Attention Please! Deep-dive into Image Captioning Efficacy

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Motivation

The success of seminal research paper “Attention is All You Need” has highlighted the power of self-attention mechanisms in language modeling tasks, and has spurred a wave of research into transformer-based models. As companies like OpenAI continue to push the boundaries of what's possible with generative text models, it's clear that the race is far from over.

Image captioning is a challenging task in computer vision that requires a deep understanding of both visual and linguistic content. Our group aims to we aim to investigate and compare the performance of different transformer-based models for image captioning.

Problem

Foundational Models: *Too Big to Fail?*

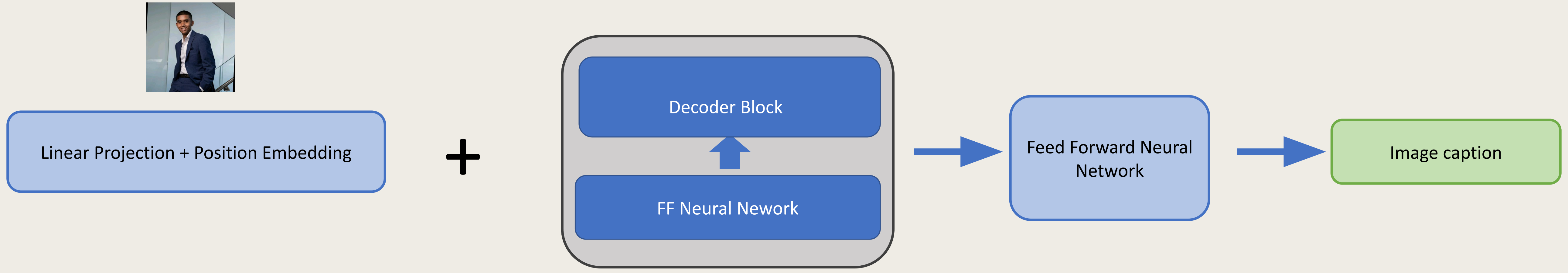
While image extractors like VGG19, ResNet, and InceptionX have achieved impressive results on a wide range of image recognition tasks, there is a growing concern that their generalized nature may lead to blind spots in the AI. This lack of specificity poses a significant problem for image captioning, as it can limit the model's ability to accurately describe and contextualize images. Our group aim to investigate this issue by comparing efficacy of un-tuned base image captioning models relative to a fine-tuned an image captioning model on a specific dataset.

Goal

Our Action Items

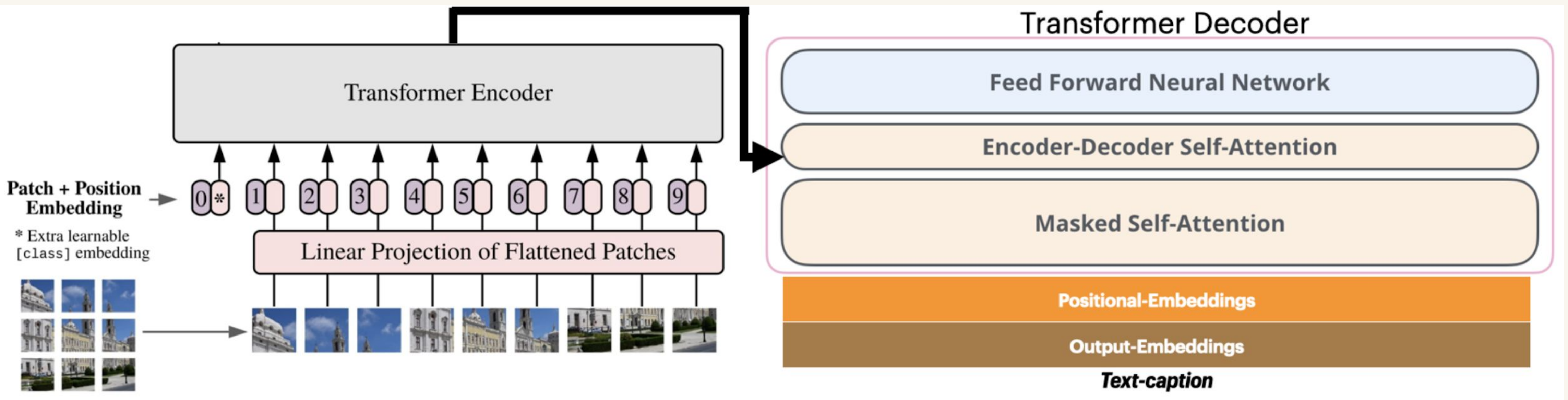
1. Implement a simple image captioning model by hand that utilized seq2seq architecture. Use different datasets and model architectures
2. Compare the efficacy of pre-existing models such as opensource ViT-GPT2, Microsoft Research Team’s GIT, and Saleforce’s BLIP
3. Fine-tune the GIT base models, retraining on niche datasets, to investigate model efficacy prior and after fine-tuning

