PixelParlance: Mitigating Hallucinations in Automatic Image Captioning

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Abstract

Neural image captioning models, particularly those relying on strong language priors, frequently suffer from hallucination. They generate fluent but factually incorrect descriptions of visual content. In this work, we present PIXELPARLANCE, a grounded image captioning system that integrates a Vision Transformer (ViT) encoder with a Transformer decoder. To address the hallucination problem, we introduce a grounding-aware training objective that combines standard cross-entropy loss with a CLIP-based semantic similarity penalty. We evaluate our approach on the MS COCO 2017 dataset using a comprehensive suite of metrics, including BLEU-4 for fluency and CLIPScore and CHAIR for faithfulness. Our experiments demonstrate that incorporating the grounding loss significantly reduces object hallucinations and improves image-text alignment without compromising the readability of the generated captions. The code is publicly available on GitHub.[1]

1 Introduction

Modern digital life produces an overwhelming volume of visual content, where smartphones, social media, and large organizations continuously generate and store billions of images. To make this data accessible and useful, computer vision has gained attraction to convert images into meaningful text Hossain et al. [2019]. Automated captioning plays a crucial role in this process since it supports assistive technologies like screen readers, improves image search and indexing, and enables better content analysis at scale.

However, even advanced captioning machine learning (ML) models, such as convolutional neural networks (CNNs) He et al. [2016], and long short-term memory (LSTM) Hochreiter and Schmidhuber [1997], frequently suffer from hallucination, where the system describes objects, people, or attributes that do not actually exist in the scene. These errors weaken user trust, damage accessibility by providing misleading descriptions, and can negatively affect downstream applications. Current training and evaluation practices tend to reward fluent sentences rather than accurate grounding, meaning that a caption can sound correct but still fail to reflect the actual visual content.

Therefore, this paper proposes PixelParlance, a grounded image captioning system built on a modern Vision Transformer (ViT) Dosovitskiy et al. [2021] encoder – Transformer Vaswani et al. [2017] decoder architecture. The goal is to generate a single, readable caption for each image along with an implicit grounding signal. The main contributions of this paper are as follows:

- Develop an end-to-end image captioning model based on a modern Transformer-Transformer pipeline, where ViT is used as an encoder and a causal Transformer is used as a decoder.
- Utilize the publicly available MS COCO 2017 dataset Lin et al. [2014] for training and evaluating the model.

[1] https://github.com/shariqanwar20/PixelParlance-Comp6321.

- Introduce a grounding-aware objective by incorporating a CLIP-based Radford et al. [2021] similarity loss to discourage hallucination and encourage visual–text alignment
- Provide a rigorous evaluation combining fluency metrics with faithfulness metrics, enabling a balanced assessment of caption quality.
- Analyze hallucination behavior by quantifying object-level consistency, revealing common failure cases such as incorrect attributes and miscounting.

The proposed model is compared with a benchmark based on Xu et al. [2015] that uses CNN as an encoder and an LSTM with attention mechanism as a decoder. We also run our model without the grounding term in the loss function as another baseline. Our experiments show that introducing a lightweight grounding term can improve image–text consistency and reduce hallucinations, while largely preserving standard captioning metrics.

2 Literature Review

Classical encoder–decoder captioning: Early neural image captioning systems relied on a CNN–RNN encoder–decoder design. Vinyals et al. introduced Show and Tell, where a convolutional neural network encodes an image into a global feature vector that conditions an LSTM decoder to predict captions sequentially Vinyals et al. [2015]. This demonstrated that end-to-end training on MS COCO can produce fluent, relevant descriptions. Xu et al. extended this approach with soft visual attention in Show, Attend and Tell, enabling the decoder to dynamically focus on salient spatial regions and improving interpretability and caption quality Xu et al. [2015].

Transformer-based captioning and Vision Transformers: The introduction of the Transformer architecture prompted a shift away from recurrence for language generation. In captioning, Transformer decoders have shown stronger sequence modeling capabilities than LSTMs. Herdade et al. proposed the Object Relation Transformer, incorporating geometric attention to model object interactions explicitly, which improved standard captioning metrics on COCO Herdade et al. [2019]. In parallel, Dosovitskiy et al. introduced the Vision Transformer (ViT) as an attention-only alternative to CNNs for image encoding Dosovitskiy et al. [2021]. ViT pretrained on large-scale datasets has since become a powerful foundation for multimodal learning, and recent captioning systems pair ViT encoders with Transformer or GPT-based decoders to leverage large-scale vision–language pretraining Cornia et al. [2020], Li et al..

