

# Nonnegative Rank Factorization

## A Heuristic Approach via Rank Reduction

*(Work in Progress)*

Moody T. Chu

(Joint work with Bo Dong and Matthew Lin)

North Carolina State University

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一曲新詞酒一杯,去年天氣舊亭臺,  
夕陽西下幾時回.  
無可奈何花落去,似曾相識燕歸來,  
小園香徑獨徘徊.

--- 宋·宴殊·浣溪沙

## Take Home Question

Given a nonnegative matrix  $A$ , write

$$A = \sum_{i=1}^k \mathbf{u}_i \mathbf{k}_i^T$$

where  $\mathbf{u}_i, \mathbf{k}_i \geq 0$  and  $k$  is minimal.

# Outline

## Background

Nonnegative Rank

Nonnegative Rank Factorization

## Generic Phenomenon

Geometry of NRF

Probability Issues

Perturbation Theory

## Wedderburn Formula

Subtractivity

Rank Reduction

## Algorithm

Maximin Problem

## Other Applications

Completely Positive Matrices

Maximal Nonnegative Rank Splitting

## Conclusion

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# Nonnegative Rank

- ▶ Given  $A \in \mathbb{R}_+^{m \times n}$ , write

$$A = UV.$$

- $U \in \mathbb{R}_+^{m \times k}$  and  $V \in \mathbb{R}_+^{k \times n}$  with  $k \leq \min\{m, n\}$
  - Always possible.
- ▶ Interested in the *smallest*  $k$  rendering this factorization.
- Denote by  $\text{rank}_+(A)$ .
- ▶ A trivial fact —

$$\text{rank}(A) \leq \text{rank}_+(A) \leq \min\{m, n\}.$$

- ▶ A challenge —
- Determining the exact nonnegative rank is NP-hard.

## This Is Not ...

- ▶  $A = UV$  is a special nonnegative factorization of  $A$ .
- ▶ Should be unequivocally distinguished from what is known as the nonnegative matrix factorization (NMF).
  - Misnamed!
  - Is only a low rank approximation from

$$\min_{U \in \mathbb{R}_+^{m \times p}, V \in \mathbb{R}_+^{p \times n}} \|A - UV\|_F.$$

- $p < \min\{m, n\}$  is preassigned.
- Many numerical techniques.
- Cannot guarantee the required equality in a complete factorization even with  $p = \text{rank}_+(A)$ .



## NMF Fails!

- ▶ Almost all NMF techniques adapt conventional mathematical programming schemes.
- ▶ The objective function in NMF is non-convex.
- ▶ The factors  $U$  and  $V$  retrieved by NMF techniques are typically local minimizers only.
- ▶ Cannot ensure equality to  $A$ .

# Nonnegative Rank Factorization

$$\mathfrak{R}(m, n) := \{A \in \mathbb{R}_+^{m \times n} \mid \text{rank}(A) = \text{rank}_+(A)\}.$$

► Interested in

- Identifying if  $A \in \mathfrak{R}(m, n)$ .
- Procuring a nonnegative factorization for  $A \in \mathfrak{R}(m, n)$ .
  - Is called a *nonnegative rank factorization* (NRF) of  $A$ .

## An Example

- ▶ Not every nonnegative matrix has an NRF.
- ▶ The simplest non-NRF matrix:

$$\mathcal{C} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix}.$$

- $\text{rank}(\mathcal{C}) = 3$ .
- $\text{rank}_+(\mathcal{C}) = 4$ .
- ▶ There is a necessary and sufficient condition qualifying an NRF matrix (Thomas'1974).
  - Not suitable for computation.

