End-to-end Dense Video Captioning as Sequence Generation

Anonymous ACL submission

Abstract

Dense video captioning aims to identify the events of interest in an input video, and generate descriptive captions for each event. Previous approaches usually follow a two-stage generative process, which first proposes a segment for each event, then renders a caption for each identified segment. Recent advances in large-scale sequence generation pretraining has seen great success in unifying task formulation for a great variety of tasks, but so far, more complex tasks such as dense video captioning are not able to fully utilize this powerful paradigm. In this work, we show how to model the two subtasks of dense video captioning jointly as *one* sequence generation task, and simultaneously predict the events and the corresponding descriptions. Experiments on YouCook2 and ViTT show encouraging results and indicate the feasibility of training complex tasks such as end-to-end dense video captioning integrated into large-scale pretrained models.

1 Introduction

Online videos have become an important source from which people acquire knowledge and skills (O'Neil-Hart, 2017). In order to help users locate the information of interest, search engines and video platforms often show anchors at "key moments", usually accompanied by descriptions of the segment's content (Baheti, 2019). This is a direct application of the dense video captioning task (Krishna et al., 2017), and therefore solutions for improving this task are highly relevant for any video platform.

Intuitively, dense video captioning can be decomposed into two subtasks: event localization and segment-level video captioning. Prior work (Krishna et al., 2017; Zhou et al., 2018a; Li et al., 2018; Wang et al., 2018; Zhou et al., 2018c; Mun et al., 2019; Iashin and Rahtu, 2020) followed this task decomposition, and solved the dense video captioning task using a two-stage, "localize-then-describe" pipeline. Such methods usually involve two separate modules with different underlying model architectures for event localization and event captioning, with captions for dense events rendered based on the predicted event spans.

Recently, with the advance of large-scale datasets and model architectures, there has been an explosion of pretrained multimodal (for text, image, video) Transformer models (Tan and Bansal, 2019; Sun et al., 2019; Li et al., 2019; Luo et al., 2020; Li et al., 2020a,b; Gan et al., 2020; Kim et al., 2021). Such models have proven to be highly effective when fine-tuned for a wide range of downstream tasks, such as visual question answering (Agrawal et al., 2015), image captioning (Chen et al., 2015), visual common sense reasoning (Zellers et al., 2019), visual entailment (Xie et al., 2019), etc. These end-tasks can be expressed as sequence generation tasks in a straightforward manner. In contrast, this is non-trivial for dense video captioning, as the segmentation subtask does not lend itself naturally to such a formulation. Does this mean more complex tasks cannot benefit from the pretraining paradigm in an end-to-end fashion? In this work, we study dense video captioning as an example of a complex task that can be cast as sequence generation and, as a result, can benefit from large-scale pretraining.

More specifically, we propose to solve the dense video captioning task as a single sequence-to-sequence modeling task using a multimodal Transformer. To this end, we design several task formulations to encode both segmentation and captioning prediction in one target string. Instead of invoking the two-stage scheme, our task formulation allows the model to simultaneously predict event locations and corresponding captions in one pass, using one decoder. This opens the door for enjoying the benefit of training from large-scale pre-trained models, as well as the possibility of participating in large-scale multi-task training more easily by re-using existing infrastructure.

We evaluate our model on two dense video captioning benchmarks, YouCook2 (Zhou et al., 2018a) and ViTT (Huang et al., 2020a). We found our sequence generation formulation a feasible path forward – we obtain encouraging results compared to prior work that used a two-stage scheme with specialized architectures for each step. On the pre-training front: (a) we are able to benefit from models pre-trained on very different data and tasks, such as T5 (Raffel et al., 2020), (b) pretraining on more domain-specific data (WikiHow) and pre-training task (predicting headings for how-to steps) lead to similar amount of gain, but (c) having the domain-specific pre-training start from a T5 checkpoint (T5 + WikiHow) provides significantly bigger gain. The noteworthy result here is that, even in the presence of large-scale domain- and task-specific pretraining (WikiHow), one can still observe measurable benefits due to a task-agnostic general-purpose pretrained model (T5).

While the main motivation for modeling the two tasks jointly is to be able to utilize the pretraining paradigm, the segmentation subtask (finding event boundaries) and the captioning subtask (describing what happens in an event) are related tasks, and intuitively stand to benefit from being modeled jointly. Our experimental results are aligned with this intuition: a model that does both segmentation and captioning at the same time outperforms (in terms of segmentation accuracy) a variant that focuses only on the segmentation task.

Overall, our results point to an viable alternative direction for modeling complex tasks such as end-to-end dense video captioning, in which we can leverage the large-scale pretraining paradigm to achieve modeling improvements.

2 Related Work

2.1 Multimodal Transformer

Recently, vision-and-language pre-training has attracted a lot of attention for jointly learning from visual and textual inputs in order to better solve multimodal tasks. Following the success of BERT (Devlin et al., 2019), multimodal pre-training usually adopts the Transformer (Vaswani et al., 2017) encoder structure to encode both the visual features and textual features. The late-fusion approaches first process visual and textual information separately and subsequently fuse them using another Transformer layer (Tan and Bansal, 2019; Lu et al., 2019). The early-fusion approaches jointly encode visual and texual representations (Chen et al., 2020; Sun et al., 2019; Li et al., 2019; Luo et al., 2020; Li et al., 2020a; Qi et al., 2020; Huang et al., 2020b; Li et al., 2020b; Lin et al., 2020; Gan et al., 2020; Kim et al., 2021). During pre-training, tasks such as masked language modeling, masked region modeling, and image-text matching are used to learn a cross-modal encoding which benefits downstream multimodal tasks.

2.2 Dense Video Captioning

Krishna et al. (2017) introduced the dense video captioning (DVC) task and proposed a solution based on two separate modules: one for proposing events, and another for captioning them. Recent work (Zhou et al., 2018a; Li et al., 2018; Wang et al., 2018; Zhou et al., 2018c; Mun et al., 2019; Iashin and Rahtu, 2020) follows the two-stage "detect-then-describe" framework, in which the event proposal module first predicts a set of event segments, then the captioning module constructs captions for each candidate event segment. Another line of work (Deng et al., 2021; Wang et al., 2021) removes the explicit event proposing process. Deng et al. (2021) tackles the DVC task from a top-down prospective, in which they first generate a video-level story, then ground each sentence in the story to a video segment. Wang et al. (2021) considers the DVC task as a set prediction problem, and applies two parallel prediction heads for event localization and captioning. To the best of our knowledge, our work is the first to simultaneously conduct event localization and captioning in a single run within the same prediction head.

