

Which Viewpoint Shows it Best? Language for Weakly Supervising View Selection in Multi-view Instructional Videos

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Abstract

Given a multi-view video, which viewpoint is most informative for a human observer? Existing methods rely on heuristics or expensive “best-view” supervision to answer this question, limiting their applicability. We propose a weakly supervised approach that leverages language accompanying an instructional multi-view video as a means to recover its most informative viewpoint(s). Our key hypothesis is that the more accurately an individual view can predict a view-agnostic text summary, the more informative it is. To put this into action, we propose LANGVIEW, a framework that uses the relative accuracy of view-dependent caption predictions as a proxy for best view pseudo-labels. Then, those pseudo-labels are used to train a view selector, together with an auxiliary camera pose predictor that enhances view-sensitivity. During inference, our model takes as input only a multi-view video—no language or camera poses—and returns the best viewpoint to watch at each timestep. On two challenging datasets comprised of diverse multi-camera setups and how-to activities, our model consistently outperforms state-of-the-art baselines, both with quantitative metrics and human evaluation. Project: <https://vision.cs.utexas.edu/projects/which-view-shows-it-best>.

1. Introduction

Videos are an essential vehicle for communicating how to perform a new skill, as evidenced by the millions of “how-to” videos online, for everything from frosting a cake to perfecting a basketball layup. The more intricate the task, however, the more important the *viewpoint* used to film the instructional video. For example, a close-up view of the hands is desirable when a knitter shows how to add stitches of yarn to a needle, or when a rock-climber demonstrates a particular hold—whereas a view from afar may be preferable when the knitter shows the knitted sweater being worn, or the climber shows their selected path up the wall. In general, the information available in any given viewpoint of an activity varies. Not all views are created equal.

Shooting a video with multiple cameras offers a holistic

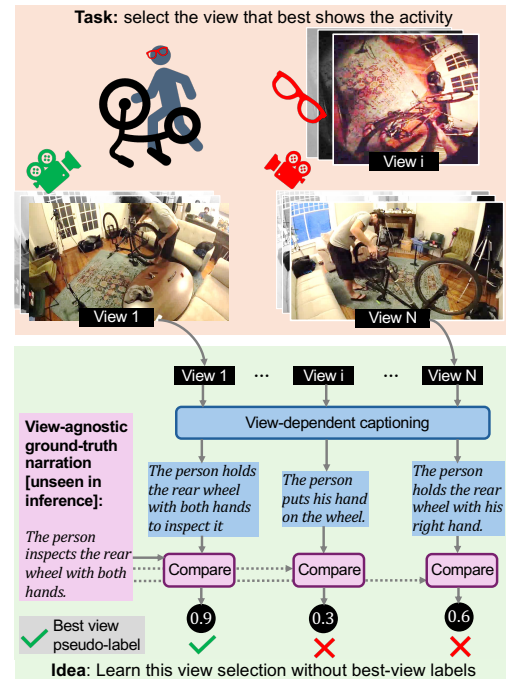


Figure 1. LANGVIEW idea: given multi-view instructional videos, we aim to learn a view selection model that can identify the best view for seeing how to perform the activity shown in the videos, in the *absence of best view labels*. To achieve this, we compare each estimated view-dependent caption to the view-agnostic ground-truth video narration of the human activity, and use their respective accuracies as a proxy for view quality. These quality scores then serve as pseudo-labels for learning to select the most informative view. In this example, the 1st view most clearly shows all entities involved in the activity—the wheel and the person’s hands, and how they interact—and hence, produces a caption that best matches the ground-truth, making it a positive pseudo-label for view selection.

view of the activity taking place in a scene, by capturing it from different locations and angles, and *multi-view video* is developing as a new frontier in computer vision research [33, 44, 66, 86, 92], especially in instructional settings [33, 44]. However, multi-view videos are generally not suitable for direct human consumption; digesting multiple views at once imposes a high cognitive burden [21]. Thus, in practice, the

status quo is to orchestrate view selection in how-to videos manually with either active camera work or post-production video editing, which is time consuming and tedious.

What if instead a vision model learned to automatically perform *view selection*, at every time step deciding which camera from the multi-view video to adopt? View selection has traditionally been studied in the context of automatic cinematography for specialized domains, e.g., 360° panoramas [56, 89], sports clips [12, 43], virtual environments [26, 40, 41, 67], or lecture videos [27, 91, 109]. Aside from their specialized domains, existing work is limited by relying on hand-coded heuristics [3, 26, 40] or assuming access to manual labels indicating the favored views for training [12, 17, 43, 56, 89, 100]. Such labels are expensive and quite special purpose.

Conscious of these shortcomings, we propose to learn view selection in multi-view instructional videos in the *absence of best view labels*. Towards that goal, we hypothesize that *view-agnostic* natural language descriptions of the activity shown in the videos [33, 44, 50]—commonly referred to as “narrations”¹, can act as a source of weak supervision. Specifically, our core idea is that for any multi-view video clip, the viewpoint that is most predictive of such a narration is likely to be the most informative of the activity, and hence, can be pseudo-labeled as the best view for training a view selector. For example, given a multi-view video of a person repairing a bike (Figure 1), independent captions on each view will emphasize different visible components of the scene (the wheel, the person’s hands, other objects in the scene, etc.); the caption most aligned with the view-agnostic narration “*the person removes the rear wheel with both hands*” indicates which view is most informative for the *whole* activity content in that clip. Unlike explicit best-view labels, the vision-language annotations that fuel today’s captioners are open-world, versatile, and widely available.

