Localizing Moments in Video with Natural Language

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https://people.eecs.berkeley.edu/~lisa_anne/didemo.html

Figure 1: We consider localizing moments in video with natural language and demonstrate that incorporating local and global video features is important for this task. To train and evaluate our model, we collect the Distinct Describable Moments (DiDeMo) dataset which consists of over 40,000 pairs of localized video moments and corresponding natural language.

Abstract

We consider retrieving a specific temporal segment, or moment, from a video given a natural language text description. Methods designed to retrieve whole video clips with natural language determine what occurs in a video but not when. To address this issue, we propose the Moment Context Network (MCN) which effectively localizes natural language queries in videos by integrating local and global video features over time. A key obstacle to training our MCN model is that current video datasets do not include pairs of localized video segments and referring expressions, or text descriptions which uniquely identify a corresponding moment. Therefore, we collect the Distinct Describable Moments (DiDeMo) dataset which consists of over 10,000 unedited, personal videos in diverse visual settings with pairs of localized video segments and referring expressions. We demonstrate that MCN outperforms several baseline methods and believe that our initial results together with the release of DiDeMo will inspire further research on localizing video moments with natural language.

1. Introduction

Consider the video depicted in Figure 1, in which a little girl jumps around, falls down, and then gets back up to start jumping again. Suppose we want to refer to a particular temporal segment, or moment, from the video, such as when the girl resiliently begins jumping again after she has fallen. Simply referring to the moment via an action, object, or attribute keyword may not uniquely identify it. For example, important objects in the scene, such as the girl, are present in each frame. Likewise, recognizing all the frames in which the girl is jumping will not localize the moment of interest as the girl jumps both before and after she has fallen. Rather than being defined by a single object or activity, the moment may be defined by when and how specific actions take place *in relation* to other actions. An intuitive way to refer to the moment is via a natural language phrase, such as "the little girl jumps back up after falling".

Motivated by this example, we consider localizing moments in video with natural language. Specifically, given a video and text description, we identify start and end points in the video which correspond to the given text description. This is a challenging task requiring both language and video understanding, with important applications in video retrieval, such as finding particular moments from a long personal holiday video, or desired B-roll stock video footage from a large video library (e.g., Adobe Stock[1], Getty[2], Shutterstock[3]).

Existing methods for natural language based video retrieval [21, 48, 43] retrieve an entire video given a text string but do not identify *when* a moment occurs within a video. To localize moments within a video we propose to learn a joint video-language model in which referring expressions and video features from corresponding moments are close

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[1]https://stock.adobe.com
[2]http://www.gettyimages.com
[3]https://www.shutterstock.com

in a shared embedding space. However, in contrast to whole video retrieval, we argue that in addition to video features from a specific moment, global video context and knowing when a moment occurs within a longer video are important cues for moment retrieval. For example, consider the text query "The man on the stage comes closest to the audience". The term "closest" is relative and requires temporal context to properly comprehend. Additionally, the temporal position of a moment in a longer video can help localize the moment. For the text query "The biker starts the race", we expect moments earlier in the video in which the biker is racing to be closer to the text query than moments at the end of the video. We thus propose the Moment Context Network (MCN) which includes a global video feature to provide temporal context and a temporal endpoint feature to indicate when a moment occurs in a video.

A major obstacle when training our model is that current video-language datasets do not include natural language which can uniquely localize a moment. Additionally, datasets like [17, 25] are small and restricted to specific domains, such as dash-cam or cooking videos, while datasets [5, 29, 42, 47] sourced from movies and YouTube are frequently edited and tend to only include entertaining moments (see [35] for discussion). We believe the task of localizing moments with natural language is particularly interesting in unedited videos which tend to include uneventful video segments that would generally be cut from edited videos. Consequently, we desire a dataset which consists of distinct moments from unedited video footage paired with descriptions which can uniquely localize each moment, analogous to datasets that pair distinct image regions with descriptions [14, 19].

To address this problem, we collect the Distinct Describable Moments (DiDeMo) dataset which includes distinct video moments paired with descriptions which uniquely localize the moment in the video. Our dataset consists of over 10,000 unedited videos with 3-5 pairs of descriptions and distinct moments per video. DiDeMo is collected in an open-world setting and includes diverse content such as pets, concerts, and sports games. To ensure that descriptions are referring and thus uniquely localize a moment, we include a validation step inspired by [14].

