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Contents

Tensor Regression

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ABSTRACT

The presence of multidirectional correlations in emerging multidimensional data poses a challenge to traditional regression modeling methods. Traditional modeling methods based on matrix or vector, for example, not only overlook the data's multidimensional information and lower model performance, but also add additional computations and storage requirements. Driven by the recent advances in applied mathematics, tensor regression has been widely used and proven effective in many fields, such as sociology, climatology, geography, economics, computer vision, chemometrics, and neuroscience. Tensor regression can explore multidirectional relatedness, reduce the number of model parameters and improve model robustness and efficiency. It is timely and valuable to summarize the developments of tensor regression in recent years and discuss promising future directions, which will help accelerate the research process of tensor regression, broaden the research direction, and provide tutorials for researchers interested in high dimensional regression tasks.

The fundamentals, motivations, popular algorithms, related applications, available datasets, and software resources for

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tensor regression are all covered in this monograph. The first part focuses on the key concepts for tensor regression, mainly analyzing existing tensor regression algorithms from the perspective of regression families. Meanwhile, the adopted low rank tensor representations and optimization frameworks are also summarized. In addition, several extensions in online learning and sketching are described. The second part covers related applications, widely used public datasets and software resources, as well as some real-world examples, such as multitask learning, spatiotemporal learning, human motion analysis, facial image analysis, neuroimaging analysis (disease diagnosis, neuron decoding, brain activation, and connectivity analysis) and chemometrics. This survey can be used as a basic reference in tensor-regression-related fields and assist readers in efficiently dealing with high dimensional regression tasks.

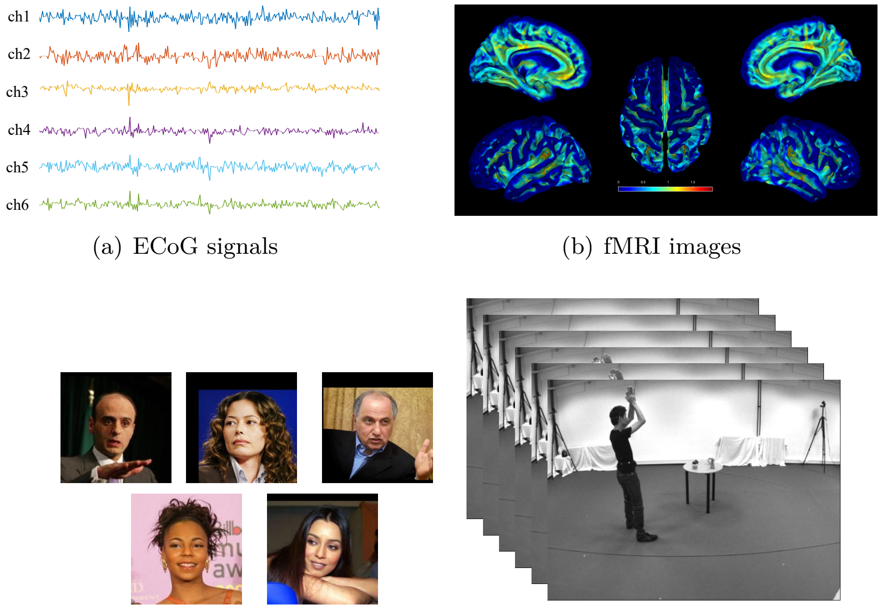
1

Introduction

Regression analysis is a key area of interest in the field of data analysis and machine learning. Regression analysis is devoted to exploring the dependencies between variables, thereby exploring the objective causal relationship of things and further predicting the possible state of things in the future.

Every day, a considerable amount of high dimensional data is collected and stored due to the rapid growth of digital imaging and sensing technologies. For example, numerous neuroimaging technologies, such as electroencephalography (EEG), electrocorticography (ECoG), and functional magnetic resonance imaging (fMRI), generate a lot of multidimensional data. Color images, hyperspectral images, or video sequences in computer vision can also be considered as three-dimensional or four-dimensional tensors. Data in climatology is usually organized in three modes: location, time, and variable type. Social network data also has many indexes, such as user, destination, and time. Fig. 1.1 provides some examples of high dimensional datasets, which are selected from some public datasets.

The emergence of high dimensional data has brought challenges to traditional data representation methods. Tensors, as high order ex-



(a) ECoG signals

(b) fMRI images

(c) Facial images

(d) Video sequences

Figure 1.1: Some examples of high dimensional datasets.

tensions of vectors, are considered as natural representations of high order data (Kolda and Bader, 2009; Cichocki *et al.*, 2015; Sidiropoulos *et al.*, 2017). Exploring the internal structure information of tensors can help people better represent high order data with fewer parameters, extract and interpret their attributes, and achieve data compression, storage, processing, and analysis. Tensor-based learning approaches have been proven to be more effective than classic vector-based methods, and have gotten a lot of attention in recent years, such as tensor completion (Long *et al.*, 2019), tensor principal component analysis (Lu *et al.*, 2016; Feng *et al.*, 2020), tensor sparse representation (Qi *et al.*, 2016; Xie *et al.*, 2017), tensor subspace learning (Lu *et al.*, 2011; Makantasis *et al.*, 2019), tensor clustering (Sun and Li, 2019; Poullis, 2019), tensor regression and classification (Tao *et al.*, 2005; Stoudenmire and Schwab, 2016; Wimalawarne *et al.*, 2016).

