A Distributed Tensor-based Approach for Multidimensional Dictionary Learning

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Abstract—The abstract goes here.

I. Introduction

Dictionary Learning is a signal processing technique useful for sparse representation of signals throught the estimation of basis vectors and learning sparse representations of training data. The sparse representation in terms of such dictionaries has attracted increased interest for compressive sensing and in solving problems such as denoising, compression, classification, data decomposition, feature extraction and image processing.

In some applications the data and its dictionary are multidimensional, e.g., when estimating jointly bahavior of users in social networks or when evaluating correlation between audio and video. Computing tensor decompositions of multi-way datasets is particularly useful to extract hidden patterns and structure in data analytics problems. Tensor-based algorithms for dictionary learning can improve the performance for cases of multidimensional and separable data, regarding the dictionary identification rating, the required number of training samples and iterations for the optimization problem [1]. However, tensor-based algorithms face challenges to achieve reasonable performance to handle large-scale tensor factorizations, demanding efforts in order to explore distributed techniques for tensor-based big data analytics.

Distributed tensor-based...

Distributed tensor based dictionary learning...

II. Data Model

$$X = A \cdot S + W, \tag{1}$$

where $X \in \mathbb{C}^{M \times T}$ represents T consecutive observations from M features, $A \in \mathbb{C}^{M \times N}$ is the overcomplete dictionary, $S \in \mathbb{C}^{N \times T}$ represents the sparse coefficient matrix and $W \in \mathbb{C}^{M \times T}$ is the additive noise.

$$X = (A^{(1)} \otimes A^{(2)}) \cdot S + W, \tag{2}$$

where $A = (A^{(1)} \otimes A^{(2)})$.

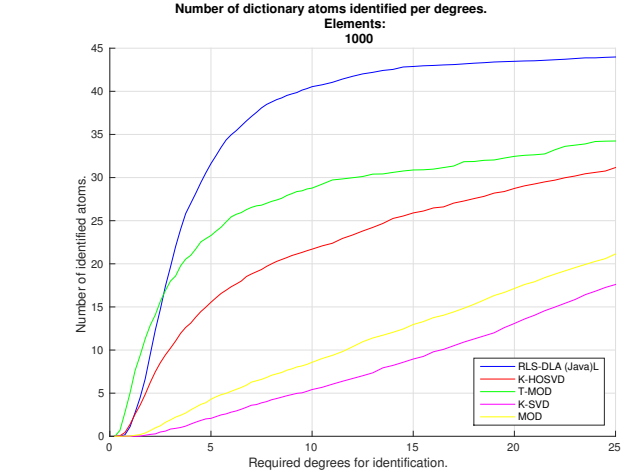$$\mathcal{X} = \mathcal{S} \times_1 A^{(1)} \times_2 A^{(2)} + \mathcal{W}, \tag{3}$$

Fig. 1. Matrix of 1.000 elements, 2000 sample training, 100 iterations
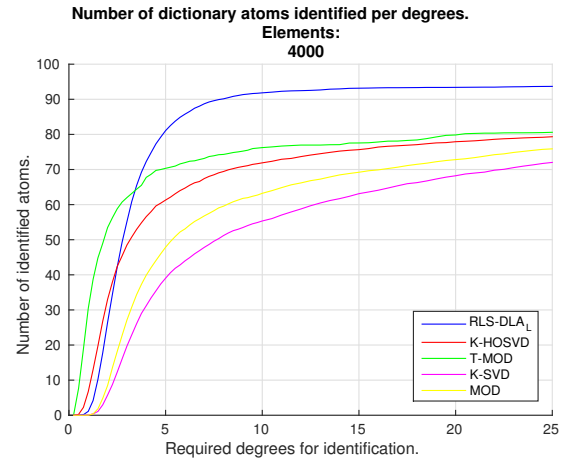

Fig. 2. Matrix of 4.000 elements, 2000 sample training, 100 iterations

where $\mathcal{X} \in \mathbb{C}^{M_1 \times M_2 \times T}$, $\mathcal{S} \in \mathbb{C}^{N_1 \times N_2 \times T}$, and $\mathcal{W} \in \mathbb{C}^{M_1 \times M_2 \times T}$ are rearranged versions of the matrices X, S, and W such that $X = [\mathcal{X}]_{(3)}^T$, $S = [\mathcal{S}]_{(3)}^T$, and $W = [\mathcal{W}]_{(3)}^T$, respectively.

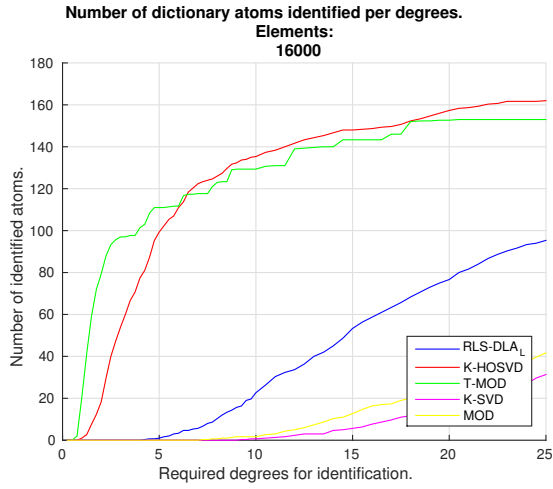We adopt the signal-to-noise ratio (snr) of 20 and the

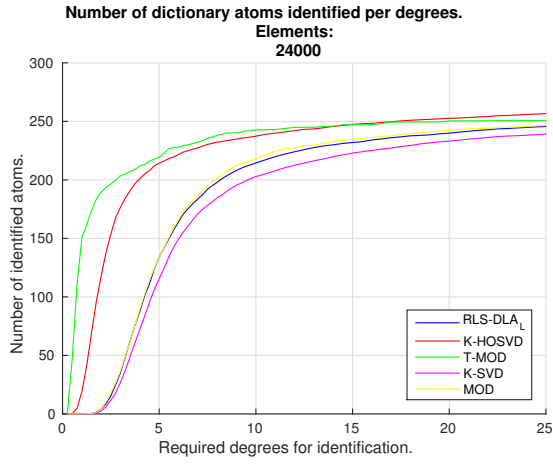Fig. 3. Matrix of 16.000 elements, 500 sample training, 100 iterations

Fig. 4. Matrix of 24.000 elements, 2000 sample training, 100 iterations

sparseness factor of 5 in order to generate the separable dictionary $\boldsymbol{A}$ according to $\boldsymbol{A} = (\boldsymbol{A}^{(1)} \otimes \boldsymbol{A}^{(2)})$ of a gaussian distributed data $\boldsymbol{A}^{(1)} \otimes \boldsymbol{A}^{(2)}$.

$$\boldsymbol{X}^{(q)} = \boldsymbol{U}^{(q)} + \boldsymbol{N}^{(q)} + \boldsymbol{A}^{(q)}, \qquad (4)$$

III. PROPOSED APPROACH

IV. EXPERIMENTS

V. CONCLUSION

The conclusion goes here.

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