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CPD-Structured Multivariate Polynomial Optimization

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ABSTRACT

We introduce the Tensor-Based Multivariate Optimization (TeMPO) framework for use in nonlinear optimization problems commonly encountered in signal processing, machine learning, and artificial intelligence. Within our framework, we model nonlinear relations by a multivariate polynomial that can be represented by low-rank symmetric tensors (multi-indexed arrays), making a compromise between model generality and efficiency of computation. Put the other way around, our approach both breaks the curse of dimensionality in the system parameters and captures the nonlinear relations with a good accuracy. Moreover, by taking advantage of the symmetric CPD format, we develop an efficient second-order Gauss–Newton algorithm for multivariate polynomial optimization. The presented algorithm has a quadratic per-iteration complexity in the number of optimization variables in the worst case scenario, and a linear per-iteration complexity in practice. We demonstrate the efficiency of our algorithm with some illustrative examples, apply it to the blind deconvolution of constant modulus signals, and the classification problem in supervised learning. We show that TeMPO achieves similar or better accuracy than multilayer perceptrons (MLPs), tensor networks with tensor trains (TT) and projected entangled pair states (PEPS) architectures for the classification of the MNIST and Fashion MNIST datasets while at the same time optimizing for fewer parameters and using less memory. Last but not least, our framework can be interpreted as an advancement of higher-order factorization machines: we introduce an efficient second-order algorithm for higher-order factorization machines.

Keywords: multivariate polynomial, numerical optimization, tensor decomposition, Gauss-Newton algorithm, factorization machines, higher order factorization machines, tensor network, image classification

1 INTRODUCTION

Many problems in data science, signal processing, machine learning and artificial intelligence (AI) can be thought of determining the nonlinear relationship between input and output data. Several strategies have been developed to efficiently model these nonlinear interactions. However, due to the higher-order nature of input and output data, developing scalable algorithms to model these nonlinear interactions is a challenging

research direction. Another major issue is the large number of system parameters needed to model the physical phenomena under consideration. For example, large numbers of layers and neurons are needed in deep neural networks (DNNs). Multivariate polynomials are also utilized to model nonlinear continuous functions. However, this approach suffers from an exponential increase in the number of coefficients with the degree of the polynomial. This is known as the curse of dimensionality and is a major drawback that inhibits the development of efficient algorithms.

Tensor decompositions such as canonical polyadic decomposition (CPD) and tensor trains (TT) are promising tools for breaking the curse of dimensionality. Tensors are multi-indexed arrays. They preserve the higher-order structure which is inherent in data, are able to model nonlinear interactions, and can be decomposed uniquely under mild conditions (Sidiropoulos et al., 2017; Cichocki et al., 2015; Kolda and Bader, 2009). Efficient numerical optimization algorithms have been developed for tensor decompositions. In the context of CPD, the Gauss–Newton algorithm using both line search and trust-region frameworks have been effectively implemented by exploiting the CPD structure (Sorber et al., 2013, 2012; Vervliet and De Lathauwer, 2019). A low complexity damped Gauss-Newton algorithm has also been proposed (Phan et al., 2013). Moreover, a randomized block sampling approach has been proposed which achieves linear time complexity for the CPD of large tensors by utilizing the Gauss–Newton algorithm (Vervliet and De Lathauwer, 2016). Many data science problems such as latent factor analysis have been solved by reformulating them as tensor decomposition problems (Comon and Jutten, 2009; Vervliet et al., 2014, 2016; Vervliet, 2018). An inexact Gauss–Newton algorithm has been proposed for scaling the CPD of large tensors with non-least-squares cost functions (Vandecappelle et al., 2021). Moreover, generalized Gauss–Newton algorithm with its efficient parallel implementation has been proposed for tensor completion with generalized loss functions (Singh et al., 2021). Our aim in this work is to extend the efficient numerical approaches to a broader class of problems that includes not only tensor decompositions but also the optimization of multilinear/polynomial cost functions. Examples include, but are not limited to matrix and tensor eigenvalue problems, nonlinear dimensionality reduction, nonlinear blind source separation, multivariate polynomial regression, and classification problems.

In this study, we develop a framework called Tensor-Based Multivariate Polynomial Optimization (TeMPO) to deal with nonlinear optimization problems commonly encountered in signal processing, machine learning and artificial intelligence. A preliminary version, where only rank-1 CPD is considered with application in blind identification, appeared as the conference paper (Ayvaz and De Lathauwer, 2021). In the TeMPO framework, these nonlinear functions are approximated or modeled by multivariate polynomials. Then, low-rank tensors are used to represent the polynomial under consideration. This approach reduces the number of parameters that define the system, and hence enables us to develop efficient numerical optimization algorithms. To further elaborate on the proposed methodology, let us consider the optimization problem

$$\min_{p} \quad l(p(\mathbf{z}), \boldsymbol{\theta}), \tag{1}$$

where $l : \mathbb{R} \times \mathbb{R}^M \to \mathbb{R}^+$ denotes a loss function such as the mean squared error, $p : \mathbb{R}^I \to \mathbb{R}$ denotes an unknown multivariate polynomial, $\mathbf{z} \in \mathbb{R}^I$ denotes input data, and $\boldsymbol{\theta} \in \mathbb{R}^M$ denotes output data. We compactly represent the polynomial $p(\mathbf{z})$ through low-rank tensors. One possible way to do this is to write the polynomial as a sum of homogeneous polynomials as follows:

$$p(\mathbf{z}) := \sum_{j=0}^{d} \mathcal{T}_j \mathbf{z}^j, \tag{2}$$

where $\mathcal{T}_j$ denotes a low-rank tensor of order j, and $\mathcal{T}_j\mathbf{z}^j$ denotes the mode-n product (See Section 2.1) of a tensor $\mathcal{T}_j$ and the vector $\mathbf{z}$ for all modes. As by convention, $\mathcal{T}_0$ is assumed to be scalar and $\mathbf{z}^0$ is assumed to be scalar 1. From now on, we call (2) a type I model. We can represent a multivariate polynomial with a single tensor by utilizing a process called homogenization, and augmenting the independent variable $\mathbf{z}$ by a constant 1 as

$$p(\widetilde{\mathbf{z}}) := \mathcal{W}\widetilde{\mathbf{z}}^d, \tag{3}$$

where $\mathcal{W}$ is a tensor of order d, and $\widetilde{\mathbf{z}} = [1; \mathbf{z}]$. Hereafter, we call (3) a type II model.

An n-variate polynomial of degree d has $\mathcal{O}\left(n^d\right)$ coefficients. This exponential dependence on d is the so-called curse of dimensionality. In the TeMPO framework, we break the curse of dimensionality by assuming low-rank structure in the coefficient tensors. For example, when rank- R symmetric CPD structure is used, the number of parameters needed to represent the n-variate polynomial of degree d is ndR which is linear in the number of variables. Several low-rank structures for tensors have been introduced in the literature (Sidiropoulos et al., 2017; Cichocki et al., 2015; Grasedyck et al., 2013), e.g., canonical polyadic decomposition (CPD), Tucker decomposition, hierarchical Tucker decomposition (HT) (Grasedyck, 2010), tensor train decomposition (TT) (Oseledets and Tyrtyshnikov, 2009). All of these structures can be incorporated into the TEMPO framework; however, in this paper we restrict ourselves to symmetric CPDs. Note that different types of low-rank structure allow us to represent different sub-classes of polynomials. Of course, different representations differ in storage space, and computational complexity. A more detailed exposition will be given in Section 3.2. Note also that the type I model allows us to constrain each term separately while the type II model does not. Therefore, the type I model is a more general representation of multivariate polynomials which may provide better results depending on the applications.

Besides breaking the curse of dimensionality, exploiting low-rank representations of tensors enables us to derive efficient expressions for objective function and gradient evaluations. These then lead us to develop scalable algorithms. We apply our framework for image classification by adapting the second-order Gauss–Newton algorithm and exploiting the symmetric CPD structure in two different tensor representations of multivariate polynomials. We show that the TeMPO framework with symmetric CPD structure achieves similar or better accuracy than various methods such as MLPs, and tensor networks with different structures for the classical MNIST and Fashion MNIST datasets while using fewer parameters and therefore less memory.

Related Work

Several tensor-based methods have been reported in the literature for regression and classification, two problems that are in the class of problems (1). In most of these approaches, a linear model

$$y = \langle \mathcal{W}, \mathcal{X} \rangle + b, \tag{4}$$

is used where $\mathcal{W}$ denotes a weight tensor and $\mathcal{X}$ represents nonlinear features of the input data. This model corresponds to the type II model when a symmetric CPD structure is imposed on the weight tensor $\mathcal{W}$ and $\mathcal{X}$ is composed of polynomial features of input data. Clearly, imposing different structures to the weight tensor $\mathcal{W}$ and using different nonlinear features in the tensor $\mathcal{X}$ leads to a different representation of the nonlinear interaction between input data and output data. For example, *exponential machines* utilize the tensor train format in the weight tensor with a norm regularization term in the optimization (Novikov et al., 2017). In this approach, the Riemannian gradient descent algorithm is used for solving the optimization problem.

In a similar approach, tensor trains is used with the feature map $\phi(x_j) = \left[\cos\left(\frac{\pi x_j}{2}\right), \sin\left(\frac{\pi x_j}{2}\right)\right]$, by using the density matrix renormalization group (DMRG) algorithm and the first-order ADAM algorithm for the optimization of different cost functions (Stoudenmire and Schwab, 2016; Efthymiou et al., 2019). The same feature map is also used for the linear model (4) by imposing projected entangled pair states (PEPS) structure on the weight tensor $\mathcal{W}$ (Cheng et al., 2021). The CPD format in model (4) has also been studied in the realm of tensor regression with the Frobenius norm and group sparsity norm regularization terms while using a coordinate-descent approach (Guo et al., 2012). A similar model is also considered by utilizing the symmetric CPD format and the second-order Gauss–Newton algorithm with algebraic initialization for multivariate polynomial regression (Hendrikx et al., 2019). Several approaches have been proposed that utilize CPD or Tucker formats in tensor regression that use different regularization strategies to prevent the overfitting (Rabusseau and Kadri, 2016; Yu and Liu, 2016). Also, the hierarchical Tucker (HT) format has been used in the tensor regression context for the generalized linear model (GLM) $y = \boldsymbol{\alpha}^{\mathrm{T}}\mathbf{x} + \langle \mathcal{W}, \mathcal{X} \rangle$. This approach was successfully applied to brain imaging data sets and uses a block relaxation algorithm, which solves a sequence of lower dimensional optimization problems (Hou and Chaib-Draa, 2015).

Similarly, several models related to the type I model are considered in various settings. For example, Kar and Karnick use random polynomial features and parameterize the coefficients of the polynomial under consideration (Kar and Karnick, 2012). The parameterization used in this approach has been shown to be equivalent to imposing the CPD format to the weight tensor $\mathcal{W}$ (Yang and Gittens, 2015). Another approach is *factorization machines* which use a multivariate polynomial kernel in the realm of support vector machines (SVM)(Rendle, 2010). For second-order factorization machines a first-order stochastic gradient descent algorithm has been proposed. This approach has a linear time complexity. Higher-order factorization machines use the ANOVA kernel to achieve a linear time complexity and have been successfully applied to link prediction models using stochastic gradient descent (Blondel et al., 2016a). The ANOVA kernel does not use symmetric tensors in the representation and instead only considers combinations of distinct features (Blondel et al., 2016a). Also, factorization machines in the symmetric CPD format have been considered using first-order and BFGS type algorithms (Blondel et al., 2016b). *Tensor machines* generalize both the Kar-Karnick random features approach and factorization machines. It has been shown that these approaches correspond to specific types of tensor machines in the CPD format. Further, it has been shown that empirical risk minimization is an efficient method for finding locally optimal tensor machines if the optimization algorithm avoids saddle points (Yang and Gittens, 2015).

As can be seen from the literature summary above, one of the differences between our approach and the above methods is the model used. The type I model (2) has not been examined with the symmetric CPD structure in the weight tensors, to the best of our knowledge. Another difference of our approach from the above methods is the algorithm used. While first-order algorithms are used in most of these approaches, we utilize the second-order batch Gauss–Newton (GN) algorithm. Although first-order methods have the advantage of lower per-iteration complexity, second-order GN algorithms generally require fewer iterations to converge and fewer hyperparameters to be optimized. Moreover, the GN algorithm using trust-region is more robust in the sense that it converges to a (local) minimum for any starting point under mild conditions and it is less prone to swamps (many iterations with little to no improvement) (Nocedal and Wright, 2006; Sorber et al., 2012; Vervliet and De Lathauwer, 2019).

We summarize our contributions as follows:

- We develop a TeMPO framework that is able to solve many nonlinear problems with ubiquitous applications in signal processing, machine learning and artificial intelligence. Moreover, we develop an efficient second-order Gauss–Newton algorithm for optimizing multivariate polynomials in the CPD format.
- We determine the conditions where the tensorized linear model (4) with polynomial features and the multivariate polynomial model (2) coincide when the symmetric CPD format is used in their representations.
- We show that TeMPO achieves similar or better accuracy than various methods such as multilayer perceptrons (MLPs), tensor networks with different architectures including tensor trains (TT), tree tensor networks, and projected entangled pair states (PEPS). We also show that TeMPO requires the optimization for fewer parameters and less memory than these methods for the classification of the MNIST and Fashion MNIST datasets.
- Last but not least, our framework can be interpreted as an advancement of higher-order factorization machines; we introduce an efficient second-order Gauss–Newton algorithm for higher-order factorization machines.

The remaining part of this paper is organized as follows. In Section 2, we describe notation and background information concerning tensors. In Section 3, we describe the TeMPO framework in a more detailed manner. Section 3 also covers the details of representation of polynomials by symmetric CPD structured tensors. In Section 3, we also show how to exploit the symmetric CPD structure to obtain efficient expressions for the gradient and Jacobian-vector products which are necessary for the Gauss–Newton algorithm. The formulation of the image classification problem in the context of TeMPO, numerical experiments and related discussions will be covered in Section 4.3. We conclude our paper with future remarks in the last section.

2 PRELIMINARIES

2.1 Notation

A tensor is a higher-order generalization of a vector (first-order) and a matrix (second-order). Following established conventions, we denote scalars, vectors, matrices and tensors by a, $\mathbf{a}$, $\mathbf{A}$, and $\mathcal{A}$, respectively. The transpose of a matrix $\mathbf{A}$ is denoted as $\mathbf{A}^{\mathrm{T}}$. The ith column vector of a matrix $\mathbf{A}$ is denoted as $\mathbf{a}_i$, i.e., $\mathbf{A} = (\mathbf{a}_1, \mathbf{a}_2 \ldots)$. The entry with row index i and column index j in a matrix $\mathbf{A}$, i.e. $(\mathbf{A})_{ij}$, is denoted by a_{ij}. Similarly, $(\mathcal{A})_{i_1 i_2 \ldots i_N}$ is denoted by $a_{i_1 i_2 \ldots i_N}$. $\mathrm{Diag}(\mathbf{a})$ denotes the diagonal matrix whose entries are composed from the vector $\mathbf{a}$. On the other hand, $\mathrm{diag}(\mathbf{A})$ denotes a vector composed from the diagonal elements of $\mathbf{A}$. The vectorization operator $\mathrm{vec}(\mathbf{A})$ for $\mathbf{A} \in \mathbb{K}^{I \times J}$ stacks all the columns of $\mathbf{A}$ into a column vector $\mathbf{a} \in \mathbb{K}^{IJ}$. The reverse operation $\mathrm{unvec}(\mathbf{a})$ reshapes a vector $\mathbf{a}$ into a matrix $\mathbf{A} \in \mathbb{K}^{I \times J}$. The identity matrix of size $(K \times K)$ is denoted by $\mathbf{I}_K$. A vector of length K with all entries equal to 1 is denoted by $\mathbf{1}_K$. The l_2 norm of a vector $\mathbf{a}$ is denoted by $||\mathbf{a}||_2$. The row-wise and column-wise concatenation of two vectors $\mathbf{a}$ and $\mathbf{b}$ is denoted by $[\mathbf{a}, \mathbf{b}]$ and $[\mathbf{a}; \mathbf{b}]$, respectively. The outer product, Kronecker product, Khatri–Rao product, and Hadamard product are denoted by $\otimes$, $\otimes$, $\odot$, and $*$, respectively. The nth power of a vector $\mathbf{x}$ with respect to Kronecker product is defined as $\mathbf{x}^{\otimes n} = \mathbf{x} \otimes \mathbf{x}^{\otimes (n-1)}$, with $\mathbf{x}^{\otimes 0} = 1$. Similarly, $\mathbf{x}^{\odot n}$ and $\mathbf{x}^{*n}$ denotes the nth power of vector $\mathbf{x}$ with respect to Khatri–Rao product and Hadamard product, respectively. The mode-n product of a tensor $\mathcal{A} \in \mathbb{K}^{I_1 \times I_2 \times \ldots \times I_N}$ (with $\mathbb{K}$ meaning either $\mathbb{R}$ or $\mathbb{C}$) and a vector $\mathbf{x} \in \mathbb{K}^{I_n}$, denoted by $\mathcal{A} \cdot_n \mathbf{x}^{\mathrm{T}}$, is defined element-wise as $(\mathcal{A} \cdot_n \mathbf{x}^{\mathrm{T}})_{i_1 i_2 \cdots i_{n-1} i_{n+1} \cdots i_N} = \sum_{i_n=1}^{I_N} a_{i_1 i_2 \cdots i_n \cdots i_N} x_{i_n}$. The

mode-n product of a tensor $\mathcal{A} \in \mathbb{K}^{I\times I\times\ldots\times I}$ of order k and a vector $\mathbf{x} \in \mathbb{K}^I$ for all modes is defined as

$$\mathcal{A}\mathbf{x}^k \overset{\text{def}}{=} \mathcal{A} \bullet_1 \mathbf{x}^{\mathrm{T}} \bullet_2 \mathbf{x}^{\mathrm{T}} \ldots \bullet_k \mathbf{x}^{\mathrm{T}}.$$

A mode-n vector or mode-n fiber of a tensor $\mathcal{A} \in \mathbb{K}^{I_1\times I_2\times\ldots\times I_N}$ is a vector obtained by fixing every index except the nth. The mode-n matricization of $\mathcal{A}$ is a matrix $\mathbf{A}_{[n;N,N-1,\ldots,n+1,n-1,\ldots,1]}$ collecting all the mode-n vectors as its columns. For example, an entry $a_{i_1i_2i_3}$ of a tensor $\mathcal{A} \in \mathbb{K}^{I\times J\times K}$ is mapped to the (i_2, q) entry of the matrix $\mathbf{A}_{[2;3,1]}$ with $q = i_1 + (i_3 - 1)I$. The binomial coefficient is denoted by $C_n^k = \frac{n!}{(n-k)!k!}$. Some useful definitions are listed below.

