Zero-Shot Video Captioning with Evolving Pseudo-Tokens

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Abstract

We introduce a zero-shot video captioning method that employs two frozen networks: the GPT-2 language model and the CLIP image-text matching model. The matching score is used to steer the language model toward generating a sentence that has a high average matching score to a subset of the video frames. Unlike zero-shot image captioning methods, our work considers the entire sentence at once. This is achieved by optimizing, during the generation process, part of the prompt from scratch, by modifying the representation of all other tokens in the prompt, and by repeating the process iteratively, gradually improving the specificity and comprehensiveness of the generated sentence. Our experiments show that the generated captions are coherent and display a broad range of real-world knowledge. Our code is available at: https://github.com/YoadTew/zero-shot-video-to-text.

1 Introduction

Image captioning is becoming increasingly accurate and can successfully tackle more complex benchmarks than ever before. However, the progress in video captioning is slower due to both methodological reasons and dataset construction challenges. First, the video captioning task itself has more possible definitions than image captioning. For example, do we want a complete description of the events in the video or a general description of it? Second, even considerably more limited tasks, such as action recognition in pre-trimmed videos, are still technologically challenging. Third, the descriptions attached to web videos are often not an accurate depiction of the content and events in the video, making the construction of web-scale datasets more challenging.

These challenges mean that strategies used in related tasks are less suitable for the task of video captioning. (i) One cannot train on large and noisy datasets, since the amount of noise would be too high. (ii) Learning on a carefully curated dataset would be too restrictive in terms of the obtained coverage, and too limited in the use of language (due to the nature of cost-effective human annotation). (iii) A divide-and-conquer approach that captions single frames would still require a sophisticated way of combining all information and text. (iv) Relying on pretrained action recognition models would lead to inaccurate results that are very much limited in the scope of captured actions.

In light of the challenges faced by model-learning approaches, the method we introduce is a zero-shot method. It uses the information stored in two pre-trained and frozen networks to perform the video captioning task. One model is an autoregressive language model that can generate natural and mostly logical sentences. The second model is an image-text matching model that is used to steer the language model, via a contrastive loss, toward sentences that match a set of input frames.

We make extensive use of the fact that the autoregressive process is conditioned on its prompt. Our method's generative process employs a prompt that contains three parts: (i) pseudo-tokens that are vectors in the latent space of the language models, (ii) a random prompt such as "Image of" that provides context for the captioning task, but also varies ("Photo of", "Video of", etc.) as a form of inference-time augmentation, and (iii) the previously generated tokens.

Since the sentence generation process is autoregressive, the initial words of the generated sentence employed pseudo-tokens that were not optimized based on the signal obtained from the entire sentence. We, therefore, repeat the process and start the autoregressive process with the pseudo-tokens that were obtained at the end of the previous generation iteration. As we show in Fig. 1, this leads to increasingly concrete prompts. The process is repeated sixteen times, and the sentence that maximizes the image-text matching score is selected.

In our implementation, we use the GPT-2 language model [36], due to its availability, and the CLIP image-text...
matching model [35], which is often used in zero-shot learning. We experiment with both video captioning and describing image sets. Our results show a clear advantage over the state-of-the-art video captioning methods and over recent zero-shot image captioning methods. Our code is attached as supplementary.

2 Related Work

Image captioning is a fundamental vision and language task. Early methods applied RNNs [27, 16]. Attention was added to identify relevant salient objects [55, 38]. Graph neural networks and transformers helped model spatial and semantic interactions [57, 15, 56].

Other video-based tasks include action recognition [43], paragraph captioning [58], and video object segmentation [33]. Some approaches to video analysis use different experts, including speech, audio, motion, OCR, appearance, and face detection [25, 1]. This work considers video captioning by generating a single sentence that adequately describes a set of frames. Despite the lack of temporal information in a set, we find that the language model generates a logical order of events.

In various contributions, sparse sampling along with better spatial reasoning have proved sufficient for handling reasoning tasks, such as video dialogs [39] and video retrieval [17, 61, 37, 18]. An attention module that selects the relevant frames can reduce the temporal dimension [2, 9]. In our work, we also employ sparse sampling that utilizes distances in the CLIP embedding space to construct a set of the most relevant frames.

Significant improvements have been achieved by using large-scale unsupervised vision-language data sets with millions of image and text pairs [60, 8, 21] and million of videos [29, 62, 26]. The unsupervised data is used in a pre-training phase. Fine-tuning for a particular task is done in the final stage, using smaller datasets annotated by humans. Although this process has been shown to boost performance, it remains highly dependent on the human annotations. Our experiments show that captions learned based on human annotations are dull. Moreover, the same repetitive patterns are produced by significantly different baseline methods [34, 6].

As a way to reduce dependence on supervision, CLIP has been using web-based learning to study language-image relationships [35]. CLIP’s strength lies in the amount of data it collects. CLIP is trained in a contrastive manner, using 400M image-text pairs from the web, unlike supervised methods, which typically use thousands of samples. The method learns a bimodal distance metric between an input image and a text sentence, which we refer to as the CLIP score. Matching videos to text also benefited from a contrastive approach [53, 19]. However, video data can be challenging to collect. In our case, we used CLIP to guide a language generator in a zero-shot manner.

Contrastive learning is effective for zero-shot capabili-
ties, achieving good results for several tasks, including image classification and action recognition. However, generative tasks based directly on the CLIP score are rare, since the score requires seeing both text and image. Instead, multiple contributions rely on CLIP’s image and text encodings, which are known to improve performance in vision+language tasks [40], especially in image captioning [30] and video captioning [46]. However, fine-tuning distorts the latent semantics of CLIP’s encoder [47]. MAGIC employs CLIP scores to shift PLM logits towards image correspondence [44]. Despite this, they fine-tunes the PLM on the text corpus of MS-COCO captions, so robustness is still compromised. Alternatively, CLIP can be used as part of a loss term to guide generative processes to match language and text, for example, as a loss term for 3D mesh generation [28] or text-guided image generation [32, 5].

Recently, it was suggested to use CLIP loss to guide a Pretrained Language Model (PLM) for image captioning [47]. Compared with ours, their method optimizes each generated token individually, aiming to obtain the token closest to the given image. In contrast, our method optimizes pseudo-tokens through iteratively generating sentences, aiming to steer the generation process of the entire sentence. Although their process is effective in describing one visual cue, it is challenged by the more difficult task of describing multiple images coherently. We demonstrate that the ability to manipulate an entire sentence without committing to a single generation path has beneficial effects. Optimizing an entire sentence also means not requiring sequence generation strategies such as beam search.

The literature on tuning prior knowledge within large-scale PLMs, such as GPT-2 [36], is growing rapidly. There are several on-going directions: (i) Fine-tuning, e.g., by using GANs [63] or RL [59]; (ii) Disentangling the latent representations [41]; (iii) Training a controllable LM with fixed control codes [14]; (iv) Trainable decoding [12]; (v) Decoding steering [7]; and (vi) Prompt engineering [42], as well as prompt learning [50, 22, 10, 24]. In this work, we present a novel PLM decoding approach that combines steering and prompt tuning by generating sentences iteratively and applying prompt tuning.

3 Method

Our goal is to create a sentence \( S = \{t_1, \ldots, t_M\} \) of length \( M \) that describes a set of video frames \( \mathcal{F} = \{F_1, \ldots, F_N\} \), where \( N \) is the number of frames. When \( N = 1 \), the problem corresponds to traditional image captioning.

Two components are at the core of our solution. The first is a pre-trained language model (PLM) that generates sentences, for which we use GPT-2. The second, CLIP, is a pre-trained model that computes the distance between a frame \( F \) and a sentence \( S \), and guides the PLM during inference.

