

# Approximating Submodular Functions Everywhere

Nick Harvey

University of Waterloo  
Department of Combinatorics & Optimization

October 4th, 2009

Joint work with M. Goemans, S. Iwata and V. Mirrokni

# Motivating Example

- ▶ Microsoft Office consists of a set  $A$  of products.  
e.g.,  $A = \{\text{Word, Excel, Outlook, PowerPoint, ...}\}$ .
- ▶ The typical consumer has a utility function  $f : 2^A \rightarrow \mathbb{R}$
- ▶ Want to learn  $f$  without asking consumer too many questions  
(Perhaps useful in pricing different bundles of Office?)

# Motivating Example

- ▶ Microsoft Office consists of a set  $A$  of products.  
e.g.,  $A = \{\text{Word, Excel, Outlook, PowerPoint, ...}\}$ .
- ▶ The typical consumer has a utility function  $f : 2^A \rightarrow \mathbb{R}$
- ▶ Want to learn  $f$  without asking consumer too many questions  
(Perhaps useful in pricing different bundles of Office?)
- ▶ Some assumption on  $f$  is required  
**Submodularity** is natural assumption

# Submodular Functions

## ► Definition

$f : 2^{[n]} \rightarrow \mathbb{R}$  is **submodular** if, for all  $A, B \subseteq [n]$ :

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

## Equivalent definition

$f$  is submodular if, for all  $A \subseteq B$  and  $i \notin B$ :

$$f(A \cup \{i\}) - f(A) \geq f(B \cup \{i\}) - f(B)$$

- Discrete analogue of convex functions [Lovász '83]
  - Arise in combinatorial optimization, probability, economics (diminishing returns), geometry, etc.
- ## ► Fundamental Examples
- Rank function of a matroid, cut function of a graph, ...

# Optimizing Submodular Functions

(Given Oracle Access)

## Minimization

- ▶ Can solve  $\min_S f(S)$  with polynomially many oracle calls [GLS], [Schrijver '01], [Iwata, Fleischer, Fujishige '01], ...

Example: Given matroids  $M_1 = (E, \mathcal{I}_1)$  and  $M_2 = (E, \mathcal{I}_2)$

$$\max\{|I| : I \in \mathcal{I}_1 \cap \mathcal{I}_2\} = \min\{r_1(S) + r_2(E \setminus S) : S \subseteq E\}$$

## Maximization

- ▶ Can approximate  $\max_S f(S)$  to within  $2/5$ , assuming  $f \geq 0$ . [Feige, Mirrokni, Vondrák '07]

# Approximating Submodular Functions Everywhere

## Definition

$f : 2^{[n]} \rightarrow \mathbb{R}$  is **monotone** if, for all  $A \subseteq B \subseteq [n]$ :

$$f(A) \leq f(B)$$

## Problem

Given a monotone, submodular  $f$ , construct using  $\text{poly}(n)$  oracle queries a function  $\hat{f}$  such that:

$$\hat{f}(S) \leq f(S) \leq \alpha(n) \cdot \hat{f}(S) \quad \forall S \subseteq [n]$$

# Approximating Submodular Functions Everywhere

## Definition

$f : 2^{[n]} \rightarrow \mathbb{R}$  is **monotone** if, for all  $A \subseteq B \subseteq [n]$ :

$$f(A) \leq f(B)$$

## Problem

Given a monotone, submodular  $f$ , construct using  $\text{poly}(n)$  oracle queries a function  $\hat{f}$  such that:

$$\hat{f}(S) \leq f(S) \leq \alpha(n) \cdot \hat{f}(S) \quad \forall S \subseteq [n]$$

## Approximation Quality

- ▶ How small can we make  $\alpha(n)$ ?
- ▶  $\alpha(n) = n$  is trivial

# Approximating Submodular Functions Everywhere

## Positive Result

### Problem

Given a monotone, submodular  $f$ , construct using  $\text{poly}(n)$  oracle queries a function  $\hat{f}$  such that:

$$\hat{f}(S) \leq f(S) \leq \alpha(n) \cdot \hat{f}(S) \quad \forall S \subseteq [n]$$

### Our Positive Result

A deterministic algorithm that constructs  $\hat{f}(S) = \sqrt{\sum_{i \in S} c_i}$  with

- ▶  $\alpha(n) = \sqrt{n+1}$  for matroid rank functions  $f$ , or
- ▶  $\alpha(n) = O(\sqrt{n} \log n)$  for general monotone submodular  $f$

Also,  $\hat{f}$  is submodular:  $\hat{f}(S) = \sqrt{\sum_{i \in S} c_i}$  for some scalars  $c_i$ .

