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# Stable recovery of the factors from a deep matrix product 

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#### Abstract

We study a deep matrix factorization problem. It takes as input the matrix $X$ obtained by multiplying $K$ matrices (called factors) and aims at recovering the factors. When $K=1$, this is the usual compressed sensing framework; $K=2$ : Examples of applications are dictionary learning, blind deconvolution, self-calibration; $K \geq 3$ : includes convolution network problems as well as many fast transforms.

Using a Lifting, we provide : a necessary and sufficient conditions for the identifiability of the factors (up to a scale rearrangement); an analogue of the Null-Space-Property, called the Deep-Null-SpaceProperty which is necessary and sufficient to guarantee the stable recovery of the factors.


## I. Introduction

Let $K \in \mathbb{N}^{*}, m_{1} \ldots m_{K+1} \in \mathbb{N}$, write $m_{1}=m, m_{K+1}=n$. We impose the factors to be structured matrices defined by a (typically small) number $S$ of unknown parameters. More precisely, for $k=$ $1 \ldots K$, let

$$
\begin{aligned}
M_{k}: \mathbb{R}^{S} & \longrightarrow \mathbb{R}^{m_{k} \times m_{k+1}}, \\
h & \longmapsto M_{k}(h)
\end{aligned}
$$

be a linear map.
We assume that we know the matrix $X \in \mathbb{R}^{m \times n}$ which is provided by

$$
\begin{equation*}
X=M_{1}\left(\mathbf{h}_{1}\right) \cdots M_{K}\left(\mathbf{h}_{K}\right)+e, \tag{1}
\end{equation*}
$$

for an unknown error term $e$ and parameters $\mathbf{h}=\left(\mathbf{h}_{k}\right)_{1 \leq k \leq K} \in$ $\mathcal{M}^{\bar{L}} \subset \mathbb{R}^{S \times K}$ for some $\bar{L}$, where we assume that we know a collection of models $\mathcal{M}=\left(\mathcal{M}^{L}\right)_{L \in \mathbb{N}}$ such that, for every $L$, $\mathcal{M}^{L} \subset \mathbb{R}^{S \times K}$.

This work investigates models/constraints imposed on (1) for which we can (up to obvious scale rearrangement) identify or stably recover the parameters h from $X$. A preliminary version of this work is presented in [1].

Set $\mathbb{N}_{K}=\{1, \ldots, K\}$ and

$$
\mathbb{R}_{*}^{S \times K}=\left\{\mathbf{h} \in \mathbb{R}^{S \times K}, \forall k \in \mathbb{N}_{K},\left\|\mathbf{h}_{k}\right\| \neq 0\right\} .
$$

Define an equivalence relation in $\mathbb{R}_{*}^{S \times K}$ : for any $\mathbf{h}, \mathbf{g} \in \mathbb{R}^{S \times K}$, $\mathbf{h} \sim \mathbf{g}$ if and only if there exists $\left(\lambda_{k}\right)_{k \in \mathbb{N}_{K}} \in \mathbb{R}^{K}$ such that

$$
\prod_{k=1}^{K} \lambda_{k}=1 \quad \text { and } \quad \forall k \in \mathbb{N}_{K}, \mathbf{h}_{k}=\lambda_{k} \mathbf{g}_{k}
$$

Denote the equivalence class of $\mathbf{h} \in \mathbb{R}_{*}^{S \times K}$ by $[\mathbf{h}]$. We consider a metric denoted $d_{p}$ on $\mathbb{R}_{*}^{S \times K} / \sim$. It is based on the $l^{p}$ norm.

We say that a tensor $T \in \mathbb{R}^{S^{K}}$ is of rank 1 if and only if there exists a collection of vectors $\mathbf{h} \in \mathbb{R}^{S \times K}$ such that $T$ is the outer product of the vectors $\mathbf{h}_{k}$, for $k \in \mathbb{N}_{K}$, that is, for any $\mathbf{i} \in \mathbb{N}_{S}^{K}$,

$$
T_{\mathbf{i}}=\mathbf{h}_{1, i_{1}} \ldots \mathbf{h}_{K, i_{K}} .
$$

The set of all the tensors of rank 1 is denoted by $\Sigma_{1}$.

Moreover, we parametrize $\Sigma_{1} \subset \mathbb{R}^{S^{K}}$ by the Segre embedding

$$
\begin{aligned}
P: \mathbb{R}^{S \times K} & \longrightarrow \Sigma_{1} \subset \mathbb{R}^{S^{K}} \\
\mathbf{h} & \longmapsto\left(\mathbf{h}_{1, i_{1}} \mathbf{h}_{2, i_{2}} \ldots \mathbf{h}_{K, i_{K}}\right)_{\mathbf{i} \in \mathbb{N}_{S}^{K}}
\end{aligned}
$$

