Complexity of decomposing a symmetric matrix as a sum of a diagonal and low-rank matrix

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#### Problems under consideration

P1 Given  $A \in \mathbb{S}_{+}^{n}$  and r, write A = D + R, where  $D \in \mathbb{S}_{+}^{n}$  is diagonal and  $R \in \mathbb{S}_{+}^{n}$  has rank $\leq r$ . P2 Given  $A \in \mathbb{S}^{n}$  and r, write A = D + R, where  $D \in \mathbb{S}^{n}$  is diagonal and  $R \in \mathbb{S}_{+}^{n}$  has rank $\leq r$ . Notation:

- ▶  $S^n = n \times n$  symmetric matrices,
- $\mathbb{S}^n_+$  = positive semidefinite symmetric matrices,

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•  $\mathbb{S}_{++}^n$  = positive definite symmetric matrices

# Applications

- Problems P1 and P2 have appeared in various bodies of literature for almost a century.
- Example application of P1: Given an empirically measured covariance matrix A of n stock prices, seek interpretation of A as a sum of r market factors, r le n, that influence all stock prices plus n independent stock variabilities.
- Example application of P2: fit an ellipsoid in R<sup>n</sup> through n given data points (Saunderson, Chandrasekaran, Parrilo, Willsky 2011)

## Related work

- Albert (1944): Factor analysis
- Saunderson et al. (2011): SDP relaxation
- ▶ Wu et al. (2020): Block coordinate descent
- Gao & Absil (2022): Manifold optimization

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 Recht & Ré (2023): Stochastic gradient descent

## Our results

- P1 and P2 are solvable in time polynomial in n for fixed r. (Superexponential in r.)
- P1 and P2 are NP-hard. Furthermore, even if we allow approximate data and approximate solutions, they remain NP-hard.
- P2 is ∃ℝ-complete. (This result assumes exact data and exact solution.)

# Solving P2 in the case r = 1 (I)

- To illustrate our algorithm, consider the special case of P2 when r = 1: Given A ∈ S<sup>n</sup>, find decomposition A = D + uu<sup>T</sup> for some u ∈ ℝ<sup>n</sup>.
- WLOG A is hollow, i.e., A(i, i) = 0 $\forall i = 1, \dots, n$
- Clearly  $A(i,j) = u_i u_j \ \forall i \neq j \text{ and } D(i,i) = -u_i^2$  $\forall i$
- Assume  $A(2:n,1) \neq \mathbf{0}$  (else reduce problem to A(2:n,2:n))

# Solving P2 in the case r = 1 (II)

- Assumption implies  $u_1 \neq 0$  and D(1,1) < 0
- $A(i,1) = u_1u_i \ \forall j > 1 \text{ and } A(i,j) = u_iu_j \ \forall i > j > 1.$
- ▶ Yields equation:  $-A(1,i)A(1,j)/D(1,1) = A(i,j) \forall i > j > 1$ (numerator is  $u_1^2 u_i u_j$ ; denominator is  $-u_1^2$ ).
- ▶ ⇒ many linear equations for x := 1/D(1,1)
- Solve any one of these equations to obtain D(1,1); let  $u_1 = \sqrt{-D(1,1)}$ .
- Obtain  $D(i, i) = -u_i^2$ , i > 1, via  $-A(1, i)^2/D(1, 1) = (u_1u_i)^2/u_1^2 = u_i^2$ .

# Solving P2 in the case r = 1 (III)

- Algorithm on previous slide fails if all linear equations are 0 · x = 0.
- This happens iff all but one entry (say A(1,2)) of A(1,2:n) are zeroes.
- This can happen only if u(3:n) = 0.
- In this case, problem reduces to 2 × 2 case, easily handled.
- The 2 × 2 case, though trivial, requires a solution of both equations and inequalities.

## Solving P2 in the case r > 1

- Full algorithm in our paper proposes algorithm for rank-r case.
- For 'generic' data, all entries of D are found by solving overdetermined linear equations.
- But for nongeneric data (interesting cases that include hard instances), one obtains O(n<sup>r</sup>) polynomial systems each with O(r<sup>2</sup>) variables and O(r<sup>2</sup>) constraints.

## NP-hardness of P1 and P2

- Our reductions are from the problem of testing graph 3-colorability.
- Recall: a graph is 3-colorable if there is an assignment of colors red, green, blue to each node such that there is no monochromatic edge.
- Proved by Garey, Johnson & Stockmeyer (1976) that deciding whether a graph is 3-colorable is NP-complete.

# Partially specified matrices

- Start from a *partially specified* matrix  $A \in (\mathbb{R} \cup \{*\})^{m \times n}$ .
- A completion of A is matrix A<sup>#</sup> ∈ ℝ<sup>m×n</sup> such that A<sup>#</sup>(i,j) = A(i,j) for all (i,j) such that A(i,j) ≠ \*.
- Given a partially specified A, let C(A) be the set of all its completions.
- P2 can be described as: Given a symmetric A ∈ (ℝ∪{\*})<sup>n×n</sup> in which A(i,j) = \* ⇔ i = j, find a low-rank semidefinite element of C(A).

