NRTR: A No-Recurrence Sequence-to-Sequence Model For Scene Text Recognition

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Abstract

Scene text recognition has attracted a great many researches for decades due to its importance to various applications. Existing sequence-to-sequence (seq2seq) recognizers mainly adopt Connectionist Temporal Classification (CTC) or Attention based Recurrent or Convolutional networks, and have made great progresses in scene text recognition. However, we observe that current methods suffer from slow training speed because the internal recurrence of RNNs limits training parallelization, and high complexity because of stacking too many convolutional layers in order to extract features over long input sequence. To tackle the above problems, this paper presents a no-recurrence seq2seq model, named NRTR, that relies only on the attention mechanism dispensing with recurrences and convolutions entirely. NRTR consists of an encoder that transforms an input sequence to the hidden feature representation, and a decoder that generates an output sequence of characters from the encoder output. Both of the encoder and the decoder are based on self-attention module to learn positional dependencies, which could be trained with more parallelization and less complexity. Besides, we also propose a modality-transform block to effectively transform the input image to the corresponding sequence, which could be used by the encoder directly. NRTR is end-to-end trainable and is not confined to any predefined lexicon. Extensive experiments on various benchmarks, including the IIIT5K, SVT and ICDAR datasets, show that NRTR achieves the state-of-the-art or highly-competitive performances in both lexicon-free and lexicon-based scene text recognition tasks, while requiring only one order of magnitude less time for model training compared to current methods.

1 Introduction

Scene text recognition, which aims to read texts in natural images, has drawn increasing interests from both multimedia and computer vision. The popularity is mainly due to its essential role in extracting rich semantic information that is highly relevant to scene or object, and therefore it has been applied to a wide range of applications, such as geo-location, caption reading, augmented reality and image interpretation. Although extensive studies have been carried out in the past few years, text recognition in natural scene is still challenging due to several difficulties, e.g., low resolution (small texts), low visual quality (blur), complex geometric deformations and cluttered background, see Figure 1.

![Examples of complicated images and their text labels.](image)

Figure 1: Examples of complicated images and their text labels. Subfigures (a) - (f) represent normal, different sizes, blur, occlusion, cluttered background and complex geometric deformation respectively.

Unlike general objects that often occur in isolation, scene texts tend to appear in the form of sequences with variable lengths. Recent state of the arts \cite{Cheng et al., 2017, Shi et al., 2017, Shi et al., 2016, Lee and Osindero, 2016} usually apply sequence-to-sequence (seq2seq) models to encode input images and generate target texts, by means of recurrent neural network (RNN) with Connectionist Temporal Classification (CTC) \cite{Graves et al., 2006} or attention schemes. For CTC-based recognizers \cite{Shi et al., 2017, He et al., 2016}, RNN is first built to model sequential dependencies for each slice in feature sequence, then CTC is used to translate per-slice prediction produced by recurrent layers into a label sequence. For attention-based recognizers \cite{Cheng et al., 2017, Shi et al., 2016}, they mainly adopt the encoder-decoder framework, where the encoder transforms an input image into a sequence of feature vectors by CNNs or RNNs, and the decoder uses recurrent layers to generate target characters based on the history of target labels and the glimpse vectors computed by the attention network.
Although the above seq2seq models have shown great success in scene text recognition, they still suffer from some drawbacks. As RNN is effective to learn contextual information and capture long-term dependencies, it is indispensable in most existing methods. However, the inherently sequential nature of RNN confines it to depend on previous computation at each step, and can only predict outputs one by one. This mechanism precludes computation parallelization, and brings heavy time and computational burdens when the input image sequence is long, as memory constraints limit batching across examples. Besides, the training process of RNN is sometimes tricky due to the problem of gradient vanishing/exploding [Bengio et al., 1994].