DEFINITION 1 (Symmetric Tensor). *A tensor $\mathcal{A} \in \mathbb{K}^{I\times I\times\ldots\times I}$ of order k is called symmetric if its entries are invariant under the permutation of its indices.*

As a consequence of this definition, the matrix representations of symmetric tensors in different modes are all equal.

DEFINITION 2 (Rank of a Tensor). *A rank-1 tensor of order N is the outer product of N nonzero vectors. The rank of a tensor is equal to the minimal number of rank-1 terms that yield the tensor as their sum.*

DEFINITION 3 (Kronecker Product). *Given two matrices $\mathbf{A} \in \mathbb{K}^{I\times J}$ and $\mathbf{B} \in \mathbb{K}^{K\times L}$, their Kronecker product is*

$$\mathbf{A} \otimes \mathbf{B} = \begin{bmatrix} a_{1,1}\mathbf{B} & \cdots & a_{1,J}\mathbf{B} \\ \vdots & \ddots & \vdots \\ a_{I,1}\mathbf{B} & \cdots & a_{I,J}\mathbf{B} \end{bmatrix} \in \mathbb{K}^{IK\times JL}.$$

DEFINITION 4 (Khatri–Rao Product). *Given two matrices $\mathbf{A} \in \mathbb{K}^{I\times K}$ and $\mathbf{B} \in \mathbb{K}^{J\times K}$ with the same number of columns, their Khatri–Rao product, also known as columnwise Kronecker product, is*

$$\mathbf{A} \odot \mathbf{B} = [\mathbf{a}_1 \otimes \mathbf{b}_1, \mathbf{a}_2 \otimes \mathbf{b}_2, \ldots, \mathbf{a}_K \otimes \mathbf{b}_K] \in \mathbb{K}^{IJ\times K},$$

where $\mathbf{a}_i$ and $\mathbf{b}_i$ denote the ith column of the matrices $\mathbf{A}$ and $\mathbf{B}$, respectively.

DEFINITION 5 (Hadamard Product). *Given two matrices $\mathbf{A} \in \mathbb{K}^{I\times J}$ and $\mathbf{B} \in \mathbb{K}^{I\times J}$ with the same size, their Hadamard product is the elementwise product, i.e.,*

$$\mathbf{A} * \mathbf{B} = \begin{bmatrix} a_{1,1}b_{1,1} & \cdots & a_{1,J}b_{1,J} \\ \vdots & \ddots & \vdots \\ a_{I,1}b_{I,1} & \cdots & a_{I,J}b_{I,J} \end{bmatrix} \in \mathbb{K}^{I\times J}.$$

The following properties will be useful for our derivations.

PROPERTY 1. *Let $\mathbf{A} \in \mathbb{K}^{I\times J}, \mathbf{X} \in \mathbb{K}^{J\times K}, \mathbf{B} \in \mathbb{K}^{K\times L}$. Then*

$$\mathit{vec}(\mathbf{AXB}) = \left(\mathbf{B}^{\mathrm{T}} \otimes \mathbf{A}\right) \mathit{vec}(\mathbf{X}) \in \mathbb{K}^{IL}.$$

Moreover, if $\mathbf{X} \in \mathbb{K}^{J\times J}$ is a diagonal matrix and $\mathbf{B} \in \mathbb{K}^{J\times L}$, then

$$\mathit{vec}(\mathbf{AXB}) = \left(\mathbf{B}^{\mathrm{T}} \odot \mathbf{A}\right) \mathit{diag}(\mathbf{X}) \in \mathbb{K}^{IL}.$$

PROPERTY 2. *Let* $\mathbf{A} \in \mathbb{K}^{I\times J}, \mathbf{B} \in \mathbb{K}^{K\times J}, \mathbf{C} \in \mathbb{K}^{I\times L}$*, and* $\mathbf{D} \in \mathbb{K}^{K\times L}$*. Then*

$$(\mathbf{A} \odot \mathbf{B})^{\mathrm{T}} (\mathbf{C} \odot \mathbf{D}) = \left(\mathbf{A}^{\mathrm{T}}\mathbf{C}\right) * \left(\mathbf{B}^{\mathrm{T}}\mathbf{D}\right) \in \mathbb{K}^{J\times L}.$$

PROPERTY 3. *For matrices* $\mathbf{A} \in \mathbb{R}^{I\times J}$ *and* $\mathbf{B} \in \mathbb{R}^{J\times K}$*, and for the function* $f(\mathbf{A}, \mathbf{B}) = \mathbf{AB}$*, the following equations hold:*

$$\frac{\partial vec(f(\mathbf{A}, \mathbf{B}))}{\partial vec(\mathbf{A})} = \mathbf{B}^{\mathrm{T}} \otimes \mathbf{I}_I, \quad \frac{\partial vec(f(\mathbf{A}, \mathbf{B}))}{\partial vec(\mathbf{B})} = \mathbf{I}_K \otimes \mathbf{A}.$$

2.2 Canonical Polyadic Decomposition

Here, we will briefly describe the canonical polyadic decomposition. A more detailed description of CPD can be found in (Sidiropoulos et al., 2017) and references therein. The CPD writes a tensor $\mathcal{T} \in \mathbb{K}^{I_1\times I_2\times \ldots \times I_N}$ as a sum of R rank-1 tensors and is denoted by $\left[\!\left[\mathbf{U}^{(1)}, \ldots, \mathbf{U}^{(N)}\right]\!\right]$, with its factor matrices $\mathbf{U}^{(n)} \in \mathbb{K}^{I_n\times R}$, where R equals the rank of the tensor. This is a shortcut notation for

$$\mathcal{T} = \sum_{r=1}^{R} \mathbf{u}_r^{(1)} \otimes \mathbf{u}_r^{(2)} \otimes \ldots \otimes \mathbf{u}_r^{(N)},$$

where $\mathbf{u}_r^{(n)}$ denotes the rth column of the factor matrix $\mathbf{U}^{(n)}$. CPD is essentially unique under mild conditions (Kruskal, 1977; Sidiropoulos and Bro, 2000; Domanov and De Lathauwer, 2013, 2017), and has found many applications in signal processing and machine learning (Sidiropoulos et al., 2017).

For symmetric tensors, all the factor matrices are equal, i.e.

$$\mathcal{T} = \left[\!\left[\mathbf{U}, \mathbf{U} \ldots, \mathbf{U}; \mathbf{c}^{\mathrm{T}}\right]\!\right] = \sum_{r=1}^{R} c_r(\mathbf{u}_r \otimes \mathbf{u}_r \otimes \ldots \otimes \mathbf{u}_r) \in \mathbb{K}^{I\times I\times \ldots \times I},$$

where $\mathbf{U} \in \mathbb{K}^{I\times R}$, and $\mathbf{c} \in \mathbb{K}^R$ is a vector of weights which allows us to give minus signs to the factors for even-degree symmetric tensors, see Figure 1. The matrix unfolding of a symmetric CPD is given by

$$\mathbf{T} = \mathbf{U}\mathrm{Diag}(\mathbf{c})(\mathbf{U} \odot \mathbf{U} \odot \cdots \odot \mathbf{U})^{\mathrm{T}}.$$

3 TENSOR-BASED MULTIVARIATE POLYNOMIAL OPTIMIZATION

The primary aim of the TeMPO framework is to develop efficient algorithms for modeling nonlinear phenomena commonly encountered in the areas of signal processing, machine learning and artificial intelligence (Ayvaz and De Lathauwer, 2021). To achieve this, we assume structure in the nonlinear function $f : \mathbb{R}^I \to \mathbb{R}^N$ that maps the input data to output data. In our framework, we first assume smoothness in f and approximate it as multivariate polynomial $p : \mathbb{R}^I \to \mathbb{R}^N$. Then, we approximate p with low-rank tensors. This allows us to achieve efficiency both in storing the coefficients of the approximation and in performing computations with those coefficients. Although any continuous function on a compact domain can be approximated by polynomials arbitrarily well according to the Stone–Weierstrass theorem, polynomial approximations used in practice can pose several numerical issues such as the Runge phenomenon. Several strategies have been proposed to overcome these numerical issues, such as using different polynomial bases

and Tikhonov regularization (Boyd and Ong, 2009; Trefethen, 2019). In this work, we will focus more on computational issues of the TeMPO framework; however, it is possible to incorporate these strategies with TeMPO using slight modifications. In the remaining part of this section, we describe the scope of TeMPO. Then we will describe two types of tensor representations of multivariate polynomials where the symmetric CPD structure is imposed on the coefficient tensors. Next we will briefly describe the Gauss–Newton algorithm using the dogleg trust-region method and show how to exploit the symmetric CPD structure in the computation of Jacobian and Jacobian-vector products that are necessary for the Gauss–Newton algorithm.

3.1 Scope of the TeMPO Framework

The TeMPO framework concerns optimization problems with continuous cost functions on compact domains, namely multilinear/polynomial cost functions with or without additional constraints, which is a more general setting than tensor decomposition or retrieval of a tensor factorization. To better describe the scope, let us consider the following class of objective functions:

$$l(\boldsymbol{\theta}, p(\mathbf{z})), \tag{5}$$

where $l : \mathbb{R} \times \mathbb{R}^M \to \mathbb{R}^+$ denotes the performance measure of the model to be optimized, $p : \mathbb{R}^I \to \mathbb{R}$ denotes a multivariate polynomial represented by low-rank tensors, $\mathbf{z} \in \mathbb{R}^I$ denotes input data, and $\boldsymbol{\theta} \in \mathbb{R}^M$ denotes output data. A broad range of objective functions are in the class of (5). For example, the objective function for the estimation of the CPD of a third-order tensor $\mathcal{T}$ can be written as

$$\frac{1}{2}\left|\left|\boldsymbol{\theta} - p(\mathbf{A}, \mathbf{B}, \mathbf{C})\right|\right|_2^2, \quad \text{where} \quad p(\mathbf{A}, \mathbf{B}, \mathbf{C}) = \text{vec}\left(\llbracket \mathbf{A}, \mathbf{B}, \mathbf{C} \rrbracket\right).$$

Other tensor decomposition problems, such as block term decomposition (BTD), also fit into TeMPO. The symmetric best rank-1 approximation problem (De Lathauwer et al., 2000), which can also be formulated as

$$\max_{\mathbf{z} \in \mathbb{R}^I} \quad \mathcal{T}\mathbf{z}^d, \quad \text{subject to} \quad ||\mathbf{z}|| = 1, \tag{6}$$

is another example problem that fits into the framework. Note that (6) is expressed as the maximization of an objective function, rather than as the decomposition of a tensor; indeed TeMPO allows one to address more general problems. For the symmetric best rank-1 approximation problem, several approaches such as higher-order power method (De Lathauwer et al., 2000), generalized Rayleigh–Newton iteration and the alternating least squares methods (Zhang and Golub, 2001), SVD-based algorithms (Guan et al., 2018), semi-definite relaxations (Nie and Wang, 2013) have been proposed. Problems from unsupervised learning such as nonlinear dimensionality reduction, manifold learning, nonlinear blind source separation, and nonlinear independent component analysis also fit into TeMPO. Similarly, problems from supervised learning fit into TeMPO as well. In this work, we will focus on the regression and classification problem and derive expressions for Jacobian and Jacobian-vector products, which are necessary for the Gauss–Newton algorithm. However, the derivations here can be extended to the other problems without much effort.

Given data points $(y_k, \mathbf{z}_k)$, the regression problem can be formulated within the TeMPO framework for the type I model as

$$\min_{\mathcal{T}_0,\ldots,\mathcal{T}_d} \; p(\mathcal{T}_0, \ldots, \mathcal{T}_d, \mathbf{Z}) = \min_{\mathcal{T}_0,\ldots,\mathcal{T}_d} \; \frac{1}{2}\sum_{k=1}^{K}\left(y_k - \mathcal{T}_0 - \sum_{j=1}^{d}\mathcal{T}_j\mathbf{z}_k^j\right)^2, \quad \text{subject to} \quad \text{rank}(\mathcal{T}_j) = R_j \tag{7}$$

where $R_j \in \mathbb{N}^+$ is a small integer, $\mathcal{T}_j \in \mathbb{R}^{I \times I \times \ldots \times I}$ denotes the low-rank structured coefficient tensor of order j to be optimized, $\mathcal{T}_0 \in \mathbb{R}$ denotes a scalar, $\mathbf{Z} \in \mathbb{R}^{I \times K}$ denotes the data matrix, $\mathbf{z}_k$ denotes the kth column of $\mathbf{Z}$ and K is the number of available data points. For the type II model, the regression problem takes the form

$$\min_{\mathcal{T}} \;\; p(\mathcal{T}, \widetilde{\mathbf{Z}}) = \min_{\mathcal{T}} \;\; \frac{1}{2} \sum_{k=1}^{K} \left(y_k - \mathcal{T} \widetilde{\mathbf{z}}_i^d \right)^2, \quad \text{subject to} \quad \text{rank}(\mathcal{T}) = R \tag{8}$$

where $\mathcal{T}$ denotes the low-rank structured coefficient tensor of order d to be optimized, $\widetilde{\mathbf{Z}} \in \mathbb{R}^{(I+1) \times K}$ denotes the augmented input data matrix, and $\widetilde{\mathbf{z}_k}$ denotes the kth column of $\widetilde{\mathbf{Z}}$, i.e., $\widetilde{\mathbf{z}}_k = [1; \mathbf{z}_k]$.

3.2 Tensor Representation of Polynomials

In this subsection, we examine the type I and type II model in detail. A (symmetric) tensor $\mathcal{T}$ of order d and dimension n can be associated with a homogeneous n-variate polynomial $p(\mathbf{z})$ of degree d (Brachat et al., 2010), as shown in equation (3).

Type I: Since any polynomial can be written as a sum of homogeneous polynomials of increasing degrees, any polynomial of degree d can be written by using tensors of order up to d, as shown in equation (2). Note that in the tensor representation of polynomials, any tensor can be assumed to be symmetric without loss of generality. Indeed, any homogeneous polynomial $p(\mathbf{z})$ of degree $d \in \mathbb{N}$ can be represented by a multilinear form $\mathcal{T}\mathbf{z}^d$, where $\mathcal{T} \in \mathbb{K}^{I \times I \times \ldots \times I}$ is a symmetric tensor of order d and $\mathbf{z} \in \mathbb{K}^I$.

To see this, suppose a homogeneous polynomial $p(\mathbf{z})$ is represented as

$$p(\mathbf{z}) = \widetilde{T}\mathbf{z}^d = \sum_{i_1, i_2 \ldots, i_d = 1}^{I} \widetilde{t}_{i_1 i_2 \ldots i_d} z_{i_1} z_{i_2} \ldots z_{i_d},$$

where $\widetilde{\mathcal{T}} \in \mathbb{K}^{I \times I \times \ldots \times I}$ is a tensor of order d. Since the terms $z_{i_1} z_{i_2} \ldots z_{i_d}$ are invariant under the permutation of indices, we may write

$$p(\mathbf{x}) = \sum_{i_1, i_2 \ldots, i_d = 1}^{I} t_{i_1 i_2 \ldots i_d} z_{i_1} z_{i_2} \ldots z_{i_d}, \quad \text{where} \quad t_{i_1 i_2 \ldots i_d} = \frac{1}{d!} \sum_{(i_1, i_2, \ldots, i_d) \in \Pi(i_1 i_2 \ldots i_d)} \widetilde{t}_{i_1 i_2 \ldots i_d},$$

here $\Pi(i_1 i_2 \ldots i_d)$ denotes the collection of all permutation of indices $(i_1, i_2, \ldots, i_d)$. Since the entries of $\mathcal{T}$ are invariant under the permutation of indices, we can conclude that $\mathcal{T}$ is symmetric.