To validate our hypothesis, we design a novel framework called LANGVIEW, which is composed of two key elements: a best view pseudo-labeler, and a best view selector. The pseudo-labeler automatically generates best view pseudo-labels for a multi-view video during training. This is done by using off-the-shelf video captioners [58, 110] to score and rank views on the basis of how well the predicted narration from a view matches the view-agnostic ground-truth narration. The selector takes a multi-view video as input, and predicts the best view labels. During training, the selector also solves an auxiliary task of predicting the relative camera pose between different views, to increase its view-sensitivity and improve its selection accuracy. During inference, our model requires as input only a multi-view video, but no

language or camera poses.

We evaluate LANGVIEW using two challenging multi-view instructional video datasets encompassing diverse activity scenarios and multi-camera setups, Ego-Exo4D [33] and LEMMA [50]. On both, our model outperforms multiple baselines and state-of-the-art methods for view selection on several automatic and human evaluation metrics. More broadly, our work offers a novel way for language to elicit the information content of video.

2. Related work

Temporal video summarization. Temporal video summarization [8, 39, 69, 72, 76, 82] creates a synopsis of a long video by identifying and stitching together its most representative clips. Early unsupervised methods use hand-crafted features, optimizing for metrics like object saliency [62] and motion attention [71], while recent efforts [31, 38, 57, 60] use labeled data [37, 87] for supervised training. To mitigate the supervision cost, other work leverages web priors [10, 52, 53] to target settings with insufficient or unreliable annotations [52, 74, 87, 103] or unpaired data [69, 81, 106]. Different from all of the above, we tackle the problem of label scarcity in the context of *view selection* in multi-view videos, a distinct task from video summarization. In multi-video summarization, the input videos are either captured with multi-view cameras in indoor surveillance [28, 73] or street [25, 28, 111] settings, or grouped using shared visual concepts [18, 64, 72, 83, 98]. Such methods can select multiple views at the same time, and hence, are not applicable in our setting. Unlike all video summarization methods, where the goal is to create a *sparse* temporal summary of one or more videos, our task requires choosing the appropriate camera view at *each* time step (clip).

Automatic cinematography. Automatic cinematography involves automatically choosing the best camera angles, positions, and zoom levels for human consumption of a video scene. Existing work explores camera control in virtual environments [26, 40, 41, 67], or addresses a narrow domain like lecture videos [27, 29, 42, 91, 109], social settings with multiple egocentric cameras [3], or panoramic 360° input videos [17, 56, 88, 89, 100]. Prior learning-based methods require manual labels to guide selection [12, 43, 56, 88, 89]. In contrast, we show how to train a view selector *without* manual labels, by exploiting the accuracy of predicted narrations from different views as a proxy for view quality. In continued complementary research, we explore how to leverage *single-view* instructional videos during training [63].

Active next view selection. Active next view selection [4] requires an embodied agent to smartly control its camera for solving tasks like object recognition [2, 14, 24, 45, 47, 79, 80], reconstruction [46, 49, 79, 80, 85], and semantic

¹Narrations in multi-view datasets [33, 44, 50] are produced by human annotators who watch all views and write down a view-independent description of how the activity is performed, and in the wild they correspond to the “how-to” descriptions spoken by a person demonstrating a task [65].

