obtained by including only entries in the rows/columns given by A. Then:

$$f(A) = \log\det(\mathbf{\Sigma}_A) \text{ is submodular.} \tag{26}$$

Proof.

Suppose $x \in \mathbf{R}^n$ is multivariate Gaussian, that is

$$x \in p(x) = \frac{1}{\sqrt{|2\pi\mathbf{\Sigma}|}} \exp\left(-\frac{1}{2}(x-\mu)^T\mathbf{\Sigma}^{-1}(x-\mu)\right) \tag{27}$$

...

Log Determinant

$$f(A) = \log\det(\mathbf{\Sigma}_A) \text{ is submodular.} \tag{26}$$

...cont.

Then the (differential) entropy of the r.v. X is given by

$$h(X) = \log \sqrt{|2\pi e \mathbf{\Sigma}|} = \log \sqrt{(2\pi e)^n |\mathbf{\Sigma}|} \tag{27}$$

and in particular, for a variable subset A,

$$f(A) = h(X_A) = \log \sqrt{(2\pi e)^{|A|} |\mathbf{\Sigma}_A|} \tag{28}$$

Entropy is submodular (conditioning reduces entropy), and moreover

$$f(A) = h(X_A) = m(A) + \frac{1}{2} \log |\mathbf{\Sigma}_A| \tag{29}$$

where $m(A)$ is a modular function. $\square$

Concave over non-negative modular

Let $m \in \mathbb{R}_+^E$ be a modular function, and g a concave function over $\mathbb{R}$. Define $f : 2^E \to \mathbb{R}$ as

Proof.

$$f(A) = g(m(A))$$

□

then f is submodular.

Proof.

Given $A \subseteq B \subseteq E \setminus v$, we have $0 \leq a = m(A) \leq b = m(B)$, and $0 \leq c = m(v)$. For g concave, we have $g(a+c) - g(a) \geq g(b+c) - g(b)$, and thus

$$g(m(A) + m(v)) - g(m(A)) \geq g(m(B) + m(v)) - g(m(B)) \qquad (30)$$

□

The converse is true as well. Exercise: prove this.

Monotone difference of two functions

Let f and G both be submodular functions on subsets of V and let $(f - g)(\cdot)$ be either monotone increasing or monotone decreasing. Then $h : 2^V \to R$ defined by

$$h(A) = \min(f(A), g(A)) \tag{31}$$

is submodular.

Proof.

If $h(A)$ agrees with either f or g on both X and Y, the result follows since

$$\begin{matrix} f(X) + f(Y) \\ g(X) + g(Y) \end{matrix} \geq \min(f(X \cup Y), g(X \cup Y)) + \min(f(X \cap Y), g(X \cap Y)) \tag{32}$$

...

Monotone difference of two functions

Let f and G both be submodular functions on subsets of V and let $(f - g)(\cdot)$ be either monotone increasing or monotone decreasing. Then $h : 2^V \to R$ defined by

$$h(A) = \min(f(A), g(A)) \tag{31}$$

is submodular.

...cont.

Otherwise, w.l.o.g., $h(X) = f(X)$ and $h(Y) = g(Y)$, giving

$$h(X) + h(Y) = f(X) + g(Y) \geq f(X \cup Y) + f(X \cap Y) + g(Y) - f(Y) \tag{32}$$

By monotonicity, $f(X \cup Y) + g(Y) - f(Y) \geq g(X \cup Y)$ giving

$$h(X) + h(Y) \geq g(X \cup Y) + f(X \cap Y) \geq h(X \cup Y) + h(X \cap Y) \tag{33}$$

□

Min

Let $f : 2^V \to \mathbb{R}$ be an increasing or decreasing submodular function and let k be a constant. Then the function $h : 2^V \to \mathbb{R}$ defined by

$$h(A) = \min(k, f(A)) \tag{34}$$

is submodular.

Proof.

