

# Reformulations of nonlinear binary optimization problems

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# Outline

- 1 Nonlinear 0-1 optimization
- 2 Quadratization
- 3 Symmetric functions
- 4 Upper bounds
- 5 Lower bounds
- 6 Conclusions

# Definitions

## Pseudo-Boolean functions

A pseudo-Boolean function is a mapping  $f : \{0, 1\}^n \rightarrow \mathbb{R}$ , that is, a real-valued function of 0 – 1 variables.

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## Example:

$$f = 4 - 9x_1 - 5x_2 - 2x_3 + 13x_1x_2 + 13x_1x_3 + 6x_2x_3x_4 - 13x_1x_2x_3x_4$$

# Multilinear optimization in binary variables

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The quadratic case has attracted much attention:

- many examples arise in this form: MAX CUT, MAX 2SAT, simple computer vision models,...
- efficient exact algorithms and heuristics have been proposed for this case
- higher-degree cases can be efficiently reduced to the quadratic case, and this leads to good optimization algorithms.



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## Observations

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$$f(x) := \min\{g(x, y) \mid y \in \{0, 1\}^m\}$$

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- Conversely...

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The quadratic function  $g(x, y)$ ,  $(x, y) \in \{0, 1\}^{n+m}$  is an *m-quadratization* of the pseudo-Boolean function  $f(x)$ ,  $x \in \{0, 1\}^n$ , if

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- $\min\{f(x) \mid x \in \{0, 1\}^n\} = \min\{g(x, y) \mid (x, y) \in \{0, 1\}^{n+m}\}.$
- Akin to linearization procedures for MOB.
- Does every function  $f$  have a quadratization?

# Existence

## Existence of quadratizations (Rosenberg 1975)

Given the multilinear expression of a pseudo-Boolean function  $f(x)$ ,  $x \in \{0, 1\}^n$ , one can find in polynomial time a quadratization  $g(x, y)$  of  $f(x)$ .

- Idea: in each term  $\prod_{i \in A} x_i$  of  $f$ , with  $\{1, 2\} \subseteq A$ , replace the product  $x_1 x_2$  by  $y$ :

$$t(x, y) = \left( \prod_{i \in A \setminus \{1, 2\}} x_i \right) y + M(x_1 x_2 - 2x_1 y - 2x_2 y + 3y).$$

# Example

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Substitute  $x_3x_4$ :

$$\min_{x,y} 4 - 9x_1 - 5x_2 - 2x_3 + 13x_1x_2 + 13x_1x_3 + 6x_2y_{34} - 13x_1x_2y_{34} + M(x_3x_4 - 2x_3y_{34} - 2x_4y_{34} + 3y_{34})$$

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In a minimizer  $(x, y)$ ,

- if  $x_3 = x_4 = 1$ , then  $M(1 - y_{34}) = 0$  and  $y_{34} = x_3x_4 = 1$ ;
- if  $x_3 = 0$ , then  $M(-2x_4y_{34} + 3y_{34}) = 0$  and  $y_{34} = x_3x_4 = 0$ .

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Substitute  $x_1x_2$ :

$$\min 4 - 9x_1 - 5x_2 - 2x_3 + 13y_{12} + 13x_1x_3 + 6x_2y_{34} - 13y_{12}y_{34} + M(x_3x_4 - 2x_3y_{34} - 2x_4y_{34} + 3y_{34}) + M(x_1x_2 - 2x_1y_{12} - 2x_2y_{12} + 3y_{12})$$

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- Fix  $x$ . In every minimizer of  $t(x, y)$ ,  $y = x_1 x_2$  and  $t(x, y) = \prod_{i \in A} x_i$ .
- Potential drawbacks: introduces many auxiliary variables, big  $M$ .



## Questions arising...

- Many quadratization procedures proposed in recent years. Which ones are “best”? Small number of variables, of positive terms, good properties with respect to persistencies, submodularity?
- Easier question: What if  $f$  is a single monomial?
- Can we characterize all quadratizations of  $f$ ?
- How many variables are needed in a quadratization?
- etc.

