

# FORMATTING INSTRUCTIONS FOR APS360 PROJECT BASED ON ICLR CONFERENCE FORMAT

## Author One

Student# 1005678901  
author1@mail.utoronto.ca

## Author Two

Student# 1005678901  
author2@mail.utoronto.ca

## Author Three

Student# 1005678901  
author3@mail.utoronto.ca

## Author Four

Student# 1005678901  
author4@mail.utoronto.ca

## ABSTRACT

This template should be used for all your project related reports in APS360 course.  
– Write an abstract for your project here. Please review the **First Course Tutorial**  
for a quick start —Total Pages: 5

## 1 PROJECT DOCUMENT SUBMISSION FOR APS360 COURSE

The format for the submissions is a variant of the ICLR 2022 format. Please read carefully the instructions below, and follow them faithfully. There is a **9 page** limit for the main text. References do not have any limitation. This is also ICLR’s standard length for a paper submission. If your main text goes to page 10, a –20% penalty would be applied. If your main text goes to page 11, you will not receive any grade for your submission.

### 1.1 STYLE

Papers to be submitted to APS360 must be prepared according to the instructions presented here.

Authors are required to use the APS360 L<sup>A</sup>T<sub>E</sub>X style files obtainable at the APS360 website on Quercus. Tweaking the style is not permitted.

### 1.2 RETRIEVAL OF STYLE FILES

The file APS360\_Project.pdf contains these instructions and illustrates the various formatting requirements your APS360 paper must satisfy. Submissions must be made using L<sup>A</sup>T<sub>E</sub>X and the style files iclr2022\_conference.sty and iclr2022\_conference.bst (to be used with L<sup>A</sup>T<sub>E</sub>X2e). The file APS360\_Project.tex may be used as a “shell” for writing your paper. All you have to do is replace the author, title, abstract, and text of the paper with your own.

The formatting instructions contained in these style files are summarized in sections 2, 3, and 4 below.

## 2 GENERAL FORMATTING INSTRUCTIONS

The text must be confined within a rectangle 5.5 inches (33 picas) wide and 9 inches (54 picas) long. The left margin is 1.5 inch (9 picas). Use 10 point type with a vertical spacing of 11 points. Times New Roman is the preferred typeface throughout. Paragraphs are separated by 1/2 line space, with no indentation.

Paper title is 17 point, in small caps and left-aligned. All pages should start at 1 inch (6 picas) from the top of the page.

Authors' names are set in boldface, and each name is placed above its corresponding address. The lead author's name is to be listed first, and the co-authors' names are set to follow. Authors sharing the same address can be on the same line.

Please pay special attention to the instructions in section 4 regarding figures, tables, acknowledgments, and references.

There will be a strict upper limit of 9 pages for the main text of the initial submission, with unlimited additional pages for citations.

### 3 HEADINGS: FIRST LEVEL

First level headings are in small caps, flush left and in point size 12. One line space before the first level heading and 1/2 line space after the first level heading.

#### 3.1 HEADINGS: SECOND LEVEL

Second level headings are in small caps, flush left and in point size 10. One line space before the second level heading and 1/2 line space after the second level heading.

##### 3.1.1 HEADINGS: THIRD LEVEL

Third level headings are in small caps, flush left and in point size 10. One line space before the third level heading and 1/2 line space after the third level heading.

### 4 NOTABLE CONTRIBUTION

These instructions apply to everyone, regardless of the formatter being used.

#### 4.1 CITATIONS WITHIN THE TEXT

Citations within the text should be based on the `natbib` package and include the authors' last names and year (with the "et al." construct for more than two authors). When the authors or the publication are included in the sentence, the citation should not be in parenthesis using `\citet{}` (as in "See Hinton et al. (2006) for more information."). Otherwise, the citation should be in parenthesis using `\citep{}` (as in "Deep learning shows promise to make progress towards AI (Bengio & LeCun, 2007).").

The corresponding references are to be listed in alphabetical order of authors, in the REFERENCES section. As to the format of the references themselves, any style is acceptable as long as it is used consistently.

To cite a new paper, first, you need to add that paper's BibTeX information to `APS360_ref.bib` file and then you can use the `\citep{}` command to cite that in your main document.

#### 4.2 PRIMARY MODEL

The overall model architecture is described in Figure 1 flowchart.

For our haiku generation model, we continued with a Long Short-Term Memory (LSTM) architecture to capture the contextual nuances, and move towards generating coherent and accurate haikus.

