

# Polyhedral Results for A Class of Cardinality Constrained Submodular Minimization Problems

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# A Motivating Problem

- $[n]$ : Set of candidate investment projects
- $c$ : Cost vector (of size  $n$ )
- $b$ : Budget
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Mean risk combinatorial optimization

[Shen et al '03, Atamturk'08, Nikolova'10, Baumann et al'13]

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Polyhedral description/relaxation of  $\text{conv}(\mathcal{P} \cap X)$  where

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Simple case: Cardinality constraint  $X = \{x \in \{0, 1\}^n : e^\top x \leq K\}$

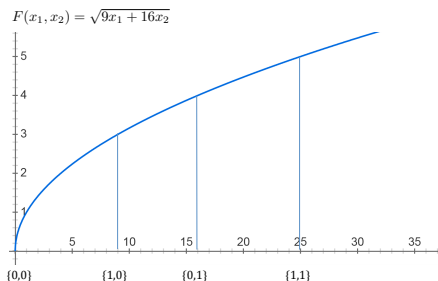
# Submodular Functions

## Definition

A function  $F : \{0, 1\}^n \rightarrow \mathbb{R}$  is *submodular* if

$$F(x + e^i) - F(x) \geq F(y + e^i) - F(y) \quad \forall x \leq y, \text{ s.t. } x_i = y_i = 0$$

If  $f$  is concave and  $a \in \mathbb{R}_+^n$  then  $F(x) := f(a^\top x)$  is submodular.



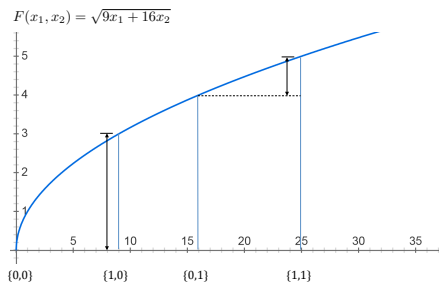
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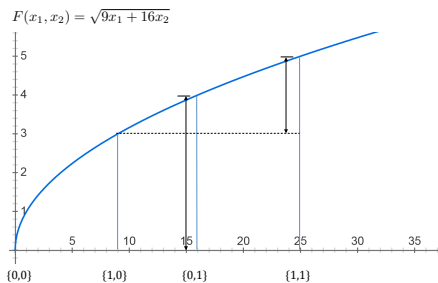
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- Submodular inequalities in MINLP:  
Atamturk et al. '08,'09,'12, Tawarmalani'10, A.+Papageorgiou'13,  
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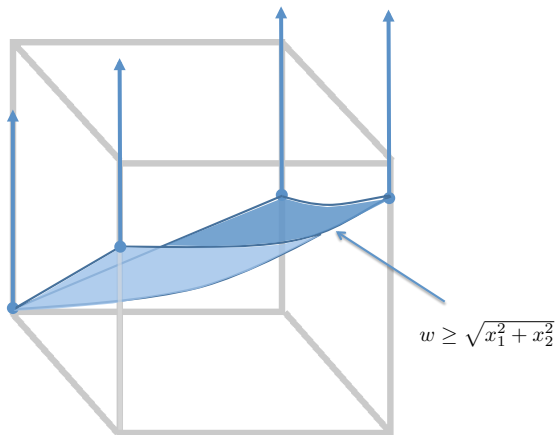
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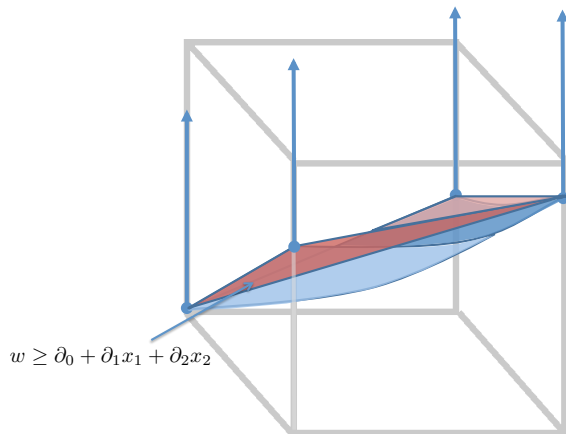
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 $\Rightarrow$  Combinatorial separation algorithm
  