Refs: Boros and Gruber (2011); Buchheim and Rinaldi (2007); Fix, Gruber, Boros and Zabih (2011); Freedman and Drineas (2005); Ishikawa (2011); Kolmogorov and Zabih (2004); Ramalingam et al. (2011); Rosenberg (1975); Rother et al. (2009); Živný, Cohen and Jeavons (2009); etc.

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M. Anthony, E. Boros, Y. Crama and M. Gruber, Quadratization of symmetric pseudo-Boolean functions, *Discrete Applied Mathematics* 203 (2016) 1–12.

M. Anthony, E. Boros, Y. Crama and M. Gruber, Quadratic reformulations of nonlinear binary optimization problems *Mathematical Programming* 162 (2017) 115-144.

E. Boros, Y. Crama and E. Rodríguez-Heck, Compact quadratizations for pseudo-Boolean functions, Working paper, 2018.

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### Observation

Every term of the form  $a \prod_{i=1}^n x_i$  can be quadratized using  $n - 2$  auxiliary variables (Rosenberg 1975), and even  $\lfloor \frac{n-1}{2} \rfloor$  auxiliary variables (Ishikawa 2011).

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So:

### Ishikawa (2011)

Every  $n$ -variable pBF has a quadratization involving  $\lfloor \frac{n-1}{2} \rfloor 2^n$  auxiliary variables.

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### Ishikawa (2011)

Every  $n$ -variable pBF has a quadratization involving  $\lfloor \frac{n-1}{2} \rfloor 2^n$  auxiliary variables.

- Best known bound, until recently.
- Digression...

# The case of symmetric functions

## Symmetric functions

A pseudo-Boolean function  $f$  is *symmetric* if the value of  $f(x)$  depends only on the Hamming weight  $|x| = \sum_{j=1}^n x_j$  (number of ones) of  $x$ .

That is, there is a discrete function  $k : \{0, 1, \dots, n\} \rightarrow \mathbb{R}$  such that  $f(x) = k(w)$  where  $w = |x|$ .

Examples:

- Monomials:  $a \prod_{i=1}^n x_i = a x_1 \dots x_n$ .
- At least  $k$ -out-of- $n$  function: takes value 1 if and only if  $|x| \geq k$ .
- Parity function: takes value 1 if and only if  $|x|$  is even.

# Upper bounds for symmetric functions

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- Negative monomial:  $N_n(x) = -\prod_{i=1}^n x_i = -x_1 \dots x_n$ .
- (Freedman and Drineas 2005)  $N_n(x) = \min_y (n - 1 - \sum_{i=1}^n x_i)y$ .

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- (Fix 2011)  $n - 1$  variables suffice for any symmetric function.
- Based on ad hoc arguments.
- In *DAM* (2016), we proposed a generic approach based on a general representation theorem for discrete functions.

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Function	Lower Bound	Upper Bound	Previous UB
Symmetric	$\Omega(\sqrt{n})$	$2\lceil\sqrt{n+1}\rceil$	$n-2$
Positive monomial	$\lceil\log(n)\rceil - 1$	$\lceil\log(n)\rceil - 1$	$\lfloor\frac{n-1}{2}\rfloor$
$k$ -out-of- $n$	$\lceil\log(k)\rceil - 1$	$\lceil\log(k)\rceil$	$\lfloor\frac{n}{2}\rfloor$
Parity	$\lceil\log(n)\rceil - 1$	$\lceil\log(n)\rceil - 1$	$\lfloor\frac{n-1}{2}\rfloor$

Basic idea:

### Positive monomial: upper bound

Assume that  $n = 2^k$ . Then,

$$g(x, y) = \left( \sum_{i=1}^n x_i - \sum_{j=0}^{k-1} 2^j y_j \right)^2$$

is a quadratization of the positive monomial  $P_n(x) = \prod_{i=1}^n x_i$  using  $k = \log(n)$  auxiliary variables.

