Fine-tuning Handwriting Recognition systems with Temporal Dropout

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Abstract—This paper introduces a novel method to fine-tune handwriting recognition systems based on Recurrent Neural Networks (RNN). Long Short-Term Memory (LSTM) networks are good at modeling long sequences but they tend to overfit over time. To improve the system's ability to model sequences, we propose to drop information at random positions in the sequence. We call our approach Temporal Dropout (TD). We apply TD at the image level as well to internal network representation. We show that TD improves the results on two different datasets. Our method outperforms previous state-of-the-art on Rodrigo dataset.

Keywords—Handwriting Recognition, HTR, CNN, RNN, LSTM, Dropout, Neural Network, Regularization

I. INTRODUCTION

Dropout is a regularization technique that is often used to prevent neuron co-adaptation which reduces overfitting and improves network generalization. The technique consists of randomly disabling individual neurons by masking out their activations (output weights) \cite{1}. A generalization of dropout, DropConnect, works by randomly disabling individual neuron weights \cite{2}. Dropout was primarily intended to be applied to intermediate layers of the network. However, it could also be applied in the input space. For instance, DeVries et al. \cite{3} improves the accuracy of a convolutional neural network (CNN) for image classification by randomly masking out a region of the input image. This technique can be regarded as an extension of dropout, but with a spatial prior applied. The main motivation behind such a technique is to improve the model's ability to handle object occlusion and take context into consideration. Even though not directly applied to the input layer, the term Spatial Dropout first appeared in the work of Tompson et al. \cite{4}, which proposed to improve the performance of CNN by randomly discarding entire feature maps instead of pixels.

In this work, we propose a new regularization technique in the form of a dropout layer, to improve the performance of a convolution recurrent neural network (CRNN) for unconstrained offline handwriting recognition. Our approach exploits the sequential mechanism that is used by most Handwritten Text Recognition (HTR) systems to process text-line images. More generally, we hypothesize that any system working on sequential data could be improved by stochastically removing (dropping out) some elements from the sequence during training. This would help the system to better model contextual information and improve its robustness toward intra-sequence variability. We propose to fine-tune our recognition system by adding a dropout layer; we call it Temporal Dropout (TD). We describe this approach in details in section II and show how it can be used at different layers of the HTR system. In section III we assess network co-adaptation with a variation of the TD approach that does not involve information loss. We present our baseline HTR system and the two datasets that we used in sections IV and V respectively. Finally, we discuss the different experiments conducted in section VI where we assess the effect of TD on the HTR system.

II. TEMPORAL DROPOUT

Most handwriting recognition systems (working at the line level) use a sliding window approach for feature extraction. The window is swiped along the horizontal axis, usually in the direction of writing (e.g., left to right for Latin handwriting), to extract specific characteristics of the script. At each position of the window, features are extracted as a vector, and then concatenated to a sequence. This spatio-temporal mapping from image pixels to feature sequence is achieved through an encoder network (usually a CNN). The features sequence is then modeled by a decoder network (usually an RNN). In the input space, our approach is similar to that of DeVries et al. \cite{3} which randomly removes a square-shaped region from the input image. Instead, we propose to remove complete column regions at random positions of the input image (see figure 1). Considering the spatio-temporal mapping performed during feature extraction, hence we named our approach Temporal Dropout (TD). That should not be confused with the temporal dropout technique applied to video frames for spatio-temporal feature learning \cite{5}.

Figure 1: Input text-line image with 30% temporal dropout.