Contributions. We consider the problem of localizing moments in video with natural language in a challenging open-world setting. We propose the Moment Context Network (MCN) which relies on local and global video features. To train and evaluate our model, we collect the Distinct Describable Moments (DiDeMo) dataset which consists of over 40,000 pairs of referring descriptions and localized moments in unedited videos.

2. Related Work

Localizing moments in video with natural language is related to other vision tasks including video retrieval, video summarization, video description and question answering, and natural language object retrieval. Though large scale datasets have been collected for each of these tasks, none fit the specific requirements needed to learn how to localize moments in video with natural language.

Video Retrieval with Natural Language. Natural language video retrieval methods aim to retrieve a specific video given a natural language query. Current methods [21, 43, 48] incorporate deep video-language embeddings similar to image-language embeddings proposed by [7, 37]. Our method also relies on a joint video-language embedding. However, to identify when events occur in a video, our video representation integrates local and global video features as well as temporal endpoint features which indicate when a candidate moment occurs within a video.

Some work has studied retrieving temporal segments within a video in constrained settings. For example, [40] considers retrieving video clips from a home surveillance camera using text queries which include a fixed set of spatial prepositions ("across" and "through") whereas [17] considers retrieving temporal segments in 21 videos from a dashboard car camera. In a similar vein, [1, 4, 33] consider aligning textual instructions to videos. However, methods aligning instructions to videos are restricted to structured videos as they constrain alignment by instruction ordering. In contrast, we consider localizing moments in an unconstrained open-world dataset with a wide array of visual concepts. To effectively train a moment localization model, we collect DiDeMo which is unique because it consists of paired video moments and referring expressions.

Video Summarization. Video summarization algorithms isolate temporal segments in a video which include important/interesting content. Though most summarization algorithms do not include textual input ([3, 8, 9, 49, 50]), some use text in the form of video titles [18, 38] or user queries in the form of category labels to guide content selection [34]. [51] collects textual descriptions for temporal video chunks as a means to evaluate summarization algorithms. However, these datasets do not include referring expressions and are limited in scope which makes them unsuitable for learning moment retrieval in an open-world setting.

Video Description and Question Answering (QA). Video description models learn to generate textual descriptions of videos given video-description pairs. Contemporary models integrate deep video representations with recurrent language models [22, 28, 44, 45, 53]. Additionally, [39] proposed a video QA dataset which includes question/answer pairs aligned to video shots, plot synopsis, and subtitles.

YouTube and movies are popular sources for joint video-

language datasets. Video description datasets collected from YouTube include descriptions for short clips of longer YouTube videos [5, 47]. Other video description datasets include descriptions of short clips sourced from full length movies [29, 42]. However, though YouTube clips and movie shots are sourced from longer videos, they are not appropriate for localizing distinct moments in video for two reasons. First, descriptions about selected shots and clips are not guaranteed to be referring. For example, a short YouTube video clip might include a person talking and the description like "A woman is talking". However, the entire video could consist of a woman talking and thus the description does not uniquely refer to the clip. Second, many YouTube videos and movies are edited, which means "boring" content which may be important to understand for applications like retrieving video segments from personal videos might not be present.

Natural Language Object Retrieval. Natural language object retrieval [12, 19] can be seen as an analogous task to ours, where natural language phrases are localized spatially in images, rather than temporally in videos. Despite similarities to natural language object retrieval, localizing video moments presents unique challenges. For example, it often requires comprehension of temporal indicators such as "first" as well as a better understanding of activities. Datasets for natural language object retrieval include *referring* expressions which can uniquely localize a specific location in a image. Descriptions in DiDeMo uniquely localize distinct moments and are thus also referring expressions.

Language Grounding in Images and Videos. [24, 26, 37] tackle the task of object grounding in which sentence fragments in a description are localized to specific image regions. Work on language grounding in video is much more limited. Language grounding in video has focused on spatially grounding objects and actions in a video [17, 52], or aligning textual phrases to temporal video segments [25, 40]. However prior methods in both these areas ([40, 52]) severely constrain natural language vocabulary (e.g., [52] only considers four objects and four verbs) and consider constrained visual domains in small datasets (e.g., 127 videos from a fixed laboratory kitchen [25] and [17] only includes 520 sentences). In contrast, DiDeMo offers a unique opportunity to study temporal language grounding in an open-world setting with a diverse set of objects, activities, and attributes.

