Learning Compact Recurrent Neural Networks with Block-Term Tensor Decomposition

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Abstract

Recurrent Neural Networks (RNNs) are powerful sequence modeling tools. However, when dealing with high dimensional inputs, the training of RNNs becomes computational expensive due to the large number of model parameters. This hinders RNNs from solving many important computer vision tasks, such as Action Recognition in Videos and Image Captioning. To overcome this problem, we propose a compact and flexible structure, namely Block-Term tensor decomposition, which greatly reduces the parameters of RNNs and improves their training efficiency. Compared with alternative low-rank approximations, such as tensor-train RNN (TT-RNN), our method, Block-Term RNN (BT-RNN), utilizes 17,388 times fewer parameters than the standard RNN in terms of both prediction accuracy and convergence rate. Specifically, BT-LSTM utilizes 17,388 times fewer parameters than the standard LSTM to achieve an accuracy improvement over 15.6% in the Action Recognition task on the UCF11 dataset.

1 Introduction

Best known for the sequence-to-sequence learning, the Recurrent Neural Networks (RNNs) belong to a class of neural architectures designed to capture the dynamic temporal behaviors of data. The vanilla fully connected RNN utilizes a feedback loop to memorize previous information, while it is inept to handle long sequences as the gradient exponentially vanishes along the time [14, 2]. Unlike the vanilla RNNs passing information between layers with direct matrix-vector multiplications, the Long Short-Term Memory (LSTM) introduces a number of gates and passes information with element-wise operations [15]. This improvement drastically alleviates the gradient vanishing issue; therefore LSTM and its variants, e.g. Gated Recurrent Unit (GRU) [6], are widely used in various Computer Vision (CV) tasks [3, 23, 40] to model the long-term correlations in sequences.

The current formulation of LSTM, however, suffers from an excess of parameters, making it notoriously difficult to train and susceptible to overfitting. The formulation of LSTM can be described by the following equations:

\[
\begin{align*}
    f_t &= \sigma(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f) \quad (1) \\
    i_t &= \sigma(W_i \cdot x_t + U_i \cdot h_{t-1} + b_i) \quad (2) \\
    o_t &= \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \quad (3) \\
    c_t &= \tanh(W_c \cdot x_t + U_c \cdot h_{t-1} + b_c) \quad (4) \\
    h_t &= f_t \odot c_{t-1} + i_t \odot c_t \quad (5) \\
    h_t &= o_t \odot \tanh(c_t), \quad (6)
\end{align*}
\]

where \( \odot \) denotes the element-wise product, \( \sigma(\cdot) \) denotes the sigmoid function and \( \tanh(\cdot) \) is the hyperbolic tangent function. The weight matrices \( W_x \) and \( U_x \) transform the input \( x_t \) and the hidden state \( h_{t-1} \), respectively, to cell update \( c_t \) and three gates \( f_t, i_t, \) and \( o_t \). Please note that given an image feature vector \( x_t \) fetch from a Convolutional Neural Network (CNN) network, the shape of \( x_t \) will raise to \( I = 4096 \) and \( J = 14 \times 14 \times 512 \) w.r.t vgg16 [36] and Inception v4 [38]. If the number of hidden states is \( J = 256 \), the total number of parameters in calculating the four \( W_x \) is \( 4 \times I \times J \), which can up to \( 4.1 \times 10^6 \) and \( 1.0 \times 10^8 \), respectively. Therefore, the giant matrix-vector multiplication, i.e., \( W_x \cdot x_t \), leads to the major inefficiency – the current parameter-intensive design not only subjects the model

Figure 1: Architecture of BT-LSTM. The redundant dense connections between input and hidden state is replaced by low-rank BT representation.
difficult to train, but also lead to high computation complexity and memory usage.

In addition, each \( W_s \cdot x_t \) essentially represents a fully connected operation that transforms the input vector \( x_t \) into the hidden state vector. However, extensive research on CNNs has proven that the dense connection is significantly inefficient at extracting the spatially latent local structures and local correlations naturally exhibited in the image [21, 11]. Recent leading CNNs architectures, e.g., DenseNet [16], ResNet [12] and Inception v4 [38], also try to circumvent one huge cumbersome dense layer [39]. But the discussions of improving the dense connections in RNNs are still quite limited [29, 33]. It is imperative to seek a more efficient design to replace \( W_s \cdot x_t \).