Guiding a PLM with CLIP has recently shown promising results for image captioning [47, 45]. These approaches use CLIP to optimize the next token to fit the image; we call this technique token-level optimization. However, the application of these approaches to videos is limited, especially in the case of low homogeneity between frames. In this case, maintaining language fluency is difficult, since: (i) a single token has to describe a set of non-homogeneous frames, and (ii) the generation commits to a single direction, restricting the flexibility of the process. By contrast, rather than optimizing tokens, our method performs a sentence-level optimization. To achieve this, the inference starts with randomly initialized pseudo-tokens. These tokens do not need to be actual words in the dictionary, but rather hidden states of words, that can be optimized using gradient descent. Description of visual content is driven using prefix-tokens, such as ‘Video showing’. The next step consists of generating multiple sentences and continuously optimizing the pseudo-tokens. This is accomplished by calculating two types of losses: (i) \( L_{\text{vision}} \), which is the sum of the distance between all frames in \( \mathcal{F} \) and the generated sentence, and (ii) \( L_{\text{language}} \) which takes into account language characteristics by considering the PLM token distribution. With no additional supervision or training, we benefit from the extensive knowledge embedded in CLIP and GPT-2. Our autoregressive process is depicted in Fig. 2.

PLM Guidance with Prompt Learning PLMs are trained on vast web knowledge to optimize a sum of conditionals, i.e., \( \max_{p(S)} p(S) = \sum_{i=1}^{L} p_{\theta}(w_{i}|w_{1:i-1}) \), where \( \theta \) are trainable weights. The likelihood of each sub-sentence depends on its context. Thus, one can solve various tasks by altering the input context. For instance, to answer the question “what is the capital of Britain?” one could plug into the PLM the prompt “The capital of Britain is.” The PLM then finds the most likely next token (“London”) to optimize the conditional probability.

Prompt engineering entails finding the most suitable prompt for a given task. In our case, the task is to generate a sentence that maximizes similarity to a set of frames \( \mathcal{F} \). Similarity is measured in terms of CLIP’s distance metric between image and text. Any image imposes its own set of constraints, and the prompt needs to account for all of them. The prompt must be flexible enough, which is ensured by optimizing pseudo-tokens, i.e., instead of finding real tokens for each video, we tune representative embeddings of tokens.

The GPT-2 PLM is built with \( L \) layers of Transformers, each composed of key and value embeddings, to model interactions between tokens [48]. The context of previous tokens can be cached by keeping their key and value represen-
Figure 2: Illustration of our method for guiding a PLM to generate the word ‘landing’. Optimization takes place during the autoregression inference, by tuning pseudo-tokens ($\hat{C}_\Psi$). Two signals steer the pseudo-tokens’ representations, visual correspondence ($L_{vision}$) and language fluency ($L_{language}$).

Loss: At each step in the auto-regression process, we aggregate our loss, which will be used for optimization only after generating a complete sentence. Our first loss term encourages the generated text to correspond to the set of images.

Let $S_k$ be the sentence generated up until this stage, ending with the token $k$. The visual-semantic loss calculates the cross-entropy (CE) between the optimized PLM distribution and the CLIP potential similarity distribution $\theta_{CLIP}$:

$$L_{vision}(\hat{C}_\Psi) = CE \left(p_{i+1}(\hat{C}_\Psi), \theta_{CLIP} \right),$$

where $\theta_{CLIP}(k) \propto \sum_{F \in \mathcal{F}} CLIP(F, S_k)$ is the sum of CLIP’s matching scores of $S_k$ with all the frames in $\mathcal{F}$. We compute the score for the top 100 tokens according to the original PLM distribution, with the rest set to zero.

While the PLM is trained on natural text, the model in which the free-form context $C_\Psi$ is added (Eq. 1) can shift to very different distributions during optimization. In order to maintain fluent language, we define a language-related loss term,

$$L_{language}(\hat{C}_\Psi) = CE \left(p_{i+1}(\hat{C}_\Psi), PLM(t_i, [\hat{C}_p, C_i]) \right),$$

which is the cross-entropy loss of the optimized PLM, as defined in Eq. 1, with the unmodified PLM distribution.

In order to have the generated text describe the set of images using fluent language, we solve the following optimization problem:

$$\min_{\hat{C}_\Psi} \mathcal{L}(\hat{C}_\Psi) = \min_{\hat{C}_\Psi} \mathcal{L}_{vision}(\hat{C}_\Psi) + \lambda \mathcal{L}_{language}(\hat{C}_\Psi)$$

where hyper-parameter $\lambda$ calibrates the trade-off between relevance to the video and language fluency. The optimization process occurs during autoregression inference, generating sentences iteratively. We detail this process next.

Evolving Pseudo-Tokens Optimization: The optimization occurs during the generation of the entire sentence, in-
Table 1: Quantitative results for video captioning. We separate the results into two categories: (i) supervised metrics that require human references, B@4 = BLEU-4, M = METEOR, C = CIDEr, R = SPICE, and CLIP-S. (ii) Unsupervised metrics that use a pre-trained model, CLIP-S = CLIP-based image-text similarity, BLIP-S = BLIP-based image-text similarity [20], Retrieval = VideoCLIP-based video-text similarity [53], and PP = caption perplexity computed with BERT [8]. (*) denotes that the model is adapted from image captioning to video captioning.

| Dataset   | Method        | B@4 | M    | C    | R    | CLIP-S | CLIP-S | BLIP-S | Retrieval | PP   |
|-----------|---------------|-----|------|------|------|--------|--------|--------|-----------|------|
| MSR-VTT   | VNS-GRU [6]   | 0.453 | 0.299 | 0.530 | 0.634 | 0.739  | 0.626  | 0.623  | 0.446     | 118.81 |
|           | SemSynAN [34] | **0.464** | **0.304** | **0.519** | **0.647** | **0.733** | **0.619** | **0.608** | **0.437** | **155.01** |
|           | **Zero-Shot Methods** | | | | | | | | | |
|           | ZeroCap* [47] | 0.023 | 0.129 | 0.058 | 0.304 | 0.739  | 0.710  | 0.575  | 0.442     | 54.71 |
|           | MAGIC* [44]   | 0.055 | 0.133 | 0.074 | 0.354 | 0.628  | 0.566  | 0.434  | 0.392     | 30.48 |
|           | Ours          | 0.030 | 0.146 | 0.113 | 0.277 | **0.785** | **0.775** | **0.675** | **0.626** | **18.35** |
| MSVD      | VNS-GRU [6]   | **0.665** | **0.421** | **1.215** | **0.797** | **0.780** | **0.673** | **0.646** | **0.557** | **418.72** |
|           | SemSynAN [34] | 0.644  | 0.419 | 1.115 | 0.795 | 0.767  | 0.660  | 0.633  | 0.546     | 242.46 |
|           | **Zero-Shot Methods** | | | | | | | | | |
|           | ZeroCap* [47] | 0.029 | 0.163 | 0.096 | 0.354 | 0.762  | 0.765  | 0.642  | 0.500     | 28.44 |
|           | MAGIC* [44]   | 0.066 | 0.161 | 0.140 | 0.401 | 0.670  | 0.623  | 0.497  | 0.469     | 29.84 |
|           | Ours          | 0.030 | 0.178 | 0.174 | 0.314 | **0.805** | **0.822** | **0.743** | **0.569** | **18.94** |

4 Results

For all experiments, the following settings are used (see appendices for parameter sensitivity and ablations): We set λ to 0.8. During sentence generation, we pick one of the top-3 tokens at random. To avoid long repetitive sentences, the number of generated tokens per sentence was limited to 20. To avoid generating irrelevant entities, such as names, we reduce by 1 the logits of tokens with uppercase letters. Using a single Titan X GPU, each sentence takes 5 seconds to generate. All 16 sentence-generating iterations take approximately a minute and a half.

Two video datasets are used: MSR-VTT [54] and MSVD [51]. MSR-VTT is a large-scale dataset with about 50 hours of videos divided into 10,000 videos with 20 descriptions each. It includes a variety of categories, such as video games and TV shows. The test set consists of 2,990 videos. MSVD contains 1,970 short video clips, 670 of which are dedicated for testing. All experiments are carried out on the test set.

We use two types of metrics: (i) Supervised metrics that measure text correspondence to human references:
Figure 3: Examples of our video captions with two types of baselines: (i) the supervised methods SemSynAN and VNS-GRU; and (ii) the zero-shot methods ZeroCap and MAGIC. Notably, our method grounds objects from different frames and exhibits real-world knowledge. The 1st and 2nd rows provide examples of real-world knowledge.