3 Task Definition

The DVC task consists of annotating each input video into multiple segments, where each segment corresponds to an event of interest accompanied by a short description (caption). Figure 1 shows an example from the YouCook2 dataset.

Modified dense video captioning In YouCook2, each segment is marked by a start and an end time, often with gaps between segments. The burden of identifying not just the right start-time but also the right end-time increases the difficulty of the segmentation task, thus affecting the segment-level captioning performance, leading to poor end-to-end results.

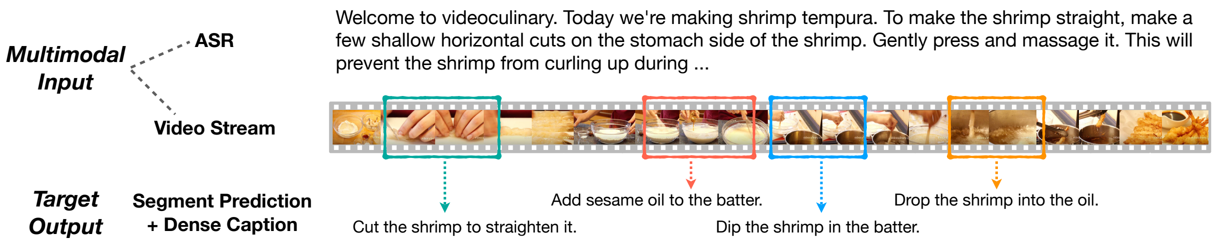

Figure 1: An example of input video and output segmentations and captions from the YouCook2 dataset.

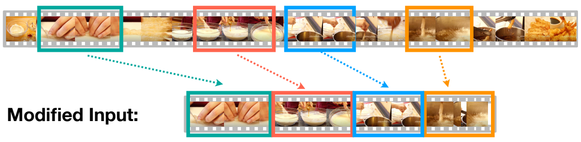

Figure 2: Modified dense video captioning: a simplified setting where the segments are concatenated to form the modified input with gaps removed.

We start our exploration with a simpler task where we introduce a variant of the YouCook2 dataset as shown in Fig. 2: all the annotated segments in a given video are concatenated to form a *modified* input, leaving out the gaps between segments. We refer to this setting as the *modified dense video captioning*: given a modified input from Fig. 2, the model only needs to predict n start times to fully define n segments. In this setting, the segmentation subtask becomes a *partition* task for identifying the set of start times of segments.

4 Method

As noted earlier, prior work often decomposes dense video captioning into two subtasks, (a) a segmentation subtask, and (b) a segment-level captioning subtask. These two subtasks are often addressed with different model architectures. In contrast, our approach solves both subtasks simultaneously with one single model.

We first describe how we jointly model segmentation and captioning subtasks as one single sequence generation task. To this end, we need to formulate target strings in ways that encode both segmentation and captioning predictions. The typical input to a DVC task includes both visual information and speech in textual form – Automatic Speech Recognition (ASR) tokens[1].

We start by introducing our target string formulations assuming only textual input, with segmentation information expressed in terms of the positions of the corresponding ASR tokens. We then describe multi-modal models where the visual information is added to the input while retaining the aforementioned scheme to represent segmentation information.

4.1 Target string formulations

We describe two approaches to formulate the target strings. We refer to a model that encodes only segmentation information in the target strings as a **Seg-only model**, and one that encodes both segmentation and captioning as a **Seg+Cap model**.

Tagging-based target formulation We encode the segmentation subtask in a manner similar to the encoding of the chunking task as tagging tokens in the IOB format (Ramshaw and Marcus, 1995). Fig. 3 illustrates how we model the segmentation task with two tags (in the modified setting): the ASR token at the start of a segment receives a special token $\langle$sep$\rangle$ as the start-of-segment tag, and the rest of tokens in the segment receive a continuation tag (we reuse the $\langle$pad$\rangle$ token). This can be extended to cover the original setting (with gaps between segments) with an additional end-of-segment tag. In this formulation, the groundtruth target output string has the exact same length as the input ASR string. To model the captioning annotation, the $\langle$sep$\rangle$ token is followed by the corresponding ground-truth caption, which is then padded till the next $\langle$sep$\rangle$ token.

While treating the segmentation task as a tagging task seems natural, the tagging-based formulation enforces equal lengths between predicted output and the input ASR tokens, which leads to potential inefficiencies: the input ASR string is usually much longer than all the descriptive captions combined, which results in many padding tokens in the target output, and leading to unnecessary slow-down in training and prediction time. Additionally, the

[1] Our motivation for treating this as a sequence generation task is to take advantage of existing pretrained sequence generation models, currently dominated by text models; thus, we take a text-centric view in this work.

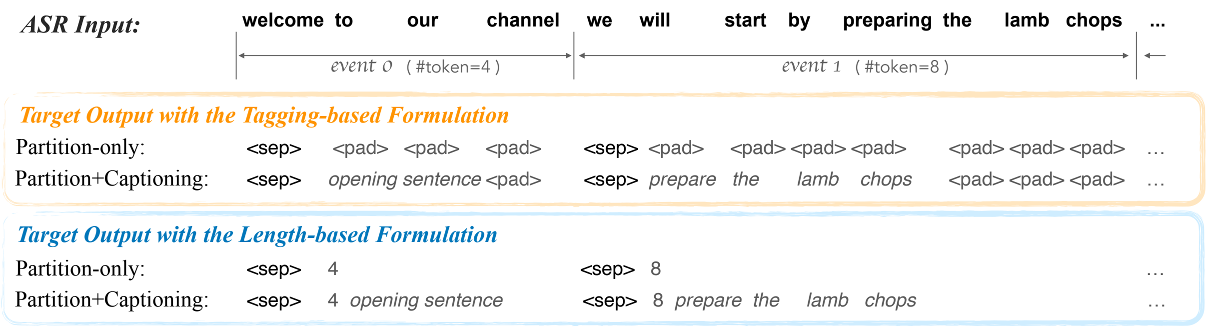

Figure 3: The tagging-based and length-based target formulations for modified dense video captioning.

longer-form target strings are markedly different from the usual generative pattern of the pretrained text decoder, which can reduce the effectiveness of the pretrained checkpoints. Furthermore, this formulation also assumes that captions are shorter than the ASR string for each segment; while this is mostly true, for segments where little is being explained (short ASR string), this formulation leaves insufficient capacity in the target string between the two consecutive ⟨sep⟩ tags to encode the corresponding caption, resulting in caption truncation.

