Image Captioning using an LSTM network

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Abstract

In this report, we ...

1 Introduction

Automatically generating a natural language description of an image, a problem known as image captioning, has recently received a lot of attention in Computer Vision. The problem is interesting not only because it has important practical applications, such as helping visually impaired people see, but also because it is regarded as a grand challenge for image understanding which is a core problem in Computer Vision. Generating a meaningful natural language description of an image requires a level of image understanding that goes well beyond image classification and object detection. The problem is also interesting in that it connects Computer Vision with Natural Language Processing which are two major fields in Artificial Intelligence.

In this assignment, we will explore the power of Recurrent Neural Networks to deal with data that has temporal structure. Specifically, we will generate captions for images. In order to achieve this, we will need an encoderdecoder architecture for this assignment. Simply put, the encoder will take the image as input and encode it into a vector of feature values. This will then be passed through a linear layer for providing the input to the LSTM. It will be trained to predict the next word at each step. we used a pre-trained convolutional network as the encoder and an LSTM model as the decoder and tried to fine tune the encoder and train the decoder by backpropagating error into it. The error will come from caption generation. The training uses images and several captions for each image generated by humans. We then run the network in generative mode to generate captions on images it has never seen before. We also tried to replace the LSTM in the encoder part with Vanilla RNN and GRU and compared the performances of them.

Preprint. Under review.

2 Related Work

Recently, several approaches have been proposed for image captioning. We can roughly classify those methods into three categories. The first category is template based approaches that generate caption templates based on detecting objects and discovering attributes within image. For example, the work [11] was proposed to parse a whole sentence into several phrases, and learn the relationships between phrases and objects within an image. In [8], conditional random field (CRF) was used to correspond objects, attributes and prepositions of image content and predict the best label. Other similar methods were presented in [15, 10, 9]. These methods are typically hard-designed and rely on fixed template, which mostly lead to poor performance in generating variable-length sentences. The second category is retrieval based approach, this sort of methods treat image captioning as retrieval task. By leveraging distance metric to retrieve similar captioned images, then modify and combine retrieved captions to generate caption [10]. But these approaches generally need additional procedures such as modification and generalization process to fit image query.

Inspired by the success use of CNN [7, 19] and Recurrent Neural Network [1, 13, 14]. The third category is emerged as neural network based methods [4, 3, 6, 17, 18]. Our work also belongs to this category. Among those work, Kiro et al.[5] can be as pioneer work to use neural network for image captioning with multimodal neural language model. In their follow up work [6], Kiro et al. introduced an encoder-decoder pipeline where sentence was encoded by LSTM and decoded with structure-content neural language model (SC-NLM). Socher et al.[16] presented a DT-RNN (Dependency Tree-Recursive Neural Network) to embed sentence into a vector space in order to retrieve images. Later on, Mao et al.[12] proposed m-RNN which replaces feed-forward neural language model in [6]. Similar architectures were introduced in NIC [17] and LRCN [2], both approaches use LSTM to learn text context.

Our work is based on the LSTM method to do the image captioning. In our approach, we used a pre-trained concolutional network as the encoder and an LSTM model as the decoder to do the image captioning. We also tried to replaced the LSTM with the Vanilla RNN and GRU to compared the model performances.

3 Methods

3.1 Dataset

For this image captioning task, we used the dataset from the well-known Common Objects in Context (COCO) repssitory. COCO is a large-scale object detection, segmentation, and captioning dataset. In this report, we used a subset (around 1/5) of the COCO 2015 Image Captioning Task. The training set contains around 82k images with roughly 410k captions while the test set has around 3k images with almost 15k captions. The original images in the dataset are of different sizes and aspect ratios, which we are resizing to 256x256 before the training.

3.2 Model

3.2.1 Baseline Model

Our captioning system us implemented based on a Long Short-Time Memory (LSTM) network (baseline model). For the encoder part, we use a forzen pretrained convolutional network, namly ResNet50, as the encoder. We removed the last layer of pre-trained abd added a trainable linear layer with outputs a feaure vector of a fixed suze for each image. This seted the initial state of the LSTM network based on the image. For baseline model, we resized the image to 256x256 and hidden size of 512.

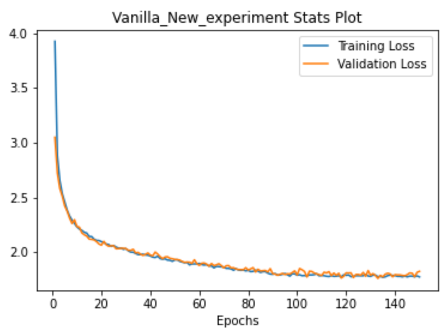
3.2.2 Vanilla RNN and GRU

For the model comparison, we also tried Vanilla RNN and GRU. For these two models, we simply replaced the LSTM module in the encoder with either a Vanilla or a GRU, while the others remained to be same. Then, trained and compared the performance of these three different models.

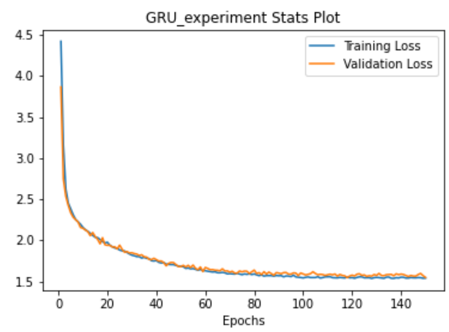
4 Results

4.1 Learning Curve

The learning curve for the Vanilla RNN and GRU could be found in Figure 1.



(a) Vanilla RNN Loss



(b) GRU Loss

Figure 1: Training and Validation loss for Vanilla RNN and GRU

4.2 Cross Entropy Loss

The test set Cross Entropy Loss of different could be found in Table 1

Table 1: Cross Entropy Loss for different models

Model	Testset Cross Entropy Loss
Baseline	TBD
Vanilla RNN	1.819
GRU	1.586
Finee tuning model	TBD

4.3 BLEU Score

For this report, we set the weight for BLEU1 to be [1, 0, 0, 0] and BLEU4 to be [0.25, 0.25, 0.25, 0.25]. The BLEU scores for different models could be found in Table 2

Table 2: BLEU scores for different models

Model	BLEU1	BLEU4
Baseline	TBD	TBD
Vanilla RNN	54.59	8.93
GRU	65.16	17.17
Finee tuning model	TBD	TBD

4.4 Images Visualization of the Best Performance Model

5 Discussion

5.1 Baseline with different Temperatures

5.2 Baseline LSTM vs Vanilla RNN vs GRU

5.2.1 Learning Curve

5.2.2 Cross Entropy Loss

5.2.3 BLEU Score

5.3 Baseline model vs fine tuning model

5.3.1 Learning Curve

5.3.2 Cross Entropy Loss

5.3.3 BLEU Score

6 Individual contributions to the project

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