Cap2TxT: CAPTCHA Image to Text Sequence, An End-to-End Hybrid Neural Network for Captcha Image Text Sequence Recognition

2020 Spring ML Class Final Project Submission

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Abstract

Recent developments of deep neural networks including CNN(Convolutional Neural Network) and RNN(Recurrent Neural Network) made object classification and detection process much more easier. However, many real-world sequence learning tasks require the prediction of sequences of labels from noisy, unsegmented input data. In this paper, I propose ***Cap2TxT****, a light-weight end-to-end fashion network for captcha image recognition problem. Code has been available at author's github repository.*[1]

1. Introduction

Recently, in the light of the great success in deep learning networks, computer's pattern recognition capabilities has been remarkably improved. Especially, the pattern recognition for image in the computer vision field started to be in the limelight. However, most of the recent deep neural networks are focusing on solving object classification and semantic/instance segmentation problem. This project deals with the problem of image-based text sequence detection, a problem that has been covered a lot in the field of computer vision in the past but rarely has a deep learning-based approach. In particular, we limit the problem domain to the CAPTCHA image consisting only of English alphabets and arabic numbers. I coined my network ***Cap2TxT*** for Captcha Image to Text Sequence.

Unlike image classification in which deep learning and CNN are most actively used, recognizing objects inherently have the properties of sequence(*e.g*. text information in CAPTCHA, the musical score) has some challenges. Those objects that have the feature of sequence can't be handled as image classification problem since the number of labels or classes are infinity. Thus, it is more natural to predict the order or sequence of labels rather than to give a single label. Also, an important difference between objects with ordering properties is that the length of the sequence can vary significantly.(*e.g*. "Bob" versus "Josephine") Therefore, famous existing successful CNN networks such as AlexNet[7], GoogLeNet[14], ResNet[4] and DenseNet[5] cannot be applied directly to this area without modification. So in this work I leveraged RNN to handle those sequence-based objects. The Cap2TxT framework extracts feature sequences through CNN as the first step. Then, the text sequence is predicted for each time step(The time sequence in the RNN is the horizontal sequence of input image.)through the RNN. Finally the loss function between per-sequence-predicted results and ground truth texts(which are unsegmented at sequence level) is computed by the method inspired by [3]. I will describe the details of network architecture later in this paper in section 3.

1.1. Related Works

In this subsection, I would give a brief overview of the research area related to my work including OCR and deep neural networks.

OCR(Optical Character Recognition) is the automated translation of images of typed, printed or handwritten text into coded text, whether from a scanned document, a photo of a document, from subtitle text overlying on an image.[10] OCR enables a large number of useful applications[6]. During the early days, OCR has been used for mail sorting, bank cheque reading and signature verification[13]. In addition, there are a lot of applications of OCR such as helping blind and visually impaired people to read text[1], processing utility bills, passport validation, pen computing and automated number plate recognition[11].

Before the deep neural network was used for OCR, the classical pipeline of OCR is as follows: 1) Image acquisi-

[1] https://github.com/changwoonchoi/mlfinal

tion, 2) Preprocessing, 3) Character segmentation, 4) Feature Extraction, 5) Classification, 6) Post-processing. As you can see, the classical OCR was very cumbersome and computationally and time consuming.

Deep Neural Networks. Recent years, due to the rapid development of the hardware such as GPU(Graphics Processing Unit), the study of deep neural networks has flourished. But the success in deep neural network is not just the result of powerful hardwares or larger datasets, but mainly a result of new algorithms and novel network architectures. By LeCun *et al*. [9],which was pretty simple model, CNN is first used for image classification task. Nowadays, deeper and powerful models have been studied through AlexNet[7], GoogLeNet[14], ResNet[4] and DenseNet[5].

If CNN has already had great results in image classification, deep neural networks have been very successful with the advent of RNN in areas such as NLP(Natural Language processing). RNN was first introduced in [12]. But as the network grew deeper, problems such as banishing gradients arose. [8] introduced LSTM(Long Short-Term Memory) to deal with those problems, and led to remarkable results. Therewithal, [2] presented GRU(Gated Recurrent Unit), which also achieved a great success in sequence predicting.

1.2. Main Contribution

The main contribution of this paper is three-fold. In summary, the contributions are as follows:

- The neural network model I proposed doesn't leverage the certain characteristic of character.(*e.g*. English alphabet, arabic numeral) So Cap2TxT can be trained to recognize the alphabet of all kinds of languages. In theory, it can even learn to recognize non-linguistic image data like musical notes.

- Since proposed network does not utilize any dictionary vocabulary information during the training/learning process, Cap2TxT can flexibly cope with any string(or text sequence) even if it is a nonsense word. That is, it is very suitable for CAPTCHA recognition.