For constant k, we have that $(f - k)$ is increasing (or decreasing) so this follows from the previous result.
Note also, $g(a) = \min(k, a)$ for constant k is a concave function, so we can use the earlier result about composing a concave function with a submodular function to get this result as well. $\square$

More on Min - saturate trick

In general, the minimum of two submodular functions is not submodular. However, when wishing to maximize two monotone non-decreasing submodular functions, we can define function $h : 2^V \to \mathbb{R}$ as

$$h(A) = \frac{1}{2}(\min(k, f) + \min(k, g)) \tag{35}$$

then h is submodular, and $h(A) \geq k$ if and only if both $f(A) \geq k$ and $g(A) \geq k$.
We plan to revisit this again later in the quarter.

Arbitrary functions as difference between submodulars

Given an arbitrary set function f, it can be expressed as a difference between two submodular functions: $f = g - h$ where both g and h are submodular.

Define

Proof.

Let f be given and arbitrary.

$$\alpha \triangleq \min_{X,Y} f(X) + f(Y) - f(X \cup Y) - f(X \cap Y) \tag{36}$$

If $\alpha \geq 0$ then f is submodular, so by assumption $\alpha < 0$. Now let h be an arbitrary strict submodular function and define

$$\beta \triangleq \min_{X,Y} h(X) + h(Y) - h(X \cup Y) - h(X \cap Y) \tag{37}$$

Strict means $\beta > 0$. . . .

Arbitrary functions as difference between submodulars

Given an arbitrary set function f, it can be expressed as a difference between two submodular functions: $f = g - h$ where both g and h are submodular.

...cont.

Define $f' : 2^V \to \mathbb{R}$ as

$$f'(A) = f(A) + \frac{|\alpha|}{\beta} h(A) \tag{36}$$

Then f' is submodular, and $f = f'(A) - \frac{|\alpha|}{\beta} h(A)$, a difference between two submodular functions as desired. □

Submodular Definitions

Definition (submodular)

A function $f : 2^V \to \mathbb{R}$ is submodular if for any $A, B \subseteq V$, we have that:

$$f(A) + f(B) \geq f(A \cup B) + f(A \cap B) \tag{1}$$

An alternate and equivalent definition is:

Definition (diminishing returns)

A function $f : 2^V \to \mathbb{R}$ is submodular if for any $A \subseteq B \subset V$, and $v \in V \setminus B$, we have that:

$$f(A \cup \{v\}) - f(A) \geq f(B \cup \{v\}) - f(B) \tag{2}$$

This means that the incremental "value", "gain", or "cost" of v decreases (diminishes) as the context in which v is considered grows from A to B.

Submodular Definitions

An alternate and equivalent definition is:

Definition (group diminishing returns)

A function $f : 2^V \to \mathbb{R}$ is submodular if for any $A \subseteq B \subset V$, and $C \subseteq V \setminus B$, we have that:

$$f(A \cup C) - f(A) \geq f(B \cup C) - f(B) \tag{37}$$

This means that the incremental "value" or "gain" of set C decreases as the context in which v is considered grows from A to B (diminishing returns)

Submodular Definitions

Proposition

group diminishing returns implies diminishing returns

Proof.

Obvious, set $C = \{v\}$. $\square$

Submodular Definitions

Proposition

diminishing returns implies *group diminishing returns*

Proof.

Let $C = \{c_1, c_2, \ldots, c_k\}$. Then diminishing returns implies

$$f(A \cup C) - f(A) \tag{38}$$

$$= f(A \cup C) - \sum_{i=1}^{k-1} \Big(f(A \cup \{c_1, \ldots, c_i\}) - f(A \cup \{c_1, \ldots, c_i\}) \Big) - f(A) \tag{39}$$

$$= \sum_{i=1}^{k} f(A \cup \{c_1 \ldots c_i\}) - f(A \cup \{c_1 \ldots c_{i-1}\}) \tag{40}$$

$$\geq \sum_{i=1}^{k} f(B \cup \{c_1 \ldots c_i\}) - f(B \cup \{c_1 \ldots c_{i-1}\}) \tag{41}$$

$$= f(B \cup C) - \sum_{i=1}^{k-1} \Big(f(B \cup \{c_1, \ldots, c_i\}) - f(B \cup \{c_1, \ldots, c_i\}) \Big) - f(B) \tag{42}$$

$$= f(B \cup C) - f(B) \tag{43}$$

Submodular Definitions are equivalent

Proposition

The two aforementioned definitions of submodularity submodular and diminishing returns are identical.

