CS230

Automated LaTeX Code Generation from Handwritten Mathematical Expressions Category: Computer Vision

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Abstract

Training a model that learns handwritten mathematical expressions from images and generates equivalent LaTeX code. The goal is experiment and study different model architectures (CNN, LSTM, etc) and hyper-parameters, evaluate the with different evaluation metrics, and share our finding.

1 Introduction

Converting handwritten mathematical expressions into digital formats is time consuming, specifically LaTeX code. Our goal is to train a ML model that is capable of encoding handwritten notes and converting to the source code seamlessly. The input to our algorithm is an image of a handwritten mathematical expression. The challenge of our project is to convert an image to a text LaTeX sequence which will require the use of both computer vision and NLP techniques. We will use concepts related to these areas that we learn from this course to train the model. We will explore different evaluation metrics (text based, and image based), and share our findings.

2 Dataset and Features

We will use the datasets from two main repositories: `Im2latex-100k` (Kanervisto [2016]) and `Im2latex-230k` (Gervais et al. [2024]). The `Im2latex-100k` (Kanervisto [2016]) dataset, available at Zenodo, contains 100,000 image-formula pairs. The `Im2latex-230k` (Gervais et al. [2024]) dataset, also known as `Im2latexv2`, contains 230,000 samples. It includes both OpenAI-generated and handwritten examples, further enhancing the diversity of the data. This dataset is available at Im2markup. The training data format is `<image file name> <formula id>`.

The dataset disk size is 849 MB. The images are gray scales with 50x200 pixels. The numbers of symbols (Figure 1) in the latex formulas vary from range varies from 1 to 150 symbols. Voabulary contains 540 symbols, refer **??** and **??** for the list of popular and least occurring symbols with their frequency.

CS230: Deep Learning, Winter 2018, Stanford University, CA. (LateX template borrowed from NIPS 2017.)

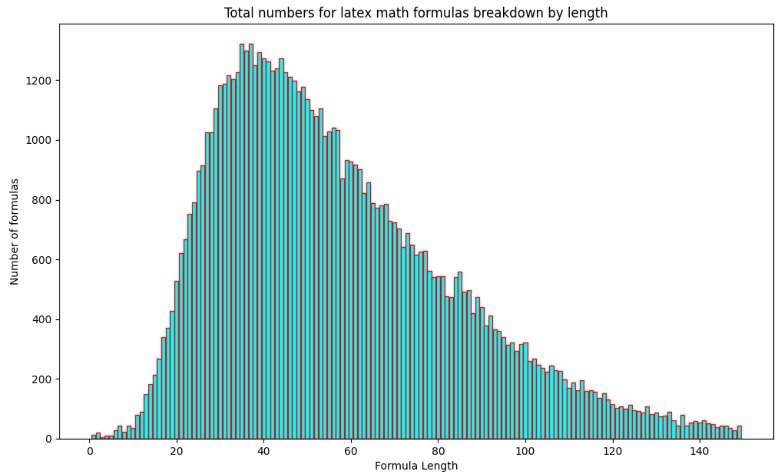


Figure 1: Formulas breakdown by length

3 Experiments

3.1 Setup

We use the single AWS P2.xlarge instance (tesla 80 GPU) for training. The training time varies between 1 hr 30 mins and 2 hrs. We use the ‘sparse categorical loss‘ with ‘adam‘ optimizer for 20 epoches. These hyperparameter are not modified between different configurations to observe the differences in outcome.

3.2 CNN encoder and GRU/LSTM

As a baseline, We use the CNN Encoder to encode the image input of resized image (50x200) with 1 channel (greyscale). We use 3x3 convolutional filter followed by 2x2 max pooling layer. This previous block is repeated three times and followed fully connected layer.

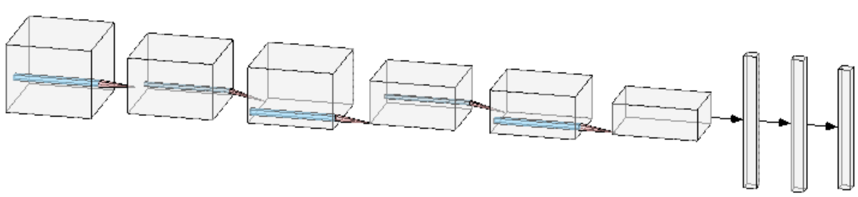
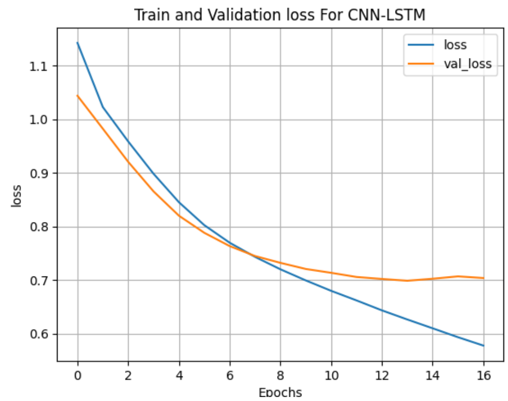


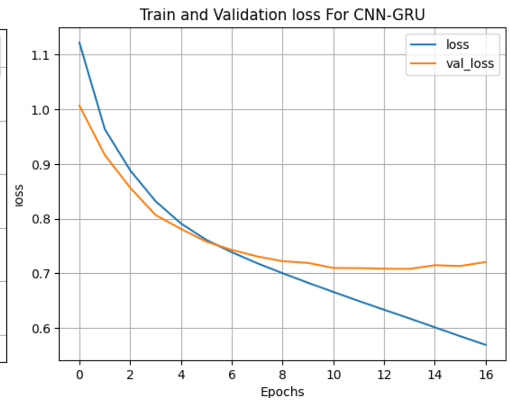
Figure 2: Encoder architecture consists of 3 convolution-max pooling blocks (50,200) -> (25,100) -> (12,5) which is flattened and fed into Dense layer (256 units)

During decoding, We compute the embedding for formula tokens and concatenated with image encoded embedding. The concatenation of image and token embedding fed into LSTM/GRU units, followed by fully connected network. The activation is softmax. Overall model architecture is:

Input Image I $\rightarrow$ CNN (Encoder) $\rightarrow$ LSTM/GRU (Decoder) $\rightarrow$ Output LaTeX Sequence T

Here are the training curves with CNN - LSTM/GRU architectures:





We can see there is no noticeable differences between GRU/LSTM

3.3 LSTM with funetuning with pretrained Resnet50

In this experiment, we use the pretained ResNet50 model as a encoder (98Mb disk size). However, ResNet50 expects the image with fixed size 254x254 and 3 channels. Our input images are grey scale. So, we transform the input image to the ResNet50 input using `tf.keras.layers.Lambda(lambda x: tf.image.grayscale_to_rgb(x)`.

4 Future Work

1. Work in-progress by Ben Compute the **accuracy** between images generated from original latex code and generated latex code. Also look at BLEU score, Levenshtein Distance.
2. We're aiming to inspect the accuracy losses and ensure that mis-predicted examples are correctly identified with increased weighting.
3. Work in Progress by Akhil. We're in the middle of trying to explore VisionTransformer architecture for this task.
4. Work in Progress by JP During inference time, we're using the greedy algorithm to pick the token with maximum logit score at every time. It terminates when the <END> token is predicted or reaches the maximum sequence length. We will explore beam search in this experiment.

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