**Proof.** (Sketch.) For all  $(x, y)$ ,  $g(x, y) \geq 0$  and  $0 \leq \sum_{j=0}^{k-1} 2^j y_j \leq n - 1$ .

If  $\sum_{i=1}^n x_i < n$ , then one can make  $g(x, y) = 0$ .

If  $\sum_{i=1}^n x_i = n$ , then  $\min_y g(x, y) = 1$ .

Refinement:

### Positive monomial: improved upper bound

Assume that  $n = 2^k$ . Then,

$$g(x, y) = \frac{1}{2} \left( \sum_{i=1}^n x_i - \sum_{j=1}^{k-1} 2^j y_j \right) \left( \sum_{i=1}^n x_i - \sum_{j=1}^{k-1} 2^j y_j - 1 \right)$$

is a quadratization of the positive monomial  $P_n(x) = \prod_{i=1}^n x_i$  using  $k - 1 = \log(n) - 1$  auxiliary variables.

We also have a matching lower bound.

## Positive monomial: lower bound

Every quadratization of the positive monomial  $P_n(x) = \prod_{i=1}^n x_i$  must use at least  $\log(n) - 1$  auxiliary variables.



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**Proof.** (Sketch.) For a quadratization  $g(x, y)$ , define  $r(x) = \prod_{y \in \{0,1\}^m} g(x, y)$ .

- The degree of  $r(x)$ ,  $\deg(r)$ , is at most  $2^{m+1}$ , by definition.
- For every  $x$  with  $|x| < n$ , there is  $y \in \{0, 1\}^m$  such that  $g(x, y) = 0$ . So,  $r(x) = 0$ .
- When  $|x| = n$ ,  $g(x, y) \geq 1$  for all  $y \in \{0, 1\}^m$ , and hence  $r(x) \geq 1$ .
- It follows that  $\deg(r) = n$
- We get:  $\deg(r) = n \leq 2^{m+1}$ .

- Similar ideas and bounds extend to  $k$ -out-of- $n$  (“exact” or “at least”) and to parity functions.

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- For symmetric functions:

### General symmetric functions: Lower bound

- Some symmetric functions have no  $m$ -quadratization using less than  $\sqrt{n}$  auxiliary variables. (Anthony, Boros, Crama, Gruber 2017).
- Every symmetric function has a quadratization using at most  $2\lceil\sqrt{n+1}\rceil$  auxiliary variables. (Boros, Crama, Rodríguez-Heck 2018.)

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- **Note:** Proofs rely on techniques developed for the analysis of the size of threshold circuits, and of slicing or covering of the vertices of the hypercube by hyperplanes (work by Alon, Füredi, Linial, Radhakrishnan, Saks, etc.)

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# Upper bound

- Worst-case bound based on termwise quadratizations:

## Corollary

Every function  $f$  of  $n$  variables has a quadratization involving at most  $O(\log(n) 2^n)$  auxiliary variables.

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- We can prove:

## Theorem: upper bound (*Math. Prog.* (2017))

Every function  $f$  of  $n$  variables has a quadratization involving at most  $O(2^{n/2})$  auxiliary variables.

# Pairwise cover

Based on a construction using small *pairwise covers*:

## Pairwise cover

A hypergraph  $\mathcal{H}$  is a *pairwise cover* of  $\{1, \dots, n\}$  if, for every  $S \subseteq \{1, \dots, n\}$  with  $|S| \geq 3$ , there are sets  $A, B \in \mathcal{H}$  such that  $|A| < |S|$ ,  $|B| < |S|$  and  $A \cup B = S$ .

- Pairwise covers are (almost) identical to so-called *2-bases* investigated by Erdős, Füredi and Katona (2006), Frein, Lévêque and Sebö (2008), Ellis and Sudakov (2011).