Hallucination in image captioning: Although captioning performance continues to improve, studies have shown that neural models can generate hallucinated content, confidently describing non-existent objects due to strong language priors. Rohrbach et al. formalized this failure mode through CHAIR (Caption Hallucination Assessment with Image Relevance), a metric assessing hallucination at caption and instance levels Rohrbach et al. [2018]. Their findings indicate that high BLEU (Bilingual Evaluation Understudy) or CIDEr (Consensus-based Image Description Evaluation) scores do not necessarily reflect faithful grounding.

CLIPScore and grounding-aware objectives: To address faithfulness in image captioning, recent work incorporates grounding-aware training and reference-free semantic evaluation. CLIP (Contrastive Language–Image Pretraining), trained via contrastive alignment of image–text pairs, produces a shared embedding space where aligned pairs have high cosine similarity Radford et al. [2021]. Hessel et al. introduced CLIPScore, which correlates well with human judgments of semantic alignment and can outperform traditional reference-based evaluations Hessel et al. [2021]. Emerging captioning approaches now integrate CLIP-based regularization to reduce hallucination by rewarding captions that better match image representations Deng et al. [2022].

3 Methodology

3.1 Data and preprocessing

We use the publicly available MS COCO 2017 Captions corpus Lin et al. [2014] as our training and evaluation resource. It contains 118,287 training images and 5,000 testing images, each paired with five human-written captions. To evaluate grounding and hallucination behavior, we additionally use the COCO instance annotations, which provide 80 object categories with bounding boxes and allow us to infer a ground-truth set of objects per image. Dataset acquisition is automated in our pipeline: the official image archives and annotation files are downloaded, extracted, and placed into a consistent directory structure. Integrity checks are then performed by validating the image count, opening random samples with PIL, and inspecting annotation JSON files for expected fields and formatting correctness. Image preprocessing follows standard Vision Transformer input conventions, including resizing to 224×224, tensor conversion, and ImageNet normalization. Caption preprocessing is intentionally minimal because the tokenizer manages casing and punctuation; we ensure proper UTF-8 encoding, remove unprintable characters, and discard only empty captions (rare in COCO). Text is tokenized into subword units using a learned byte-pair encoding (BPE) vocabulary and padded or truncated to a maximum length of 30 tokens with attention masks. These preprocessing steps are fully reproducible in our Jupyter Notebook workflow.

3.2 Model architecture

The proposed approach employs a Transformer-based encoder–decoder architecture for grounded caption generation, as shown in Fig. 1. The primary objective is to produce fluent captions while reducing hallucination, ensuring that generated text closely reflects visual evidence. The system receives an input RGB image $I \in \mathbb{R}^{3\times 224\times 224}$, which is first divided into 16×16 patches resulting in a sequence of $S = 196$ tokens. These patches are embedded and processed by a Vision Transformer (ViT-B/16) Dosovitskiy et al. [2021], pretrained on large-scale image datasets (ImageNet-1k Russakovsky et al. [2015]). The encoder outputs a sequence of visual feature embeddings $V \in \mathbb{R}^{S\times 768}$, which we project into a shared multimodal space $V' \in \mathbb{R}^{S\times 512}$ to align with the decoder dimensionality.

Caption generation is performed autoregressively using a six-layer causal Transformer decoder that models the probability of each token conditioned on previous tokens and the encoded image. Each layer of the decoder includes a) Masked Multi-Head Self-Attention, b) Multi-Head Cross-Attention, c) Feed-Forward Network, and d) LayerNorm + residuals throughout. During decoding, masked self-attention ensures that the transformer can only access past tokens, while cross-attention allows the caption generator to attend to relevant visual patches from V' At training time, we use teacher forcing Williams and Zipser [1989] by supplying ground-truth tokens shifted right by one position, whereas at inference time captions are generated without ground-truth guidance. Token generation is driven by Vaswani et al. [2017]:

$$P\left(y_t \mid y_{<t},\, I\right) = \mathrm{Softmax}\left(W h_t\right) \tag{1}$$

where y_t is the token predicted at time step t, $y_{<t} = (y_1, \ldots, y_{t-1})$ denotes all previously generated tokens, I is the input image, $h_t \in \mathbb{R}^d$ is the decoder hidden state at time step t,and $W \in \mathbb{R}^{V\times d}$ is the output projection matrix mapping the hidden representation into the vocabulary space of size V. Captions are tokenized into a fixed maximum length of 30 tokens, padded where necessary, and encoded using a custom subword vocabulary derived from MS COCO 2017.