In this work, we propose to design a sparsely connected tensor representation, i.e., the Block-Term decomposition (BTD) [8], to replace the redundant and densely connected operation in LSTM 1. The Block-Term decomposition is a low-rank approximation method that decomposes a high-order tensor into a sum of multiple Tucker decomposition models [42]. In detail, we represent the four weight matrices (i.e., \( W_s \)) and the input data \( x_t \) into a various order of tensor. In the process of RNNs training, the BTD layer automatically learns inter-parameter correlations to implicitly prune redundant dense connections rendered by \( W_s \cdot x \). By plugging the new BTD layer into current RNNs formulations, we present a new BT-RNN model with a similar representation power but several orders of fewer parameters. The refined LSTM model with the Block-term representation is illustrated in Fig. 1.

The major merits of BT-RNN are shown as follows:

- The low-rank BTD can compress the dense connections in the input-to-hidden transformation, while still retaining the current design philosophy of LSTM. By reducing several orders of model parameters, BT-LSTM has better convergence rate than the traditional LSTM architecture, significantly enhancing the training speed.

- Each dimension in the input data can share weights with all the other dimensions as the existence of core tensors, thus BT representation has the strong connection between different dimensions, enhancing the ability to capture sufficient local correlations. Empirical results show that, compared with the Tensor Train model [32], the BT model has a better representation power with the same amount of model parameters.

- The design of multiple Tucker models can significantly reduce the sensitivity to noisy input data and widen network, leading to a more robust RNN model. In contrary to the Tensor Train based tensor approaches [48, 31], the BT model does not suffer from the difficulty of ranks setting, releasing researchers from intolerable work in choosing hyper-parameters.

In order to demonstrate the performance of the BT-LSTM model, we design three challenging computer vision tasks – Action Recognition in Videos, Image Caption and Image Generation – to quantitatively and qualitatively evaluate the proposed BT-LSTM against the baseline LSTM (TT-LSTM). Experimental results have demonstrated the promising performance of the BT-LSTM model.

2 Related Work

The poor image modeling efficiency of full connections in the perception architecture, i.e., \( W \cdot x \) [44], has been widely recognized by the Computer Vision (CV) community. The most prominent example is the great success made by Convolutional Neural Networks (CNNs) for the general image recognition. Instead of using the dense connections in multi-layer perceptions, CNNs relies on sparsely connected convolutional kernels to extract the latent regional features in an image. Hence, going sparse on connections is the key to the success of CNNs [9, 17, 30, 13, 37]. Though extensive discussions toward the efficient CNNs design, the discussions of improving the dense connections in RNNs are still quite limited [29, 33].

Compared with aforementioned explicit structure changes, the low-rank method is one orthogonal approach to implicitly prune the dense connections. Low-rank tensor methods have been widely studied in machine learning area [18, 52, 25, 22, 5] and successfully applied to address the redundant dense connection problem in CNNs [31, 48, 1, 41, 19, 27]. Since the key operation in one perception is \( W \cdot x \). Sainath et al. [34] decompose \( W \) with Singular Value Decomposition (SVD), reducing up to 30% parameters in \( W \), but also demonstrates up to 10% accuracy loss [47]. The accuracy loss majorly results from losing the high-order spatial information, as intermediate data after image convolutions are intrinsically in 4D.

In order to capture the high order spatial correlations, recently, tensor methods were introduced into Neural Networks to approximate \( W \cdot x \). For example, Tensor Train (TT) method was employed to alleviate the large computation \( W \cdot x \) and reduce the number of parameters [31, 48, 41]. Yu et al. [49] also used a tensor train representation to forecast long-term information. Since this approach targets in long historic states, it increases additional parameters, leading to a difficulty in training. Other tensor decomposition methods also applied in Deep Neural Networks (DNNs) for various purposes [20, 50, 19].