Length-based target formulation To cope with the limitations of the tagging-based formulation, we predict the *length* of each segment explicitly.

Let l_i be the number of ASR tokens in the i-th segment. In the modified setting, the segmentation information for an input string with n segments is fully specified by the sequence $\{l_1, l_2, ..., l_n\}$. Fig. 3 provides an example of this length-based formulation. The groundtruth target string in a Seg-only model is simply a sequence of numbers corresponding to segment lengths (measured by the number of tokens); in a Seg+Cap model, each number is followed by the caption for that segment.

In the original setting with gaps between segments, let g_i be the offset from the last ASR token in previous segment to the start of segment i. The target string will now aim to predict both (g_i, l_i) instead of just l_i for each segment. The sequence of all (g_i, l_i) will fully specify all segment boundaries and can be used to compute the index of the start and end ASR tokens for each segment.

This formulation has the advantage of a more efficient representation of the segmentation information, and thus much shorter target length. The segmentation information is now explicitly expressed as numbers in the target strings, so the model needs to figure out both segmentation boundaries *and* also be able to count appropriately. We explicitly want to empirically measure the ability of our models to do the latter.

4.2 Input formulation for multimodal signals

Simple Concatenation (SimpleConcat) Visual information for a given video is represented as a fixed-length sequence of pre-computed frame-level features. These features are projected to the token embedding space via a fully connected layer. We simply concatenate the sequence of ASR token embeddings and the sequence of projected visual features to form the multimodal input to the encoder. There's one potential caveat: while the visual features are extracted at a fixed frame rate, the ASR tokens are often *not* spoken at a fixed speed; thus positions in this multimodal input sequence do not provide straightforward information on which visual frames are temporally aligned with a certain ASR span. Since segmentation prediction is expressed relative to the ASR-token position index, it is not clear whether the model is able to take full advantage of visual information, absent how these two modalities align temporally .

Prior work on multimodal pretraining has found visual-textual information alignment to be a reasonably solvable task. Huang et al. (2020a) reported 87% accuracy for aligning video segments and ASR spans in HowTo100M (Miech et al., 2019), so it is possible that the decoder can learn to attend to appropriate visual information while "counting" the ASR tokens.

Temporal embedding (Emb$_{\text{TIME}}$) We can also express the temporal alignment more explicitly in the input by adding temporal embeddings to both ASR tokens and visual frames. In this formulation, we learn a temporal embedder shared between the text modality and the visual modality, which maps timestamps to temporal embeddings. Embeddings computed from token timestamps are then added to

Dataset	Train	Validation	Test
YouCook2	925	206	105
ViTT	4736	932	932

Table 1: The number of videos in the train, validation and test sets for YouCook2 and ViTT.

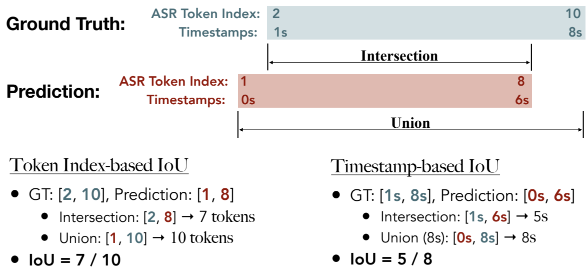

Figure 4: Comparisons between the token index-based and timestamp-based IoU used in our study.

ASR token embeddings, and embeddings computed from frame timestamps are added to projected visual frame features. This way, ASR tokens and frames that are temporally close to each other receive similar temporal embeddings, making their representations closer to each other.

For more explorations on explicitly expressing temporal alignment in the input, see Appendix A.1 for an additional method to insert explicit timestamp markers into the input text sequence.

5 Experiments

5.1 Datasets

Dense Video Captioning Datasets We use two publicly available datasets to verify the effectiveness of our model formulations: YouCook2 (Zhou et al., 2018a) and ViTT (Huang et al., 2020a).[2] The YouCook2 dataset is restricted to videos retrieved from YouTube from the cooking domain, targeting 89 recipes; each event segment is manually marked with a start and end time, along with a human-generated caption for each tightly-bounded segment. The ViTT dataset contains instructional videos from YouTube-8M (Abu-El-Haija et al., 2016) and covers a wider range of topics. Its segment annotation focuses on event start time, along with rater-provided captions for the corresponding segment (spanning two consecutive start-time annotations). Both datasets are annotated with captions written in English.

Note that while the YouCook2 data release contains training, dev, and test sets, its test set does not come with human annotations. Thus, we split the original validation set into validation and test splits for our experiments. For ViTT, we use the original train/val/test splits provided with the data. Table 1 summarizes the size of each dataset, indicating the number of videos available for use at the time of our work[3].

[2] YouCook2 released under an MIT license; ViTT released under an "AS IS" license.

[3] As of 2021; note that YouTube videos are subject to user deletion.

Domain-specific pre-training with WikiHow In addition to general-purpose pretrained models like T5, we also experiment with domain-specific pretraining. To this end, we use the WikiHow dataset (Koupaee and Wang, 2018). WikiHow consists of instructional (how-to) articles, which makes it *in-domain data* for the two dense video captioning datasets considered here, while being much larger in size[4]. In addition, WikiHow articles contain detailed step-by-step instructions. Each step comes with a summary, which usually serves as the section title. Both the step boundaries and summaries are easily extracted according to the page meta-data. This provides the groundtruth annotation for a "dense document caption" task: given the full article as a sequence of text tokens, predict the step boundaries and summaries. This enables us to also include a *domain-specific pretraining task* that closely resembles our task. For each formulation described in Sec. 4, we experiment with a checkpoint pretrained on the WikiHow data using the corresponding target string formulation.