The goal of reducing sequential computation forms the foundation of some latest recognizers [Gao et al., 2017; Yin et al., 2017]. They attempt to leverage CNN instead of RNN as the basic building block in their models. Convolutional layers apply filters over the entire sequence, and enable to compute hidden representations in parallel for all input and output positions. However, the number of operations required to relate signals from two arbitrary input or output positions grows along with the distance, specifically, linearly for the convolutional seq2seq model. This makes these recognizers difficult to learn dependencies among distant input positions [Hochreiter et al., 2001], especially for images whose widths are longer than 100, because it has to stack much more convolutional layers, which in turn increases the complexity of these methods.

To address the above dilemma, in this paper we present a no-recurrence seq2seq scene text recognizer, named NRTR, that dispenses with recurrences and convolutions entirely. Inspired by recent work Transformer [Vaswani et al., 2017] that relies solely on attention mechanism and is trained with more parallelization on the machine translation task, NRTR uses self-attention as its fundamental module, a mechanism relating various positions of a single sequence in order to compute a whole representation of the sequence. Since self-attention could draw global dependencies between different input and output positions at once rather than one by one in RNNs and the whole operation is reduced to a constant number unlike that in CNNs, it allows for significantly more computation parallelization, which is exactly needed by the seq2seq model in scene text recognition. NRTR follows the widely used encoder-decoder framework, and consists three major subnetworks: the encoder that uses stacked self-attention to transform an input sequence to the hidden feature representation, the decoder that also applies stacked self-attention but to generate an output sequence of characters based on the encoder output, and the proposed modality-transform block that is a preprocessing step to convert an input image to the corresponding input sequence, thus could be used by the encoder directly. To validate the proposed method, we conduct extensive experiments on four widely used benchmarks, including the IIIT5K, SVT and ICDAR datasets. Results in both lexicon-free and lexicon-based cases demonstrate that, compared with 22 existing methods, NRTR achieves the state-of-the-art or highly-competitive performances accompanied with one order of magnitude less time for model training.

Main contributions of this paper are summarized as follows:

- We point out, for the first time, two existing problems lying in current seq2seq models that severely affect the accuracy and efficiency of scene text recognition, i.e., the parallelization problem in RNNs-based recognizers and the complexity problem in CNNs-based recognizers.
- We propose a no-recurrence seq2seq model dispensing with recurrences and convolutions entirely to solve the above problems, where the whole architecture is based on self-attention module and could be trained with more computation parallelization and less complexity.
- We come up with a novel modality-transform block to map an input image to the corresponding encoding sequence, combined with the encoder, to extract more discriminative features.
- We conduct extensive experiments on various benchmarks, which demonstrate the superiority of our model over the current state-of-the-arts in both accuracy and training speed.

2 Related Work

Scene text recognition has attracted many studies over the past years, and quite a few of literatures have been reported. Comprehensive surveys could refer to Ye and Doermann, 2015; Zhu et al., 2016. Generally, there are two types of text recognizers: treating text images as general objects in most traditional works or as sequence objects in largely recent works.

Among the traditional models, many adopt the bottom-up scheme by first detecting individual characters using sliding window [Wang et al., 2011; Wang and Belongie, 2010], connected components [Neumann and Matas, 2012], or Hough voting [Yao et al., 2014], then integrating these characters into the output text by means of dynamic programming, lexicon search [Wang et al., 2011], etc. Others adopt the top-down scheme, where text is directly recognized from the original image, rather than split into single characters and then detected one by one [Almazán et al., 2014; Jaderberg et al., 2014a; Jaderberg et al., 2016]. For example, Almazán et al. [Almazán et al., 2014] propose to predict label embedding vectors from input images. Jaderberg et al. [Jaderberg et al., 2016] treat scene text recognition as an image classification problem, and assign a class label to each English word (90k words in total).

