Live, Laugh, Learn: A Deep Learning Model for Meme Captioning

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CSE 493: Introduction to Deep Learning, Spring 2025

Introduction

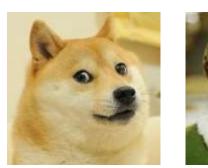
Humor is **HARD**:

- 1. Need to understand the sociocultural context of an image
- 2. Humor is subjective and always evolving



Existing Work

1. Lack of Diverse Data





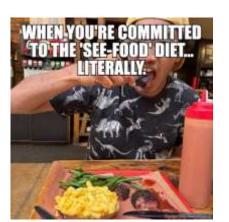




4 Templates from MemeGenerator.net

2. Old/Generic Captions

3. Training Pipeline [4]







Goal

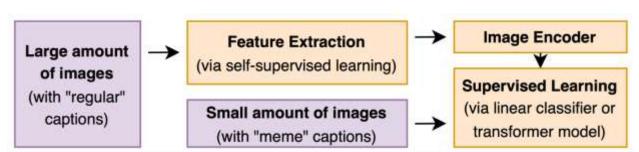
Develop a lightweight model that humorously captions diverse images using contextual understanding rivaling larger LLMs with fewer parameters and less compute.

Conclusion

- Learning humor requires a diverse, massive, constantly-updating dataset
- Attributes unique to humor (diversity, inconsistent phrasing, subtle clues) make it especially hard to train

Future Work

- Self-Supervised Learning
- Pre-train on regular image captions, Post-train on meme captions



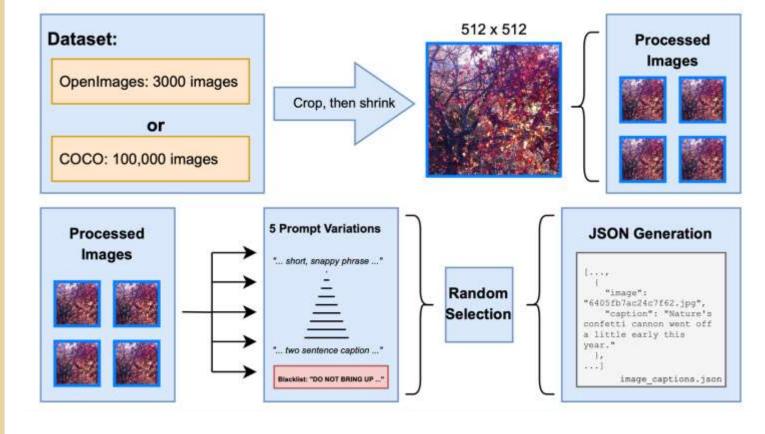
- Different architectures/data (e.g. a "meaning" along with caption)
- Increase the dataset size, quality (better prompts)

That's not a serve; it's a meticulously choreographed interpretive dance about the existential angst of a rogue tennis ball. Apparently, the judges are impressed.

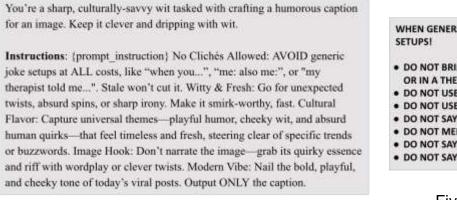




Data Collection



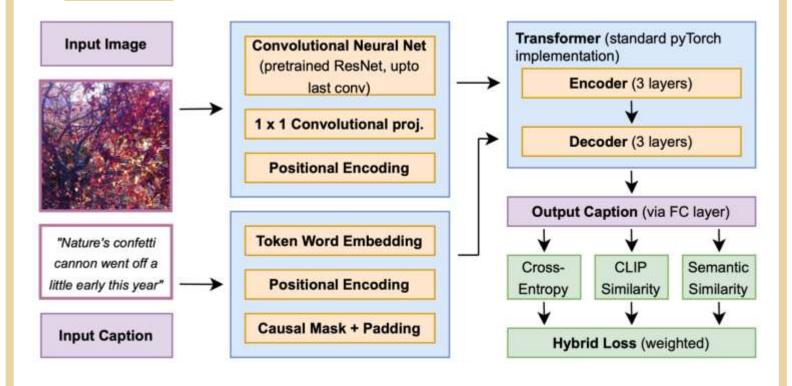
- **Q**: Why these datasets?
- A: Diverse dataset matches real-world images
- **Q**: Why do we generate our own captions?
- A: No meme caption dataset exists for diverse images
- → distillation via Gemini



WHEN GENERATING YOUR RESPONSE, AVOID THE FOLLOWING CLICHED DO NOT SAY "I swear, [X]", and AVOID bringing up "my inner child".

