TCTN: A 3D-Temporal Convolutional Transformer Network for Spatiotemporal Predictive Learning

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Abstract

Spatiotemporal predictive learning is to generate future frames given a sequence of historical frames. Conventional algorithms are mostly based on recurrent neural networks (RNNs). However, RNN suffers from heavy computational burden such as time and long back-propagation process due to the seriality of recurrent structure. Recently, Transformer-based methods have also been investigated in the form of encoder-decoder or plain encoder, but the encoder-decoder form requires too deep networks and the plain encoder is lack of short-term dependencies. To tackle these problems, we propose an algorithm named 3D-temporal convolutional transformer (TCTN), where a transformer-based encoder with temporal convolutional layers is employed to capture short-term and long-term dependencies. Our proposed algorithm can be easy to implement and trained much faster compared with RNN-based methods thanks to the parallel mechanism of Transformer. To validate our algorithm, we conduct experiments on the MovingMNIST and KTH dataset, and show that TCTN outperforms state-of-the-art (SOTA) methods in both performance and training speed.

Introduction

Spatiotemporal predictive learning is to generate future frames given a sequence of historical frames, which has received much attention in various fields such as prediction of traffic flows (Zhang, Zheng, and Qi 2017), precipitation nowcasting (Shi et al. 2015; Wang et al. 2021), video frame prediction (Liu et al. 2020), etc. Solving spatiotemporal predictive learning requires capturing both temporal and spatial dependencies. Temporal dependencies involve short-term and long-term information, and the spatial ones consist of short-range and long-range information.

Recent works on spatiotemporal predictive learning usually adopt the neural network as learned model due to its great power of function approximation, which has achieved great improvement. Most of these are based on convolutional neural networks (CNNs) (Liu et al. 2017; Wu et al. 2020), recurrent neural networks (RNNs) (Srivastava, Mansimov, and Salakhudinov 2015) or the mixed of both (Ranzato et al. 2014; Shi et al. 2015; Wang et al. 2021). However, CNN is weak at capturing long-term temporal dependencies, while RNN suffers from heavy computational burden such as time and long back-propagation process due to the seriality of recurrent structure.

Aside from CNN and RNN based methods, there have been some works based on the Transformer architecture, which was originally developed in natural language processing (NLP) (Vaswani et al. 2017) and soon transferred to the field of computer vision (Dosovitskiy et al. 2020; Carion et al. 2020). Compared with RNN based methods, the Transformer architecture can extract long-term dependencies more efficiently and get rid of the limitation of seriality. Convolutional Transformer (ConvTransformer) (Liu et al. 2020) adopts a similar encoder-decoder architecture as the one in the original Transformer network (Vaswani et al. 2017). "Spatio-temporal Transformer" (ST-Transformer) stacks multiple Transformer blocks to encode input frames, where both spatial attention and temporal attention are introduced (Aksan et al. 2020). However, the encoder-decoder architecture usually leads to very deep networks and the plain encoder is lack of short-term dependencies.

To tackle these problems, we propose an algorithm named 3D-temporal convolutional Transformer network (TCTN), where a Transformer-based encoder with temporal convolutional layers is employed to capture short-term and long-term dependencies. The introduction of the 3D-temporal convolution operation is naturally fit in the masked self-attention in the Transformer block, which prevents the leakage of future information. Our proposed network can be implemented in parallel and trained fast while keeping good performance.

To validate our algorithm, we conduct experiments on the MovingMNIST and KTH dataset. The results show that our proposed model outperforms state-of-the-art (SOTA) methods in both performance and training speed.

Related work

We focus on researches on spatiotemporal predictive learning with neural networks due to their great power of function approximation.

