Figuring Out Figures: Using Textual References to Caption Scientific Figures

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The Problem & Background

Figures are essential channels for densely communicating complex ideas in papers. Automatic captioning could:

1. Reduce the burden for authors to write high-quality captions;
2. Improve accessibility to impaired readers;
3. Extract useful information as text from figures that could be used in later pipelines.

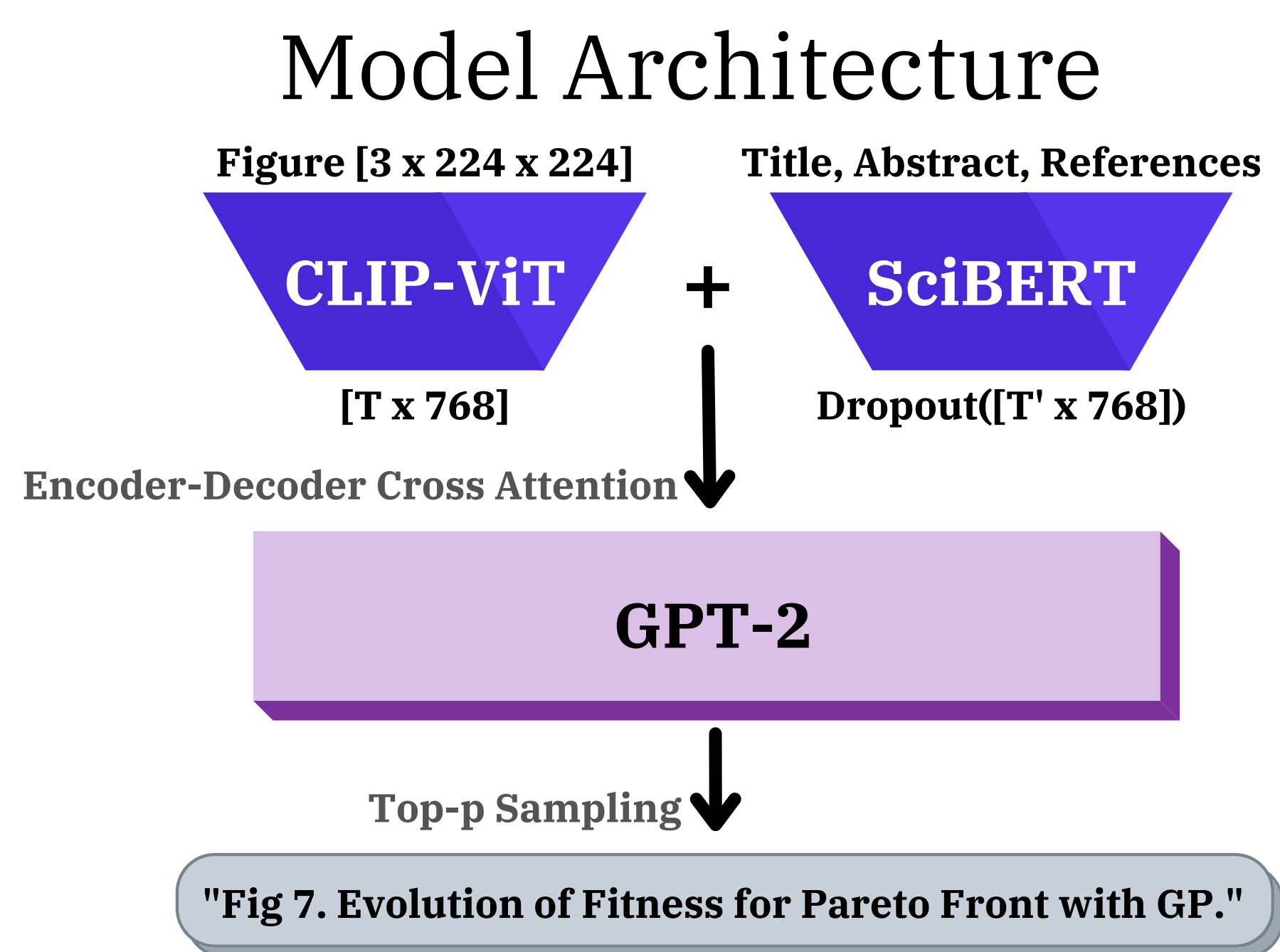**However, captioning scientific figures is harder than normal images:**

- State of the art models rely on region/object extraction (unavailable for figures).
- Even after trying more advanced architectures, best performance is currently achieved with a CNN+LSTM.