3. Moment Context Network

Our moment retrieval model effectively localizes natural language queries in longer videos. Given input video frames $v = \{v_t\}$, where $t \in \{0, \ldots, T-1\}$ indexes time, and a proposed temporal interval, $\hat{\tau} = \tau_{start} : \tau_{end}$, we extract visual temporal context features which encode the

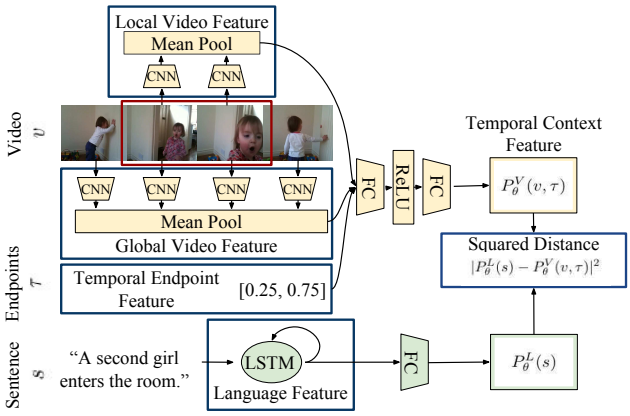


Figure 2: Our Moment Context Network (MCN) learns a shared embedding for video temporal context features and LSTM language features. Our video temporal context features integrate local video features, which reflect what occurs during a specific moment, global features, which provide context for the specific moment, and temporal endpoint features which indicate when a moment occurs in a video. We consider both appearance and optical flow input modalities, but for simplicity only show the appearance input modality here.

video moment by integrating both local features and global video context. Given a sentence s we extract language features using an LSTM [11] network. At test time our model optimizes the following objective

$$\hat{\tau} = \underset{\tau}{\operatorname{argmin}} D_\theta(s, v, \tau), \tag{1}$$

where D_θ is a joint model over the sentence s, video v, and temporal interval τ given model parameters θ (Figure 2).

Visual Temporal Context Features. We encode video moments into visual temporal context features by integrating local video features, which reflect what occurs within a specific moment, global video features, which provide context for a video moment, and temporal endpoint features, which indicate when a moment occurs within a longer video. To construct local and global video features, we first extract high level video features using a deep convolutional network for each video frame, then average pool video features across a specific time span (similar to features employed by [45] for video description and [43] for whole video retrieval). Local features are constructed by pooling features within a specific moment and global features are constructed by averaging over all frames in a video.

When a moment occurs in a video can indicate whether or not a moment matches a specific query. To illustrate, consider the query "the bikers start the race." We expect moments closer to the beginning of a video in which bikers are racing to be more similar to the description than moments at the end of the video in which bikers are racing.

To encode this temporal information, we include temporal endpoint features which indicate the start and endpoint of a candidate moment (normalized to the interval $[0, 1]$). We note that our global video features and temporal endpoint features are analogous to global image features and spatial context features frequently used in natural language object retrieval [12, 19].

Localizing video moments often requires localizing specific activities (like "jump" or "run"). Therefore, we explore two sources of visual input modalities; appearance or RGB frames (v_t) and optical flow frames (f_t). We extract fc_7 features from RGB frames using VGG [36] pre-trained on ImageNet [32]. We expect these features to accurately identify specific objects and attributes in video frames. Likewise, we extract optical flow features from the penultimate layer from a competitive activity recognition model [46]. We expect these features to help localize moments which require understanding action.

Temporal context features are extracted by inputting local video features, global video features, and temporal endpoint features into a two layer neural network with ReLU nonlinearities (Figure 2 top). Separate weights are learned when extracting temporal context features for RGB frames (denoted as P_θ^V) and optical flow frames (denoted as P_θ^F).

Language Features. To capture language structure, we extract language features using a recurrent network (specifically an LSTM [11]). After encoding a sentence with an LSTM, we pass the last hidden state of the LSTM through a single fully-connected layer to yield embedded feature P_θ^L. Though our dataset contains over 40,000 sentences, it is still small in comparison to datasets used for natural language object retrieval (e.g., [14, 19]). Therefore, we find that representing words with dense word embeddings (specifically Glove [23]) as opposed to one-hot encodings yields superior results when training our LSTM.

Joint Video and Language Model. Our joint model is the sum of squared distances between embedded appearance, flow, and language features

$$D_\theta(s, v, \tau) = |P_\theta^V(v, \tau) - P_\theta^L(s)|^2 + \eta |P_\theta^F(f, \tau) - P_\theta^L(s)|^2, \tag{2}$$

where η is a tunable (via cross validation) "late fusion" scalar parameter. η was set to 2.33 via ablation studies.