Convolutional neural network (CNN) and recurrent neural network (RNN) are two of fundamental networks in deep learning. Deep voxel flow (DVF) adopts a fully-convolutional encoder-decoder architecture for video frame synthesis (Liu et al. 2017). To decouple the background
scene and moving objects for understanding the complex scene dynamics, generative adversarial network (GAN) is employed along with CNN (Wu et al. 2020). However, CNN is weak at capturing long-term dependencies, while RNN can handle it well. The work in Srivastava, Mansimov, and Salakhudinov (2015) proposes a composite model that combines both input reconstruction and future prediction, where an encoder-decoder-predictor architecture based on long short-term memory (LSTM) is employed. Nevertheless, the plain RNN architecture cannot capture spatial dependencies well, which motivates the combination of CNN and RNN.

Recurrent convolutional neural network (rCNN) introduces CNN layers into the RNN cell to better handle spatial correlations, and replaces single image patch with nearby patches to better capture temporal dependencies (Ranzato et al. 2014). Convolutional LSTM (ConvLSTM) further extends the idea of rCNN by applying convolutional structures in both the input-to-state and state-to-state transitions, which establishes a seminal framework for spatiotemporal predictive learning. Predictive recurrent neural network (PredRNN) designs a zigzag memory flow that propagates in both bottom-up and top-down direction across all layers, which aims to communicate the learned visual dynamics at different levels (Wang et al. 2017). The improved predictive recurrent neural network (PredRNN++) proposes a new recurrent structure named Causal LSTM for modeling short-term dependencies, which adds more non-linear layers to recurrent transition and employs a gradient highway unit (GHU) to alleviate the vanishing gradient problem (Wang et al. 2018a). EIDETIC 3D LSTM (E3D-LSTM) introduces 3D-convolution into the LSTM cell to capture short-term dependencies more efficiently (Wang et al. 2018b). PredRNN-V2 further improves PredRNN by decoupling the interlayer spatiotemporal memory and inner-layer temporal memory in latent space and proposes a new curriculum learning strategy (Wang et al. 2021). Spatiotemporal convolutional long short-term memory (ST-ConvLSTM) adds an attention block into the LSTM cell so as to model long-range and long-term spatiotemporal dependencies (Zhong et al. 2020). Similarly, self-attention ConvLSTM (SA-ConvLSTM) employs a more complicated self-attention memory into the LSTM cell to capture long-range dependencies efficiently (Lin et al. 2020). Though numerous variants of ConvLSTM have been developed, these methods suffer from heavy computation burden such as time and long back-propagation process due to the seriality of recurrent structure.

Another line of research relevant to our work is based on Transformer (Vaswani et al. 2017), which was originally proposed in natural language processing (NLP) and soon transferred to the field of computer vision including spatiotemporal predictive learning. Compared with RNN based methods, Transformer can capture long-term dependencies efficiently and can be implemented in parallel, which achieves both good performance and fast training speed. Convolutional Transformer (ConvTransformer) (Liu et al. 2020) adopts a similar encoder-decoder form as the one in (Vaswani et al. 2017), where both encoder and decoder are stacked by multiple Transformer blocks to capture the long-range spatial and temporal dependencies. Such an encoder-decoder architecture usually leads to very deep networks and thus leads to huge computational resource. In contrast, “spatio-temporal Transformer” (ST-Transformer) stacks multiple Transformer blocks to encode input frames, where both spatial attention and temporal attention are employed to extract spatiotemporal dependencies for 3D human motion prediction (Aksan et al. 2020). However, the fully linear layers adopted in ST-Transformer is lack of short-term dependencies, which limits its applicability.

In summary, there are different drawbacks in prior models for spatiotemporal predictive learning, which motivates us to develop the 3D-temporal convolutional Transformer network (TCTN). TCTN uses only a Transformer based encoder where 3D-temporal convolutional layers (Lea et al. 2016) are employed to extract short-term dependencies and masked self-attention layers are used to capture long-term dependencies. Meanwhile, the 3D-temporal convolutional operation is suit for the sequence masked mechanism in self-attention naturally, which can be combined without loss of parallelism. In this way, TCTN is applied successfully to spatiotemporal predictive learning with good performance and fast training speed.

