

Numerical tensor methods: algorithms and tools

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What this talk is about

Many people work on tensors

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Many people work on tensors

Meaning different things

To name a few

- ▶ Eigenvalues of tensors (E-, Z-)
- ▶ Canonical forms
- ▶ Low parametric representation

Our goal

We work on a specific problem on **low-parametric approximation** of high-dimensional tensors using the idea of **separation of variables**

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We work on a specific problem on **low-parametric approximation** of high-dimensional tensors using the idea of **separation of variables**

Not only approximation, but also efficient large computation of basic operations

What kind of operations

We want fast operations in the tensor format

- ▶ Basic linear algebra operations
- ▶ Recovery from few samples
- ▶ Computation of such operations as convolution, solution of linear systems
- ▶ Ability to do “rounding” (recompression)

Standard

The standard approach is the **canonical format**

$$A(i_1, \dots, i_d) = \sum_{\alpha=1}^r U_1(i_1, \alpha) \dots U_d(i_d, \alpha)$$

See review by Kolda and Bader

Problems with canonical format

de Silva, Lim:

- ▶ Best approximation may not exist
- ▶ No robust algorithms
- ▶ Rank depends on the field

Novel tensor formats

This motivated the development of **novel tensor formats**

- ▶ H-Tucker format (Hackbusch, Kuhn, Gradedyck, 2009)
- ▶ Tensor Train (Oseledets, Tyrtysnikov, 2009)
- ▶ **Known to physicists and chemists under different names, Matrix Product States, MCTDH**

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Great development in algorithms in software has been made

I will talk about the Tensor Train (TT) format

Definition

Tensor is said in the TT-format, if

$$A(i_1, \dots, i_d) = G_1(i_1)G_2(i_2) \dots G_d(i_d),$$

where $G_k(i_k)$ — matrix of size $r_{k-1} \times r_k$, $r_0 = r_d = 1$

r_k are called **TT-ranks**

$G_k(i_k)$ (which are $r_{k-1} \times n_k \times r_k$ tensors) are called **cores**

TT in a nutshell

- ▶ \mathbf{A} — canonical rank $r \rightarrow r_k \leq r$
- ▶ TT-ranks are matrix ranks, **TT-SVD**
- ▶ All arithmetic, linear in d , polynomial in r
- ▶ Fast **TENSOR ROUNDING**
- ▶ TT-cross, **exact interpolation formula**, recent: quasioptimality results (D. Savostyanov)
- ▶ Q(Quantics, Quantized)-TT decomposition — binarization (or tensorization) of vectors and matrices (B. Khoromskij, O.)
- ▶ TT-Toolbox – software, S. V. Dolgov, I.V. Oseledets, D. V. Savostyanov, V. A. Kazeev

TT-ranks — matrix ranks

Define unfoldings:

$$A_k = A(i_1 \dots i_k; i_{k+1} \dots i_d), n^k \times n^{d-k} \text{ matrix}$$

TT-ranks — matrix ranks

Define unfoldings:

$A_k = A(i_1 \dots i_k; i_{k+1} \dots i_d), n^k \times n^{d-k}$ matrix

Theorem: There exists a TT-decomposition with TT-ranks

$$r_k = \text{rank } A_k$$

TT-ranks — matrix ranks

The proof is constructive and gives the TT-SVD algorithm (Vidal algorithm in quantum information)

TT-ranks — matrix ranks

There is no exact low ranks need stability estimate!

Theorem (Approximation theorem)

If $A_k = R_k + E_k$, $\|E_k\| = \varepsilon_k$

$$\|\mathbf{A} - \mathbf{T}\mathbf{T}\|_F \leq \sqrt{\sum_{k=1}^{d-1} \varepsilon_k^2}.$$

Fast linear algebra

Addition, Hadamard product, scalar product
All linear in d

Fast linear algebra

$$C(i_1, \dots, i_d) = A(i_1, \dots, i_d)B(i_1, \dots, i_d)$$

$$C_k(i_k) = A_k(i_k) \otimes B_k(i_k),$$

ranks are multiplied

Tensor rounding

\mathbf{A} is given in TT-format with suboptimal ranks.
Who to reapproximate?

Tensor rounding

It can be done in $\mathcal{O}(dnr^3)$ operations

Cross approximation in d-dimensions

What if a tensor is given as a “black box”?