5.2 Evaluation Metrics

Segmentation Performance Following previous works (Zhou et al., 2018b; Shi et al., 2019), we use the mean Intersection-over-Union (mIoU) metric to evaluate the segmentation performance. Recall that the groundtruth segments are marked by start (and end) times, whereas the predicted segments are expressed according to the position of the corresponding ASR token. For the modified dense video captioning task, we compute the token index-based IoU: each groundtruth segment is defined by the start and end ASR token index, and will be compared against the predicted index. For the original task, we compute the timestamp-based IoU: predicted index are mapped into the corresponding

[4] WikiHow training is 157,116 articles, validation is 5,593 articles.

*	Target Formulation	Checkpoint	Seg-only model				Seg+Cap model					
			mIoU	Precision	Recall	F1	mIoU	F1	B@4	METEOR	CIDEr	ROUGE-L
0	Random Partition		37.3	26.45	27.89	24.69	-	-	-	-	-	-
1	Tagging-based	-	33.59	23.04	29.37	24.46	19.72	17.09	0.07	0.91	0.03	2.07
2	Tagging-based	T5	12.06	1.78	7.46	2.81	6.73	0.24	0.00	0.01	0.00	0.03
3	Length-based	-	36.30	26.23	28.79	25.81	33.62	24.69	0.24	1.62	0.04	4.03
4	Length-based	T5	42.71	31.85	33.04	31.21	42.82	32.16	1.83	4.17	0.21	8.74

Table 2: Preliminary experiments comparing the tagging-based and the length-based formulation on YouCook2 modified dense video captioning. We report the evaluation results on the validation set (one run per setting) with models initialized from random variables and from T5 checkpoints.

ASR token timestamps and compared against the segment's groundtruth start and end timestamps. Fig. 4 provides an example of the two types of IoU used.

An IoU score can be computed for each (groundtruth, predicted) segment pair. The mIoU measure provides a summary score for segmentation performance over the entire video: for each ground-truth segment, we take its maximal IoU to predicted segments as the IoU score for this ground-truth segment, and mIoU is the average of this value across all ground-truth segments. The individual mIoU for each video is then averaged across the test data and reported as the overall mIoU.

For diagnostic purposes, we also compute: 1) the percentage of predicted segments which have an IoU score with at least one ground-truth segment, above a certain threshold t (precision@t); 2) the percentage of groundtruth segments which have an IoU score with at least one predicted segment, above a certain threshold t (recall@t), as well as their geometric mean as F1. Following prior work, we compute these scores for a set of IoU thresholds t=$\{0.3, 0.5, 0.7, 0.9\}$, and report the average over these thresholds.

Captioning Performance We compute BLEU-4 (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), CIDEr (Vedantam et al., 2015), and ROUGE (Lin, 2004) scores between generated captions and the ground truth when the predicted and ground-truth segment "match" (i.e., with IoU score above a given threshold t); if a ground truth segment does not have a matching prediction, it contributes a zero to the average score for the corresponding threshold. Again, we compute this for a set of IoU thresholds of $\{0.3, 0.5, 0.7, 0.9\}$, and report the average over these thresholds.

5.3 Implementation Details

Models were trained on 4x4 TPUs and we used about 180k GPU hours for around 1380 training runs including pretraining the WikiHow checkpoint, pilot studies with toy examples, debugging and hyperparameter tuning. The models have around 70 million parameters. We used the Adafactor (Shazeer and Stern, 2018) optimizer and a learning rate schedule of 1000 warmup steps followed by square-root decay. We did a few initial exploratory runs over base learning rates of $\{0.001, 0.01, 0.05, 0.1, 0.2, 0.5, 0.8, 1, 2, 5\}$ to determine that a base learning rate of 1 worked well and used it for all the experiments reported.

For our visual representations, we computed 3D CNN features pretrained on the Kinetics (Carreira and Zisserman, 2017; Kay et al., 2017) dataset for frames sampled at 1fps.

5.4 Experiments in the modified setting

Experimental setup We conduct comparisons of the two different target formulations – tagging-based and length-based– in the modified setting, using the following experimental setup: (a) Max input text length and target length are set to 1024, and max input visual feature length is set to 800; this can truncate longer ASR sequences, but allow us to quickly iterate through different settings with fewer computational resources; (b) Only one run for each setting. We report results on the validation set in Table 2.

Target formulations The best performing model (length-based with T5 checkpoint) outperforms a random partition baseline[5] (row #0 in Table 2), This indicates our target formulation approach to the

[5] For the random parition baseline, a video is randomly split into n segments, where n is sampled from 1 to 15 (ground truth averages at 8).

*	Input Formulation	Checkpoint?	Seg-only model	Seg+Cap model				
			mIoU	mIoU	B@4	METEOR	CIDEr	ROUGE-L
YouCook2								
0	Random Segmentation		21.79 ± 0.56	-	-	-	-	-
1	SimpleConcat	-	12.99 ± 1.55	16.45 ± 8.72	0.17 ± 0.11	0.66 ± 0.04	0.02 ± 0.01	1.99 ± 0.20
2	SimpleConcat	T5	24.14 ± 1.07	24.21 ± 1.64	0.88 ± 0.04	1.50 ± 0.12	0.09 ± 0.01	3.34 ± 0.27
3	SimpleConcat	WikiHow	22.58 ± 1.09	23.33 ± 0.79	0.67 ± 0.15	1.47 ± 0.05	0.08 ± 0.01	3.51 ± 0.13
4	SimpleConcat	WikiHow T5	**27.77** ± 0.09	**30.26** ± 1.24	**2.96** ± 0.28	**3.49** ± 0.30	**0.25** ± 0.03	**7.00** ± 0.42
5	+ Emb_{TIME}	-	18.51 ± 1.95	18.71 ± 0.17	0.12 ± 0.07	0.48 ± 0.08	0.02 ± 0.01	1.41 ± 0.22
6	+ Emb_{TIME}	T5	23.02 ± 1.05	23.96 ± 0.08	1.32 ± 0.08	1.91 ± 0.07	0.11 ± 0.01	4.20 ± 0.13
7	+ Emb_{TIME}	WikiHow	21.68 ± 1.93	21.88 ± 0.86	0.69 ± 0.19	1.30 ± 0.07	0.07 ± 0.01	3.06 ± 0.13
8	+ Emb_{TIME}	WikiHow T5	26.51 ± 0.45	28.70 ± 0.92	2.58 ± 0.19	3.23 ± 0.10	0.22 ± 0.01	6.45 ± 0.17
ViTT								
9	Random Segmentation		26.16 ± 0.06	-	-	-	-	-
10	SimpleConcat	-	33.85 ± 0.70	32.69 ± 0.71	0.11 ± 0.01	3.76 ± 0.35	0.08 ± 0.01	3.86 ± 0.28
11	SimpleConcat	T5	37.89 ± 0.10	38.07 ± 0.65	0.57 ± 0.03	5.92 ± 0.37	0.16 ± 0.02	6.59 ± 0.69
12	SimpleConcat	WikiHow	38.20 ± 0.27	37.80 ± 0.62	0.40 ± 0.07	5.48 ± 0.18	0.14 ± 0.01	6.02 ± 0.34
13	SimpleConcat	WikiHow T5	**41.87** ± 0.26	42.40 ± 0.30	**1.29** ± 0.07	**8.10** ± 0.34	**0.25** ± 0.01	**9.26** ± 0.39
14	+ Emb_{TIME}	-	33.89 ± 0.21	35.37 ± 3.18	0.04 ± 0.03	3.42 ± 0.61	0.07 ± 0.01	3.28 ± 0.83
15	+ Emb_{TIME}	T5	37.78 ± 0.15	38.50 ± 0.55	0.75 ± 0.10	6.37 ± 0.39	0.18 ± 0.01	7.19 ± 0.48
16	+ Emb_{TIME}	WikiHow	37.27 ± 0.08	36.97 ± 0.48	0.38 ± 0.06	5.31 ± 0.06	0.13 ± 0.01	5.82 ± 0.23
17	+ Emb_{TIME}	WikiHow T5	41.64 ± 0.12	**43.22** ± 0.72	1.22 ± 0.08	8.05 ± 0.20	**0.25** ± 0.01	9.18 ± 0.45

