A Strong Baseline for Temporal Video-Text Alignment

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Abstract

In this paper, we consider the problem of temporally aligning the video and texts from instructional videos, specifically, given a long-term video, and associated text sentences, our goal is to determine their corresponding timestamps in the video. To this end, we establish a simple, yet strong model that adopts a Transformer-based architecture with all texts as queries, iteratively attending to the visual features, to infer the optimal timestamp. We conduct thorough experiments to investigate: (i) the effect of upgrading ASR systems to reduce errors from speech recognition, (ii) the effect of various visual-textual backbones, ranging from CLIP to S3D, to the more recent InternVideo, (iii) the effect of transforming noisy ASR transcripts into descriptive steps by prompting a large language model (LLM), to summarize the core activities within the ASR transcript as a new training dataset. As a result, our proposed simple model demonstrates superior performance on both narration alignment and procedural step grounding tasks, surpassing existing state-of-the-art methods by a significant margin on three public benchmarks, namely, 9.3% on HT-Step, 3.4% on HTM-Align and 4.7% on CrossTask. We believe the proposed model and dataset with descriptive steps can be treated as a strong baseline for future research in temporal video-text alignment. All codes, models, and the resulting dataset will be publicly released to the research community.

1. Introduction

The research on visual-language representation learning has recently made great progress. It is primarily driven by contrastive learning on image-caption pairs crawled from the Internet at scale [\[14,](#page-8-0) [15,](#page-8-1) [25\]](#page-9-0), and has shown remarkable performance on zero-shot image classification. However, in videos, the time dimension adds extra complexity that requires temporally corresponding captions/descriptions, posing challenges to learning fine-grained representation for video understanding tasks, such as temporal action localization, visual-language grounding, and grounded visual question answering.

Instructional videos, for example, HowTo100M [\[19\]](#page-8-2), have been widely used for learning video representations [\[12,](#page-8-3) [16,](#page-8-4) [18,](#page-8-5) [20\]](#page-8-6), with the textual narrations acquired from Automatic Speech Recognition (ASR) system. However, unlike manually annotated captions, training model with these ASR transcripts naturally incurs three issues: (i) off-the-shelf ASR systems may introduce recognition errors; (ii) spoken narrations are generally not of descriptive style, thus contain redundancy or ambiguity, *e.g.*, talking about a specific ingredient or using ambiguous pronouns (it, them); (iii) transcripts may not be well aligned with the visual signals, *e.g.*, greetings from the speaker, associating with inaccurate timestamps, or describing the action after performing it. According to the statistics from the previous work [\[12\]](#page-8-3), only 30% of the narrations are visually alignable, and only 15% are naturally well-aligned with correct start/end timestamp, as presented in Fig. [1.](#page-1-0)

In this paper, we consider training a video-text alignment network on the large-scale instructional dataset – HowTo100M, where the associated ASR transcriptions have significant noise, and are only weakly aligned with the visual signal when relevant. Once trained, the model can tackle two challenging tasks, namely, narrations alignment [\[12\]](#page-8-3) and procedural steps grounding [\[18\]](#page-8-5). Specifically, given one long video sequence from the HowTo100M dataset, with associated narrations transcribed by the ASR system, or procedural steps from instructional articles on Wikihow^{[1](#page-0-0)}, that are related to the activity shown in the video, the narrations alignment task aims to: (i) justify if a sentence in narration is alignable with the video; (ii) determine its temporal segment if it is alignable. While the procedural steps grounding task aims to temporally ground the procedural steps in the video.

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¹<https://www.wikihow.com/Main-Page>

Figure 1. An example of the video-text alignment problem in an instructional video. The green, yellow, and red timelines denote narrations with their acoustic timestamps in the ASR transcript. Narrations might be **visually alignable**, but not well aligned with the starting and ending point of the visual signals, while some narrations are not visually alignable at all.

We present a lightweight Transformer-based architecture, termed as Narrations / Steps to Video Aligner (NSVA), where the narration or procedural steps are used as queries, to iteratively attend the video features, and output the alignability or optimal temporal windows. Specifically, we start by investigating the effect of updating visual-textual backbones for video-text alignment, from S3D to CLIP, to the recent InternVideo. To resolve the aforementioned problems in ASR transcripts, we first replace the original YouTube transcripts with the ones generated from WhisperX [\[3\]](#page-8-7), to explore the effect of improving the ASR system in order to reduce the punctuation and recognition error in narrations, then we transform the ASR transcripts into descriptive steps, by prompting the large language model and temporally align them to the video through a two-stage determination procedure, *i.e.*, approximate estimation, and then further refinement. As a result, we establish an automatic, scalable pipeline to construct high-quality data for training the video-text alignment network and obtain a large video-text dataset named HowToStep.