As for recent models, they tend to regard scene text recognition as a sequence recognition problem, where images and texts are separately represented as patch sequences and character sequences. Su et al. [Su and Lu, 2014] extract sequences of HOG features to represent images, and predict their corresponding character sequences with RNN. Shi et al. [Shi et al., 2017] propose an end-to-end trainable sequence recognition network, which combines CNN and RNN to learn the spatial dependencies, and uses CTC to translate the per-slice prediction into a label sequence. They also develop an attention-based spatial transformer network to rectify text distortion that is robust to irregular text [Shi et al., 2016]. Besides, Lee et al. [Lee and Osindero, 2016] and Cheng et al. [Cheng et al., 2017] both construct attention-based recurrent
Figure 2: (left) Scaled Dot-Product Attention with a simple illustration of its running process. (right) Multi-Head Attention consists of multiple Scaled Dot-Product Attention running in parallel.

network to decode feature sequence and predict labels recurrently. Instead of RNNs, Gao et al. [Gao et al., 2017] and Yin et al. [Yin et al., 2017] rather apply stacked convolutional layers solely to sequence modeling, for the pursuit of greater computational parallelism.

In this paper, we also adopt the sequence scheme, but present a no-recurrence seq2seq recognizer dispensing with RNNs and CNNs, which is quite different from the above existing approaches. Our model is inspired by the latest framework, named Transformer [Vaswani et al., 2017], that uses solely self-attention mechanism as its fundamental module, to draw global dependencies between input and output. The Transformer has shown great superiority of parallelism and efficiency on machine-based English-to-French translation task. We argue that these properties are also exactly desired by the seq2seq modeling in scene text recognition, and propose a no-recurrence recognizer by introducing them with necessary modifications in order to tackle our task. To the best of our knowledge, this is the first work of scene text recognition that relies entirely on self-attention to compute representations of its input and output, without using sequence-aligned RNNs or CNNs.

3 Proposed Model

The proposed NRTR follows the encoder-decoder framework widely used in previous seq2seq text recognizers. Here, the encoder transforms an input sequence of image representations \((x_1, \ldots, x_T)\) to the hidden feature representation \(h = (h_1, \ldots, h_T)\). Given \(h\), the decoder then generates an output sequence \((y_1, \ldots, y_T)\) of characters. NRTR uses stacked self-attention and point-wise, fully connected layers for both the encoder and decoder, as shown in the left and right halves of Figure 3 respectively. We will elaborate these core modules and the overall architecture of NRTR.

3.1 Core Modules of NRTR

Scaled Dot-Product Attention
Self-attention is an attention mechanism that extracts useful information from different positions of an input sequence for each position of the outputs. Specifically, it has three inputs: queries, keys and values. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a designed function of the query with the corresponding key. Here, we use Scaled Dot-Product Attention, an effective self-attention mechanism demonstrated in [Vaswani et al., 2017]. As shown in the left half of Figure 2, queries, keys and values are represented as \(K \in t_k \times d_k\), \(Q \in t_q \times d_q \) and \(V \in t_v \times d_v \) respectively, where \(t_*\) means element numbers of corresponding inputs and \(d_*\) is the corresponding element dimensions. In general, we set \(t_k = t_v\) and \(d_q = d_k\). Thus, the outputs are computed as:

\[
\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V
\]  

Note that the scalar \(\frac{1}{\sqrt{d_k}}\) is used to prevent softmax function into regions where it has extremely small gradients.

Multi-Head Attention
Multi-head attention is one of the core module of NRTR, allowing the model to jointly attend to information from different representation subspaces at different positions. As depicted in the right half of Figure 2, multi-head attention uses \(h\) times Scaled Dot-Product Attention, where \(h\) is called the head number. Before performing each attention, there are three different linear projections to linearly project the queries, keys, and values to more discriminative representations respectively. Then each Scaled Dot-Product Attention is performed in parallel, and their outputs are concatenated.
and once again projected to get the final $d_{\text{model}}$-dimensional outputs:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h) W^O$$ (2)

where $\text{head}_i = \text{Attention}(Q W^Q_i, K W^K_i, V W^V_i)$

Since $Q, K, V$ have the same dimension of $d_{\text{model}}$, the predictions are parameter matrices $W^Q_i \in d_{\text{model}} \times d_k$, $W^K_i \in d_{\text{model}} \times d_k$, $W^V_i \in d_{\text{model}} \times d_v$ and $W^O \in d_v \times d_{\text{model}}$, where $d_c = h \times d_v$ and in this paper, $d_q = d_k = d_v = d_{\text{model}}/h$.