Ranking Loss for Moment Retrieval. We train our model with a ranking loss which encourages referring expressions to be closer to corresponding moments than negative moments in a shared embedding space. Negative moments used during training can either come from different segments within the same video (intra-video negative moments) or from different videos (inter-video negative moments). Revisiting the video depicted in Figure 1, given a phrase "the little girl jumps back up after falling" many intra-video negative moments include concepts mentioned in the phrase such as "little girl" or "jumps". Consequently, our model must learn to distinguish between subtle differences within a video. By comparing the positive moment to the intra-video negative moments, our model can learn that localizing the moment corresponding to "the little girl jumps back up after falling" requires more than just recognizing an object (the girl) or an action (jumps). For training example i with endpoints τ_i, we define the following intra-video ranking loss

$$\mathcal{L}_i^{intra}(\theta) = \sum_{n \in \Gamma \setminus \tau^i} \mathcal{L}^R \left(D_\theta(s^i, v^i, \tau^i), D_\theta(s^i, v^i, n) \right), \tag{3}$$

where $\mathcal{L}^R(x, y) = \max(0, x - y + b)$ is the ranking loss, Γ are all possible temporal video intervals, and b is a margin. Intuitively, this loss encourages text queries to be closer to a corresponding video moment than all other possible moments from the same video.

Only comparing moments within a single video means the model must learn to differentiate between subtle differences without learning how to differentiate between broader semantic concepts (e.g., "girl" vs. "sofa"). Hence, we also compare positive moments to inter-video negative moments which generally include substantially different semantic content. When selecting inter-video negative moments, we choose negative moments which have the same start and end points as positive moments. This encourages the model to differentiate between moments based on semantic content, as opposed to when the moment occurs in the video. During training we do not verify that inter-video negatives are indeed true negatives. However, the language in our dataset is diverse enough that, in practice, we observe that randomly sampled inter-video negatives are generally true negatives. For training example i, we define the following inter-video ranking loss

$$\mathcal{L}_i^{inter}(\theta) = \sum_{j \neq i} \mathcal{L}^R \left(D_\theta(s^i, v^i, \tau^i), D_\theta(s^i, v^j, \tau^i) \right). \tag{4}$$

This loss encourages text queries to be closer to corresponding video moments than moments outside the video, and should thus learn to differentiate between broad semantic concepts. Our final inter-intra video ranking loss is

$$\mathcal{L}(\theta) = \lambda \sum_i \mathcal{L}_i^{intra}(\theta) + (1 - \lambda) \sum_i \mathcal{L}_i^{inter}(\theta), \tag{5}$$

where λ is a weighting parameter chosen through cross-validation.

4. The DiDeMo Dataset

A major challenge when designing algorithms to localize moments with natural language is that there is a dearth of large-scale datasets which consist of referring expressions and localized video moemnts. To mitigate this issue,

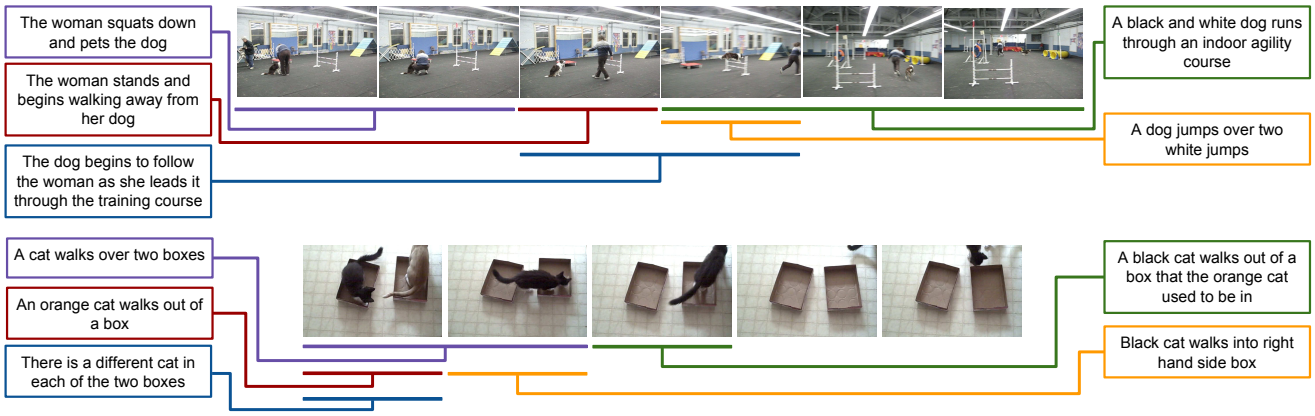


Figure 3: Example videos and annotations from our Distinct Describable Moments (DiDeMo) dataset. Annotators describe moments with varied language (e.g., "A cat walks over two boxes" and "An orange cat walks out of a box"). Videos with multiple events (top) have annotations which span all five-second segments. Other videos have segments in which no distinct event takes place (e.g., the end of the bottom video in which no cats are moving).

we introduce the Distinct Describable Moments (DiDeMo) dataset which includes over 10,000 25-30 second long personal videos with over 40,000 localized text descriptions. Example annotations are shown in Figure 3.