Our final model sets state-of-the-art performance on both procedural steps grounding and narrations alignment across three public benchmarks, surpassing existing models by a large margin, specifically, 9.3% on HT-Step [\[18\]](#page-8-5), 3.4% on HTM-Align [\[12\]](#page-8-3) and 4.7% on CrossTask [\[37\]](#page-9-1). We will release all codes, models, and the resulting dataset to facilitate future research.

2. Related Work

Large-Scale Video-Text Datasets. Multi-modal video datasets are crucial for video understanding tasks. Conventional video-text datasets [\[6,](#page-8-8) [36\]](#page-9-2) are often manually labeled, suffer from short video lengths, limited scale, and coarse label granularity, and prevent the model from learning a generalized video representation. In the recent literature, scalability becomes an essential factor for constructing datasets, Youtube-8m [\[1\]](#page-8-9) collects YouTube videos with metadata provided by the users, Instagram65M [\[11\]](#page-8-10) uses the associated hashtags as labels to supply weak supervision for training. In order to get descriptive sentences or captions with richer semantics, instructional videos are collected at scale, as they naturally come with dense narrations, obtained from ASR systems, by far, the largest video-text dataset is HowTo100M [\[19\]](#page-8-2). As an alternative, Fit [\[2\]](#page-8-11) comprises over two million videos with weak captions scraped from the internet, while the captions are manually generated, they are not temporally aligned, and thus are insufficient for learning fine-grained temporal representation. In this work, we transform the noisy ASR transcripts into descriptive procedural steps, and propose to train a model to improve the video-text correspondence for instructional videos, mitigating the flaws of the HowTo100M dataset for visual representation learning.

Video-Text Alignment. Video-text alignment aims to temporally assign narrations or procedural activity steps to the corresponding video segments. Initially, [\[4,](#page-8-12) [37\]](#page-9-1) tries to delineate the video segments corresponding to a given action list. Instead of an action list, scripts describing a series of events in the video are given for transcript alignment [\[9,](#page-8-13) [23\]](#page-8-14). The availability of large-scale video-text datasets such as HowTo100M has prompted many works on joint videotext embedding training. Specifically, TAN [\[12\]](#page-8-3) investigated directly aligning contextualized narration representations generated from ASR transcripts to video segments. Given that the ASR can be rather noisy, DistantSup [\[16\]](#page-8-4) proposes using distant supervision from a textual knowledge base, namely WikiHow [\[13\]](#page-8-15) to denoise text narrations from ASR. More recently, instead of aligning a video's narrations, VINA [\[18\]](#page-8-5) proposes to ground procedural activity steps sourced from the instructional article, however, as the order of instructions from Wikihow does not necessarily follow those in the video, grounding procedural steps is thus more challenging. In this paper, we aim to tackle the two problems simultaneously, namely, narration alignment [\[12\]](#page-8-3)

and procedural step grounding [\[18\]](#page-8-5), while previous studies have only focused on one aspect, leading to the inability to better integrate the two types of textual information (narrations and steps) to complete the video-text alignment tasks.

Dataset Curation with Large Language Models. In the recent literature, large language models (LLMs) such as GPT [\[5,](#page-8-16) [21,](#page-8-17) [24\]](#page-9-3) and Alpaca [\[28\]](#page-9-4) have achieved great success in natural language processing. Constructing multimodal datasets while generating pseudo-labels using LLMs becomes an efficient way to exploit the common sense knowledge in LLMs, and save human efforts for annotations. For instance, VQA-T [\[33\]](#page-9-5) generates question-answer pairs for instructional video ASR transcripts by LLMs, which are then coupled with the related video. The VQA model pre-trained on the generated dataset exhibits enhanced generalization capabilities in various downstream tasks. Similarly, VQ^2A [\[7\]](#page-8-18) adopts LLMs to automatically derive question-answer pairs at scale for images, by leveraging the existing image-caption annotations. In addition to generating a dataset directly, some works use the LLMs to create pseudo-labels for large-scale video data that are later used for multi-modal vision tasks. For example, LAV-ILA [\[35\]](#page-9-6) first trains a video captioning model on egocentric videos, and proposes to rephrase the densely generated captions from the model. After finetuning, the model demonstrates improved performance. As a concurrent work, [\[27\]](#page-9-7) adopts LLMs to transform the ASR transcripts of instructional videos, however, there exists one crucial difference, we transform the transcripts into concise steps, rather than dense captions as in their work.