# Probability Simplex

- ▶ Given  $A \in \mathbb{R}_+^{m \times n}$ , define

$$\sigma(A) := \text{diag}\{\|\mathbf{a}_1\|_1, \dots, \|\mathbf{a}_n\|_1\}$$

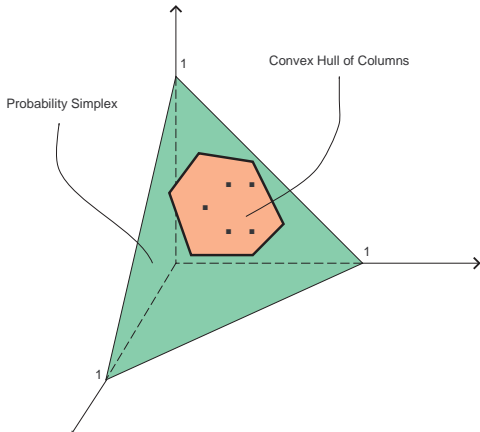
$$\vartheta(A) := A\sigma(A)^{-1}.$$

- ▶ Columns of  $\vartheta(A)$  are points on the probability simplex  $\mathcal{D}_m$  in  $\mathbb{R}_+^m$ .

$$\mathcal{D}_m := \{\mathbf{a} \in \mathbb{R}_+^m \mid \mathbf{1}_m^\top \mathbf{a} = \mathbf{1}\},$$



# Convex Hull of $\mathcal{V}(A) \in \mathbb{R}_+^{3 \times 11}$





## Minimal Convex Polytope

▶  $A = UV = (UD^{-1})(DV)$  with any invertible diagonal matrix  $D$ .

- May assume  $\sigma(U) = I_n$ .

▶ Write

$$A = \vartheta(A)\sigma(A) = UV = \vartheta(U)\vartheta(V)\sigma(V).$$

- It must be such that

$$\vartheta(A) = \vartheta(U)\vartheta(V),$$

$$\sigma(A) = \sigma(V).$$

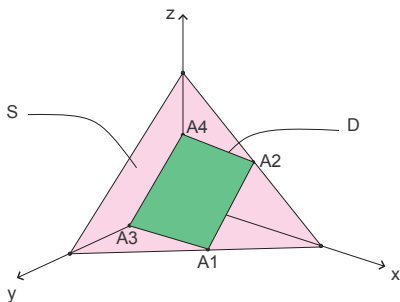
- Columns of  $\vartheta(A)$  are in the convex hull of  $\vartheta(U)$ .

### Lemma

*The nonnegative rank  $\text{rank}_+(A)$  stands for the minimal number of vertices on  $\mathcal{D}_m$  so that the resulting convex polytope encloses all columns of the pullback  $\vartheta(A)$ .*



## Visualizing $\vartheta(\mathcal{C})$



- ▶ Suffices to represent the probability simplex  $\mathcal{D}_4$  by the unit tetrahedron  $S$  in the first octant of  $\mathbb{R}^3$ .
- ▶ Columns of  $\vartheta(\mathcal{C})$  can be interpreted as points  $A_1, A_2, A_3, A_4$ .
  - Coplanar because  $\text{rank}(\vartheta(\mathcal{C})) = 3$ .
  - Four “edges” sitting on separate facets of the tetrahedron.
  - The minimum number of vertices for a convex set in the unit tetrahedron to cover  $D$  is four.

## How Often Can This Happen?

### Question

**(R2R<sub>+</sub>)** : *Given an arbitrary nonnegative 4 by 4 matrix of rank 3, what is the probability that its nonnegative rank is 3?*

- ▶ No easy answer!

### Question

**Sylvester's Four-Point Problem** *What is the probability of four random, independent, and uniform points from a compact set such that none of them lies in the triangle formed by the other three?*

- ▶ "This problem does not admit of a determinate solution!" (Sylvester'1865).

## Flipped Side Question

### Question

$(\mathbf{R}_+ \mathbf{2R})$  : Given an arbitrary nonnegative 4 by 4 matrix of nonnegative rank 3, what is the probability that its rank is 3?

### Theorem

Given  $k < \min\{m, n\}$ , let  $R_+(k)$  denote the manifold of nonnegative matrices in  $\mathbb{R}_+^{m \times n}$  with nonnegative rank  $k$ . Then the conditional probability of  $\text{rank}(A) = k$ , given  $A \in R_+(k)$ , is one.

- ▶ Matrices which have an NRF are generic.