- Having an end-to-end fashioned pipeline, it is easy to train network compared to other usual models for OCR that consisted of multiple processes chunks.

- In the light of architecture of proposed network, it handles image containing text sequence of various lengths.

The rest of this paper is organized as follows. Section 2 gives a detailed description of the *Cap2TxT* network architecture that I proposed in this final project. In Section 3, I describe the experimental results and methods, and introduce several candidate models for *Cap2TxT* network that have undergone trial and error during the project, and Section 4 concludes.

2. Proposed Network Architecture

The whole *Cap2TxT* network architecture is shown in Figure 1. The network is consisted of three parts: 1) CNN layers 2) RNN layers 3) Measuring Loss Value Step.

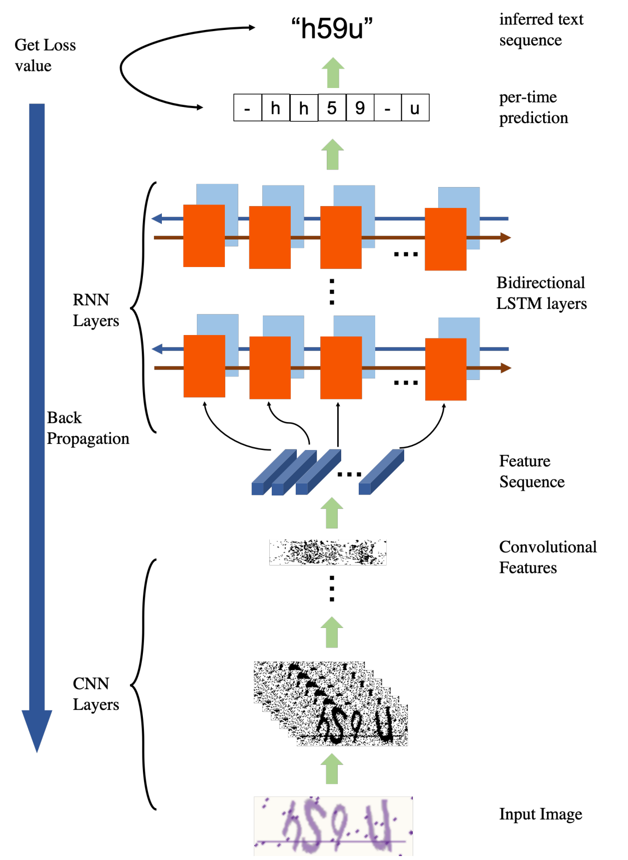

Figure 1: The overview of Cap2Txt architecture. The network is composed of two parts: 1) CNN layers: It takes captcha image as input, extract a feature sequence. 2) RNN layers: It takes a feature sequence for input and returns per time predicted character labels. 3) Measuring Loss value step : from per time prediction, it transcripts and calculates the loss between ground truth text.

2.1. CNN Layers

The first part of proposed network is a convolutional layer block. Inspired by [14] as assignment3, CNN layers are consisted of deep-layered inception blocks, which contains bottleneck layers, 1x1 convolution layers, to reduce the dimensions and parameters remarkably. For easy and fast code implementation, I preprocessed the image data to make same height(64 pixels) with opencv library. Since the original CAPTCHA images have 60 pixels for height, I added extra black((r,g,b)=(0,0,0)) pixels at the bottom of

type	patch size/ stride/ padding	output size (WxHxc)	depth	# 1X1	# 3X3 reduce	# 3X3	# 5X5 reduce	# 5X5	pool proj
convolution	7x7/1/3	160x64x64	1						
ReLU			0						
max pool	3x3/2/1	80x32x64	0						
convolution	1x1/1/0	80x32x64	1						
ReLU			0						
convolution	3x3/1/1	80x32x192	1						
ReLU			0						
max pool	3x3/2/1	40x16x192	0						
inception		40x16x256	2	64	96	128	16	32	32
inception		40x16x480	2	128	128	192	32	96	64
max pool	3x3/2/1	20x8x480	0						
inception		20x8x512	2	192	96	208	16	48	64
inception		20x8x512	2	160	112	224	24	64	64
inception		20x8x512	2	128	128	256	24	64	64
inception		20x8x528	2	112	144	288	32	64	64
inception		20x8x832	2	256	160	320	32	128	128
max pool	3x3/2/1	10x4x832	0						
inception		10x4x832	2	256	160	320	32	128	128
inception		10x4x1024	2	384	192	384	48	128	128
avg pool	4x4/1/0	**7x1x1024**	0						

Table 1: Network configuration summary of CNN Layers. The first row is input layer, and the last row is final output layer.

images. Then the image passes through multiple layers composed of a number of convolution layers, ReLU activations, pooling layers and inception blocks. The Cap2TxT CNN configuration I used is summarized in Table 1. Note that the final output shape is (7x1xchannel#). I modified CNN configuration to made the output shape as (Tx1xc) on purpose. From the fact that convolutional layers and pooling layers doesn't transform the position of pixels, making the output shape (Tx1xc) allows to compress the image in the vertical direction(column-wise) and **preserve the text sequence information which was recorded in horizontal direction**. Thus the final output extracted from CNN layers implies the feature sequence in width-oriented time sequence domain. The core of concepts I explained is illustrated in Figure 2.