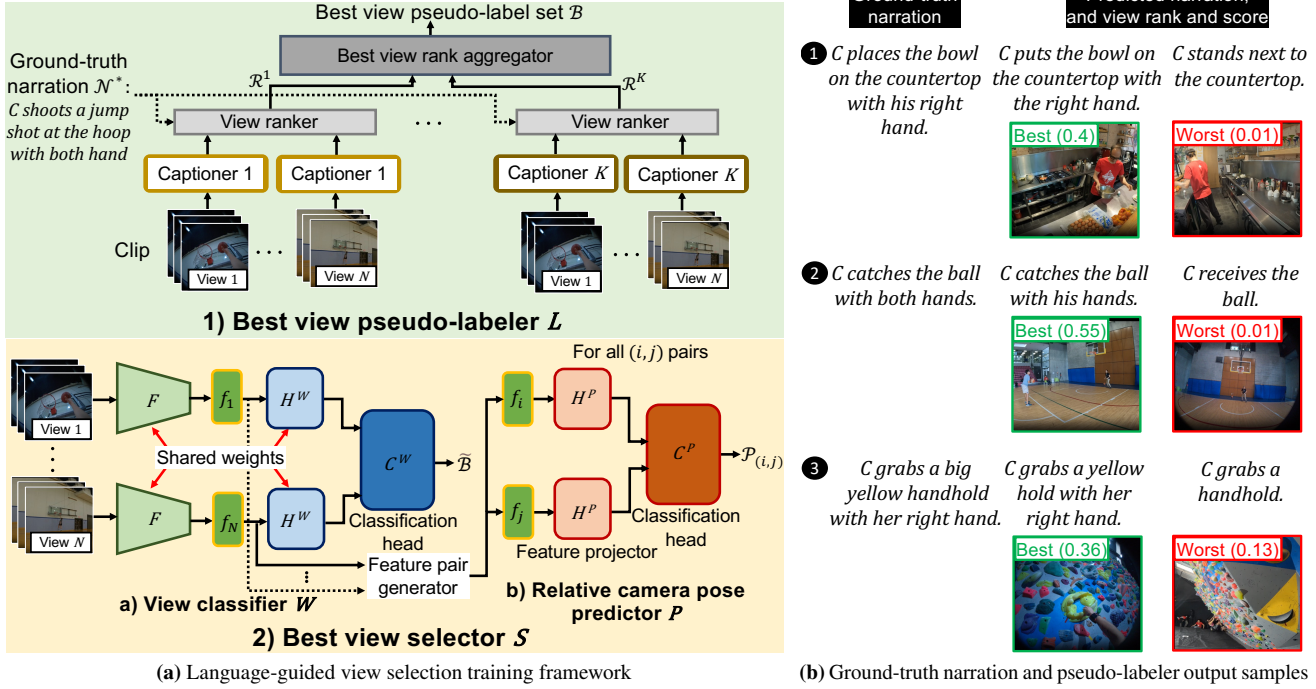


Figure 2. (a) Our model uses language guidance to train a view-selector for multi-view instructional videos, such that the chosen views best help understand the shown activity. To do so, we first generate best view pseudo-labels during training by leveraging clip narrations, where each narration is a *view-agnostic* and detailed description of the activity. Specifically, given a training clip, we use off-the-shelf video captioners to predict a caption per view, score the views by comparing their captions to the ground-truth narration, and finally rank the views to generate a best view pseudo-label for the clip. Given the multi-view clip, our view classifier (bottom-left) encodes it with a visual encoder, and predicts a pseudo-label estimate. We also solve an auxiliary task of relative camera pose prediction (bottom-right) that increases the view sensitivity of the classifier. (b) Examples of predicted narrations, and the ranks and scores of the views per our pseudo-labeler, shown alongside ground-truth view-agnostic narrations. “C” refers to the person who is performing the activity. Note that at inference time, there is no ground truth narration, just the video input.

segmentation [84, 85] within a time budget. Whereas such setups require moving the camera to capture a better view for the agent performing its task, our goal is to select the best view from multiple cameras recording simultaneously to facilitate human viewing.

Captioning for weak supervision. Prior work studies using ground-truth [22, 95, 107] or predicted [23, 104] captions for weakly supervising action recognition [36], object detection [55, 59, 61, 90, 105, 108], semantic segmentation [97, 99, 101], and visual question answering [5, 35, 102]. In contrast, we tackle view selection by using the quality of predicted [58, 110] narrations as weak supervision.

3. Approach

Our goal is to train a model to identify a sequence of best views for watching a multi-view instructional video, such that the identified views are most informative of the activity in the video. Importantly, we aim to do this in the *absence of best view labels*. We first formally define our task (Sec. 3.1), and then decompose it into three key questions: (1) how to source the best view pseudo-labels to train our model

(Sec. 3.2), (2) how to model multi-view videos to discriminate between visually similar views when identifying the best one (Sec. 3.3), and (3) how to train the model (Sec. 3.4).

3.1. View selection task

Given a set of instructional videos with multiple camera views, the goal is to automatically predict views that most comprehensively capture the fine-grained details—minute aspects of the actions and objects involved, precise body movements useful for skill learning. Critically, we aim to achieve this without any manually provided best-view labels, but by instead using natural language narrations of the videos as a source of weak supervision.

Let V be an instructional video recorded with multiple cameras (Fig. 1). The video V consists of M clips, such that $V = [\mathcal{V}_1, \dots, \mathcal{V}_M]$. Each clip \mathcal{V}_m has N RGB image streams, one from each camera/viewpoint, such that $\mathcal{V}_m = \{\mathcal{V}_{m,1}, \dots, \mathcal{V}_{m,N}\}$. Our goal is to select the best view \mathcal{B}_m^* for each clip \mathcal{V}_m to create an output video that is ideal for understanding the activity in the video. Therefore, we aim to find $\mathcal{B}^* = [\mathcal{B}_1^*, \dots, \mathcal{B}_M^*]$, where $\mathcal{B}_m^* \in \{\mathcal{V}_{m,i}\}_{i=1}^N$.

Rather than assume any best-view labels on the training

clips \mathcal{V}_m , we turn instead to *narrations*—human-provided descriptions of the activity in the video. Narrations are common in instructional videos [20, 32, 33, 50, 65, 112], and for recent multi-view datasets [33, 50] they are specifically gathered in a *view-agnostic* manner: human annotators watch a collage of *all* views of a clip and write a holistic description of the person’s actions and the objects involved. See Fig. 2 (center). While the narrations themselves are a form of annotation, they are more widely available, versatile, and scalable than specialized best-view labels, and hence provide a compelling source of weak supervision.

