HOMEWORK 3

16824 VISUAL LEARNING AND RECOGNITION (FALL 2024)
https://piazza.com/cmu/fall2024/16824/

RELEASED: Monday, 28th Oct 2024
DUE: 11:59 PM ET, Friday, 15th Nov 2024
Instructor: Jun-Yan Zhu
TAs: Hsu-kuang Chiu, M. Yunus Seker

START HERE: Instructions

- **Collaboration policy:** All are encouraged to work together BUT you must do your own work (code and write up). If you work with someone, please include their name in your write-up and cite any code that has been discussed. If we find highly identical write-ups or code or lack of proper accreditation of collaborators, we will take action according to strict university policies. See the Academic Integrity Section detailed in the initial lecture for more information.
- **Late Submission Policy:** There are a **total of 5** late days across all homework submissions. Submissions that use additional late days will incur a 10% penalty per late day.
- **Submitting your work:**
  - We will be using Gradescope (`https://gradescope.com/`) to submit the Problem Sets. Please use the provided template only. You do **not** need any additional packages and using them is **strongly discouraged**. Submissions must be written in LaTeX. All submissions not adhering to the template will not be graded and receive a zero.
  - **Deliverables:** Please submit all the `.py` files. Add all relevant plots and text answers in the boxes provided in this file. To include plots you can simply modify the already provided latex code. Submit the compiled `.pdf` report as well.

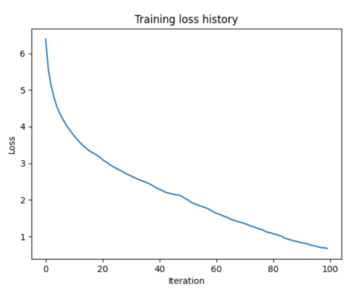
NOTE: Partial points will be given for implementing parts of the homework even if you don't get the mentioned accuracy as long as you include partial results in this pdf.

1 Image Captioning with Transformers (70 points)

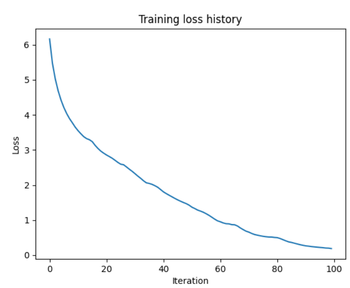
We will be implementing the different pieces of a Transformer decoder (Transformers), and train it for image captioning on a subset of the COCO dataset.

- **Setup:** Run the following command to extract COCO data, in the `transformer_captioning/datasets` folder : `./get_coco_captioning.sh`
- **Question:** Follow the instructions in the `README.md` file in the `transformer_captioning` folder to complete the implementation of the transformer decoder.
- **Deliverables:** After implementing all parts, use run.py for training the full model. The code will log plots to `plots`. Extract plots and paste them into the appropriate section below.
- **Expected results:** These are expected training losses after 100 epochs. Do not change the seed in run.py.
  - 2-heads, 2-layers, lr 1e-4: Final loss ≤ 1
  - 4-heads, 6-layers, lr 1e-4: Final loss ≤ 0.3
  - 4-heads, 6-layers, lr 1e-3: Final loss ≤ 0.05

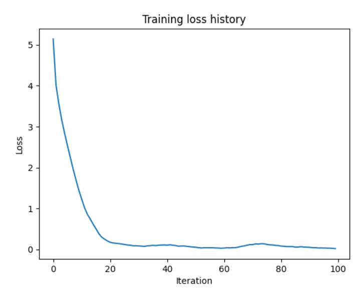
1. Paste training loss plots for each of the three hyper-param configs
   2-heads-2-layers-lr-1e-4: **0.812**
   4-heads-6-layers-lr-1e-4: **0.238**
   4-heads-6-layers-lr-1e-3: **0.024**