# Approximating Submodular Functions Everywhere

Almost Tight

## Our Positive Result

A deterministic algorithm that constructs  $\hat{f}(S) = \sqrt{\sum_{i \in S} c_i}$  with

- ▶  $\alpha(n) = \sqrt{n+1}$  for matroid rank functions  $f$ , or
- ▶  $\alpha(n) = O(\sqrt{n} \log n)$  for general monotone submodular  $f$

## Our Negative Result

With polynomially many oracle calls,  $\alpha(n) = \Omega(\sqrt{n}/\log n)$   
(even for randomized algs)

# Application

## Submodular Load Balancing

Problem (Svitkina and Fleischer '08)

Given submodular functions  $f_i : 2^V \rightarrow \mathbb{R}$  for  $i \in [k]$ ,  
partition  $V$  into  $V_1, \dots, V_k$  to

$$\min_{V_1, \dots, V_k} \max_i f_i(V_i)$$

For  $f_i(S) = \sum_{j \in S} c_{i,j}$ , this is scheduling on unrelated machines.  
[Lenstra, Shmoys, Tardos '90]

# Application

## Submodular Load Balancing

### Problem (Svitkina and Fleischer '08)

Given submodular functions  $f_i : 2^V \rightarrow \mathbb{R}$  for  $i \in [k]$ , partition  $V$  into  $V_1, \dots, V_k$  to

$$\min_{V_1, \dots, V_k} \max_i f_i(V_i)$$

For  $f_i(S) = \sum_{j \in S} c_{i,j}$ , this is scheduling on unrelated machines. [Lenstra, Shmoys, Tardos '90]

### Our solution

Approximate  $f_i$  by  $\hat{f}_i(S) = \sqrt{\sum_{j \in S} c_{i,j}}$  for each  $i$ . Then solve

$$\min_{V_1, \dots, V_k} \max_i \hat{f}_i^2(V_i)$$

using Lenstra, Shmoys, Tardos. Get  $O(\sqrt{n} \log n)$ -approx solution.

# Application

## Submodular Max-Min Fair Allocation

Problem (Golovin '05, Khot and Ponnuswami '07)

Given submodular functions  $f_i : 2^V \rightarrow \mathbb{R}$  for  $i \in [k]$ ,  
partition  $V$  into  $V_1, \dots, V_k$  to

$$\max_{V_1, \dots, V_k} \min_i f_i(V_i)$$

For  $f_i(S) = \sum_{j \in S} c_{i,j}$ , this is Santa Claus problem.

There is a  $\tilde{O}(\sqrt{k})$ -approximation algorithm [Asadpour-Saberi '07].

Immediately get  $\tilde{O}(\sqrt{n} k^{1/4})$ -approximate solution.

## Definition

Given submodular  $f$ , **polymatroid**

$$P_f = \left\{ x \in \mathbb{R}_+^n : \sum_{i \in S} x_i \leq f(S) \text{ for all } S \subseteq [n] \right\}$$

A few properties [Edmonds '70]:

- ▶ Can optimize over  $P_f$  with greedy algorithm
- ▶ Separation problem for  $P_f$  is **submodular fctn minimization**
- ▶ For **monotone**  $f$ , can reconstruct  $f$ :

$$f(S) = \max_{x \in P_f} \langle \mathbf{1}_S, x \rangle$$

# Our Approach: Geometric Relaxation

We know:

$$f(S) = \max_{x \in P_f} \langle \mathbf{1}_S, x \rangle$$

Suppose that:

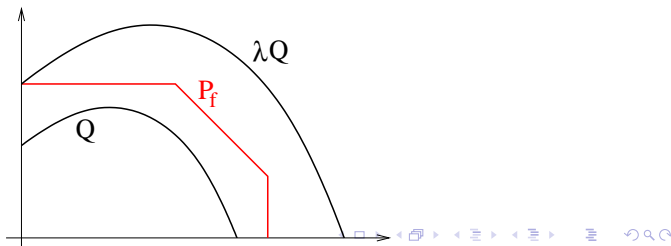
$$Q \subseteq P_f \subseteq \lambda Q$$

Then:

$$\hat{f}(S) \leq f(S) \leq \lambda \hat{f}(S)$$

where

$$\hat{f}(S) = \max_{x \in Q} \langle \mathbf{1}_S, x \rangle$$



# John's Theorem [1948]

## Maximum Volume Ellipsoids

### Definition

A convex body  $K$  is **centrally symmetric** if  
 $x \in K \iff -x \in K$ .