When applied to the input space, our approach could be seen more as a data augmentation method rather than a dropout. However, we do extend this approach to intermediate layers of the network. More specifically, we perform TD on the CNN encoder output (input of the RNN decoder) by removing (zeroing) vectors at random positions in the feature sequence (see figure 2). More formally, a Long Short-Term Memory (LSTM) network
can be represented by the following equations:

\[
\begin{align*}
    (i_t, f_t, o_t, g_t) &= \left( \sigma(W_i[x_t, h_{t-1}] + b_i), \sigma(W_f[x_t, h_{t-1}] + b_f), \sigma(W_o[x_t, h_{t-1}] + b_o), \sigma(W_g[x_t, h_{t-1}] + b_g) \right) \\
    c_t &= f_t \cdot c_{t-1} + i_t \cdot g_t \\
    h_t &= o_t \cdot f(c_t)
\end{align*}
\]  

(1)

(2)

(3)

where \(i_t, f_t, o_t, g_t\) are the input, forget, and output gates at time step \(t\) respectively; \(c_t\) is the cell update vector while \(c_{t-1}\) and \(h_t\) are the updated cell vector and the hidden state respectively. We denote by \(\sigma\) the sigmoid activation function and \(\ast\) the element-wise multiplication operator. Introducing a dropout mechanism to recurrent neural networks could be addressed in many ways. A direct application of dropout to handwriting recognition is the work of [6] where the authors chose to apply dropout to feed forward connections only, restricting its use to input-hidden and hidden-output connections. The authors claim that one shall not apply dropout to recurrent connections as it would hurt the RNN’s ability to model sequences. On the other hand, [7] proposed to apply dropout on the previous hidden state \(h_{t-1}\) while [8] and [9] chose to apply it either directly on the cell values \(c_{t-1}\), or on the cell update vector \(g_t\), respectively. In this work, we propose to apply dropout directly on the input sequence. At each time step, equation 1 could be rewritten as:

\[
\begin{align*}
    (i_t, f_t, o_t, g_t) &= \left( \sigma(W_i[d(x_t), h_{t-1}] + b_i), \sigma(W_f[d(x_t), h_{t-1}] + b_f), \sigma(W_o[d(x_t), h_{t-1}] + b_o), \sigma(W_g[d(x_t), h_{t-1}] + b_g) \right) \\
    c_t &= f_t \cdot c_{t-1} + i_t \cdot g_t \\
    h_t &= o_t \cdot f(c_t)
\end{align*}
\]  

(4)

where \(d(x_t)\) is the dropout function defined as:

\[
d(x_t) = \begin{cases} 
    m \cdot x_t, & \text{if train phase} \\
    x_t, & \text{otherwise}
\end{cases}
\]  

(5)

In contrast to the previous approaches where the activation vector is partially dropped, we chose to drop all the activations at once. The input vector is multiplied by a constant \(m\) sampled, for each time step, from a Bernoulli distribution with success probability \(p\). Because all vector values are either kept or dropped, no scaling is required. Compared to the other methods our approach can be seen as a special case with the same analogy as the relation between dropout (where entire columns of the weights matrix are dropped) and drop-connect.

III. COMPLEMENTARY INPUT REPRESENTATIONS

In general, the Temporal Dropout approach falls under Noise Injection Regularization Techniques (NIRT), which have shown to improve the performance of neural networks [10][11]. Network regularization could take different forms. For instance, one could target network weights by injecting adaptive Gaussian noise [12] or by applying random changes to the weights [13]. At a higher level, some methods aim to regularize the network architecture. For instance, [14] regularizes sub-network paths by randomly dropping operands of the join layers. Whereas [15] performs network depth regularization as a way to solve the problem of vanishing gradients for very deep networks.

Inspired by the work of [16], which attempts to apply data augmentation to internal representations, we propose to add a complementary RNN decoder (\(RNN_{\text{comp}}\)) to which we feed the dropped out feature vectors of the CNN encoder (see figure 3). We end up having two RNNs working in parallel, processing complementary input representations. The final output of the system is a sum of both networks:

\[
y_t = RNN(m \cdot x_t) + RNN_{\text{comp}}((1 - m) \cdot x_t)
\]  

(6)

In contrast to the TD approach presented in the previous section, this time, there is no loss of information. Despite having partial feature sequences presented to each RNN decoder, the total information is preserved within the network. Considering that each RNN decoder sees a complementary version of the input, hence we name this approach Temporal Dropout with Complementary Input Representation. The main intuition behind this approach is to assess the performance of TD without loss of information, as well as to assess the RNN decoders co-adaptation with respect to this specific information routing. Note that during inference, all the input is presented equally to both decoders without any dropout.

