

# Lower Bounds on LP extensions

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# Abstract

This text mainly focuses on providing lower-bound results for some NP-hard problems. In order to do so, they provide a lower bound in complexity in terms of another NP-hard problem. That being said, this text only focuses on methods to do so and not on any real example. We end this presentation by claiming a result that is derived using this method.

## Control flow of ideas

- Lower bounding LP formulations using properties of the constraint matrix
- Upper bounding NP-hard (communication complexity) problem in the same terms as constraint matrix.
- Using lower bound results derived for communication complexity and applying them to lower bound LP- formulations

## Note 1.1

We define terms like extension complexity and also mention theorems in order that is useful for comprehensive understanding rather than the order

# Extended formulation

## Def 0.1 Projecting Polytopes by eliminating extra variables

Projection of a polytope  $P$  of  $d$  dimensions to its first  $k$  dimensions is

$$\pi_k(P) = \{x \in \mathbb{R}^k \mid \exists y \in \mathbb{R}^{d-k}, (x, y) \in P\}$$

## Def 0.2 Extended Formulation

An extended formulation of a polytope  $P \subset \mathbb{R}^n$  defined by  $Ax \leq b$  is a polytope  $P^1 \subset \mathbb{R}^{n+r}$  defined by a system

$$Cx + Dy \leq d, x \in \mathbb{R}^n, y \in \mathbb{R}^r$$

such that  $P = \pi_n(P^1)$ .

Intuition: Polyhedra usually have fewer high dimensional facets than lower dimensional facets.

# Extended formulation: an example

For any integer  $n$ , the permutahedron  $P_n$  is defined as the convex hull of the set of all permutations of the numbers  $[n] = \{1, 2, 3, \dots, n\}$ .

## Claim 0.1 Low Dimensional Polytope for Permutahedron

$$P_n = \{x \in \mathbb{R}^n : \sum_{i=1}^n x_i = n(n+1)/2 \text{ and } \sum_{i \in S} x_i \geq |S|(|S|+1)/2, \forall S \subset [n]\}$$

## Proof of Claim 0.1

Page 12 of Goemans's notes.

This low-dimensional polytope with  $n$  variables gives us  $2^n - 2$  facets defining  $P_n$ .

## Extended formulation: an example

Instead, let's try and switch to a higher dimensional polytope by introducing extra variables  $y_{i,j}$  for all pairs  $i, j$ .  $y_{i,j}$  intuitively represents the indicator function  $\chi(\pi(i) = j)$  where  $\pi$  is a permutation, not the projection polytope.

### Claim 0.2 Higher Dimensional Polytope for Permutahedron

$P_n = \pi_n(P^1)$  where  $P^1$  is a  $n^2 + n$  dimensional polytope defined as

$$\begin{aligned} P^1 = \{ & (x_1, \dots, x_n, y_{1,1}, \dots, y_{n,n}) \in \mathbb{R}^{n^2+n} : \\ & \sum_j y_{i,j} \leq 1, \forall i \in [n] \\ & \sum_i y_{i,j} \leq 1, \forall j \in [n] \\ & y_{i,j} \geq 0, \forall i, j \\ & x_i = \sum_{j=1}^n j y_{i,j}, \forall i \in [n] \} \end{aligned}$$

Note that  $P_1$  has only  $n^2 + 3n$  facets defining it, so we can efficiently solve LP problems on  $P^1$ .

# Extended formulation: an example

## Proof of Claim 0.2

Prove using the Birkoff-von Neumann theorem. For details check out section 3 of Sitan Chen's notes.

## Def 0.3 extension complexity

The extension complexity  $xc(P)$  of a polytope  $P$  is the minimum size of an extended formulation  $P_n^1$  of  $P$ .

It is easy to see that for the permutahedron,  $xc(P_n) \leq n^2 + 3n$

Fun Fact: The lower bound on extension complexity for a permutahedron is  $O(n \log n)$  and is in fact tight. ( Reference: Goemans's paper)

# Yannakakis rank

## Def 1.1 Yannakakis Rank

Denoted as  $rank_+(M)$ .  $M$  has  $rank_+(M) \leq r$  if it can be written as  $M = AB$  where  $A$  is a non-negative  $m \times r$  matrix and  $B$  is a non-negative  $r \times n$  matrix.