Data

- **SciCap dataset**, curated by Hsu et al. as a starting point, which contains **figures and captions** for CS papers from 2010-2020.
    - **133K** figures without subfig, split 80/10/10 train/val/test
    - Extracts first sentence of caption
- arXiv metadata to pull **titles and abstracts** for each paper
- Custom data pipeline to search the full text of each paper for **references**. Original verbatim caption found through Striped Smith-Waterman algorithm and masked out.

Methods

- Modeled as a sequence to sequence problem
- Fully transformer architecture
- **Vision Encoder Decoder architecture**: (figure, title, abstract, references) → caption
    - **Encoder**: CLIP ViT-B/32 + SciBERT-base (text features)
    - CLIP used as model trained on general Internet imagery
    - **Decoder**: GPT-2 base model or DistilGPT2
- **We used the original captions from SciCap**, rather than the normalized ones, to encourage equation/number prediction
- To generate the caption, we use top-p sampling with $p = 0.9$. A diagram is shown to the right.

Model Architecture

Figure [3 x 224 x 224] — **CLIP-ViT** [T x 768]

Title, Abstract, References — **SciBERT** Dropout([T' x 768])

Encoder-Decoder Cross Attention

GPT-2

Top-p Sampling

"Fig 7. Evolution of Fitness for Pareto Front with GP."

Data Example — Figure 1/13.3K (test set)

INPUTS

SciCap:

Title: Pseudorandomness in Central Force Optimization

Abstract: Central Force Optimization is a deterministic metaheuristic for...