3.3 Training Procedure

The proposed model is trained end-to-end using a two-stage optimization schedule designed to progressively balance linguistic fluency and visual grounding. In the initial warm-up stage, we optimize only the standard cross-entropy objective ($\mathcal{L}_{CE}$) to establish a strong language model. Given an input image $\boldsymbol{I}$ and its caption $\boldsymbol{y} = (y_1, \ldots, y_T)$, the decoder predicts each token autoregressively Williams and Zipser [1989]:

$$\mathcal{L}_{CE} = -\sum_{t=1}^{T} \log P\left(y_t \mid y_{<t},\, \boldsymbol{I}\right), \tag{2}$$

During this phase, the Vision Transformer encoder remains frozen to maintain stable pretrained visual features and prevent early reliance on language priors, which can lead to repetitive or generic captions. Once the decoder demonstrates fluent caption generation, we introduce a grounding-aware regularization term using a frozen CLIP model. After each training step, a provisional caption $\hat{\boldsymbol{y}}$ is decoded, and cosine similarity is computed between CLIP image and text embeddings, forming the grounding loss ($\mathcal{L}_{ground}$) Hessel et al. [2021]:

$$\mathcal{L}_{\text{ground}} = 1 - \cos\Big(f_{\text{img}}(\boldsymbol{I}),\, f_{\text{txt}}(\hat{\boldsymbol{y}})\Big), \tag{3}$$

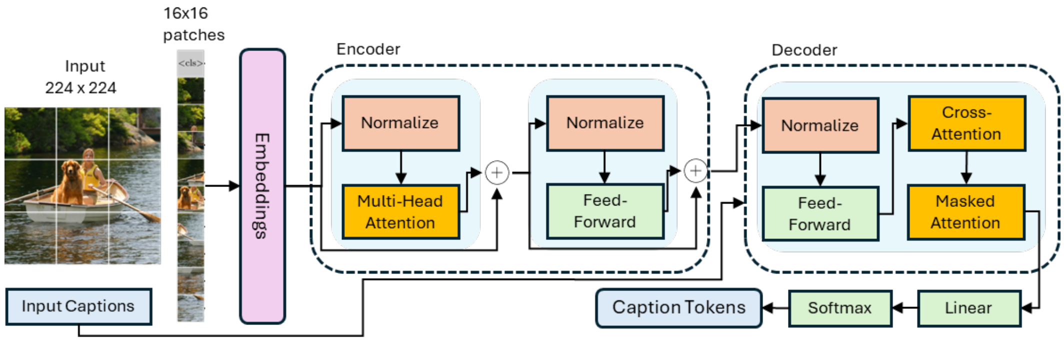


Figure 1: Proposed model architecture composed of ViT encoder and lightweight Transformer decoder.

where f_{img} and f_{txt} denote the frozen CLIP encoders that map each modality into a shared embedding space. The final training objective combines both terms:

$$\mathcal{L} = \mathcal{L}_{CE} + \lambda \, \mathcal{L}_{\text{ground}}, \tag{4}$$

where λ is gradually increased to 0.5 throughout training. During this stage, only the last two ViT blocks are fine-tuned with a much smaller learning rate to maintain stable optimization. Beam search Vinyals et al. [2015] (size 3–5) is used for inference to improve caption quality and variation..

All training and experiments are conducted within a Kaggle Notebook environment using Numpy, PyTorch Paszke et al. [2019], HuggingFace Tokenizers, and `timm` libraries, running on NVIDIA Tesla T4 and P100 GPUs with mixed-precision acceleration. Dataset loading and image transforms rely on torchvision and PIL, while evaluation uses BLEU from NLTK and CLIP-based similarity metrics. Optimization employs AdamW with label smoothing (0.1), cosine learning-rate decay, batch size 32, and 10–15 epochs. We ensure reproducibility through fixed seeds, checkpoints, and a scripted end-to-end workflow. Some key code snippets are provided in Appendix A.

