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# Image Captioning using an LSTM network

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## Abstract

In this report, we ...

## 1 Introduction

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## 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 (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 pre-trained and 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, LSTM 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.

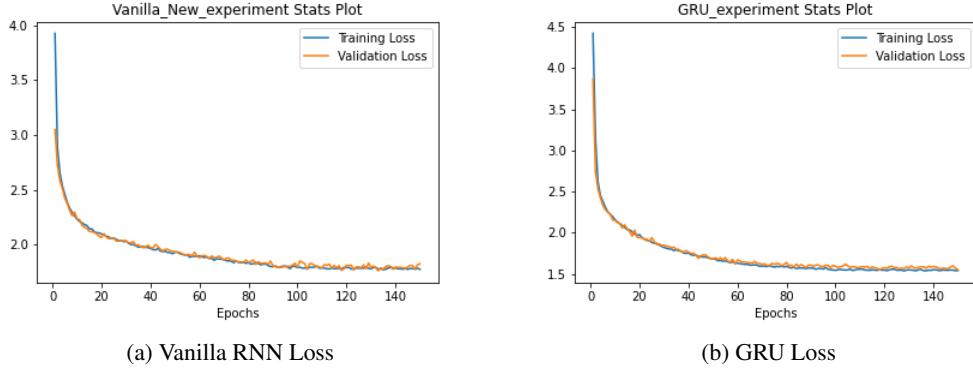


Figure 1: Training and Validation loss for Vanilla RNN and GRU

### 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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