Position-wise Feed-Forward Network

Position-wise feed-forward network is another core module of NRTR. It consists of two linear transformations with a RELU activation in between.

$$\text{FFN}(x) = \max (0, x W_1 + b_1) W_2 + b_2$$ (3)

where the weights are $W_1 \in d_{\text{model}} \times d_{ff}$ and $W_2 \in d_{ff} \times d_{\text{model}}$, and the bias are $b_1 \in d_{ff}$ and $b_2 \in d_{\text{model}}$. The linear transformations are the same across different positions.

3.2 Overall Architecture

The overall architecture of NRTR contains an encoder, a decoder and the proposed modality-transform block. Based on the above core modules, the details of these components are as follows.

Modality-Transform Block

Before the proposed seq2seq model, we put forward a modality-transform block to transform an input image to the corresponding sequence. As a preprocessing step, this process is also known as input encoding, because only after that the resulted image sequence could be fed into the encoder directly. Specifically, the proposed modality-transform block consists of several basic layers, e.g., convolution or recurrence, as the main component. For each input image, it goes through these layers for dimensions conversion. Then a concatenation operation is leveraged to reshape the previous result into an encoder-length vector, each element of which has $d_{\text{model}}$-dimension. Thus the final output could flow into the encoder for the following seq2seq modeling. Intuitively, considering memory consumption, there are simply two convolutional layers with more than one strides. We also apply other layers, like convolutional LSTM layer (CNNLSTM) [Zhang et al., 2017], for possibly better image feature extraction. More information is detailed in Section 4.3.2.

Encoder

As shown in the left half of Figure 3 at the bottom of the encoder, besides the input encoding, there is a positional encoding. Since our seq2seq model contains no recurrence and no convolution, in order to make use of the order of the sequence, the $d_{\text{model}}$-dimensional positional encoding is added to the input encoding.

where pos indicates the position in sequence and $i$ indicates the $i$-th dimension. We choose this function since for arbitrary fixed offset $k$, $PE_{\text{pos}+k}$ can be represented as a linear function of $PE_{\text{pos}}$. After that we get the final encoder input by adding the positional encoding to the input encoding.

The encoder body is a stack of $N_e$ number identical encoder-blocks, each of which has two sub-layers: the first a multi-head self-attention mechanism whose queries, keys and values come from the outputs of the previous block, and the second a simple, position-wise fully connected feed-forward network. Meanwhile, layer normalization and residual connection are introduced into each sub-layer for effective training. Given each sub-layer $x$, the corresponding outputs are:

$$\text{LayerNorm}(x + \text{Sublayer}(x))$$ (4)

Decoder

As shown in the right half of Figure 3 at first we use a learned character-level embedding to convert the input character targets to vectors of dimension $d_{\text{model}}$. The resulted sequences are then added with the positional encoding, and fed into a stack of $N_d$ number identical decoder-blocks to get the final decoder outputs. Different from the encoder block, each decoder-block has three sub-layers: the first a masked multi-head attention to ensure that the predictions for position $j$ can only depend on the known outputs at positions less than $j$, the second a multi-head attention whose keys and values come from the encoder outputs, and queries come from the previous decoder block outputs, and the third also a position-wise feed-forward network. As in the encoder, layer normalization and residual connection are performed to each sub-layer in the decoder. And at last, the decoder outputs are transformed to the probabilities of output classes by a linear projection and a subsequent softmax function.