**Methods**

**Overview**

Spatiotemporal predictive learning is to generate future frames given a sequence of historical frames. Formally, given a frame sequence of length $J$ denoted as $X = \{X_{t-1}, \ldots, X_t\}$ where $X_t \in \mathbb{R}^{H \times W \times C}$ is the frame with $H$-height $W$-width and $C$-channel at time $t$, the goal is to generate the most probable length-$K$ sequence in the future:

$$\hat{X}_{t+1}, \ldots, \hat{X}_{t+K} = \arg \max_{X_{t+1}, \ldots, X_{t+K}} P(X_{t+1}, \ldots, X_{t+K} | X),$$

(1)

where $P(\cdot | \cdot)$ represents the conditional probability. We define the predicted sequence as $\hat{X} = \{\hat{X}_{t+1}, \ldots, \hat{X}_{t+K}\}$ for simplicity.

To solve this, we propose 3D-temporal convolutional Transformer network (TCTN). Concretely, we first employ a spatial embedding to capture a coarse short-range spatial dependencies. Then, the spatiotemporal encoder takes advantage of the self-attention mechanism and 3D-temporal convolution operation to extract short-term and long-term dependencies. Finally, a linear transformation is employed to generate future frames. The overview of TCTN is given in Figure 1.

**Spatial Embedding**

In spatial embedding block, historical frames $X$ are fed to two convolutional layers to capture coarse short-range spatial dependencies, where a short-cut is added to prevent vanishing gradient (He et al. 2016). The mathematical description is given in Eq. (2):

$$G = \sigma(W_{E1} \ast X),$$

$$M = \sigma(W_{E2} \ast G) + G,$$

(2)
where $M \in \mathbb{R}^{J \times H \times W \times D}$ represents feature maps with $D$ channels, $W_{E1}$ and $W_{E2}$ are the convolutional kernels, $\sigma(\cdot)$ represents the leaky rectified linear unit (LReLU) activation function and $\ast$ denotes the 2D convolution operation.

Then, we take positional encoding to add some information about relative or absolute position of input frames as in (Liu et al. 2020). To be specific, the positional encoding is given in Eq. (3) and (4):

$$P_{j, h, w, 2d} = \sin(j/10000^{2d/D}),$$
$$P_{j, h, w, 2d+1} = \cos(j/10000^{2d/D}),$$

where $j \in [1, J]$, $h \in [1, H]$, $w \in [1, W]$, and $d$ denotes the channel dimension.

Finally, we apply element-wise addition to the feature map and the positional encoding as the input of the following encoder:

$$E = M \oplus P,$$

where $\oplus$ represents the element-wise addition.

### Spatiotemporal Encoder

Motivated by (Lea et al. 2017), we modify the standard Transformer block (Vaswani et al. 2017) by introducing 3D-temporal convolution into the self-attention layer and feed forward layer. And we take the first modified Transformer block as an example to describe how the block performs.

Concretely, we first apply layer normalization $LN(\cdot)$ proposed by (Ba, Kiros, and Hinton 2016) on inputs of the encoder and obtain $\hat{E} = LN(E)$. Then, we send it to temporal convolutional self-attention layer (TC Self-Attention), where 3D-temporal convolution is first applied to obtain the query $Q \in \mathbb{R}^{J \times H \times W \times D}$, key $K \in \mathbb{R}^{J \times H \times W \times D}$ and value $V \in \mathbb{R}^{J \times H \times W \times D}$ as follows:

$$Q = W_q \ast \hat{E},$$
$$K = W_k \ast \hat{E},$$
$$V = W_v \ast \hat{E},$$

where $W_q$, $W_k$ and $W_v$ represent the trainable 3D-temporal convolutional kernels. With slight abuse of notation, we also denote $\ast$ as the 3D-temporal convolution operation. Compared with the plain linear transformation in the standard Transformer block, short-term dependencies can be captured better with the 3D-temporal convolution operation. Meanwhile, the intrinsic property that only considers previous frames makes 3D-temporal convolution free of future frames leaking and naturally suit for the following masked self-attention structure. The masked self-attention mechanism is based on scaled dot-product attention method as given in Eq. (9):