Figure 4: Evolution of video captions. We show the sentence with the highest CLIP score at different generation iterations. Grounded words are highlighted.

BLEU [31], METEOR [4], CIDER [49], SPICE [3]. Lastly, CLIP-SRef [13] measures semantic similarity by utilizing CLIP’s textual encoder. (ii) Unsupervised metrics that are computed without referring to the human annotation. Relatedness to the visual cue is measured by averaging CLIP or BLIP image similarity scores to the generated sentence across the frames. Relatedness to the video is measured by the VideoCLIP [53] video-to-text distance metric (“Retrieval” in the results table). Language quality is estimated using the perplexity score of the generated caption, employing BERT [8].

Quantitative analysis In Tab. 1, we compare our approach with supervised state-of-the-art baselines for video captioning. We also compare it with zero-shot video captioning baselines we created by modifying CLIP-based zero-shot image captioning methods: ZeroCap [47], a zero-shot method for image captioning, which also optimizes the generated sentence during inference. We adapt their method from image captioning to video captioning by replacing their single image CLIP loss with ours (i.e., a sum of CLIP losses for each frame). MAGIC [44], another zero-shot method for image captioning, which uses MAGIC scores, i.e., a CLIP-based measure of how closely a sentence ending with a given token matches an image, to skew the next-token distribution of a pre-trained language model to match a given image. To adapt their model to videos, we aggregate the CLIP score of all sampled frames to calculate the magic score before applying a softmax.

As expected, the supervised models VNS-GRU [6] and SemSynAN [34] perform significantly better on supervised metrics, based on correspondence to human references. However, when considering semantic relatedness to annotations (i.e., CLIPScoreRef), our method is better (0.785 vs. 0.739 and 0.733). We next look at unsupervised metrics. BLIP-Score suggests that our text is more relevant to the frames (0.675 vs. 0.623 and 0.608). Furthermore, when considering the entire video temporally, our method has the lowest VideoCLIP text-to-video distance (0.504 vs. 0.446 and 0.437). To understand the source of the weakness of the supervised methods, we measure the novelty of the generated sentences. Aggregated over the entire MSR-VTT test set, our method has a vocabulary size of 4,372. In contrast, SemSynAN and VNS-GRU use only 359 and 435 words,
Table 2: Quantitative results for image captioning methods. We evaluate supervised metrics that measure text correspondence to human references and unsupervised metrics that are computed without referring to the human annotation.

| Method          | Supervised Metrics | Unsupervised Metrics |
|-----------------|--------------------|----------------------|
|                 | B@4    | M     | C    | S     | CLIP-S<sup>Ref</sup> | CLIP-S | PP |
| VinVL [60]      | 0.41   | 0.311 | 1.409| 0.252 | 0.83                | 0.780  | 24.16 |
| Zero-Shot Methods |       |       |      |       |                     |       |     |
| ZeroCap [47]    | 0.029  | 0.12  | 0.131| 0.055 | 0.778               | 0.870  | 25.737 |
| MAGIC [44]      | 0.129  | 0.174 | 0.493| 0.113 | 0.763               | 0.737  | 37.126 |
| Ours            | 0.022  | 0.127 | 0.172| 0.073 | 0.798               | 0.885  | 19.049 |

Table 3: Mean Opinion Score (MOS, scale of 1–5) for caption quality using real-world images and videos.

| Method          | Image | Video |
|-----------------|-------|-------|
| MAGIC [44]      | 1.65  | 1.77  |
| ZeroCap [47]    | 2.52  | 2.30  |
| Ours            | 4.01  | 4.14  |

respectively, with roughly 40% of the generated sentences existing in the training set.

Focusing next on zero-shot methods, Zero-Cap has higher CLIP-related scores than the supervised method. However, in all other metrics, it falls short. One of the main limitations of this technique is that the generated token is optimized until convergence in a greedy manner, without the option of altering past tokens. In contrast, our approach optimizes the generation of an entire sentence, which is beneficial for coherent generation from noisy signals resulting from multiple visual cues. MAGIC samples a next token at each generation step from a distribution that combines both CLIP potentials and the distribution computed using a language model. To ensure that the resulting captions lie in the text domain of image captions, they fine-tune the language model on the text corpus of MS-COCO captions. While MAGIC is comparable to our method with regards to the supervised metrics, it falls short in all other metrics. We hypothesize that MAGIC’s per token greedy decoding harms the ability to handle the noisy signal of multiple visual cues found in a video.

Qualitative Analysis: In Fig. 3, we show examples of our video captions. First, we evaluate captions created using supervised methods. Despite having significantly different architectures, the supervised methods produce very similar captions. Although supervised methods may be on topic, their grounding capabilities are limited to relatively abstract objects. For example, the supervised method recognizes that the video is about a car or phone in the first row. However, it misses the true intent of the video.

Our model displays real-world knowledge. For instance, it can detect brands. The video in the first row, on the left, shows Samsung’s advertisement (i.e., Samsung Galaxy) about credit card payments, which is recognized by our method. The video on the right shows an Audi navigation commercial. Our model identifies the Audi brand and the video’s purpose. The video in the 2nd row, on the left, demonstrates TV animation. Our method recognizes the character Ash from Pokemon. Next, we demonstrate that our model can recognize events from various frames. In the 2nd row, right side, our model describes the entire scene, both the audience and the comedian being interviewed.

We also compare our method to two other zero-shot methods, ZeroCap and MAGIC. We find that captions generated by other methods are often broad, failing in videos that require real-world knowledge or aggregating information from multiple frames. For instance, both methods miss the Samsung brand. Furthermore, they often identifies a related but wrong entity (e.g., Pickachu in the Pokemon video). Often, they miss events from different frames, e.g., they do not describe the comedian or the interviewer in the right video on the 2nd row.

In Fig. 4 we evaluate how sentences evolve during the inference process. We first note that, quantitatively, the CLIP score increases between generation iterations, e.g., on the left, at the fourth sentence iteration, the clip score is 0.58, while at the 16th iteration, the score is 0.89. This improvement can also be seen qualitatively. In the left video, we see that the sentence grounds the truck, which is visible in all frames, after four iterations. The model grounded both the truck and trailer in its eighth iteration. Only after the 16th iteration does the model recognize it as a Lego truck. We note an interesting failure case in which, after 16 iterations, the model incorrectly identifies the type of video as a trailer. The video on the right shows similar behavior. In the 16th sentence iteration, the CLIP score increased from 0.70 to 0.88. In the fourth iteration, the video was grounded to more abstract objects (e.g., soldier, battle, alien), while the
Figure 5: Counterfactual examples, which reorder the events in generated sentences. The analysis shows that temporal knowledge is embedded in the language and in visual cues.

eighth iteration identified the characters from Halo. As a final step, the model figures out that the video is an animated cartoon in the 16th iteration.

Tab. 2 compares our method to state-of-the-art image captioning approaches, ZeroCap, and MAGIC. These approaches optimize at the token level resulting in a drop in the PP metric. Our sentence-level optimizations generate more fluent captions compared to token-level optimizations. We also assess supervised metrics aimed at language correspondence against human references. MAGIC excels on the supervised metrics. As the method fine-tunes the PLM on the human references, it allows the language to relate to their style. When evaluating captions using CLIP-based scores, performance drops. Our next step is to explore the reason by using a small sample of images outside the COCO dataset. A significant advantage of zero-shot captioning methods is that they can describe images not included in the training set. In Tab. 3, we assess the caption quality of zero-shot methods when presented with images or videos requiring real-world knowledge. We asked 20 annotators to consider three properties: language fluency, human-likeness, and grounding, and rank each caption between 1 (lowest score) and 5 (highest score). The test included 10 images randomly sampled from the web, and 10 videos randomly sampled from the MSR-VTT [54] test set. Our approach is significantly better for videos (4.14 vs. 2.30) and images (4.01 vs. 2.52). In Fig. 13, we show different samples from the human evaluation. Generally, our method’s captions provide a coherent description of the given entity. MAGIC, on the other hand, does not perform well. The proposed method may be hindered by the fine-tuning of the language model, which still interferes with the method’s ability to discuss real-world entities.