- Goal: Extend the submodular inequalities to incorporate cardinality constraint

# Illustration

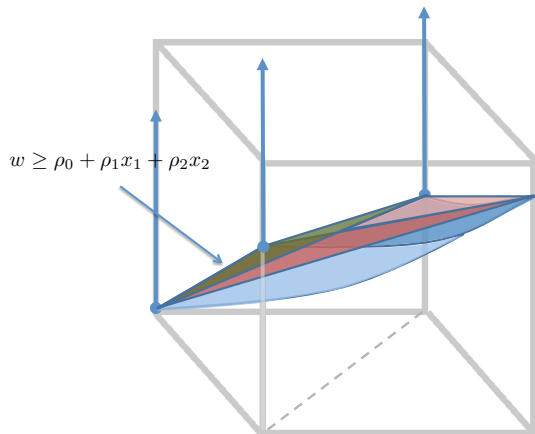




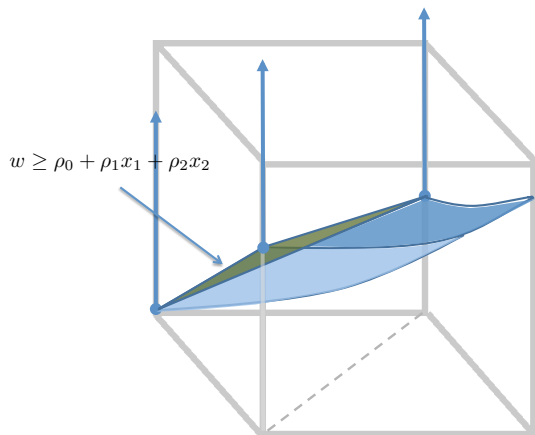
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- Computational results for mean-risk knapsack

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- The primal LP:

$$\begin{aligned} \min \quad & \sum_{S \in \mathcal{S}} f(|S|) P(S) \\ \text{s.t.} \quad & \sum_{S \in \mathcal{S}: i \in S} P(S) = x_i \quad \forall i \in [n] \\ & \sum_{S \in \mathcal{S}} P(S) = 1, P(S) \geq 0 \quad \forall S \in \mathcal{S} \end{aligned}$$

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$$\rho_i = \begin{cases} f(0) & i = 0 \\ f(i) - f(i-1) & 1 \leq i \leq i_0 \\ \frac{f(K) - f(i_0)}{K - i_0} & i_0 < i \leq n \end{cases}$$

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- The lhs of (\*):

$$\partial_0 + \sum_{i \in S_1} \partial_i + \sum_{i \in S_2} \rho_i \leq f(i_1) + i_2 \cdot \frac{f(K) - f(i_0)}{K - i_0}$$

by construction and validity of the usual submodular inequality corresponding to  $S_1$

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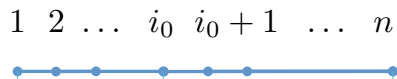
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- The above inequality can be shown using concavity of  $f(i)$  and  $i_1 \leq i_0 \leq K$



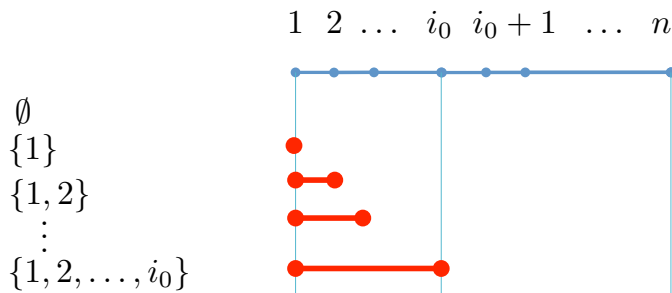
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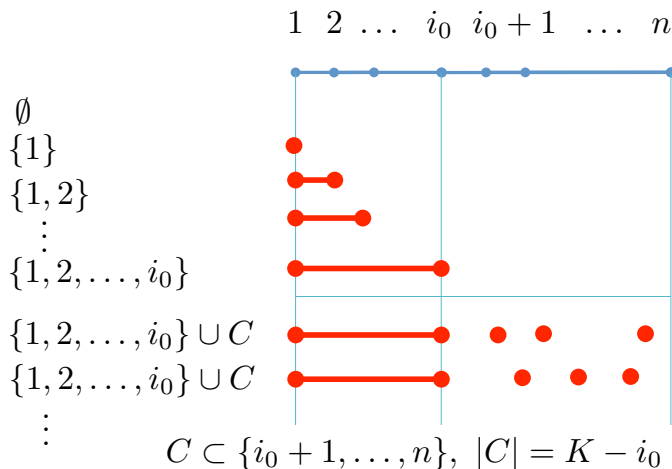
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- $P(\{1, \dots, i_0\} \cup C) = Q(C)$  for all  $C \in \mathcal{C}$