Although TT decomposition has obtained a great success in addressing dense connections problem, there are some limitations which block TT method to achieve better performance: 1) The optimal setting of TT-ranks is that they are small in the border cores and large in middle cores, e.g., like an olive [51]. However, in most applications, TT-ranks are set equally, which will hinder TT’s representation ability. 2) TT-ranks has a strong constraint that the rank in border tensors must set to 1 (\( R_{t+1} = R_{t+1} = 1 \)), leading to a seriously

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1We focus on LSTM in this paper, but the proposed approach also applies for other variants such as GRU.
limited representation ability and flexibility \cite{48,51}. Instead of difficulty finding the optimal TT-ranks setting, BTD has these advantages: 1) Tucker decomposition introduces a core tensor to represent the correlations between different dimensions, achieving better weight sharing. 2) ranks in core tensor can be set to equal, avoiding unbalance weight sharing in different dimensions, leading to a robust model toward different permutations of input data. 3) BTD uses a sum of multiple Tucker models to approximate a high-order tensor, breaking a large Tucker decomposition to several smaller models, widening network and increasing representation ability. Meanwhile, multiple Tucker models also lead to a more robust RNN model to noisy input data.

3 Tensorizing Recurrent Neural Networks

The core concept of this work is to approximate \( \mathbf{W} \cdot \mathbf{x} \) with much fewer parameters, while still preserving the memorization mechanism in existing RNN formulations. The technique we use for the approximation is Block Term Decomposition (BTD), which represents \( \mathbf{W} \cdot \mathbf{x} \) as a series of light-weighted small tensor products. In the process of RNN training, the BTD layer automatically learns inter-parameter correlations to implicitly prune redundant dense connections rendered by \( \mathbf{W} \cdot \mathbf{x} \). By plugging the new BTD layer into current RNN formulations, we present a new BT-RNN model with several orders of magnitude fewer parameters while maintaining the representation power.

This section elaborates the details of the proposed methodology. It starts with exploring the background of tensor representations and BTD, before delving into the transformation of a regular RNN model to the BT-RNN; then we present the back propagation procedures for the BT-RNN; finally, we analyze the time and memory complexity of the BT-RNN compared with the regular one.

3.1 Preliminaries and Background

Tensor Representation. We use the boldface Euler script letter, e.g., \( \mathbf{X} \), to denote a tensor. A \( d \)-order tensor represents a \( d \) dimensional multiway array; thereby a vector and a matrix is a 1-order tensor and a 2-order tensor, respectively. An element in a \( d \)-order tensor is denoted as \( X_{i_1,\ldots,i_d} \).

Tensor Product and Contraction. Two tensors can perform product on a \( k \)th order if their \( k \)th dimension matches. Let’s denote \( \bullet_k \) as the tensor-tensor product on \( k \)th order \cite{18}. Given two \( d \)-order tensors \( \mathbf{A} \in \mathbb{R}^{I_1 \times \cdots \times I_d} \) and \( \mathbf{B} \in \mathbb{R}^{J_1 \times \cdots \times J_d} \), the tensor product on \( k \)th order is:

\[
(\mathbf{A} \bullet_k \mathbf{B})_{i_k,j_k} = \sum_{p=1}^{I_k} \mathbf{A}_{i_k-p,j_k} \mathbf{B}_{p,j_k}. \tag{7}
\]

To simplify, we use \( i_k^- \) denotes indices \((i_1, \ldots, i_{k-1})\), while \( i_k^+ \) denotes \((i_{k+1}, \ldots, i_d)\). The whole indices can be denoted as \( \vec{i}_k := (i_k^-, i_k, i_k^+) \). As we can see that each tensor product will be calculated along \( I_k \) dimension, which is consistent with matrix product.

Contraction is an extension of tensor product \cite{7}; it conducts tensor products on multiple orders at the same time. For example, if \( I_k = J_k, I_{k+1} = J_{k+1} \), we can conduct a tensor product according the \( k \)th and \((k+1)\)th order:

\[
(\mathbf{A} \bullet_{k,k+1} \mathbf{B})_{i_k^+,j_{k+1}^+} = \sum_{p=1}^{I_k} \sum_{q=1}^{I_{k+1}} \mathbf{A}_{i_k^- + p,j_{k+1}^- + q} \mathbf{B}_{j_k^- + q,j_{k+1}^- + p}. \tag{8}
\]

Figure 2: Block Term decomposition for a 3-order case tensor. A 3-order tensor \( \mathbf{X} \in \mathbb{R}^{I_1 \times I_2 \times I_3} \) can be approximated by \( N \) Tucker decompositions. We call the \( N \) the CP-rank, \( R_1, R_2, R_3 \) the Tucker-rank and \( d \) the Core-order.