Cross approximation in d-dimensions

What if a tensor is given as a “black box”?

O., Tyrtyshnikov, 2010:

TT-cross approximation of multidimensional arrays

We can exactly interpolate a rank- r tensor on $\mathcal{O}(dnr^2)$ elements

$$\mathcal{J}_k = (i_1^{(\alpha)}, \dots, i_k^{(\alpha)}),$$

$$\mathcal{J}_k = (i_k^{(\beta)}, \dots, i_d^{(\alpha)})$$

$$A_k = A(\mathcal{J}_k, i_k, \mathcal{J}_{k+1})$$

Making everything a tensor: QTT

- ▶ Prequel: E. E. Tyrtysnikov (2003)
- ▶ I. V. Oseledets (2009)
- ▶ B. N. Khoromskij (2009)

“Simple” idea: **to make everything a tensor** (we have software,
need examples)

Making everything a tensor: QTT

Let $f(x)$ – function of one variable ($f(x) = \sin x$).

If v – vector of values on a uniform grid with 2^d nodes.

Reshape v into a $2 \times 2 \times \dots \times 2$ d -dimensional tensor.

Compute TT-decomposition!

It is a **QTT-format**

Making everything a tensor: QTT

If $f(x)$ is such that

$$f(x + y) = \sum_{\alpha=1}^r u_{\alpha}(x)v_{\alpha}(y),$$

then QTT-ranks are bounded by r

Conclusion:

- ▶ $f(x) = \exp(\lambda x)$
- ▶ $f(x) = \sin(\alpha x + \beta)$
- ▶ $f(x)$ - polynom
- ▶ $f(x)$ - Rational function

TT-Toolbox

Software: <http://github.com/oseledets/TT-Toolbox>

- ▶ Basic operations in TT-format
- ▶ Advanced operations in TT-format (linear systems, eigenvalues, non-stationary problems, interpolation)
- ▶ Main operators
- ▶ Open-source
- ▶ S. V. Dolgov, V. A. Kazeev, I. V. Oseledets, D. V. Savostyanov, ...

What we can do

TT-Toolbox:

Available both in MATLAB and in Python,

<http://github.com/oseledets/TT-Toolbox>

<http://github.com/oseledets/ttpty>

- ▶ We have a very efficient implementation of a **black-box tensor approximation** (cross method)
- ▶ We have a very efficient implementation of basic operations
- ▶ Several advanced solvers (linear systems, convolution)

Wavelet tensor train decomposition

The QTT idea seems to be very reasonable for the compression of
images

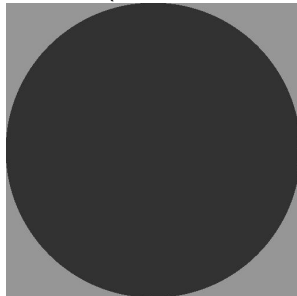
Idea of QTT can be interpreted as a wavelet-type transform!

QTT of simple images

QTT compression: 50 bytes



QTT compression: 70
KBytes (no compression)



WTT idea

The idea of wavelet tensor train (Oseledets, Tyrtshnikov, 2011):

QTT can be interpreted as an application of filters!

The signal is written as

$y = Ws$, where W is constructed from data, s is (pseudo) sparse

WTT-matrix

V. Kazeev, I. V. Oseledets

Under a suitable permutation of coefficients, the WTT-matrix has
small TT-ranks!

Order- r – matrix has TT-ranks $r^2 + 1$

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Example: Haar wavelet transform has QTT-rank 2

Compare to FFT

Fast Fourier Transform (FFT) is one of the important signal processing tools.

The FFT matrix has large QTT ranks (D. V. Savostyanov)

But $y = Fx$ can be computed in $\mathcal{O}(\log^\alpha N)$ if the result is in the low-rank format

Compression

- ▶ We can apply WTT idea for the compression of large-scale data (images, video, 3D video)
- ▶ Simple to use (see the talk by Pavel Khariuk)
- ▶ Many questions: the current version uses the SVD to compute filters

Conclusions

- ▶ The software is in good shape
- ▶ Need to find the limits of applicability

<http://oseledets.github.io> – my Skoltech group webpage

<http://spring.inm.ras.ru/osel> – personal webpage

<http://github.com/oseledets/TT-Toolbox/> – MATLAB code

<http://github.com/oseledets/ttypy/> – Python code