Basic model architecture

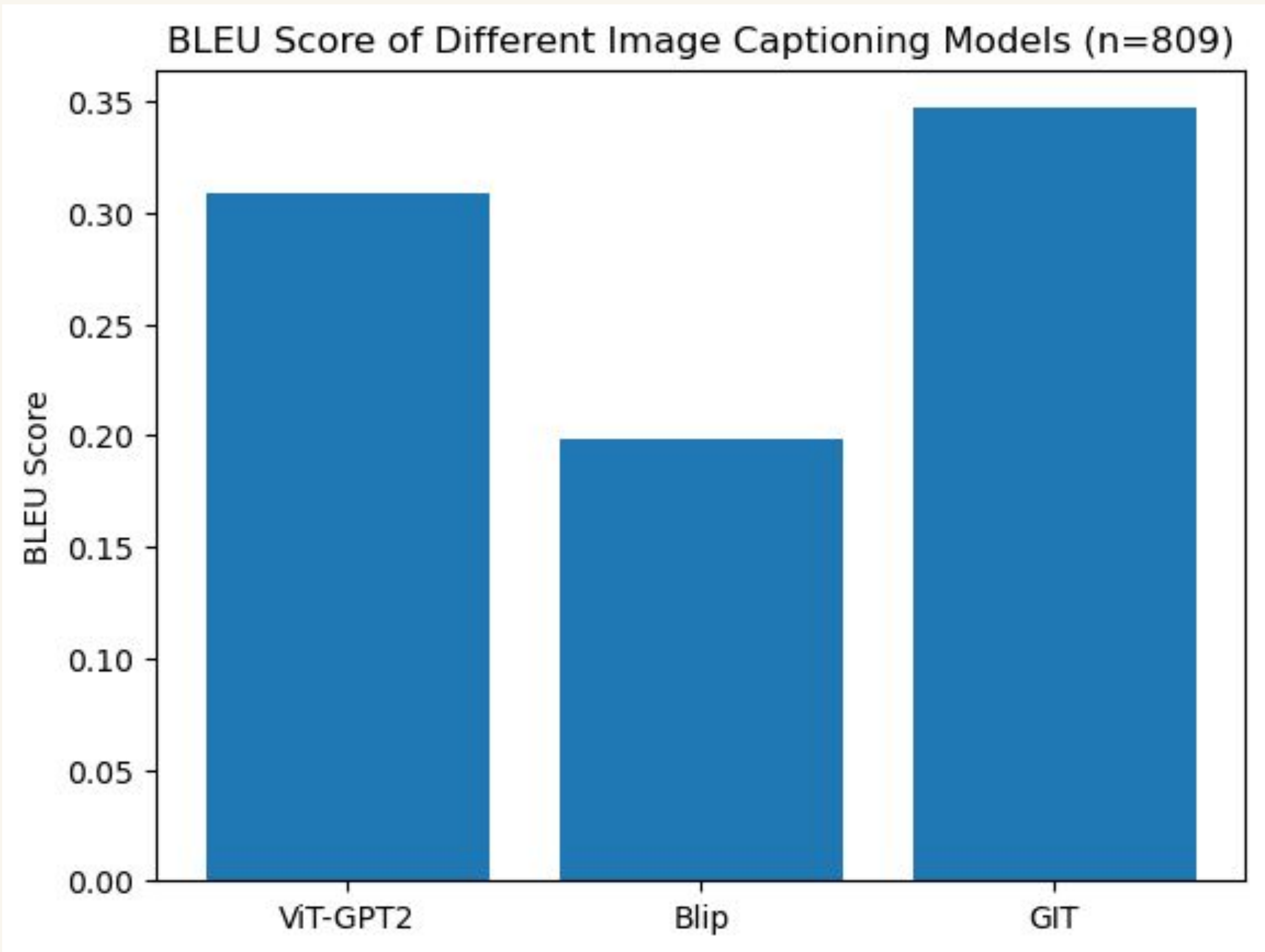

Linear Projection + Position Embedding
+
Decoder Block
FF Neural Nework
Feed Forward Neural Network
Image caption

- The basic model was fairly straightforward: It utilized an image-feature extractor (experimented with VGG16, ResNet, InceptionV3) and Spacy-processed captions and was fed to a Seq2Seq model that predicted the next token (only one that predicted sensible tokens). We utilized GLOVE embeddings
- Experimented with RNN/LSTM/GRU and a TransformerBlock architecture on smaller subset of Flickr8k Dataset.
- Experimented with Greedy Search, which seemed to have limitations, and implemented Beam Search
- Had Flickr30k and COCO120K data created, but could not find resources to test: Possibly would improve performance