# John's Theorem [1948]

## Maximum Volume Ellipsoids

### Definition

A convex body  $K$  is **centrally symmetric** if

$$x \in K \iff -x \in K.$$

### Definition

An ellipsoid  $E$  is an  **$\alpha$ -ellipsoidal approximation** of  $K$  if

$$E \subseteq K \subseteq \alpha \cdot E.$$

# John's Theorem [1948]

## Maximum Volume Ellipsoids

### Definition

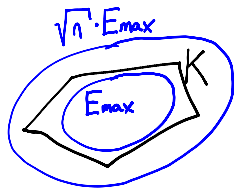
A convex body  $K$  is **centrally symmetric** if  $x \in K \iff -x \in K$ .

### Definition

An ellipsoid  $E$  is an  **$\alpha$ -ellipsoidal approximation** of  $K$  if  $E \subseteq K \subseteq \alpha \cdot E$ .

### Theorem

Let  $K$  be a centrally symmetric convex body in  $\mathbb{R}^n$ .  
Let  $E_{\max}$  (or **John ellipsoid**) be maximum volume ellipsoid contained in  $K$ . Then  $K \subseteq \sqrt{n} \cdot E_{\max}$ .



# John's Theorem [1948]

## Maximum Volume Ellipsoids

### Definition

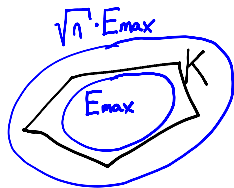
A convex body  $K$  is **centrally symmetric** if  $x \in K \iff -x \in K$ .

### Definition

An ellipsoid  $E$  is an  **$\alpha$ -ellipsoidal approximation** of  $K$  if  $E \subseteq K \subseteq \alpha \cdot E$ .

### Theorem

Let  $K$  be a centrally symmetric convex body in  $\mathbb{R}^n$ .  
Let  $E_{\max}$  (or **John ellipsoid**) be maximum volume ellipsoid contained in  $K$ . Then  $K \subseteq \sqrt{n} \cdot E_{\max}$ .



Algorithmically?

## Definition

- ▶ An ellipsoid is

$$E(A) = \{x \in \mathbb{R}^n : x^T A x \leq 1\}$$

where  $A \succ 0$  is positive definite matrix.

## Handy notation

- ▶ Write  $\|x\|_A = \sqrt{x^T A x}$ . Then

$$E(A) = \{x \in \mathbb{R}^n : \|x\|_A \leq 1\}$$

## Optimizing over ellipsoids

- ▶  $\max_{x \in E(A)} \langle c, x \rangle = \|c\|_{A^{-1}}$

## Explicitly Given Polytopes

- ▶ Can find  $E_{max}$  in P-time (up to  $\epsilon$ ) if explicitly given as  $K = \{x : Ax \leq b\}$   
[Grötschel, Lovász and Schrijver '88], [Nesterov, Nemirovski '89], [Khachiyan, Todd '93], ...

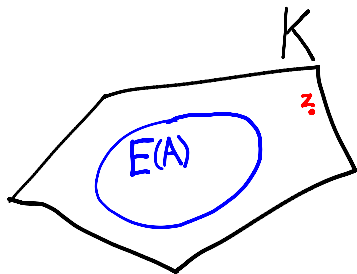
## Polytopes given by Separation Oracle

- ▶ **only**  $n + 1$ -ellipsoidal approximation for convex bodies given by **weak separation oracle** [Grötschel, Lovász and Schrijver '88]
- ▶ No (randomized)  $n^{1-\epsilon}$ -ellipsoidal approximation [J. Soto '08]