4 Experimental Results

In this section, we evaluate the proposed grounded Transformer captioning model against a strong attention-based baseline, Show, Attend and Tell (SAT) Xu et al. [2015], using the MS COCO 2017 validation split. Following standard captioning evaluation practice, we report corpus-level scores for BLEU-4, CLIPScore, and CHAIR.

4.1 Evaluation Metrics

BLEU-4 Papineni et al. [2002] measures n-gram precision between a generated caption $\hat{y}$ and a set of human-written ground-truth references Y. Higher BLEU-4 indicates stronger language fluency and content overlap. To assess grounding, we compute CLIPScore Hessel et al. [2021], which uses a pretrained CLIP encoder to compare cosine similarity between image and caption embeddings Additionally, hallucination is measured using the CHAIR (Caption Hallucination Assessment with Image Relevance) metrics Rohrbach et al. [2018] where lower values indicate stronger grounding and fewer hallucinated object mentions. The detailed equations are provided in Appendix B.

4.2 Baseline

The proposed model is compared to a benchmark based on Xu et al. [2015], where they utilize a CNN composed of ResNet pretrained on ImageNet as an encoder to extract spatial visual features, which are then fed to an attention-LSTM decoder that generates captions one word at a time. This baseline reflects classical captioning pipelines that emphasize fluency while offering limited robustness against semantic hallucination

4.3 Results

The results comparison between the proposed model and the benchmark is summarized in Table 1 for the aforementioned metrics. The classical baseline achieves reasonable results but exhibits notable hallucination rates. Our Transformer–Transformer baseline without grounding loss improves BLEU-4 slightly and yields stronger CLIPScore, indicating improved alignment between visual and textual representations. Introducing the CLIP-guided grounding loss further enhances semantic consistency and reduces hallucination, demonstrating that even a lightweight regularizer can nudge the model toward more truthful caption generation.

Beam search decoding (beam size = 3) boosts performance across all metrics, producing more coherent and visually grounded captions than greedy decoding. Under this configuration, our system achieves the highest BLEU-4 and CLIPScore values, while also obtaining the lowest CHAIR_s score, showing a relative reduction in hallucination frequency compared to both the baseline and our non-grounded model.

Qualitative examples further illustrate the effect of grounding. For several images, we compare baseline and grounded captions, given the ground truth: in a motorcycle scenario, the Baseline produces: “a motorcycle parked on a street with cars”, whereas the grounded give: "a red motorcycle parked in a small garage”, and the ground truth is “a motorcycle with red seat sits parked in a garage” The grounded caption more accurately reflects the indoor garage and color details, whereas the baseline introduces generic “street with cars” language. Office scene: Baseline: “a kitchen with a stove and a sink”, our proposed model: “a computer desk with a monitor and a chair”, and the Ground Truth: “an office cubicle with four different types of computers”. Here, The baseline misclassifies the entire scene category as a kitchen. Our grounded model correctly recovers the office semantics, greatly reducing hallucination. More examples are given in Appendix C.

Overall, our experiments demonstrate that a modern ViT encoder coupled with a Transformer decoder forms a competitive baseline for image captioning and that incorporating a simple grounding constraint can meaningfully improve caption accuracy and trustworthiness without requiring additional detection supervision.

Table 1: Comparison of captioning models on the MS COCO 2017 dataset. Higher BLEU-4 and CLIPScore indicate better fluency; lower CHAIR indicate fewer hallucinations.