IV. BASELINE HTR SYSTEM

Our baseline system [1] follows an encoder-decoder architecture similar to the one described in [7] except

1https://github.com/0x45447415244/HandwritingRecognitionSystem
Figure 3: HTR recognition pipeline with 50% temporal dropout applied to the CNN encoder output. Dropped feature vectors (represented in black) are fed as complementary input to another RNN decoder. We add the output of both decoders to produce the final transcription.

that we do not define an explicit sliding window. A 7-layer CNN encoder (see table I) generates a sequence of observations by scanning the text-line image (normalized to 64 pixels in height) in the direction of the writing (e.g., left to right for Latin scripts). We sample the image at a rate of 1/4 (selected empirically), which means that the encoder generates one feature vector for every 4 pixels. Extracted feature vectors are fed into a 3-layer Bidirectional LSTM (BLSTM) decoder with 256 single-cell, peephole-enabled, units per layer. We chose to keep the network simple with a relatively small number of parameters. We thus combine the forward and backward outputs at the end of the BLSTM decoder rather than at each BLSTM layer. We also chose not to add additional fully-connected layers. The network is trained in an end-to-end fashion with the Connectionist Temporal Classification (CTC) loss function [18]. Spatial pooling (max) is employed after some convolutional layers with a stride equal to 2 (except for the last layer). Because of the CTC limitation, we only apply pooling twice in the horizontal direction to keep the number of observations (per line) greater than the number of labels.

V. DATASETS

We performed our experiments on the Rodrigo dataset [21], a corpus obtained from the digitization of the “Historia de España del arzobispo Don Rodrigo” book, written in ancient Spanish in 1545. The dataset consists of 9000 lines for training, 1000 lines for validation and 5100 lines for testing. Other experiments were performed on the READ16 dataset [22], a subset of documents from the Ratsprotokolle collection, composed of minutes of the council meetings held from 1470 to 1805. The dataset, written in Early Modern German, consists of 8360 lines for training and 1040 lines for validation. It is worth noting that raw grayscale text-line images are fed directly into the encoder network without any preprocessing.

VI. EXPERIMENTS

We fine-tune our baseline system that has already converged to a sub-optimal solution by retraining it on the same data with TD applied to even-numbered mini-batches. In table II, we show the performance of the system on the two datasets. We notice that TD improves the performance when applied at the input layer as well as at the CNN encoder output. A combination of both approaches improves the performance even more with 15% and 16% reduction in relative raw label error rate on READ16 and Rodrigo datasets, respectively. The TD with Complementary Input Representation (CIR) seems to improve the performance when implemented at the decoder level as well as when used in combination with TD applied to the input image. The difference in performance between TD CIR and the baseline TD method can be interpreted as due to the RNN decoders co-adaptation with regard to the proposed information routing.

Table I: Encoder CNN. All convolutions use the leaky ReLU as activation function (with \(\alpha = 0.2\)) [19], followed by a batch normalization layer [20].

| Output | 4 × 1 Max pooling |
|--------|-------------------|
|        | 3 × 3 Convolution, 512 features |
|        | 2 × 1 Max pooling |
|        | 3 × 3 Convolution, 512 features |
|        | 3 × 3 Convolution, 512 features |
|        | 2 × 1 Max pooling |
|        | 3 × 3 Convolution, 256 features |
|        | 3 × 3 Convolution, 256 features |
|        | 2 × 2 Max pooling |
|        | 3 × 3 Convolution, 128 features |
|        | 2 × 2 Max pooling |
|        | 3 × 3 Convolution, 64 features |
| Input  |                  |

Table II: Raw label error rate on the validation data of Rodrigo and READ16 datasets.

