Low-Rank 3D Tensor Completion

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Overview

1. Motivations
2. Overview of algebraic tools
3. Description of the problem and algorithms
   - ALS
   - GeomCG
4. Examples

Motivations

- Movies
- Signal processing
- Multiple parameters approximation

Norm and matricization

- Generalization of Frobenius norm for $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$:

$$\|\mathcal{X}\| = \sqrt{\sum_{i=1}^{I_1} \sum_{j=1}^{I_2} \sum_{k=3}^{I_3} x_{i,j,k}^2}$$

- Unfolding $\mathcal{X}$ in the i^{th} dimension:

$$X_{(i)} \in \mathbb{R}^{I_i \times (I_j \cdot I_k)},\ j \neq i,\ k \neq i, j$$

- n-mode product:

$$\mathcal{Y} = \mathcal{X} \times_n U \iff Y_{(n)} = UX_{(n)}$$

- n-rank of a tensor:

$$rank_n(\mathcal{X}) := \text{rank of } X_{(n)}$$

Tucker Decomposition

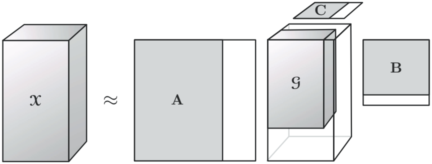
- Core tensor $\mathcal{G} \in \mathbb{R}^{R_1 \times R_2 \times R_3}$, principal components in each mode $A_1 \in \mathbb{R}^{I_1 \times R_1}, A_2 \in \mathbb{R}^{I_2 \times R_2}, A_3 \in \mathbb{R}^{I_3 \times R_3}$:

$$\mathcal{X} = \mathcal{G} \times_1 A_1 \times_2 A_2 \times_3 A_3$$

- Higher-Order SVD: Find components that best capture the variation in mode-n, independently of other modes

Higher Order Singular Value Decomposition

procedure `HOSVD`($\mathcal{X}$,R_1,$R_2, \ldots, R_N$)
    for $n = 1, \ldots, N$ **do**
        $\mathbf{A}^{(n)} \leftarrow R_n$ leading left singular vectors of $\mathbf{X}_{(n)}$
    end for
    $\mathcal{G} \leftarrow \mathcal{X} \times_1 \mathbf{A}^{(1)\mathsf{T}} \times_2 \mathbf{A}^{(2)\mathsf{T}} \cdots \times_N \mathbf{A}^{(N)\mathsf{T}}$
    return $\mathcal{G}, \mathbf{A}^{(1)}, \mathbf{A}^{(2)}, \ldots, \mathbf{A}^{(N)}$
end procedure



Problem as in ALS

- Each frame is divided into Macro-Blocks (MBs) of size N
- For each incomplete Macro-Block P^0, look for $K-1$ complete MBs minimizing

$$S_i = \|P^0_\Omega - P^i_\Omega\|$$

- Stack all selected P^i into a tensor $\mathcal{X}$ with P^0 at the top.