Table 3: Performance on the dense video captioning on YouCook2 and ViTT test set with the length-based and the Timestamp markers formulations. We ran 3 set of repeating experiments for each setting, and report the evaluation results (mean ± std) with models initialized from random weights, T5 checkpoints, WikiHow checkpoints, and T5 checkpoints further pretrained on WikiHow. Seg: segmentation task. Cap: captioning task.

segmentation task are capturing some segmentation information effectively.

When trained from scratch, the length-based formulation achieves higher performance across the board (#3 vs #1), with a smaller gap for the Seg-only model, and more marked lead for the Seg+Cap model. We hypothesize that while treating the segmentation task as a tagging task is more or less feasible on its own, combining segmentation tags and captions are not a good formulation for the combined task – to the point that the Seg+Cap model underperforms the Seg-only model in segmentation metrics (mIoU of 19.72 vs 33.59 in #1).

The length-based formulation overall benefits from the T5 checkpoint (#3 vs #4 in Table 2) across different sub-tasks. Note that for the Seg-only model, the target strings (sequences of numbers) are not typically seen in T5 pre-training, but the T5 checkpoint still boosts its performance. In contrast, the tagging-based is not able to benefit from the T5 checkpoint at all. One possible explanation is that the target strings in tagging-based (with large chunks of padding tokens) are just too different from the T5 pretraining targets.

Given the results obtained in the modified setting, we focus our efforts on using length-based target formulation in the more challenging original setting.

Ablation studies We also conducted ablation studies on input modalities (not surprisingly, text-only models stand to benefit more from the pre-trained checkpoints than visual-only models) and ablation studies on loading partial checkpoints from pretrained models (loading checkpoints for both encoder and decoder works the best). See Appendix (A.2) for more details.

5.5 Experiments in the original setting

Experimental setup Using length-based target formulation, we conduct a more extensive comparison of the effect of different pretraining strategies, as well as different input formulations on the original dense video captioning task on both YouCook2 and ViTT. Max sequence lengths are set to ensure no truncation happens in either dataset – input text: 4096; visual feature: 800 (YouCook2) / 500 (ViTT); target: 512 (YouCook2) / 256 (ViTT). We ran each each experiment with different seeds for 3 times to account for performance variance from random initializations. We report the mean and standard deviation (using 3 runs) for each metric in Table 3. We chose the checkpoint according to performance on the validation set, and report the corresponding performance on the test set.

Effects of Pretraining For both datasets, there are significant performance improvements from utilizing pretrained checkpoints in terms of both segmentation metrics and captioning metrics. Interestingly, training from the WikiHow checkpoint (using in-domain task over in-domain data) provides similar performance improvement to T5 alone (see, for instance, #2 vs #3, or #11 vs #12 in Table 3). However, starting from the generic-language T5 checkpoint and adding in-domain WikiHow pretraining (WikiHow T5, e.g., #4 and #13) boosts all metrics by a large and significant margin.

Effects of Joint Modeling If we compare the mIoU score achieved by Seg+Cap model vs the mIoU score by Seg-only model in Table 3, across different settings, we observe a general trend where the Seg+Cap model outperforms the Seg-only model on this segmentation metric. This indicates that with the right formulation, the segmentation subtask (predicting event boundary) can indeed benefit from joint learning with a related captioning subtask (summarizing event content).

Input formulations Comparing results using SimpleConcat against their counterparts using Emb_{TIME} in Table 3, results are largely inconclusive. While Emb_{TIME} seems to bring non-trivial improvement to models trained from scratch, the trained from scratch settings also have the largest variance in our experiments[6]. That said, the Seg+Cap model did achieve its best mIoU score on ViTT using Emb_{TIME}. More work is needed to fully understand the potential of the temporal embedding.

Comparison against prior work for YouCook2[7] Table 4 provides a summary of dense video captioning performance on YouCook2 reported in prior work. The related work is provided for reference but results are not always strictly and directly comparable (due to, e.g., dataset changing overtime). Some of the prior work focused only on the segmentation subtask (which in turn can be decomposed into event proposal and candidate ranking), some approached the end-to-end task as a two-stage task and solved the two subtasks separately. In this context, we find the results from our first attempt at a simple approach quite encouraging, and hope this inspires future studies to fully realize the potential of this alternative approach.

[6]To the extent that the Seg+Cap model performance in #1 can be considered an outlier: its mIoU scores for the 3 runs are (11, 11, 26), which resulted in a large std value not seen anywhere else in the table. We intend to run more repeats to investigate this issue, but wanted to report results from these 3 original runs to avoid cherry picking.