The above discussion reveals the fact that there are infinitely many representations of a given polynomial. Indeed two representations with tensors $\mathcal{T}$ and $\mathcal{W}$ are equal so long as the summation of the corresponding entries over the permutation of indices remains the same, i.e.,

$$\sum_{(i_1, i_2, \ldots, i_d) \in \Pi(i_1 i_2 \ldots i_d)} t_{i_1 i_2 \ldots i_d} = \sum_{(i_1, i_2, \ldots, i_d) \in \Pi(i_1 i_2 \ldots i_d)} w_{i_1 i_2 \ldots i_d}$$

In the ANOVA kernel used in higher-order factorization machines, all $t_{\Pi(i_1 i_2 \ldots i_d)}$ are set to zero except $t_{(i_1 < i_2 < \ldots < i_d)}$ (Blondel et al., 2016a), which leads to a sparse representation. In this paper, we use symmetric tensors for two reasons. The first reason is that the CPD of a symmetric tensor can be expressed by a

single factor matrix. Therefore, the symmetric CPD representation of multivariate polynomial requires fewer number of parameters in comparison with a non-symmetric representation. The second reason is that there is a rich history of the representation of polynomials with symmetric tensors in the field of algebraic geometry under the name of the Waring problem (Alexander and Hirschowitz, 1995).

Type II: Augmenting the independent variable vector $\mathbf{z}$, by a constant 1[1], i.e $\widetilde{\mathbf{z}} = [1; \mathbf{z}^{\mathrm{T}}]$ leads to a different representation of non-homogeneous polynomials that uses a single dth order symmetric tensor for the inhomogeneous multivariate polynomial of degree d, as shown in equation (3). This process is called homogenization (Debals, 2017) and is graphically illustrated in Figure 2. If we just use full tensors, the type I and II models are interchangeable. However, it is important to note that *when low-rank structure is imposed on the coefficient tensors,* both representations yield different classes of low-rank multivariate polynomial. Hence, these approaches may lead to different results depending on the application. The former approach requires more parameters since it uses more factor matrices. The difference in the number of parameters should be taken into account to prevent underfitting and overfitting. A more detailed description for storage complexity is given in Section 3.5. Moreover, the type I model allows us to constrain each term in the representation separately. In modelling multivariate polynomials, one might not wish the terms of different order to have some shared structure, in which case one should choose the type I model to work with. Similarly, the type II model should be chosen, if some shared structure is desired in the terms of different order. To further elaborate on the effects of homogenization on the rank of a tensor, let us consider the following proposition.

PROPOSITION 1. *Let $p(\mathbf{z}) : \mathbb{R}^I \to \mathbb{R}$ be a multivariate polynomial of order d defined as in equation* (2) *by a scalar $\mathcal{T}_0$ and symmetric tensors $\mathcal{T}_j \in \mathbb{R}^{I \times I \times \ldots \times I}$ for $j = 1, 2, \ldots, d$. Moreover, let $\mathcal{W} \in \mathbb{R}^{(I+1)\times\ldots\times(I+1)}$ be the corresponding tensor obtained from the homogenization process. The tensors $\mathcal{W}$ and $\mathcal{T}_j$ have the same rank R if and only if the tensors $\mathcal{T}_j$ admit unique CPDs with shared factor matrices and a weight vector $\mathbf{c}$, i.e.,*

$$\mathcal{T}_j = \left[\!\!\left[\mathbf{U}, \ldots, \mathbf{U}; C_d^j (\mathbf{c}^{\mathrm{T}})^{\odot(d-j)} \right]\!\!\right], \quad \textit{and} \quad \mathcal{T}_0 = \sum_{r=1}^{R} \left((\mathbf{c}^{\mathrm{T}})^{\odot d} \right)_r .$$

PROOF. *Let the CPD of the tensor $\mathcal{W}$ be defined as $[\![\mathbf{V}, \ldots, \mathbf{V}]\!]$, where, for convenience but without loss of generality, the weights of the rank-1 terms are assumed to be 1. Since $\mathcal{W}$ is obtained by the homogenization process, partitioning $\mathbf{V}$ as $[\mathbf{v}^{\mathrm{T}}; \mathbf{Q}]$ and using the definition of CPD, we obtain*

$$\mathcal{T}_j = \left[\!\!\left[\mathbf{Q}, \ldots, \mathbf{Q}; C_d^j (\mathbf{v}^{\mathrm{T}})^{\odot(d-j)} \right]\!\!\right], \quad \textit{and} \quad \mathcal{T}_0 = \sum_{r=1}^{R} \left((\mathbf{v}^{\mathrm{T}})^{\odot d} \right)_r . \tag{9}$$

Since the CPDs of the tensors $\mathcal{T}_j$ are unique, the equality (9) *holds if and only if the equalities $\mathbf{Q} = \mathbf{U}$ and $\mathbf{v} = \mathbf{c}$ also hold.*

REMARK 1. *In the above proof, we assumed that the vector $\mathbf{v}$ does not contain any zero elements. Note that if the vector $\mathbf{v}$ does contain zero elements, it cancels the corresponding rank-1 terms. Therefore, in that case rank$(\mathcal{W})$ > rank$(\mathcal{T}_j)$, for $j = 1, \ldots, d-1$. Moreover, the uniqueness of the CPDs of $\mathcal{T}_j$ implies that rank$(\mathcal{W}) \geq$ rank$(\mathcal{T}_j)$. Since the equality rank$(\mathcal{W})$ = rank$(\mathcal{T}_j)$ holds only when the tensors $\mathcal{T}_j$ have shared factor matrices as described above, we can conclude that in all other cases rank$(\mathcal{W})$ > rank$(\mathcal{T}_j)$.*

[1] Since the weight vector $\mathbf{c}$ is used in the parametrization of tensors, different choices of constant in $\widetilde{\mathbf{z}}$ lead to mathematically equivalent cost functions in the optimization problems. On the other hand, the choice of the constant may imply numerical differences — in situations of this type, one should generally choose a constant that "makes sense for the application".

Proposition 1 together with Remark 1 reveals the fact that if $\mathcal{W}$ admits a rank-R CPD, there exists tensors $\mathcal{T}_j$ that admit rank-R_j CPDs with shared factors and $R_j \leq R$. Hence, the expressive power of the type II model is weaker than the type I model, i.e. the type II model requires higher rank values than the type I model to be able to model functions of the same complexity. In other words, the set of polynomials represented by the type II model is a strict subset of the set of polynomials represented by the type I model for the same rank values.

Although we focus in this study on the type I and type II models in the symmetric CPD format, the TeMPO framework is not limited to these. TeMPO collects low-rank tensor representations of multivariate polynomials under a roof by utilizing various other tensor decompositions such as TT, HT, and non-symmetric and partially symmetric CPD formats [2]. In this way, TeMPO breaks the curse of dimensionality and makes it possible to develop second-order efficient algorithms for the optimization of a more general class of multivariate polynomials. Moreover, use of structured tensors and multilinear algebra makes it easy to incorporate other polynomial bases and, more generally, other nonlinear feature maps rather than the standard polynomial bases to the TeMPO framework. From this point of view, TeMPO can be interpreted as a generalization of higher-order factorization machines that use particular types of multivariate polynomials with the standard polynomial bases and utilize first-order and BFGS type algorithms (Rendle, 2010; Blondel et al., 2016a,b, 2017).

3.3 Gauss–Newton Algorithm

Most standard first-order and second-order numerical optimization algorithms can be used for solving problem (8). Since the objective function under consideration is a least-squares function, we will utilize the second-order batch Gauss–Newton (GN) algorithm using a trust-region to take advantage of its attractive properties such as quadratic convergence near a local optimum point, resistant to swamps, suitable to incorporate constraints easily and eligible to exploit multilinear structure. In the case the objective function is not least squares, the inexact GN algorithm can also be utilized. Below, we briefly describe the GN algorithm using a trust-region, and then derive the expressions for Jacobian and Jacobian-vector products for tensors in the symmetric CPD format. In nonlinear least-squares problems, the objective function is the squared error between a data vector $\mathbf{y}$ and a nonlinear model $m(\mathbf{z})$ (Nocedal and Wright, 2006; Vervliet and De Lathauwer, 2019):

$$f(\mathbf{z}) = \frac{1}{2}\left|\left|m(\mathbf{z}) - \mathbf{y}\right|\right|_2^2 = \frac{1}{2}\mathbf{r}^{\mathrm{T}}\mathbf{r}, \tag{10}$$

where $\mathbf{z} \in \mathbb{R}^I$. The algorithm updates the initial guess iteratively by taking a step length α_k in the direction $\mathbf{p}_k$ at the iteration k, i.e.,

$$\mathbf{z}_k = \mathbf{z}_{k-1} + \alpha_k \mathbf{p}_k,$$

until some stopping criteria are satisfied. Line search and trust-region are the two main approaches used to determine α_k and $\mathbf{p}_k$. Here, we focus on the dogleg trust-region approach. In this approach, one sets $\alpha_k = 1$. Then, given a trust-region of radius δ_k, the GN step $\mathbf{p}_k^{gn}$ and the steepest descent step $\mathbf{p}_k^{sd}$ for the current iteration, the step direction $\mathbf{p}_k$ is determined by the following procedure:

- If $\left|\left|\mathbf{p}_k^{gn}\right|\right|_2 \leq \delta_k$, then $\mathbf{p}_k = \mathbf{p}_k^{gn}$.
- If $\left|\left|\mathbf{p}_k^{gn}\right|\right|_2 > \delta_k$ and $\left|\left|\mathbf{p}_k^{sd}\right|\right|_2 > \delta_k$, then $\mathbf{p}_k = \delta_k \mathbf{p}_k^{sd} / \left|\left|\mathbf{p}_k^{sd}\right|\right|_2$.

[2] Note that the non-symmetric and partially symmetric CPD formats are fairly straightforward variants of the symmetric CPD format, and derivations presented in Section 3.4 can be generalized to these formats with slight modifications.

- If $\left|\left|\mathbf{p}_k^{gn}\right|\right|_2 > \delta_k$ and $\left|\left|\mathbf{p}_k^{sd}\right|\right|_2 \leq \delta_k$, then $\mathbf{p}_k = \tau_k \mathbf{p}_k^{sd} + \beta_k(\mathbf{p}_k^{gn} - \tau_k \mathbf{p}_k^{sd})$, where $\tau_k = -\left|\left|\mathbf{p}_k^{sd}\right|\right|_2^2 / \left|\left|\mathbf{J}_k \mathbf{p}_k^{sd}\right|\right|_2^2$, and β_k is selected such that $||\mathbf{p}_k||_2 = \delta_k$.

The steepest descent step $\mathbf{p}_k^{sd}$ is given by $-\mathbf{J}_k^{\mathrm{T}}\mathbf{r}_k$. To compute the GN step, a second order Taylor series approximation for the objective function is used. The optimal direction for the GN step $\mathbf{p}^*$ can be obtained by solving the optimization problem,

$$\mathbf{p}_k^{gn} = \arg\min_{\mathbf{p}} \widetilde{f}(\mathbf{p}), \quad \text{with} \quad \widetilde{f}(\mathbf{p}) = f(\mathbf{z}_k) + \mathbf{p}^{\mathrm{T}}\mathbf{g}_k + \frac{1}{2}\mathbf{p}^{\mathrm{T}}\mathbf{H}_k\mathbf{p}, \tag{11}$$

where $\mathbf{g}_k$ denotes the gradient and $\mathbf{H}_k$ denotes the Hessian at the current iteration. Setting $\partial\widetilde{f}(\mathbf{p})/\partial\mathbf{p}$ to zero, the solution of (11) can be obtained by solving the linear system of equations

$$\mathbf{H}_k\mathbf{p}_k^{gn} = -\mathbf{g}_k, \quad \text{with} \quad \mathbf{g}_k = \mathbf{J}_k^{\mathrm{T}}\mathbf{r}_k, \tag{12}$$

where $\mathbf{J}_k$ denotes the Jacobian of $f(\mathbf{z}_k)$ at iteration k, and $\mathbf{r}_k = m(\mathbf{z}_k) - \mathbf{y}$. However, in real-life applications, explicit computation of the Hessian is often expensive. To overcome this, GN approximates the Hessian by the Grammian matrix as

$$\mathbf{H}_k \approx \mathbf{J}_k^{\mathrm{T}}\mathbf{J}_k.$$

In this study, we used the conjugate gradient (CG) algorithm for solving (12) together with the dogleg trust-region approach which is implemented in Tensorlab (Vervliet et al., 2016). The overall algorithm is summarized in Algorithm 1.

3.4 Exploiting the Symmetric CPD Format

As described above, the GN algorithm minimizes a cost function in the form of equation (10). The gradient of this objective function can be written as $\mathbf{J}^{\mathrm{T}}\mathbf{r}$, and the Hessian is approximated by $\mathbf{J}^{\mathrm{T}}\mathbf{J}$, where $\mathbf{J}$ is the Jacobian matrix composed of partial derivatives of the residual vector $\mathbf{r}$. Hence, it is sufficient to derive expressions for the Jacobian and Jacobian-vector products. We begin with the first-order derivatives of the multilinear form $\mathcal{T}\mathbf{z}^d$, where $\mathcal{T}$ is in the symmetric CPD format, with respect to its factors and then proceed to the derivation of Jacobian and Jacobian-vector products for problems (7) and (8). The derivations made here can be used in other TeMPO problems with slight modifications.

3.4.1 Derivatives of the Multilinear Form in the Symmetric CPD Format

By using the matrix unfolding of the tensor in the symmetric CPD format and Property 2 of Khatri–Rao product, the multilinear form $\mathcal{T}\mathbf{z}^d$ can be written as

$$\mathcal{T}\mathbf{z}^d = \mathbf{c}^{\mathrm{T}}\left(\mathbf{U}^{\mathrm{T}}\mathbf{z}\right)^{*d}, \tag{13}$$

which will be useful for our derivations below.

LEMMA 1. *Let $\mathcal{T} \in \mathbb{K}^{I\times I\times\ldots\times I}$ be a symmetric tensor of order d and its CPD given as $\mathcal{T} = [\![\mathbf{U},\ldots,\mathbf{U};\mathbf{c}^{\mathrm{T}}]\!]$. Then the derivative of the multilinear form $\mathcal{T}\mathbf{z}^d$ with respect to vec$(\mathbf{U})$ can be obtained as*

$$\frac{\partial\mathcal{T}\mathbf{z}^d}{\partial vec(\mathbf{U})} = ((\mathbf{c} * \mathbf{w}) \otimes \mathbf{z})^{\mathrm{T}},$$

where $\mathbf{w} = d\,(\mathbf{U}^{\mathrm{T}}\mathbf{z})^{*(d-1)}$.

PROOF. *The proof immediately follows from equation* (13) *and successive application of Property 3.*

LEMMA 2. *Let* $\mathcal{T} \in \mathbb{K}^{I\times I\times\ldots\times I}$ *be symmetric tensor of order* d *and its CPD is given as* $\mathcal{T} = [\![\mathbf{U},\ldots,\mathbf{U};\mathbf{c}^{\mathrm{T}}]\!]$. *Then the derivative of multilinear form* $\mathcal{T}\mathbf{z}^d$ *with respect to vector* $\mathbf{c}$ *can be obtained as*

$$\frac{\partial \mathcal{T}\mathbf{z}^d}{\partial \mathbf{c}} = \left(\mathbf{z}^{\mathrm{T}}\mathbf{U}\right)^{*d}.$$

PROOF. *The proof immediately follows from Property 3 and equation* (13).

3.4.2 Exploiting Structure in the Type I Model

Objective Function: The construction of the residual vector $\mathbf{r}$ and the computation of its l_2 norm is sufficient for computing the objective function in (7). By utilizing Property 2 and equation (13), the residual vector can be expressed as $\mathbf{r} = \mathbf{y} - \boldsymbol{\mu}$, where each entry of the vector $\boldsymbol{\mu} \in \mathbb{R}^K$ is defined as

$$\boldsymbol{\mu}_k = \mathcal{T}_0 + \sum_{j=1}^{d} \mathbf{c}_j^{\mathrm{T}}\mathbf{w}_{j,k}^{*j},$$

in which $\mathbf{w}_{j,k} = \mathbf{U}_j^{\mathrm{T}}\mathbf{z}_k$ with $\mathbf{U}_j \in \mathbb{R}^{I\times R}$, and $\mathbf{w}_{j,k}^{*j}$ denotes the jth elementwise power of the vector $\mathbf{w}_{j,k}$. By defining $\mathbf{W}_j = \left[\mathbf{w}_{j,1}, \mathbf{w}_{j,2}, \ldots, \mathbf{w}_{j,K}\right]$, we can write the residual vector $\mathbf{r}$ in a compact form as

$$\mathbf{r} = \mathbf{y} - \mathcal{T}_0 \cdot \mathbf{1}_K - \sum_{j=1}^{d} \left(\mathbf{c}_j^{\mathrm{T}}\left(\mathbf{W}_j^{*j}\right)\right)^{\mathrm{T}}, \tag{14}$$

Using the above equation (14), the objective function can be computed as the l_2 norm of the residual vector $\mathbf{r}$.