## Almost Surely?

- ▶ If  $A = UV$  with randomly generated  $U \in \mathbb{R}_+^{m \times k}$  and  $V \in \mathbb{R}_+^{k \times n}$ ,
  - *Almost surely* we have  $\text{rank}(A) = k$ .
  - The converse is not true.
- ▶ Those matrices whose rank are not equal to the nonnegative rank form a measure zero set.
  - Not necessarily mean that the set is “unobservable”, nor that nontrivial “exceptions” are difficult to come by.

# Euclidean Distance Matrices

- Given  $n$  distinct points in  $\mathbb{R}^r$ :

$$E(\mathbf{q}_1, \dots, \mathbf{q}_n) := [\|\mathbf{q}_i - \mathbf{q}_j\|_2^2].$$

- Of rank  $r + 2$ , regardless of the number  $n$  of points.
- If  $r = 1$ , then generically of nonnegative rank  $n$  (Chu'2010).
- Certainly not have the generic phenomenon described above.
- Form a large and characterizable set, but is too specific to have a nonzero measure.

# Perturbation Theory

- ▶ Very little perturbation analysis for NRF in general has been studied in the literature.
- ▶ Some open questions:
  1. Given a nonnegative matrix  $A$  which has an NRF, under what condition will the perturbed nonnegative matrix  $A + E$  still have an NRF?
  2. Given a nonnegative matrix  $A$  which has an NRF, let  $U$  and  $V$  be the nonnegative factors found by our (or any) numerical algorithm so that  $UV$  is a numerical NRF of  $A$ . Is  $UV$  the exact NRF of some perturbed nonnegative matrix  $A + E$ ?

# Local Rank Condition

## Theorem

Given an  $m \times n$  non-negative matrix with  $\text{rank}_+(A) = k$ , then

1. There exists a ball  $B(A; \epsilon)$  such that  $\text{rank}_+(N) \geq k$  for all  $N \in B(A; \epsilon)$ .
2. For any  $\epsilon > 0$ , there exists  $N \in B(A; \epsilon)$  such  $\text{rank}_+(N) = \text{rank}_+(A)$  and  $N \neq \lambda A$  for any  $\lambda$ .



## Chipping Away a Nonnegative Portion

- ▶  $B \geq 0$  is a *nonnegative component* (NC) of  $A \geq 0$  iff  $A - B \geq 0$ .
  - Compute the “maximum” rank-one NC of  $A$  (Levin’1985).
  - The residual after an NC subtraction might have higher rank.
  - Might end up with an infinite series of NC matrices.
- ▶  $B \geq 0$  is a *nonnegative element* (NE) of  $A \geq 0$  iff  $B$  is a rank-one NC and  $\text{rank}(A - B) = \text{rank}(A) - 1$ .
- ▶ The matrix  $\mathcal{C}$  has many NCs, but has no NE at all.
- ▶ Need to gradually distribute  $A$  over a sequence of NEs.

## A Major Difficulty

- ▶  $A$  has an NRF,  $\implies A = \sum_{i=1}^k \mathbf{u}_i \mathbf{k}_i^\top$ .
  - Each  $\mathbf{u}_i \mathbf{k}_i^\top$  is an NE.
- ▶ Miss the particular sequence of NE's (not known to begin with)?
  - Any bad choices of NE's in the intermediate stages could cause the rank reduction process to break down.
    - ▶ Get stuck at a matrix that has no more NE at all.
- ▶ A major challenge:
  - Could not foresee which NE would be a "good" NE to continue on the rank reduction.
  - Finding the right NE's is precisely why the NRF problem is so challenging.
  - A weakness of our approach.
    - ▶ Still might be the first sensible way to crack the nut!