#### Peeters result

- Let \* denote an unspecified entry that must be filled in with a nonzero number.
- Peeters (1996) proved: Given a graph G, one can construct a partially specified symmetric matrix B all of whose diagonal entries are \*. Graph G is 3-colorable iff there exists a completion B whose rank is 3.
- Our NP-hardness proofs all rely on Peeters' construction.











### Construction of K and U

 K is a node-edge adjacency matrix, two 1's per column

► U constructed as follows:  $B = \begin{pmatrix} \hat{*} & 0 & * & \cdots & 0 \\ 0 & \hat{*} & 0 & \cdots & * \\ \hat{*} & 0 & \hat{*} & & \\ \vdots & \vdots & & \ddots & \\ 0 & \hat{*} & & & \hat{*} \end{pmatrix} \rightarrow U = \begin{pmatrix} H & Z & S & \cdots & Z \\ Z & H & Z & \cdots & S \\ S & Z & H & & \\ \vdots & \vdots & & \ddots & \\ Z & S & & H \end{pmatrix} \text{ where }$   $H = \begin{pmatrix} 1 & 1 & 1 \\ 1 & \hat{*} & 1 \\ 1 & 1 & \hat{*} \end{pmatrix}, Z = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}, S = \begin{pmatrix} 2 & 2 & 2 \\ 2 & 2 & 2 \\ 2 & 2 & 2 \end{pmatrix}.$ 

## How this works

- The entries of the upper left diagonal block can be chosen so that, after its elimination, the '2' entries in U are decreased (e.g., to 0 or 1).
- The rank of the completion is equal to q plus the rank of the Schur complement after elimination of the diagonal block.
- In order for rank of the Schur complement to be ≤ 3:
  - The diagonal blocks of the Schur complement must be filled in with 1's.
  - The 0-1 pattern must correspond to three color classes.

## NP-hardness of P1

- Similar construction as in P2 works, except we place large entries on the diagonal instead of 0's.
- ► This is because P1 can only subtract elements from the diagonal (R = A - D in P1, where D ∈ S<sup>n</sup><sub>+</sub>)

Same Schur complement argument applies.

## Approximate P1 and P2

- Approximate P1: Given A ∈ S<sup>n</sup><sub>+</sub> and a promise that there exists a rank-r semidefinite R<sub>0</sub> and positive definite diagonal D<sub>0</sub> such that ||A − D<sub>0</sub> − R<sub>0</sub>|| ≤ ε (A, r, ε given; D<sub>0</sub>, R<sub>0</sub> not given).
- Find positive definite diagonal *D*, semidefinite matrix *R* such that ||*A* − *D* − *R*|| ≤ *ec<sub>n</sub>*, where *c<sub>n</sub>* depends on *n* and can be arbitrary.
- We show: This problem is NP-hard. So is Approximate P2 (much more complicated argument).

## $\exists \mathbb{R} \text{ complete problems}$

- ► The canonical ∃R problem: Given a sequence of multivariate polynomial equations and inequalities with integer coefficients, does the system have a real root?
- A general decision problem is in ∃ℝ if it can be transformed to a question about polynomial equations as in the first bullet.

▶ It is known:  $NP \subseteq \exists \mathbb{R} \subseteq PSPACE$  (Canny).

## Matrix completion is $\exists \mathbb{R}$ -complete

- Shitov showed: matrix completion is ∃ℝ complete.
- Specifically, Shitov showed that given a polynomial system, one can construct from it a partly specified symmetric matrix that has a semidefinite rank-3 completion iff the system has a real root.

# Our reduction

- In order to use Shitov's construction for P2, we need to overcome the same issues as mentioned earlier:
  - In P2, unspecified entries are confined to the diagonal, and
  - ▶ In P2, all diagonal entries must be unspecified.
- We reuse the similar techniques as before, namely,
  - We use take Schur complement of two diagonal matrices to transform a matrix-completion problem with an arbitrary pattern of unspecified entries to one in which all unspecified entries are on the diagonal.
  - We make multiple copies of certain rows/columns diagonal elements must have certain values in any rank-3 completion.

## P1 is not known to be $\exists \mathbb{R}$ -complete

- P1 NP-hardness proof: Replace \*'s on the diagonal in P2 gadget A with big numbers to get a P1 instance.
- However, for general integer matrices, the norm of D in the P2 solution can be double exponentially larger than the norm of A.
- This follows because the ∃R-completeness of P2 shows that the system: x<sub>0</sub> = 2, x<sub>1</sub> = x<sub>0</sub><sup>2</sup>, x<sub>2</sub> = x<sub>1</sub><sup>2</sup>, ..., x<sub>n</sub> = x<sub>n-1</sub><sup>2</sup> can be encoded as an O(n)-sized matrix completion problem even though the solution has x<sub>n</sub> = 2<sup>(2<sup>n</sup>)</sup>.
- These big diagonal entries cannot be written down in polynomial time, so not clear how to transform a polynomial system to P1.