[7]ViTT is a relatively newer dataset and past work has only reported performance of the segment-level captioning subtask using groundtruth segments; we are not aware of existing work reporting end-to-end dense video captioning performance.

Model	mIoU	Prec.	Rec.	B@4	M
vsLSTM (Zhang et al., 2016)	33.9	24.1	22.1	-	-
SCNN-prop (Shou et al., 2016)	28.0	23.2	28.2	-	-
ProcNet (Zhou et al., 2018b)	37.5	30.4	37.1	-	-
Bi-LSTM + TempoAttn (Yao et al.)	-	-	-	0.08	4.62
End2end Transformer (Zhou et al., 2018c)	-	-	-	0.30	6.58
Context-aware Fusion (Shi et al., 2019)	41.4	-	-	2.61	17.43
End2end Sequence Generation (Ours)	30.3	20.8	20.7	3.0	3.5

Table 4: Dense video captioning performance on YouCook2 in the context of prior work. Segmentation performance is measured by the mIoU, precision (Prec.) and recall (Rec.). Captioning performance is measured by BLEU-4 (B@4) and METEOR (M).

6 Discussion

Limitations and Risks Our experiments are conducted only on videos with available English ASR annotations, as we inherit this limitation from the available data for this task. We use existing datasets based on public YouTube videos. As a consequence, any videos that are no longer publicly available on YouTube (e.g., removed by user) at the time of the study needed to be excluded from our experimental setup. Our models are experimental, and their outputs are not meant to be used outside the intended research work presented in this paper.

7 Conclusion

In this paper, we describe different task formulations for solving the dense video captioning task in an end-to-end manner, which allows us to take advantage of pretrained text-only encoder-decoder models. We conduct experiments on the YouCook2 and the ViTT dataset with several pretraining settings. Experimental results show text-only pretrained models can improve video partitioning and segmentation performance. Also, the segmentation subtask benefits from jointly modeling with the captioning subtask. We hope our work can inspire future studies on utilizing pretrained models and large-scale text corpora to further improve language generation tasks in multimodal settings.

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A Appendix

A.1 Timestamp markers (T-marker)

Here we describe an alternative way to encode temporal alignment between textual and visual input. Since the frames are extracted at a fixed rate, we can explicitly add time markers to the text input to "mark" out tokens spoken at the corresponding time points. In our work, the video features are extracted with a frame rate of 1 frame per second. For each frame, we insert a time marker after the last ASR token spoken before the corresponding timestamp. A time marker consists of a special anchor token, followed by the timestamp token (an integeter corresponding to the timestamp in seconds).

Performance using this input formuation can be found in the T-marker rows in Table 7. For models trained from scratch, including the timestamp markers can have a positive impact on model performance, indicating that these markers do indeed provide useful information. However for any model trained from an existing checkpoint, adding these markers only hurt the performance. We hypothesize that this is because the text sequence with frequent markers is too different from the pretrained datasets, leaving the pretrained checkpoints less effective for models using this input formulation.

A.2 Ablation studies

Ablation on Input Data Table 5 lists out the comparisons of different input sources on YouCook2 dense video captioning task. For all three ablated settings, pre-training on WikiHow has the best performance on the two subtasks, and loading the T5 checkpoint has better performance than training from scratch. With the pre-trained WikiHow checkpoint, the "Text-only" setting has comparable performance as the "Text+Video" setting that takes both the ASR transcript and the video features as input. Using the video features alone results in worse performance, indicating the high-value of text transcripts to the captioning task.

Ablation on T5 Checkpoint Table 6 lists out the comparisons of using different pretrained checkpoints on YouCook2 modified dense video captioning. Both the T5 an the WikiHow T5 checkpoints surpass the model initialized from random weights, which verifies the effectiveness of pretraining. Among all three ablated settings, using the complete checkpoint has better performance than only loading the Transformer encoder or decoder.

A.3 Comprehensive experimental results

Table 7 provides a more comprehensive summary of our experimental results in the original setting. It is the same experimental setting as Table 3, but we also report additional performance metrics for the segmentation tasks, as well as performance for the T-marker input formulation. Table 8 is again under the same experimental setting, but reports median instead of (mean, std) to summarize the 3 repeats for each setting, so that the metrics are less affected by occasional outliers.

Input	Checkpoint	Segmentation			Segmentation + Captioning				
		Precision	Recall	F1	F1	B@4	METEOR	CIDEr	ROUGE-L
Text-only	-	31.86	30.66	31.25	30.39	0.55	1.88	0.07	5.23
	T5	36.22	37.06	36.64	37.89	3.36	4.76	0.28	10.61
	WikiHow T5	**71.13**	**63.77**	**67.25**	**58.71**	9.57	**11.99**	0.85	23.21
Video-only	-	28.02	19.48	22.98	27.5	0.52	1.89	0.07	4.82
	T5	27.43	27.25	27.34	27.86	0.40	1.65	0.05	4.11
	WikiHow T5	25.45	24.93	25.19	23.19	0.42	1.48	0.05	3.84
Text + Video	-	32.53	30.90	31.69	29.09	0.34	1.68	0.06	4.78
	T5	36.96	37.99	37.47	32.58	2.99	4.22	0.26	9.20
	WikiHow T5	71.07	62.76	66.66	57.84	**9.87**	11.96	**0.86**	**23.25**

Table 5: Ablation on input modalities. Performance using length-based target formulation on YouCook2 dense video captioning task with IoU threshold=50%. Results are reported on three ablated input settings: "Text-only" feeds in the ASR tokens, "Video-only" reveals the video features, while "Text+Video" provides both the ASR and the video features as input.

Checkpoint	F1	B@4	METEOR	CIDEr	ROUGE-L
-	30.39	0.55	1.88	0.07	5.23
T5 (full)	37.89	3.36	4.76	0.28	10.61
T5 (enc-only)	31.00	0.28	1.93	0.07	4.88
T5 (dec-only)	32.37	1.39	3.02	0.14	7.73
WikiHow T5 (full)	58.71	**9.57**	**11.99**	**0.85**	**23.21**
WikiHow T5 (enc-only)	**59.30**	8.44	11.72	0.80	22.89
WikiHow T5 (dec-only)	36.88	0.99	3.19	0.15	8.00

Table 6: Ablation on pretrained checkpoints. Performance using length-based target formulation on YouCook2 modified dense video captioning with IoU threshold=50%. Results are reported on three settings: "full" loads the complete checkpoint, "enc-only" loads the Transformer encoder weights, while "dec-only" loads the Transformer decoder weights.