Submodular Definitions are equivalent

Proof.

Assume submodular. Assume $A \subset B$ as otherwise trivial.
Let $B \setminus A = \{v_1, v_2, \ldots, v_k\}$ and define $A^i = A \cup \{v_1 \ldots v_i\}$, so $A^0 = A$.
Then by submodular,

$$f(A^i + v) + f(A^i + v_{i+1}) \geq f(A^i + v + v_{i+1}) + f(A^i) \tag{44}$$

or

$$f(A^i + v) - f(A^i) \geq f(A^i + v_{i+1} + v) - f(A^i + v_{i+1}) \tag{45}$$

we apply this inductively, and use

$$f(A^{i+1} + v) - f(A^{i+1}) = f(A^i + v_{i+1} + v) - f(A^i + v_{i+1}) \tag{46}$$

and that $A^{k-1} + v_k = B$. . . .

Submodular Definitions are equivalent

...cont.

Assume group diminishing returns. Assume $A \neq B$ otherwise trivial. Define $A' = A \cap B$, $C = A \setminus B$, and $B' = B$. Then

$$f(A' + C) - f(A') \geq f(B' + C) - f(B') \tag{47}$$

giving

$$f(A' + C) + f(B') \geq f(B' + C) + f(A') \tag{48}$$

or

$$f(A \cap B + A \setminus B) + f(B) \geq f(B + A \setminus B) + f(A \cap B) \tag{49}$$

which is the same as

$$f(A) + f(B) \geq f(A \cup B) + f(A \cap B) \tag{50}$$

Submodular Definitions

Definition (singleton)

A function $f : 2^V \to \mathbb{R}$ is submodular if for any $A \subset V$, and any $a, b \in V \setminus A$, we have that:

$$f(A \cup \{a\}) + f(A \cup \{b\}) \geq f(A \cup \{a, b\}) + f(A) \tag{51}$$

This follows immediately from diminishing returns. To achieve diminishing returns, assume $A \subset B$ with $B \setminus A = \{b_1, b_2, \ldots, b_k\}$. Then

$$\begin{aligned}
f(A + a) - f(A) &\geq f(A + b_1 + a) - f(A + b_1) && (52)\\
&\geq f(A + b_1 + b_2 + a) - f(A + b_1 + b_2) && (53)\\
&\geq \ldots && (54)\\
&\geq f(A + b_1 + \cdots + b_k + a) - f(A + b_1 + \cdots + b_k) && (55)\\
&= f(B + a) - f(B) && (56)
\end{aligned}$$

Gain

It is often the case that we wish to express the gain of an item $j \in V$ in some context, say A, namely $f(A \cup \{j\}) - f(A)$. This is used so often, that there are equally as many ways to notate this. I.e.,

$$f(A \cup \{j\}) - f(A) \triangleq \rho_j(A) \tag{57}$$

$$\triangleq \rho_A(j) \tag{58}$$

$$\triangleq f(\{j\}|A) \tag{59}$$

$$\triangleq f(j|A) \tag{60}$$

We'll use either $\rho_j(A)$ or $f(j|A)$. Note, diminishing returns can now be stated as saying that $\rho_j(A)$ is a monotone non-increasing function of A, since $\rho_j(A) \geq \rho_j(B)$ whenever $B \supseteq A$.

Equivalent Definitions of Submodularity

$$f(A) + f(B) \geq f(A \cup B) + f(A \cap B), \quad \forall A, B \subseteq E \tag{61}$$

$$\rho_j(S) \geq \rho_j(T), \ \forall S \subseteq T \subseteq E, \ \text{with } j \in E \setminus T \tag{62}$$

$$\rho_j(S) \geq \rho_j(S \cup \{k\}), \ \forall S \subseteq E \text{ with } j \in E \setminus (S \cup \{k\}) \tag{63}$$

$$f(T) \leq f(S) + \sum_{j \in T \setminus S} \rho_j(S) - \sum_{j \in S \setminus T} \rho_j(S \cup T - \{j\}), \ \forall S, T \subseteq E \tag{64}$$

$$f(T) \leq f(S) + \sum_{j \in T \setminus S} \rho_j(S), \ \forall S \subseteq T \subseteq E \tag{65}$$

$$f(T) \leq f(S) + \sum_{j \in S \setminus T} \rho_j(S \setminus \{j\}), \ \forall T \subseteq S \subseteq E \tag{66}$$

$$f(T) \leq f(S) - \sum_{j \in S \setminus T} \rho_j(S \setminus \{j\}) + \sum_{\in T \setminus S} \rho_j(S \cap T) \ \forall S, T \subseteq E \tag{67}$$