3.2 BT-RNN model

This section demonstrates the core steps of BT-RNN model. 1) We transform \( \mathbf{W} \) and \( \mathbf{x} \) into tensor representations, \( \mathbf{W} \) and \( \mathbf{X} \); 2) then we decompose \( \mathbf{W} \) into several low-rank core tensors \( \mathcal{G}_n \) and their corresponding factor tensors \( \mathcal{A}_n^{(d)} \) using BTD; 3) subsequently, the original product \( \mathbf{W} \cdot \mathbf{x} \) is approximated by the tensor contraction between decomposed weight tensor \( \mathbf{W} \) and input tensor \( \mathbf{X} \); 4) finally, we present the gradient calculations amid Back Propagation Through Time (BPTT) \cite{46,45} to demonstrate the learning procedures of BT-RNN model.

Although our discussion mainly focuses on LSTM, the proposed method can easily be generalized into other RNN variants such as Gated Recurrent Unit (GRU) by following above procedures.
Tensorizing \( \mathbf{W} \) and \( \mathbf{x} \) we tensorize the input vector \( \mathbf{x} \) to a high-order tensor \( \mathbf{X} \) to capture spatial information of the input data, while we tensorize the weight matrix \( \mathbf{W} \) to decomposed weight tensor \( \mathbf{W} \) with BTD.

Formally, given an input vector \( \mathbf{x}_i \in \mathbb{R}^I \), we define the notation \( \varphi \) to denote the tensorization operation. It can be either a stack operation or a reshape operation. We use reshape operation for tensorization as it does not need to duplicate the element of the data. Essentially reshaping is regrouping the data. Fig. 3 outlines how we reshape a vector and a matrix into 3-order tensors.

Decomposing \( \mathbf{W} \) with BTD. Given a 2 dimensions weight matrix \( \mathbf{W} \in \mathbb{R}^{J \times I} \), we can tensorize it as a 2d dimensions tensor \( \mathbf{W} \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_d \times J} \), where \( I = I_1 I_2 \cdots I_d \) and \( J = J_1 J_2 \cdots J_d \). Following BTD in Eq. (9), we can decomposes \( \mathbf{W} \) into:

\[
BTD(\mathbf{W}) = \sum_{n=1}^{N} \mathbf{G}_n \circ \mathbf{A}_n^{(1)} \circ \cdots \circ \mathbf{A}_n^{(d)},
\]

where \( \mathbf{G}_n \in \mathbb{R}^{I_1 \times \cdots \times I_d} \) denotes the core tensor, \( \mathbf{A}_n^{(d)} \in \mathbb{R}^{I_d \times J} \) denotes the factor tensor, \( N \) is the CP-rank and \( d \) is the Core-order. From the mathematical property of BT’s ranks [18], we have \( R_{ik} \leq I_k \) (and \( J_k \)), \( k = 1, \ldots, d \). If \( R_k > I_k \) (or \( J_k \)), it is difficult for the model to obtain bonus in performance. What’s more, to obtain a robust model, in practice, we set each Tucker-rank to be equal, e.g., \( R_i = R, i \in [1, d] \), to avoid unbalanced weight sharing in different dimensions and to alleviate the difficulty in hyper-parameters setting.

Computation between \( \mathbf{W} \) and \( \mathbf{x} \) After substituting the matrix-vector product by BT representation and tensorized input vector, we replace the input-to-hidden matrix-vector product \( \mathbf{W} \cdot \mathbf{x}_i \) with the following form:

\[
\phi(\mathbf{W}, \mathbf{x}_i) = BTD(\mathbf{W}) \circ_{1,2,\ldots,d} \mathbf{X}_i,
\]

where the tensor contraction operation \( \circ_{1,2,\ldots,d} \) will be computed along all \( I_k \) dimensions in \( \mathbf{W} \) and \( \mathbf{X} \), yielding the same size in the element-wise form as the original one. Fig. 4 demonstrates the substitution intuitively.

Training BT-RNN. The gradient of RNN is computed by Back Propagation Through Time (BPTT) [46]. We derive the gradients amid the framework of BPTT for the proposed BT-RNN model.