*	Input Formulation	Checkpoint?	Seg-only model				Seg+Cap model					
			mIoU	Precision	Recall	F1	mIoU	F1	B@4	METEOR	CIDEr	ROUGE-L
YouCook2												
0	Random Segmentation		21.79 ± 0.56	12.51 ± 0.46	12.34 ± 0.68	11.71 ± 0.54	-	-	-	-	-	-
1	SimpleConcat	-	12.99 ± 1.55	12.24 ± 1.08	8.60 ± 0.90	9.39 ± 0.75	16.45 ± 8.72	11.23 ± 5.16	0.17 ± 0.11	0.66 ± 0.04	0.02 ± 0.01	1.99 ± 0.20
2		T5	24.14 ± 1.07	14.22 ± 0.16	15.09 ± 0.85	14.10 ± 0.44	24.21 ± 1.64	14.20 ± 1.35	0.88 ± 0.04	1.50 ± 0.12	0.09 ± 0.01	3.34 ± 0.27
3		WikiHow	22.58 ± 1.09	13.39 ± 0.96	14.57 ± 1.19	13.27 ± 1.00	23.33 ± 0.79	14.22 ± 0.94	0.67 ± 0.15	1.47 ± 0.05	0.08 ± 0.01	3.51 ± 0.13
4		WikiHow T5	$\mathbf{27.77} \pm 0.09$	$\mathbf{16.68} \pm 1.04$	$\mathbf{18.43} \pm 0.75$	$\mathbf{16.87} \pm 0.62$	$\mathbf{30.26} \pm 1.24$	$\mathbf{20.24} \pm 1.06$	$\mathbf{2.96} \pm 0.28$	$\mathbf{3.49} \pm 0.30$	$\mathbf{0.25} \pm 0.03$	$\mathbf{7.00} \pm 0.42$
5	+ T-marker	-	20.13 ± 2.59	13.68 ± 1.78	12.18 ± 1.88	12.01 ± 1.91	18.41 ± 2.65	9.99 ± 1.55	0.08 ± 0.02	0.44 ± 0.04	0.01 ± 0.00	1.33 ± 0.15
6		T5	20.29 ± 1.30	12.13 ± 2.52	11.43 ± 0.64	11.09 ± 1.38	22.12 ± 1.29	12.56 ± 0.74	0.88 ± 0.23	1.38 ± 0.22	0.08 ± 0.02	3.07 ± 0.39
7		WikiHow	19.98 ± 0.55	10.54 ± 1.36	12.11 ± 1.29	10.68 ± 1.32	20.84 ± 1.02	11.82 ± 0.64	0.39 ± 0.05	0.99 ± 0.09	0.05 ± 0.00	2.44 ± 0.18
8		WikiHow T5	20.98 ± 0.69	11.99 ± 1.07	12.49 ± 0.60	11.86 ± 0.82	20.22 ± 0.70	11.20 ± 0.70	0.38 ± 0.08	0.92 ± 0.05	0.05 ± 0.00	2.27 ± 0.13
9	+ $\mathrm{Emb}_{\mathrm{TIME}}$	-	18.51 ± 1.95	10.85 ± 0.59	11.42 ± 1.16	10.29 ± 0.58	18.71 ± 0.17	9.80 ± 0.80	0.12 ± 0.07	0.48 ± 0.08	0.02 ± 0.01	1.41 ± 0.22
10		T5	23.02 ± 1.05	13.52 ± 0.76	14.15 ± 0.94	13.23 ± 0.77	23.96 ± 0.08	15.44 ± 0.67	1.32 ± 0.08	1.91 ± 0.07	0.11 ± 0.01	4.20 ± 0.13
11		WikiHow	21.68 ± 1.93	13.13 ± 1.42	13.88 ± 1.60	12.83 ± 1.41	21.88 ± 0.86	13.15 ± 0.74	0.69 ± 0.19	1.30 ± 0.07	0.07 ± 0.01	3.06 ± 0.13
12		WikiHow T5	26.51 ± 0.45	15.61 ± 0.61	17.08 ± 0.58	15.82 ± 0.62	28.70 ± 0.92	18.71 ± 0.94	2.58 ± 0.19	3.23 ± 0.10	0.22 ± 0.01	6.45 ± 0.17
ViTT												
13	Random Segmentation		26.16 ± 0.06	14.69 ± 0.11	16.0 ± 0.21	14.81 ± 0.13	-	-	-	-	-	-
14	SimpleConcat	-	33.85 ± 0.70	23.54 ± 0.36	24.04 ± 0.40	22.98 ± 0.22	32.69 ± 0.71	22.49 ± 0.36	0.11 ± 0.01	3.76 ± 0.35	0.08 ± 0.01	3.86 ± 0.28
15		T5	37.89 ± 0.10	28.16 ± 1.18	27.15 ± 0.19	27.15 ± 0.53	38.07 ± 0.65	27.39 ± 0.91	0.57 ± 0.03	5.92 ± 0.37	0.16 ± 0.02	6.59 ± 0.69
16		WikiHow	38.20 ± 0.27	26.95 ± 0.67	27.71 ± 0.25	26.85 ± 0.41	37.80 ± 0.62	26.74 ± 0.81	0.40 ± 0.07	5.48 ± 0.18	0.14 ± 0.01	6.02 ± 0.34
17		WikiHow T5	$\mathbf{41.87} \pm 0.26$	$\mathbf{31.75} \pm 1.94$	$\mathbf{31.74} \pm 0.34$	$\mathbf{31.26} \pm 1.10$	42.40 ± 0.30	32.01 ± 0.50	$\mathbf{1.29} \pm 0.07$	$\mathbf{8.10} \pm 0.34$	$\mathbf{0.25} \pm 0.01$	$\mathbf{9.26} \pm 0.39$
18	+ T-marker	-	32.19 ± 1.17	20.05 ± 1.89	21.62 ± 0.82	20.04 ± 0.48	32.03 ± 0.14	20.89 ± 0.28	0.05 ± 0.00	2.96 ± 0.13	0.06 ± 0.00	2.93 ± 0.07
19		T5	34.94 ± 0.37	21.24 ± 0.11	23.95 ± 0.41	22.07 ± 0.21	37.56 ± 0.78	27.50 ± 0.69	0.59 ± 0.09	5.11 ± 0.52	0.16 ± 0.01	6.26 ± 0.56
20		WikiHow	33.00 ± 0.10	19.13 ± 0.87	22.02 ± 0.13	20.05 ± 0.54	35.14 ± 0.99	22.88 ± 0.41	0.23 ± 0.04	3.51 ± 0.14	0.09 ± 0.01	4.12 ± 0.37
21		WikiHow T5	34.23 ± 0.55	21.01 ± 1.34	23.26 ± 0.51	21.62 ± 0.94	33.20 ± 1.65	19.63 ± 0.98	0.16 ± 0.02	3.01 ± 0.22	0.08 ± 0.01	3.40 ± 0.36
22	+ $\mathrm{Emb}_{\mathrm{TIME}}$	-	33.89 ± 0.21	20.75 ± 2.37	23.69 ± 0.08	21.27 ± 1.49	35.37 ± 3.18	22.28 ± 0.49	0.04 ± 0.03	3.42 ± 0.61	0.07 ± 0.01	3.28 ± 0.83
23		T5	37.78 ± 0.15	25.98 ± 0.20	27.12 ± 0.16	26.05 ± 0.16	38.50 ± 0.55	27.95 ± 0.46	0.75 ± 0.10	6.37 ± 0.39	0.18 ± 0.01	7.19 ± 0.48
24		WikiHow	37.27 ± 0.08	25.96 ± 0.38	26.87 ± 0.04	25.91 ± 0.21	36.97 ± 0.48	26.37 ± 0.36	0.38 ± 0.06	5.31 ± 0.06	0.13 ± 0.01	5.82 ± 0.23
25		WikiHow T5	41.64 ± 0.12	31.07 ± 0.67	31.53 ± 0.12	30.84 ± 0.33	$\mathbf{43.22} \pm 0.72$	$\mathbf{32.49} \pm \mathbf{0.25}$	1.22 ± 0.08	8.05 ± 0.20	$\mathbf{0.25} \pm 0.01$	9.18 ± 0.45