For regression tasks with high dimensional predictors or responses, how to effectively explore the multidirectional correlation of these high dimensional data has become an important research topic in the field of image processing and machine learning (Zhou *et al.*, 2013). Most classical regression statistical models are modeled based on vectors as regression coefficients and are not suitable for high dimensional regression problems. There are two main disadvantages for simply employing the traditional regression methods. On the one hand, using traditional regression methods requires first performing vectorization operations on the multiway data, which will ignore the inherent multiway structural information contained in the high dimensional data, resulting in a degradation in terms of model performance. On the other hand, a huge vector-based model will require a large number of parameters, suffering from storage and computational burden and undesired numerical instability.

The objective of this review is to provide a systematic study and analysis of tensor-based regression models and their applications in recent years. Here we give some examples with multidimensional inputs or outputs that will be discussed in this review.

Example 1: Weather forecasting

Weather forecasting is a common task to predict the state of weather at a given space based on historical recordings. The data for this example comes from the U.S. Historical Climatology Network (USHCN). It records the monthly measurements of four climate variables including maximum, minimum, and average temperatures over a month, and total monthly precipitations of approximately 1200 USHCN stations from 1915 to 2014. Table 1.1 lists the recordings for the four variables of some selected stations at a specific time. It records the temperature in degrees Fahrenheit and precipitation in hundreds of inches.

The objective is to design a regressor that could predict the possible value of these four variables at timepoint t based on the previous recordings at $t-1, \cdots, t-K$. Let $\mathcal{X}(:, t, m) \in \mathbb{R}^P$ represent the recording of m-th variable at time t of all the stations, then we aim to construct

Table 1.1: The monthly average of four climate variables for some selected stations in U.S. We have listed the recording for January 2014.

Stations	Maximum temperature (F)	Minimum temperature (F)	Average temperature (F)	Total monthly precipitations
BREWTON 3 SSE	56.3	32.0	44.2	3.15
FAIRHOPE 2 NE	55.5	30.0	42.7	2.34
GAINESVILLE LOCK	50.3	24.3	37.3	1.90
GREENSBORO	50.0	25.2	37.6	1.47
HIGHLAND HOME	50.9	23.0	36.9	3.35
MUSCLE SHOALS AP	47.8	22.9	35.3	1.71
SAINT BERNARD	44.3	20.1	32.2	2.99
···	···	···	···	···
WORLAND	31.1	5.1	18.1	0.38
YELLOWSTONE PK MAMMOTH	34.3	15.8	25.0	0.62

a data generation process as follows

$$\mathcal{X}(:,t,m) = \sum_{k=1}^{K} \mathcal{B}_k(:,:,m)\mathcal{X}(:,t-k,m) + \mathcal{E}(:,t,m) \tag{1.1}$$

where $\mathcal{B}_k \in \mathbb{R}^{P\times P\times M}$, $m = 1,\cdots,M$, $M = 4$ denotes the number of climate variables, $\mathcal{E}$ is the bias. In order to characterize both the spatial and temporal correlations of the climate data, the low rank constraint is commonly used over the coefficient tensor $\mathcal{B} \in \mathbb{R}^{P\times KP\times M}$ which is obtained by putting all the $\{\mathcal{B}_k\}_{k=1}^{K}$ together along the second mode. We have discussed a number of different methods for tackling this learning problem in this monograph.

Example 2: Age estimation

Estimating age automatically from facial images or brain images has attracted a lot of attention in recent years. It is a challenging problem since the impact factors for the aging process are complex. Meanwhile, the facial images and brain images are indexed by multiple dimensions, commonly represented as a 3rd order tensor. Therefore, a lot of parameters are needed to predict the age as in the following model

$$y_n = \langle \mathcal{X}_n, \mathcal{B} \rangle + \epsilon_n, \tag{1.2}$$

where $\mathcal{X}$ is the employed brain images like MRI or fMRI images for n-th sample, y_n is the corresponding sample age, the coefficient tensor $\mathcal{B}$ is in the same size as the predictor, ϵ_n is the bias for n-th sample.

Here we consider the UK biobank dataset for the age estimation task. The T1-weighted 3D structured MRI images and corresponding age labels are exploited to train the regression model. The MRI images are all sized at $182 \times 218 \times 182$. Thus, the parameters needed for model (1.2) will reach $7,000,000$, which makes the learning problem intractable.