# Unweighted Case: Primal Solution

- $P(\emptyset) = 1 - x_1$   
 $P(\{1, \dots, i\}) = x_i - x_{i+1}$  for  $i = 1, \dots, i_0 - 1$   
 $P(\{1, \dots, i_0\}) = \frac{z_{i_0} - y}{K - i_0}$

- **Key Lemma:**

There exists a nonnegative solution to the following linear system

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- $P(\{1, \dots, i_0\} \cup C) = Q(C)$  for all  $C \in \mathcal{C}$
- The constructed primal solution is feasible and has the same objective value as that of the dual problem



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- Resulting (facet-defining) lifted inequality (LI):

$$\partial_0 + \sum_{i \in S} \partial_i x_i + \sum_{i \notin S} \lambda_i x_i \leq w$$

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- Proof:  $0 \leq \gamma_i \leq \lambda_i$  for all  $i > K$

# Weighted Case: Remarks on Approximate Lifting

- The approximate lifting inequality is a version of the unweighted inequality corresponding to  $i_0 = K - 1$
- $\partial_i \leq \gamma_i$  for all  $i > K$  with the inequality being strict when  $f$  is strictly monotone (e.g. square root)
- Can be computed in  $O(n \log n)$  time

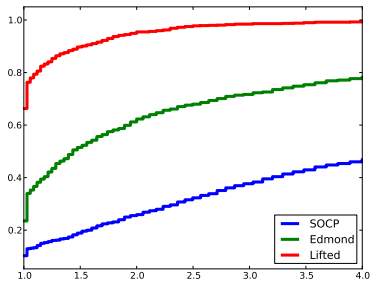
- Mean-risk Knapsack:

$$\min \left\{ - \sum_i \mu_i x_i + \lambda \sqrt{\sum_i \sigma_i^2 x_i} : c^\top x \leq b, x \in \{0, 1\}^n \right\}$$

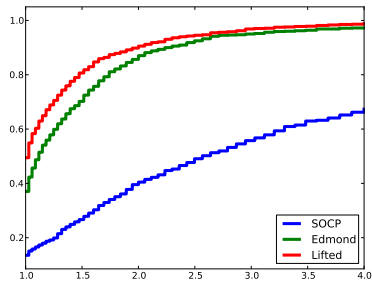
- 1,080 unweighted and 1,080 weighted instances randomly generated ( $n = 50, 80, 100$ )
- Knapsack to Cardinality: Let  $c_1 \leq \dots \leq c_n$  and pick  $K$  such that  $c_1 + \dots + c_K \leq b$  and  $c_1 + \dots + c_{K+1} > b$

- Compare branch-and-cut time and nodes for
  - Mixed Integer SOCP formulation (Replace  $x_i$  by  $x_i^2$ ) [SCOP]
  - SOCP + 5 rounds of usual submodular inequalities [Edmonds]
  - SOCP + 5 rounds of exact separated inequalities in the unweighted case, or SOCP + 5 rounds of approximate lifted inequality in the weighted case [Lifted]
- Implemented in Python + Gurobi 5.6

# Computations: Performance profiles (Time)



Unweighted



Weighted

# Computations: Averages

	SOCP	Edmonds	Lifted
<hr/>			
<u>Unweighted</u>			
Time:	703	528	295
Nodes:	221,111	135,444	75,811
<hr/>			
<u>Weighted</u>			
Time:	208	132	122
Nodes:	59,779	34,366	27,928
<hr/>			



# Concluding Remarks

$$\mathcal{P} = \{(w, x) \in \mathbb{R} \times \{0, 1\}^n : w \geq f(\mathbf{a}^\top x)\} \quad X = \{x \in [0, 1]^n : \mathbf{e}^\top x \leq K\}$$

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- Summary:

- Unweighted case (identical  $a_i$ 's): Complete description of  $\text{conv}(\mathcal{P} \cap X)$
- Weighted case (general  $a_i$ ): Family of facets/valid inequalities by lifting
- Computational results for mean-risk knapsack

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- Some open issues:

- Handle correlations  $\sqrt{x^\top \Sigma x}$  by introducing new variables for cross terms
- Mixed integer setting
- "Submodular relaxations" of other classes of MINLP