References: ...Fig. 7 plots CFO's " Davg curve" for GP. Davg is the normalized average distance between the probe with th...
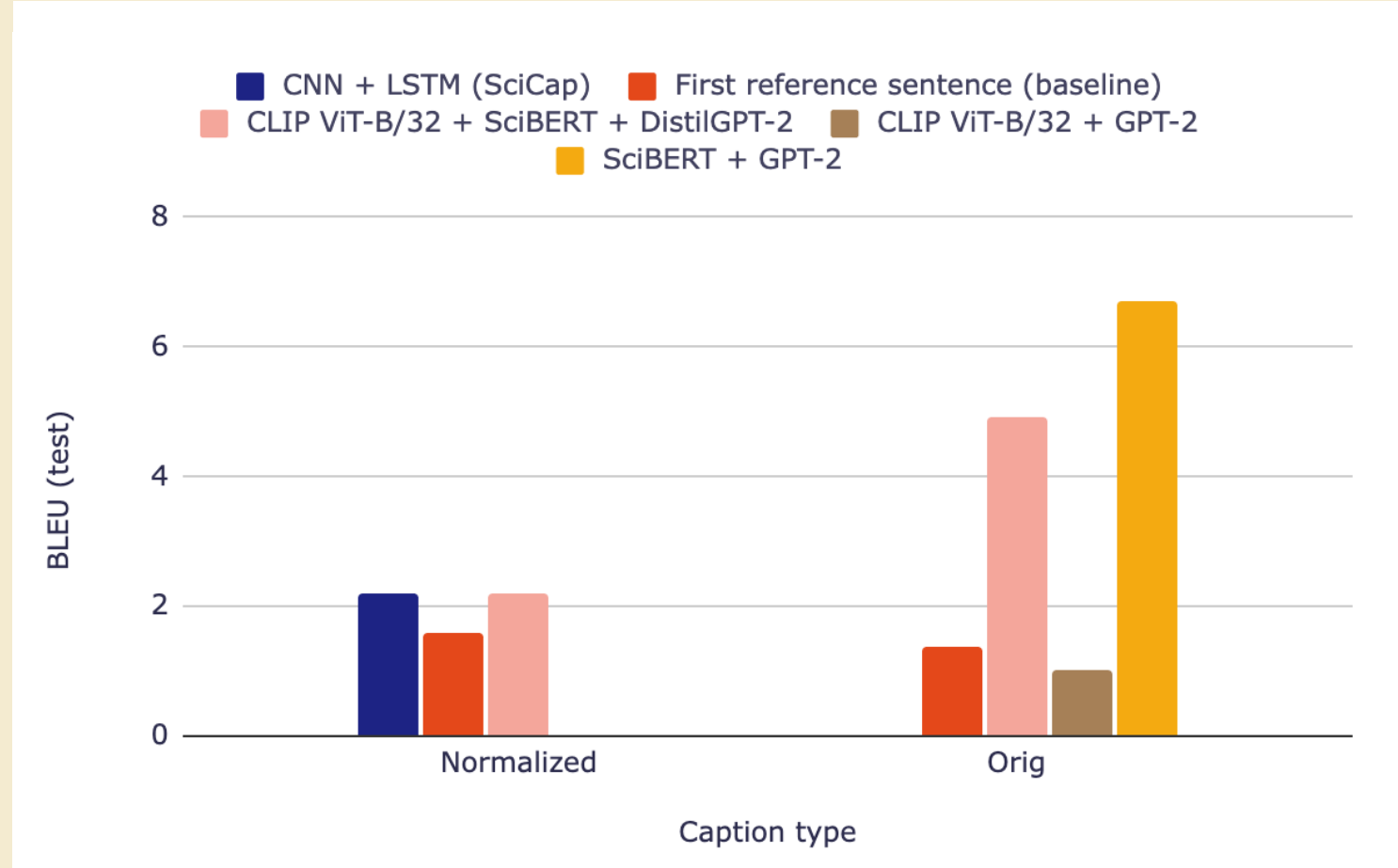
OUTPUTS

Ground truth caption: Fig. 7. Evolution of GP Function avgD

**Predicted:** Fig. 7. Evolution of Fitness for Pareto Front with GP.

Experiments

- Ablations over image/text inputs performed
- Extensive model/hyperparameter search: DeiT, GPT-2, CLIP ViT/L-14, lr scheduling, text dropout to encourage image usage

Image?	Text?	Caption type	Model	BLEU (test)	ROUGE-L F1 (test)
✓		Normalized	CNN + LSTM (SciCap)	2.19	—
	✓	Normalized	First reference sentence (baseline)	1.59	0.09
✓	✓	Normalized	CLIP ViT-B/32 + SciBERT + DistilGPT-2	2.21	0.18
	✓	Orig	First reference sentence (baseline)	1.38	0.10
✓	✓	Orig	CLIP ViT-B/32 + SciBERT + DistilGPT-2	4.92	0.26
✓	✓	Orig	CLIP ViT-B/32 + GPT-2	1.02	0.13
	✓	Orig	SciBERT + GPT-2	6.71	0.30