Table 7: Performance on the dense video captioning on YouCook2 and ViTT test set with the length-based and the Timestamp markers formulations. We report the evaluation results (mean $\pm$ std) with models initialized from random weights, T5 checkpoints, WikiHow checkpoints, and T5 checkpoints further pretrained on WikiHow.

*	Dataset	Input Formulation	Checkpoint	Seg-only model				Seg+Cap model					
				mIoU	Precision	Recall	F1	mIoU	F1	B@4	METEOR	CIDEr	ROUGE-L
0	YouCook2	Random Segmentation		21.55	12.25	12.2	11.55	-	-	-	-	-	-
1		SimpleConcat	-	12.83	12.80	8.62	9.07	11.47	8.78	0.22	0.64	0.03	1.95
2			T5	24.18	14.19	14.83	13.89	25.13	14.09	0.86	1.47	0.09	3.39
3			WikiHow	22.36	13.11	14.42	12.99	23.00	14.16	0.66	1.50	0.08	3.48
4			WikiHow T5	**27.81**	**17.21**	**18.16**	**17.01**	**30.97**	**20.57**	**2.85**	**3.48**	**0.24**	**7.02**
5		+ T-marker	-	18.82	14.42	11.28	11.38	17.18	9.53	0.06	0.45	0.01	1.34
6			T5	20.91	13.21	11.48	11.65	22.75	12.87	0.90	1.42	0.08	3.19
7			WikiHow	19.76	10.17	11.52	10.19	21.09	11.79	0.37	0.94	0.05	2.35
8			WikiHow T5	21.26	12.34	12.83	12.24	20.56	11.35	0.38	0.89	0.05	2.31
8		+ Emb_{TIME}	-	19.52	10.99	11.70	10.26	18.77	9.83	0.11	0.52	0.02	1.46
10			T5	22.93	13.84	13.78	13.30	24.00	15.70	1.34	1.90	0.11	4.24
11			WikiHow	21.41	13.11	13.88	12.76	22.08	13.18	0.79	1.30	0.07	3.09
12			WikiHow T5	26.61	15.86	17.28	16.08	28.80	18.41	2.67	3.18	0.23	6.41
13	ViTT	Random Segmentation		26.16	14.69	16.03	14.81	-	-	-	-	-	-
14		SimpleConcat	-	33.74	23.71	23.95	23.10	33.10	22.59	0.12	3.78	0.08	3.87
15			T5	37.90	28.28	27.14	27.13	38.35	27.66	0.57	5.85	0.15	6.36
16			WikiHow	38.23	26.82	27.78	26.89	37.75	26.92	0.44	5.58	0.14	6.06
17			WikiHow T5	**41.78**	**31.00**	**31.62**	**30.78**	42.25	31.85	**1.34**	7.97	**0.25**	**9.21**
18		+ T-marker	-	32.62	19.94	22.02	20.27	32.01	20.90	0.05	2.96	0.06	2.95
19			T5	34.83	21.20	23.89	22.08	37.36	27.80	0.57	5.31	0.16	6.46
20			WikiHow	33.00	19.12	22.09	20.09	35.54	23.09	0.23	3.43	0.09	4.03
21			WikiHow T5	33.92	21.12	23.01	21.52	34.04	19.46	0.16	2.96	0.07	3.23
14		+ Emb_{TIME}	-	33.79	21.21	23.68	21.61	34.56	22.37	0.05	3.12	0.06	2.92
15			T5	37.75	25.97	27.13	26.13	38.44	27.94	0.69	6.18	0.18	7.15
16			WikiHow	37.22	25.85	26.86	25.84	37.07	26.39	0.37	5.28	0.13	5.73
17			WikiHow T5	41.62	30.76	31.52	30.68	**43.51**	**32.50**	1.19	**8.05**	**0.25**	9.02

Table 8: Performance on the dense video captioning on YouCook2 and ViTT test set with the length-based and the Timestamp markers formulations. We report the evaluation results with models initialized from random weights, T5 checkpoints, WikiHow checkpoints, and T5 checkpoints further pretrained on WikiHow. We ran 3 set of repeating experiments for each setting, and report the **median** value on each metric in this Table.