3.3 Lexicon-free/based Recognition

At inference stage, there are two modes of converting the per-slice prediction made by the decoder into a label sequence, namely the lexicon-free and lexicon-based recognitions. In the lexicon-free (unconstrained) text recognition, we straightforwardly select the character with the highest probability. While in the lexicon-based (constrained) recognition, normally the prediction is generated by choosing the word with the highest probability distribution according to one of the pre-defined lexicons of different sizes, like lexicon-50 and lexicon-1k etc. However, computing iteratively over all lexicon words is time-consuming. We instead adopt an approximate method [Gao et al., 2017] by comparing the edit distance between the predicted sequence in the lexicon-free setting and words in the lexicon, then choosing the word with the smallest distance as the output label.

4 Experiment

To evaluate the effectiveness of the proposed NRTR, we conduct experiments on a number of standard benchmarks commonly used in the literature. The datasets for training and testing are given in Sec.4.1, the detailed implementation is provided in Sec.4.2, and the results with comprehensive ablation study and comparisons are reported in Sec.4.3 and Sec.4.4 respectively.
4.1 Datasets
For all the experiments on the proposed method, we use the synthetic dataset (Synth) released by Jaderberg et al. [Jaderberg et al., 2014] at training stage. Synth contains 8 millions synthetic scene-text images, each of which has an text overlaid on appropriate background regions sampled from natural images. These texts look realistic, as the overlaying follows laid on appropriate background regions sampled from natural.

Our method is evaluated on four public benchmarks: IIIT 5K-Words (IIIT5K), Street View Text (SVT), ICDAR 2003 (IC03) and ICDAR 2013 (IC13).

IIIT5K [Mishra et al., 2012] contains 3000 cropped text images in its test set. It is collected from the Internet and each text image has a 50-word lexicon and a 1k-word lexicon, both of which include the ground truth words and other randomly picked words.

SVT [Wang et al., 2011] contains 647 cropped text images in its test set. It is collected from Google Street View and many images are severely corrupted by noise and blur, or have very low resolutions. Each image has a 50-word lexicon defined by Wang et al. [Wang et al., 2011].

IC03 [Lucas et al., 2005] contains 251 scene images labeled with text bounding boxes. For fair comparison, similar to [Wang et al., 2011], we discard images that either contain non-alphanumeric characters or have less than three characters. The resulting dataset contains 860 cropped text images, each of which is associated with a 50-word lexicon defined by Wang et al. [Wang et al., 2011]. Besides, a full lexicon is built by combining all the per-image lexicons.

IC13 [Karatzas et al., 2013] inherits most of its data from IC03. After filtering samples as done in IC03, the dataset contains 857 cropped text images in its test set.

4.2 Implementation Details
NRTR is trained purely on the Synth dataset, and evaluated on all above four real-world benchmarks without any fine-tuning on their training sets. In both training and inference stages, heights of the word images are set to 60, while widths are proportionally scaled with heights. Following the evaluation protocol in [Wang et al., 2011], we perform recognition on word images that contain only alphanumeric characters and at least three characters. The output alphabet of target text consists of 38 classes, including 26 lowercase letters, 10 digits, space and end-of-sequence token.

In training stage, samples are batched together by approximate lengths of input encoding sequences. Each training batch includes a set of sentence pairs containing approximately 20000 image tokens and target tokens. We use the Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.98$, $\epsilon = 10^{-9}$, and vary the learning rate over the course of training, according to the formula:

$$lrate = d^{-0.5} \cdot \min\left(n^{-0.5}, n \cdot \text{warmup}_n^{-1.5}\right)$$

where $n$ represents the current training step number and \text{warmup}_n controls over the learning rate firstly increase and then decrease. We use $\text{warmup}_n = 16000$. In order to prevent over-fitting, we set residual dropout to 0.1, where it is applied to the output of each sub-layer before adding the residual information. We train our model on one machine with an NVIDIA Titan X GPU for a total of 120k steps, that is about 6 epochs before convergence. After training, we average the last 10 checkpoints, which are written at 10-minute intervals in Tensorflow framework [Abadi et al., 2016]. Then we perform decoding as mentioned in Section 3.3.