4.1. Dataset Collection

To ensure that each description is paired with a single distinct moment, we collect our dataset in two phases (similar to how [14] collected text to localize image regions). First, we asked annotators to watch a video, select a moment, and describe the moment such that another user would select the same moment based on the description. Then, descriptions collected in the first phase are validated by asking annotators to watch videos and mark moments that correspond to collected descriptions.

Harvesting Personal Videos. We randomly select over 14,000 videos from YFCC100M [41] which contains over 100,000 Flickr videos with a Creative Commons License. To ensure harvested videos are unedited, we run each video through a shot detector based on the difference of color histograms in adjacent frames [20] then manually filter videos which are not caught. Videos in DiDeMo represent a diverse set of real-world videos, which include interesting, distinct moments, as well as uneventful segments which might be excluded from edited videos.

Video Interface. Localizing text annotations in video is difficult because the task can be ambiguous and users must digest a 25-30s video before scrubbing through the video to mark start and end points. To illustrate the inherent ambiguity of our task, consider the phrase "The woman leaves the room." Some annotators may believe this moment begins as soon as the woman turns towards the exit, whereas others may believe the moment starts as the woman's foot first crosses the door threshold. Both annotations are valid, but result in large discrepancies between start and end points.

To make our task less ambiguous and speed up annotation, we develop a user interface in which videos are presented as a timeline of temporal segments. Each segment is displayed as a gif, which plays at 2x speed when the mouse is hovered over it. Following [51], who collected localized text annotations for summarization datasets, we segment our videos into 5-second segments. Users select a moment by clicking on all segments which contain the moment. To validate our interface, we ask five users to localize moments in ten videos using our tool and a traditional video scrubbing tool. Annotations with our gif-based tool are faster to collect (25.66s vs. 38.48s). Additionally, start and end points marked using the two different tools are similar. The standard deviation for start and end points marked when using the video scrubbing tool (2.49s) is larger than the average difference in start and end points marked using the two different tools (2.45s).

Moment Validation. After annotators describe a moment, we ask three additional annotators to localize the moment given the text annotation and the same video. To accept a moment description, we require that at least three out of four annotators (one describer and three validators) be in agreement. We consider two annotators to agree if one of the start *or* end point differs by at most one gif.

4.2. DiDeMo Summary

Table 1 compares our Distinct Describable Moments (DiDeMo) dataset to other video-language datasets. Though some datasets include temporal localization of natural language, these datasets do not include a verification step to ensure that descriptions refer to a single moment. In contrast, our verification step ensuring that descriptions in DiDeMo are *referring expressions*, meaning that they refer

Dataset	# Videos/# Clips	# Sentences	Video Source	Domain	Temporal Localization	Un-Edited	Referring Expressions
YouCook [6]	88/-	2,668	YouTube	Cooking			
Charades [35]	10,000/-	16,129	Homes	Daily activities		✓	
TGIF [16]	100,000 /-	125,781	Tumblr GIFs	Open			
MSVD [5]	1,970/1,970	70,028	YouTube	Open	✓		
MSR-VTT [47]	7,180/10,000	200,000	YouTube	Open	✓		
LSMDC 16 [30]	200/128,085	128,085	Movie	Open	✓		
TV Dataset [51]	4/1,034	1,034	TV Shows	TV Shows	✓		
KITTI [17]	21/520	520	Car Camera	Driving	✓	✓	
TACoS [25, 31]	123/7,206	18,227	Lab Kitchen	Cooking	✓	✓	
TACoS multi-level[27]	185/14,105	52,593	Lab Kitchen	Cooking	✓	✓	
UT Egocentric [51]	4/11,216	11,216	Egocentric	Daily Activities	✓	✓	
Disneyland [51]	8/14,926	14,916	Egocentric	Disneyland	✓	✓	
DiDeMo	10,464/26,892	40,543	Flickr	Open	✓	✓	✓

Table 1: Comparison of DiDeMo to other video-language datasets. DiDeMo is unique because it includes a validation step ensuring that descriptions are referring expressions.

to a specific moment in a video.