Each clip thus has a ground-truth view-agnostic narration \mathcal{N}_m^* , that captures the activity as viewed from any and all angles; it is view-independent. The descriptions include details about actions taken by the camera wearer as well as relevant events from the environment and important objects. We aim to use these narrations to train a model \mathcal{F} that, given the video V , predicts a viewpoint sequence i.e., $\mathcal{F}(V) = \mathcal{B}^*$. We stress that the narrations are available only for training videos, not at test time.

3.2. Sourcing best view pseudo-labels for training

Next, we describe our framework (Fig. 2a) for tackling this *language-guided* task. We first source best-view pseudo-labels for training our view selector. We hypothesize that the relative quality of predicted narrations from different views indicates how accurately each view captures the fine details of the activity, and we show how this view-dependent quality of predicted narrations can be used to train a view selector. For example, consider a video showing how to fix a bicycle (Fig. 1). Some camera angles may have the person’s body or the bike blocking the view, making it hard to see what is happening. As a result, the captioner cannot properly describe the activity using such views, indicating that these views are of poor quality. In contrast, a view that clearly shows the hands, bike parts, tools, etc., will allow the captioner to accurately describe the activity, making it a more informative view.

Best view pseudo-labeler L . We devise our pseudo-labeler L to generate the best-view pseudo-label for a training clip \mathcal{V}_m by first predicting the narration for each view separately, and then scoring the views by comparing their predicted narrations to the *view-agnostic* ground-truth narration \mathcal{N}_m^* .² We aggregate results over multiple independent captioners in order to bolster robustness, essentially smoothing over their outputs. To this end, we use K off-the-shelf video captioning models: 1) Video-Llama [110] with Llama2 [94] LLM decoder, 2) Video-Llama [110] with Vicuna [94] LLM decoder, and 3) VideoChat2 [58]. See Fig. 2a top.

In particular, we predict the narrations for the N views separately using each captioner, where $\mathcal{N}^k =$

$\{\mathcal{N}_1^k, \dots, \mathcal{N}_N^k\}$ denotes the predicted narrations from the k^{th} captioner. Next, we pass each set \mathcal{N}^k to a view ranker, which scores its narrations by comparing them to the ground-truth narration \mathcal{N}^* using a standard captioning metric [6, 75, 96], and computes a set of ranks \mathcal{R}^k for the corresponding views. Finally, a best view rank aggregator is used to reach an agreement across all captioners. The rank aggregator extracts the consensus: given all rank sets $\{\mathcal{R}^1, \dots, \mathcal{R}^K\}$, it finds the views ranked the highest within each individual captioner, and uses *all* views that are top-ranked across all captioners to build a best view pseudo-label set \mathcal{B} .

Essentially, our pseudo-labeler uses multiple strong captioners to rank views based on the accuracy of their predicted narrations, and achieves consensus on the top ranked views, thereby automatically producing high-quality best view pseudo-labels. See Fig. 2b and Supp. for examples.

3.3. Best view selector S

We use the pseudo-label set \mathcal{B} from Sec. 3.2 to train our best view selector S , which must reason across all views to identify the best one.³ Simply using a view classifier as the selector is not enough in our setting, as our captioning-based labels can sometimes be insufficiently discriminative, *i.e.*, multiple views might be pseudo-labeled as the best view due to the nature of the off-the-shelf video captioners’ training. They were originally designed to learn features that are predictive of the narration regardless of the view, and consequently, can end up collapsing all views into similar representations that are unable to capture the important nuances between them.

To address this, we design a view selector composed of 1) a view classifier W , and 2) a relative camera pose predictor P . During training, while our view classifier (Fig. 2a bottom-left) tries to identify the best viewpoint given our pseudo-labels, the pose predictor (Fig. 2a bottom-right) simultaneously acts as a regularizer and mitigates the effect of spurious pseudo-labels by solving an auxiliary task of relative camera pose prediction for each pair of viewpoints. This ensures that the features learned by our view classifier remain sensitive to viewpoint changes, and our model does not overfit to the pseudo-labels during training, thereby improving the quality of view selection, as we show in results.

View classifier W . Our view classifier W consists of a visual encoder F with a TimeSformer [7, 77] architecture, which encodes each view n into a set of visual features f_n that spatially correspond with frame patches in the input view, where $f_n = F(\mathcal{V}_n)$. Owing to its patch-level nature and the end-to-end training (cf. Sec. 3.4) of the classifier using our pseudo-labels, f_n provides fine-grained cues about the human activity—what parts of it are visible in

²For simplicity, we omit the clip index m from subscript, henceforth.

³Note that it is not possible to simply apply the pseudo-labeler at inference time, since it requires access to ground-truth narrations.

a viewpoint, and how the dynamic elements (*e.g.* moving objects, body parts) evolve over time, thereby facilitating high-quality view selection. Next, the model uses a projector H^W to embed f_n into a lower-dimensional feature h_n providing a higher-level representation of a view’s ability to capture activity details. Formally, $h_n = H^W(f_n)$. Finally, we concatenate h_n from all views, and feed them to a classification head C^W . The classification head compares these representations across views and outputs its best view estimate \tilde{B} , such that $\tilde{B} = C^W([h_1, \dots, h_N])$.