Following the regular LSTM back-propagation procedure, the gradient \( \frac{\partial L}{\partial \mathbf{W}} \) can be computed by the original BPTT algorithm, where \( \mathbf{y} = \mathbf{W} \mathbf{x}_t \). Using the tensorization operation same to \( \mathbf{y} \), we can obtain the tensorized gradient \( \frac{\partial L}{\partial \mathbf{W}} \). For a more intuitive understanding, we rewrite Eq. (11) in element-wise case:

\[
y_j = \sum_{n=1}^{N} \sum_{\vec{r}} \sum_{\vec{i}} \prod_{k=1}^{d} \mathbf{X}_{\vec{i},\vec{r}} \mathbf{A}_{n,\vec{i},\vec{r}}^{(k)} \mathbf{G}_{n,\vec{r}}. \quad (12)
\]

Here, for simplified writing, we use \( \vec{i} \), \( \vec{j} \) and \( \vec{r} \) to denote the indices \( (i_1, \ldots, i_d) \), \( (j_1, \ldots, j_d) \) and \( (r_1, \ldots, r_d) \), respectively. Since the right hand side of Eq. (12) is a scalar, the element-wise gradient for parameters in BT-RNN is as follows:

\[
\frac{\partial L}{\partial \mathbf{A}_{n,\vec{i},\vec{r}}^{(k)}} = \\
\sum_{\vec{r} \neq \vec{r}_k} \sum_{\vec{i} \neq \vec{i}_k} \sum_{\vec{j} \neq \vec{j}_k} \prod_{k=1}^{d} \mathbf{S}_{n,\vec{r}} \mathbf{A}_{n,\vec{i} \cdot \vec{j},\vec{r}_k} \mathbf{X}_{\vec{t},\vec{i}} \frac{\partial L}{\partial \mathbf{y}_j}. \quad (13)
\]

\[
\frac{\partial L}{\partial \mathbf{G}_{n,\vec{r}}} = \sum_{\vec{r}} \sum_{\vec{i}} \prod_{k=1}^{d} \mathbf{A}_{n,\vec{i},\vec{r}} \mathbf{X}_{\vec{t},\vec{i}} \frac{\partial L}{\partial \mathbf{y}_j}. \quad (14)
\]

3.3 Hyper-Parameters and Complexity Analysis

3.3.1 Hyper-Parameters Analysis

Total # Params. BTD decomposes \( \mathbf{W} \) into \( N \) block terms and each block term is a tucker representation [19, 18].
hyper-parameter is conceptually similar to the number of orders of magnitude larger than it in the BTD representation. When the BTD representation is the simplest way to reduce the computational complexity in the backward process, we present the Tucker-rank $R$ (N) The CP-rank $N$ controls the number of block terms. If $N = 1$, BTD degenerates to a Tucker decomposition. As we can see from Table 1 that $N$ does not affect the memory usage in forward and backward passes, so if we need a more memory saving model, we can enlarge $N$ while decreasing $R$ and $d$ at the same time.

### 3.3.2 Computational Complexity Analysis

#### Complexity in Forward Process

Eq. (10) raises the computation peak, $O(IJR)$, at the last tensor product $\phi_d$, according to left-to-right computational order. However, we can reorder the computations to further reduce the total model complexity $O(NdIJR)$. The reordering is:

$$\phi(W, x_t) = \sum_{n=1}^{N} X_t \cdot 1 A_n^{(1)} \cdot 2 \ldots d A_n^{(d)} \cdot 1, 2, \ldots, d \mathcal{G}_n.$$  

(16)

The main difference is each tensor product will be first computed along all $R$ dimensions in Eq. (11), while in Eq. (16) along all $I$ dimensions. Since BTD is a low-rank decomposition method, e.g., $R \leq J_k$ and $J_{max} R^{(d-1)} \leq J$, the new computation order can significantly reduce the complexity of the last tensor product from $O(IJR)$ to $O(IJ_{max} R^d)$, where $J = J_1 J_2 \ldots J_d$, $J_{max} = \max_k (J_k)$, $k \in [1, d]$. And then the total complexity of our model reduces from $O(NdIJJR)$ to $O(NdIJ_{max} R^d)$. If we decrease Tucker-rank $R$, the computation complexity decreases logarithmically in Eq. (16) while linearly in Eq. (11).