## Cor 1.1 Yannakakis Rank

$rank_+(M) \leq r$  iff  $M = \sum_{i=1}^r M_i$  where each  $M_i$  is a non negative matrix with  $rank(M_i) = 1$ .

## Def 1.2 Slack Matrix

If  $P$  is a polytope bounded by  $V$  vertices  $(x_1, x_2, \dots, x_v)$  and  $P$  is defined by the set of inequalities  $Ax \leq b$ , then

$$S_{i,j} = b_i - A_i \cdot x_j$$

$S$  is a  $v \times f$  matrix. Clearly,  $S \geq 0$ .



# Yannakakis theorem

## Theorem 1.1(Yannakakis Theorem)

$$xc(P) = rank_+(S_P)$$

**Proof:** Using farkas lemma, if

$$Ax \leq b \implies A_i^T x \leq c_i$$

then we have

$$\exists y \ A_i^T = A^T y \text{ and } c_i^T \geq b^T y$$

Consider the following lemma which is the core of proof:

### lemma 1.1

$rank_+(S_P) \leq m$  where  $S_P$  is a  $m \times n$  matrix. In other terms  $rank_+(S_P)$  is bounded by number of facets in the system.

Proof of this lemma is trivial as we can split the matrix  $m_i$  where

$$m_i = [000 \dots M_i^T 0]^T \text{ as this is at-least a rank one matrix.}$$

# Yannakakis theorem

We now see another lemma that helps us to convert  $S_P$  into a more efficient form defined by extension formulation

lemma 1.2

$$\text{rank}_+(M) \geq \text{rank}_+(yM) \quad \forall y \geq 0$$

To see the proof of this lemma, we just need to see that  $yM$  can be split into  $ym_i$  as  $y \geq 0$  and  $ym_i$  has rank at most

$$1(\text{rank}(AB) \leq \min(\text{rank}(A), \text{rank}(B)))$$

Now consider the matrix  $S_P$

$$S_P^{ij} = b_i - A_i V_j$$

Use farkas lemma from the extension matrix  $A^1 x^1$  and  $b^1$  to see that

$$\exists y_i \quad A_i = y_i A^1 \text{ and } b_i \geq y_i b_i^1 \quad \forall i$$

# Yannakakis theorem

To make this proof more readable, we are assuming that  $A$  is padded with zeros to suit the equations.

Now observe that

$S_P^{ij} = y_i(b^1 - A^1 V_j) + \text{rem}_i$ ,  $\text{rem}_i \geq 0$  is the remainder term from the inequality of farkas lemma

$S_P = Y S_P^1 + \text{rem}$ ,  $\text{rem} \geq 0$  is atmost rank one matrix

$Y = [y_1^T, y_2^T \dots]$  and  $S_P^1$  is the matrix defined using extended equations

Now carefully use lemma 1.2 on  $S_P$  and  $S_P^1$  to see that

$$\text{rank}_+(S_P) \leq \text{rank}_+(S_P^1)$$

Use lemma 1.1 to conclude that

$$\text{rank}_+(S_P) \leq \text{xc}(P)$$

Fortunately, we only need the inequality moving forward

# Communication Complexity

## Def 2.1 Communication Complexity Problem

let  $n_1, n_2$  be two positive integers and

$$f: [n_1] \times [n_2] \rightarrow \{0, 1\}$$

be a function represented by  $M_f$

The problem asks us to find minimum number of bits needed to convince users  $a, b$  that hold  $x, y$  indices that  $f(x, y) = 1$  in a case that it is. (it is not guaranteed always to  $a, b$  that it is)

## Def 2.2 $FV(P)$

$FV(P)$  is the function defined by the matrix

$$J^{ij} = \begin{cases} 0 & \text{if } S_P^{ij} = 0 \\ 1 & \text{otherwise} \end{cases}$$

# Communication Complexity

## Theorem 2.1

$$ncc(FV(P)) \leq \log_2(\text{rank}_+(S_P))$$

**Proof:** To see proof of such equations, we try and find a mechanism that can convince a,b. Before defining the mechanism, consider the following lemma

## lemma 2.1

let  $M$  be a  $m \times n$  matrix

$$\text{rank}(M) = 1 \implies \exists \alpha \in R^{m \times 1} \exists \beta \in R^{1 \times n} \ M = \alpha \beta$$

This result can either be seen as corollary of positive rank in the case of positive matrices or can also be easily proved by vector space results.