4.3 Ablation Study
In this section, we empirically investigate the contributions made by the key components of the proposed method, namely: the architectures of the encoder and decoder, the position-wise feed-forward network and the modality-transform block. All experiments are executed following the same training strategies, and their performances are reported on unconstrained benchmarks.

Exploration of the core module architectures
We explore different super parameters of the core modules in NRTR, including the encoder block number $N_e$, the decoder block number $N_d$ and the feed-forward inner dimension $d_{ff}$. During the comparisons, the model dimension $d_{model} = 512$ and the head number $h = 8$ are kept unchanged, and the modality-transform block only contains two convolutional layers all the time. Experiment results are listed in Table 1.

In Table 1, we regard the 6enc6dec model as our baseline, where $N_e = 6$, $N_d = 6$ and $d_{ff} = 1024$. We first keep the total block number of the encoder and the decoder identical (6enc6dec), and find that the model with more encoder blocks achieves the better performance. We then deepen the encoder/decoder by adding more blocks (8enc4dec, 10enc5dec, 12enc6dec), and see that the deepest model (12enc6dec) obtains the highest accuracy. We no longer increase the block number consid-

| Model                  | IIIT5K | SVT  | IC13 | IC03 |
|------------------------|--------|------|------|------|
| base model with 2Conv  | 85.4   | 86.8 | 93.5 | 92.8 |
| base model with 3Conv  | 84.4   | 87.0 | 93.7 | 93.5 |
| base model with 7Conv  | 77.4   | 89.2 | 89.1 | 89.5 |
| base model with 2CNNLSTM| 85.5   | 86.0 | 94.1 | 94.4 |

| Model                  | IIIT5K | SVT  | IC13 | IC03 |
|------------------------|--------|------|------|------|
| big model with 2Conv   | 86.5   | 88.3 | 95.4 | 94.7 |
| big model with 2CNNLSTM| 84.7   | 84.8 | 94.1 | 93.4 |

Table 1: Performance of different modality-transform blocks on unconstrained benchmarks.
h/GPU’ indicates the time cost per epoch at training stage on their GPUs.

## Table 3: Recognition accuracies (%) and training time on four benchmarks. “50”, “1k” and “Full” are lexicon sizes. “None” means the lexicon-free case.