Relative camera pose predictor P . Our relative camera pose predictor P uses the view classifier’s visual features to predict the relative camera pose for all view pairs. Specifically, we formulate the pose prediction as a classification task [13, 68]. Given the ground-truth relative camera pose $P_{(i,j)}^*$ for an arbitrary pair of viewpoints (i, j) , we discretize the angles of its direction of displacement and rotation matrix using bins of a fixed size. This formulation ensures that our pose prediction task is tractable, and helps our model learn view-dependent visual features that improve task performance. That is because it requires predicting the rough direction of one camera center relative to another instead of the exact relative displacement, which is ill-posed due to unknown object sizes.

To perform this classification for a viewpoint pair (i, j) , our pose predictor P uses the fine-grained visual features f_i and f_j produced by our view classifier for viewpoints i and j , and embeds them into more abstract representations h_i^P and h_j^P using a feature projector H^P , such that $[h_i^P, h_j^P] = [H^P(f_i), H^P(f_j)]$. Whereas the fine-grained features f help learn patch-level correspondences [7, 77], which are crucial for accurate pose prediction, the features h act as a bridge between these detailed representations and the higher-level relative pose estimate. Finally, similar to VLocNet++ [78], we concatenate features h_i^P and h_j^P , and pass them to a pose classification head C^P , which computes their correlation [9] and outputs a relative pose estimate $P_{i,j}$. Formally, $P_{i,j} = C^P([h_i^P, h_j^P])$. The estimates are used in an auxiliary loss defined below. See Fig. 2a bottom-right.

3.4. Model training

Video captioner training. We train the off-the-shelf video captioners [58, 110] in the best view pseudo-labeler L (cf. Sec. 3.2) by initializing them with the pretrained parameters released by their authors, and subsequently finetuning them on our multi-view videos with the standard negative log-likelihood loss [58, 110]. This helps us leverage the knowledge from internet-scale pretraining and improve the captioning performance.

View selector training. We train our view selector with a combination of two losses: a) a view classification loss \mathcal{L}^W ,

and b) a relative camera pose prediction loss \mathcal{L}^P . While \mathcal{L}^W provides a direct learning signal to the view classifier W , \mathcal{L}^P helps its visual encoder F generate visual features that capture the important inter-viewpoint differences.

We propose a novel loss formulation for \mathcal{L}^W , which accounts for the cases where there is more than one best view pseudo-label in \mathcal{B} (cf. Sec. 3.2). Specifically, we set \mathcal{L}^W to

$$\mathcal{L}^W = \min\{\mathcal{L}_{CE}(\tilde{B}, \hat{B}) \mid \hat{B} \in \mathcal{B}\}, \quad (1)$$

where \tilde{B} is our best view estimate (cf. Sec. 3.3) and \mathcal{L}_{CE} denotes the cross-entropy loss. Our formulation for \mathcal{L}^W encourages our view classifier to learn to predict as its estimate whichever among the pseudo-labels it finds the easiest to predict [34, 48, 70], thereby stabilizing training and improving task performance, as we show in results.

We set the relative camera pose prediction loss \mathcal{L}^P to

$$\mathcal{L}^P = \frac{1}{N^2} \sum_{(i,j) \in \mathbb{N}} \mathcal{L}_{CE}^P(\mathcal{P}_{(i,j)}, \mathcal{P}_{(i,j)}^*). \quad (2)$$

Here, \mathcal{L}_{CE}^P is the average cross-entropy loss over all discretized angles in \mathcal{P}^* (cf. Sec. 3.3), and $\mathbb{N} = \{1, \dots, N\} \times \{1, \dots, N\}$ is the set of all possible view pairs.

We set our final training loss \mathcal{L}^S for the view selector to $\mathcal{L}^S = \mathcal{L}^W + w * \mathcal{L}^P$, where w is the weight on the pose prediction loss, and jointly train W and P .

4. Experiments

We overview all setup details and then provide results.

4.1. Experimental setup

Dataset. We evaluate our model on two multi-view instructional video datasets: Ego-Exo4D [33] and LEMMA [50]⁴. Ego-Exo4D contains both physical (*e.g.* basketball, dancing) and procedural (*e.g.* cooking, bike repair) activities with each video containing 5 time-synced views—one is egocentric (ego) and recorded by the participant with a head-worn camera, and the remaining views are exocentric (exo) and recorded with stationary cameras kept around the scene. LEMMA has videos of people performing household activities (*e.g.* making juice, watering plant), where each video has the participant’s ego view and an exo view from a fixed camera placed facing the activity. Both have narrations: the Ego-Exo4D annotators provide temporally dense written descriptions of the participants’ actions and relevant objects involved in the activity, while the LEMMA annotators describe action verbs and objects being interacted with using a pre-defined vocabulary. These two datasets let us evaluate different exo view setups (multiple in EgoExo-4D vs. single in LEMMA) and diverse activity scenarios (physical and

⁴Note that other instructional video datasets like HowTo100M [65], CrossTask [113], and COIN [93] are single-view and thus not suitable.

procedural in Ego-Exo4D vs. household in LEMMA). Ego-Exo4D and LEMMA provide a total of 86 hours and 20 hours of video data, resulting in 648,665 and 63,538 clip-narration pairs, respectively. See Supp. for details, including our clip segmentation strategy.