Jacobian: The Jacobian matrix for problem (7), with the tensors $\mathcal{T}_j$ in their symmetric CPD format, can be written in a compact form as

$$\mathbf{J} = [\mathbf{J}_1;\ldots;\mathbf{J}_K], \quad \text{where} \quad \mathbf{J}_k = \left[1, \frac{\partial \mathbf{r}_k}{\partial \mathrm{vec}(\mathbf{U}_1)}, \ldots, \frac{\partial \mathbf{r}_k}{\partial \mathrm{vec}(\mathbf{U}_d)}, \frac{\partial \mathbf{r}_k}{\partial \mathbf{c}_1}, \ldots, \frac{\partial \mathbf{r}_k}{\partial \mathbf{c}_d}\right]. \tag{15}$$

Note that we used the fact $\partial \mathbf{r}_k / \partial \mathcal{T}_0 = 1$ in the above equation. By utilizing Lemma 1 and Lemma 2, the derivative of each term of the residual vector with respect to $\mathbf{U}_j$ and $\mathbf{c}_j$ can be expressed as

$$\frac{\partial \mathbf{r}_k}{\partial \mathrm{vec}(\mathbf{U}_j)} = -j\left[\left(\mathbf{c}_j * \mathbf{w}_{j,k}^{*(j-1)}\right) \otimes \mathbf{z}_k\right]^{\mathrm{T}}, \quad \text{and} \quad \frac{\partial \mathbf{r}_k}{\partial \mathbf{c}_j} = \left(\mathbf{w}_{j,k}^{*j}\right)^{\mathrm{T}}. \tag{16}$$

By defining $\widetilde{\mathbf{W}}_j = -j\left(\mathbf{W}_j^{*(j-1)}\right)$ for $j = 1,\ldots,d$, and $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_K]$, the Jacobian matrix $\mathbf{J}$ in (15) can be obtained in the following compact block form:

$$\mathbf{J} = \left[\mathbf{1}_K, \left((\mathbf{C}_1\widetilde{\mathbf{W}}_1) \odot \mathbf{Z}\right)^{\mathrm{T}}, \ldots, \left((\mathbf{C}_d\widetilde{\mathbf{W}}_d) \odot \mathbf{Z}\right)^{\mathrm{T}}, \mathbf{V}\right], \tag{17}$$

where $\mathbf{V}$ is a $K \times d$ block matrix in which each block is defined as $\mathbf{V}_{k,j} = \left(\mathbf{w}_{j,k}^{*j}\right)^{\mathrm{T}}$, $\mathbf{C}_j = \mathrm{Diag}(\mathbf{c}_j)$, and d is the degree of the polynomial under consideration. Since we only need the Jacobian-vector products for the GN algorithm, the explicit construction of the Jacobian matrix is not required. The Jacobian-vector products can be obtained in a more memory-efficient way as described below.

Jacobian-Vector Product: The product of Jacobian $\mathbf{J}$ by a vector $\mathbf{x}$ can be obtained using block matrix operations. The product of each block term by a vector $\mathrm{vec}(\mathbf{X}_j) = \mathbf{x}_j$ can be obtained by utilizing properties 1 and 2 as

$$((\mathbf{C}_j\widetilde{\mathbf{W}}_j) \odot \mathbf{Z})^{\mathrm{T}}\mathbf{x}_j = \left[\left(\mathbf{X}_j^{\mathrm{T}}\mathbf{Z}\right) * (\mathbf{C}_j\widetilde{\mathbf{W}}_j)\right]^{\mathrm{T}}\mathbf{1}_R. \tag{18}$$

Note that the multiplication of a matrix by $\mathbf{1}_R$ from the right is equivalent to summing the columns of the matrix under consideration. Therefore neither the multiplication by $\mathbf{1}_R$ nor the transposition of the matrix $\left(\mathbf{X}_j^{\mathrm{T}}\mathbf{Z}\right) * (\mathbf{C}_j\widetilde{\mathbf{W}}_j)$ in equation (18) is necessary to obtain the Jacobian-vector product. Note also that, since the matrices $\mathbf{C}_j$ are diagonal, the product $\mathbf{C}_j\widetilde{\mathbf{W}}_j$ can be obtained in a memory efficient way by multiplying the rows of $\widetilde{\mathbf{W}}_j$ by the corresponding diagonal elements of $\mathbf{C}_j$ without explicitly forming the matrices $\mathbf{C}_j$. Overall, the product of the Jacobian $\mathbf{J}$ and the vector $\mathbf{x}$ can be obtained by partitioning the vector $\mathbf{x}$ i.e., $\mathbf{x} = [x_1; \mathbf{x}_1; \mathbf{x}_2; \ldots; \mathbf{x}_d; \mathbf{x}_v]$, and by using the equations (17) and (18) as

$$\mathbf{J}\mathbf{x} = x_1 \cdot \mathbf{1}_K + \sum_{j=1}^{d}\left[\left(\mathbf{X}_j^{\mathrm{T}}\mathbf{Z}\right) * (\mathbf{C}_j\widetilde{\mathbf{W}}_j)\right]^{\mathrm{T}}\mathbf{1}_R + \mathbf{V}\mathbf{x}_v,$$

where $\mathbf{X}_j = \mathrm{unvec}(\mathbf{x}_j)$.

Jacobian Transpose -Vector Product and Gradient: In a similar way, block-wise multiplication of the Jacobian transpose $\mathbf{J}^{\mathrm{T}}$ by a vector can be obtained from the expression

$$((\mathbf{C}_j\widetilde{\mathbf{W}}_j) \odot \mathbf{Z})\mathbf{x} = \mathrm{vec}\left(\mathbf{Z}\mathrm{Diag}(\mathbf{x})(\mathbf{C}_j\widetilde{\mathbf{W}}_j)^{\mathrm{T}}\right). \tag{19}$$

Note that right multiplication by a diagonal matrix can be done efficiently by only multiplying the columns of the matrix with the corresponding diagonal elements without explicitly forming the diagonal matrix. Overall, by defining $\boldsymbol{\xi}_j = \mathrm{vec}\left(\mathbf{Z}\mathrm{Diag}(\mathbf{x})(\mathbf{C}_j\widetilde{\mathbf{W}}_j)^{\mathrm{T}}\right)$, we can obtain the product of the Jacobian transpose $\mathbf{J}^{\mathrm{T}}$ and a vector $\mathbf{x}$ in the following form:

$$\mathbf{J}^{\mathrm{T}}\mathbf{x} = \left[\sum_{k=1}^{K} x_k; \boldsymbol{\xi}_1; \boldsymbol{\xi}_2; \ldots; \boldsymbol{\xi}_d; \mathbf{V}^{\mathrm{T}}\mathbf{x}\right]. \tag{20}$$

The gradient can be obtained by the product of the Jacobian transpose $\mathbf{J}^{\mathrm{T}}$ and the residual vector $\mathbf{r}$. Defining $\boldsymbol{\eta}_j = \mathrm{vec}\left(\mathbf{Z}\mathrm{Diag}(\mathbf{r})(\mathbf{C}_j\widetilde{\mathbf{W}}_j)^{\mathrm{T}}\right)$ and utilizing the equations (19) and (20), we can obtain the gradient as

$$\mathbf{g} = \left[\sum_{k=1}^{K} r_k; \boldsymbol{\eta}_1; \boldsymbol{\eta}_2; \ldots; \boldsymbol{\eta}_d; \mathbf{V}^{\mathrm{T}}\mathbf{r}\right].$$

3.4.3 Exploiting Structure in the Type II Model

Objective Function: The computation of the objective function for the type II model is similar to that of the type I model. Utilizing Property 2 and equation (13), the residual vector for problem (8) can be obtained as $\mathbf{r} = \mathbf{y} - \boldsymbol{\mu}$ with

$$\boldsymbol{\mu} = \left[\mathbf{c}^{\mathrm{T}}\mathbf{w}_1^{*d}\,;\, \mathbf{c}^{\mathrm{T}}\mathbf{w}_2^{*d}\,;\, \ldots;\, \mathbf{c}^{\mathrm{T}}\mathbf{w}_K^{*d}\right], \tag{21}$$

where $\mathbf{w}_k = \mathbf{U}^{\mathrm{T}}\widetilde{\mathbf{z}}_k$. By defining $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_K]$, we can write the residual vector $\mathbf{r}$ in a compact form as

$$\mathbf{r} = \mathbf{y} - \left(\mathbf{c}^{\mathrm{T}}\left(\mathbf{W}^{*d}\right)\right)^{\mathrm{T}}, \tag{22}$$

Using the above equation (22), the objective function can be computed as the l_2 norm of the residual vector $\mathbf{r}$.

Jacobian: The Jacobian matrix of the cost function in (8) can be defined in a compact form as

$$\mathbf{J} = [\mathbf{J}_1; \mathbf{J}_2; \ldots; \mathbf{J}_K], \quad \text{where} \quad \mathbf{J}_k = \left[\frac{\partial \mathbf{r}_k}{\partial \mathrm{vec}(\mathbf{U})}, \frac{\partial \mathbf{r}_k}{\partial \mathbf{c}}\right]. \tag{23}$$

Utilizing Lemma 1 and Lemma 2 and using the equations in (16), the parts of $\mathbf{J}_k$ in equation (23) can be written as

$$\frac{\partial \mathbf{r}_k}{\partial \mathrm{vec}(\mathbf{U})} = -d\Big[\left(\mathbf{c} * \mathbf{w}_k^{*(d-1)}\right) \otimes \widetilde{\mathbf{z}}_k\Big]^{\mathrm{T}}, \quad \frac{\partial \mathbf{r}_k}{\partial \mathbf{c}} = \left(\mathbf{w}_k^{*d}\right)^{\mathrm{T}}.$$

By defining $\widetilde{\mathbf{W}} = -d\left(\mathbf{W}^{*(d-1)}\right)$, $\mathbf{V} = \left[\frac{\partial \mathbf{r}_1}{\partial \mathbf{c}}; \frac{\partial \mathbf{r}_2}{\partial \mathbf{c}}; \ldots; \frac{\partial \mathbf{r}_K}{\partial \mathbf{c}}\right]$, and $\mathbf{Z} = [\widetilde{\mathbf{z}}_1, \widetilde{\mathbf{z}}_2, \ldots, \widetilde{\mathbf{z}}_K]$, the Jacobian matrix can be obtained in the following compact form:

$$\mathbf{J} = \left[\left((\mathbf{C}\widetilde{\mathbf{W}}) \odot \mathbf{Z}\right)^{\mathrm{T}}, \mathbf{V}\right]. \tag{24}$$

As mentioned earlier, explicit construction of the Jacobian matrix $\mathbf{J}$ is not required. We only require the Jacobian-vector and Jacobian transpose-vector products and derive efficient expressions for these products below.

Jacobian-Vector Product: The product of the Jacobian matrix $\mathbf{J}$ and a vector $\mathbf{x}$ can be obtained in a similar way as for the type I model, by partitioning the vector $\mathbf{x}$, i.e. $\mathbf{x} = [\mathbf{x}_u; \mathbf{x}_c]$ and utilizing properties 1 and 2 and equation (24), as

$$\mathbf{J}\mathbf{x} = \left[\left(\mathbf{X}_u^{\mathrm{T}}\mathbf{Z}\right) * \left(\mathbf{C}\widetilde{\mathbf{W}}\right)\right]^{\mathrm{T}}\mathbf{1}_R + \mathbf{V}\mathbf{x}_c, \tag{25}$$

where $\mathbf{X}_u = \mathrm{unvec}(\mathbf{x}_u)$. As mentioned earlier for equation (18), explicit construction of the diagonal matrix $\mathbf{C}$ is not required. The product $\mathbf{C}\widetilde{\mathbf{W}}$ can be obtained in a memory efficient way by multiplying the rows of $\widetilde{\mathbf{W}}$ by the corresponding diagonal elements of $\mathbf{C}$.

Jacobian Transpose -Vector Product and Gradient: In similar way, utilizing properties 1 and 2 and equation (24), the product of Jacobian transpose $\mathbf{J}^{\mathrm{T}}$ and a vector $\mathbf{x}$ can be written as

$$\mathbf{J}^{\mathrm{T}}\mathbf{x} = \left[\mathrm{vec}\left(\mathbf{Z}\mathrm{Diag}(\mathbf{x})(\mathbf{C}\widetilde{\mathbf{W}})^{\mathrm{T}}\right); \mathbf{V}^{\mathrm{T}}\mathbf{x}\right]. \tag{26}$$

Since the gradient is the product of the Jacobian transpose $\mathbf{J}^{\mathrm{T}}$ and the residual vector $\mathbf{r}$, it directly follows from the above equation (26) as

$$\mathbf{g} = \left[\mathrm{vec}\left(\mathbf{Z}\mathrm{Diag}(\mathbf{r})(\mathbf{C}\widetilde{\mathbf{W}})^{\mathrm{T}}\right); \mathbf{V}^{\mathrm{T}}\mathbf{r}\right]. \tag{27}$$

3.5 Complexity Analysis

We now analyze the storage and computational complexity of TeMPO where we are optimizing over symmetric rank-R CPD structured tensors $\mathcal{T} \in \mathbb{K}^{I\times I\times\ldots\times I}$ of order d. The analysis is presented here for the type II model. However, since the number of optimization parameters of the type I and type II models (see equations (2) and (3)) for an I-variate polynomial of degree d are proportional to each other, the analysis also applies to the type I model. Indeed, the computational complexity of the type I model is d times the computational complexity of the type II model. We also compare with the storage and computational complexity of TT and PEPS tensor networks.

Representing a multivariate polynomial with I independent variables and of degree d in dense format requires storing $C^d_{(I+d)}$ elements. Using Stirling's approximation, it can be shown that the storage complexity for a multivariate polynomial represented in dense format is $\mathcal{O}\left(I^d\right)$ for $d \ll I$. In the symmetric CPD format, we need to store only the factor matrix $\mathbf{U} \in \mathbb{R}^{I\times R}$ and the vector of weights $\mathbf{c} \in \mathbb{R}^R$, where R is the rank of the symmetric CPD. Therefore, the storage complexity for the type II model using the symmetric CPD format is $\mathcal{O}\left(IR\right)$. This shows that the symmetric CPD format breaks the curse of dimensionality, since the storage complexity in this format is linear in terms of rank R and dimension I.

As is clear from equation (22), the construction of the matrix $\mathbf{W}$ and its dth Hadamard (elementwise) power dominates the computational complexity of the objective function. The construction of a single column of the matrix $\mathbf{W}$ requires the multiplication of $\mathbf{U}^{\mathrm{T}} \in \mathbb{R}^{R\times I}$ and $\widetilde{\mathbf{z}}_k \in \mathbb{R}^I$. Thus, the computational complexity of constructing the matrix $\mathbf{W}$ is $\mathcal{O}\left(IKR\right)$. The dth Hadamard power of the matrix $\mathbf{W}$ can be computed recursively by using the relation $\mathbf{W}^{*(2m)} = \left(\mathbf{W}^{*m}\right)^{*2}$. Thus, the computational complexity of the dth Hadamard power of the matrix $\mathbf{W} \in \mathbb{R}^{R\times K}$ is $\mathcal{O}\left(\log(d)RK\right)$. Therefore, the total computational complexity for computing the objective function for a batch of size K is $\mathcal{O}\left((I+\log(d))KR\right)$. Since $\log(d) \ll I$, the computational complexity for the objective function in equation (8) is $\mathcal{O}\left(IKR\right)$.

The gradient of the objective function in equation (8) can be obtained by multiplying the Jacobian transpose $\mathbf{J}^{\mathrm{T}}$ by the residual vector $\mathbf{r}$. As shown in equation (27), this operation requires multiplication of a matrix $\mathbf{Z} \in \mathbb{R}^{I\times K}$ by a diagonal matrix $\mathrm{Diag}(\mathbf{r})$, and the multiplication of the matrices $\mathbf{Z}\mathrm{Diag}(\mathbf{r})$ and $(\mathbf{C}\widetilde{\mathbf{W}})^{\mathrm{T}}$ with sizes $(I \times K)$ and $(K \times R)$, respectively. Note that the entries of the product $\mathbf{C}\widetilde{\mathbf{W}}$ were already obtained in the computation of the objective function. Further, the computational complexity for the product $\mathbf{Z}\mathrm{Diag}(\mathbf{r})$ is $\mathcal{O}\left(IK\right)$. Consequently, the computational complexity for the multiplication of $\mathbf{Z}\mathrm{Diag}(\mathbf{r})$ and $(\mathbf{C}\widetilde{\mathbf{W}})^{\mathrm{T}}$ is $\mathcal{O}\left(IKR\right)$. In addition, the computation of $\mathbf{V}^{\mathrm{T}}\mathbf{r}$ in equation (27) requires $\mathcal{O}\left(KR\right)$ operations. However $KR \ll IKR$. Therefore, the total computational complexity for computing the gradient is $\mathcal{O}\left(IKR\right)$ for $R \gg 1$.