Vocabulary. Because videos are curated from Flickr, DiDeMo reflects the type of content people are interested in recording and sharing. Consequently, DiDeMo is human-centric with words like "baby", "woman", and "man" appearing frequently. Since videos are randomly sampled, DiDeMo has a long tail with words like "parachute" and "violin", appearing infrequently (28 and 38 times).

Important, distinct moments in a video often coincide with specific camera movements. For example, "the camera pans to a group of friends" or "zooms in on the baby" can describe distinct moments. Many moments in personal videos are easiest to describe in reference to the viewer (e.g., "the little boy runs towards the camera"). In contrast to other dataset collection efforts [5], we allow annotations to reference the camera, and believe such annotations may be helpful for applications like text-assisted video editing.

Table 2 contrasts the kinds of words used in DiDeMo to two natural language object retrieval datasets [14, 19] and two video description datasets [30, 47]. The three left columns report the percentage of sentences which include camera words (e.g., "zoom", "pan", "cameraman"), temporal indicators (e.g., "after" and "first"), and spatial indicators (e.g., "left" and "bottom"). We also compare how many words belong to certain parts of speech (verb, noun, and adjective) using the natural language toolkit part-of-speech tagger [2]. DiDeMo contains more sentences with temporal indicators than natural language object retrieval and video description datasets, as well as a large number of spatial indicators. DiDeMo has a higher percentage of verbs than natural language object retrieval datasets, suggesting understanding action is important for moment localization in video.

	% Sentences			% Words		
	Camera	Temp.	Spatial	Verbs	Nouns	Adj.
ReferIt [14]	0.33	1.64	43.13	5.88	52.38	11.54
RefExp [19]	1.88	1.00	15.11	8.97	36.26	11.82
MSR-VTT [47]	2.10	2.03	1.24	18.77	36.95	5.12
LSMDC 16 [30]	1.09	7.58	1.49	13.71	37.44	3.99
DiDeMo	19.69	18.42	11.62	16.06	35.26	7.89

Table 2: DiDeMo contains more camera and temporal words than natural language object recognition datasets [14, 19] or video description datasets [47, 30]. Additionally, verbs are more common in DiDeMo than in natural language object retrieval datasets suggesting natural language moment retrieval relies more heavily on recognizing actions than natural language object retrieval.

Annotated Time Points. Annotated segments can be any contiguous set of gifs. Annotators generally describe short moments with 72.34% of descriptions corresponding to a single gif and 22.26% corresponding to two contiguous gifs. More annotated moments occur at the beginning of a video than the end. This is unsurprising as people generally choose to begin filming a video when something interesting is about to happen. In 86% of videos annotators described multiple distinct moments with an average of 2.57 distinct moments per video.

5. Evaluation

In this section we report qualitative and quantitative results on DiDeMo. First, we describe our evaluation criteria and then evaluate against baseline methods.

Metrics: Accounting for Human Variance. Our model ranks candidate moments in a video based on how well

	Baseline Comparison (Test Set)			
	Model	Rank@1	Rank@5	mIoU
1	Upper Bound	74.75	100.00	96.05
2	Chance	3.75	22.50	22.64
3	Moment Frequency Prior	19.40	66.38	26.65
4	CCA	18.11	52.11	37.82
5	Natural Lang. Obj. Retrieval [12]	16.20	43.94	27.18
6	Natural Lang. Obj. Retrieval [12] (re-trained)	15.57	48.32	30.55
7	MCN (ours)	**28.10**	**78.21**	**41.08**
	Ablations (Validation Set)			
8	LSTM-RGB-local	13.10	44.82	25.13
9	LSTM-Flow-local	18.35	56.25	31.46
10	LSTM-Fusion-local	18.71	57.47	32.32
11	LSTM-Fusion + global	19.88	62.39	33.51
12	LSTM-Fusion + global + tef (MCN)	**27.57**	**79.69**	**41.70**

Table 3: Our Moment Context Network (MCN) outperforms baselines (rows 1-6) on our test set. We show ablation studies on our validation set in rows 8-12. Both flow and RGB modalities are important for good performance (rows 8-10). Global video features and temporal endpoint features (tef) both lead to better performance (rows 10-12).