Implementation. We use $K = 3$ captioners in our pseudo-labeler: Video-Llama [110] with Llama-2-Chat [94] or Vicuna [16] as the LLM decoder, and VideoChat2 [58], respectively, and the CIDEr [96] captioning metric to score views. We finetune the captioners on our datasets before using them to score views. On the basis of a disjoint validation set, we set the bin size to 30 degrees for generating relative camera pose labels (cf. Sec. 3.3), and the weight on the pose prediction loss to $w = 0.5$. See Supp. for more details.

Baselines. We compare against the following baselines and state-of-the-art methods:

- **Ego-only, Random, Random-exo:** a set of naive baselines that predict the ego view (**Ego-only**), or a view randomly chosen from just exo (**Random-exo**) or all (**Random**) views, as the best view.
- **Hand-object, Body-area, Joint-count:** a set of baselines that predict the view with the highest hand and object detection confidence per a state-of-the-art hand and object detector [15] (**Hand-object**), or the largest body area (**Body-area**) or joint count (**Joint-count**) per a state-of-the-art body pose detector [51], as the best view.
- **Snap angles [11, 100]:** an automatic cinematography method that predicts the view with the highest foreground pixel count as the best view. We upgrade it to use today’s SOTA segmentation models [54, 61].
- **Longest-caption:** a baseline that uses our finetuned Video-Llama captioner [110] to predict captions for each input view, and selects the one that produces the longest narration as the best view. Intuitively, here caption length is used a proxy for informativeness. Recall that our model does not infer captions on test data.

While the first set of baselines are naive heuristics to test if intelligent selection is even necessary, the second set accounts for the prior that visibility of people and person-object interactions are strongly linked to the informativeness of a view. The third represents the most relevant existing methods. Finally, the Longest-caption baseline offers an alternative way to incorporate language for our task.

Evaluation metrics. We perform both *automatic* and *human* evaluation. For **automatic evaluation**, we measure how well the selected view predicts two things: narrations and action/object terms. For the former, we use a state-of-the-art video captioner [58, 110] to predict the narrations given our chosen views, and then compare the predictions with the view-agnostic ground-truth narrations through standard captioning metrics: CIDEr [96] and METEOR [6]. For the

latter, we use 1) **Verb IoU (V-IoU)**, 2) **Noun IoU (N-IoU)**, and 3) **Noun-chunk IoU (NC-IoU)**, which measure the overlap in the sets of verbs, nouns, and noun chunks between the ground-truth and predicted narrations, where noun chunks are nouns grouped with their modifiers (*e.g.* adjective, article). In short, the more the view deemed as “best” by our model predicts things consistent with the comprehensive view-agnostic ground truth, the better it is. We stress that this suite of metrics, together with the human evaluation below, goes beyond CIDEr (used in our language-guided training) to gauge the quality of the selected views.

Through **human evaluation**, we assess two important model aspects: 1) pseudo-label quality, and 2) view selection performance. We conduct both assessments through pairwise comparison of views, which reduces the cognitive load on human judges and increases their reliability [1, 19, 30]. Given a view pair, the human judge can select either view or both, depending on if they prefer one over the other specifically for the purpose of activity understanding (*i.e.*, a *win* for the preferred view, and a *loss* for the other), or find them equally informative (*tie*). Critically, we do not show the evaluators the ground-truth narrations. In other words, our study *directly evaluates the human-preferred viewpoints*—independent of narrations—and hence is unbiased by the fact our model leverages language during training. We obtain human judgments on 1) pseudo-label quality by pairing the best and the worst views per our pseudo-labeler (cf. Sec. 3.2), and 2) view prediction quality by pairing the views predicted by our and the best baseline’s predicted views. We decide the view order in each pair randomly. We do each study for both datasets with 10 participants and 70 randomly chosen test view pairs. Our inter-evaluator agreement rate is 78.5%.

4.2. Results

Automatic evaluation. Table 1 top shows our automatic evaluation results. The naive baselines generally perform the worst, indicating that blindly choosing the ego view at all times, or picking a random view is not enough for our challenging task. Interestingly, while random-exo improves over ego-only and random on Ego-Exo4D [33], it fares worse on LEMMA [50], possibly because activities like rock climbing or basketball in Ego-Exo4D involve more head and body motion than the household activities (*e.g.* cooking, watching TV) in LEMMA, and consequently, require stationary exo cameras for better coverage. Using intelligent heuristics like the visibility of hands and objects (Hand-object), or the body (Joint-count and Body-area), or foreground object prevalence (Snap angles [11, 100]) generally improve task performance, showing that these methods provide useful cues for our task. The Longest-caption baseline generally underperforms the naive baselines, possibly because the view with the longest predicted narration provides excessive details about the scene that are irrelevant to the activity.

