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 Related work

Schechter et al. [2017] investigated a variety of methods like neural networks, CNNs, Random Forests, SVMs, OCR, CGrp, and SA. However, most state of the art the methods utilize encoder-decoder architectures involving CNNs and LSTM architectures like Genthial and Sauvestre [2017a]. In recent works like Bian et al. [2022], both left-to-right and right-to-left decoders are utilized. The CNN-RNN architecture will serve as a baseline for our work.

Transformer architectures (Vaswani et al. [2023]) are state-of-the-art for NLP tasks . Dosovitskiy et al. [2021] introduced vision transformers which uses sequences of image patches to replace convolutions. We will leverage a vision transformer encoder and transformer decoder architecture and compare it to the baseline.

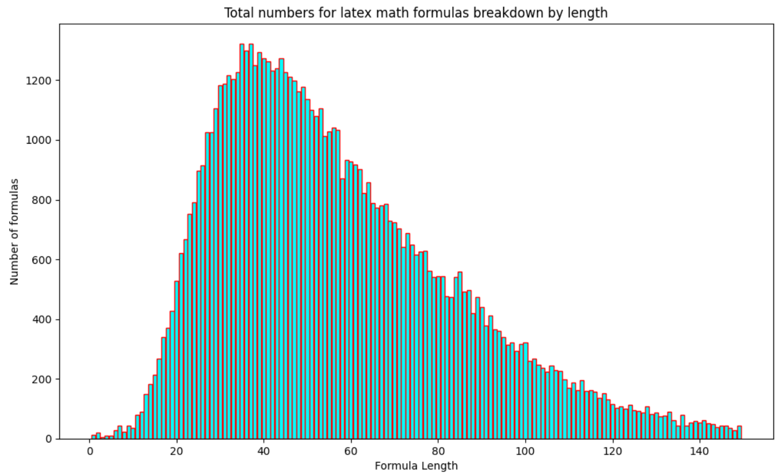


Figure 1: Formulas breakdown by length

3 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.

4 Experiments

4.1 Setup

We use a single AWS G6.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.

4.2 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.

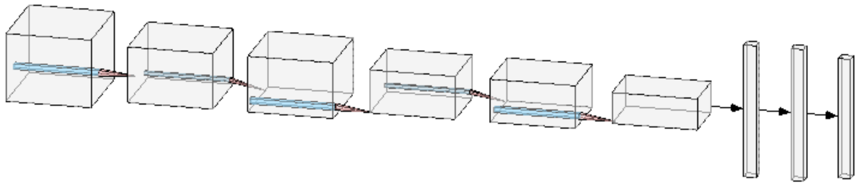
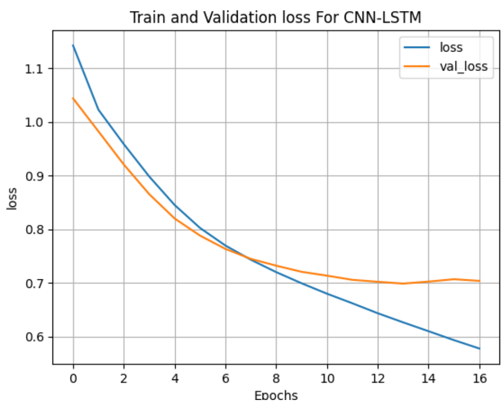


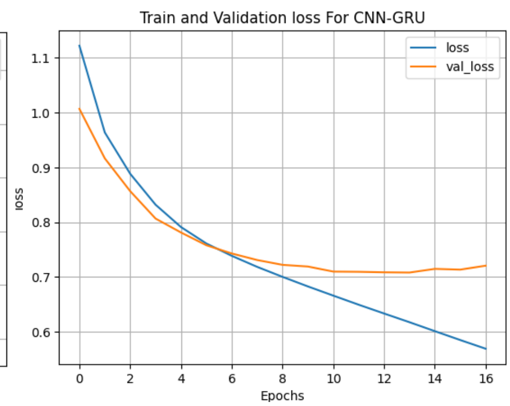
Figure 2: Encoder architecture consists of 3 convolution-max pooling blocks (50,200) -> (25,100) -> (12,5) which is flattened and fed into Dense layer (256 units)

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 → CNN (Encoder) → LSTM/GRU (Decoder) → Output LaTeX Sequence T

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





4.3 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)`.

4.4 Vision transformer encoder and transformer decoder

4.4.1 Vision Transformer Encoder

We create patches of 10 X 10. Since our images are of size 50 X 200, we have a total of 100 patches per image.

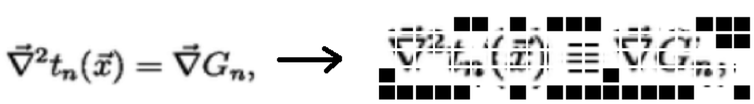


Figure 3: Original latex image and the generated patches

In the vision transformer encoder, these patches are taken and embedded linearly and added to the positional embeddings. That is fed into a standard transformer layer. We use 8 transformer layers for our architecture that have 4 attention heads and 2 layer multi-layer perceptron with 2048 and 1024 units.

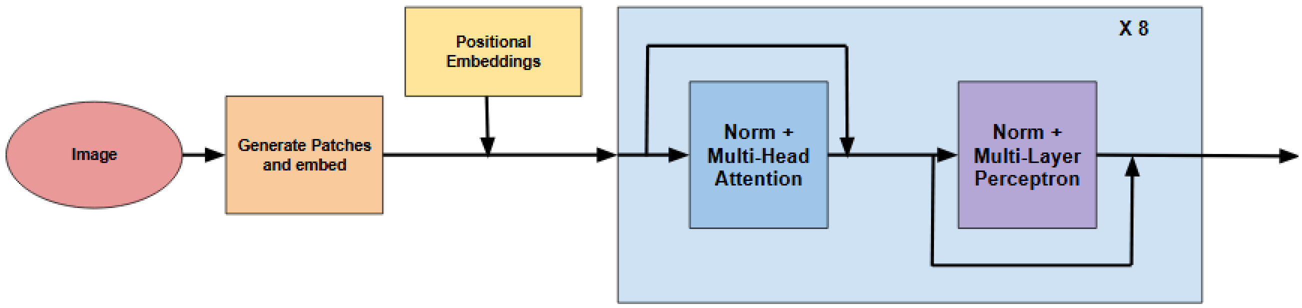


Figure 4: Transformer encoder architecture

4.5 Overall results

Architecture	Loss	Accuracy	Masked Loss	Masked Accuracy
CNN-RNN	0.6479	0.8470	1.6941	0.6008
Vision Transformer Encoder + Transformer Decoder	0.5209	0.8738	1.4722	0.6417

We can see that the transformer architecture gets significantly lower loss and higher accuracy compared to the baseline CNN-RNN model.

5 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.

6 Contributions

Jayaprakash Sundararaj: Initial report, researching the dataset and existing methods. Implementing the full CNN and LSTM as a baseline. Extending to pre-trained ResNet50 model with finetuning.

Akhil: Ideation, AWS/GPU setup, Extending to CNN + GRU as a baseline, vision transformer encoder + transformer decoder model, masked loss.

Ben: TODO

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