they match a text description. Candidate moments come from the temporal segments defined by the gifs used to collect annotations. A 30 second video will be broken into six five-second gifs. Moments can include any contiguous set of gifs, so a 30-second video contains 21 possible moments. We measure the performance of each model with Rank@1 (R@1), Rank@5 (R@5), and mean intersection over union (mIoU). Instead of consolidating all human annotations into one ground truth, we compute the score for a prediction and each human annotation for a particular description/moment pair. To account for outlier annotations, we consider the highest score among sets of annotations A' where A' are the four-choose-three combinations of all four annotations A. Hence, our final score for a prediction P and four human annotations A using metric M is: $score(P, A) = \max_{A' \in \binom{A}{3}} \frac{1}{3} \sum_{a \in A'} M(P, a)$. As not all annotators agree on start and end points it is impossible to achieve 100% on all metrics (c.f., upper bounds in Table 3).

Baseline: Moment Frequency Prior. Though annotators may mark any contiguous set of gifs as a moment, they tend to select short moments toward the beginning of videos. The moment frequency prior selects moments which correspond to gifs most frequently described by annotators.

Baseline: CCA. Canonical correlation analysis (CCA) achieves competitive results for both natural language image [15] and object [24] retrieval tasks. We use the CCA model of [15] and employ the same visual features as the MCN model. We extract language features from our best MCN language encoder for fair comparison.

Baseline: Natural Language Object Retrieval. Natural language object retrieval models localize objects in a text image. We verify that localizing objects is not sufficient for moment retrieval by running a natural language object retrieval model [12] on videos in our test set. For every tenth frame in a video, we score candidate bounding boxes with the object retrieval model proposed in [12] and compute the score for a frame as the maximum score of all bounding boxes. The score for each candidate moment is the average of scores for frames within the moment. Additionally, we re-train [12] using the same feautures used to train our MCN model; instead of candidate bounding boxes, we provide candidate temporal chunks and train with both appearance and flow input modalities. More details, baselines, and ablations can be found in our appendix [10].

Implementation Details. DiDeMo videos are split into training (8,395), validation (1,065), and testing (1,004) sets. Videos from a specific Flickr user only appear in one set. All models are implemented in Caffe [13] and have been publicly released [4]. SGD (mini-batch size of 120) is used for optimization and all hyperparamters, such as embedding size (100), margin (0.1), and LSTM hidden state size (1000), are chosen through ablation studies.

5.1. Results

Table 3 compares different variants of our proposed retrieval model to our baselines. Our ablations demonstrate the importance of our temporal context features and the need for both appearance and optical flow features.

Baseline Comparison. Rows 1-7 of Table 3 compare the Moment Context Network (MCN) model to baselines on our test set. Though all baselines we trained (lines 4-6) have similar R@1 and R@5 performance, CCA performs substantially better on the mIoU metric. Scoring video segments based on the scores from a natural language object retrieval model [12] does fairly well, performing similarly to the same model retrained with our features. This suggests that pre-training with a dataset designed for natural language object retrieval and incorporating spatial localization into our model could improve results. We believe that retraining [12] leads to poor results on our dataset because it relies on sentence generation rather than directly retrieving a moment. Additionally, our model does substantially better than the moment frequency prior.

Visual Temporal Context Feature. Rows 9-12 of Table 3 demonstrate the importance of temporal context for moment retrieval. The inclusion of both the global video feature and temporal endpoint feature increase performance considerably. Additionally, we find that combining both appearance and optical flow features is important for best performance.