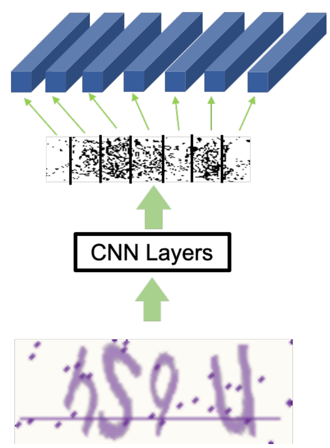

Figure 2: The CNN layers preserves the width-oriented time sequence of original image. So it can leverage the original text sequence information in image to extract feature sequence.

2.2. RNN layers

The extracted feature sequence from CNN layers is directly fed into RNN layers. (Txc) shape can be considered as sequence length T and c-dimensional inputs. I used bidirectional LSTM model which implemented in pytorch library to boost performance. Also, by heuristic, I thought reducing (c=1024) dimension into (# of classes = 37) is too hasty, so I stacked two bidirectional LSTM layers which is illustrated in Figure 3. The Network configuration is shown in Table 2.

2.3. Measuring Loss

Instead of using cross-entropy erros between one-hot encoded vectors or multi label softmax loss, I adopt the conditional probability method of [3], named CTC(Connectionist Temporal Classification) which is able to train RNNs to

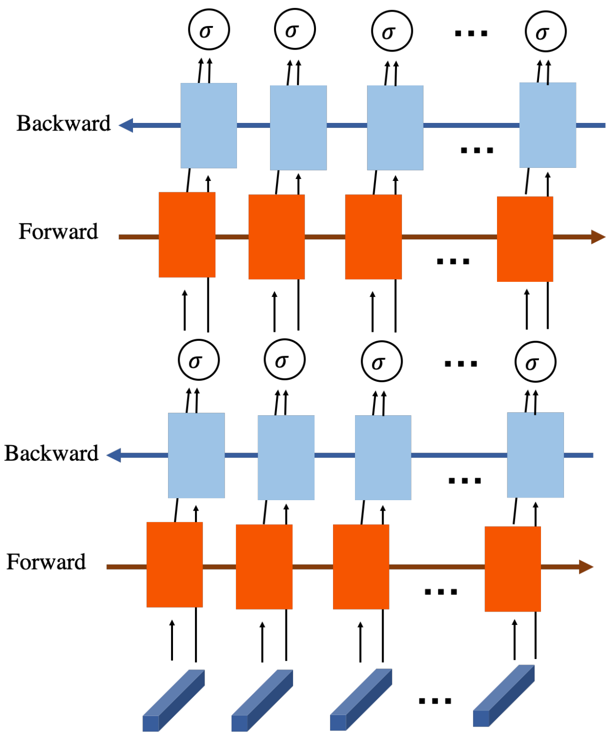

Figure 3: Stacked LSTM layers.

type	sequence length	hidden dim	output shape
bi-LSTM	7	256x2	(7x512)
fc			(7x256)
bi-LSTM	7	256x2	(7x512)
fc			(7x37)

Table 2: configuration summary of RNN Layers.

label unsegmented sequences directly and very suited to Cap2TxT network since output of the network doesn't have sequence-wise(time-wise) ground truth labels. The CTCLoss function is already implemented in torch.nn package.

3. Experiments & Discussion

3.1. Experiment Details& Results

3.2. Trials not Adopted as Final Model

I tried some other methods before adopting the final Cap2TxT Network.

4. Conclusion

In this paper, I have proposed an end-to-end deep neural network framework, called *Cap2TxT*, which interprets the CAPTCHA image and returns the text sequence in it. Cap2TxT consists of a stacked layers of deep CNN, RNN layers.

Networks	char accuracy	word accuracy
Candidate1	12	13
Candidate2	14	15
Candidate3	14	15
Candidate4	14	15
Candidate5	14	15
Cap2TxT	**88.2%**	**77.9%**

Table 3: Recognition accuracy(%) on test dataset with final Cap2TxT and other candidate network models.

Acknowledgement

Everything I've learned in this class has helped me figure out what I can see myself doing as a career because I genuinely enjoy what I learn from your class. Thank you so much for everything during the class.

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