| Methods        | IIT5K          | SVT            | IC03           | IC13           | Train-Time |
|----------------|----------------|----------------|----------------|----------------|-------------|
|                | 50 | 1k | None | 50 | None | 50 | Full | None | None | h/GPU |
| ABBYY [Wang et al., 2011] | 24.3 | - | - | 35.0 | - | 56.0 | 55.0 | - | - | - |
| Wang et al. [Wang et al., 2011] | - | - | - | 57.0 | - | 76.0 | 62.0 | - | - | - |
| Mishra et al. [Mishra et al., 2012] | 64.1 | 57.5 | - | 73.2 | - | 81.8 | 67.8 | - | - | - |
| Wang et al. [Wang et al., 2012] | - | - | - | 70.0 | - | 90.0 | 84.0 | - | - | - |
| Goel et al. [Goel et al., 2013] | - | - | - | 77.3 | - | 89.7 | - | - | - | - |
| Bissacco et al. [Bissacco et al., 2013] | - | - | - | 90.4 | 78.0 | - | - | 87.6 | - | - |
| Alsharif and Pineau et al. [Alsharif and Pineau, 2013] | 91.2 | 82.1 | - | 89.2 | - | - | - | - | - | - |
| Altmazin et al. [Altmazin et al., 2014] | 80.2 | 69.3 | - | 75.9 | - | - | 80.3 | - | - | - |
| Yao et al. [Yao et al., 2014] | 76.1 | 57.4 | - | 70.0 | - | - | - | - | - | - |
| Rodriguez-Serrano et al. [Rodriguez-Serrano et al., 2015] | - | - | - | 86.1 | - | 96.2 | 91.5 | - | - | - |
| Jaderberg et al. [Jaderberg et al., 2014] | - | - | - | 83.0 | - | 92.0 | 82.0 | - | - | - |
| Su and Lu et al. [Su and Lu, 2014] | 93.3 | 86.6 | - | 91.8 | - | - | - | - | - | - |
| Jaderberg et al. [Jaderberg et al., 2016] | 97.1 | 92.7 | - | 95.4 | 80.7 | 98.7 | 98.6 | 93.1 | 90.8 | - |
| Jaderberg et al. [Jaderberg et al., 2014] | 95.5 | 89.6 | - | 93.2 | 71.7 | 97.8 | 97.0 | 89.6 | 81.8 | - |
| Shi et al. [Shi et al., 2015] | 97.6 | 94.4 | 78.2 | 96.4 | 80.8 | 98.7 | 97.6 | 89.4 | 86.7 | - |
| Shi et al. [Shi et al., 2016] | 96.2 | 93.8 | 81.9 | 95.5 | 81.9 | 98.3 | 96.2 | 90.1 | 88.6 | 16/Titan X |
| Lee et al. [Lee and Osindero, 2016] | 96.8 | 94.4 | - | 96.3 | 80.7 | 97.9 | 97.0 | 88.7 | 90.0 | - |
| Ghosh et al. [Ghosh et al., 2017] | - | - | - | 95.2 | 80.4 | 95.7 | 94.1 | 92.6 | - | - |
| Yin et al. [Yin et al., 2017] | 98.9 | 96.7 | 81.6 | 95.1 | 76.5 | 97.7 | 96.4 | 84.5 | 85.2 | - |
| Guo et al. [Guo et al., 2017] | 99.1 | 97.9 | - | 97.4 | 82.7 | 98.7 | 96.7 | 89.2 | 88.0 | - |
| Cheng et al. [Cheng et al., 2017] | 99.3 | 97.5 | 87.4 | 97.1 | 85.9 | 99.2 | 97.3 | 94.2 | 93.3 | 40/M40 |
| NRTR          | 99.2 | 98.8 | 86.5 | 98.0 | 88.3 | 98.9 | 97.9 | 95.4 | 94.7 | 2.8/Titan X |

**Figure 4:** Examples of the proposed modality-transform block. (left) The general CNN block. (right) The CNNLSTM block.

Exploration of the modality-transform block

We investigate the performance of adding different layers into the modality-transform block, and depict some structures of them in Figure 4. Firstly, we explore the block with different convolutional layer numbers. As described above, the base model contains two convolutional layers with strides 2 in the modality-transform block. When added with more layers, the accuracy of base model begins to decrease, see the first three columns in Table 2. We also apply a seven-layer convolutional network widely used in CRNN [Shi et al., 2017] and RARE [Shi et al., 2016], but get even worse results. The reason may be that more convolutional layers could extract more high-level information from input images, but also leads to the loss of much input details due to resolution subsampling. When the resulted sequence flowed into the encoder, it can not perform well as the information loss outweighs the gain from the increased convolutions. Because the encoder itself also has strong feature extraction ability, we prefer to apply a two-layer convolution in the modality-transform block, and combine it with the encoder to draw more discriminative features. Then we try to use CNNLSTM [Zhang et al., 2017] in the block, which could captures more temporal information by recurrent connections. Results show that it gets performance improvement in the base model, but a little reduction in the big model. The reason we analyze is probably due to the redundant extraction of image information when associates CNNLSTM with excessive encoder/decoder components.