Equivalent Definitions of Submodularity

We've already seen that Eq. 61 $\equiv$ Eq. 62 $\equiv$ Eq. 63. We next show that Eq. 63 $\Rightarrow$ Eq. 64 $\Rightarrow$ Eq. 65 $\Rightarrow$ Eq. 63.

Eq. 63 $\Rightarrow$ Eq. 64

Let $T \setminus S = \{j_1, \ldots, j_r\}$ and $S \setminus T = \{k_1, \ldots, k_q\}$.
First, we upper bound the gain of T in the context of S:

$$f(S \cup T) - f(S) = \sum_{t=1}^{r} \Big(f(S \cup \{j_1, \ldots, j_t\}) - f(S \cup \{j_1, \ldots, j_{t-1}\}) \Big) \tag{68}$$

$$= \sum_{t=1}^{r} \rho_{j_t}(S \cup \{j_1, \ldots, j_{t-1}\}) \leq \sum_{t=1}^{r} \rho_{j_t}(S) \tag{69}$$

$$= \sum_{j \in T \setminus S} \rho_j(S) \tag{70}$$

Eq. 63 $\Rightarrow$ Eq. 64

Let $T \setminus S = \{j_1, \ldots, j_r\}$ and $S \setminus T = \{k_1, \ldots, k_q\}$.
Next, lower bound S in the context of T:

$$f(S \cup T) - f(T) = \sum_{t=1}^{q} [f(T \cup \{k_1, \ldots, k_t\}) - f(T \cup \{k_1, \ldots, k_{t-1}\})] \tag{68}$$

$$= \sum_{t=1}^{q} \rho_{k_t}(T \cup \{k_1, \ldots, k_t\} \setminus \{k_t\}) \geq \sum_{t=1}^{q} \rho_{k_t}(T \cup S \setminus \{k_t\} \tag{69}$$

$$= \sum_{j \in S \setminus T} \rho_j(S \cup T \setminus \{j\}) \tag{70}$$

Eq. 63 $\Rightarrow$ Eq. 64

Let $T \setminus S = \{j_1, \ldots, j_r\}$ and $S \setminus T = \{k_1, \ldots, k_q\}$.
So we have the upperbound

$$f(S \cup T) - f(S) \leq \sum_{j \in T \setminus S} \rho_j(S) \tag{68}$$

and the lower bound

$$f(S \cup T) - f(T) \geq \sum_{j \in S \setminus T} \rho_j(S \cup T \setminus \{j\}) \tag{69}$$

and subtracting the 2nd from the first gives the result.

Eq. 64 $\Rightarrow$ Eq. 65

This follows immediately since if $S \subseteq T$, then $S \setminus T = \emptyset$, and the last term of Eq. 64 vanishes.

Eq. 65 $\Rightarrow$ Eq. 63

Here, we set $T = S \cup \{j,k\}$, $j \notin S \cup \{k\}$ into Eq. 65 to obtain

$$\begin{aligned} f(S \cup \{j,k\}) &\leq f(S) + \rho_j(S) + \rho_k(S) && (70)\\ &= f(S) + f(S + \{j\}) - f(S) + f(S + \{k\}) - f(S) && (71)\\ &= f(S + \{j\}) + f(S + \{k\}) - f(S) && (72)\\ &= \rho_j(S) + f(S + \{k\}) && (73) \end{aligned}$$

giving

$$\begin{aligned} \rho_j(S \cup \{k\}) &= f(S \cup \{j,k\}) - f(S \cup \{k\}) && (74)\\ &\leq \rho_j(S) && (75) \end{aligned}$$

Sources for Today's Lecture

Lovasz-1983, Nemhauser,Wolsey,Fisher-1978, Narayanan-1997, and Narasimhan,Bilmes-2005.