The architecture of the model is as follows:

First, the input data is passed through an embedding layer. It transforms this data into vector representations that capture the relationships between words throughout the data. The layer takes in the number of unique words in the dataset, including our special tokens. These special tokens consist of the following:

- Padding token - used to make sequences uniform in length within a batch.

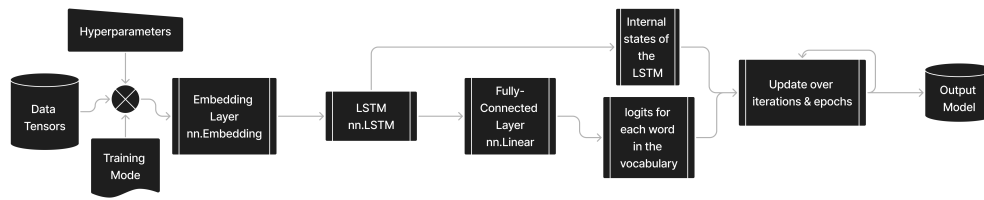


Figure 1: Model Architecture

- Unknown token - represents a word that is not in the vocabulary.
- End-of-Sequence token - signifies where the model should stop generating text.

The embedding dimensions are also inputs to this layer, which are the size of each word in the embedding vector, as is the padding index - the index reserved for our padding tokens that ensure padded positions don't contribute to the learning process.

Next, the output of the embedding layer is passed through the LSTM layer. This layer serves to process the sequence of embeddings to capture contextual information across words. It takes in the numbers of features in the hidden states of the LSTM, the number of stacked LSTM layers, and the batch size. The resulting output of this layer is a tensor that has the output features from the LSTM, as well as the hidden states of the LSTM for each layer.

Finally, the output of the LSTM layer is passed through a fully-connected layer. This maps the LSTM outputs to our vocabulary set, and produces logits for each word in this vocabulary. The input features are equal to the LSTM's hidden dimensions, and the output features are equal to the size of the vocabulary.

In our current configuration, we used 128 embedding dimensions, 256 hidden dimensions, and 2 LSTM layers.

With our current training data, we have a vocabulary size of 50554 words.

The embedding layer has  $50554 \cdot 128 = 6470912$  parameters.

Next the the LSTM layer has  $2 \cdot 4 \cdot (256 \cdot (128 + 256) + 256) = 788480$  parameters. The four is to account for the input gate, forget gate, cell gate, and output gate in an LSTM.

Finally, the fully-connected layer has  $256 \cdot 50554 + 50554 = 12992378$  parameters.

Therefore, the total number of parameters in the current model is 20251770.

As for our training hyperparameters, we chose to train over 50 epochs, with a learning rate of 0.001, a batch size of 64, an Adam optimizer<sup>1</sup>, and a Cross Entropy Loss criterion<sup>2</sup>.

### Quantitative Results:

We tested out model with 300 one or two word prompts to the model, and counted the syllables in the output haiku.

As we can see in Figure 2, the vast majority of generated haikus are between 17 and 19 syllables, with a few outliers. These can be explained by either the model incorrectly counting syllables from words that are not in the CMU Pronouncing Dictionary (University, 2014), or the syllable counting algorithm miscounting on the output. We are aiming to have our model only output 17 syllable haikus, so we have more methods we will be integrating into the model.

### Qualitative Results:

The model generates a mix of interesting or funny haikus, and incoherent outputs:

<sup>1</sup>Chosen from findings in (Kingma & Ba, 2017)

<sup>2</sup>Chosen from approach in (TensorFlow Team, 2023)