In order to control model complexity and explore multidirectional relatedness, the low rank constraint is naturally considered, namely low rank tensor regression, which we will discuss later in this review.

Example 3: A study for autism spectrum disorder

One major issue in neuroimaging analysis is to infer clinical assessments or human traits from neuroimages, such as the age estimation from the fMRI images described above. In addition to this, through modeling the data from a reverse perspective, we can obtain a tensor response regression task that aims to generate corresponding brain images in response to changes in disease state or age. In this way, it is easy to find out the activity pattern between different groups of subjects.

Specifically, here we consider the data from the Autism Brain Imaging Data Exchange (ABIDE) for autism spectrum disorder (ASD). ASD is a series of complex neurodevelopmental disorders that can affect children's social behavior and communication abilities. Studying the different patterns of information processing in the brains of people with ASD and normal children can better help the diagnosis and treatment of ASD. In other words, it is an important research topic to compare and analyze the neural images of normal children and children with ASD through existing data, and to find the brain regions or activity patterns that are most likely to distinguish the two groups. We could view this task as a tensor response regression problem, with the fMRI images being the response and three predictors including the ASD status, age, and sex.

Since there is a high dimensionality in the response, like the fractional amplitude of low-frequency fluctuations (fALFF) data sized at $91 \times 109 \times 91$ in ABIDE, the number of model parameters required will be very large, far exceeding the number of samples, which makes the problem difficult to solve. Therefore, how to explore the multidirectional correlation between data, and how to accurately reduce the dimensionality while ensuring that the model fitting error is small, become very important. This is also an issue that this review aims to deal with.

Contributions

The main contributions of this review are summarized as follows:

- This is the first thorough overview of the fundamentals, motivations, popular algorithms, strategies for efficient implementation, related applications, available datasets, and software resources for tensor-based regression analysis. There is presently no comprehensive overview for tensor-based regression methods. Only some reviews for tensor-based analysis (Sun *et al.*, n.d.; Cichocki *et al.*, 2017) include a subsection for regression analysis, covering only a part of popular algorithms. And there is no classification and discussion of existing methods from multiple perspectives, nor a systematic summary of algorithms, applications, datasets, etc.

- This review groups and illustrates the existing tensor-based regression methods mainly from the perspective of different regression families, such as simple linear tensor regression, generalized tensor regression, penalized tensor regression, Bayesian tensor regression, quantile tensor regression, projection based tensor regression, kernelized tensor regression, tensor Gaussian process regression, tensor additive models, random forest based tensor regression and deep tensor regression. Meanwhile, a discussion of these methods is also given in terms of modeling (tensor-on-vector regression, vector-on-tensor regression, tensor-on-tensor regression), tensor representations (CP, Tucker, t-SVD, TT, TR), and optimization frameworks (ADMM, AM, GD).

- Another highlight of this overview is the use of some real cases in both Chapter 1 and 7 to help readers better understand the application background of tensor regression analysis, such as the forecasting task of spatio-temporal data, human motion trajectories reconstruction from corresponding image sequences, age estimation and disease diagnosis from brain images, a study of the difference between the neural images of children with ASD and normal children, and decoding electroencephalogram signals.

Who should read this review

This review intends to give non-specialists and students interested in tensor regression analysis a decent starting point. The basics, core ideas, and theoretical characteristics of most tensor-based regression methods are covered, but it may be beneficial for readers to have some background in convex optimization, machine learning, and statistics.

We attempt to construct a more comprehensive overview covering most existing tensor regression methods. Moreover, we may pay more attention to the core ideas of the algorithms rather than the specific details and theoretical properties of the algorithms. This is our focus because we want to help readers understand the possible solutions to tensor regression tasks and the main ideas, advantages, and disadvantages of these solutions conceptually rather than mathematically.

In addition, those who are interested in starting related works can also read this review to learn how to use existing tensor-based regression methods to solve specific regression tasks with multiway data, what datasets can be selected, and what software packages are available to start related work as soon as possible.

Organization of this review

The remaining part of the review proceeds as follows: Chapter 2 provides the notations, basic tensor-related operations, and some popular decomposition methods used in this review. The traditional regression methods are introduced in Chapter 3 and extended into the tensor field in Chapter 4 and Chapter 5. Meanwhile, Chapter 4 gives a comprehensive illustration, discussion, comparison, and summary of existing popular linear tensor regression methods. Chapter 5 illustrates the key concepts and algorithms of nonlinear tensor regression models. Then some strategies for efficient implementation, including sketching and online learning, are discussed in Chapter 6. Chapter 7 summarizes the common application fields and gives some practical examples in order to guide the research on tensor regression and validate the effectiveness of some tensor regression approaches. Finally, Chapter 8 concludes the open-source software, and Chapter 9 draws some conclusions and makes recommendations for possible future research works.

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