Qualitative Results. Figure 4 shows moments predicted

[4] https://people.eecs.berkeley.edu/~lisa_anne/didemo.html

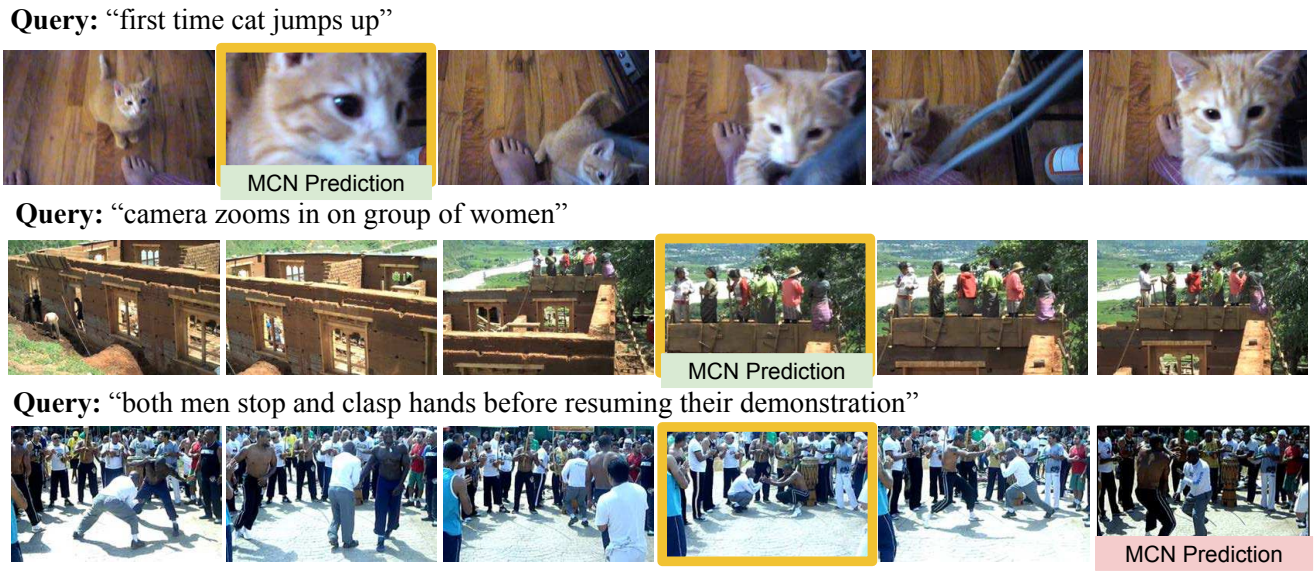
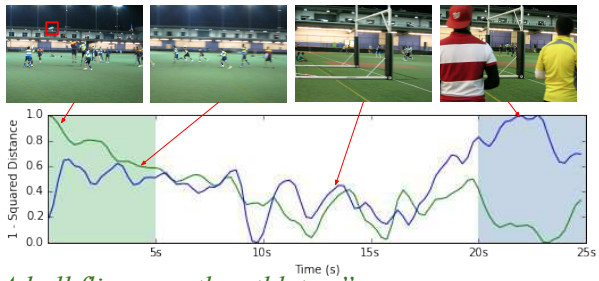


Figure 4: Natural language moment retrieval results on DiDeMo. Ground truth moments are outlined in yellow. The Moment Context Network (MCN) localizes diverse descriptions which include temporal indicators, such as “first” (top), and camera words, such as “camera zooms” (middle).



“A ball flies over the athletes.”
“A man in a red hat passed a man in a yellow shirt.”

Figure 5: MCN correctly retrieves two different moments (light green rectangle on left and light blue rectangle on right). Though our ground truth annotations are five-second segments, we can evaluate with more fine-grained temporal proposals at test time. This gives a better understanding of when moments occur in video (e.g., “A ball flies over the athletes” occurs at the start of the first temporal segment).

by MCN. Our model is capable of localizing a diverse set of moments including moments which require understanding temporal indicators like “first” (Figure 4 top) as well as moments which include camera motion (Figure 4 middle). More qualitative results are in our appendix [10].

Fine-grained Moment Localization Even though our ground truth moments correspond to five-second chunks, we can evaluate our model on smaller temporal segments at test time to predict moment locations with finer granularity. Instead of extracting features for a five second segment, we evaluate on individual frames extracted at $\sim$ 3 fps. Figure 5 includes an example in which two text queries (“A ball flies over the athletes” and “A man in a red hat passed a man in a yellow shirt”) are correctly localized by our model. The frames which best correspond to “A ball flies over the athletes” occur in the first few seconds of the video and the moment “A man in a red hat passed a men in a yellow shirt” finishes before the end point of the fifth segment. More qualitative results are in our appendix [10].

Discussion. We introduce the task of localizing moments in video with natural language in a challenging, open-world setting. Our Moment Context Network (MCN) localizes video moments by harnessing local video features, global video features, and temporal endpoint features. To train and evaluate natural language moment localization models, we collect DiDeMo, which consists of over 40,000 pairs of localized moments and referring expressions. Though MCN properly localizes many natural language queries in video, there are still many remaining challenges. For example, modeling complex (temporal) sentence structure is still very challenging (e.g., our model fails to localize “dog stops, then starts rolling around again”). Additionally, DiDeMo has a long-tail distribution with rare activities, nouns, and adjectives. More advanced (temporal) language reasoning and improving generalization to previously unseen vocabulary are two potential future directions.

Acknowledgements

TD was supported by DARPA, AFRL, DoD MURI award N000141110688, NSF awards IIS-1427425, IIS-1212798, and the Berkeley AI Research (BAIR) Lab.

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