$$A = \text{Softmax} \left( \text{Mask}(\frac{QK^T}{\sqrt{D}}) \right) V,$$

where $\text{Mask}(\cdot)$ is introduced to prevent leftward information flow to preserve the auto-regressive property, i.e., consumes the previously generated frame as additional input when generating the next one. Actually, the masked self-attention is one-head variant of multi-head attention in the standard Transformer network. We use only one head because it is better than multiple heads (e.g. 2, 4, and 8 heads) in our observations. In this way, long-term dependencies can be extracted for spatiotemporal predictive learning. Thereafter, with $\hat{A}$ produced by a linear transformation on $A$, a regular shortcut operation is employed to alleviate vanishing gradient issue, which is performed as $S = E \oplus \hat{A}$.

With layer normalization performed on $S$ as $\hat{S} = LN(S)$, we pass $\hat{S}$ to the temporal convolutional feed forward layer.

Figure 1: The overview of TCTN with $N$ Transformer blocks.
Figure 2: (a) 3D-temporal convolutional network (TCN) takes advantage of only previous inputs to generate each feature map, and thus prevent leakage of future information. (b) Temporal convolutional self-attention (TC Self-Attention) employs TCN and scaled dot-product attention to capture both short-term and long-term dependencies.

(TC Feed Forward), where the regular fully connected structure is replaced by 3D-temporal convolution for capturing short-term and short-range dependencies better as shown in Eq. (10):

\[ F = W_{F2} \ast (\sigma(W_{F1} \ast \hat{S})) \]

where \( \sigma(\cdot) \) denotes the LReLU activation function, \( W_{F1} \) and \( W_{F2} \) represent the 3D-temporal convolutional kernels.

Then, a regular shortcut operation is also added as the input of next Transformer block.

With multiple Transformer blocks stacked, short-term and long-term dependencies can be both captured, including short-range dependencies. We denote the output of the final Transformer block as \( Z \in \mathbb{R}^{J \times H \times W \times D} \).

During the training process, we also employ dropout technique (Srivastava et al. 2014) onto the output of each sub-layer including the attention score produced by Softmax(\( \cdot \)).

Frame Forecaster

With historical length-\( J \) frames, we aim to generate the most probable length-\( K \) frames. It can be achieved by a linear transformation as given in Eq. (11):

\[ \hat{X} = ZW_{\hat{X}} \]

where \( W_{\hat{X}} \) represents the learnable weight.

During the training process, we take \( \{X_{t-J+1}, \ldots, X_{t+K-1}\} \) as input to generate the most probable \( \{\hat{X}_{t-J+2}, \ldots, \hat{X}_{t+K}\} \) for computing training loss.

During the process of inference, we generate \( \hat{X} \) frame by frame. Concretely, we take \( \{X_{t-J+1}, \ldots, X_{t}\} \) to generate \( \hat{X}_{t+1} \) and concatenate it to form \( \{X_{t-J+1}, \ldots, X_{t}, \hat{X}_{t+1}\} \) as the next input. After applying it repeatedly, we can generate the future length-\( K \) frames successfully.

Experiments

Dataset

To validate our proposed algorithm, we conduct experiments on a synthetic MovingMNIST dataset and a real-world KTH (Schuldt, Laptev, and Caputo 2004) dataset. Their basic information is given as follows:

- MovingMNIST: we generate a 20-frames long dataset as described in (Srivastava, Mansimov, and Salakhudinov 2015). Specifically, each frame contains two handwritten digits that are selected randomly from the training set of MNIST dataset\(^1\) and bounce inside a 64 \( \times \) 64 patch. Their initial positions and velocity directions are chosen uniformly randomly with the velocity amplitude chosen uniformly randomly in [3, 5]. The previous 10 frames are used for input while the rest 10 frames are targets of prediction. We train TCTN with 2000, 10000 and 50000 sequences, respectively, and test it with 3000 sequences.

