From Submodular to k-Submodular Maximization

Justin Ward

Joint Work with Stanislav Živný

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Let U be a set of n elements.

Let $f : 2^U \to \mathbb{R}_{\geq 0}$ assign a value to each subset of U.

We say that f is submodular if

$$f(A) + f(B) \ge f(A \cap B) + f(A \cup B)$$

Submodularity is also characterized by diminishing returns:

$$f(A+x) - f(A) \ge f(B+x) - f(B)$$

for all $A \subseteq B$ and $x \notin B$.

A biset function f is bisubmodular [Qi, 1988] if

 $\begin{array}{l} f(A_1,A_2)+f(B_1,B_2) \geq \\ f(A_1 \cap B_1, A_2 \cap B_2)+f(A_1 \cup B_1 \setminus (A_2 \cup B_2), A_2 \cup B_2 \setminus (A_1 \cup B_1)) \end{array}$

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Alternatively f is bisubmodular if and only if [Ando, Fujishige, Naitoh 1996]:

• The function $g(S) = f(S \cap A_1, S \cap A_2)$ is submodular for any partition (A_1, A_2) of U.

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- $f(A_1 + e, A_2) + f(A_1, A_2 + e) \ge 2f(A_1, A_2)$

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- $[f(A_1 + e, A_2) f(A_1, A_2)] + [f(A_1, A_2 + e) f(A_1, A_2)] \ge 0$

k-Submodular Functions

We can identify a solution (S_1, \ldots, S_k) with a vector **v** in $\{0, 1, \ldots, k\}^U$, where $v_e = i$ iff $e \in S_i$, and $v_e = 0$ iff v_e in neither set. Then, let:

$$\min_0(s,t) = egin{cases} 0, & s
eq 0, t
eq 0, s
eq t \ \min(s,t), & ext{otherwise} \end{cases}$$

$$\max_0(s,t) = egin{cases} 0, & s
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k-submodularity, is then

$$f(\mathbf{a}) + f(\mathbf{b}) \ge f(\min_0(\mathbf{a}, \mathbf{b})) + f(\max_0(\mathbf{a}, \mathbf{b}))$$



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Related Work

Bisubmodular functions have many mathematical applications:

- Arose in the context of delta-matroids and pseudomatroids [Bouchet 87, Chandrasekaran and Kabadi 1988]
- Have recently been studied in the area of valued CSPs [Huber, Krokhin, and Powell 2013].
- (Strongly) polynomial algorithms for minimization [Fujishige, lwata 2006; McCormick, Fujishige 2010].

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Recently, there has been some interest in maximization [Singh, Guillory, and Bilmes 2012].

- Give conditions under which bisubmodular maximization can be reduced to submodular.
- Use a single submodular function with a matroid constraint to enforce disjointness.
- Give examples of bisubmodular functions that require the related submodular function to be *negative*.

Consider the following randomized algorithm (inspired by [Buchbinder, Feldman, Naor, Schwartz, 2012]):

• Set
$$S = (S_1, \ldots, S_k) = (\emptyset, \ldots, \emptyset)$$

• For each $e \in U$:

• Set
$$x_i = \max(0, f(S_1, ..., S_i + e, ..., S_k) - f(S)).$$

• Add e to
$$S_i$$
 with probability $\frac{x_i}{\beta}$

Theorem

Randomized Greedy is a
$$\frac{1}{\left(1+\sqrt{\frac{k}{2}}\right)}$$
-approximation algorithm for *k*-submodular maximization.

Let $S^{(j)} = (S_1^{(j)}, \ldots, S_k^{(j)})$ be the current solution after j elements have been considered.

Suppose we move these *j* elements in the optimal solution so they agree $S^{(j)}$ and call the result $O^{(j)}$.

Then, $O^{(0)}$ is the optimal solution, and $O^{(n)} = S^{(n)}$ is the greedy solution.

It suffices to bound the expected decrease in $O^{(j)}$ at each phase.

Proof Sketch

Consider the (j + 1)th element e, and suppose that $e \in O_p$. Remove e from $O^{(j)}$ and call the result A.

• As in the algorithm,

$$x_i = \max(0, f(S_1, \ldots, S_i + e, \ldots, S_k) - f(S))$$

• Also, define

$$a_i = f(A_1, \ldots, A_i + e, \ldots, A_k) - f(A)$$

Then, from bisubmodularity, we have:

•
$$a_i \leq x_i$$
 for all $1 \leq i \leq k$.
• $\sum_{i=1}^k a_i \geq 0$.

Proof Sketch

$$\mathbb{E}[f(O^{(j)}) - f(O^{(j+1)})] = \frac{1}{\beta} \sum_{i=1}^{k} x_i (a_p - a_i)$$
$$\mathbb{E}[f(S^{(j+1)}) - f(S^{(j)})] = \frac{1}{\beta} \sum_{i=1}^{k} x_i^2$$
We show that $\sum_{i=1}^{k} x_i (a_i - a_p) \le \sqrt{\frac{k}{2}} \sum_{i=1}^{k} x_i^2$

Main idea: consider extreme point solutions of the LP

$$\begin{array}{ll} \text{maximize} & \sum_{i=1}^k x_i(a_p-a_i) \\ \text{subject to} & a_i \leq x_i \qquad 1 \leq i \leq k \\ & \sum_{i=1}^k a_i \geq 0 \end{array}$$

Summing up the expected losses over all phases

$$egin{aligned} &f(O^{(0)}) - f(O^{(n)}) \leq \sqrt{rac{k}{2}} \left[f(S^{(n)}) - f(S^{(0)})
ight] \ &f(O) - f(S) \leq \sqrt{rac{k}{2}} f(S) \end{aligned}$$

Let $g : 2^U \to \mathbb{R}_{\geq 0}$ be a submodular function. [Fujishige, Iwata, 2005] consider the following embedding:

$$f(A,B) = g(A) + g(U \setminus B)$$

Note that $f(A, U \setminus A) = 2g(A)$.

Recall: $[f(A + x, B) - f(A, B)] + [f(A, B + x) - f(A, B)] \ge 0.$

So, we can extend any solution to a partition without any loss in f. Thus, f preserves approximation, and so our randomized greedy 1/2-approximation is tight. What does the randomized greedy algorithm look like on this embedding?

$$f(A,B) = g(A) + g(U \setminus B)$$

- We maintain 2 solutions X = A and $Y = U \setminus B$.
- Initially, we $X = \emptyset$ and Y = U.
- At each step we either add *e* to *X* or remove *e* from *Y* with probability proportional to the increase in *g*.

Exactly the algorithm of [Buchbinder, Feldman, Naor, Schwarz, 2012].

k =	1	2	\geq 3
Deterministic Greedy	1/3	1/3	1/(k+1)
Random Greedy	1/2	1/2	$1/(1+\sqrt{k/2})$
Naive Random	1/4	1/4	1/k

- Are our results tight for $k \ge 3$?
- Can we attain better approximations for specific cases (like the monotone case).
- What about constrained optimization (budget, knapsack, matroid, etc.)?
- What about other variants, such as skew bisubmodularity?
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Thank You