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Tutorial 6 (Solving partial differential equations using a Tucker Ansatz)

Tensor network methods are a powerful tool for solving PDEs which almost “factorize” in coordinate directions. As specific example, we consider Poisson’s equation

$$\begin{aligned} -\Delta\phi &= \mathbf{b} \quad \text{on } \Omega = [0, 1]^3, \\ \phi|_{\partial\Omega} &= 0 \end{aligned}$$

Here $\Delta = \partial_x^2 + \partial_y^2 + \partial_z^2$ is the Laplace operator, $\mathbf{b} : \Omega \rightarrow \mathbb{R}$ is a given function, we search for a solution $\phi : \Omega \rightarrow \mathbb{R}$, and $\phi|_{\partial\Omega} = 0$ means that ϕ should be zero on the boundary of Ω (i.e., the faces of the unit cube). We will discretize this PDE and approximate ϕ by a Tucker format representation.¹

- (a) Let $\mathbf{f} : [0, 1] \rightarrow \mathbb{R}$ be a smooth function. Provide a short derivation of the finite difference approximation

$$-\mathbf{f}''(x) = \frac{-\mathbf{f}(x+h) + 2\mathbf{f}(x) - \mathbf{f}(x-h)}{h^2} + \mathcal{O}(h^2).$$

- (b) We now discretize the interval $[0, 1]$ using the grid points $x_i = ih$ for $i = 0, 1, \dots, n$ with $h = \frac{1}{n}$ and some large integer n . Together with zero boundary conditions $\mathbf{f}(0) = \mathbf{f}(1) = 0$, \mathbf{f} is discretized as vector $\mathbf{f} = (\mathbf{f}(x_1), \dots, \mathbf{f}(x_{n-1})) \in \mathbb{R}^{n-1}$, omitting the points x_0 and x_n . Assemble a matrix $A \in \mathbb{R}^{(n-1) \times (n-1)}$ such that $A\mathbf{f}$ is the discretized negative second derivative of \mathbf{f} .
- (c) Using such a discretization A of $-\partial_x^2$ in one dimension, show that a discretization of $-\Delta$ on $\Omega = [0, 1]^3$ with zero boundary conditions is given by

$$L = A \otimes I \otimes I + I \otimes A \otimes I + I \otimes I \otimes A \quad \hat{=} \quad \begin{array}{c} \text{---} \textcircled{A} \text{---} \\ \text{---} \text{---} \text{---} \end{array} + \begin{array}{c} \text{---} \text{---} \text{---} \\ \text{---} \textcircled{A} \text{---} \end{array} + \begin{array}{c} \text{---} \text{---} \text{---} \\ \text{---} \text{---} \textcircled{A} \end{array}$$

where the identity matrix I has the same size as A . Thus $L \in \mathbb{R}^{(n-1)^3 \times (n-1)^3}$.

Now the problem of solving Poisson’s equation amounts to solving the linear system

$$L\phi = b. \tag{1}$$

To allow for optimizing a tensor Ansatz for ϕ , we want to convert this to a variational minimization problem. This is achieved by the least squares formulation (using that L is positive semidefinite):

$$\min_{\phi} \frac{1}{2} \langle \phi, L\phi \rangle - \langle \phi, b \rangle \tag{2}$$

- (d) Show that (1) and (2) are equivalent when admitting a general vector ϕ , by computing the gradient of (2) with respect to the entries of ϕ . Why must L be positive semidefinite?

To approximate the solution, we use the Tucker format as Ansatz for ϕ , with isometries U^1, U^2, U^3 and a core tensor C :

$$\phi = \begin{array}{c} \text{---} \textcircled{U^1} \text{---} \\ \text{---} \textcircled{U^2} \text{---} \\ \text{---} \textcircled{U^3} \text{---} \end{array} \textcircled{C} \quad \text{with} \quad U^\ell \in \mathbb{R}^{(n-1) \times k_\ell} \text{ for } \ell = 1, \dots, 3, \quad C \in \mathbb{R}^{k_1 \times k_2 \times k_3}$$

and $k_1, k_2, k_3 \ll n$.

- (e) Express $\langle \phi, L\phi \rangle$ and $\langle \phi, b \rangle$ in terms of diagrams, assuming that b is likewise stored in Tucker format.
- (f) Specify a corresponding “alternating least squares” (ALS) algorithm to obtain an approximate solution.

¹In this tutorial all functions and tensors are real-valued.

Solution

- (a) We can apply a finite difference scheme for the first derivative twice to obtain the discretized second derivative of f :

$$-f''(x) \approx -\frac{f'(x) - f'(x-h)}{h} \approx -\frac{\frac{f(x+h)-f(x)}{h} - \frac{f(x)-f(x-h)}{h}}{h} = \frac{-f(x+h) + 2f(x) - f(x-h)}{h^2}$$

Alternative derivation based on series $f(x+h) = f(x) + hf'(x) + \frac{1}{2}h^2f''(x) + \mathcal{O}(h^3)$ possible.)

- (b) Matrix-vector form of discretized $f''(x)$, with $f_i = f(x_i)$: Af with

$$A = \frac{1}{h^2} \begin{pmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & & \ddots & \\ & & & -1 & 2 \end{pmatrix} \in \mathbb{R}^{(n-1) \times (n-1)}$$

Remark: A is symmetric (clear) and positive semidefinite (proof not discussed here)

- (c) Idea: discretized function on unit cube $\Omega = [0, 1]^3$ has three indices: ϕ_{i_1, i_2, i_3} , one index for each coordinate. Thus ϕ can be regarded as tensor of degree 3. For the linear system in Eq. (1), we interpret ϕ as long vector with $(n-1)^3$ entries.