Furthermore, we stress-test our model by captioning sets of random images, which explores its ability to create a coherent text that describes unrelated images, see Sec. B.2 for further discussion.

5 Discussion and Limitations

Despite showing video as the main application in most of our experiments, our method is invariant to the order of frames in the sequences. This is a result of using a zero-shot strategy, in which the underlying models are trained per frame. Examining the results, the generated captions display a logical order. This is not surprising, since ordering frames is typically not an extremely challenging visual understanding task, and is also used as a self-supervised task [52]. Evidently, the information that exists in both the Language Model and the CLIP network is sufficient for generating sentences that adhere to the natural order of events.

To further examine this, we created counterfactual sentences in which the order of events is altered, and measured the PLM and CLIP scores. As can be seen in the examples of Fig. 5, changing the order leads to a drop in both scores. For example, judges giving a score before a contestant sings has a higher perplexity, or a player’s pose can be used to identify them as someone who throws a ball and not someone who catches it.

A limitation of large-scale models is that they can sometimes generate sexist, or otherwise toxic language. Before viewing the examples (see appendix Fig. 18), readers are advised that they contain harsh language. CLIP and GPT-2 may be at fault because they use web-based, uncurated data [11]. It is advisable to be aware of these weaknesses before deploying our method or any other method that uses these models.

6 Conclusions

We present a method for creating natural-sounding captions from a video. The method is a zero-shot method based on two frozen networks: a language model and an image-text matching model. The method is based on learning, for each input, a sequence of vectors that serve as pseudo-tokens that drive the generation process. An autoregressive process generates the caption while updating the pseudo-tokens. Once the caption is generated, the process repeats, using the learned pseudo-tokens as the starting point, leading to increasingly concrete and well-grounded captions. Our experiments show that our model generates novel captions that ground objects from multiple images into one coherent narrative.
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A Appendix

In this appendix we provide additional results and ablation studies.

B Quantitative Results

B.1 Image Captioning

Tab. 4 shows results for single-image captioning, evaluated on the MS-COCO test-set [23]. We compare our method with another zero-shot method, ZeroCap. Unlike the baseline, our method is trained with a perturbed prefix instead of ‘Image of a’. As a result, our method is more robust to prefix changes. Notably, the perplexity score is significantly higher when the prefix is removed from the baseline sentence (109.959 vs. 25.737). Furthermore, compared to the baseline’s 0.870 CLIP score, our method has a higher CLIP score of 0.885. CLIPScoreRef is also improved (0.778 vs. 0.798), which means that our caption matches human references better. In particular, we optimize complete sentences, resulting in a significant improvement in language fluency (19.049 vs. 25.737).

B.2 Image Set Captioning

In order to stress-test our method, we consider the task of captioning random image sets. The goal is to describe a set of images with one coherent sentence. We use the MS-COCO test-set [23] for images. The number of images varies between one and four, one being the conventional image captioning task.

It is expected that the more heterogeneous the image set, the harder it is to generate a coherent caption. To quantify this, we measure the homogeneity of a set by the average CLIP score between the human captions of each image and the rest of the images in the set. Intuitively, this tells us whether the images depict similar concepts or not. In addition to comparing sets by their size, we also differentiate them based on their level of homogeneity. The results are shown in Fig. 6. The graphs reveal that the CLIP score increases with homogeneity, which is expected, since a single sentence can describe homogeneous images better. Our approach has a higher CLIP score at all levels of homogeneity and for all set sizes.

In Fig. 7, an experiment similar to the one above, based on BERT-based perplexity, is conducted to measure language quality. We find that our method produces much better sentences. A particularly interesting case is that of homogeneous pairs (i.e., homogeneity level of 0.8). Only in this case, which involves two very similar images, does ZeroCap perform as well as we do (logPP of 3.0 vs. 3.5).
Table 4: Quantitative results for image captioning on the MS-COCO test set using different prefixes.

This highlights the ability of our approach to generate coherent sentences that describe a set of images across various challenges.

C Ablation Study

To assess different hyperparameters, we use the MSVD [51] validation set, which consists of 100 videos. We examine two properties: (i) Video correspondence, which we examine with the Retrieval score, and (ii) language fluency, which we analyze with the BERT perplexity score. Additionally, we report CLIP Score and BLIP score, which measure image correspondence with the selected frames.

In Fig. 8, we study different values for \( \lambda \), which controls the trade-off between CLIP loss \( L_{\text{CLIP}} \) and language fluency loss \( L_{\text{PLM}} \). Increasing the value of \( \lambda \) decreases the Retrieval score. Our results show that \( \lambda = 0.8 \) provides a good trade-off between image correspondence and language fluency (i.e., low perplexity).

In Fig. 9, we ablate the learning rate (i.e., \( \alpha \)). Since optimization occurs during inference, the number of iterations is fixed, so a higher learning rate ensures convergence. In our experiments, we use \( \alpha = 0.1 \), which has the lowest perplexity, and the highest Retrieval score. Note that the graphs might be misleading due to the wide range of values. The method is relatively stable to this parameter.

In Fig. 10, we study different prompts. In our method, we perturbed a prompt for each generated sentence to increase robustness to different scenarios (e.g., image set captioning and videos). Note that while the option of no prefix at all results in good performance, we find it less focused for the task of visual captioning.

In Fig. 11, we assess our CLIP-based sampling method. Our method employs CLIP’s visual encoder to compute image similarity. The Retrieval score increases, as can be expected, with the CLIP image similarity. The perplexity score is relatively stable, but there is a trade-off between the two.

In Fig. 12, we demonstrate how the CLIP score progresses during the generation process. We report the following statistics: (i) Mean is the average CLIP score at the given iteration across the set (ii) Max is the maximum CLIP score at the given iteration across the set (iii) Best Mean is the best mean score up to this iteration. The challenge of fitting to multiple visual cues can cause performance instability during optimization. Thus, we suggest selecting the sentence with the highest CLIP score from all the generated sentences.

D Qualitative Analysis

In Fig. 13 we demonstrate the ability of our model to caption images while incorporating real-world knowledge. We provide comparison with two baseline zero-shot image captioning models: ZeroCap [47] and MAGIC [44]. The baseline models fail to describe the images with fluent natural language, nor do they provide real-world information. Our model recognizes Bill Gates, the Great Wall of China and the map of Italy, and incorporates that knowledge in rich descriptive captions.

In Fig. 14 we illustrate the progression of captions during the optimization process. The left image set shows two very different pictures of a toy bear and a baseball game. Earlier captions discuss the crowd and the dinner separately. The eighth iteration improves grounding, and the method recognizes the baseball game. A coherent narrative is built in the 16th iteration. It is described as a table of a pitcher at a dinner party. There are baseball cards on the table, and bears serve as a metaphor for phrasing a quote. For the right image set, after four iterations our method generates a caption that includes the word Pyongyang as the location and the word ‘wildlife’. At the eighth iteration, the caption identifies the animal as a bird. As a result of detecting Pyongyang as the location, the bird is described as being from the DPRK. A reference is also made to the flowers.

In Fig. 15 we illustrate captions generated for sets of various sizes. We are able to identify and describe the content of two images even if there is no significant correlation be-
between them. A stop sign and surfing images are translated to “Surfing stops...”, while pictures of a toilet and ladies in formal attire are captioned with “The toilets at the wedding reception.”. Also, pictures of a sheep and a birthday cake are captioned with “Sheep’s birthday...”.

When three images can be described with a coherent story, the model can do so. As an example, for a set of images of a bus, a hotel bed, and a beach, our method generates the caption: “Photo of bus driver sleeping on the beach from the hotel.”. This caption grounds all the images while still creating a plausible narrative. In addition, even when real-world knowledge is necessary, e.g., a picture of Obama, the caption relates to it.

Our method was able to produce a coherent narrative even when dealing with a complex case of four images. It describes a narrative of an image of birds taken while cycling in Melbourne. We note that ZeroCap’s sentences tends to create an irrational context, e.g., “Captive Obama...”, which is perhaps the result of token-based optimization rather than sentence-based optimization.

