
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.

2 Related Work

3 Methods

3.1 Dataset

For this image captioning task, we used the dataset from the well-known Common Objects in Context[2] (COCO) repository. 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 is implemented based on a Long Short-Time Memory (LSTM) network (baseline model). For the encoder part, we use a frozen pretrained convolutional network, namely ResNet50, as the encoder. We removed the last layer of the network and added a trainable linear layer that outputs a feature vector with a fixed size for each image. This feature becomes the initial hidden state and cell state of the LSTM network. For baseline model, we resized the image to 256x256.

3.2.2 Vanilla RNN and GRU

For the model comparison, we also tried Vanilla RNN and GRU[1]. GRU is a variant of recurrent neural networks. GRU is like a long short-term memory (LSTM) with a forget gate, but has fewer parameters than LSTM, as it lacks an output gate.[3] 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.

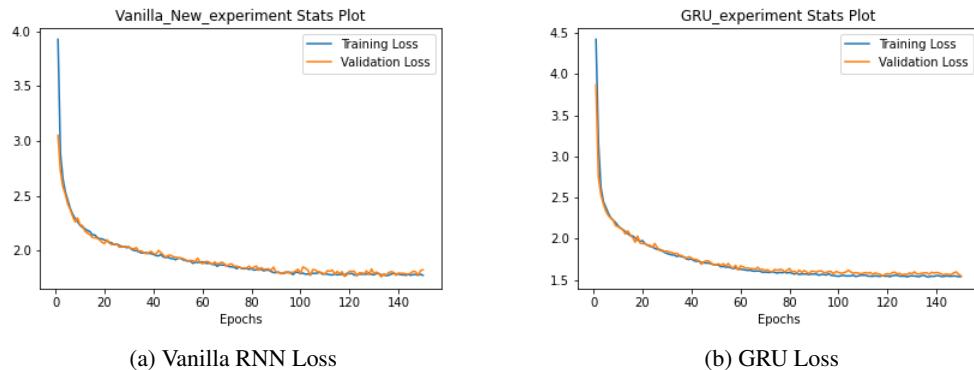


Figure 1: Training and Validation loss for Vanilla RNN and GRU

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	1.966
Vanilla RNN	1.819
GRU	1.586
Fine 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	56.48	7.75
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

Table 3: BLEU scores for baseline model with different temperature

Temperature	BLEU1	BLEU4
0.01	0.117	0.022
0.1	0.107	0.020
0.2	0.099	0.018
0.7	0.106	0.020
1	0.118	0.022
1.5	0.142	0.026
2	0.152	0.028
5	0.169	0.032

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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References

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