Regarding the Laplace operator $\Delta = \partial_x^2 + \partial_y^2 + \partial_z^2$, the derivatives act along each Cartesian coordinate direction separately, and likewise we have to apply A to each dimension of ϕ separately. Written as large matrix, this leads to the representation

$$L = A \otimes I \otimes I + I \otimes A \otimes I + I \otimes I \otimes A,$$

with I the $(n-1) \times (n-1)$ identity matrix. Note that this also requires that we can use the same grid along each Cartesian coordinate, which is the case due to the cubit domain Ω .

- (d) To find a possible solution of the minimization problem in (2) we compute the derivative and equate it to zero. The derivative with respect to a single element is:

$$\frac{d}{d\phi_k} \left(\frac{1}{2} \sum_{i,j} \phi_i L_{ij} \phi_j - \sum_i \phi_i b_i \right) = \frac{1}{2} \sum_{j \neq k} L_{kj} \phi_j + \frac{1}{2} \sum_{i \neq k} \phi_i L_{ik} + L_{kk} \phi_k - b_k$$

Note that L is symmetric, so

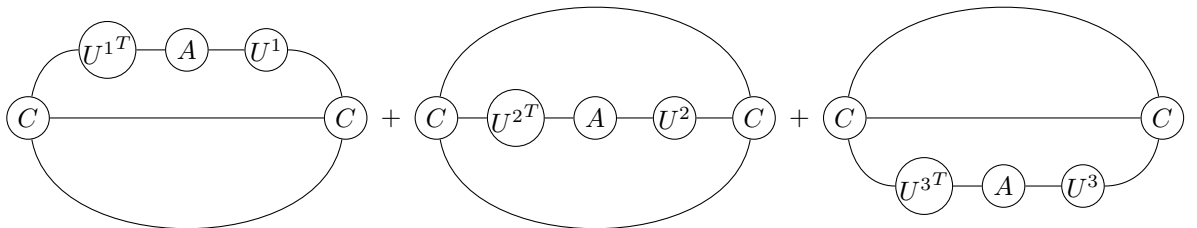
$$\frac{d}{d\phi_k} \left(\frac{1}{2} \sum_{i,j} \phi_i L_{ij} \phi_j - \sum_i \phi_i b_i \right) = \sum_i L_{ki} \phi_i - b_k,$$

and therefore

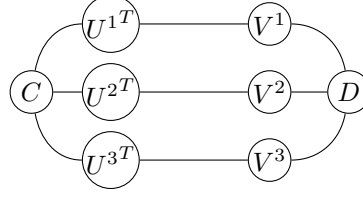
$$\frac{d}{d\phi} \left(\frac{1}{2} \langle \phi, L\phi \rangle - \langle \phi, b \rangle \right) = L\phi - b = 0.$$

This gives $L\phi = b$ as in (1). In order for this to be a minimum, L must be positive semidefinite.

- (e) $\langle \phi, L\phi \rangle$:



$\langle \phi, b \rangle$:



- (f) From the above diagrams one can see that it's possible to split the algorithm into smaller least squares problems. For example, $\min_{U^1} \frac{1}{2} \langle U^1, K^1 U^1 \rangle - \langle U^1, b^1 \rangle$, where K^1 is the operator inside the round brackets here:

$$\begin{aligned}
 & \text{Diagram 1} + \text{Diagram 2} + \text{Diagram 3} \\
 &= \text{Diagram 4} + \text{Diagram 5} + \text{Diagram 6} \\
 &= \boxed{U^1} = \left(\text{Diagram 7} + \text{Diagram 8} + \text{Diagram 9} \right) = \boxed{U^1}
 \end{aligned}$$

The diagrams in the equation are as follows:

- Diagram 1:** A tensor network with nodes $U^{1T}, U^1, U^{2T}, U^2, U^{3T}, U^3$ and C on both ends. U^{1T} is connected to U^1 via node A .
- Diagram 2:** Similar to Diagram 1, but U^{2T} is connected to U^2 via node A .
- Diagram 3:** Similar to Diagram 1, but U^{3T} is connected to U^3 via node A .
- Diagram 4:** A simplified tensor network with U^1 in a box on the left and right, and C nodes at the bottom. Node A is in the middle.
- Diagram 5:** Similar to Diagram 4, but with node M^2 instead of A .
- Diagram 6:** Similar to Diagram 4, but with node M^3 instead of A .
- Diagram 7:** A tensor network with U^1 in a box on the left and right, and C nodes at the bottom. Node A is in the middle.
- Diagram 8:** Similar to Diagram 7, but with node M^2 instead of A .
- Diagram 9:** Similar to Diagram 7, but with node M^3 instead of A .

and

$$b^1 = \text{Diagram 10}$$

Diagram 10 is a tensor network with nodes $U^{2T}, U^{3T}, V^1, V^2, V^3$ and C on the left, and D on the right. U^{2T} is connected to V^1 via a horizontal line. U^{3T} is connected to V^2 and V^3 via a horizontal line. C is connected to U^{2T} and U^{3T} .

The same can be done for U^2 , U^3 and C , so we can iterate over these optimizations until we reach convergence for ϕ .