#### Complexity in Backward Process

To derive the computational complexity in the backward process, we present gradients in the tensor product form. The gradients of factor tensors and core tensors are:

$$\frac{\partial L}{\partial A_{n}^{(k)}} = \frac{\partial L}{\partial y} \cdot x_t \cdot 1 A_n^{(1)} \cdot 2 \ldots k-1 A_n^{(k-1)} \cdot k+1 A_n^{(k+1)} \cdot k+2 \ldots d A_n^{(d)} \cdot 1, 2, \ldots, d \mathcal{G}_n.$$  

(17)

$$\frac{\partial L}{\partial \mathcal{G}_n} = x_t \cdot 1 A_n^{(1)} \cdot 2 \ldots d A_n^{(d)} \cdot 1, 2, \ldots, d \frac{\partial L}{\partial y}.$$  

(18)

Since Eq. (17) and Eq. (18) follow the same form of Eq. (11), the backward computational complexity is same as the forward pass $O(dIJ_{max} R^d)$. Therefore, the $N \cdot d$ factor tensors demonstrate a total complexity of $O(Nd^2IJ_{max} R^d)$.
| Method         | Time                  | Memory                     |
|---------------|-----------------------|----------------------------|
| RNN forward   | 0(\|J\|)             | 0(\|J\|)                   |
| RNN backward  | 0(\|J\|)             | 0(\|J\|)                   |
| TT-RNN forward| 0(dIR^2J_{\text{max}}) | 0(RI)                     |
| TT-RNN backward | 0(dIR^2J_{\text{max}}) | 0(R^2I)                   |
| BT-RNN forward | 0(NdIR^4J_{\text{max}}) | 0(R^4I)                   |
| BT-RNN backward | 0(NdIR^2J_{\text{max}}) | 0(R^4I)                   |

Table 1: Comparison of complexity and memory usage of vanilla RNN, Tensor-Train representation RNN (TT-RNN) [31, 48] and our BT representation RNN (BT-RNN). In this table, the weight matrix’s shape is \( I \times J \). The input and hidden tensors’ shapes are \( I = I_1 \times \cdots \times I_d \) and \( J = J_1 \times \cdots \times J_d \), respectively. Here, \( J_{\text{max}} = \max_k(J_k), k \in [1, d] \). Both TT-RNN and BT-RNN are set in same rank \( R \).

**Complexity Comparisons** We analyze the time complexity and memory usage of RNN, Tensor Train RNN, and BT-RNN. The statistics are shown in Table 1. In our observation, both TT-RNN and BT-RNN hold lower computation complexity and memory usage than the vanilla RNN, since the extra hyper-parameters are several orders smaller than \( I \) or \( J \). As we claim that the suggested choice of Core-order is \( d \in [2, 5] \), the complexity of TT-RNN and BT-RNN should be comparable.

Since all dimensions share weights through core tensors in BT model while TT only shares weights through two dimensions nearby, BT model can capture sufficient spatial information across multiple dimensions.

### 4 Experiments

RNN is a versatile and powerful modeling tool widely used in various computer vision tasks. We design three challenging computer vision tasks-Action Recognition in Videos, Image Caption and Image Generation-to quantitatively and qualitatively evaluate proposed BT-LSTM against baseline LSTM and other low-rank variants such as Tensor Train LSTM (TT-LSTM). Finally, we design a control experiment to elucidate the effects of different hyper-parameters.

#### 4.1 Implementations

Since operations in \( f_t, i_t, o_t \) and \( c_t \) follow the same computation pattern, we merge them together by concatenating \( W_f, W_i, W_o \) and \( W_c \) into one giant \( W \), and so does \( U \). This observation leads to the following simplified LSTM formulations:

\[
(f'_t, i'_t, c'_t, o'_t) = W \cdot x_t + U \cdot h_{t-1} + b, \quad (19)
\]
\[
(f_t, i_t, c_t, o_t) = (\sigma(f'_t), \sigma(i'_t), \tanh(c'_t), \sigma(o'_t)). \quad (20)
\]

We implemented BT-LSTM on the top of simplified LSTM formulation with Keras and TensorFlow. The initialization of baseline LSTM models use the default settings in Keras and TensorFlow, while we use Adam optimizer with the same learning rate (lr) across different tasks.

#### 4.2 A Quantitative Evaluation of BT-LSTM on the Task of Action Recognition in Videos

We use UCF11 YouTube Action dataset [28] for action recognition in videos. The dataset contains 1600 video clips, falling into 11 action categories. Each category contains 25 video groups, within each contains at least 4 clips. All video clips are converted to 29.97fps MPG. We acquire the dataset from here\(^2\). We scale down original frames from \( 320 \times 240 \times 3 \) to \( 160 \times 120 \times 3 \), then we sample 6 random frames in ascending order from each video clip as the input data. For more details on the preprocessing, please refer to [48].

