

# Submodular functions and random $k$ -subsets

Yuval Filmus

April 11, 2012

## Abstract

We relate the average value of a submodular function on  $k$ -subsets to various quantities, including its value on the empty set, on the universe and on the  $k$ -subset maximizing its value. As a result, we deduce that on non-negative functions, the random set algorithm has an approximation ratio of  $k(n-k)/n(n-1)$ .

## 1 Introduction

A set-function  $f$  defined on subsets of a set  $U$  is *submodular* if

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

for any two subsets  $A, B$  of  $U$ . Denote all subsets of  $U$  of size  $k$  by  $\binom{U}{k}$ . We define

$$E_k(f) = \mathbb{E}_{A \in \binom{U}{k}} f(A), \quad M_k(f) = \max_{A \in \binom{U}{k}} f(A).$$

How small can  $E_k(f)$  be, compared to other prominent values of  $f$ ? We answer this question in the two theorems below.

**Theorem 1.** *Let  $f$  be a submodular function on a set  $U$  of size  $n$ . For  $0 \leq k \leq n$ ,*

$$E_k(f) \geq \frac{k}{n} f(U) + \frac{n-k}{n} f(\emptyset).$$

This theorem is tight for linear functions.

**Theorem 2.** *Let  $f$  be a submodular function on a set  $U$  of size  $n$ . For  $0 \leq k \leq n$  and any set  $O \in \binom{U}{k}$ ,*

$$E_k(f) \geq \frac{k(n-k)}{n(n-1)} (f(O) + f(U \setminus O)) + \frac{k(k-1)}{n(n-1)} f(U) + \frac{(n-k)(n-k-1)}{n(n-1)} f(\emptyset).$$

This theorem is tight for the directed cut function on the directed complete bipartite graph  $K_{k,n-k}$ , taking as  $O$  one side of the bipartition.

**Corollary 3.** *Let  $f$  be a submodular function on a set  $U$  of size  $n$ . For  $0 \leq k \leq n$ ,*

$$E_k(f) \geq \frac{k(n-k)}{n(n-1)} M_k(f) + \frac{k(k-1)}{n(n-1)} f(U) + \frac{(n-k)(n-k-1)}{n(n-1)} f(\emptyset).$$

If  $f$  is non-negative, then Corollary 3 implies that

$$\frac{E_k(f)}{M_k(f)} \geq \frac{k(n-k)}{n(n-1)}.$$

This is the approximation ratio of the random set algorithm for the problem of maximizing  $f$  over  $\binom{U}{k}$ .

If  $f$  is symmetric ( $f(A) = f(U \setminus A)$ ), then the same argument used to deduce the corollary from the theorem shows that the approximation ratio of the random set algorithm for the problem of maximizing  $f$  over  $\binom{U}{k}$  is

$$\frac{E_k(f)}{M_k(f)} \geq \frac{2k(n-k)}{n(n-1)}.$$

## 2 Proofs

**Theorem 1.** *Let  $f$  be a submodular function on a set  $U$  of size  $n$ . For  $0 \leq k \leq n$ ,*

$$E_k(f) \geq \frac{k}{n}f(U) + \frac{n-k}{n}f(\emptyset).$$

*Proof.* The proof is by induction on  $k$ . When  $k = 0$ , there is nothing to prove. Assuming the theorem is true for some  $k$ , we prove it for  $k + 1$ . Let  $A \in \binom{U}{k}$ . Repeated application of submodularity gives

$$\sum_{x \in U \setminus A} f(A \cup \{x\}) \geq (n-k-1)f(A) + f(U).$$

Averaging over all choices of  $A$ , we deduce

$$(n-k)E_{k+1}(f) \geq (n-k-1)E_k(f) + f(U).$$

The induction hypothesis gives

$$\begin{aligned} E_{k+1}(f) &\geq \frac{n-k-1}{n-k}E_k(f) + \frac{1}{n-k}f(U) \\ &\geq \frac{n-k-1}{n}f(\emptyset) + \frac{(n-k-1)k}{n(n-k)}f(U) + \frac{1}{n-k}f(U) \\ &= \frac{n-k-1}{n}f(\emptyset) + \frac{k+1}{n}f(U). \end{aligned} \quad \square$$