### 4.4 Comparisons with State-of-the-arts

Based on the above analysis, our final scene text recognizer NRTR is constructed by setting the encoder number $N_e = 12$, the decoder number $N_d = 6$, the feed-forward dimension $d_{ff} = 4096$ and two convolutional layers in the modality-
All the recognition accuracies, obtained by the proposed NRTR and 22 existing approaches on the four public benchmarks, are shown in Table 3. From Table 3, we can see that, compared to current methods, NRTR achieves the new state-of-the-art or highly competitive performance in both constrained and unconstrained cases, while requiring only one order of magnitude less time for model training. This demonstrates the effectiveness and superiority of our model.

Specifically, in the constrained lexicon case, NRTR substantially outperforms the existing models on almost all benchmarks, and in average beats the best scene text recognizer proposed in [Cheng et al., 2017]. More concretely, our model obtains superior performance by margin of 1.3% on IIIT5K with the "1k" lexicon, 0.9% on SVT and 0.6% on IC03 with the "Full" lexicon, only a litter lower accuracy on IIIT5K (0.1%) and IC03 (0.3%) with the "50" lexicons. Note that the model in [Cheng et al., 2017] adopts a more focusing network for adjusting attention drift. NRTR does not perform any special operation aiming at handling irregular text or low-quality images, which shows the tolerance of our network to spatial distortions of scene text.

In the unconstrained lexicon case, NRTR also achieves the best performance among most state-of-the-art approaches. As listed in Table 3, our method significantly outperforms the previous best model by a large margin of 2.4% on SVT, 1.2% on IC03 and 1.4% on IC13, except for a litter performance reduction (0.9%) on IIIT5K dataset. It is observed that most existing approaches do not report their results in the lexicon-free condition because they are incapable of performing recognition without a dictionary. By contrast, our model is available in both lexicon-constrained and lexicon-unconstrained settings.

Table 3 also shows training speed of each epoch among these approaches. Only a few of methods publicly report their training time. From Table 3, the model in [Shi et al., 2016] costs 16 hours per epoch on an Nvidia Titan X GPU and converges after ~3 epochs. The best previous model [Cheng et al., 2017] needs 40 hours per epoch on a Tesla M40 GPU and also needs about 3 epochs before convergence. Note that Titan X and M40 have approximately the same single-precision floating point performance at 7 TFLOPS. As for the proposed NRTR, it only takes 2.8 hours on an Nvidia Titan X GPU for each epoch, and needs 6 epochs before convergence. The total training speed (~16.8 hours), which is at least 8 times faster than the existing best recognizer, validates the efficiency of NRTR.

Some representative results of NRTR are presented in Figure 5, including both the correct and incorrect recognitions. As can be seen, NRTR demonstrates excellent capability on recognizing extremely challenging text images, including but not limited to low resolution, low visual quality, complex geometric deformations and cluttered background, some of which are even hard to human. For the incorrect recognitions, we analyze them carefully and group the caused reasons into three types. First, the input image contains extra characters that are not included in target text, seeing that the image of 'day' contains extra 'y' and 's' in Figure 5. Second, texts are severely occluded by other objects, e.g., tree or barrier in example of 'college' and 'redwood'. Third, the mixed characters which look similar, like 'k' in image of 'kaffee' and its fault result 'x'. These failed examples also highlight future research directions of the proposed NRTR.

5 Conclusions

In this work, we point out two problems lying in most current RNNs-based and CNNs-based scene text recognition methods, and present NRTR, a novel no-recurrence seq2seq model.
aiming at mitigating computation parallelization and complexity. NRTR follows the encoder-decoder framework but leverages self-attention as its fundamental component, combined with the proposed modality-transform block. The proposed architecture could efficiently capture both contextual information and long-term dependencies. Extensive experiments over several benchmarks indicate that the proposed NRTR significantly outperforms existing state-of-the-arts in both accuracy and training speed. Our future work includes extending the proposed ideas to scene text detection, and constructing an end-to-end scene text spotting system.

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