> Five different prompts and blacklist responses encourage diverse captions

Our Model

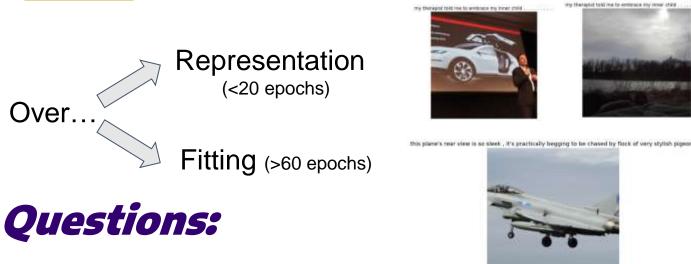


Loss weights change over the course of training (right):

- Cross-Entropy: text vs. text
- Semantic similarity: text embedding vs text embedding
- CLIP Similarity: image embedding vs text embedding (regularizer, doesn't backpropagate to model)

Semantic Loss

Initial Results



- 1. Make it **comprehensible**?
- 2. How to balance underfitting/overfitting? (some sort of semantic score for early stopping)



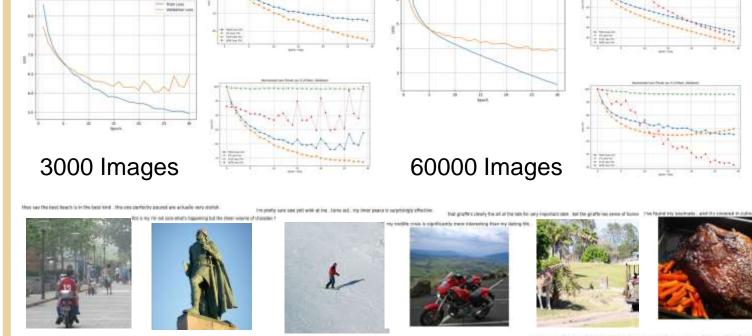




1. Are we just training an image classifier, and then **overfitting** to image in training set?

Experiments

1. More Training Data





3K Dataset







60K Dataset

2. Byte-Pair Encoding (BPE)

Vocab: 20K



Hard to learn semantic

punctuation

structure w/o more data • Reflects overuse of

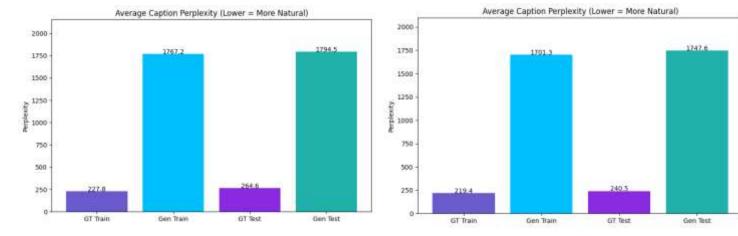
Blocky with Inconsistent

punctuation in meme captions

3. Semantics

Vocab:

Evaluating grammar and fluency via GPT2 perplexity scores, compared to target captions (ground-truth)



3000 Images

60000 Images

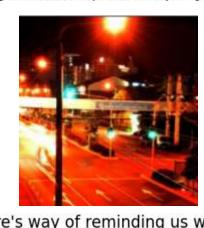
So ... Does it Understand Context? Kinda...







he wasn't sure if he was summoning bike trick , but the squirrels are already calling it into the sunset



Is it funny? ...Sometimes:)

traffic lights nature's way of reminding us we're all just waiting for the traffic lights .

References

[1] Yuyan Chen, Songzhou Yan, Zhihong Zhu, Zhixu Li, and Yanghua Xiao. Xmecap: Meme caption generation with subimage adaptability, 2024. 2

[2] Taraneh Ghandi, Hamidreza Pourreza, and Hamidreza Mahyar. Deep learning approaches on image captioning: A review.

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[5] Andreas Refsgaard and Frederik Lauenborg. MemeCam, 2023.