Model	Ego-Exo4D [33]					LEMMA [50]				
	Captioning		Actions and objects			Captioning		Actions and objects		
	CIDEr [96]	METEOR [6]	V-IoU	N-IoU	NC-IoU	CIDEr [96]	METEOR [6]	V-IoU	N-IoU	NC-IoU
Ego-only	12.2	47.2	32.2	36.7	30.6	41.7	71.1	38.2	41.3	17.5
Random	11.5	45.9	30.4	36.6	31.0	30.9	63.1	31.2	33.2	12.8
Random-exo	11.9	46.0	30.5	37.0	30.9	17.7	51.3	21.6	22.4	6.8
Hand-object	12.6	47.4	33.6	36.7	29.6	40.7	72.7	38.5	41.5	17.9
Body-area	12.9	48.2	32.5	37.2	31.1	42.1	73.8	38.6	41.3	17.6
Joint-count	12.6	46.6	31.5	29.1	27.7	17.8	51.4	21.7	22.4	6.7
Snap angles [11, 100]	12.2	46.7	30.7	35.8	29.1	38.9	70.6	37.1	40.2	17.1
Longest-caption	10.7	47.3	30.5	34.6	28.8	32.7	65.4	36.9	37.9	15.3
LANGVIEW (Ours)	13.5	48.4	33.7	39.2	32.9	42.7	74.4	40.1	42.9	18.9

Table 1. View selection results. All metrics are in % and higher is better.

Assessment type	Win	Loss	Tie
<i>Pseudo-label: best vs. worst view</i>			
Ego-Exo4D [33]	53.3	28.9	17.8
LEMMA [50]	46.7	38.9	14.4
<i>View prediction: ours vs. best baselines</i>			
Ego-Exo4D [33]			
Ours vs. Hand-object	52.2	40.0	7.8
Ours vs. Body-area	55.1	39.3	5.6
LEMMA [50]			
Ours vs. Hand-object	43.3	41.1	15.6
Ours vs. Body-area	46.7	35.5	17.8

Table 2. Human evaluation results for our pseudo-label and view prediction quality. All values are in %. Significance, $p \leq 0.05$.

Our model significantly outperforms all baselines across metrics, on both datasets. It shows our idea of pseudo-labeling by using the view-dependent quality of predicted narrations is effective in practice. Furthermore, our model’s improvement over the heuristics illustrates that our language-guided training facilitates complex but essential reasoning about the interplay between human actors and interacting objects, more than what is possible with hand/object or body pose detectors. Finally, our superior performance on both datasets underlines the efficacy of our design and its ability to generalize to different activity types (both physical and non-physical in Ego-Exo4D vs. household in LEMMA) and camera setups (single vs. multiple exo cameras in LEMMA and Ego-Exo4D, respectively). See Supp. for single exo camera and 3-fold evaluation with Ego-Exo4D.

Human evaluation. Table 2 shows our human evaluation results using *win*, *loss* and *tie* percentages. In our pseudo-label quality study, the human preference for the best view per our pseudo-labels is significantly higher than the worst view. Given that the participants were asked to base their responses on the views’ suitability for activity understanding, this validates our hypothesis that the view-specific quality of predicted narrations is correlated with human preference for informative views, and can be exploited for sourcing best view pseudo-labels. Furthermore, a significant *tie* rate indicates a considerable presence of instances with multiple good views, reinforcing that our task is challenging.

In our view selection assessment, we find that our selected views are preferred significantly more than the two top baselines on both datasets. We achieve a strong win rate boost of at least $\sim 11\%$ over the baselines across different evaluation scenarios. The only exception is our model vs. Hand-object [15] on LEMMA, where the improvement margin is a more modest $\sim 2\%$, likely because the view that best shows hand-object interactions is a reasonably good view for showing LEMMA-style activity (cooking, watering plant, etc.). These results show that our weakly-supervised method is better capable of implicitly modeling human view preference. Finally, our consistent performance gains on human evaluation reinforce our automatic evaluation metrics.

Qualitative examples. Fig. 3 (left) shows some success cases. Note how our model chooses views that clearly show the essential elements of the actions, including the different entities involved and their motion. E.g., in clip 2, our model chooses the ego view as it clearly shows the horizontal knife motion and vegetables on the cutting board, whereas in clip 3, it selects an exo view that best shows the joined hands and the dancers’ sideways movement. Thus, depending on the activity, our model adaptively chooses a view that shows its important details. See Supp. video for more examples.

We also observe two common failure types. The first type occurs when there are multiple high-quality views. See Fig. 3 (right). In the second one, our model chooses different views for very similar activities, which involve very similar types, positions and motion of relevant objects and body parts, even when the views are not equally good. This occurs possibly because our selector occasionally picks on spurious cues that are not as viewpoint-dependent as the activity itself but also do not help with its understanding.

Ablations. In Table 3 (top) we report our model ablation results on the large-scale Ego-Exo4D [33] dataset. Not predicting inter-view camera pose in training significantly hurts performance on all metrics except METEOR [6]. This shows that our pose predictor enhances the selector’s view sensitivity. Training our model with a standard cross-entropy loss by randomly choosing a sample from our pseudo-label set, instead of our proposed loss (c.f. Sec. 3.4) hurts perfor-