Following [2], [3], [4], [5], [6], [7] where problems such that $K=$ 2 are studied, we can lift the problem and show that the map

$$
\left(\mathbf{h}_{1}, \ldots, \mathbf{h}_{K}\right) \longmapsto M_{1}\left(\mathbf{h}_{1}\right) M_{2}\left(\mathbf{h}_{2}\right) \ldots M_{K}\left(\mathbf{h}_{K}\right),
$$

uniquely determines a linear map

$$
\mathcal{A}: \mathbb{R}^{S^{K}} \longrightarrow \mathbb{R}^{m \times n}
$$

such that for all $\mathbf{h} \in \mathbb{R}^{S \times K}$

$$
M_{1}\left(\mathbf{h}_{1}\right) M_{2}\left(\mathbf{h}_{2}\right) \ldots M_{K}\left(\mathbf{h}_{K}\right)=\mathcal{A} P(\mathbf{h}) .
$$

When $\|e\|=0$, we can prove that every element of $\mathbf{h} \in \mathcal{M}$ is identifiable (i.e. the elements of $[\mathbf{h}]$ are the only solutions of (1)) if and only if for any $L$ and $L^{\prime} \in \mathbb{N}$

$$
\operatorname{Ker}(\mathcal{A}) \cap\left(P\left(\mathcal{M}^{L}\right)-P\left(\mathcal{M}^{L^{\prime}}\right)\right)=\{0\}
$$

When $\|e\| \leq \delta$, we further assume that we have a way to find $L^{*}$ and $\mathbf{h}^{*} \in \mathcal{M}^{\bar{L}^{*}}$ such that, for some parameter $\eta>0$,

$$
\begin{equation*}
\left\|\mathcal{A} P\left(\mathbf{h}^{*}\right)-X\right\|^{2} \leq \eta . \tag{2}
\end{equation*}
$$

Using the following definition we can prove Theorem 1.

## Definition 1. Deep-Null Space Property

Let $\gamma>0$, we say that $\operatorname{Ker}(\mathcal{A})$ satisfies the deep-Null Space Property (deep-NSP) with respect to the model collection $\mathcal{M}$ with constant $\gamma$ if there exists $\varepsilon>0$ such that for any $L$ and $L^{\prime} \in \mathbb{N}$, any $T \in P\left(\mathcal{M}^{L}\right)-P\left(\mathcal{M}^{L^{\prime}}\right)$ satisfying $\|\mathcal{A} T\| \leq \varepsilon$ and any $T^{\prime} \in$ $\operatorname{Ker}(\mathcal{A})$, we have

$$
\|T\| \leq \gamma\left\|T-T^{\prime}\right\| .
$$

## Theorem 1. Sufficient condition for stable recovery

Assume $\operatorname{Ker}(\mathcal{A})$ satisfies the deep-NSP with respect to the collection of models $\mathcal{M}$ and with the constant $\gamma>0$. For any $\mathbf{h}^{*}$ as in (2) with $\eta$ and $\delta$ sufficiently small, we have

$$
\left\|P\left(\mathbf{h}^{*}\right)-P(\overline{\mathbf{h}})\right\| \leq \frac{\gamma}{\sigma_{\min }}(\delta+\eta)
$$

where $\sigma_{\text {min }}$ is the smallest non-zero singular value of $\mathcal{A}$. Moreover, if $\overline{\mathbf{h}} \in \mathbb{R}_{*}^{S \times K}$
$d_{p}\left(\left[\mathbf{h}^{*}\right],[\overline{\mathbf{h}}]\right) \leq \frac{7(K S)^{\frac{1}{p}} \gamma}{\sigma_{\text {min }}} \min \left(\|P(\overline{\mathbf{h}})\|_{\infty}^{\frac{1}{K}-1},\left\|P\left(\mathbf{h}^{*}\right)\right\|_{\infty}^{\frac{1}{K}-1}\right)(\delta+\eta)$.
We also prove that the deep-NSP condition is necessary for the stable recovery of the factors. We study a variante of the deepNSP, dedicated to models $\mathcal{M}$ enforcing sparsity, and discuss the applications of these results for the stable recovery of convolution network.

## REFERENCES

[1] F. Malgouyres and J. Landsberg, "On the identifiability and stable recovery of deep/multi-layer structured matrix factorization," in IEEE, Info. Theory Workshop, Sept. 2016.
[2] A. Ahmed, B. Recht, and J. Romberg, "Blind deconvolution using convex programming," IEEE Transactions on Information Theory, vol. 60, no. 3, pp. 1711-1732, 2014.
[3] S. Choudhary and U. Mitra, "Identifiability scaling laws in bilinear inverse problems," arXiv preprint arXiv:1402.2637, 2014.
[4] X. Li, S. Ling, T. Strohmer, and K. Wei, "Rapid, robust, and reliable blind deconvolution via nonconvex optimization," CoRR, vol. abs/1606.04933, 2016. [Online]. Available: http://arxiv.org/abs/1606.04933
[5] S. Bahmani and J. Romberg, "Lifting for blind deconvolution in random mask imaging: Identifiability and convex relaxation," SIAM Journal on Imaging Sciences, vol. 8, no. 4, pp. 2203-2238, 2015.
[6] S. Ling and T. Strohmer, "Blind deconvolution meets blind demixing: Algorithms and performance bounds," arXiv preprint arXiv:1512.07730, 2015.
[7] -, "Self-calibration and biconvex compressive sensing," Inverse Problems, vol. 31, no. 11, p. 115002, 2015.

