# Rank optimality for the Burer-Monteiro factorization

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## Semidefinite programming

minimize  $\operatorname{Trace}(CX)$  such that  $\mathcal{A}(X) = b$ ,  $X \succeq 0$ .

#### Here,

- ightharpoonup X, the unknown, is an  $n \times n$  matrix;
- ▶ C is a fixed  $n \times n$  matrix (cost matrix);
- $ightharpoonup \mathcal{A}: \operatorname{Sym}_n \to \mathbb{R}^m \text{ is linear};$
- ▶ b is a fixed vector in  $\mathbb{R}^m$ .

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### **Motivations**

Various difficult problems can be "lifted" to SDPs, and solving these lifted SDPs may solve the original problems.

Particularly important example : relaxation of *MaxCut*.

minimize 
$$\operatorname{Trace}(CX)$$
 such that  $\operatorname{diag}(X) = 1$ ,  $X \succeq 0$ .

Relaxes the *Maximum Cut* problem from graph theory. [Delorme and Poljak, 1993] Appears also in phase retrieval,  $\mathbb{Z}_2$  synchronization ...

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#### Numerical solvers

SDPs can be solved at a given precision in polynomial time. But the order of the polynomial may be large.

Interior point solvers, for instance, have a per iteration complexity of  $O(n^4)$  in full generality (when m and n are of the same order).

First-order ones, applied to a smoothed problem, have a  $O(n^3)$  complexity, but require more iterations.

→ Numerically, high dimensional SDPs are difficult to solve.

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## Exploiting the low rank

To speed up these algorithms : exploit the structure of the problem.

Here, the "structure" we consider is the fact that there exists a low-rank solution.

▶ There is always a solution with rank  $r_{opt}$  at most

$$\left|\sqrt{2m+1/4}-1/2\right|.$$

[Pataki, 1998]

▶ In many situations, there is actually a solution with rank  $r_{opt} = O(1)$ .



### Burer-Monteiro factorization

We focus on one heuristic that takes advantage of the low rank: the Burer-Monteiro factorization.
[Burer and Monteiro, 2003]

If there is a solution with rank  $r_{opt}$ , we can write X under the form

$$X = VV^T$$

with V an  $n \times p$  matrix, and  $p \geq r_{opt}$ .

 $\rightarrow$  We optimize over V instead of optimizing over X.

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$$\begin{array}{c} \text{minimize } \operatorname{Trace}(\mathit{CX}) \\ \text{for } X \in \mathbb{R}^{n \times n} \text{ such that } \mathcal{A}(X) = b, \\ X \succeq 0. \end{array}$$



$$\begin{array}{l} \text{minimize } \mathrm{Trace}(\mathit{CVV}^\mathsf{T}) \\ \text{for } V \in \mathbb{R}^{n \times p} \text{ such that } \mathcal{A}(\mathit{VV}^\mathsf{T}) = b. \end{array}$$

Remark: The factorization rank p must be chosen. It can be different from  $r_{opt}$ , the rank of the solution.

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$$\begin{array}{l} \text{minimize } \operatorname{Trace}(\mathit{CVV}^\mathsf{T}) \\ \text{for } \mathit{V} \in \mathbb{R}^{\mathit{n} \times \mathit{p}} \text{ such that } \mathcal{A}(\mathit{VV}^\mathsf{T}) = \mathit{b}. \end{array}$$

We assume that  $\{V \in \mathbb{R}^{n \times p}, \mathcal{A}(VV^T) = b\}$  is a "nice" manifold.

 $\rightarrow$  Riemannian optimization algorithms.

## Main advantage of the factorized formulation

The number of variables is not  $O(n^2)$  anymore, but O(np), with possibly  $p \ll n$ .

→ Less computationally-demanding algorithms can be used.



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#### Main drawback of the factorized formulation

Contrarily to the SDP, this problem is non-convex.

→ Riemannian optimization algorithms may get stuck at a critical point instead of finding a global minimizer.

This issue can arise or not, depending on the factorization rank p.

 $\Rightarrow$  How to choose p?



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### Outline

#### 1. Literature review

- ▶ In practice, algorithms work when  $p = O(r_{opt})$ .
- ▶ In particular situations, this phenomenon is understood.
- ▶ In a general setting, no guarantees for  $p \lesssim \sqrt{2m}$ .
- Why this gap?

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### Outline

#### 1. Literature review

- ▶ In practice, algorithms work when  $p = O(r_{opt})$ .
- ▶ In particular situations, this phenomenon is understood.
- ▶ In a general setting, no guarantees for  $p \lesssim \sqrt{2m}$ .
- Why this gap?
- 2. Optimal rank for the Burer-Monteiro formulation
  - ▶ Up to a minor improvement,  $p \approx \sqrt{2m}$  is the optimal rank for which general guarantees can be derived.
  - ▶ Consequently, when  $p \lesssim \sqrt{2m}$ , Riemannian optimization algorithms cannot be certified correct without assumptions on C.

