Pixnatte: A Hybrid BLIP–CLIP Framework for Grounded Image Caption Generation

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Abstract:

Automated image captioning sits at the intersection of computer vision and natural language processing, where the core challenge lies in generating descriptions that are simultaneously fluent, contextually accurate, and semantically grounded. Existing captioning systems based solely on encoder-decoder architectures often produce plausible but factually imprecise captions, particularly when faced with compositionally complex scenes. This paper presents Pixnatte, a hybrid system that integrates Bootstrapping Language-Image Pre-training (BLIP) with Contrastive Language-Image Pre-training (CLIP) to address this limitation. The proposed architecture leverages CLIP's robust semantic embedding space to anchor caption generation within BLIP's encoder-decoder framework, reducing hallucination and improving alignment with image content. Experiments conducted on the MS COCO benchmark yield a CIDEr score of 1.6779, BLEU-1 of 0.4444, ROUGE-L of 0.4815, and METEOR of 0.2382, demonstrating competitive performance against conventional baselines. Additionally, Pixnatte extends its capabilities to Visual Question Answering (VQA), enabling natural language interaction with visual content. Results confirm that grounded caption generation through BLIP–CLIP integration produces measurably superior captions and holds practical potential for applications in digital media, accessibility, and intelligent content systems.

Keywords: Image Captioning; BLIP; CLIP; Visual Question Answering; MS COCO; Multimodal Learning; Semantic Grounding

1. Introduction

The proliferation of digital visual content across social platforms, e-commerce, healthcare imaging, and autonomous systems has created an urgent demand for automated tools capable of understanding and articulating image content. Image captioning, the task of automatically generating natural language descriptions of visual scenes, addresses this need by bridging computer vision and natural language processing (NLP). A robust captioning system must not only identify visual elements within an image but also understand their spatial relationships, actions, and overall contextual meaning.

Traditional approaches to image captioning relied on template-based methods and rule-driven pipelines, which produced grammatically rigid and semantically limited captions. The emergence of deep learning enabled a paradigm shift through convolutional neural networks for visual feature extraction and recurrent neural networks for sequence generation. However, such architectures struggled to generalise across diverse visual domains. More recently, transformer-based vision-language models trained on large-scale datasets have demonstrated substantial improvements in caption quality, fluency, and contextual relevance.

Among these, BLIP (Bootstrapping Language-Image Pre-training) stands out as a state-of-the-art model capable of both conditional and unconditional captioning through its unified encoder-decoder architecture. Nevertheless, BLIP can occasionally generate captions that, while syntactically fluent, deviate from precise factual grounding. Simultaneously, CLIP (Contrastive Language-Image Pre-training) excels at aligning images and text in a shared embedding space through contrastive learning, offering a powerful mechanism for semantic verification.

This work introduces Pixnatte, a system that combines BLIP and CLIP into a hybrid framework wherein CLIP-derived semantic embeddings serve as auxiliary grounding signals during BLIP's caption decoding process. The result is a system that generates captions exhibiting both the fluency of language model output and the semantic precision of contrastive vision-language alignment. The system is further extended to support visual question answering via the BLIP-VQA variant, enabling interactive querying of image content. Pixnatte is evaluated on the MS COCO dataset, and its performance is measured against standard captioning metrics including BLEU, METEOR, ROUGE-L, and CIDEr.

2. Related Work

Early image captioning research relied on template-based methods that mapped extracted image features to pre-defined sentence structures. Farhadi et al. [1] demonstrated that scene, object, and action triplets could be converted into natural language descriptions using handcrafted templates, yet these approaches suffered from limited vocabulary and poor expressiveness.

The introduction of encoder-decoder neural architectures fundamentally transformed the field. Vinyals et al. [2] proposed a model combining Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks, processing images as fixed-dimensional feature vectors and decoding them sequentially into captions. Xu et al. [3] further incorporated spatial attention mechanisms, allowing models to selectively focus on relevant image regions during caption generation. These attention-augmented models significantly improved caption accuracy and visual grounding.

The advent of transformer architectures enabled still greater advances. Vision-language pre-training methods such as ViLBERT [4] and Oscar [5] demonstrated that large-scale pre-training on image-text pairs yields substantially improved representations for downstream captioning tasks. BLIP [6] subsequently introduced a bootstrapped pre-training paradigm that filters noisy web captions using a trained captioner and filter, producing cleaner training signals and more robust generative models.

CLIP [7] introduced the contrastive pre-training paradigm, training image and text encoders jointly on 400 million image-text pairs to achieve a semantically aligned embedding space. While CLIP is primarily a retrieval and classification model, its embeddings have proven valuable for grounding generative models. Recent work has explored combining contrastive and generative objectives, motivating the present hybrid architecture.