(a) 2-heads-2-layers-lre-4

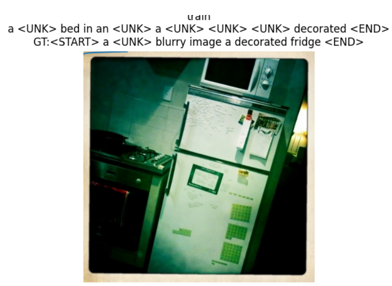


(b) 4-heads-6-layers-lre-4

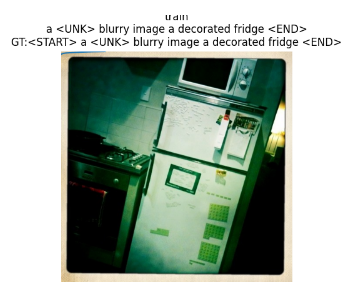


(c) 4-heads-6-layers-lre-3

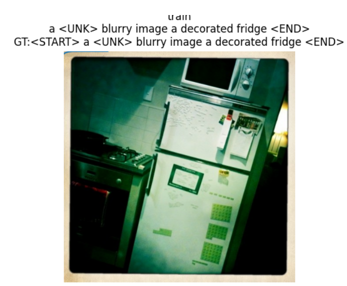
2. Paste any three generated captioning samples from the training set with the three different settings. The provided code creates these plots at the end of training.



(a) Sample1: 2-heads-2-layers-lre-4



(b) Sample2:4-heads-6-layers-lre-4



(c) Sample3:4-heads-6-layers-lre-3

3. Based on the observations of the three different settings, What would you change in the training procedure to get better validation performance? Why tweaking these hyper-parameters will lead to better performances?

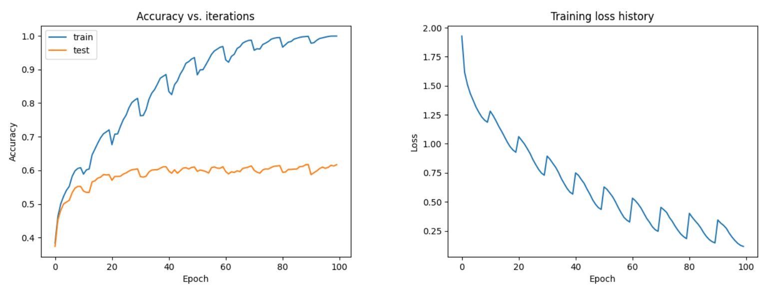
Solution:
We made two adjustments to the hyperparameters in this experiment. First, we modified the number of heads and layers, gradually increasing them to enhance model complexity. The multi-head attention mechanism helps capture diverse relationships within the data. It allows the model to learn various types of dependencies and examine the data from different perspectives in parallel.
However, we must be cautious of overfitting. An overly complex model that performs too well on the training set may generalize poorly to unseen data.

Second, we adjusted the learning rate. A larger learning rate can speed up convergence, enabling the model to learn more quickly. However, if the learning rate is too high, it may cause the model to oscillate near a local minimum, hindering effective learning.

2 Classification with Vision Transformers (30 points)

We will use the transformer you implemented in the previous part to implement a Vision Transformer (ViT), for classification on CIFAR10.

- **Question:** Follow the instructions in the `README.md` file in the `vit_classification` folder. You are encouraged to resuse code from the previous question.
- **Deliverables:** Run training using `run.py` for training the full model. The code will log plots `acc_out.png` (train and test accuracy) and `loss_out.png` (train loss).
- **Expected Results:** After 100 epochs, test accuracy should be $\geq 65\%$, train accuracy should be $\approx 100\%$, and training loss ≤ 0.3.



(a) Train/test accuracy (b) Training loss

Solution:
Test Accuracy: **0.624**

Train Accuracy: **0.995**

Training Loss: **0.127**

Collaboration Survey Please answer the following:

1. Did you receive any help whatsoever from anyone in solving this assignment?

   ○ Yes

   ● No

   - If you answered 'Yes', give full details:
   - (e.g. "Jane Doe explained to me what is asked in Question 3.4")

2. Did you give any help whatsoever to anyone in solving this assignment?

   ○ Yes

   ● No

   - If you answered 'Yes', give full details:
   - (e.g. "I pointed Joe Smith to section 2.3 since he didn't know how to proceed with Question 2")

3. Note that copying code or writeup even from a collaborator or anywhere on the internet violates the Academic Integrity Code of Conduct.