# Finding Larger and Larger Inscribed Ellipsoids

## Informal Statement

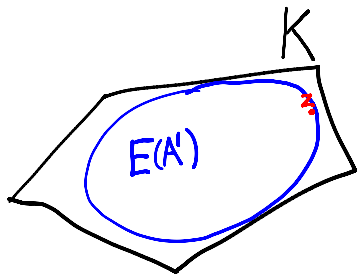
- ▶ We have  $A \succ 0$  such that  $E(A) \subseteq K$ .
- ▶ Suppose we find  $z \in K$  but  $z$  **far outside** of  $E(A)$ .
- ▶ Then should be able to find  $A' \succ 0$  such that
  - ▶  $E(A') \subseteq K$
  - ▶  $\text{vol } E(A') > \text{vol } E(A)$



# Finding Larger and Larger Inscribed Ellipsoids

## Informal Statement

- ▶ We have  $A \succ 0$  such that  $E(A) \subseteq K$ .
- ▶ Suppose we find  $z \in K$  but  $z$  **far outside** of  $E(A)$ .
- ▶ Then should be able to find  $A' \succ 0$  such that
  - ▶  $E(A') \subseteq K$
  - ▶  $\text{vol } E(A') > \text{vol } E(A)$



# Finding Larger and Larger Inscribed Ellipsoids

## Formal Statement

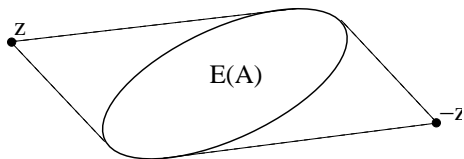
### Theorem

If  $A \succ 0$  and  $z \in \mathbb{R}^n$  with  $d = \|z\|_A^2 \geq n$  then  $E(A')$  is max volume ellipsoid inscribed in  $\text{conv}\{E(A), z, -z\}$  where

$$A' = \frac{n}{d} \frac{d-1}{n-1} A + \frac{n}{d^2} \left(1 - \frac{d-1}{n-1}\right) A z z^T A$$

Moreover,  $\text{vol } E(A') = k_n(d) \cdot \text{vol } E(A)$  where

$$k_n(d) = \sqrt{\left(\frac{d}{n}\right)^n \left(\frac{n-1}{d-1}\right)^{n-1}}$$



# Finding Larger and Larger Inscribed Ellipsoids

## Formal Statement

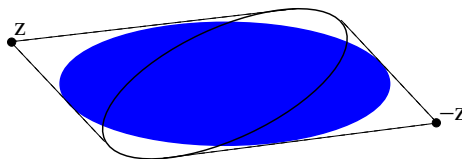
### Theorem

If  $A \succ 0$  and  $z \in \mathbb{R}^n$  with  $d = \|z\|_A^2 \geq n$  then  $E(A')$  is max volume ellipsoid inscribed in  $\text{conv}\{E(A), z, -z\}$  where

$$A' = \frac{n}{d} \frac{d-1}{n-1} A + \frac{n}{d^2} \left(1 - \frac{d-1}{n-1}\right) A z z^T A$$

Moreover,  $\text{vol } E(A') = k_n(d) \cdot \text{vol } E(A)$  where

$$k_n(d) = \sqrt{\left(\frac{d}{n}\right)^n \left(\frac{n-1}{d-1}\right)^{n-1}}$$



# Finding Larger and Larger Inscribed Ellipsoids

## Remarks

$\text{vol } E(A') = k_n(d) \cdot \text{vol } E(A)$  where

$$k_n(d) = \sqrt{\left(\frac{d}{n}\right)^n \left(\frac{n-1}{d-1}\right)^{n-1}}$$

## Remarks

- ▶  $k_n(d) > 1$  for  $d > n$  proves John's theorem
- ▶ Significant volume increase for  $d \geq n + 1$ :  
 $k_n(n + 1) = 1 + \Theta(1/n^2)$
- ▶ **Polar statement previously known** [Todd '82]  
 $A'$  gives formula for minimum volume ellipsoid containing

$$E(A) \cap \{x : -b \leq \langle c, x \rangle \leq b\}$$

# Review of Plan

- ▶ Given monotone, submodular  $f$ , make  $n^{O(1)}$  queries, construct  $\hat{f}$  s.t.

$$\hat{f}(S) \leq f(S) \leq \tilde{O}(\sqrt{n}) \cdot \hat{f}(S) \quad \forall S \subseteq V.$$

# Review of Plan

- ▶ Given monotone, submodular  $f$ , make  $n^{O(1)}$  queries, construct  $\hat{f}$  s.t.

$$\hat{f}(S) \leq f(S) \leq \tilde{O}(\sqrt{n}) \cdot \hat{f}(S) \quad \forall S \subseteq V.$$

- ▶ Can reconstruct  $f$  from the polymatroid

$$P_f = \{x \in \mathbb{R}_+^n : \sum_{i \in S} x_i \leq f(S) \quad \forall S \subseteq [n]\}$$

by  $f(S) = \max_{x \in P_f} \langle \mathbf{1}_S, x \rangle$ .