- KTH: it records 6 types of human actions performed by 25 persons in 4 different scenarios, which involves walking, jogging, running, boxing, hand-waving and hand-clapping. With a static camera in a frame rate of 25 FPS, the videos are 4 seconds long on average. We divide persons 1-16 for training and persons 17-25 for testing, where each frame is resized to 64 \( \times \) 64. Further, the first frame is restricted to containing someone’s appearance.

\(^1\)http://yann.lecun.com/exdb/mnist/
Table 1: Performances on the MovingMNIST dataset, where high values of PSNR and SSIM represents good performances while low values of MAE represent good performances.

| MODEL                   | PSNR  | SSIM  | MAE   | PSNR  | SSIM  | MAE   | PSNR  | SSIM  | MAE   |
|-------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|                         | 2000 sequences | 10000 sequences | 50000 sequences |
| ConvLSTM (Shi et al. 2015) | 18.55 | 0.861 | 147.07 | 21.04 | 0.89  | 112.96 | 24.44 | 0.943 | 71.77 |
| ST-ConvLSTM (Zhong et al. 2020) | 18.66 | 0.86 | 141.93 | 22.35 | 0.920 | 89.37  | 23.62 | 0.933 | 78.3  |
| SA-ConvLSTM (Lin et al. 2020)       | 17.829 | 0.83 | 166.16 | 18.526 | 0.74 | 183.39 | 21.68 | 0.75  | 177.03 |
| ConvTransformer (Liu et al. 2020) | 18.93 | 0.728 | 210.63 | 18.526 | 0.74 | 183.39 | 21.68 | 0.75  | 177.03 |
| PredRNN-V2 (Wang et al. 2021) | 20.52 | 0.862 | 126.77 | -     | -     | -     | 23.78 | 0.933 | 78.66 |
| TCTN                    | 20.40 | **0.886** | **122.09** | 23.44 | **0.926** | 83.73 | **25.4** | **0.945** | **66.43** |

The task is also to predict future 10 frames given previous 10 frames. Finally, we obtain a training set of 8488 sequences and a test set of 5041 sequences.

**Compared Models & Metrics**

We adopt the ConvLSTM (Shi et al. 2015) as the baseline while involving more advanced video prediction models for further comparison, including

- SA-ConvLSTM (Lin et al. 2020), ST-ConvLSTM (Zhong et al. 2020), PredRNN-V2 (Wang et al. 2021) for comparison of RNN-based methods, where SA-ConvLSTM and PredRNN-V2 are claimed state-of-the-art (SOTA), respectively.
- ConvTransformer (Liu et al. 2020) for comparison of the Transformer-based method.

To measure the performance of methods, we adopt the following metrics:

- Peak Signal to Noise Ratio (PSNR): estimates the pixel-level similarity between the predicted frames and the true ones. The higher it is, the better it is.
- Structural Similarity Index Measure (SSIM) (Wang et al. 2004): estimates the similarity of structural information within the spatial neighbors. The higher it is, the better it is.
- Mean Absolute Error (MAE): estimates the difference between the predicted frames and the true ones. The lower it is, the better it is.

**Implementation Detail**

We conduct all the experiments with Intel Xeon(R) Gold 6132 CPU @2.60GHz, four NVIDIA V100 GPUs and 240GB memory. The operating system is CentOS 7.4.1708. For each method, we implement it with six layers or blocks with $D = 128$. Further, the size of 3D-temporal convolutional kernel in TCTN is $3 \times 3 \times 3$ while the size of convolutional kernel in the rest is set as $5 \times 5$ for fairness. We set the mini-batch as 8 for all the methods. The dropout is set as 0.1 in TCTN.

We select mean square error (MSE) as the loss function for all the methods. We further adopt the ADAM optimizer with $10^{-4}$ learning rate and the cosine annealing schedule (Loshchilov and Hutter 2016) to train our proposed TCTN while compared models are trained as described in their papers. We train all the networks with 80 and 150 epochs, respectively, and select the best one of each.