ViT-GPT2 Model Architecture


Transformer Encoder
Patch + Position Embedding
* Extra learnable [class] embedding
0 *
1
2
3
4
5
6
7
8
9
Linear Projection of Flattened Patches
Transformer Decoder
Feed Forward Neural Network
Encoder-Decoder Self-Attention
Masked Self-Attention
Positional-Embeddings
Output-Embeddings
Text-caption

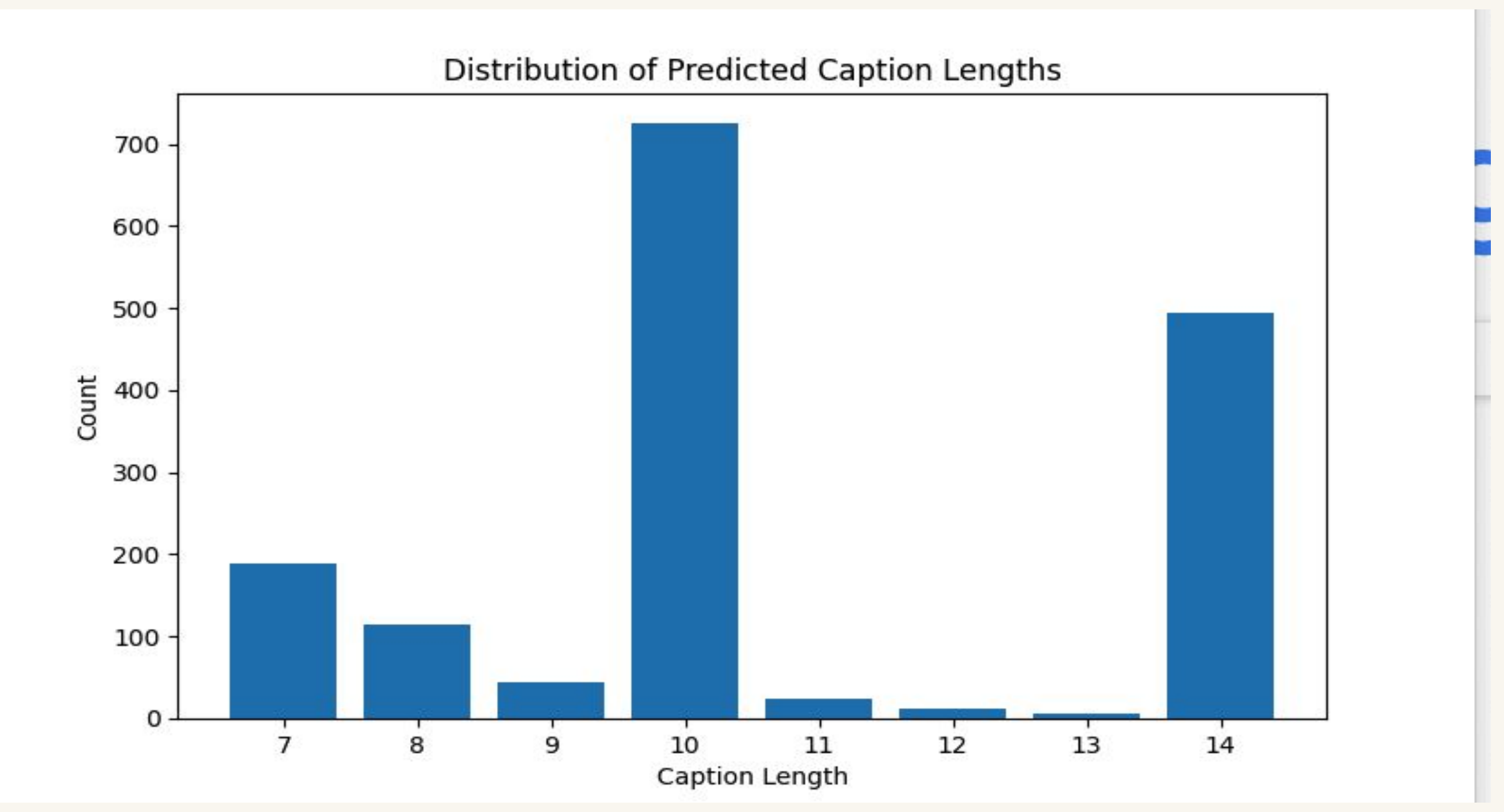
Results

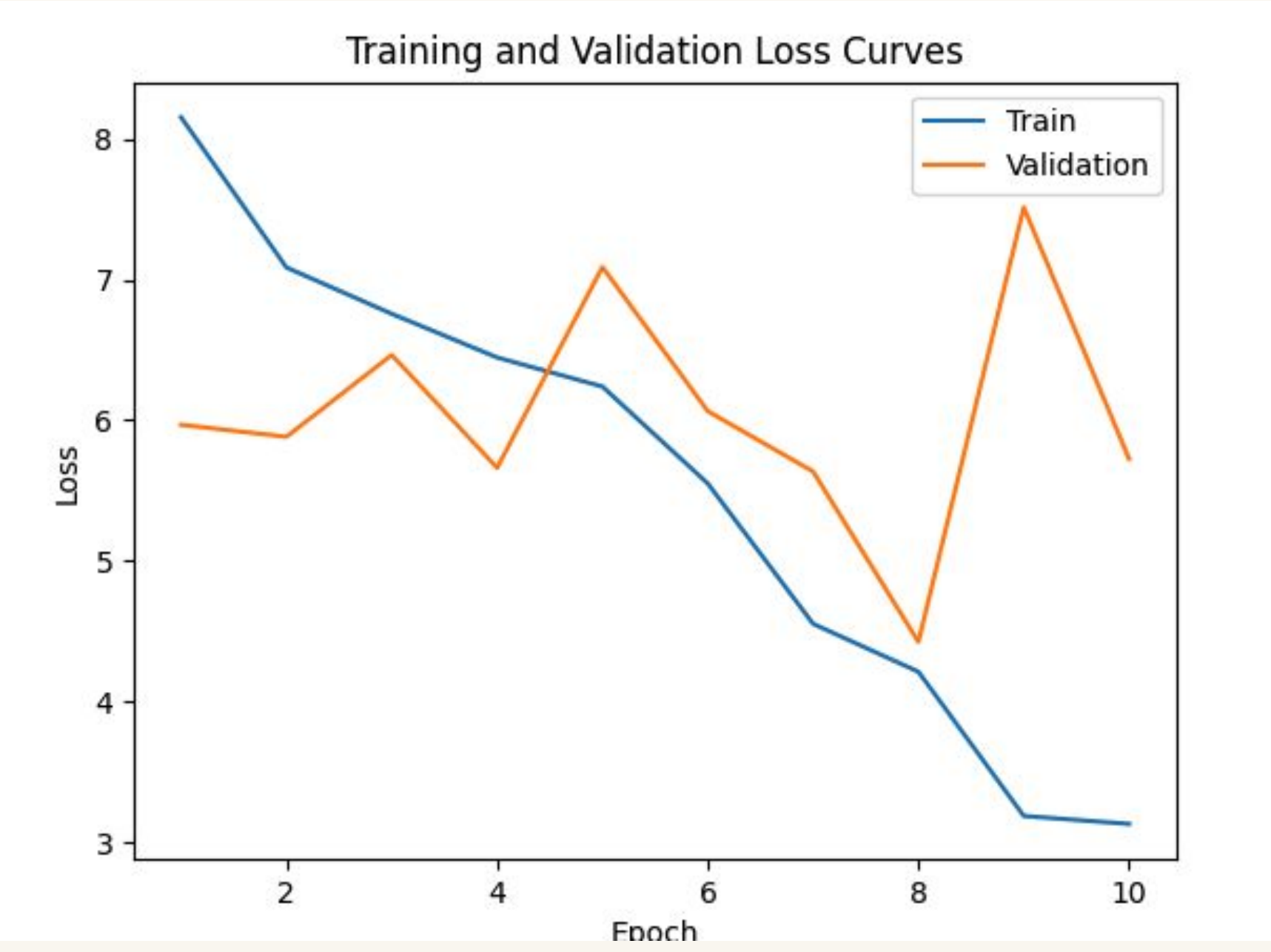


'a stuffed animal with a flower in it'

'a green and red toy with red eyes'

More results and Limitations





- For the basic model, lack of computational resources available became a large issue in our model’s weaknesses
  - Best BLEU score: 0.05. Not very strong, but we believe the use of Greedy Search + low data limits affected our performance. Greedy Search favored very specific tokens and required careful engineering. We implemented Beam Search but it wasn’t computationally efficient.
  - Performance on fine-tuned obviously did not go as plan given lack of generality on general data

References

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Lambda. “Pokemon-Blip-Captions.” Huggingface.co, 13 Dec. 2022
adityajn105. “Flickr 8k Dataset.” Kaggle.com, 2020, www.kaggle.com/datasets/adityajn105/flickr8k

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