# Communication Complexity

Assume that we put some constraints on  $\beta_i$  so that both players know the exact value of  $\alpha_i, \beta_i$  for all  $M_i$  that sum up to  $S_P$

Proof that we submit to players is index  $k$  such that

$$\alpha_k^i \beta_k^j > 0$$

Note that for all  $M^{ij} > 0$ , there must exist such proof as all the matrices  $M_i$  are non . Other side is trivial to observe as well.

Observe that this proof requires only  $\log_2(\text{rank}_+(S_P))$  number of bits proving our upper bound.

# Connection to approximate LP problems

## Def 3.1 $\rho$ -approximate extended formulation

A formulation  $P^1$  is called  $\rho$ -approximate extended formulation of  $P$  if for all linear objective functions  $w$

$$\max\{w^T x : x \in P\} \leq \max\{w^T x : x \in P^1\} \leq \rho \max\{w^T x : x \in P\}$$

## Def 3.2 $xc_\rho(P)$

It is defined as the minimum size of such  $P^1$

The following definition is not present in the reading text and is defined for the ease of reader,

## Def 3.3 $xc_\rho(P, Q)$

It is defined as the minimum size of  $\rho$ -approximate extended formulation  $P^1$  of  $P$  such that

$$P \subseteq P^1 \subseteq Q$$

# Connection to approximate LP problems

## Def 3.4 $S_{P,Q}$

In a setting  $P \subseteq Q$ , we define  $S_{P,Q}$  as follows,

$$S_{P,Q} = (b_i - A_i V_j)_{i,j}$$

where

$Q := Ax \leq b$  and  $\{V_1, V_2, \dots\}$  are vertices of  $P$ .

## lemma 3.1

For any  $\rho$ -approximate extended formulation  $P^1$  of  $P$ , we have

$$P^1 \subseteq \rho P \text{ and } P \subseteq P^1$$

To see proof of this lemma, observe that any optimal value in  $\rho P$  is  $\rho$  times optimal value in  $P$ . Following this, if we have a point outside of  $\rho P$  in  $P^1$ , we construct a separating hyperplane and provide a contradiction.

The second part is trivial to see in the same way.



# Connection to approximate LP problems

This lemma 3.1 helps us to reformulate  $\rho$ -approximate extensions by searching in  $(P, \rho Q)$  where  $P \subseteq Q$

Theorem 3.1(Braun et al.)

$$xc_{\rho}(P) = rank_{+}(S_{P, \rho Q})$$

We instead need(for the sake of lower bounds) a weaker Theorem that we can easily prove.

Theorem 3.2

$$\forall P^1(Q \subseteq P^1) \implies xc_{\rho}(P) \geq rank_{+}(S_{P, \rho Q})$$

**Proof:** We need clever definitions of  $Q$  in order to satisfy the first clause, observe that  $P$  satisfies all the properties we need.

# Connection to approximate LP problems

## lemma 3.2

$$Q \subseteq P^1 \implies \text{rank}_+(S_{P,P^1}) = \text{rank}_+(S_{P,\rho Q})$$

Follow the same methodology of proof used to prove Theorem 1.1 to observe this result.

This lemma 3.2 in combination with the fact that

$$xc_\rho(P) \geq \text{rank}_+(S_{P,P^1})$$

where  $P^1$  is the extended formulation with least size.  
will prove Theorem 3.2

## Note 3.1

Whenever we refer to  $P^1$  in this presentation section 3, it is assumed that it is  $\rho$ -approximate extended formulation of  $P$ .

# Examples

This theorem is proved using Theorem 3.2 we proved and a result from communication complexity lower bound.

## Theorem 4.1(Braverman-Moitra)

Obtaining a  $n^{1-\epsilon}$ -*approximation* of max clique has extension complexity lower bound of  $2^{(n^\epsilon)}$

**Proof:** Please follow the reference in section 5 for proof.

# References



Sitan Chen (2016)

Lecture 22: CS229r at

<http://people.seas.harvard.edu/~madhusudan/courses/Spring2016/scribe/lect22.pdf>



Michael X. Goemans (2017)

Linear Programming and Polyhedral Combinatorics

*Third Lecture for MIT's course 18.453:*

<https://math.mit.edu/~goemans/18453S17/polyhedral.pdf>



Michael X. Goemans

Smallest Compact Formulation for the Permutahedron

<https://math.mit.edu/~goemans/PAPERS/permutahedron.pdf>

Thank You