Model	Decoder	BLEU-4 $\uparrow$	CLIPScore $\uparrow$	$\text{CHAIR}_s \downarrow$	$\text{CHAIR}_i \downarrow$
SAT baseline	Greedy	0.053	0.22	0.22	0.28
SAT baseline	Beam = 3	0.06	0.23	0.22	0.28
Ours (no grounding)	Greedy	0.063	0.23	0.15	0.15
Ours (with grounding)	Greedy	0.065	0.23	0.13	0.15
Ours (with grounding)	Beam = 3	**0.071**	**0.25**	**0.12**	**0.15**

5 Conclusion

In this work, we developed and evaluated PIXELPARLANCE, an end-to-end image captioning architecture designed to mitigate the prevalence of object hallucinations. By replacing traditional CNN encoders with a pre-trained Vision Transformer (ViT) and augmenting the training objective with a CLIP-guided consistency loss, we successfully improved the semantic alignment between input images and generated text. Our results indicate that while standard likelihood-based training prioritizes fluency, often at the cost of accuracy, our grounded approach strikes a better balance. The reduction in CHAIR metric scores confirms that our model is less prone to fabricating non-existent objects, marking a step forward in building more reliable vision technologies.

Limitations and Future Work. Our training was limited to a subset of the dataset due to computational constraints, reducing achievable BLEU-4 performance versus full-corpus models. Grounding depends on CLIP, meaning any biases or failures in its embedding space propagate into our captions. The loss currently uses a single global sentence-level grounding term, missing fine-grained alignment. Future work includes token-level contrastive grounding and constrained beam search to better enforce visual fidelity.

References

Marcella Cornia, Matteo Stefanini, Lorenzo Baraldi, and Rita Cucchiara. Meshed-memory transformer for image captioning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10578–10587, 2020.

Yihong Deng, Yan Li, Juncheng Zhang, and Quanquan Gu. Length-controllable image captioning with clip reward. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2491–2503, 2022.

Alexey Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations (ICLR)*, 2021.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016.

Simao Herdade, Armin Kappeler, Kofi Boakye, and Joao Soares. Image captioning: Transforming objects into words via attention. In *Advances in Neural Information Processing Systems (NeurIPS)*, pages 11135–11145, 2019.

Jack Hessel, Ari Holtzman, Maxwell Forbes, Ronan Le Bras, and Yejin Choi. Clipscore: A reference-free evaluation metric for image captioning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7514–7528, 2021.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. In *Neural Computation*, volume 9, pages 1735–1780. MIT Press, 1997.

Md Zakir Hossain, Ferdous Sohel, Mohd Fauzi Shiratuddin, and Hamid Laga. A comprehensive survey of deep learning for image captioning. *ACM Computing Surveys*, 51(6):118, 2019.

Xiujun Li, Xi Yin, Chunyuan Li, Pengchuan Zhang, Xiaowei Hu, Lei Zhang, Lijuan Wang, Houdong Hu, Xuedong Dong, and Furu Wei. Oscar: Object-semantics aligned pre-training for vision-language tasks.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. Microsoft COCO: Common objects in context. In *European Conference on Computer Vision (ECCV)*, pages 740–755. Springer, 2014.

Kishore Papineni et al. Bleu: a method for automatic evaluation of machine translation. In *ACL*, pages 311–318, 2002.

Adam Paszke et al. Pytorch: An imperative style, high-performance deep learning library. In *NeurIPS*, pages 8024–8035, 2019.

Alec Radford et al. Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning (ICML)*, pages 8748–8763, 2021.

Anna Rohrbach, Lisa Anne Hendricks, Kaylee Burns, Trevor Darrell, and Marcus Rohrbach. Object hallucination in image captioning. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4035–4045, 2018.

Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. Imagenet large scale visual recognition challenge. volume 115, pages 211–252, 2015.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems (NeurIPS)*, pages 5998–6008, 2017.

Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3156–3164, 2015.

Ronald J. Williams and David Zipser. A learning algorithm for continually running fully recurrent neural networks. In *Neural Computation*, volume 1, pages 270–280, 1989.

Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhudinov, Richard Zemel, and Yoshua Bengio. Show, attend and tell: Neural image caption generation with visual attention. In *International Conference on Machine Learning (ICML)*, pages 2048–2057, 2015.