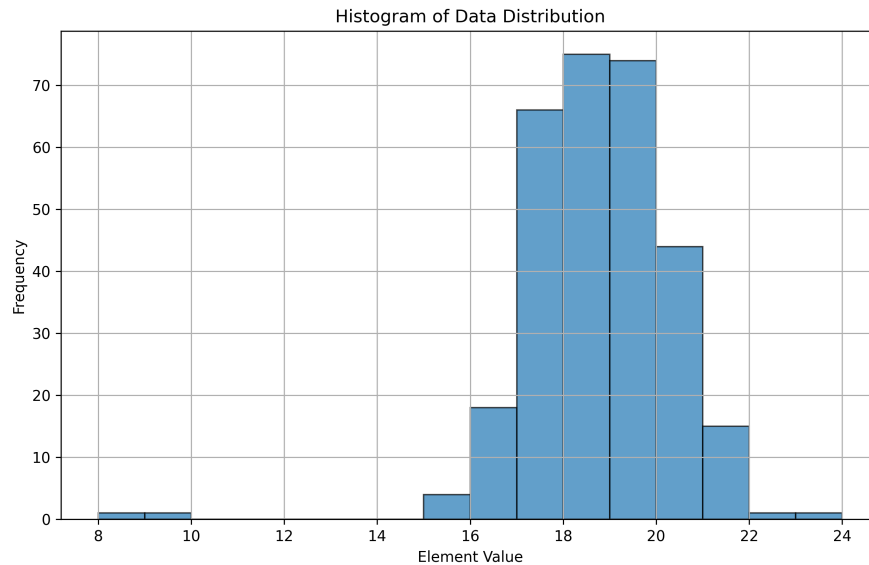


Figure 2: Syllables per haiku from 300 outputs

- *“river flows wildly  
air patches on the surface  
dissipates in life”*
- *“rainfall through the roof  
dancers from serenity  
as his life goes by”*
- *“grass on the wayside  
looking for the light to come  
warm clouds and weather”*
- *“bloom gives way to me  
for i am not your hero  
i am george carlin”*
- *“pond ripples to steal  
winters for having their gaze  
beg for hope bears now”*
- *“branch and wood filters  
of night bright and sunny day  
hot lemonade waits”*
- *“stream sits and pure fish  
in between and i am glad  
with what we i”*
- *“ancient tree freedom  
anxiety creation  
ignites and section”*

As we can see, the model is able to generate haikus that could pass for human-written, however, it still generates incoherent haikus. Moving towards generating more coherent outputs will be a focus of our as we improve to model.

The main challenges we faced making this model were related to ensuring syllable structure and was maintained and the syllable counts were accurate, and slow training times.

Because of irregularities in the English Language, we found it difficult to come up with a reliable method to count the number of syllables in a given word. Our current solution involves referencing the CMU Pronouncing Dictionary (University, 2014) to get the syllable count of a given word. However, this method is not perfect, as the CMU Pronouncing Dictionary does not contain all words that may show up in our vocabulary. This causes issues when a word is not in the dictionary, so we are looking to integrate algorithms that can help resolve this, although this still only provides an approximation which can lead to slight issues during generation.

The slow training times were due to the large amount of data and limited access to compute resources. We tested differing batch sizes to reach a reasonable training time given our resources, however we are looking into ways to gain access to more powerful GPUs to speed up training.

## 5 DEFAULT NOTATION

In an attempt to encourage standardized notation, we have included the notation file from the textbook, *Deep Learning* Goodfellow et al. (2016) available at [https://github.com/goodfeli/dlbook\\_notation/](https://github.com/goodfeli/dlbook_notation/). Use of this style is not required and can be disabled by commenting out `math_commands.tex`.

## 6 FINAL INSTRUCTIONS

Do not change any aspects of the formatting parameters in the style files. In particular, do not modify the width or length of the rectangle the text should fit into, and do not change font sizes (except perhaps in the REFERENCES section; see below). Please note that pages should be numbered.

### AUTHOR CONTRIBUTIONS

If you'd like to, you may include a section for author contributions as is done in many journals. This is optional and at the discretion of the authors.

### ACKNOWLEDGMENTS

Use unnumbered third level headings for the acknowledgments. All acknowledgments, including those to funding agencies, go at the end of the paper.

## REFERENCES

- Yoshua Bengio and Yann LeCun. Scaling learning algorithms towards AI. In *Large Scale Kernel Machines*. MIT Press, 2007.
- Ian Goodfellow, Yoshua Bengio, Aaron Courville, and Yoshua Bengio. *Deep learning*, volume 1. MIT Press, 2016.
- Geoffrey E. Hinton, Simon Osindero, and Yee Whye Teh. A fast learning algorithm for deep belief nets. *Neural Computation*, 18:1527–1554, 2006.
- Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2017. URL <https://arxiv.org/abs/1412.6980>.
- TensorFlow Team. Text generation with an rnn, 2023. URL [https://www.tensorflow.org/text/tutorials/text\\_generation](https://www.tensorflow.org/text/tutorials/text_generation).
- Carnegie Mellon University. The carnegie mellon university pronouncing dictionary, 2014. URL <http://www.speech.cs.cmu.edu/cgi-bin/cmudict>.