In Fig. 16, we demonstrate our method’s zero-shot image captioning capabilities. We compare with ZeroCap. We find that ZeroCap’s captions are more direct, whereas the narrative of our captions is more natural. For example, in the first row, on the left, the captions describe the girls and indicate that it is their summer vacation, whereas ZeroCap mentions what appears in the image. These results might come from the way we construct sentences. By letting the PLM construct sentences, we improve language fluency. ZeroCap, on the other hand, alternates each token to correspond to the image, which might hinder the language.

In Fig. 17, we illustrate the CLIP-based mechanism we use to pick novel and diverse frames. As a result of using CLIP image similarity, the method is able to find frames with a very different content, e.g. where the environment or objects change. We highlight the selected frames with a red border. For example, the first row contains a frame depicting a pitcher, followed by a frame showing the catcher.
Frames following this one are ignored until the ball is hit. In the following video, only four frames are selected, filtering out many repetitions. The strategy also works with animations, as shown in the third video.

In Fig. 19, we show more examples for the full generation process for videos. We present the frames selected by our CLIP-based sampling method for each video. Additionally, we report BERT-based perplexity score and CLIP score. The low perplexity score indicates that early sentences have good language, but subsequent sentences improve the CLIP score significantly. Our method can ground objects and generate coherent sentences in various contexts.

In Fig. 20, we illustrate the evolution of sentences, using two images. Interestingly, the method uses stories to weave the photos into a coherent story. For instance, the image of prison and a bedroom photo results in a caption about a prisoner’s bedroom.

In Fig. 21, three images are employed, and the generation process is displayed. Often, creating a coherent sentence from three images is too challenging. Therefore, in those cases, it is better to choose the sentence based on the perplexity indicator rather than using the CLIP score. Thus, the language will be fluent as it describes a story line without describing everything in every image. Fig 22 shows the same phenomenon when there are four images.
Figure 8: Ablation study for the hyper-parameter $\lambda$.

Figure 9: Ablation study for the learning rate, i.e., $\alpha$. 
Figure 10: Ablation study for different prompts.

Figure 11: Ablation study for the CLIP-based frame selection method. We ablate different threshold values used to pick significant frames.
Figure 12: CLIP Score progress over the generation process.
A genius CEO is not a genius in the world of Silicon Valley billionaires.

MAGIC: A man smiling while holding glasses of wine.
Ours: Microsoft billionaire and philanthropist Bill Gates, who is chairman of the foundation that has been criticized for supporting..

ZeroCap: A wall in the Chinese city of Gansu is a great hit hit.
MAGIC: A view of a big tower with a clock on it.
Ours: The world's largest wall in China, complete with a stunning view from above.

ZeroCap: A city in the Chinese blockchain network Zha dong (not a city in MAGIC).
MAGIC: A view of a city street from a tower.
Ours: Beijing's futuristic office building, which is expected to be one of the most expensive buildings in history.

ZeroCap: A city in Cairo taken from Shutterstock The Egyptian city of Cairo has been given a..
MAGIC: A view of a city street with a big, beautiful clock tower.
Ours: Cairo's ancient city center and its many wonders, including the pyramids.

ZeroCap: A historic Taj Mahal in India.
MAGIC: A view of a very big, luxurious,
Ours: Taj Mahal, which is a tourist destination in India's westernmost state.

ZeroCap: A map that shows the state is in the hands.
MAGIC: A red and green tour bus stands idly in the middle of a
Ours: Italian state logo on a map showing the country's borders, with its name and symbols of national identity.

Figure 13: Examples of our image captions on examples that require real-world knowledge, with two zero-shot image captioning baselines.
‘a few hundred people gathered in the crowd at dinner table, with some sitting around watching’ says

Image shows baseball player and former mayor of the city, who is now a member club dinner.

Picture shows pitcher’s table at ballpark dinner party, baseball card says it was a hit for the bear.

how the animal is being used as part of a conservation project by wildlife experts in Pyongyang.

Photo shows Pyongyang’s new bird sanctuary in the sky.

Image shows DPRK’s birds, flowers and wildlife statues at the memorial park in Pyongyang.

Figure 14: Evolution of image pair captions. We show the sentence with the highest CLIP score at different generation iterations.

Sign falling to the surfboard.
ZeroCap: Surfing stops at a beach stop sign.
Ours: The toilets at a wedding reception.

Few sheepid sheepidi in the sheepid flock activity area.
ZeroCap: Sheep birthday party, where a female member of the flock is seen with her head turned to one side.
Ours: Sheepid sheepidi in the sheepid flock activity area.

Captive Obama dinner in the park from the video.
ZeroCap: Obama picnic with dogs at the prison camp in a cage.
Ours: Obama picnic with dogs at the prison camp in a cage.

Young bus driver resting in Stockholm Hotel.
ZeroCap: Photo of bus driver sleeping at the beach in front hotel.
Ours: Photo of bus driver sleeping at the beach in front hotel.

Pair of men parked on the stepset.
ZeroCap: Pair of men parked on the stepset.
Ours: Image showing the pair of birds, taken from an outdoor bike ride in Melbourne’s CBD.

Figure 15: Examples of our image set captioning, for different set sizes. We compare our method with ZeroCap, another zero-shot method.
Figure 16: Examples of image captions.

Figure 17: Illustration of our CLIP-based sampling strategy. The picked frames are outlined in red.
Dunking on the screen, a video clip and then you’re like oh shit.

A video of the comedian saying ‘fuck you guys’, which was later deleted.

The sex act with her ass and pussy in a movie trailer.

Figure 18: Example of harsh language being generated by our model. This illustrates a limitation of web-scale models.
Figure 19: The evolution of captions for videos. (below and for multiple pages)
Figure 20: The evolution of captions for two images in an image set. (below and for multiple pages)

Iteration 1: the aftermath of a massive fire in downtown Toronto. CLIP-S: 0.32, PP: 22.61
Iteration 2: how to get started in the industry, with a simple and easy way of meeting people. CLIP-S: 0.51, PP: 10.13
Iteration 3: the night from a helicopter flying over sea ice on board ship at sunset in harbour. CLIP-S: 0.34, PP: 7.87
Iteration 4: the dinner table dining group of four people at restaurant, which was closed to public view. CLIP-S: 0.55, PP: 6.82
Iteration 5: a dinner at the waterfront restaurant, Pierpiers. CLIP-S: 0.64, PP: 21.19
Iteration 6: the sea pier in downtown Portland's harbour on Sunday evening, when a group of young people gather for CLIP-S: 0.65, PP: 10.51
Iteration 7: the dining group of sea bass tasting dinner at downtown. CLIP-S: 0.59, PP: 15.78
Iteration 8: the dining room of a restaurant in downtown, where people were discussing what to do after the pier was CLIP-S: 0.61, PP: 8.82
Iteration 9: boat piersgoers enjoying lunch at sea restaurant, harbour views. CLIP-S: 0.58, PP: 10.66
Iteration 10: a dinner boat at sea with its pier. CLIP-S: 0.56, PP: 31.34
Iteration 11: the pier tasting dinner at a restaurant in San Francisco, where they were told by their guests to leave CLIP-S: 0.62, PP: 10.90
Iteration 12: dinner at the waterfront restaurant where a man was stabbed by his own dogs has been posted on social media CLIP-S: 0.53, PP: 7.76
Iteration 13: a tasting room at the pier of 'dinner club', where people were eating in a boat, CLIP-S: 0.62, PP: 8.54
Iteration 14: a pier in San Diego with dinner birds. CLIP-S: 0.64, PP: 35.63
Iteration 15: the tasting of pier food at an outdoor restaurant in downtown. CLIP-S: 0.62, PP: 16.12
Iteration 16: the dinner tasting at Pierpont, a waterfront pub on Long Island's harborside. CLIP-S: 0.69, PP: 7.13
Iteration 17: a dinner party at the pier, tasting wine from nearby restaurants. CLIP-S: 0.71, PP: 25.30
Iteration 18: tasting piersgoers enjoying lunch at sea restaurant, harbour views. CLIP-S: 0.68, PP: 14.07
Iteration 20: the harbourside dining pier in a restaurant. CLIP-S: 0.62, PP: 30.55