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#### 1. Literature review

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- 2. Optimal rank for the Burer-Monteiro formulation
  - ▶ Up to a minor improvement,  $p \approx \sqrt{2m}$  is the optimal rank for which general guarantees can be derived.
  - ▶ Consequently, when  $p \lesssim \sqrt{2m}$ , Riemannian optimization algorithms cannot be certified correct without assumptions on C.
- 3. Open questions



## **Empirical observations**

- 1. [Burer and Monteiro, 2003] Numerical experiments on various problems, notably MaxCut and minimum bisection relaxations. The factorization rank is  $p \approx \sqrt{2m}$ , and algorithms always find a global minimizer. (The authors do not test smaller values of p.)
- 2. [Journée, Bach, Absil, and Sepulchre, 2010] Numerical experiments on MaxCut relaxations (with a particular initialization scheme). The algorithm proposed by the authors always finds a global minimizer when  $p = r_{opt}$ .

## Empirical observations (continued)

[Boumal, 2015]
 Numerical experiments on problems coming from orthogonal synchronization.
 Here, r<sub>opt</sub> = 3 and the algorithm finds the global minimizer as soon as p > 5.

4. Similar results on "SDP-like" problems. See for example [Mishra, Meyer, Bonnabel, and Sepulchre, 2014].

## Theoretical explanations in particular cases

[Bandeira, Boumal, and Voroninski, 2016] SDP instances coming from  $\mathbb{Z}_2$  synchronization and community detection problems, under specific statistical assumptions.

 $\rightarrow$  With high probability,  $r_{opt} = 1$ . If p = 2, Riemannian algorithms find the global minimizer.

Other particular SDP-like problems have been studied.

 $\rightarrow$  Under strong assumptions,  $p \ge r_{opt}$  is enough so that a global minimizer is found.

[Ge, Lee, and Ma, 2016] ...

minimize 
$$\operatorname{Trace}(\mathit{CVV}^T)$$
 for  $V \in \mathbb{R}^{n \times p}$  such that  $\mathcal{A}(\mathit{VV}^T) = b$ .

## Main hypothesis (approximately)

$$\mathcal{M}_p \stackrel{\text{def}}{=} \{ V \in \mathbb{R}^{n \times p}, \mathcal{A}(VV^T) = b \}$$
 is a manifold.

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## Main hypothesis (approximately)

$$\mathcal{M}_p \stackrel{def}{=} \{V \in \mathbb{R}^{n \times p}, \mathcal{A}(VV^T) = b\}$$
 is a manifold.

[More precisely : for all  $V \in \mathcal{M}_p$ ,

$$\phi_{V}: \dot{V} \in \mathbb{R}^{n \times p} \to \mathcal{A}(V\dot{V}^{T} + \dot{V}V^{T}) \in \mathbb{R}^{m}$$

is surjective.]



minimize 
$$\operatorname{Trace}(\mathit{CVV}^T)$$
, for  $V \in \mathcal{M}_p$ .

Riemannian optimization algorithms typically converge to second-order critical points :

A matrix  $V_0 \in \mathcal{M}_p$  is a second-order critical point if

- ▶ Hess  $f_C(V_0) \succeq 0$ ,

where  $f_C \stackrel{\text{def}}{=} (V \in \mathcal{M}_p \to \text{Trace}(CVV^T))$ .

#### **Theorem**

Under suitable hypotheses, for almost all matrices C, if

$$p>\left\lfloor\sqrt{2m+\frac{1}{4}}-\frac{1}{2}\right\rfloor,$$

all second-order critical points of the factorized problem are global minimizers.

Consequently, Riemannian optimization algorithms always find a global minimizer.

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Consequently, Riemannian optimization algorithms always find a global minimizer.

Remark: The value of p does not depend on  $r_{opt}$ .

## Summary

 In empirical experiments, as well as in the few particular cases that have been studied, algorithms seem to always work when

$$p = O(r_{opt}).$$

► The only available general result guarantees that algorithms work when

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## Summary

 In empirical experiments, as well as in the few particular cases that have been studied, algorithms seem to always work when

$$p = O(r_{opt}).$$

 The only available general result guarantees that algorithms work when

$$p \gtrsim \sqrt{2m}$$
.

As  $r_{opt}$  is often much smaller than  $\sqrt{2m}$ , this leaves a big gap.

 $\rightarrow$  Is it possible to obtain general guarantees for  $p \ll \sqrt{2m}$ ?

### Overview of our results

▶ A minor improvement is possible over the result by [Boumal, Voroninski, and Bandeira, 2018], but it does not change the leading order term

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▶ A minor improvement is possible over the result by [Boumal, Voroninski, and Bandeira, 2018], but it does not change the leading order term

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▶ With this improvement, the result is essentially optimal, even if  $r_{opt} \ll \sqrt{2m}$ .

## Improving [Boumal, Voroninski, and Bandeira, 2018]

### **Theorem**

Under suitable hypotheses, for almost all matrices C, if

$$p>\left\lfloor\sqrt{2m+\frac{9}{4}}-\frac{3}{2}\right\rfloor,$$

all second-order critical points of the factorized problem are global minimizers.