# Wedderburn Rank Reduction Formula

## Theorem

Let  $\mathbf{u} \in \mathbb{R}^m$  and  $\mathbf{v} \in \mathbb{R}^n$ . Then the matrix

$$B := A - \sigma^{-1} \mathbf{u} \mathbf{v}^\top$$

satisfies the rank subtractivity  $\text{rank}(B) = \text{rank}(A) - 1$  if and only if there are vectors  $\mathbf{x} \in \mathbb{R}^n$  and  $\mathbf{y} \in \mathbb{R}^m$  such that

$$\mathbf{u} = A\mathbf{x}, \quad \mathbf{v} = A^\top \mathbf{y}, \quad \sigma = \mathbf{y}^\top A\mathbf{x}.$$

## Theorem

Suppose  $U \in \mathbb{R}^{m \times k}$ ,  $R \in \mathbb{R}^{k \times k}$ , and  $V \in \mathbb{R}^{n \times k}$ . Then

$$\text{rank}(A - UR^{-1}V^\top) = \text{rank}(A) - \text{rank}(UR^{-1}V^\top)$$

if and only if there exist  $X \in \mathbb{R}^{n \times k}$  and  $Y \in \mathbb{R}^{m \times k}$  such that

$$U = AX, \quad V = A^\top Y, \quad \text{and} \quad R = Y^\top AX.$$

# Applications

- ▶ Provide a mechanism to break down a matrix into a sum of rank-one matrices.
  - Define a sequence  $\{A_k\}$  of matrices by

$$A_{k+1} := A_k - (\mathbf{y}_k^\top A_k \mathbf{x}_k)^{-1} A_k \mathbf{x}_k \mathbf{y}_k^\top A_k.$$

- Properly chosen vectors  $\mathbf{x}_k \in \mathbb{R}^n$  and  $\mathbf{y}_k \in \mathbb{R}^m$  satisfying  $\mathbf{y}_k^\top A_k \mathbf{x}_k \neq 0$ .
  - The process can be continued so long as  $A_k \neq 0$ .
  - The sequence  $\{A_k\}$  must be finite.
- ▶ Almost all classical matrix decompositions can be found in this way (Chu, Funderlic, Golub'1995).

## Wedderburn for NRF

- ▶ For NRF,
  - Break down a nonnegative matrix by taking away one NE a time.
  - An NE must assume the Wedderburn form

$$(\mathbf{y}_k^\top \mathbf{A}_k \mathbf{x}_k)^{-1} \mathbf{A}_k \mathbf{x}_k \mathbf{y}_k^\top \mathbf{A}_k.$$

- $\mathbf{A}_{k+1}$  must be nonnegative after the subtraction.
    - ▶ The most difficult part.
- ▶ Two probable causes for premature termination.
  - $A$  is not a matrix in  $\mathfrak{R}(m, n)$  to begin with.
    - ▶ A welcome conclusion.
    - ▶ Notion of maximal nonnegative rank splitting of  $A$ .
  - Bad starting points have branched  $A_k$  into a “dead end”, i.e.,  $A_k$  has no NE.
    - ▶ A restart might remedy the problem.
- ▶ Only a heuristic way to find the (approximate) NRF.
- ▶ Need more analysis to conclude whether  $A$  has an NRF or not.

# Maximin Problem

$$\max_{\mathbf{x}_k \in \mathbb{R}^n, \mathbf{y}_k \in \mathbb{R}^m} \min [A_k - A_k \mathbf{x}_k \mathbf{y}_k^\top A_k],$$

$$\text{subject to } \begin{aligned} A_k \mathbf{x}_k &\geq 0, \\ \mathbf{y}_k^\top A_k &\geq 0, \\ \mathbf{y}_k^\top A_k \mathbf{x}_k &= 1, \end{aligned}$$

- ▶  $A_k - A_k \mathbf{x}_k \mathbf{y}_k^\top A_k \leq A_k$ .
  - maximizer of  $\min [A_k - A_k \mathbf{x}_k \mathbf{y}_k^\top A_k]$  always exists.
- ▶ Nonnegative objective value  $\implies A_{k+1} \geq 0$ .
  - A feasible NE is found.