In addition, TeMPO uses the GN algorithm for the optimization. However, this is not a requirement and first-order methods can also be utilized within TeMPO as well. GN requires solving the linear system of equations in (12). Tensorlab's implementation of GN uses the conjugate-gradient (CG) method which requires only the Grammian-vector product for solving (12). This operation requires multiplication of the Jacobian and its transpose by a vector. The computational complexity of multiplying the transpose of

Jacobian by a vector is $\mathcal{O}(IKR)$ as described above. The computationally most expensive operations in the multiplication of Jacobian by a vector are the multiplication of matrices $\mathbf{X}_u^{\mathrm{T}}$ and $\mathbf{Z}$ with sizes $(R \times I)$ and $(I \times K)$, and the Hadamard product of two matrices of size $(R \times K)$ as shown in equation (25). Hence, the computational complexity of computing $\mathbf{Jx}$ is $\mathcal{O}(IKR)$. Note that the entries of the product $\mathbf{C}\widetilde{\mathbf{W}}$ were already obtained in the computation of the objective function. Therefore, the total computational complexity for a single CG iteration is $\mathcal{O}(2IKR)$. Note that a large number of CG iterations in the solution of linear equations for the GN algorithm might increase the computation time compared to first-order algorithms. In fact, the number of CG iterations scales with the number of optimization variables (IR), if the exact solution is desired in the solution of the normal equations. This may lead to an quadratic complexity of $\mathcal{O}\left(2(IR)^2K\right)$. However, we observed in our experiments that a small number of CG iterations were sufficient to obtain accurate results. For example, we set the maximum number CG iterations to 10 for the classification of the MNIST and Fashion MNIST datasets, where the number of unknowns is $784 \times R$ with R ranging from 10 to 150.

The storage complexity of a tensor network with TT architecture is bounded by $\mathcal{O}\left(nIR_{TT}^2\right)$ for a tensor of order I with dimensions $(n \times n \times \ldots \times n)$, where R_{TT} denotes the TT-rank (Khoromskij, 2018). n is equal to 2 and I is the size of a single image in the image classification applications presented in (Stoudenmire and Schwab, 2016; Efthymiou et al., 2019). Note that the storage complexity of TT increases with powers of the TT-rank R_{TT}. The total computational complexity of TT for computing the objective function has been reported as $\mathcal{O}\left(nIR_{TT}^2 + R_{TT}^3 \log(I)\right)$, when the contraction order defined in (Efthymiou et al., 2019) is used. When the sweeping algorithm described in (Stoudenmire and Schwab, 2016) is used, the computational complexity of the objective function for TT is $\mathcal{O}\left(n^3 R_{TT}^3 I\right)$ for a single data point of size I. Similar to the storage complexity, the computational complexity of the objective function for TT increases with powers of the TT-rank of the tensor under consideration. On the other hand, automatic differentiation (AD) is one of methods used to compute the gradient of TT. The computational complexity of automatic differentiation is linear in the complexity of the evaluation of the objective function (Margossian, 2019). Therefore, the computational complexity of the gradient for TT tensor network presented in (Efthymiou et al., 2019) is $\mathcal{O}\left(\alpha\left(nIKR_{TT}^2 + KR_{TT}^3 \log(I)\right)\right)$, for a batch size of K with $\alpha > 1$. The total computational complexity of TT tensor network for a batch size of K has been reported as $\mathcal{O}\left(mR_{TT}^2(R_{TT} + K)\right)$ for a single iteration of the stochastic Riemannian gradient descent algorithm (Novikov et al., 2017). As it is clear from the above discussion, both the storage and the computational complexity of TT increases with a power of the TT-rank regardless of the algorithm used, while for TeMPO it increases linearly with the symmetric CPD rank in the symmetric CPD case.

The computational complexity of a single forward pass of PEPS for a batch size of K is $\mathcal{O}\left(KR_{BT}^3 R_{PS}^6\right)$, when the boundary matrix product state method is used. Here R_{BT} is the bond dimension (rank) of the boundary matrix product state of PEPS and R_{PS} is the bond dimension of PEPS. In addition, the backward pass for PEPS requires $\mathcal{O}\left(\alpha K R_{BT}^3 R_{PS}^6\right)$ operations (with $\alpha > 1$), when automatic differentiation is used (Cheng et al., 2021).

The above analysis shows that TeMPO is computationally less expensive than TT and PEPS, even though it uses a second-order algorithm. All these results are summarized in Table 1. The fundamental reason for this is the linear storage complexity of the symmetric CPD format. Both TT and PEPS involve third and higher-order tensors, which makes their computational complexity increase with powers of the bond dimension. On the other hand, the CPD format is known to be numerically less stable than the TT format, which relies on orthogonal matrices.

4 NUMERICAL EXPERIMENTS

We conducted an experiment on the regression problem using synthetic data to illustrate the TeMPO framework and compared TeMPO with different implementations of SVMs in Subsection 4.1. Next, we applied our framework to the blind deconvolution of constant modulus (CM) signals and compared with the analytical CM algorithm (ACMA) (van der Veen and Paulraj, 1996), the optimal step-size CM algorithm (OSCMA) (Zarzoso and Comon, 2008), and the LS-CPD framework (Boussé et al., 2018) in Subsection 4.2. In Subsection 4.3, we further illustrate TeMPO with the image classification problem. We performed experiments on the MNIST and Fashion MNIST datasets and compared the accuracy and number of optimization parameters with MLPs, and TT and PEPS tensor networks. We performed experiments on a computer with an Intel Core i7-8850H CPU at 2.60GHz with 6 cores and 32GB of RAM using MATLAB R2021b and Tensorlab 3.0 (Vervliet et al., 2016).

In our blind deconvolution experiments, we used the complex GN algorithm with the conjugate gradient Steihaug method. We used the second-order batch Gauss–Newton algorithm for the regression and classification, following the same intuition as in (Gargiani et al., 2020). In each epoch of the algorithm, we randomly shuffle the data points in the training set and process all data points by dividing them into batches. In the regression and binary classification case, we optimize a single cost function. In the multi-label classification case, for each batch, we randomly select a cost function f_l defined for each label to optimize. Thus our algorithm does not guarantee that each f_l will be trained by all training images in each epoch in the multi-label classification case. To guarantee this, the algorithm can be modified such that for each batch all cost functions f_l are optimized at the cost of increasing CPU time by a factor of the number of classes L. However, in that case the algorithm might need fewer epochs to converge. The overall algorithm is summarized in Algorithm 2. Algorithm 2 is given for the type II model for the ease of explanation. Slight modifications are sufficient to obtain an algorithm for the type I model.

We define the relative error as the relative difference in l_2 norm $||\mathbf{f} - \widehat{\mathbf{f}}||_2 / ||\mathbf{f}||_2$ with $\widehat{\mathbf{f}}$ an estimate for a vector $\mathbf{f}$, and the signal-to-noise ratio (SNR) as $20 \log_{10} (||\mathbf{f}||_2 / ||\boldsymbol{\eta}||_2)$, where $\boldsymbol{\eta} = \widehat{\mathbf{f}} - \mathbf{f}$.

4.1 Regression

In this experiment, we considered a low-rank smooth function $f(\mathbf{x}) : \mathbb{R}^N \to \mathbb{R}$, namely

$$f(\mathbf{x}) = \sum_{r=1}^{R_f} \alpha_r e^{(\mathbf{a}_r^{\mathrm{T}} \mathbf{x})}, \tag{28}$$

where $\mathbf{x} \in [-1, 1]^N$, R_f is the rank of the function $f(\mathbf{x})$, and the coefficients α_r are scalars randomly chosen from the standard normal distribution. We generated 5000 test samples and 1000 training samples for $N = 50$ and $R_f = 8$. Each vector $\mathbf{a}_r \in \mathbb{R}^N$ was a unit norm vector drawn from the standard normal distribution. Each of the samples of $\mathbf{x}$ was drawn from the uniform distribution. We initialized each factor matrix with a matrix whose elements were randomly drawn from the standard normal distribution, and scaled it to unit norm. We initialized each weight vector in the same way as the factor matrices. We approximated $f(\mathbf{x})$ by the type I and type II model of degree 5 whose coefficient tensors were represented in the rank-R symmetric CPD format. We set the batch size to 500 and the maximum number GN iterations to 5 for each batch. In Figure 3, we show the median relative test and training errors for $R = \{2, 4, 8, 16\}$ as a function of the number of epochs for 100 trials. Each epoch corresponds to optimization over the full training set. It is clear from Figure 3 that TeMPO produces more accurate results and generalizes better

when using higher rank values, for both the type I and type II model. Good performance is also observed for $R = 16 > R_f = 8$, meaning that TeMPO is robust to over-estimation of the number of parameters. For low rank values, i.e., $R < R_f$, the type I model produces better results than the type II model because it involves more parameters that can be tuned, cf. the discussion of Proposition 1.

In the second stage of the experiment, we trained the type I and type II model for a multivariate polynomial of degree 5 with noisy measurements. We added Gaussian noise to the function values for a given SNR, i.e.,

$$\widetilde{f}(\mathbf{x}) = \sum_{r=1}^{R} \alpha_r e^{(\mathbf{a}_r^{\mathrm{T}}\mathbf{x})} + \eta, \tag{29}$$

where η denotes the noise. We run our algorithm with the same settings as in the noiseless case for an SNR ranging from 10 dB to 50 dB. In Figure 4, we show the median errors for 100 trials as a function of SNR. We have similar observations as in the noiseless case. Apart from these observations; although the accuracy of our algorithm decreases for SNR ≤ 20 (dB), it still maintains good accuracy for SNR > 20 (dB), as shown in Figure 4. Moreover, as can be observed from the Figure 4 (left), the type I model overfits for $R = \{8, 16\}$ and SNR ≤ 20 (dB) in agreement with the result of Proposition 1.

In our next experiment, we trained the type I and type II model with larger-size samples, i.e., $N = 250$ and $R = \{8, 16, 32, 64\}$, to assess how the CPU time depends on the rank. In Figure 5, we show the median CPU time per epoch as a function of the rank. It is evident from the figure that the computational complexity of the type I model is d times the computational complexity of the type II model (cf. Subsection 3.5). Moreover, Figure 5 confirms that the computational complexity of our algorithm is linear in the rank (cf. Subsection 3.5).

In our next experiment, we examined the generalization abilities of the Gauss–Newton and ADAM Kingma and Ba (2015) algorithms in our framework. We trained the type I model for a multivariate polynomial of degree 5 with both of these algorithms for different number of training samples to fit the rank-8 function given as in equation (29). We set $R = 8$, $N = 50$, and SNR $= 20(\mathrm{dB})$. For the ADAM algorithm, we set the step size, the exponential decay rate for the first momentum (β_1), and the exponential decay rate for the second momentum (β_2) to 0.01, 0.9, and 0.99, respectively. In Figure 6, we show the median training and test accuracies of these algorithms for the number of training samples ranging from 500 to 5000 as a function of the number of epochs for 100 trials. It is evident from Figure 6 that the presented Gauss–Newton algorithm produces more accurate results than the ADAM algorithm and also requires fewer number of epochs to converge in these experimental settings.

We also compared TeMPO with SVMs using a polynomial kernel. We run the same experiment for a number of training samples ranging from 500 to 5000. We set the rank to 8, i.e. $R = R_f$ for TeMPO. We used the built-in Matlab routine `fitrsvm` and LS-SVMlab toolbox (De Brabanter et al., 2010; Suykens et al., 2002). We set the degree of polynomial kernel to 5, i.e., equal to the degree of the type I and type II model for `fitrsvm`. LS-SVMlab automatically tunes the degree to 3 to find the best fit. In Figure 7 (left), we show the median test and training errors for SVM, the type I and type II model. It is clear from Figure 7 (left) that the type I and type II model generalize better than `fitrsvm`. A possible reason is the dense parameterization of SVMs, while TeMPO uses low-rank parameterization. Moreover, as shown in Figure 7 (right), our algorithm is faster than SVMs for numbers of training samples above 1000. This is due to the higher memory requirement of SVMs. Typically, kernel based methods such as LS-SVM have a storage and computational complexity of $\mathcal{O}\left(N^2\right)$ (De Brabanter et al., 2010), with N the number of

training samples. In contrast, Figure 7 (right) confirms that the computational complexity of TeMPO is linear in the number of training samples (cf. Subsection 3.5).

4.2 Blind Deconvolution of Constant Modulus Signals

Blind deconvolution can be formulated as a multivariate polynomial optimization (MPO) problem and hence it fits into the TeMPO framework (Ayvaz and De Lathauwer, 2021). In this illustrative example, we limit ourselves to an autoregressive single-input single-output (SISO) system (Ljung, 1999), given by

$$\sum_{l=0}^{L} w_l \cdot y[k-l] = s[k] + n[k], \text{ for } k = 1, \ldots, K, \tag{30}$$

where $y[k]$, $s[k]$, and $n[k]$ are the measured output signal, the input signal and the noise at the kth measurement, respectively, and w_l denotes the lth filter coefficient. Ignoring the noise for the ease of derivation, (30) can be written as:

$$\mathbf{Y}^{\mathrm{T}}\mathbf{w} = \mathbf{s}, \tag{31}$$

where $\mathbf{Y} \in \mathbb{C}^{L \times K}$ is a Toeplitz matrix and its rows are the subsequent observations under the assumption that we have $K + L - 1$ samples $y[-L+1], \ldots, y[K]$. The vector $\mathbf{w} \in \mathbb{K}^{L}$ contains the filter coefficients and the kth entry of the source vector $\mathbf{s} \in \mathbb{C}^{K}$ is the input signal at the kth time instance, i.e. $s_k = s[k]$. In blind deconvolution, one attempts to find the original input signal $\mathbf{s}$ and the filter coefficients $\mathbf{w}$ by only observing the output signal $\mathbf{Y}$. Thus, constraints on signals and/or channel have to be imposed to obtain interpretable results. The constant modulus (CM) criterion is a widely used input constraint (Johnson et al., 1998). The CM property, which holds for phase- or frequency-modulated signals (van der Veen, 1998; van der Veen and Paulraj, 1996) can be written as:

$$|s_k|^2 = c, \text{ for } k = 1, 2, \ldots, K. \tag{32}$$

Here, c is a constant scalar. By substituting s_k defined in (31) into (32), we obtain

$$\left(\mathbf{Y} \odot \overline{\mathbf{Y}}\right)^{\mathrm{T}} (\mathbf{w} \otimes \overline{\mathbf{w}}) = c \cdot \mathbf{1}_K. \tag{33}$$

Following the same intuition as in (De Lathauwer, 2004), by multiplying (33) from the left with a Householder reflector $\mathbf{Q}$ (Householder, 1958), generated for $c \cdot \mathbf{1}_K$, and removing the first equation[3], we obtain

$$\mathbf{M}(\mathbf{w} \otimes \overline{\mathbf{w}}) = \mathbf{0}. \tag{34}$$

Here, $\mathbf{M} = \widetilde{\mathbf{Q}}\left(\mathbf{Y} \odot \overline{\mathbf{Y}}\right)^{\mathrm{T}}$, and $\widetilde{\mathbf{Q}}$ is obtained by removing the first row of the Householder reflector $\mathbf{Q}$. In applications, $\mathbf{M}(\mathbf{w} \otimes \overline{\mathbf{w}})$ will not vanish exactly due to the presence of noise. Hence, we look for the solution which minimizes its l_2 norm as

$$\min_{\mathbf{w}, \overline{\mathbf{w}}} \; f(\mathbf{w}, \overline{\mathbf{w}}) = \min_{\mathbf{w}, \overline{\mathbf{w}}} \; \frac{1}{2} ||\mathbf{M}(\mathbf{w} \otimes \overline{\mathbf{w}})||_2^2, \quad \text{subject to } ||\mathbf{w}|| = 1. \tag{35}$$

[3] The first equation is only a normalization constraint.

The objective function in (35) is a homogeneous multivariate polynomial of degree 4 in which the coefficient tensor $\mathcal{W}$ is given as a rank-1 Hermitian symmetric CPD, i.e.,

$$\mathcal{W} = \mathbf{w} \otimes \overline{\mathbf{w}} \otimes \overline{\mathbf{w}} \otimes \mathbf{w} := [\![\mathbf{w}, \overline{\mathbf{w}}, \overline{\mathbf{w}}, \mathbf{w}]\!] . \tag{36}$$

Exploiting the rank-1 Hermitian symmetric CPD structure in (36) and the structure of $\mathbf{M}$, which is a special case of Lemma 1 and Lemma 2, efficient expressions for the computation of Jacobian-vector products for the problem (35) have been presented in (Ayvaz and De Lathauwer, 2021).

A number of algorithms have been developed to solve (33) and (34). The analytical CM algorithm (ACMA) (van der Veen and Paulraj, 1996) writes (34) as a generalized matrix eigenvalue problem in the absence of noise, and under the assumption that the null space of $\mathbf{M}$ is one dimensional, which makes ACMA more restrictive than TeMPO. In the presence of noise, ACMA writes (34) as the simultaneous diagonalization of a number of matrices and solves it by extended QZ iteration. Gradient descent and stochastic gradient descent algorithms have also been proposed for the minimization of the expected value of $\{(|\mathbf{y_n}^{\mathrm{T}}\mathbf{w}| - c)^2\}$. The optimal step-size CMA (OSCMA) (Zarzoso and Comon, 2008) algorithm uses a gradient descent algorithm, which computes the step size algebraically. The problem in (35) can also be interpreted as a linear system with a rank-1 constrained solution, which fits the LS-CPD framework in (Boussé et al., 2018). LS-CPD solves (33) by relaxing the complex conjugate $\overline{\mathbf{w}}$ to a possibly different vector $\mathbf{v} \in \mathbb{C}^L$ and utilizing the second-order GN algorithm using dogleg trust-region method. We solve (35) by utilizing the complex GN algorithm using the conjugate gradient Steihaug method implemented in TensorLab 3.0 (Vervliet et al., 2016). We compare with these algorithms in terms of computation time and accuracy.