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- $\mathcal{P}(\text{even})$  = all subsets of even integers in  $\{1, \dots, n\}$ .
- $\mathcal{P}(\text{odd})$  = all subsets of odd integers in  $\{1, \dots, n\}$ .
- $\mathcal{H} = \mathcal{P}(\text{even}) \cup \mathcal{P}(\text{odd})$  is a “small” pairwise cover with size  $O(2^{n/2})$ .

# Pairwise covers and universal sets

We prove:

**Theorem: From pairwise cover to quadratization**

If there exists a pairwise cover of  $\{1, \dots, n\}$  of size  $m$ , then every pseudo-Boolean function has an  $m$ -quadratization.

# Pairwise covers and universal sets

We prove:

## Theorem: From pairwise cover to quadratization

If there exists a pairwise cover of  $\{1, \dots, n\}$  of size  $m$ , then every pseudo-Boolean function has an  $m$ -quadratization.

- Idea of the proof: write  $\prod_{i \in S} x_i = (\prod_{j \in A} x_j)(\prod_{k \in B} x_k)$ ; substitute  $y_A$  for  $\prod_{j \in A} x_j$  and  $y_B$  for  $\prod_{k \in B} x_k$ .

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- There are pairwise covers with size  $O(2^{n/2})$ .
- Hence, every pseudo-Boolean function has a quadratization with  $O(2^{n/2})$  auxiliary variables.

# By-products and corollaries

Similarly:

## Fixed-degree functions

For every fixed  $d$ , every pseudo-Boolean function of degree  $d$  has a quadratizations with  $O(n^{d/2})$  auxiliary variables.

# Outline

- 1 Nonlinear 0-1 optimization
- 2 Quadratization
- 3 Symmetric functions
- 4 Upper bounds
- 5 Lower bounds**
- 6 Conclusions

# Lower bound

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**Theorem: lower bound (*Math. Prog.* (2017))**

There are pseudo-Boolean functions of  $n$  variables for which every quadratization must involve at least  $\Omega(2^{n/2})$  auxiliary variables.

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## Theorem: lower bound (*Math. Prog.* (2017))

There are pseudo-Boolean functions of  $n$  variables for which every quadratization must involve at least  $\Omega(2^{n/2})$  auxiliary variables.

- This lower bound matches the  $O(2^{n/2})$  upper bound.
- Non constructive proof based on dimensionality argument: if too few auxiliary variables, then we cannot generate the whole vector space of pseudo-Boolean functions.

# Proof

Main idea: dimensionality argument.

- Suppose  $f(x)$  has an  $m$ -quadratization  $g(x, y)$ : for all  $x \in \{0, 1\}^n$ ,

$$f(x) = \min\{g(x, y) : y \in \{0, 1\}^m\}. \quad (1)$$

- $g(x, y)$  has  $O(n^2 + m^2)$  coefficients.
- But the vector space of pseudo-Boolean functions on  $n$  variables has dimension  $2^n$ .
- So, if  $m$  is too small, we cannot generate the whole vector space.
- It follows that if  $m$  additional variables suffice to quadratize any pseudo-Boolean function in  $n$  variables, then  $m$  is  $\Omega(2^{n/2})$ .

Must be refined, since the relation (1) is not linear.

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For every fixed  $d$ , there are degree- $d$  pseudo-Boolean functions of  $n$  variables for which any quadratization must involve at least  $\Omega(n^{d/2})$  auxiliary variables.

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- Our quadratization procedure based on pairwise covers probably yields small quadratizations as a function of  $t$  as well, but we have no generic bounds in this case.

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# Conclusions

- Tight lower and upper bound for special classes of functions (e.g., for positive monomials).
- Tight lower and upper bounds on the number of auxiliary variables required for arbitrary and for fixed-degree functions.
- Structure and properties of quadratizations are poorly understood.
- Computational tests show that pairwise covers yield good quadratizations and efficient approaches for certain classes of nonlinear problems, but linearization remains competitive in most cases.
- Many intriguing questions and conjectures, much computational and theoretical work to be done.

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