Iteration 1: the scene where a man named 'Johnnie,' who was convicted of murdering his wife. CLIP-S: 0.62, PP: 6.70
Iteration 2: the room in which a former prison inmate was held for years. CLIP-S: 0.75, PP: 14.25
Iteration 3: a prison cell in the basement room, where prisoners are allowed to shower naked or sleep on beds with CLIP-S: 0.70, PP: 17.90
Iteration 4: a bedroom window that is believed to be used as prison cell number one. CLIP-S: 0.79, PP: 16.59
Iteration 5: bedroom in prison, from the book 'Prisoners and their families. CLIP-S: 0.81, PP: 15.08
Iteration 6: inmates at prison on a bed in solitary confinement. CLIP-S: 0.66, PP: 43.24
Iteration 7: bedroom of a prisoner in prison for killing and raping women. CLIP-S: 0.77, PP: 10.09
Iteration 8: prison bed in a bedroom where prisoners is sleeping. CLIP-S: 0.74, PP: 31.17
Iteration 9: prisoner sleeping with bed in prison yard, where it was discovered she had been locked for a month and CLIP-S: 0.64, PP: 20.49
Iteration 10: room where prisoners was held for a month before trial. CLIP-S: 0.73, PP: 40.63
Iteration 11: the bedroom of a prisoner who was held in solitary for nearly three years, and is now being read CLIP-S: 0.78, PP: 6.89
Iteration 12: the prison where they are being held in. CLIP-S: 0.62, PP: 31.29
Iteration 13: the bedroom of a jailed prisoner in prison. CLIP-S: 0.79, PP: 33.98
Iteration 14: bedroom prison in the early morning hours. CLIP-S: 0.66, PP: 76.22
Iteration 15: bedroom in which prisoners were imprisoned for writing books on the walls of their cells, according to a report CLIP-S: 0.62, PP: 8.03
Iteration 16: prison via Shutterstock, the author's home. CLIP-S: 0.70, PP: 45.50
Iteration 17: bedroom in jail cell, with books on the bedrooms door. CLIP-S: 0.81, PP: 18.90
Iteration 18: bedrooms bedroom of prison cell, bedside book. CLIP-S: 0.70, PP: 50.40
Iteration 19: room in which prisoners were sleeping, but the bedrooms of a bedroom. CLIP-S: 0.77, PP: 20.16
Iteration 20: the bedroom of imprisoned inmate in a prison cell. CLIP-S: 0.78, PP: 21.20
Iteration 1: the scene of a man's death in his home kitchen. CLIP-S: 0.46, PP: 10.67
Iteration 2: food and beverage items that have been sold in supermarkets. CLIP-S: 0.58, PP: 28.01
Iteration 3: food in the breakfast menu at an airport restaurant, which is a staple item for many people in the CLIP-S: 0.62, PP: 8.87
Iteration 4: fruit, fruits are shown on a supermarket menu. CLIP-S: 0.67, PP: 36.52
Iteration 5: food items being prepared in a supermarket fruit aisle. CLIP-S: 0.59, PP: 43.64
Iteration 6: breakfast fruits and fruit juice, which were served in the morning meal. CLIP-S: 0.58, PP: 18.89
Iteration 7: breakfast fruit and vegetable bar, with the 'healthy food', a large portion of which is served to CLIP-S: 0.62, PP: 20.78
Iteration 8: breakfast food shop in the supermarket chain. CLIP-S: 0.65, PP: 97.76
Iteration 9: fruit breakfast at the supermarket in a restaurant. CLIP-S: 0.69, PP: 28.49
Iteration 10: fruit at a cafe in the northern town, pictured on Tuesday. CLIP-S: 0.62, PP: 12.22
Iteration 11: fruit and vegetable market breakfast in front of a bakery, lunch buffet or diner serving pancakes. CLIP-S: 0.68, PP: 12.55
Iteration 12: Breakfast at the restaurant, which is a fruit salad. CLIP-S: 0.60, PP: 42.54
Iteration 13: fruits and veggies being prepared in a restaurant breakfast buffet at lunch. CLIP-S: 0.65, PP: 13.16
Iteration 14: fruits and vegetables breakfast in a diner. CLIP-S: 0.68, PP: 126.99
Iteration 15: breakfast fruits and vegetables in a shopping centre. CLIP-S: 0.64, PP: 70.03
Iteration 16: the breakfast menu at a grocery store, courtesy food. CLIP-S: 0.64, PP: 21.91
Iteration 17: breakfast fruits, fruit juices from a bakery in the morning. CLIP-S: 0.64, PP: 22.78
Iteration 18: breakfast fruit in a basket, with the price of produce on each side. CLIP-S: 0.64, PP: 42.42
Iteration 19: the fruit and vegetables in a supermarket at breakfast. CLIP-S: 0.68, PP: 38.12
Iteration 20: breakfast at a supermarket with fruits and veg, which is served in the same way. CLIP-S: 0.68, PP: 28.63

Iteration 1: the moment an officer fired his gun at a car carrying two men who had been arrested. CLIP-S: 0.39, PP: 10.88
Iteration 2: the world is getting a little bit more crowded. CLIP-S: 0.45, PP: 27.58
Iteration 3: the year is a little bit different than what's on your car. CLIP-S: 0.49, PP: 14.02
Iteration 4: the bus stop at an abandoned railway station, with its wooden sign advertising a 'free camping spot'. CLIP-S: 0.50, PP: 7.63
Iteration 5: a man carrying the bus on his back, which was spotted in front of several homes along lake shore CLIP-S: 0.42, PP: 10.25
Iteration 6: the pond in lake trout ponds, which were closed for hiking and camping. CLIP-S: 0.47, PP: 10.12
Iteration 7: bus driver enjoying scenic lake in a restaurant picnic area. CLIP-S: 0.60, PP: 13.38
Iteration 8: bus advert promoting the trail hikers' campsite in scenic area near Lake. CLIP-S: 0.53, PP: 8.68
Iteration 9: a couple hiking together in the park. CLIP-S: 0.57, PP: 48.67
Iteration 10: the bus that hikers and drivers have to use for commercial advertising in a scenic lake resort. CLIP-S: 0.58, PP: 6.65
Iteration 11: a bus advert for the restaurant in downtown lakefront village, which has been seen hiking hikers and cyclists CLIP-S: 0.55, PP: 6.84
Iteration 12: hikers enjoying hiking in the woods, which are popularly known as buses and busparks. CLIP-S: 0.60, PP: 11.06
Iteration 13: bus buses parked at a pond in the woods. CLIP-S: 0.46, PP: 30.70
Iteration 14: bus hikers in a pond outside downtown restaurants, hiking buses. CLIP-S: 0.51, PP: 21.10
Iteration 15: bus advert hiking hikers in the park near a restaurant. CLIP-S: 0.54, PP: 35.13
Iteration 16: a bus advert for the hike in front pond by photographer, via Facebook. CLIP-S: 0.58, PP: 9.20
Iteration 17: hikers in bus on the riverfront, with a couple kissing. CLIP-S: 0.57, PP: 19.81
Iteration 18: hikers in a pond with their bus. CLIP-S: 0.59, PP: 78.44
Iteration 19: bus advert in the woods near a pond, hikers enjoying romantic picnic. CLIP-S: 0.64, PP: 9.83
Iteration 20: the hikersbus and its trailer park in rural France, with signs advertising hiking. CLIP-S: 0.50, PP: 8.37
Figure 21: The evolution of captions for three images in an image set.