Alternating Least Square Algorithm

1. Form $\boldsymbol{\mathcal{X}}$ from $\boldsymbol{P}^{0,\ldots,K-1}$ using Block Matching criteria
2. $(\boldsymbol{\mathcal{X}}(:,:,1))_{\overline{\Omega}} = \left(\frac{1}{K-1}\sum_{i=1}^{K-1}\boldsymbol{P}^i\right)_{\overline{\Omega}}$
3. Choose mode ranks $\{\mathrm{R}_1, \mathrm{R}_2, \mathrm{R}_3\}$, tolerance σ;
   Initialize $\boldsymbol{A}^{(1)}, \boldsymbol{A}^{(2)}, \boldsymbol{A}^{(3)}$
4. $\boldsymbol{A}^{(3)}(:,1) = [1, \ldots, 1]^T / K$
5. for n = 1,2,3
   $\boldsymbol{\mathcal{Y}} = \boldsymbol{\mathcal{X}} \times_1 \ldots \times_{n-1} \boldsymbol{A}^{(n-1)T} \times_{n+1} \boldsymbol{A}^{(n+1)T} \ldots$
   $\boldsymbol{Y}_n \leftarrow$ unfold $\boldsymbol{\mathcal{Y}}$ in mode n
   $\boldsymbol{A}^{(n)} \leftarrow$ first R_n principal component of $\boldsymbol{Y}_n$
   end
6. $\boldsymbol{\mathcal{G}} = \boldsymbol{\mathcal{X}} \times_1 \boldsymbol{A}^{(1)T} \times_2 \boldsymbol{A}^{(2)T} \times_3 \boldsymbol{A}^{(3)T}$
7. $\boldsymbol{\mathcal{X}}_l = \boldsymbol{\mathcal{G}} \times_1 \boldsymbol{A}^{(1)} \times_2 \boldsymbol{A}^{(2)} \times_3 \boldsymbol{A}^{(3)}$
8. If $\|\boldsymbol{\mathcal{X}}_l - \boldsymbol{\mathcal{X}}\|_F \leq \sigma$ STOP, otherwise return to Step 4.
9. Recover missing area in $\boldsymbol{P}^0$: $\left(\boldsymbol{P}^0\right)_{\overline{\Omega}} = (\boldsymbol{\mathcal{X}}_l(:,:,1))_{\overline{\Omega}}$

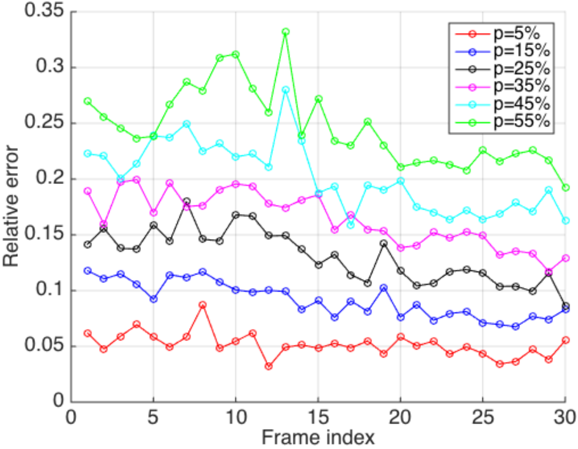
GeomCG

Optimization on the manifold

Movie reconstruction

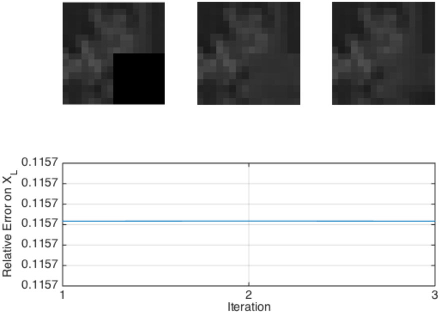
Macro-Block size: N=8

$$\text{Relative error} = \frac{\|F_{original} - F_{restored}\|}{\|F_{original}\|}$$

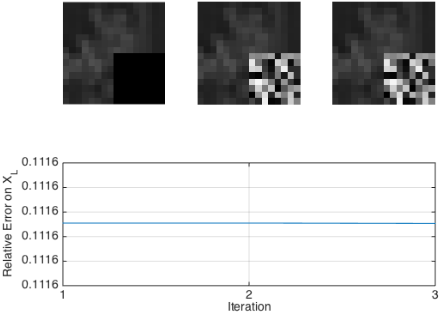


Importance of initial guess

Educated guess



Random guess



Inpainting


[1]


[2]

[1] http://www.briqueterie-chimot.fr/wpcproduct/la-brique-rouge-chimot/

[2] http://images.forwallpaper.com/files/images/0/0249/0249d4f1/113975/winter-park-snow-bench.jpg

Comparison with GeomCG

Compare results for rank 1

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