We use a single LSTM cell as the model architecture to evaluate BT-LSTM against LSTM and TT-LSTM in Fig. 6. Please note there are other orthogonal approaches aiming at improving the model such as visual attention [35] and spatial-temporal [26]. Since our discussion is limited to a single LSTM cell, we can always replace the LSTM cells

\(^2\)http://crcv.ucf.edu/data/UCF_YouTube_Action.php
Table 2: State-of-the-art results on UCF11 dataset reported in literature, in comparison with our best model.

| Method               | Accuracy |
|----------------------|----------|
| Orthogonal Approaches|          |
| Original [28]        | 0.712    |
| Spatial-temporal [26]| 0.761    |
| Visual Attention [35]| 0.850    |
| RNN Approaches       |          |
| LSTM                 | 0.697    |
| TT-LSTM [48]         | 0.796    |
| BT-LSTM              | 0.853    |

in those high-level models with BT-LSTM to acquire better accuracies. We set the hyper-parameters of BT-LSTM and TT-LSTM as follows: the factor tensor counts is $d = 4$; the shape of input tensor is $I_1 = 8$, $I_2 = 20$, $I_3 = 20$, $I_4 = 18$; and the hidden shape is $J_1 = J_2 = J_3 = J_4 = 4$; the rank of TT-LSTM is $R_1 = R_3 = 1$, $R_2 = R_4 = 3$, while BT-LSTM is set to various Tucker-ranks.

Fig. 6 demonstrates the training loss and validation accuracy of BT-LSTM against LSTM and TT-LSTM under different settings. Table 2 demonstrates the top accuracies of different models. From these experiments, we claim that:

1) $8 \times 10^4$ times parameter reductions: The vanilla LSTM has 58.9 milions parameters in $W$, while BT-LSTM delivers better accuracies even with several orders of less parameters. The total parameters in BT-LSTM follows Eq. (15). At Tucker-rank 1, 2, 4, BT-LSTM uses 721, 1470, and 3387 parameters, demonstrating compression ratios of 81693x, 40069x and 17388x, respectively.

2) faster convergence: BT-LSTM demonstrates significant convergence improvement over the vanilla LSTM based on training losses and validation accuracies in Fig. 6(a) and Fig. 6(b). In terms of validation accuracies, BT-LSTM reaches 60% accuracies at epoch-16 while LSTM takes 230 epoces. The data demonstrates 1x convergence speedup. It is widely acknowledged that the model with few parameters is easier to train. Therefore, the convergence speedup majorly results from the drastic parameter reductions. At nearly same parameters, the training loss of BT-LSTM-4 also decreases faster than TTLSTM-4 (epoches[0, 50]), substantiating that BT model captures better spatial information than the Tensor Train model.

3) better model efficiency: Though several orders of parameter reductions, BT-LSTM demonstrates extra 15.6% accuracies than LSTM. In addition, BT-LSTM also demonstrates extra 7.2% accuracies than TT-LSTM with comparable parameters. In different Tucker-ranks, BT-LSTM converges to identical losses; but increasing Tucker ranks also improves the accuracy. This is consistent with the intuition since the high rank models capture additional relevant information. Therefore, we claim BT-LSTM has better efficiency.

4.3 Qualitative Evaluations of BT-LSTM on Tasks of Image Generation and Image Captioning

We also conduct experiments on Image Generation and Image Captioning to further substantiate the efficiency of BT-LSTM.

Task 1: Image Generation  Image generation intends to learn latent representation from images, then it tires to generate new image of same style from the learned model. The model for this task is Deep Recurrent Attentive Writer (DRAW) [10]. It uses an encoder RNN network to encode images into latent representations; then an decoder RNN network decodes the latent representations to construct an image. we substitute LSTM in encoder network with our BT-LSTM.

In this task, encoder network must capture sufficient local correlations and visual features from raw images to generate high quality of feature vectors. As shown in Fig. 7, both LSTM and BT-LSTM based model generate comparable images.

Task 2: Image Captioning  Image Captioning intends to describe the content of an image. We use the model in Neural Image Caption[43] to evaluate the performance of BT-LSTM by replacing the LSTM cells.