We consider an autoregressive model of degree $L = 10$ with coefficients uniformly distributed on $[0, 1]$, sample length $K = 600$, and $c = 1$. We add scaled Gaussian noise to the measurements to obtain a particular SNR. We run 50 experiments starting from the algebraic solution presented in (Boussé et al., 2018) for LS-CPD, OSCMA and TeMPO. In Figure 8 (left), we show the median relative error on $\mathbf{w}$ as a function of SNR. It is clear from Figure 8 (left) that TeMPO achieves similar accuracy as LS-CPD and OS-CMA, which are more accurate than ACMA. In Figure 8 (right), we show the median CPU time in seconds as a function of SNR. Clearly, TeMPO is faster than ACMA, OS-CMA and LS-CPD for SNR ≥ 10(dB) by exploiting the structure of the data.

4.3 Image Classification

Multi-class image classification amounts to the determination of a possibly nonlinear function f that maps input images $\mathbf{Z}_k$ to integer scalar labels y_k, which are known for a training set. In this study, we represent f by a multivariate polynomial p. Following the one-versus-all strategy, we define a cost function f_l for each label that maps the input image $\mathbf{Z}_k$ to a scalar value as

$$f_l(p_l, \mathbf{z}_1, \ldots, \mathbf{z}_K) = \frac{1}{2} \sum_{k=1}^{K} \left(y_k - p_l(\mathbf{z}_k)\right)^2 ,$$

where $\mathbf{z}_k = \mathrm{vec}(\mathbf{Z}_k)$ and where $y_k = 1$ if $\mathbf{z}_k$ is labeled as l and $y_k = 0$ otherwise. The polynomial p_l can be chosen within the type I or the type II model class. For the type I model, the optimization problem can

be written as

$$\min_{p_l} f_l(p_l, \mathbf{z}_1, \ldots, \mathbf{z}_K), \quad \text{subject to} \quad p_l(\mathbf{z}_k) = \mathcal{T}_{l,0} + \sum_{j=1}^{d} \mathcal{T}_{l,j}\mathbf{z}_k^j, \quad \text{and} \quad \mathcal{T}_{l,j} = [\![\mathbf{U}_{l,j}, \ldots, \mathbf{U}_{l,j}; \mathbf{c}_{l,j}^{\mathrm{T}}]\!], \tag{37}$$

where d is the degree of the polynomial under consideration. Note that we substitute the symmetric CPD structure given as a constraint into the objective function, and hence obtain and solve an unconstrained optimization problem. For the type II model, the optimization problem can be written as

$$\min_{p_l} f_l(p_l, \mathbf{z}_1, \ldots, \mathbf{z}_K), \quad \text{subject to} \quad p_l(\mathbf{z}_k) = \mathcal{T}_l\mathbf{z}_k^d, \quad \text{with} \quad \mathcal{T}_l = [\![\mathbf{U}_l, \ldots, \mathbf{U}_l; \mathbf{c}_l^{\mathrm{T}}]\!].$$

After the optimization of f_l for each label l, the classification is done by computing each $p_l(\mathbf{s})$ for the data point $\mathbf{s}$ to be classified and selecting the value of l for which $|p_l(\mathbf{s})|$ is largest.

4.3.1 Experiments

We performed several experiments by varying the parameters rank and maximum number of GN iterations to illustrate the TeMPO framework for the classification of the MNIST and Fashion MNIST datasets. We kept the maximum number of CG iterations equal to 10, the degree of the multivariate polynomial to 3, the tolerance for the objective function and optimization variables equal to $1e-10$, the inner solver tolerance equal to $1e-10$, and the trust-region radius equal to 0.1, throughout the experiments.

We initialized each factor matrix with a matrix whose elements were randomly drawn from the standard normal distribution, and scaled it to unit norm. Similarly, we initialized each weight vector $\mathbf{c}_l$ with a vector whose elements were randomly drawn from the standard normal distribution and scaled it to unit norm.

Datasets

Modified National Institute of Standards and Technology (MNIST) handwritten digit database (Deng, 2012) and the Fashion MNIST database (Xiao et al., 2017) are used for this study. Both datasets contain gray scale images of size (28×28). The training sets of both datasets are composed of 60.000 images and test sets are composed of 10.000 images. The images have been size-normalized and centered in a fixed-size image. We rescale images such that every pixel value is in the interval $[0, 1]$ and the mean of each image is zero. Then, we vectorize, i.e. stack each column vertically in a vector, each image to a vector of size 784. For the type II model, we augment the resulting vector by the scalar 1. Similar prepocessing steps are necessary for also tensor networks. Additionally, they may require the encoding input data which increases the storage and the computational resource requirement.

Results and Comparisons

Results of the Type I Model: We first trained the type I model on the total MNIST training set for various rank values ranging from 10 to 150 to illustrate the effect of rank on the accuracy. We set the batch size to 100 and the maximum number of GN iterations to 1. We show the training history in Figure 9. It is evident from Figure 9 that TeMPO achieves high accuracy even for low rank values, i.e. $R = \{10, 20\}$. Increasing the rank mildly improves both the test and training accuracy, with the improvement getting smaller as the rank increases.

We repeated the same experiments for the Fashion MNIST dataset, which is harder to classify. We show the training history in Figure 10. The observations made for the MNIST dataset also apply to the Fashion

MNIST dataset. However, the test and training accuracy are lower for the Fashion MNIST dataset in agreement with previous works. Also, our algorithm requires more epochs to converge for the Fashion MNIST dataset.

In our next experiment, we set the maximum number of GN iterations to 5. We observed that our algorithm needs fewer epochs to converge and produces more accurate results with this setting. The comparison for the MNIST and Fashion MNIST dataset is shown in Figures 11 and 12, respectively. The improvement in the test accuracy for the Fashion MNIST dataset is around 1% and more pronounced than the improvement in the test accuracy for the MNIST dataset. TeMPO achieves around 98.30% test accuracy for the MNIST dataset and around 90% test accuracy for the Fashion MNIST dataset with $R = 150$.

Results of the Type II Model: We repeated the same experiments for the type II model. We used the same settings as in the type I model. However, we set the batch size to 200 to obtain an accuracy similar to that of the type I model. We show the training history in Figure 13. Similar to previous experiments, our algorithm performs well even for low rank values, and produces more accurate results for higher rank values. TeMPO achieves around 98% test accuracy and 100% training accuracy after 200 epochs with $R = 150$ for the MNIST dataset.

In Figure 14, we show the training history for the Fashion MNIST dataset. Similar to the type I model, the test and training accuracy is lower than the MNIST dataset. The algorithm converges around 100 epochs and achieves around 89.30% test accuracy with $R = 150$. Moreover, our algorithm achieves around 99% training accuracy after 400 epochs.

We repeated the same experiments with the maximum number of GN iterations set to 5. The comparisons for the MNIST and Fashion MNIST datasets are shown in Figure 15. Contrary to our observation for the type I model, the test accuracy now decreases for both datasets. A possible reason is that when the residuals are big, doing more GN iterations may not lead a better direction for minimizing (37). A similar observation has been made in (Gargiani et al., 2020), for training DNNs. It is experimentally shown that higher number of CG iterations might not produce more accurate results if the Hessian obtained by mini-batch is not reliable due to non-representative batches and/or big residuals. On the other hand, if the residuals are small, higher number of CG iterations can produce more accurate results thanks to the curvature information (Gargiani et al., 2020).

Comparisons: We now compare TeMPO with different models, namely: TT tensor networks (Efthymiou et al., 2019), TT structured tree tensor networks (TTN)(Stoudenmire, 2018), multi-layer perceptron (MLP) with $784 - 1000 - 10$ neurons, MLP with a convolution layer (CNN-MLP), PEPS, and PEPS with a convolution layer (CNN-PEPS)(Cheng et al., 2021). We compare in terms of the test accuracy for the Fashion MNIST dataset. We summarize the test accuracy of different models in Table 2. TeMPO achieves better accuracy than TT, PEPS and MLP, while optimizing for fewer parameters and using less memory (cf. Table 1). The accuracy of TeMPO is lower than CNN-MLP and CNN-PEPS as expected, since it does not use a convolution layer. Note that the accuracy of TeMPO can further be improved by tuning the parameters such as the rank, the number of CG iterations, the trust-region radius, the batch size and the degree of the multivariate polynomial.

5 CONCLUSION AND FUTURE WORK

We presented the TeMPO framework for use in nonlinear optimization problems arising in signal processing, machine learning, and artificial intelligence. We modeled the nonlinearities in these problems by multivariate polynomials represented by low rank tensors. In particular, we investigated the symmetric

CPD format in this study. By taking the advantage of low rank symmetric CPD structure, we developed an efficient second-order batch Gauss–Newton algorithm. We demonstrated the efficiency of TeMPO with some illustrative examples, and with the blind deconvolution of constant modulus signals. We showed that TeMPO achieves similar or better classification rates than MLPs, TT and PEPS tensor networks on the MNIST and Fashion MNIST datasets while optimizing for fewer parameters and using less memory space.

The non-symmetric and partially symmetric CPD formats are fairly straightforward variants of the symmetric CPD format in which the factor matrices can be mutually different. Efficient algorithms can be developed for multivariate polynomials in these formats by utilizing the derivations presented in this study. We are investigating other tensor formats such as HT and TT in our framework as well. HT and TT require more parameters than the CPD format. However, they break the curse of dimensionality in a numerically stable way. We are also exploring other polynomial bases, and more generally other nonlinear feature maps to further improve the accuracy and numerical stability of our framework.

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

MA developed the theory and Matlab implementation. MA is the main contributor to the numerical experiments and also wrote the first draft of the manuscript. LDL conceived the idea and supervised the project. All authors contributed to manuscript revision, read, and approved the submitted version.

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DATA AVAILABILITY STATEMENT

The datasets analyzed for this study can be found in the http://yann.lecun.com/exdb/mnist/ and https://github.com/zalandoresearch/fashion-mnist.

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FIGURE CAPTIONS

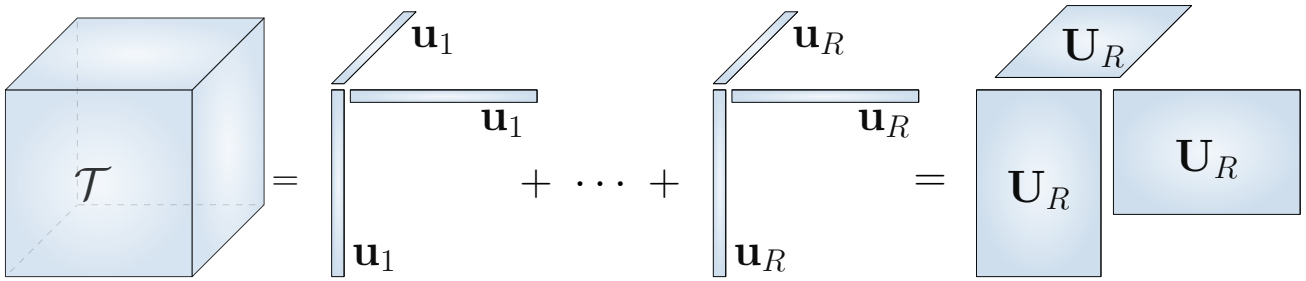

Figure 1. Polyadic decomposition of a third order symmetric tensor $\mathcal{T}$. It is called canonical (CPD) if R is equal to the rank of $\mathcal{T}$, i.e., R is minimal. It allows compact representation of polynomials.

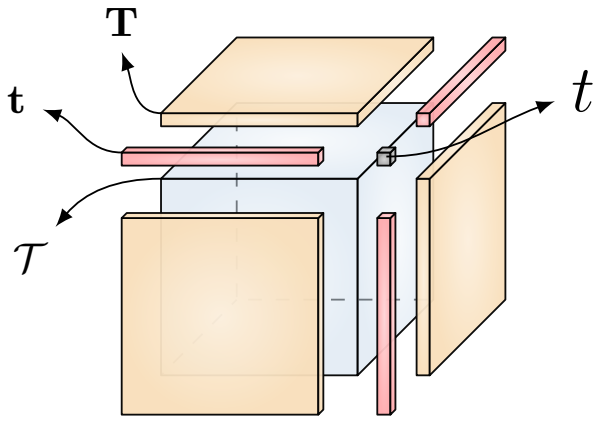

Figure 2. By applying the homogenization process, symmetric tensors can represent the coefficients of non–homogeneous polynomials. For example, by stacking the coefficients $t, \mathbf{t}, \mathbf{T}$ and $\mathcal{T}$ of the third degree polynomial into a tensor as shown above, we can represent it with a symmetric third-order tensor. Image reproduced from (Debals, 2017).

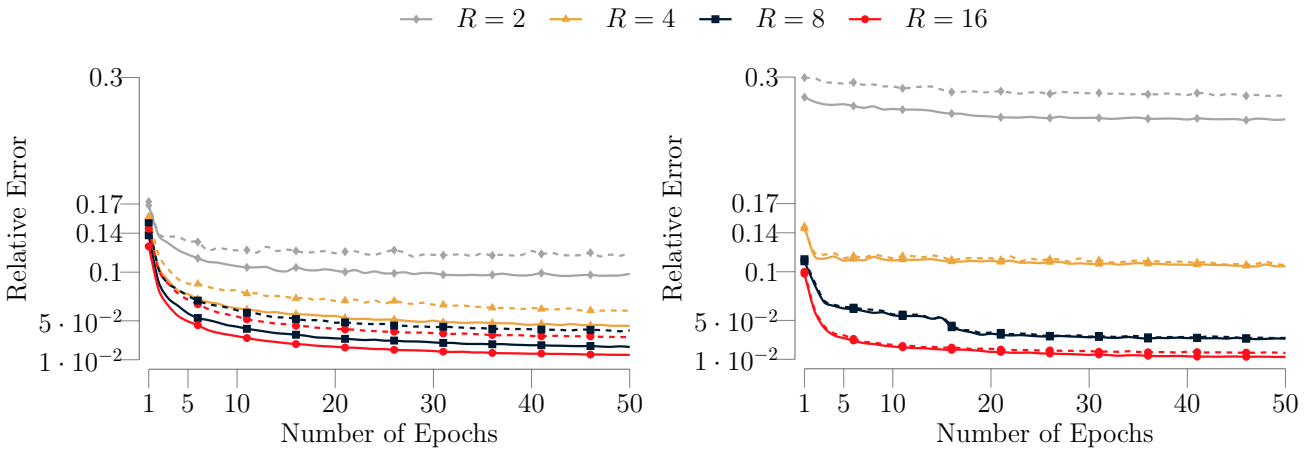

Figure 3. (Left) The median test (dashed lines) and training (solid lines) errors of the type I model for 100 trials on the synthetic data for a rank-8 function given as in equation (28). The number of samples for the training dataset is set to 5000 and for the test dataset it is set to 1000. The batch size is set to 500 and the maximum number of GN iterations is set to 5. (Right) The median test (dashed lines) and training (solid lines) errors of the type II model with the same algorithm settings. TeMPO produces more accurate results and generalizes better for higher rank values for both the type I and type II model. The performance is robust to overparameterization ($R > R_f$). The type I model produces better results for low rank values, i.e., $R < R_f$.

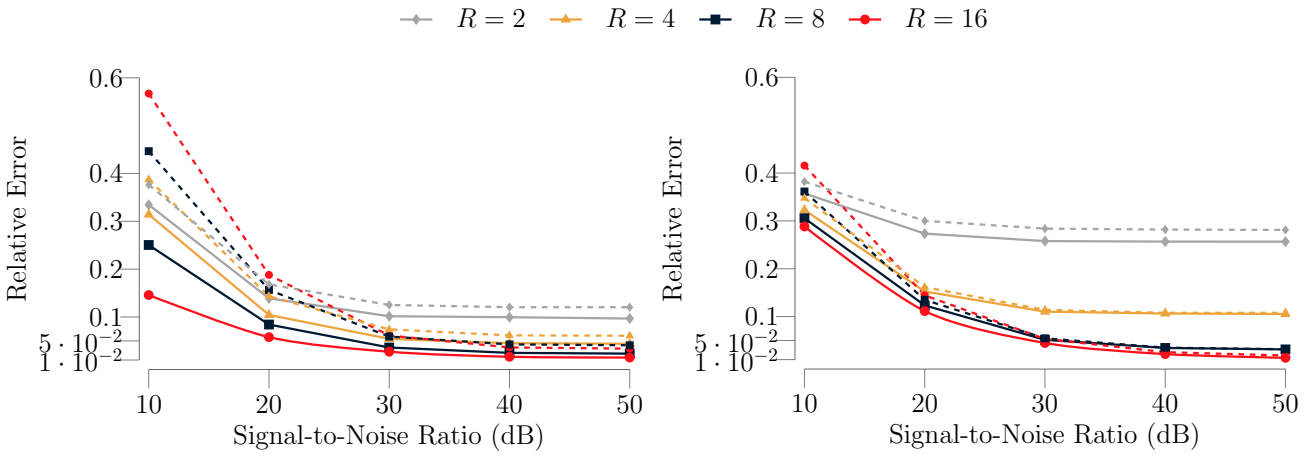

Figure 4. (Left) The median test (dashed lines) and training (solid lines) errors of the type I model for 100 trials on the synthetic noisy data for a rank-8 function given as in equation (29). The number of samples for the training dataset is set to 5000 and for test dataset is set to 1000. The batch size is set to 500 and the maximum number of GN iterations is set to 5. (Right) The median test (dashed lines) and training (solid lines) errors of the type II model with the same algorithm settings. TeMPO produces more accurate results and generalizes better for higher rank values for both the type I and type II model in the presence of noise as well. Again, the type I model produces better results for low rank values, i.e., $R < R_f$, because it involves more parameters than the type II model.