| System                  | Rodrigo | READ16 |
|-------------------------|---------|--------|
| CRNN                    | 3.02    | 10.79  |
| CRNN + TD (Image)       | 2.75    | 10.00  |
| CRNN + TD (Encoder)     | 2.75    | 10.06  |
| CRNN + TD (CIR Encoders)| 2.73    | 9.76   |
| CRNN + TD (Image & Encoder) | **2.50** | **9.13** |
| CRNN + TD (Image & CIR Encoders) | 2.59    | 9.48   |

To assess the effect of TD, we compute the average magnitude for each of the 256 features of the RNN decoder output over all samples in the test set. We can notice that
the overall features magnitudes are higher for the baseline system than for the one with TD (figure 4). The features in the system with TD tend to be more uniform by having lower standard deviation. We notice also that dead features (ones with low magnitude) are more active in the system with TD (figure 5) as it seems to make use of most features.

Figure 4: BLSTM decoder forward network features averaged over all samples in the READ16 validation set and sorted by their magnitude. Red bars are for the baseline system while the blue bars belong to the one with Temporal Dropout.

Figure 5: Unsorted version of features in figure 4

We assess the importance of features with respect to their magnitude by clipping values above a certain threshold $\gamma$. For example, with $\gamma$ equals to 0.6, all features with magnitude greater than 0.6 are considered as 0.6. In figure 6 we show the effect of features clipping for the two systems. We can see that the system with TD is more robust toward features clipping with less than 0.5% loss of accuracy for a threshold of 0.3. This can be explained as the system with TD makes use of more features with low magnitude (see figures 4 and 5).

To integrate a lexicon and a language model, we use Weighted Finite State Transducers (WFST). The WFST decoder is based on the CTC-specific implementation proposed by [23] for speech recognition. A “token” WFST was designed to handle all possible label sequences at the frame level, so as to allow for the occurrence of the blank label along with the repetition of non-blank labels. It can map a sequence of frame-level CTC labels to a single character. A search graph is built with three WFSTs ($T$, $L$ and $G$) compiled independently and combined as follows:

$$S = T \circ \min(\det(L \circ G))$$  (7)

Figure 6: System performance (lower is better) on READ16 dataset with respect to different features clipping threshold values.

$T$, $L$ and $G$ are the token, lexicon and grammar WFSTs respectively, whereas $\circ$ denote composition, determinisation and minimisation respectively. The determinisation and minimisation operations are needed to compress the search space, yielding a faster decoding.

Table III: Word and character error rates on the test data of Rodrigo dataset.

| System        | # parameters | WER/CER  |
|---------------|--------------|----------|
| CRNN          | 10.5 M       | 16.63 / 4.70 |
| CRNN + TD     | 10.5 M       | 14.37 / 3.74 |
| Deep CRNN [24]| 18.5 M       | 14.00 / 3.00 |
| Deep CRNN     | 18.5 M       | 12.93 / 2.62 |
| Deep CRNN + TD| 18.5 M       | **12.31 / 2.43** |

We report the results of the different experiments in Table III where an 8-gram character language model is used. The system prefixed with “Deep” denote the use of 13 convolutional layers in the encoder (instead of 7), as described in [17]. Besides the size of the network, one difference between the CRNN system implemented in this paper and the one in [24] is that we opted out of using an explicit sliding window on the text-line image. The encoder now performs a 2D convolution on the image as a whole, where it generate one feature vector for each 4 pixel columns. Another difference is that we now use the leaky ReLU activation function in the encoder (instead of ReLU).

VII. CONCLUSION

In this paper, we proposed a novel method to improve the performance of a recurrent convolutional neural network for handwritten text recognition. Our method fine-tunes a pretrained model by applying temporal dropout to the input image as well to internal network representation. Our results show that stochastically dropping sequence elements improves modeling accuracy. Specifically, we found out that models with temporal dropout make the most out of their output features and are more robust
toward feature clipping. We have also investigated the use of a complementary RNN decoder to process dropped out information. While this method improves the recognition accuracy compared to the baseline system, it suffers from decoders co-adaptation due to the constant dropout rate. Future work will investigate the use of a stochastic or learned dropout rate to mitigate this behavior.

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