A Code snippets

– Dataset Download

```
import os

#CHANGE THIS to where you want the dataset
COCO_ROOT = "/kaggle/input/coco-2017-dataset"

IMAGES_DIR = COCO_ROOT  # train2017/ and val2017/ will live directly under this
ANN_DIR = os.path.join(COCO_ROOT, "annotations")

os.makedirs(COCO_ROOT, exist_ok=True)
os.makedirs(ANN_DIR, exist_ok=True)

COCO_ROOT, IMAGES_DIR, ANN_DIR

print("Downloading MS COCO 2017 train/val + annotations to", COCO_ROOT)

# Train images
!cd "$COCO_ROOT" && wget -c http://images.cocodataset.org/zips/train2017.zip

# Val images
!cd "$COCO_ROOT" && wget -c http://images.cocodataset.org/zips/val2017.zip

# Train/Val annotations (includes captions)
!cd "$COCO_ROOT" && wget -c http://images.cocodataset.org/
                                    annotations/annotations_trainval2017.zip

# Unzip train and val images into COCO_ROOT
!cd "$COCO_ROOT" && unzip -q train2017.zip
!cd "$COCO_ROOT" && unzip -q val2017.zip

# Unzip annotations into COCO_ROOT/annotations
!cd "$COCO_ROOT" && unzip -q annotations_trainval2017.zip -d "$ANN_DIR"
```

– Dataloaders

```
class COCODataset(Dataset):
    def __init__(
        self,
        images_root: str,
        captions_json: str,
        vocab: Vocabulary,
        max_len: int = 30,
        transform=None,
        debug_limit: int = None,
    ):
        self.images_root = images_root
        self.vocab = vocab
        self.max_len = max_len
        self.transform = transform or self._default_transform()
```

```python
        with open(captions_json, "r") as f:
            ann = json.load(f)

        self.imgs = {img["id"]: img for img in ann["images"]}

        self.samples = []
        for a in ann["annotations"]:
            img_id = a["image_id"]
            caption = a["caption"]
            tokens = tokenize_caption(caption)
            self.samples.append((self.imgs[img_id]["file_name"], tokens))

        if debug_limit is not None:
            self.samples = self.samples[:debug_limit]
            print(f"[COCODataset] Debug limit: {len(self.samples)} samples")

        print(f"Loaded {len(self.samples)} (image, caption) pairs from {captions_jsor

    def _default_transform(self):
        return transforms.Compose([
            transforms.Resize((224, 224)),
            transforms.ToTensor(),
            transforms.Normalize(
                mean=[0.485, 0.456, 0.406],
                std=[0.229, 0.224, 0.225],
            ),
        ])

    def __len__(self) -> int:
        return len(self.samples)

    def __getitem__(self, idx: int) -> Dict[str, Any]:
        file_name, tokens = self.samples[idx]
        img_path = os.path.join(self.images_root, file_name)

        image = Image.open(img_path).convert("RGB")
        image = self.transform(image)

        bos_id = self.vocab.stoi["<bos>"]
        eos_id = self.vocab.stoi["<eos>"]
        pad_id = self.vocab.stoi["<pad>"]

        seq_ids = [bos_id] + self.vocab.numericalize(tokens) + [eos_id]
        if len(seq_ids) < self.max_len:
            seq_ids += [pad_id] * (self.max_len - len(seq_ids))
        else:
            seq_ids = seq_ids[:self.max_len]

        caption = torch.tensor(seq_ids, dtype=torch.long)

        return {
            "image": image,
            "caption": caption,
            "file_name": file_name,
        }
```