**Results**

**MovingMNIST.** The results of MovingMNIST dataset are given in Table 1. As for 50000 sequences setting, we give up PredRNN-V2 due to its too long training time over 20 days. We can see that TCTN outperforms other methods in most settings, especially in SSIM and MAE under 2000 sequences setting and all metrics under 50000 sequences setting.

We further plot frame-wise metrics of MovingMNIST dataset under 2000 sequences setting in Figure 3 where the x-axis represents the time step of future 10 frames and the y-axis is the metric for measuring the performance of pre-
dicted frames. The results show that TCTN generates the best predicted frames initially in PSNR while achieving the best frames almost all the time in SSIM and MAE.

To exhibit performances of difference methods directly, we sample a sequence from the test set under 2000 sequences and show the predicted frames of different methods in Figure 5. Note that TCNT can keep a clear and similar structure of digits as the true future frames especially in the last two frames, while other methods fail to track the dynamics exactly.

Figure 5: Predicted frames on MovingMNIST dataset under 2000 sequences setting

KTH. We evaluate the performance of different methods with PSNR and SSIM. The results are given in Table 2. We can see that TCTN achieves the highest performance compared with other models in SSIM.

We further sample a sequence from the test set of KTH dataset to show performances of different methods directly as given in Figure 6. As the process of prediction continues, most of the frames produced by the compared models become severely blurred while TCTN can still maintain a relatively clear structure of the person.

Training Speed. Since our proposed network is implemented in parallel, it is trained in a much faster speed

Table 2: Performances on KTH dataset

| MODEL                  | PSNR  | SSIM  |
|------------------------|-------|-------|
| ConvLSTM (Shi et al. 2015) | 23.82 | 0.701 |
| ST-ConvLSTM (Zhong et al. 2020) | 24.37 | 0.714 |
| SA-ConvLSTM (Lin et al. 2020) | 26.62 | 0.830 |
| PredRNN-V2 (Wang et al. 2021) | 25.28 | 0.829 |
| ConvTransformer (Liu et al. 2020) | 28.02 | 0.815 |
| TCTN                   | 25.38 | 0.832 |

Table 3: The comparisons of training time for 100 iterations.

| MODEL                  | Time (s) |
|------------------------|----------|
| ConvLSTM (Shi et al. 2015) | 84       |
| ST-ConvLSTM (Zhong et al. 2020) | 187     |
| SA-ConvLSTM (Lin et al. 2020) | 142     |
| PredRNN-V2 (Wang et al. 2021) | 375     |
| ConvTransformer (Liu et al. 2020) | 80      |
| TCTN                   | 45       |
compared with RNN-based methods. Meanwhile, TCTN requires less neural networks compared with encoder-decoder like Transformer-based method, which also leads to a faster training speed.

To compare the training speed of different methods, we count up the training time of 100 iterations for each method. The result is given in Table 2. The result shows that TCTN is 8 times faster than the state-of-the-art (SOTA) method, PredRNN-V2 [Wang et al., 2021], which consumes more than 375 seconds. Compared with ConvTransformer which achieves the highest training speed with the price of the poorest performance, TCTN is still 2 times faster.

We further calculate the full training time of MovingMNIST dataset under 2000, 10000 and 50000 training sequences, respectively. The result is given in Figure 4. Compared with other methods, TCTN always consumes the least training time with almost the best performance. Thus, TCTN outperforms SOTA methods in both performance and training speed.

Conclusion

In this paper, we propose a 3D-temporal convolutional Transformer network (TCTN) for spatiotemporal predictive learning, which combines Transformer and 3D-temporal convolutional network to capture short-term and long-term dependencies efficiently. Meanwhile, TCTN can achieve faster training speed compared with RNN based methods thanks to the parallel mechanism of Transformer. We further conduct experiments on MovingMNIST and KTH dataset to validate our proposed method. The results show that TCTN outperforms state-of-the-art (SOTA) methods in both performance and training speed.

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