Iteration 1: the aftermath of a plane crash in southern France, where one passenger was injured. CLIP-S: 0.45, PP: 9.29
Iteration 2: the front view of aircraft flying in a formation over runway at airport. CLIP-S: 0.44, PP: 25.07
Iteration 3: the day from a plane landing at sea in front yard. CLIP-S: 0.49, PP: 16.82
Iteration 4: plane landing pad in downtown area, which was owned and operated by a company called 'airport. CLIP-S: 0.48, PP: 10.78
Iteration 5: the bus station in downtown office building. CLIP-S: 0.43, PP: 37.39
Iteration 6: the plane landing at a restaurant in downtown hotel room, which is now being searched by police. CLIP-S: 0.49, PP: 7.14
Iteration 7: the runway landing of aircraft at sea port. CLIP-S: 0.50, PP: 31.44
Iteration 8: plane in the parking lot at their home apartment. CLIP-S: 0.41, PP: 16.26
Iteration 9: a van flying into the kitchen of home office cafe restaurant on runway in front room. CLIP-S: 0.63, PP: 7.86
Iteration 10: a runway of the house in question. CLIP-S: 0.53, PP: 131.14
Iteration 11: runway of a bus that crashed on the island. CLIP-S: 0.49, PP: 18.11
Iteration 12: a van flying over the runway at an apartment complex in central London. CLIP-S: 0.49, PP: 11.46
Iteration 13: the restaurant's interior, which is being investigated as part of a runway cafe development. CLIP-S: 0.56, PP: 9.22
Iteration 14: truck runway in front kitchen van pier. CLIP-S: 0.59, PP: 134.91
Iteration 15: the truck runway of a restaurant in front apartment complex, where passengers were seen boarding buses. CLIP-S: 0.53, PP: 11.91
Iteration 16: the apartment van on Facebook by airline flight crew via www. CLIP-S: 0.60, PP: 15.00
Iteration 17: Flight lounge in the kitchen floor vanishes. CLIP-S: 0.48, PP: 65.35
Iteration 18: aircraft at the airport in front of apartment building. CLIP-S: 0.47, PP: 23.46
Iteration 19: a truck flying over the restaurant's pier, which was destroyed by an explosion. CLIP-S: 0.52, PP: 11.61
Iteration 20: the runway at airport restaurant and catering truck rental company. CLIP-S: 0.60, PP: 17.48
Iteration 1: the scene after a few minutes of eating. CLIP-S: 0.51, PP: 28.43
Iteration 2: a young girl with her hair cut and dressed up as food at the restaurant where they serve pizza. CLIP-S: 0.45, PP: 8.25
Iteration 3: pizza oven food recipe from the kitchen. CLIP-S: 0.52, PP: 101.58
Iteration 4: a bird feeders in front of an open oven. CLIP-S: 0.59, PP: 25.28
Iteration 5: the food truck kitchen birds in front of a restaurant. CLIP-S: 0.47, PP: 44.22
Iteration 6: birds flying over pizza oven in kitchen. CLIP-S: 0.62, PP: 99.52
Iteration 7: food birds in ovens at home, including a turkey sandwich. CLIP-S: 0.56, PP: 19.12
Iteration 8: a pizza bird perched in front of the fireplace. CLIP-S: 0.57, PP: 18.04
Iteration 9: birds eating pizza at a restaurant in southern Turkey on the way to their dinner table, but not everyone CLIP-S: 0.59, PP: 5.64
Iteration 10: birds eating pizza, fireplace decor and more in the kitchen. CLIP-S: 0.66, PP: 11.13
Iteration 11: fireplace ovens and birds in the garden. CLIP-S: 0.52, PP: 56.40
Iteration 12: the birds is from an oven in which they were served dinner, courtesy fireplace. CLIP-S: 0.63, PP: 11.48
Iteration 13: fireplace birds and pizza ovens in a restaurant, courtesy of the kitchener. CLIP-S: 0.59, PP: 12.48
Iteration 14: the day by chef at a restaurant in which they were serving. CLIP-S: 0.53, PP: 13.13
Iteration 15: a pizza oven in the fireplace of one restaurant. CLIP-S: 0.57, PP: 21.71
Iteration 16: fireplace birds in the kitchen at home by chef and author. CLIP-S: 0.55, PP: 10.77
Iteration 17: birds flock fireplace pizza oven in the kitchen. CLIP-S: 0.60, PP: 41.41
Iteration 18: the fireplace pizza oven in a flock of birds. CLIP-S: 0.62, PP: 30.76
Iteration 19: the birds in a pizza oven, courtesy of chef. CLIP-S: 0.65, PP: 16.47

Iteration 1: the moment an officer shot dead a man in his sleep. CLIP-S: 0.44, PP: 15.21
Iteration 2: the baby in a pink diaper and toddler wearing an orange shirt, which is not his. CLIP-S: 0.49, PP: 14.14
Iteration 3: baby boy in baseball cap, batting gloves and helmet during his first game with team after birth of son CLIP-S: 0.49, PP: 8.31
Iteration 4: the pitcher's birthday party for his daughter, a toddler who died of leukemia. CLIP-S: 0.56, PP: 18.22
Iteration 5: the pitcher pitching in a birthday celebration. CLIP-S: 0.64, PP: 42.36
Iteration 6: pitcher pitching birthday cake for baby who died at party in. CLIP-S: 0.61, PP: 9.86
Iteration 7: baby pitching birthday party for pitcher who died at age of three in the park on a cake. CLIP-S: 0.64, PP: 5.66
Iteration 8: pitcher birthday cake in the backyard of his son's house. CLIP-S: 0.52, PP: 35.76
Iteration 9: the birthday boy pitching for a child in baseball uniform, but it's just not quite right. CLIP-S: 0.57, PP: 6.62
Iteration 10: pitcher pitching for a cake in front of his house. CLIP-S: 0.62, PP: 39.20
Iteration 11: pitcher birthday cake being tossed in the stands at age of baby's toddler. CLIP-S: 0.56, PP: 17.90
Iteration 12: toddler pitching birthday cake baby's age in the hospital. CLIP-S: 0.60, PP: 18.86
Iteration 13: the pitcher's birthday cake in a baseball game. CLIP-S: 0.59, PP: 17.65
Iteration 14: pitcher baby batter's birthday cake, circa the time when he was born. CLIP-S: 0.61, PP: 10.39
Iteration 15: pitcher's birthday, with his arm thrown out to the left by toddler in diaper suit. CLIP-S: 0.70, PP: 15.03
Iteration 16: pitcher Birthday baby by the diaper boy's mom, circa 'throwing pitch', c. CLIP-S: 0.63, PP: 6.87
Iteration 17: pitcher's diaper from birth day photo. CLIP-S: 0.61, PP: 25.68
Iteration 18: toddler's diaper, with the pitcher and catcher on top pitching. CLIP-S: 0.55, PP: 9.12
Iteration 19: a birthday cake toddler in the background of this photo. CLIP-S: 0.57, PP: 20.04
Iteration 20: a pitcher pitching birthday cake to child, who throws the ball back in diaper. CLIP-S: 0.60, PP: 12.83
Figure 22: The evolution of captions for four images in an image set. (below and for multiple pages)

Iteration 1: the scene where a man in his early thirties was killed by police officers who were not aware. CLIP-S: 0.46, PP: 5.72
Iteration 2: a very interesting and unique picture of the ancient temple at Kabbalah in Jerusalem on a hill. CLIP-S: 0.36, PP: 6.50
Iteration 3: a man being attacked in front garden, police said on Wednesday night. CLIP-S: 0.45, PP: 15.39
Iteration 4: up a the top of this page is very important to me, and it's not just a matter. CLIP-S: 0.48, PP: 6.18
Iteration 5: a restaurant, but it's the first thing that pops out of your mouth when you see this photo. CLIP-S: 0.55, PP: 6.77
Iteration 6: pizza church in a restaurant on the street, where he was shot dead. CLIP-S: 0.51, PP: 17.52
Iteration 7: a man's face, and his wife in front of the restaurant with pizza on her head. CLIP-S: 0.47, PP: 6.49
Iteration 8: pizza delivery man being taken into church in the street, where he is shown feeding animals. CLIP-S: 0.51, PP: 12.68
Iteration 9: animal being fed elephant meat pizza and then eaten by church altar priest. CLIP-S: 0.61, PP: 15.90
Iteration 10: Pope Francis praying at a church chapel. CLIP-S: 0.40, PP: 83.52
Iteration 11: pizza delivery elephant's penis being removed from chapel altar. CLIP-S: 0.54, PP: 19.15
Iteration 12: pizza delivery elephant chapel being destroyed by the church's owner. CLIP-S: 0.55, PP: 21.35
Iteration 13: pizza delivery hall in the chapel of St. CLIP-S: 0.53, PP: 74.06
Iteration 14: the chapel elephants taken by photographer's son. CLIP-S: 0.51, PP: 80.58
Iteration 15: the chapel in its elephant enclosure, which was built by pizza chef and animal rights activist. CLIP-S: 0.60, PP: 6.94
Iteration 16: Pizza Hut's elephant mascot, which is being filmed by a team from the University of California. CLIP-S: 0.53, PP: 7.60
Iteration 17: pizza chapel elephant trainer in his yoga pose, which was posted to social media. CLIP-S: 0.60, PP: 13.00
Iteration 18: the elephant chapel, which has been used for pizza and yoga since it was built by a man. CLIP-S: 0.61, PP: 5.70
Iteration 19: Pizza Hut in the chapel of a church elephant sanctuary. CLIP-S: 0.58, PP: 28.28
Iteration 20: Pizza chapel elephant, which is a free yoga restaurant and church in the city of London. CLIP-S: 0.62, PP: 10.43