**Theorem 2.** *Let  $f$  be a submodular function on a set  $U$  of size  $n$ . For  $0 \leq k \leq n$  and any set  $O \in \binom{U}{k}$ ,*

$$E_k(f) \geq \frac{k(n-k)}{n(n-1)}(f(O) + f(U \setminus O)) + \frac{k(k-1)}{n(n-1)}f(U) + \frac{(n-k)(n-k-1)}{n(n-1)}f(\emptyset).$$

*Proof.* For subsets  $A \subseteq U$ , we can define a function  $f_A$  on  $U \setminus A$  by  $f_A(B) = f(A \cup B)$ . It is easy to check that  $f_A$  is also submodular. We will use Theorem 1 repeatedly on such functions. We denote the restriction of a set-function  $g$  to domain  $X$  by  $g|_X$ .

Let  $\bar{O} = U \setminus O$ . We have

$$\binom{n}{k}E_k(f) = \sum_{A \in \binom{U}{k}} f(A) = \sum_{B \subseteq O} \sum_{C \in \binom{\bar{O}}{k-|B|}} f(B \cup C).$$

We can interpret the sum on  $C$  as an average:

$$\binom{n}{k} E_k(f) = \sum_{B \subseteq O} \binom{n-k}{k-|B|} E_{k-|B|}(f_B|_{\bar{O}}).$$

Using Theorem 1, we deduce

$$\begin{aligned} \binom{n}{k} E_k(f) &\geq \sum_{B \subseteq O} \binom{n-k}{k-|B|} \left( \frac{k-|B|}{n-k} f_B|_{\bar{O}}(\bar{O}) + \frac{n-2k+|B|}{n-k} f_B|_{\bar{O}}(\emptyset) \right) \\ &= \sum_{B \subseteq O} \binom{n-k-1}{k-|B|-1} f_{\bar{O}}(B) + \binom{n-k-1}{k-|B|} f(B). \end{aligned}$$

Conditioning on the size of  $B$ , we can interpret the latter sum as a linear combination of  $E_t(f_{\bar{O}})$  and  $E_t(f|_O)$ :

$$\binom{n}{k} E_k(f) \geq \sum_{t=0}^k \binom{k}{t} \left( \binom{n-k-1}{k-t-1} E_t(f_{\bar{O}}) + \binom{n-k-1}{k-t} E_t(f|_O) \right).$$

Using Theorem 1 again,

$$\begin{aligned} \binom{n}{k} E_k(f) &\geq \sum_{t=0}^k \binom{k}{t} \binom{n-k-1}{k-t-1} \left( \frac{t}{k} f_{\bar{O}}(O) + \frac{k-t}{k} f_{\bar{O}}(\emptyset) \right) \\ &\quad + \binom{k}{t} \binom{n-k-1}{k-t} \left( \frac{t}{k} f|_O(O) + \frac{k-t}{k} f|_O(\emptyset) \right) \\ &= \sum_{t=0}^k \binom{k-1}{t-1} \left( \binom{n-k-1}{k-t-1} f(U) + \binom{n-k-1}{k-t} f(O) \right) \\ &\quad + \binom{k-1}{t} \left( \binom{n-k-1}{k-t-1} f(\bar{O}) + \binom{n-k-1}{k-t} f(\emptyset) \right) \\ &= \binom{n-2}{k-2} f(U) + \binom{n-2}{k-1} f(O) + \binom{n-2}{k-1} f(\bar{O}) + \binom{n-2}{k} f(\emptyset). \end{aligned}$$

□