# Review of Plan

- ▶ Given monotone, submodular  $f$ , make  $n^{O(1)}$  queries, construct  $\hat{f}$  s.t.

$$\hat{f}(S) \leq f(S) \leq \tilde{O}(\sqrt{n}) \cdot \hat{f}(S) \quad \forall S \subseteq V.$$

- ▶ Can reconstruct  $f$  from the polymatroid

$$P_f = \{x \in \mathbb{R}_+^n : \sum_{i \in S} x_i \leq f(S) \quad \forall S \subseteq [n]\}$$

by  $f(S) = \max_{x \in P_f} \langle \mathbf{1}_S, x \rangle$ .

- ▶ Make  $P_f$  centrally symmetric by reflections:

$$S(P_f) = \{x : (|x_1|, |x_2|, \dots, |x_n|) \in P_f\}$$

# Review of Plan

- ▶ Given monotone, submodular  $f$ , make  $n^{O(1)}$  queries, construct  $\hat{f}$  s.t.

$$\hat{f}(S) \leq f(S) \leq \tilde{O}(\sqrt{n}) \cdot \hat{f}(S) \quad \forall S \subseteq V.$$

- ▶ Can reconstruct  $f$  from the polymatroid

$$P_f = \{x \in \mathbb{R}_+^n : \sum_{i \in S} x_i \leq f(S) \quad \forall S \subseteq [n]\}$$

by  $f(S) = \max_{x \in P_f} \langle \mathbf{1}_S, x \rangle$ .

- ▶ Make  $P_f$  centrally symmetric by reflections:

$$S(P_f) = \{x : (|x_1|, |x_2|, \dots, |x_n|) \in P_f\}$$

- ▶ Max volume ellipsoid  $E_{max}$  has

$$E_{max} \subseteq S(P_f) \subseteq \sqrt{n} \cdot E_{max}.$$

Take  $\hat{f}(S) = \max_{x \in E_{max}} \langle \mathbf{1}_S, x \rangle$ .

# Review of Plan

- ▶ Given monotone, submodular  $f$ , make  $n^{O(1)}$  queries, construct  $\hat{f}$  s.t.

$$\hat{f}(S) \leq f(S) \leq \tilde{O}(\sqrt{n}) \cdot \hat{f}(S) \quad \forall S \subseteq V.$$

- ▶ Can reconstruct  $f$  from the polymatroid

$$P_f = \{x \in \mathbb{R}_+^n : \sum_{i \in S} x_i \leq f(S) \quad \forall S \subseteq [n]\}$$

by  $f(S) = \max_{x \in P_f} \langle \mathbf{1}_S, x \rangle$ .

- ▶ Make  $P_f$  centrally symmetric by reflections:

$$S(P_f) = \{x : (|x_1|, |x_2|, \dots, |x_n|) \in P_f\}$$

- ▶ Max volume ellipsoid  $E_{max}$  has

$$E_{max} \subseteq S(P_f) \subseteq \sqrt{n} \cdot E_{max}.$$

Take  $\hat{f}(S) = \max_{x \in E_{max}} \langle \mathbf{1}_S, x \rangle$ .

- ▶ Compute ellipsoids  $E_1, E_2, \dots$  in  $S(P_f)$  that converge to  $E_{max}$ .

# Review of Plan

- ▶ Given monotone, submodular  $f$ , make  $n^{O(1)}$  queries, construct  $\hat{f}$  s.t.

$$\hat{f}(S) \leq f(S) \leq \tilde{O}(\sqrt{n}) \cdot \hat{f}(S) \quad \forall S \subseteq V.$$

- ▶ Can reconstruct  $f$  from the polymatroid

$$P_f = \{x \in \mathbb{R}_+^n : \sum_{i \in S} x_i \leq f(S) \quad \forall S \subseteq [n]\}$$

by  $f(S) = \max_{x \in P_f} \langle \mathbf{1}_S, x \rangle$ .