Iteration 1: the aftermath of a bomb explosion in central Baghdad on Wednesday, which killed more than half. CLIP-S: 0.37, PP: 13.90
Iteration 2: a small amount of light in the air, but it is not visible from ground bus. CLIP-S: 0.57, PP: 8.26
Iteration 3: bus on ground, which is not a part and the water level at sea. CLIP-S: 0.48, PP: 11.58
Iteration 4: the bus station tower, with a fountain on its side and an archway. CLIP-S: 0.49, PP: 16.89
Iteration 5: the fountain in front of a large tree. CLIP-S: 0.49, PP: 30.38
Iteration 6: the bus stop fountain at an outdoor water tower. CLIP-S: 0.55, PP: 20.72
Iteration 7: bus tower at the entrance of park in front parking garage on a busy street. CLIP-S: 0.47, PP: 11.34
Iteration 8: the water fountain in front of bus station. CLIP-S: 0.55, PP: 26.88
Iteration 9: busker fountain in the middle of busy street with buses and tram lines. CLIP-S: 0.49, PP: 9.00
Iteration 10: bus driver and students marching in front of the fountain. CLIP-S: 0.50, PP: 30.50
Iteration 11: the fountain tower in downtown bus field. CLIP-S: 0.58, PP: 28.25
Iteration 12: bus tower, the fountain and field in a stadium. CLIP-S: 0.55, PP: 23.81
Iteration 13: bus tower, the fountain and field in a stadium. CLIP-S: 0.55, PP: 23.81
Iteration 14: the bus stop fountain in front tower at night. CLIP-S: 0.42, PP: 21.99
Iteration 15: the bus tower, a monument to buses and water. CLIP-S: 0.59, PP: 19.33
Iteration 16: Fountain by bus stop in the background. CLIP-S: 0.54, PP: 133.53
Iteration 17: the day fountain at Busk Field, where buses are parked. CLIP-S: 0.58, PP: 13.70
Iteration 18: bus driver tower, the fountain at left and a monument to victims of buses in front yard. CLIP-S: 0.53, PP: 13.03
Iteration 19: the bus tower in front of buses parked outside a school. CLIP-S: 0.48, PP: 14.17
Iteration 20: the bus tower fountain in front of a statue on campus, with buses flying over it. CLIP-S: 0.53, PP: 8.15
Iteration 1: the moment two men were shot dead by a group of people. CLIP-S: 0.39, PP: 16.97
Iteration 2: the animal's body being eaten by elephant at its enclosure. CLIP-S: 0.50, PP: 12.57
Iteration 3: a baby elephant in an aquarium at the zoo. CLIP-S: 0.35, PP: 23.34
Iteration 4: a baby being fed by elephants in northern Thailand, where the animals are considered sacred to some tribes. CLIP-S: 0.45, PP: 6.54
Iteration 5: a woman in the village of Chagang. CLIP-S: 0.41, PP: 20.75
Iteration 6: elephants eating a cake with an elephant in it. CLIP-S: 0.52, PP: 92.28
Iteration 7: elephant cake in the kitchen, but chee is still alive. CLIP-S: 0.57, PP: 13.45
Iteration 8: a cake in the middle of this year's elephants, but it is not yet eaten. CLIP-S: 0.56, PP: 7.15
Iteration 9: elephant bear being eaten by elephants in Thailand's 'meat cake,' but the restaurant owner says it is CLIP-S: 0.48, PP: 7.34
Iteration 10: elephant cake being prepared by pizza delivery man in a restaurant near elephants' enclosure at an amusement park. CLIP-S: 0.51, PP: 9.33
Iteration 11: pizza cake being prepared by a bear, but the elephant is seen eating from its own mouth and not CLIP-S: 0.59, PP: 9.79
Iteration 12: elephants being fed cake pizza by a bear, which was filmed in the forest. CLIP-S: 0.57, PP: 14.54
Iteration 13: elephants eating cake at the zoo in southern Thailand. CLIP-S: 0.47, PP: 25.72
Iteration 14: a bear cake in the kitchen by my friend, which is not edible. CLIP-S: 0.51, PP: 9.98
Iteration 15: a cake bear in front elephants, which are not allowed to eat them but the elephant owner says CLIP-S: 0.59, PP: 6.74
Iteration 16: elephants by the photographer's wife, who is eating cake and pizza. CLIP-S: 0.56, PP: 11.71
Iteration 17: Pizza cake with elephants, elephant's head and cheese on top by the photographer. CLIP-S: 0.49, PP: 12.96
Iteration 18: pizza elephant in a bear suit and cake on the back of its head, taken by photographer. CLIP-S: 0.49, PP: 11.58
Iteration 19: a pizza elephant cake at an outdoor restaurant in Bangkok, Thailand. CLIP-S: 0.47, PP: 13.21
Iteration 20: elephants in Thailand, which is not a cake pizza. CLIP-S: 0.59, PP: 18.74

Iteration 1: the scene where a man was shot in front of his house, circa early 'nineties. CLIP-S: 0.41, PP: 7.15
Iteration 2: a painting by art artist and illustrator, the image of which is on display at a mural in CLIP-S: 0.55, PP: 13.79
Iteration 3: the day by photojournalist, author and artist. CLIP-S: 0.52, PP: 33.41
Iteration 4: the new artwork on horse wall mural at a local church. CLIP-S: 0.49, PP: 13.33
Iteration 5: the wall mural on display in a gallery, which is part of an exhibition called 'The art horse CLIP-S: 0.55, PP: 7.14
Iteration 6: a man painting horses on horseback. CLIP-S: 0.53, PP: 63.62
Iteration 7: the wall decor at a local hotel. CLIP-S: 0.43, PP: 31.94
Iteration 8: flowers and graffiti decorating a house in front of the fireplace. CLIP-S: 0.50, PP: 23.91
Iteration 9: horse paintings hanging on the wall in a hotel room window at home. CLIP-S: 0.44, PP: 13.44
Iteration 10: horses in a horse bed, fireplace and garden wall. CLIP-S: 0.54, PP: 28.01
Iteration 11: horse flowers on the wall in a fireplace. CLIP-S: 0.52, PP: 30.54
Iteration 12: horses flowers in the beach house fireplace. CLIP-S: 0.51, PP: 97.33
Iteration 13: flowers and fireplace walls in a beachfront hotel. CLIP-S: 0.50, PP: 44.60
Iteration 14: horse beach wall decor from the fireplace in an office building at a hotel. CLIP-S: 0.48, PP: 11.91
Iteration 15: a horse riding flowers in front of the fireplace. CLIP-S: 0.58, PP: 25.24
Iteration 16: flowers by the beachfront horse wall in downtown. CLIP-S: 0.49, PP: 51.60
Iteration 17: horse fireplace by the wall in a beach house. CLIP-S: 0.50, PP: 22.53
Iteration 18: fireplace at beach house on horseback. CLIP-S: 0.55, PP: 40.80
Iteration 19: graffiti fireplace in the beach room of a house on horseback horses. CLIP-S: 0.51, PP: 41.70
Iteration 20: flowers and horses at the beach house of former surf horse. CLIP-S: 0.54, PP: 37.22