The training dataset is MSCOCO [24], a large-scale dataset for the object detection, segmentation, and captioning. It contains 82783 images for training and 40775 images for testing. Each image is scaled to $224 \times 224$ in RGB channels and subtract the channel means $(103.939,116.779,123.68)$ as the input to a pretrained vgg16 model.

Fig. 8 demonstrates the image captions generated by BT-LSTM and LSTM. It is obvious that BT-LSTM generates accurate sentences to describe the content of an image than baseline LSTM. Since the input data of BT model is a compact feature vector merged with the embedding images features from VGG-16 and language features from a word.
larization and Lasso regularization, to recover the
impact of the BT model on different parameter settings,
Please note that the purpose of this experiment is to evaluate

\[ W = \mathbf{W} \cdot \mathbf{x} \]

since we use multiple Tucker models to capture information
a proper CP-rank setting will lead to a more robust model,
since we use multiple Tucker models to capture information

Figure 8: Results of image caption in MSCOCO dataset.

\[ d < 5. \text{ Parameters reduce about 1.3 times from Fig. 9(d)} \]
\[ \text{to Fig. 9(f); and } d \text{ increase from 2 to 4. With less parameters, the reconstructed } W \text{ deteriorates quickly. We claim that high Core-order } d \text{ loses important spatial information, as tensor becomes too small to capture enough latent correlations. This result is consistent with our declaration.} \]

\[ \text{Tucker-rank (R): the rank } R \text{ take effectiveness exponentially to the parameters. By comparing Fig. 9(c) and Fig. 9(d), When } R \text{ increases from 1 to 4, BT model has more parameters to capture sufficient information from input data, obtaining a more robust model.} \]

\[ \text{CP-rank (N): CP-rank contributes to the number of parameters linearly, playing an important role when } R \text{ is small. By comparing Fig. 9(c) and Fig. 9(e), we can see that the latter result has less noise in figure, showing that a proper CP-rank setting will lead to a more robust model, since we use multiple Tucker models to capture information from input data.} \]

\[ \text{Core-order (d): Parameters goes down if } d \text{ grows and} \]

5 Conclusion

We proposed a Block-Term RNN architecture to address
the redundancy problem in RNNs. By using a Block Term
tensor decomposition to prune connections in the input-to-
hidden weight matrix of RNNs, we provide a new RNN
model with a less number of parameters and stronger cor-
relation modeling between feature dimensions, leading to
easy model training and improved performance. Experiment
results on a video action recognition data set show that
our BT-RNN architecture can not only consume several or-
ders fewer parameters but also improve the model perfor-
ance over standard traditional LSTM and the TT-LSTM.
The next works are to 1) explore the sparsity in factor ten-
sors and core tensors of BT model, further reducing the
memory usage.

Figure 9: The trained \( W \) for different BT-LSTM settings.
The closer to (a), the better \( W \) is.

embedding network, our model demonstrates the qualitative
improvement in captioning. The results also demonstrate
that BT-LSTM captures local correlations missed by tradi-
tional LSTM.

4.4 Sensitivity Analysis on Hyper-
Parameters

There are 3 key hyper-parameters in BT-LSTM, which are
core-order \( d \), Tucker-rank \( R \) and CP-rank \( N \). In order to
scrutinize the impacts of these hyper-parameters, we design
a control experiment illustrate their effects.

We try to sample \( y \) from the distribution of \( y = \mathbf{W'} \cdot \mathbf{x} \),
where \( x, y \in \mathbb{R}^{64} \). Each \( x \) is generated from a Gaussian
distribution \( N(0, 0.5) \). We also add a small noise into \( x \)
to avoid overfitting. \( y \) is generated by plugging \( x \) back to
\( y = \mathbf{W'} \cdot \mathbf{x} \). Given \( x \) and \( y \), we randomly ini-
tize \( W \), and start training. Eventually, \( W \) should be similar to \( W' \)
since \( x \) and \( y \) drawn from the distribution of \( y = \mathbf{W'} \cdot \mathbf{x} \).
Please note that the purpose of this experiment is to evaluate
the impact of the BT model on different parameter settings,
despite these are many other good methods such as L1 regu-
larization and Lasso regularization, to recover the \( W \) weight
matrix.

Core-order \( (d) \): Parameters goes down if \( d \) grows and
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