- ▶ Make  $P_f$  centrally symmetric by reflections:

$$S(P_f) = \{x : (|x_1|, |x_2|, \dots, |x_n|) \in P_f\}$$

- ▶ Max volume ellipsoid  $E_{max}$  has

$$E_{max} \subseteq S(P_f) \subseteq \sqrt{n} \cdot E_{max}.$$

Take  $\hat{f}(S) = \max_{x \in E_{max}} \langle \mathbf{1}_S, x \rangle$ .

- ▶ Compute ellipsoids  $E_1, E_2, \dots$  in  $S(P_f)$  that converge to  $E_{max}$ .

Given  $E_i = E(A_i)$ , need  $z \in S(P_f)$  with  $\|z\|_{A_i} \geq \sqrt{n+1}$ .

- ▶ If  $\exists z$ , can compute  $E_{i+1}$  of larger volume.
- ▶ If  $\nexists z$ , then  $E_i \approx E_{max}$ .

# Remaining Task

## Ellipsoidal Norm Maximization

### ► Ellipsoidal Norm Maximization

Given  $A \succ 0$  and well-bounded convex body  $K$  by separation oracle.  
(So  $B(r) \subseteq K \subseteq B(R)$  where  $B(d)$  is ball of radius  $d$ .)

Solve

$$\max_{x \in K} \|x\|_A$$

# Remaining Task

## Ellipsoidal Norm Maximization

### ► Ellipsoidal Norm Maximization

Given  $A \succ 0$  and well-bounded convex body  $K$  by separation oracle.  
(So  $B(r) \subseteq K \subseteq B(R)$  where  $B(d)$  is ball of radius  $d$ .)

Solve

$$\max_{x \in K} \|x\|_A$$

### ► Bad News

Ellipsoidal Norm Maximization NP-complete for  $S(P_f)$  and  $P_f$ .  
(Even if  $f$  is a graphic matroid rank function.)

# Remaining Task

## Ellipsoidal Norm Maximization

### ▶ Ellipsoidal Norm Maximization

Given  $A \succ 0$  and well-bounded convex body  $K$  by separation oracle.  
(So  $B(r) \subseteq K \subseteq B(R)$  where  $B(d)$  is ball of radius  $d$ .)

Solve

$$\max_{x \in K} \|x\|_A$$

### ▶ Bad News

Ellipsoidal Norm Maximization NP-complete for  $S(P_f)$  and  $P_f$ .  
(Even if  $f$  is a graphic matroid rank function.)

### ▶ Approximations are good enough

P-time  $\alpha$ -approx. algorithm for Ellipsoidal Norm Maximization  
 $\implies$  P-time  $\alpha\sqrt{n+1}$ -ellipsoidal approximation for  $K$   
(in  $O(n^3 \log(R/r))$  iterations)

# Ellipsoidal Norm Maximization

Taking Advantage of Symmetry

## Our Task

Given  $A \succ 0$ , and  $f$  find  $\max_{x \in S(P_f)} \|x\|_A$ .

# Ellipsoidal Norm Maximization

## Taking Advantage of Symmetry

### Our Task

Given  $A \succ 0$ , and  $f$  find  $\max_{x \in S(P_f)} \|x\|_A$ .

### Observation: Symmetry Helps

$S(P_f)$  invariant under axis-aligned reflections.

(Diagonal  $\{\pm 1\}$  matrices.)

$\implies$  same is true for  $E_{max}$

$\implies E_{max} = E(D)$  where  $D$  is **diagonal**.

# Remaining Task

## Ellipsoidal Norm Maximization

### Our Task

Given diagonal  $D \succ 0$ , and  $f$  find

$$\max_{x \in S(P_f)} \|x\|_D$$

Equivalently,

$$\begin{aligned} \max \quad & \sum_i d_i x_i^2 \\ \text{s.t.} \quad & x \in P_f \end{aligned}$$

- ▶ Maximizing convex function over convex set  
⇒ max attained at vertex.

# Remaining Task

## Ellipsoidal Norm Maximization

### Our Task

Given diagonal  $D \succ 0$ , and  $f$  find

$$\begin{aligned} \max \quad & \sum_i d_i x_i^2 \\ \text{s.t.} \quad & x \in P_f \end{aligned}$$

- ▶ Maximizing convex function over convex set  
⇒ max attained at vertex.

### Matroid Case

If  $f$  is **matroid rank function**

⇒ vertices in  $\{0, 1\}^n \implies x_i^2 = x_i$ .