## A Pathological Example

- ▶ Consider  $A = [\mathcal{C}; \mathbf{c}]$ .
  - $\mathbf{c} \geq 0$  is random.
  - $\text{rank}_+(A) = \text{rank}(A) = 4$ .
  - Splitting  $A$  by its rows is automatically an NRF.
- ▶ The matrix  $\Delta := [0_4, \mathbf{c}]$  an NE.
  - Leave behind a nonnegative matrix  $A - \Delta = [\mathcal{C}; \mathbf{0}]$  of rank 3.
  - $[\mathcal{C}; \mathbf{0}]$  does not have any NRF.
  - Iteration would get stuck.
- ▶ Restart  $\implies$

$$\begin{bmatrix} 1.0000 & 1.0000 & 0 & 0 & 0.0781 \\ 1.0000 & 0 & 1.0000 & 0 & 0.6690 \\ 0 & 1.0000 & 0 & 1.0000 & 0.5002 \\ 0 & 0 & 1.0000 & 1.0000 & 0.2180 \end{bmatrix} = \begin{bmatrix} 0.0000 & 0.0000 & 0.8624 & 0 & 0 \\ 0.0000 & 0.3862 & 0 & 0 & 0 \\ 3.4544 & 0 & 0 & 0 & 0 \\ 0.0000 & 0.0000 & 0.0000 & 1.7018 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0.2895 & 0.0000 & 0.2895 & 0.1448 \\ 2.5895 & 0.0000 & 2.5895 & 0.0000 & 1.7325 \\ 1.1596 & 1.1596 & 0.0000 & 0.0000 & 0.0905 \\ 0 & 0 & 0.5876 & 0.5876 & 0.1281 \end{bmatrix}.$$

# Multiple Rank Reduction

$$\max_{X_k \in \mathbb{R}^{m \times r}, Y_k \in \mathbb{R}^{n \times r}} \min [A_k - A_k X_k Y_k^T A_k],$$

subject to

$$A_k X_k \geq 0,$$

$$Y_k^T A_k \geq 0,$$

$$Y_k^T A_k X_k = I_{r \times r},$$

## Theorem

*If a nonnegative matrix has a nonnegative rank- $r$  reduction, then it must have  $r$  nonnegative rank-one reductions.*



# Completely Positive Matrices

- ▶  $A \in \mathbb{R}_+^{n \times n}$  is *completely positive* (CP) iff

$$A = BB^T.$$

- $B \geq 0$  is not necessarily square.
- Interested in the smallest number of columns of  $B$ .
  - ▶ Denoted by  $\text{rank}_{cp}(A)$ .
- ▶ Two questions (Berman'2003):
  - Determine whether a given nonnegative semi-definite matrix is CP.
  - Determine the cp-rank and compute its CP factorization.
    - ▶ More stringent than NRF.

# Symmetric Wedderburn Formula

$$\max_{\mathbf{x}_k \in \mathbb{R}^n} \min [A_k - A_k \mathbf{x}_k \mathbf{x}_k^\top A_k]$$

$$\text{subject to } \begin{aligned} A_k \mathbf{x}_k &\geq 0 \\ \mathbf{x}_k^\top A_k \mathbf{x}_k &= 1 \end{aligned}$$

# Maximal Nonnegative Rank Splitting

## Question

**(MNRS):** *Given a nonnegative matrix  $A$ , find a splitting*

$$A = B + C,$$

*where both  $B$  and  $C$  are nonnegative matrices satisfying*

$$\begin{aligned} \text{rank}(B) &= \text{rank}_+(B), \\ \text{rank}(A) &= \text{rank}(B) + \text{rank}(C), \end{aligned}$$

*and  $\text{rank}(B)$  is maximized.*

- ▶ If  $A \in \mathfrak{R}(m, n)$ , then trivially  $B = A$  and  $C = 0$ .
- ▶ If  $A \notin \mathfrak{R}(m, n)$ ,
  - $A$  might still have a few NEs.
  - Retrieve all possible NEs of  $A$ .

## Conclusion

- ▶ Detecting the nonnegative rank and computing the corresponding nonnegative factorization for a general nonnegative matrix are very challenging tasks both in theory and in practice.
- ▶ No existing algorithms can guarantee to find the NRF.
- ▶ Exploit the Wedderburn rank reduction formula to *downdate* a nonnegative matrix.
- ▶ Only a possible computational tool for the NRF problem.
- ▶ Need more perturbation analysis for NRF in general.