In [Boumal, Voroninski, and Bandeira, 2018], we had  $\left\lfloor \sqrt{2m + \frac{1}{4}} - \frac{1}{2} \right\rfloor$ . Our result is better by one unit for most values of m.

## Theorem (Quasi-optimality of the previous result)

Let  $r_0 = \min\{\operatorname{rank}(X), \mathcal{A}(X) = b, X \succeq 0\}$ . Under suitable hypotheses, if

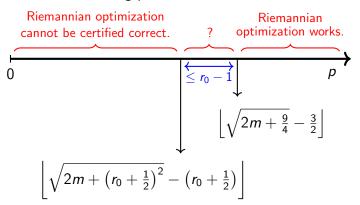
$$p \leq \left\lfloor \sqrt{2m + \left(r_0 + \frac{1}{2}\right)^2} - \left(r_0 + \frac{1}{2}\right) \right\rfloor,\,$$

then there exists a set of matrices C with non-zero Lebesgue measure such that :

- 1. The global minimizer has rank  $r_0$ .
- 2. There is a second order critical point that is not a global minimizer.

#### Comments

- ▶ In most applications,  $r_0$  is small, possibly  $r_0 = 1$ .
- ▶ We have the following picture :



## Technical comment: "under suitable hypotheses"

There must exist  $U_0 \in \mathbb{R}^{n \times r_0}$ ,  $V \in \mathbb{R}^{n \times p}$  such that

$$\mathcal{A}(U_0U_0^T) = \mathcal{A}(VV^T) = b,$$

and

$$\psi_{V}: (T, R) \in \operatorname{Sym}_{p} \times \mathbb{R}^{r_{0} \times p}$$

$$\to \mathcal{A}\left(\left(V \cup_{0}\right)\left(\begin{smallmatrix} T \\ R \end{smallmatrix}\right) V^{T} + V\left(\begin{smallmatrix} T \\ R \end{smallmatrix}\right)^{T} \left(V \cup_{0}\right)^{T}\right) \in \mathbb{R}^{m}$$

is injective.

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is injective.

Because dim  $(\operatorname{Sym}_p \times \mathbb{R}^{r_0 \times p}) \leq \dim(\mathbb{R}^m)$ , this condition is a priori generically satisfied.

## Example: MaxCut relaxations

minimize  $\operatorname{Trace}(CX)$ , such that  $\operatorname{diag}(X) = 1$ ,  $X \succeq 0$ .

(Original SDP)

minimize Trace( $CVV^T$ ), such that diag( $VV^T$ ) = 1,  $V \in \mathbb{R}^{n \times p}$ . (Burer-Monteiro factorization)

- ▶ In this case,  $r_0 = 1$ .
- ▶ The "suitable hypotheses" are satisfied.

### Example: MaxCut relaxations

▶ For almost all C, if

$$p>\left\lfloor\sqrt{2m+\frac{9}{4}}-\frac{3}{2}\right\rfloor,$$

no bad second-order critical point exists : Riemannian optimization algorithms work.

▶ If

$$p \leq \left| \sqrt{2m + \frac{9}{4}} - \frac{3}{2} \right|,$$

bad second-order critical points may exist, even when there is a rank 1 solution: Riemannian algorithms cannot be certified correct without additional assumptions on C.

## Burer-Monteiro factorization : summary

► [Literature]
In particular cases, with strong statistical assumptions on *C*, the Burer-Monteiro factorization works as soon as

$$p = r_{opt}$$
 or  $p = r_{opt} + 1$ .

► [Our result]

There are matrices C for which it can fail, unless

$$p\gtrsim\sqrt{2m}$$
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even if  $r_{opt} = O(1)$ .

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In particular cases, with strong statistical assumptions on C, the Burer-Monteiro factorization works as soon as

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► [Our result]
There are matrices *C* for which it can fail, unless

$$p \gtrsim \sqrt{2m}$$

even if  $r_{opt} = O(1)$ .

► [Empirically]

The Burer-Monteiro factorization usually works for

$$p = O(r_{opt}).$$

→ Apparently, the matrices we have constructed for which the Burer-Monteiro factorization admits bad second-order critical points are somewhat pathological, and not encountered in practice.

## Questions

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► Compute the volume, in the space of cost matrices, of matrices for which bad second-order critical points exist, as a function of *n* and *p*?

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- ► Compute the volume, in the space of cost matrices, of matrices for which bad second-order critical points exist, as a function of *n* and *p*?
- ▶ Develop guarantees for the Burer-Monteiro factorization with assumptions on *C*, but only mild ones?

[Intermediate between very specific settings, for which we have strong guarantees, and the general case, where guarantees are only for  $p \gtrsim \sqrt{2m}$ .]

## Thank you!

I. Waldspurger and A. Waters (2018). Rank optimality for the Burer-Monteiro factorization. arXiv preprint arXiv:1812.03046.