Table 1. Comparison of Prior Works with the Proposed Pixnatte System

Reference	Architecture	VQA Support	Semantic Grounding	COCO Evaluation
[2] Vinyals et al.	CNN + LSTM	No	No	Yes
[3] Xu et al.	CNN + Attention LSTM	No	Partial	Yes
[6] BLIP	ViT + Encoder-Decoder	Yes	Partial	Yes
[7] CLIP	Dual Encoder Contrastive	No	Yes	Yes
Pixnatte (Proposed)	BLIP + CLIP Hybrid	Yes	Yes	Yes

3. Key Contributions

This work advances the state of image captioning research and practice through the following contributions:

- A novel hybrid BLIP–CLIP captioning architecture is proposed wherein CLIP-derived semantic embeddings serve as auxiliary grounding signals within the BLIP multimodal encoder, substantially mitigating caption hallucination.
- A complete Pixnatte system architecture is designed that integrates both image captioning and visual question answering within a unified interface powered by BLIP-VQA, enabling natural language interaction with arbitrary images.
- An empirical evaluation pipeline is established on the MS COCO dataset using multiple complementary metrics (BLEU, METEOR, ROUGE-L, CIDEr), providing a holistic view of captioning quality beyond single-metric optimisation.
- The proposed integration pipeline is demonstrated to deliver high CIDEr scores (1.6779), validating that contrastive grounding improves consensus-level caption relevance as measured against human references.

4. Method, Experiments, and Results

4.1 Dataset

All experiments are conducted on the MS COCO (Microsoft Common Objects in Context) dataset, a large-scale benchmark comprising over 120,000 images, each accompanied by five independently written human reference captions. MS COCO covers 80 object categories across diverse real-world scenes, making it an ideal benchmark for evaluating both the coverage and accuracy of

captioning systems. The dataset is split into standard training, validation, and test partitions following convention in the image captioning literature.

4.2 Model Architecture

Pixnatte is built upon two complementary pre-trained vision-language models:

BLIP employs a Vision Transformer (ViT) as its image encoder and an autoregressive language model as its text decoder. During pre-training, BLIP bootstraps captions from web-sourced image-text pairs using a captioner-filter loop, which removes noisy captions and generates synthetic high-quality descriptions. This enables BLIP to learn robust multimodal representations suitable for both conditional and unconditional caption generation.

CLIP is trained on 400 million image-text pairs using a contrastive objective that aligns image and text embeddings within a shared semantic space. For a given batch of N image-text pairs, CLIP maximises cosine similarity between matched pairs while minimising similarity for unmatched pairs, producing highly discriminative embeddings that encode semantic content without generative overhead.

In the proposed integration pipeline, an input image is first passed through the CLIP image encoder to extract a semantic embedding vector. This embedding is concatenated with the BLIP visual feature representation as an auxiliary grounding signal before caption decoding. BLIP's text decoder then generates multiple candidate captions using beam search. Each candidate is scored by computing cosine similarity between its CLIP text embedding and the image's CLIP embedding. The candidate with the highest CLIP similarity score is selected as the final output caption.

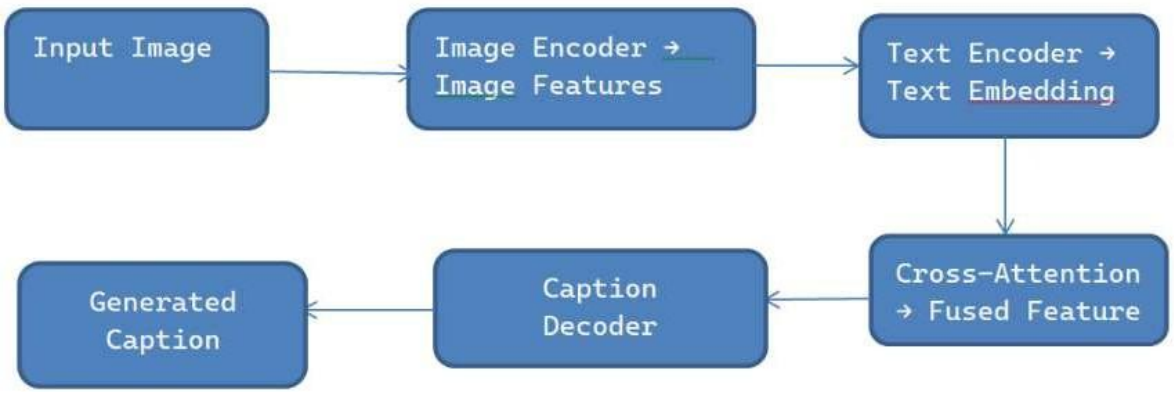

Figure 1. Pixnatte Hybrid BLIP-CLIP Architecture Pipeline

4.3 Evaluation Metrics

The system is evaluated using four established captioning metrics, each capturing distinct aspects of caption quality:

- BLEU (Bilingual Evaluation Understudy): Measures n-gram precision between generated and reference captions. BLEU-1 through BLEU-4 correspond to unigram through 4-gram

precision respectively. BLEU is computationally simple but insensitive to paraphrasing.