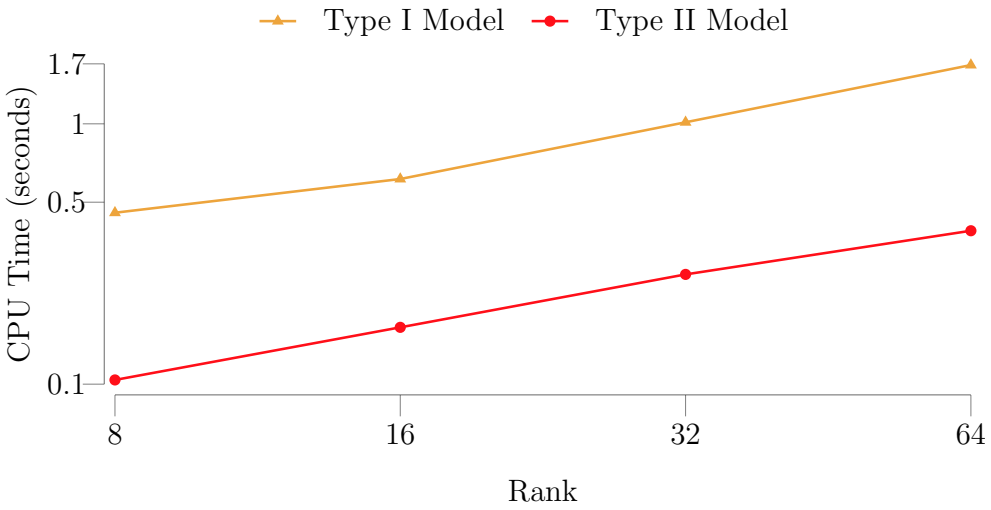

Figure 5. The median CPU time (seconds) per epoch for the type I and type II model as a function of the rank for a rank-8 function given as in equation (28) for 100 trials. The number of samples for the training dataset is set to 5000 and for the test dataset it is set to 1000. The batch size is set to 500 and the maximum number of GN iterations is set to 5. The figure confirms that the computational complexity of the type I model is d times the computational complexity of the type II model (cf. Subsection 3.5). Moreover, the computational complexity of the algorithm is linear in the rank (cf. Subsection 3.5). The figure is in a logarithmic scale on the horizontal axis.

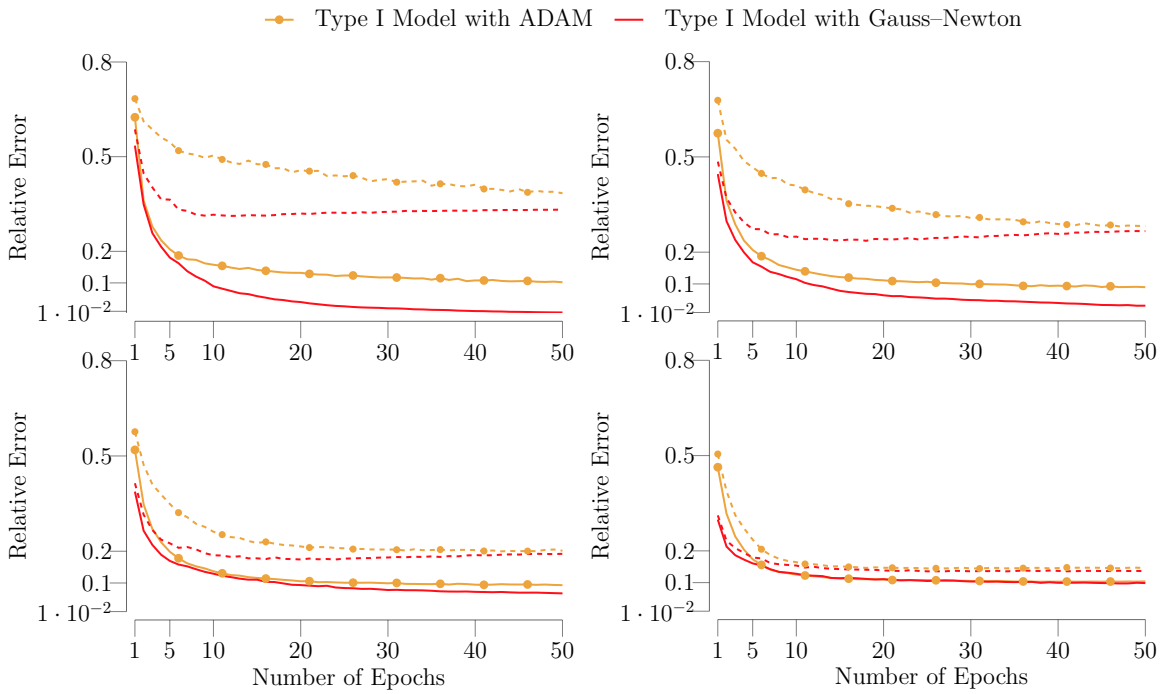

Figure 6. Comparison of the median test (dashed lines) and training (solid lines) errors of the Gauss–Newton and the ADAM algorithms as a function of the number of epochs for 100 trials. The type I model for a rank-8 function given as in equation (29) in the presence of SNR 20 dB Gaussian noise is used to generate the training and the test sets. The batch size is set to 10 percent of the training set size. For the Gauss–Newton algorithm, the maximum number of GN iterations and CG iterations is set to 1 and 5, respectively. For the ADAM algorithm, the step size, β_1 and β_2 are set to 0.01, 0.9, and 0.99, respectively. The number of training samples is set to 500 (top-left), 1000 (top-right), 2000 (bottom-left), and 5000 (bottom-right). The presented Gauss–Newton algorithm produces more accurate results than the ADAM algorithm and also requires fewer number of epochs to converge in these experimental settings.

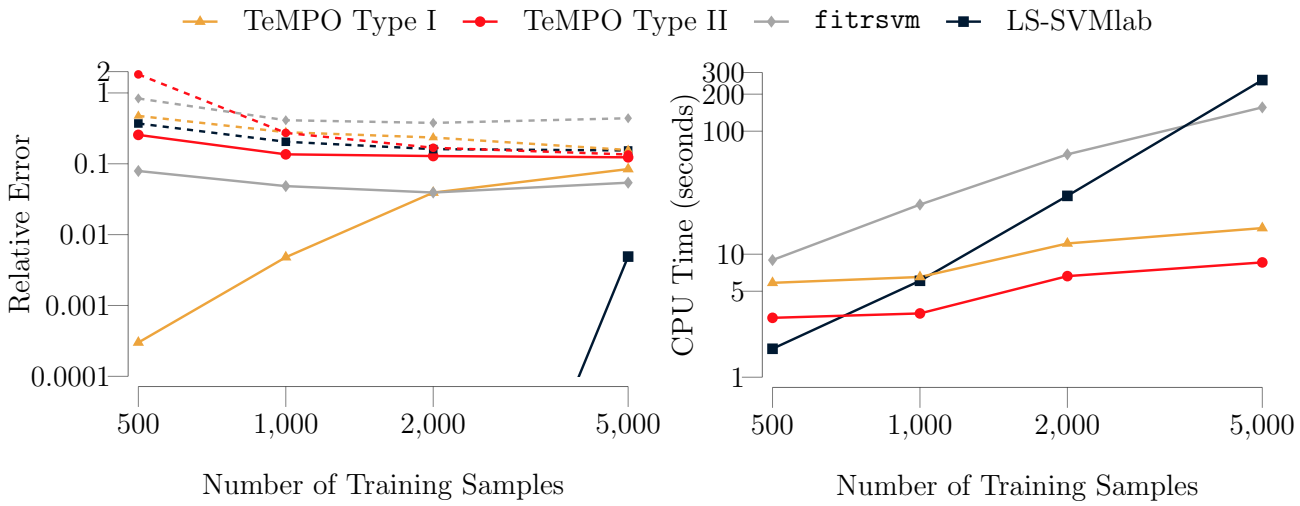

Figure 7. (Left) The median test (dashed lines) and training (solid lines) errors of SVMs with polynomial kernel, the type I and type II model for a rank-8 function given as in equation (29) in the presence of SNR 20 dB Gaussian noise as a function of the number of training samples for 100 trials. The batch size is equal to 10 percent of the training set size. The maximum number of GN iterations is set to 5 for the type I and type II model. Specifically, for the SVMs, the built-in Matlab routine `fitrsvm` and LS-SVMlab toolbox were used to obtain the results. The relative errors of LS-SVMLab for the sample sizes 500, 1000, and 2000 are $1.6\text{e}-6$, $2.2\text{e}-6$ and $3.3\text{e}-6$, respectively. The presented algorithm generalizes better than `fitrsvm` in these experimental settings. (Right) The median CPU times (seconds) with the same setting. The computational complexity of our algorithm is linear in the problem size as expected, and it is faster than SVMs for numbers of training samples above 1000. The figures are in a logarithmic scale on both the horizontal and vertical axes.

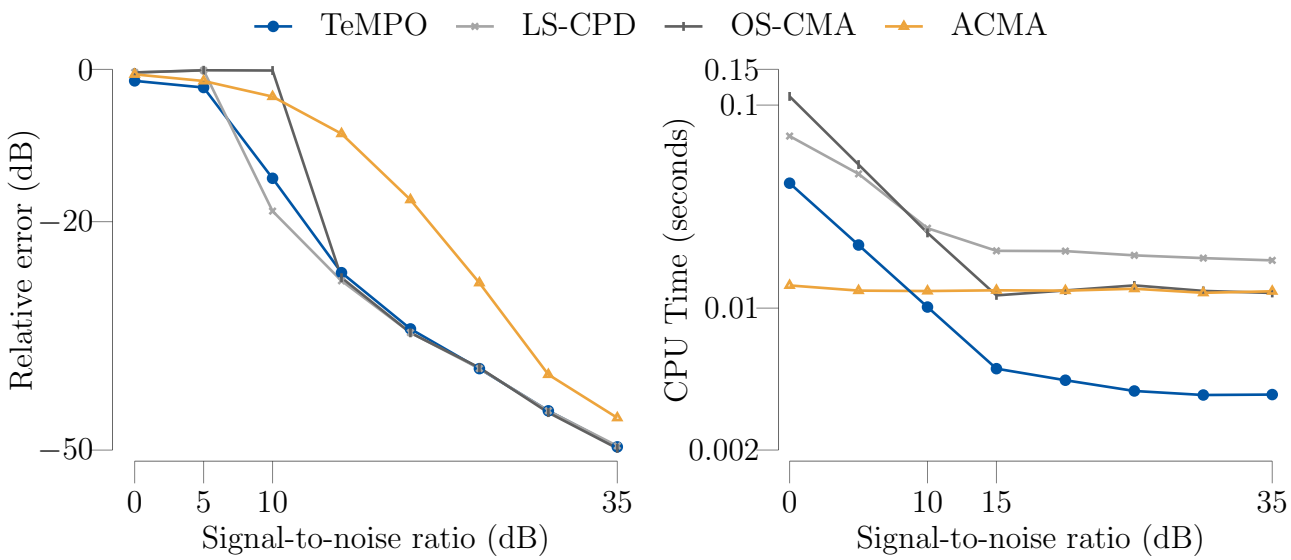

Figure 8. (Left) The median relative errors (dB) of LS-CPD, OS-ACMA, ACMA and TeMPO with respect to SNR (dB) for an autoregressive model of degree $L = 10$ with uniformly distributed coefficients between zero and one, sample length $K = 600$ for 50 trials. TeMPO obtains similar accuracy to LS-CPD, OS-CMA, while obtaining more accurate results than ACMA. (Right) The median CPU times (seconds) with the same settings. TeMPO is faster than other algorithms for SNR > 10 (dB).

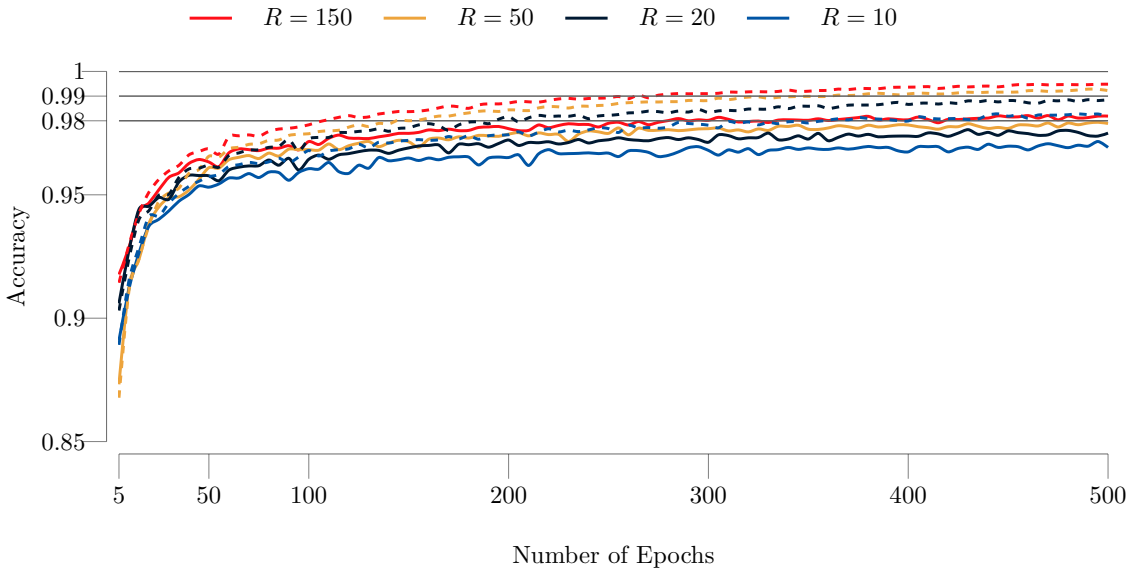

Figure 9. Test (solid lines) and training (dashed lines) accuracies of the type I model for the MNIST dataset with respect to the number of epochs. The full training set (60000 images) and test set (10000 images) are used. The batch size is set to 100 and the maximum number of GN iterations is set to 1. TeMPO achieves high accuracy even for low rank values, i.e. $R = \{10, 20\}$. Both the test and training accuracy increase mildly as the rank increases.

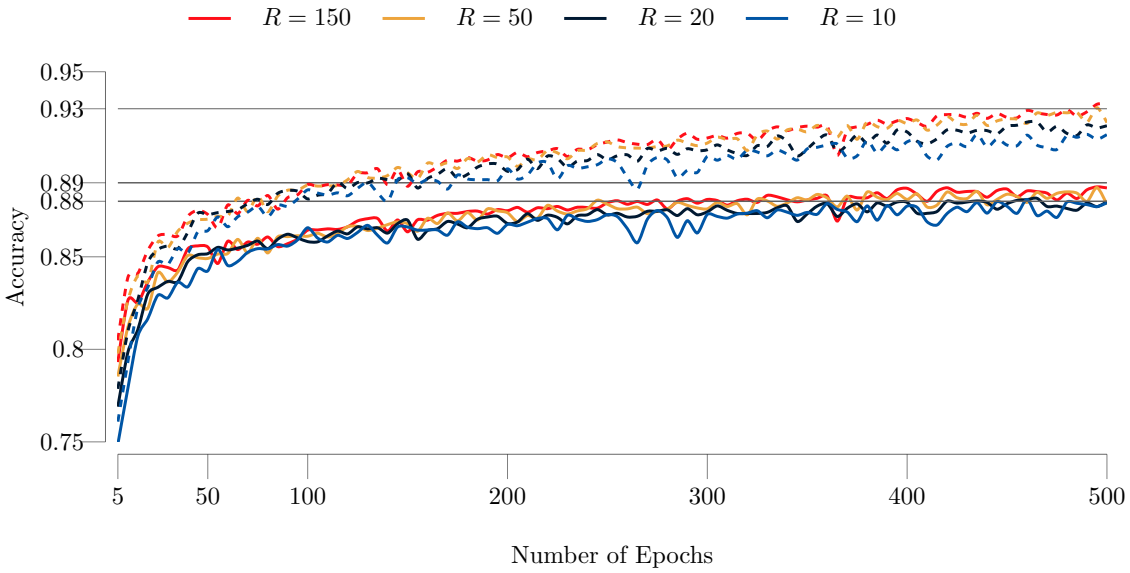

Figure 10. Test (solid lines) and training (dashed lines) accuracies of the type I model for the Fashion MNIST dataset with respect to the number of epochs. The full training set (60000 images) and test set (10000 images) are used. The batch size is set to 100 and the maximum number of GN iterations is set to 1. Similar to the MNIST dataset, TeMPO achieves good accuracy even for low rank values and both the test and training accuracy mildly increase as the rank increases.