Our task is

$$\begin{aligned} \max \quad & \sum_i d_i x_i \\ \text{s.t.} \quad & x \in P_f \end{aligned}$$

This is the max weight base problem, solvable by greedy algorithm.

# Remaining Task

## Ellipsoidal Norm Maximization

### Our Task

Given diagonal  $D \succ 0$ , and  $f$  find

$$\begin{aligned} \max \quad & \sum_i d_i x_i^2 \\ \text{s.t.} \quad & x \in P_f \end{aligned}$$

- ▶ Maximizing convex function over convex set  
⇒ max attained at vertex.

### General Monotone Submodular Case

More complicated: uses approximate maximization of submodular function [Nemhauser, Wolsey, Fischer '78], etc.

Can find  $O(\log n)$ -approximate maximum.

# Summary of Algorithm

## Theorem

In  $P$ -time, construct a (submodular) function  $\hat{f}(S) = \sqrt{\sum_{i \in S} c_i}$  with

- ▶  $\alpha(n) = \sqrt{n+1}$  for matroid rank functions  $f$ , or
- ▶  $\alpha(n) = O(\sqrt{n} \log n)$  for general monotone submodular  $f$ .

The algorithm is deterministic.

# $\Omega(\sqrt{n}/\log n)$ Lower Bound

## Theorem

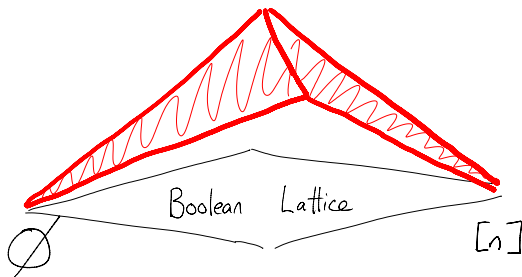
*With  $\text{poly}(n)$  queries, cannot approximate  $f$  better than  $\frac{\sqrt{n}}{\log n}$ .  
Even for randomized algs, and even if  $f$  is matroid rank function.*

# $\Omega(\sqrt{n}/\log n)$ Lower Bound

## Informal Idea

### Theorem

With  $\text{poly}(n)$  queries, cannot approximate  $f$  better than  $\frac{\sqrt{n}}{\log n}$ .  
Even for randomized algs, and even if  $f$  is matroid rank function.



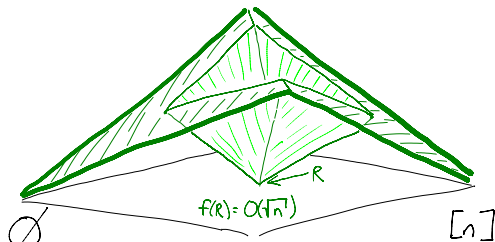
$$f(S) = \min\{|S|, n - |S|\}$$

# $\Omega(\sqrt{n}/\log n)$ Lower Bound

## Informal Idea

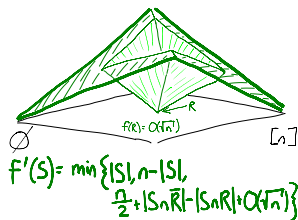
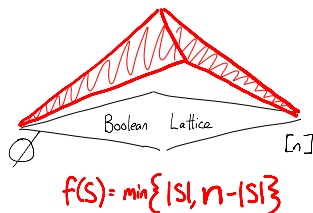
### Theorem

With  $\text{poly}(n)$  queries, cannot approximate  $f$  better than  $\frac{\sqrt{n}}{\log n}$ .  
Even for randomized algs, and even if  $f$  is matroid rank function.



$$f'(S) = \min \left\{ |S|, n - |S|, \frac{n}{2} + |S \cap \bar{R}| - |S \cap R| + O(\sqrt{n}) \right\}$$

# Discrepancy Argument

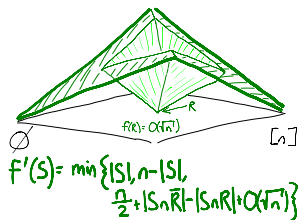
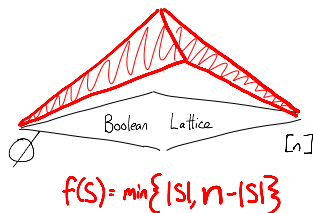


Algorithm performs queries  $S_1, \dots, S_k$ .