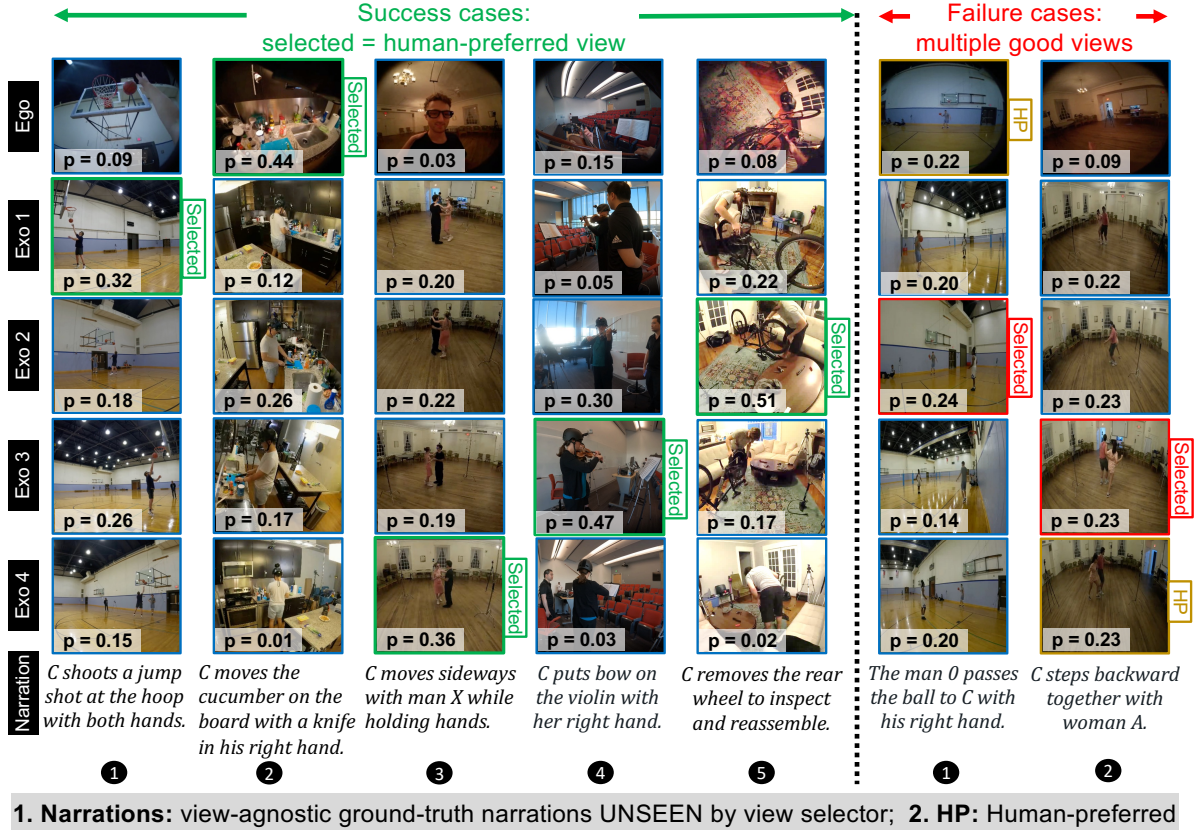


Figure 3. Left: sample successful predictions by our view selector. For each clip, our model chooses the view that shows the action, and the objects and body parts involved in it, most clearly, and hence, is most informative. Right: Sample failure cases for our model, where there are multiple high-quality views that differ only in certain nuances, which are discernible by a human but not our model trained through narration guidance. Whereas humans prefer a view that better captures the direction of the ball towards the camera-wearer in sample 1, or shows the full backward motion of the dancers in sample 2, our model choose a view that shows all entities mentioned in the narration.

Model	Captioning		Actions and objects		
	CIDEr	METEOR	V-IoU	N-IoU	NC-IoU
Ours w/o P	13.2	49.2	33.4	38.7	32.8
Ours w/o \mathcal{L}^W	13.5	48.8	34.0	37.4	32.3
Ours w/o G	13.7	48.7	34.3	38.5	32.8
Ours w/o G, \mathcal{L}^W, P	13.2	48.0	33.5	37.7	32.5
Ours	13.5	48.4	33.7	39.2	32.9

Table 3. Ablation results on the large-scale Ego-Exo4D [33] dataset. G denotes the rank aggregator in our pseudo-labeler. All metrics are in %. Significance, $p \leq 0.05$.

mance on N- and NC-IoU. This occurs possibly because the captioners in our pseudo-labeler sometimes hallucinate and add less informative views to the pseudo-label set, which when sampled causes training instability. Removing the rank aggregator to obtain pseudo-label consensus also negatively impacts performance on N- and NC-IoU, as having multiple captioners vote on the best view reduces captioning noise and improves pseudo-label quality. Finally, removing all three components consistently degrades performance across metrics, showing that the model needs *at least one compo-*

nent to perform well on different metrics.

See Supp. for additional ablations, and analyses of the view dependence of our visual features, our pseudo-labeler, the impact of the rank of our selector’s sampled view on view selection performance, and our model’s attention maps.

5. Conclusion

We tackle view selection in multi-view instructional videos in the absence of best view labels. To that end, we design a novel framework composed of a best view pseudo-labeler that uses the view-dependent quality of estimates of video descriptions to automatically generate best view pseudo-labels, and a best view selector that given a video, produces a best view prediction. Our method significantly outperforms several state-of-the-art baselines on two challenging multi-view instructional video datasets. In future work, we will explore future best-view anticipation for improving the energy efficiency of multi-view instructional video capture setups.

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