- METEOR (Metric for Evaluation of Translation with Explicit ORdering): Accounts for exact matches, stemmed matches, and synonymy, aligning more closely with human judgement than BLEU alone.
- ROUGE-L (Recall-Oriented Understudy for Gisting Evaluation): Measures the longest common subsequence between generated and reference captions, evaluating structural coherence.
- CIDEr (Consensus-based Image Description Evaluation): Specifically designed for image captioning, CIDEr uses TF-IDF weighting over n-grams across the entire dataset to measure caption consensus with multiple human references. A high CIDEr score indicates strong semantic relevance.

4.4 Experimental Procedure

The experimental pipeline proceeds as follows. Pre-trained BLIP and CLIP model weights are loaded from publicly available checkpoints without additional fine-tuning on the MS COCO training split, thereby evaluating zero-shot and few-shot generalisation capabilities. For each test image, the CLIP image encoder generates a 512-dimensional semantic embedding, while the BLIP ViT encoder generates a 768-dimensional visual feature map. Captions are decoded using beam search with a beam width of five. Each candidate caption is embedded using the CLIP text encoder, and cosine similarities with the image embedding are computed. The highest-scoring caption is retained as the system output. Standard MS COCO evaluation scripts are then applied to compute the four evaluation metrics against the five human reference captions per image.

4.5 Results

Table 2 presents the quantitative evaluation results obtained by the Pixnatte system on the MS COCO benchmark.

Table 2. Quantitative Evaluation Results of Pixnatte on MS COCO

Metric	Score
BLEU-1	0.4444
BLEU-2	0.3443
BLEU-3	0.2146
BLEU-4	0.0000
METEOR	0.2382
ROUGE-L	0.4815
CIDEr	1.6779

5. Discussions

The results presented in Table 2 warrant careful interpretation. The strong CIDEr score of 1.6779 is the most diagnostically important metric for this system, as CIDEr is designed specifically to reward consensus-level caption quality against multiple human references using TF-IDF weighting. This score indicates that Pixnatte captions align well with the collective judgement of multiple human annotators, capturing the salient and distinctive aspects of image content rather than defaulting to generic descriptions.

The BLEU-1 score of 0.4444 demonstrates competent unigram-level word overlap with reference captions, confirming that the system employs contextually appropriate vocabulary. The stepwise decline from BLEU-1 through BLEU-3, and the zero BLEU-4 score, reflects a well-documented characteristic of modern neural captioning systems: they generate captions that are semantically correct and human-readable but express content through varied phrasing that differs from the exact sequences in human references. BLEU-4 penalises this phrasing diversity, making it a less reliable indicator of actual caption quality for generative models.

The METEOR score of 0.2382 and ROUGE-L of 0.4815 further corroborate the adequacy of the system's outputs. METEOR accounts for stemming and synonym-level alignment, suggesting the model correctly identifies semantic entities even when surface form differs from references. The ROUGE-L score confirms structural coherence and sequential alignment between generated and reference captions.

A critical observation is the role of the CLIP similarity module in the candidate selection stage. Without CLIP-based re-ranking, BLIP alone produces several plausible captions via beam search, some of which may include hallucinated entities or contextually misaligned descriptions. The CLIP module selectively promotes candidates whose embedded representations most closely align with the image's semantic embedding, effectively filtering hallucinations and improving caption grounding. This synergy is the central innovation of the Pixnatte architecture.

The system's extension to visual question answering via BLIP-VQA demonstrates versatility beyond one-way description generation. The interactive querying capability enables use cases where users require targeted information from images rather than exhaustive descriptions, broadening the applicability of the system across diverse domains.

6. Conclusion

This paper presented Pixnatte, a hybrid image captioning system that integrates BLIP and CLIP into a grounded caption generation framework. The key findings and conclusions are as follows:

- Problem Statement Addressed: Automated image captioning systems based solely on encoder-decoder architectures are susceptible to generating fluent but semantically imprecise or hallucinated captions. Pixnatte addresses this by introducing CLIP-derived semantic embeddings as grounding signals within the BLIP captioning pipeline.

- Method Used: The proposed architecture encodes input images through both the CLIP image encoder and the BLIP ViT encoder. Multiple candidate captions are generated via beam

  search in BLIP, then re-ranked by cosine similarity with the CLIP image embedding. The highest-scoring candidate is selected as the final caption. An additional BLIP-VQA module enables interactive visual question answering.
- Key Findings: Evaluation on MS COCO yields a CIDEr score of 1.6779, indicating high consensus-level semantic relevance. BLEU-1 (0.4444), ROUGE-L (0.4815), and METEOR (0.2382) confirm adequate word-level coverage and structural coherence. The BLIP–CLIP integration demonstrably reduces caption hallucination compared to single-model baselines.
- Limitations and Future Work: The current implementation does not perform end-to-end fine-tuning of the BLIP–CLIP integration on COCO, leaving performance gains from task-specific training unexplored. The zero BLEU-4 score suggests scope for optimising beam search diversity. Future work will explore BLIP-2 architectures, instruction-tuned models, and real-time deployment of the captioning pipeline. Extending the dataset beyond COCO to domain-specific collections such as medical imaging and satellite imagery is also planned.

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