Analysis

- Reference data improves performance over pure image input
- However, creates balance issues between modalities (text-only outperforms image + text models)
- Potential benefits from scale, text dropout (improvements from ViT-L)
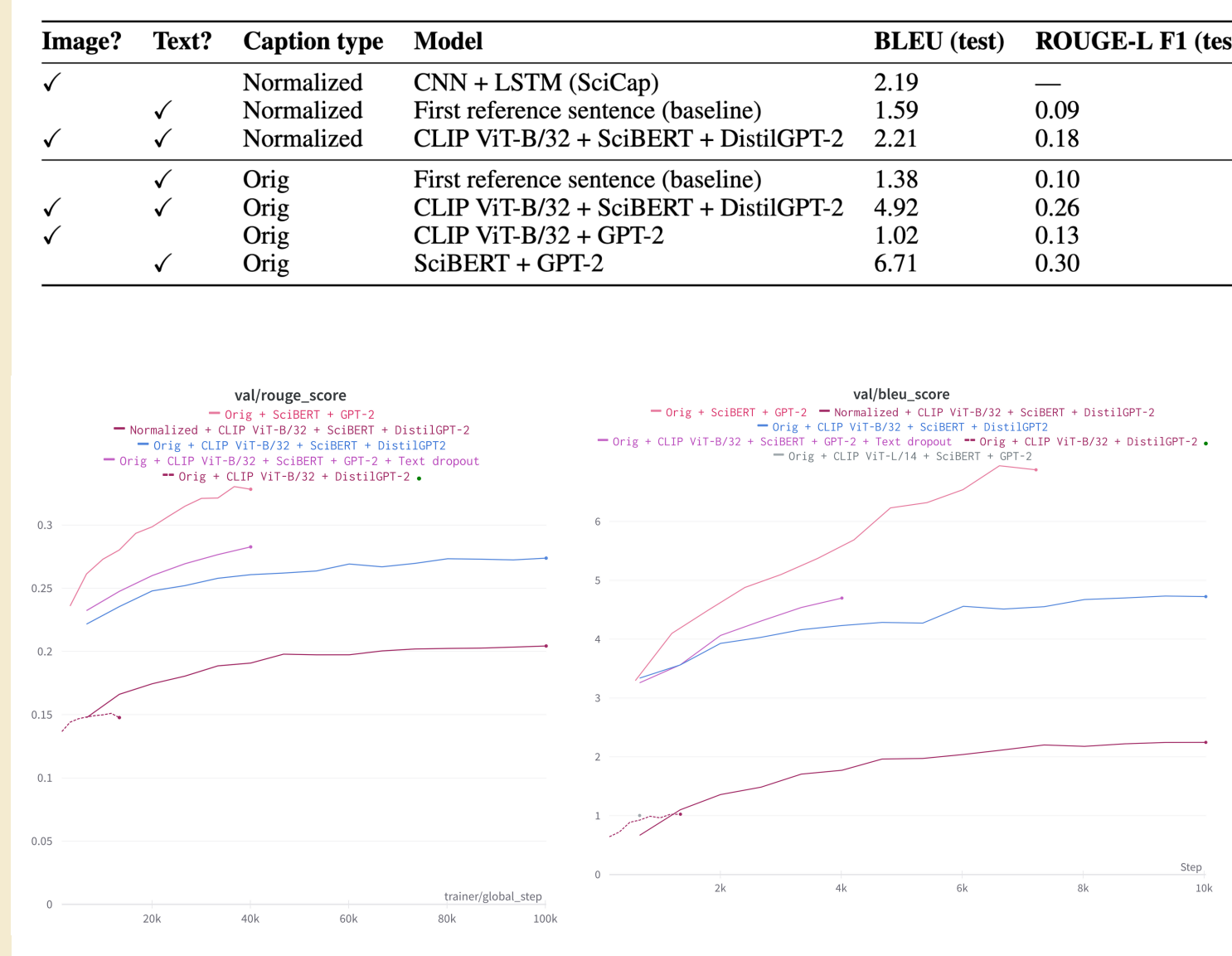
Conclusion

- Transformer model architecture achieves a better performance than the CNN+LSTM model when it is given textual metadata (e.g., references to the figure, the title, and the abstract).
- However, because our model learns more from textual references, experimentation should be done with more expressive image encoders, or perhaps improving the image encoder architecture.
- Pre-processing the image a valuable path forward (e.g., vectorizing, LaTeX), because the vision encoder could leverage the patterns found in the consistency from image pre-processing.

References

Ting-Yao Hsu, C Lee Giles, and Ting-Hao Huang. SciCap: Generating captions for scientific figures. In Findings of the Association for Computational Linguistics: EMNLP 2021, pages 3258–3264, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.

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