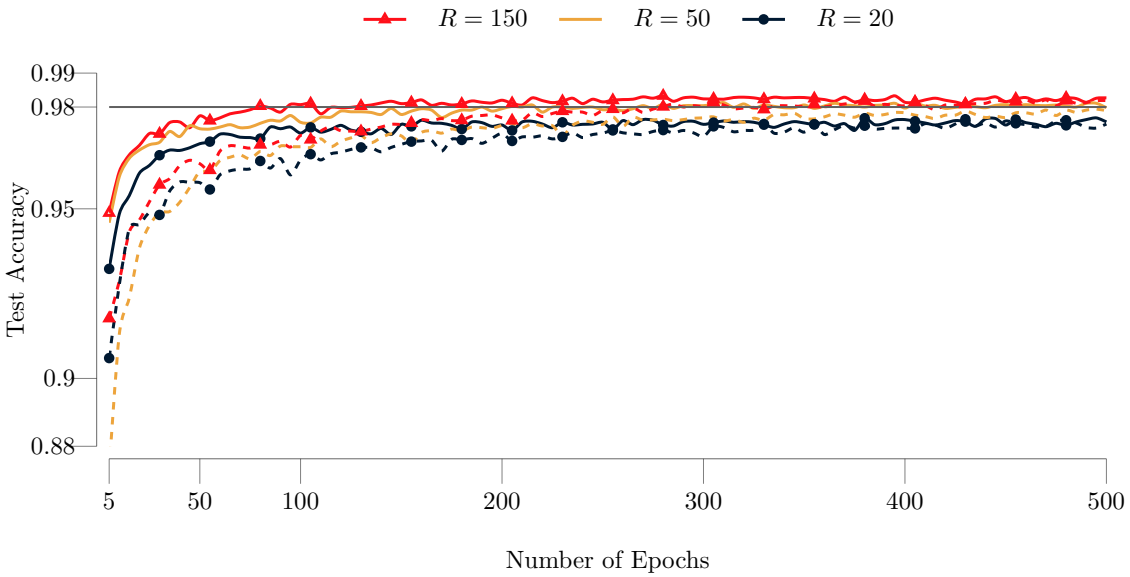

Figure 11. Comparison of test accuracies of the type I model on the MNIST dataset for different maximum number of GN iterations as a function of the number of epochs. The full training set (60000 images) and test set (10000 images) are used. The batch size is set to 100 and the maximum number of GN iterations is set to 1 (dashed lines) and to 5 (solid lines).

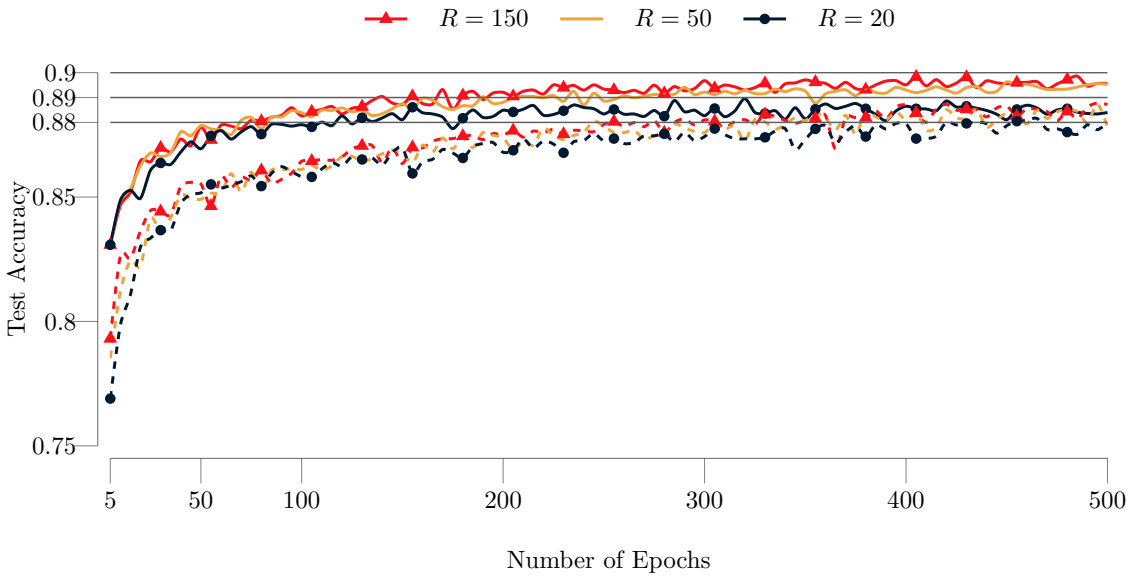

Figure 12. Comparison of test accuracies of the type I model on the Fashion MNIST dataset for different maximum number of GN iterations as a function of the number of epochs. The full training set (60000 images) and test set (10000 images) are used. The batch size is set to 100 and the maximum number of GN iterations is set to 1 (dashed lines) and to 5 (solid lines).

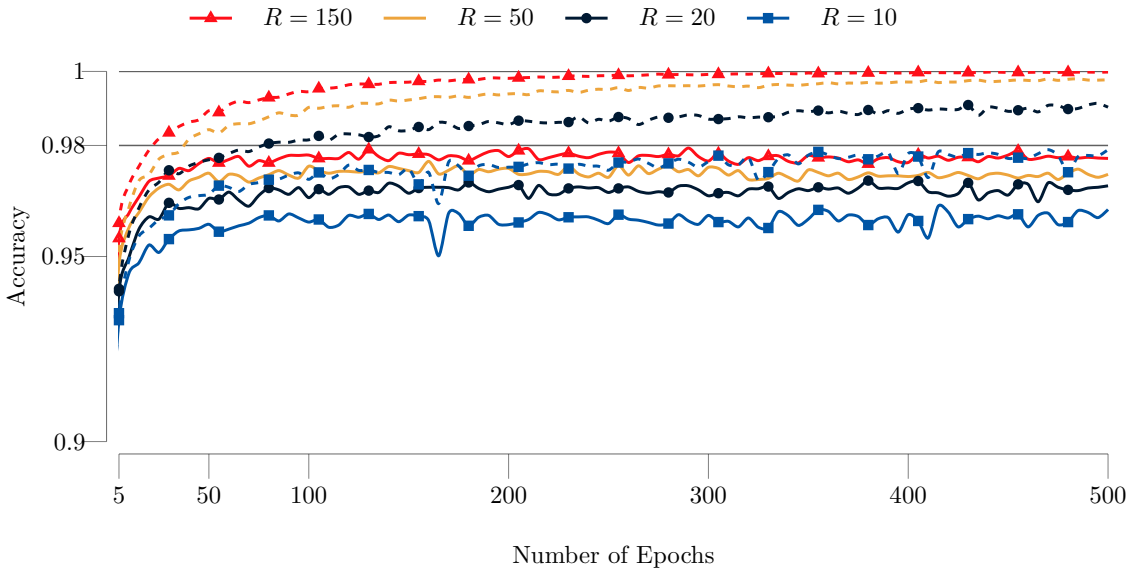

Figure 13. Test (solid lines) and training (dashed lines) accuracies of the type II model for the MNIST dataset with respect to the number of epochs. The full training set (60000 images) and test set (10000 images) are used. The batch size is set to 200 and the maximum number of GN iterations is set to 1. Both the test and training accuracy increase as the rank increases. The improvement in the accuracy gets smaller as the rank increases. The algorithm achieves around 100% training accuracy after 200 epochs.

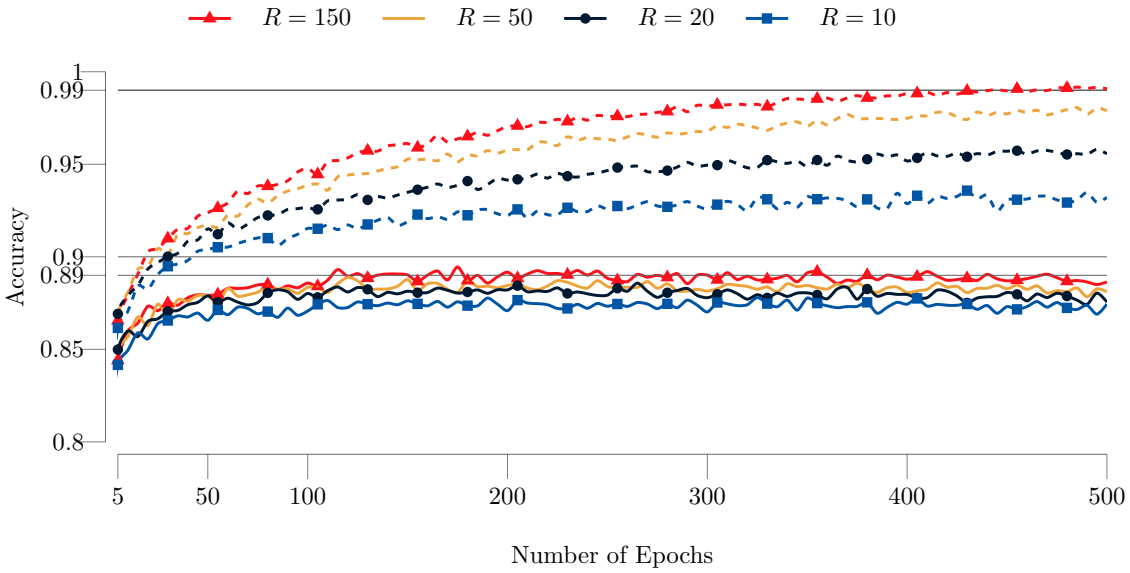

Figure 14. Test (solid lines) and training (dashed lines) accuracies of the type I model for the MNIST dataset with respect to the number of epochs. The full training set (60000 images) and test set (10000 images) are used. The batch size is set to 200 and the maximum number of GN iterations is set to 1. Both the test and training accuracy increase as the rank increases. Also the improvement in the accuracy gets smaller as the rank increases. The algorithm achieves around 99% training accuracy after 400 epochs.

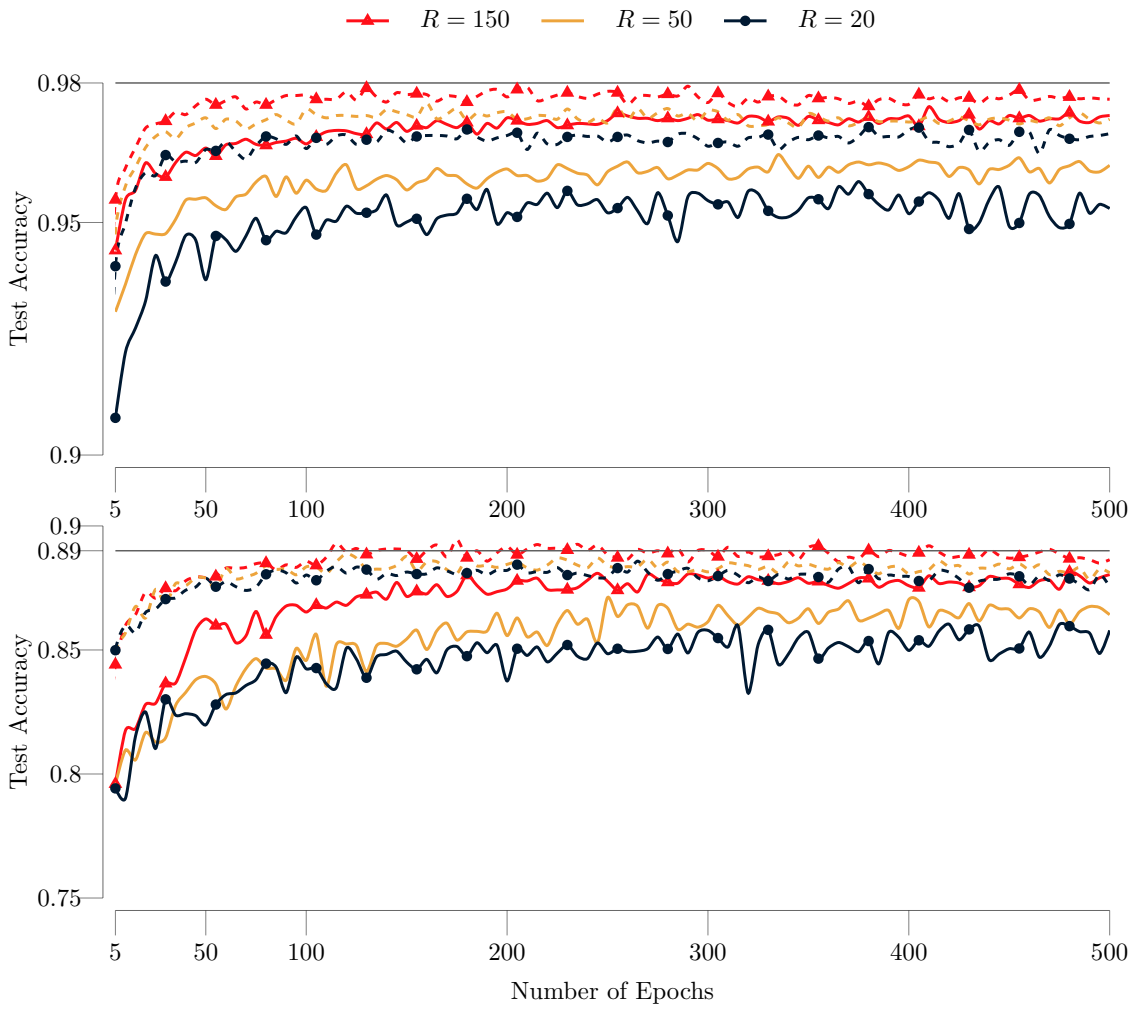

Figure 15. Comparison of test accuracies of the type II model on the MNIST (top) and Fashion MNIST (bottom) datasets for different maximum number of GN iterations as a function of the number of epochs. The full training set (60000 images) and test set (10000 images) are used. The batch size is set to 200 and the maximum number of GN iterations is set to 1 (dashed lines) and to 5 (solid lines).

TABLES

Table 1. The comparison of the computational complexity of TEMPO with TT and PEPS tensor networks for a batch size of K

	Calls (per iter)	TEMPO (Type I Model)	PEPS	TT-N
Storage		$\mathcal{O}\left(dIR\right)$		$\mathcal{O}\left(nIR_{TT}^2\right)$
Objective func.	1	$\mathcal{O}\left((dIKR\right)$	$\mathcal{O}\left(KR_{BT}^3R_{PS}^6\right)$	$\mathcal{O}\left(nIR_{TT}^2 + R_{TT}^3\log(I)\right)$
Gradient	1	$\mathcal{O}\left(dIKR\right)$	$\mathcal{O}\left(\alpha KR_{BT}^3R_{PS}^6\right)$	$\mathcal{O}\left(\alpha\left(nIKR_{TT}^2 + KR_{TT}^3\log(I)\right)\right)$
Gramian-vector	it_{CG}	$\mathcal{O}\left(2dIKR\right)$	$-$	$-$

Table 2. The test accuracy of different models for the Fashion MNIST dataset

Model	Test Accuracy (%)
TT	88.0
MLP	88.3
PEPS	88.3
TTN	89.0
TeMPO (Type II)	**89.3**
TeMPO (Type I)	**89.9**
CNN - MLP	91.0
CNN - PEPS	91.2

Algorithm 1: GN algorithm using dogleg trust-region for the type II model

Input : $\mathbf{Z}$ – Input data matrix
$\mathbf{y}$ – Vector of values (labels in the classification case) for each data point in $\mathbf{Z}$
$\mathbf{U}, \mathbf{c}$ – Initial factor matrix and weight vector
$\mathcal{T}_0$ – Initial scalar
Output : $\mathbf{U}, \mathbf{c}$ – Optimized factor matrix and weight vector
$\mathcal{T}_0$ – Optimized scalar

while *not converged* **do**
  $\mathbf{r}_k \leftarrow$ Compute residual vector using equations (21) and (22)
  $\mathbf{g}_k \leftarrow$ Compute gradient using equation (27)
  $\mathbf{p}_k \leftarrow$ Solve linear systems of equations (12) using CG method
  $\mathbf{U}$, $\mathbf{c}$, $\mathcal{T}_0 \leftarrow$ Update via dogleg trust-region explained in Subsection 3.3
end

Algorithm 2: Batched GN algorithm using dogleg trust-region for regression and classification for the type II model

Input : $\mathbf{Z}$ – Input data matrix
$\mathbf{y}$ – Vector of values (labels in the classification case) for each data point in $\mathbf{Z}$
$\mathbf{U}_1, \ldots, \mathbf{U}_L$ – Initial factor matrices for each label (single in the regression case)
$\mathbf{c}_1, \ldots, \mathbf{c}_L$ – Initial weight vectors for each label (single in the regression case)
$\mathcal{T}_{0,l}$ – Initial scalar for each label (single in the regression case)
$epoch$ – Number of epochs
$batchsize$ – Batch size
Output : $\mathbf{U}_1, \ldots, \mathbf{U}_L$ – Optimized factor matrices for each label (single in the regression case)
$\mathbf{c}_1, \ldots, \mathbf{c}_L$ – Optimized weight vectors for each label (single in the regression case)

for *each epoch* **do**
  Shuffle input data
  for *each batch* **do**
    $l \leftarrow 1$
    if *multi-label classification* **then**
      $l \leftarrow$ Randomly select label l to optimize f_l , $0 < l \leq L$
    end
    $\mathbf{U}_l, \mathbf{c}_l, \mathcal{T}_{0,l} \leftarrow$ Optimize f_l using Algorithm 1
  end
end