A query  $S_i$  distinguishes  $f$  from  $f'$  iff

$$|S_i \cap R| - |S_i \cap \bar{R}| > O(\sqrt{n})$$

# Discrepancy Argument



Algorithm performs queries  $S_1, \dots, S_k$ .

A query  $S_i$  distinguishes  $f$  from  $f'$  iff

$$|S_i \cap R| - |S_i \cap \bar{R}| > O(\sqrt{n})$$

Standard discrepancy argument: For uniformly random  $R$ ,

$$\| |S_i \cap R| - |S_i \cap \bar{R}| \| \leq \sqrt{2n \ln(2k)} \quad \forall i$$

So algorithm fails to find random  $R$ .

## Problem

Let  $f : 2^{[n]} \rightarrow \mathbb{R}_+$  be monotone and submodular. Let  $D$  be a distribution on  $2^{[n]}$ . Given  $\text{poly}(n)$  training samples  $S_1, S_2, \dots$  from  $D$ , labeled by  $f$ , construct a function  $\hat{f}$  such that

$$\hat{f}(S) \leq f(S) \leq \alpha(n) \cdot \hat{f}(S),$$

with prob. at least  $1 - \epsilon$  when  $S$  is a new test sample from  $D$ .

## Problem

Let  $f : 2^{[n]} \rightarrow \mathbb{R}_+$  be monotone and submodular. Let  $D$  be a distribution on  $2^{[n]}$ . Given  $\text{poly}(n)$  training samples  $S_1, S_2, \dots$  from  $D$ , labeled by  $f$ , construct a function  $\hat{f}$  such that

$$\hat{f}(S) \leq f(S) \leq \alpha(n) \cdot \hat{f}(S),$$

with prob. at least  $1 - \epsilon$  when  $S$  is a new test sample from  $D$ .

## Theorem (Balcan, H. 2009)

Can achieve approximation  $\alpha(n) = \sqrt{n+1}$ .

No algorithm can achieve approximation  $\alpha(n) = \Omega(n^{1/3} / \log n)$ .

## Problem

Find embedding  $\rho : \{0, 1\}^d \rightarrow \{0, 1\}^n$  and  $\alpha \ll \beta$  such that, for every **Boolean** function  $f : \{0, 1\}^d \rightarrow \{0, 1\}$ , there is a **submodular** function  $\tilde{f} : \{0, 1\}^n \rightarrow \mathbb{R}_+$  satisfying

$$f(S) = 0 \quad \Longrightarrow \quad \tilde{f}(\rho(S)) = \alpha$$

$$f(S) = 1 \quad \Longrightarrow \quad \tilde{f}(\rho(S)) = \beta$$

# Lower bound for PAC model

## Problem

Find embedding  $\rho : \{0, 1\}^d \rightarrow \{0, 1\}^n$  and  $\alpha \ll \beta$  such that, for every **Boolean** function  $f : \{0, 1\}^d \rightarrow \{0, 1\}$ , there is a **submodular** function  $\tilde{f} : \{0, 1\}^n \rightarrow \mathbb{R}_+$  satisfying

$$f(S) = 0 \quad \Longrightarrow \quad \tilde{f}(\rho(S)) = \alpha$$

$$f(S) = 1 \quad \Longrightarrow \quad \tilde{f}(\rho(S)) = \beta$$

## Theorem (Balcan, H. 2009)

This is possible with  $\alpha = \log^2 n$ ,  $\beta = n^{1/3}$  and  $d = \Theta(\log^2 n)$ .

# Summary

## Problem

Given a monotone, submodular  $f$ , construct using  $\text{poly}(n)$  oracle queries a function  $\hat{f}$  such that:

$$\hat{f}(S) \leq f(S) \leq \alpha(n) \cdot \hat{f}(S) \quad \forall S \subseteq [n]$$

## Our Positive Result

A deterministic algorithm that constructs  $\hat{f}(S) = \sqrt{\sum_{i \in S} c_i}$  with

- ▶  $\alpha(n) = \sqrt{n+1}$  for matroid rank functions  $f$ , or
- ▶  $\alpha(n) = O(\sqrt{n} \log n)$  for general monotone submodular  $f$

## Our Negative Result

With polynomially many oracle calls,  $\alpha(n) = \Omega(\sqrt{n}/\log n)$   
(even for randomized algs)