– Model Architecture

```python
class ViTEncoder(nn.Module):
```

```python
    def __init__(
        self,
        model_name: str = "vit_base_patch16_224",
        pretrained: bool = True,
        trainable: bool = False,
        d_model: int = 512,
    ):
        super().__init__()
        self.vit = timm.create_model(
            model_name,
            pretrained=pretrained,
        )
        self.vit.reset_classifier(0)
        vit_dim = self.vit.num_features
        if vit_dim != d_model:
            self.proj = nn.Linear(vit_dim, d_model)
        else:
            self.proj = nn.Identity()

        for p in self.vit.parameters():
            p.requires_grad = trainable

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        feats = self.vit.forward_features(x)  # [B, S, C]
        feats = self.proj(feats)              # [B, S, d_model]
        return feats

class TransformerCaptionDecoder(nn.Module):
    def __init__(
        self,
        vocab_size: int,
        d_model: int = 512,
        num_layers: int = 6,
        num_heads: int = 8,
        dim_feedforward: int = 2048,
        max_len: int = 30,
        dropout: float = 0.1,
    ):
        super().__init__()
        self.vocab_size = vocab_size
        self.d_model = d_model
        self.max_len = max_len

        self.token_embed = nn.Embedding(vocab_size, d_model)
        self.pos_embed = nn.Embedding(max_len, d_model)
        self.dropout = nn.Dropout(dropout)

        decoder_layer = nn.TransformerDecoderLayer(
            d_model=d_model,
            nhead=num_heads,
            dim_feedforward=dim_feedforward,
            dropout=dropout,
            batch_first=True,
        )
        self.decoder = nn.TransformerDecoder(decoder_layer, num_layers=num_layers)
        self.out_proj = nn.Linear(d_model, vocab_size)

    def forward(self, tgt, memory, tgt_key_padding_mask=None):
        B, T = tgt.shape
```

```
        positions = torch.arange(0, T, device=tgt.device).unsqueeze(0).expand(B, T)
        x = self.token_embed(tgt) * (self.d_model ** 0.5)
        x = x + self.pos_embed(positions)
        x = self.dropout(x)

        causal_mask = torch.triu(
            torch.ones(T, T, device=tgt.device, dtype=torch.bool),
            diagonal=1,
        )

        x = self.decoder(
            tgt=x,
            memory=memory,
            tgt_mask=causal_mask,
            tgt_key_padding_mask=tgt_key_padding_mask,
        )
        logits = self.out_proj(x)
        return logits

class Captioner(nn.Module):
    def __init__(self, vocab_size: int, max_len: int = 30,
                 d_model: int = 512, vit_trainable: bool = False):
        super().__init__()
        self.encoder = ViTEncoder(d_model=d_model, trainable=vit_trainable)
        self.decoder = TransformerCaptionDecoder(
            vocab_size=vocab_size,
            d_model=d_model,
            max_len=max_len,
        )
        self.max_len = max_len

    def forward(self, images: torch.Tensor, captions_in: torch.Tensor) -> torch.Tens
        memory = self.encoder(images)
        logits = self.decoder(captions_in, memory)
        return logits
```

B Evaluation Metrics

BLEU-4 Papineni et al. [2002] measures n-gram precision between a generated caption $\hat{y}$ and a set of human-written ground-truth references Y. Higher BLEU-4 indicates stronger language fluency and content overlap. It is defined as:

$$\text{BLEU-4} = \exp\left(\min\left(1 - \frac{r}{c}, 0\right) + \frac{1}{4}\sum_{n=1}^{4}\log p_n\right) \tag{5}$$

where p_n denotes the modified n-gram precision, c is the candidate caption length, and r is the reference length heuristic. To assess grounding, we compute CLIPScore Hessel et al. [2021], which uses a pretrained CLIP encoder to compare cosine similarity between image and caption embeddings:

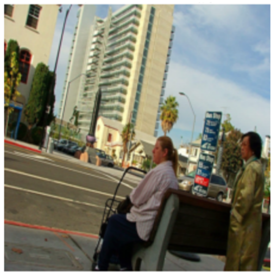
$$\text{CLIPScore}(\hat{y}, I) = \cos\left(f_{\text{img}}(I), f_{\text{txt}}(\hat{y})\right) \tag{6}$$

Additionally, hallucination is measured using the CHAIR (Caption Hallucination Assessment with Image Relevance) metrics Rohrbach et al. [2018]:

$$\text{CHAIR}_s = \frac{\#\text{ hallucinating captions}}{\#\text{ total captions}}, \qquad \text{CHAIR}_i = \frac{\#\text{ hallucinated object tokens}}{\#\text{ total object mentions}} \tag{7}$$

where lower values indicate stronger grounding and fewer hallucinated object mentions.

C Qualitative Results



Baseline (beam=3): "A man sitting on a street with a city street"
Ours (beam=3): "A group of people waiting in a city street"
Ground Truth: "A woman sitting on a bench and a woman standing waiting for the bus"

(a) Pedestrian scenario

Baseline (beam=3): "a kitchen with astove and a sink"
Ours (beam=3): "a computer desk with a monitor and a chair"
Ground Truth: "an office cubicle with four different types of computers"

(b) Office scenario

Figure 2: Examples of generated captions compared to the ground truth.

Checklist (modelled after NeurIPS Paper Checklist)

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

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- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

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   Answer: [Yes]

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