3. Method

In this section, we start by describing the problem scenario in Sec. [3.1,](#page-2-0) including narration alignment and procedural step grounding. Then we present a novel pipeline to transform noisy and redundant ASR transcripts into descriptive steps as extra training source in Sec. [3.2.](#page-2-1) Lastly, we detail our proposed video-text alignment network in Sec. [3.3.](#page-4-0)

3.1. Problem Scenario

Given an instructional video from HowTo100M, \mathcal{X} = $\{V, \mathcal{J}\}\,$, where $V = \{V_1, V_2, \ldots, V_T\}$ refers to the frames of the video, and $\mathcal{J} = \{J_1, J_2, \dots, J_K\}$ denotes the K textual segments (narrations or procedural steps) associated with the video. Our goal is to train a temporal videotext alignment network that takes video and texts as inputs, and outputs a textual-visual alignment score matrix ($\hat{A} \in$ $\mathbb{R}^{K \times T}$ with the binary visual alignability $(\hat{y} \in \mathbb{R}^{K \times 2})$ for each sentence. Formally, it can be denoted as:

$$
\{\hat{y}, \hat{\mathbb{A}}\} = \Psi_{\text{align}}(\Phi_{v\text{-enc}}(\mathcal{V}), \Phi_{t\text{-enc}}(\mathcal{J}))
$$
 (1)

In training, the ground truth label $\mathbb{Y}_{\mathcal{J}\mathcal{V}} \in \{0,1\}^{K \times T}$ takes value $\mathbb{Y}_{\mathcal{J}\mathcal{V}}^{[k,t]} = 1$ only if k-th text depicts what is happening in timestamp t in the video, and zero otherwise.

Depending on the type of given texts $\mathcal{J} \in \{N, \mathcal{S}\}\,$, we differentiate the two targeted tasks as follows:

Narration alignment [\[12\]](#page-8-3). Narrations N are textual sentences transcribed from the demonstrator's speech via the ASR system, which means these sentences have maintained a time order that can be utilized for visual grounding. Note that, some narrations are not visually alignable or not wellaligned with visual signals temporally as shown in Fig. [1.](#page-1-0)

Procedural step grounding [\[18\]](#page-8-5). Procedural Steps S are collected from Wikihow [\[13\]](#page-8-15), an external knowledge base with instructional articles explaining the procedures for completing certain tasks. Compared with narrations, the procedural steps do not necessarily have consistent temporal order as that happens in the video, or some steps may not even be present in the video at all. In addition, the training annotations $\mathbb{Y}_{\mathcal{SV}}$ for this task are scarce.

Discussion. The ASR transcript with timestamps can be used as weakly-aligned labels $\mathbb{Y}_{\mathcal{NV}}$ for training video-text alignment network as previous work [\[12\]](#page-8-3). However, as narrations essentially aim to assist people with hearing impairment, thus are not required to be descriptive of visual scenes, and can be sometimes verbose with ambiguity. Training the alignment network to tackle both tasks only based on ASR transcripts is sub-optimal. While on the other hand, procedural steps are concise and clear, that only contain the core actions to finish one specific task without redundancy. Based on this observation, we propose a pipeline to transform the noisy ASR transcripts into concise and descriptive steps for instructional videos, by exploiting the power of large language models (LLMs), which effectively augment the dataset for training the alignment network, as detailed in the following subsection.

3.2. ASR Transcripts —> Aligned Descriptive Steps

As presented in Fig. [2,](#page-3-0) the entire procedure can be divided into three parts: (i) we leverage LLM to summarize narrations from the ASR transcript into descriptive steps; (ii) we use the similarity between the original transcript and generated steps to roughly determine the start/end timestamp for each step as pseudo-label; (iii) we train the NSVA model on the generated steps with pseudo-label, and then use the trained model to refine the time range for each generated step (*i.e*., self-training). We name the final dataset as How-ToStep and present the details in the following sections.

3.2.1 Prompting LLM to Summarize Concise Steps

To generate descriptive steps, we split the complete transcript for each video into M segments, each segment G_i

Figure 2. Schematic illustration of the proposed pipeline to summarizing redundant ASR transcripts into descriptive steps *(left)*, while determining the start-end timestamp in the video *(right)*. We utilize the large language model (LLM) to summarize the narrations from ASR transcripts into descriptive steps. Afterward, we roughly get the pseudo-label by chaining the 'steps→transcript (ASR)' similarity and 'transcript (ASR)→video' timestamp to train our video-text alignment network NSVA in Stage 1. Then we use the trained model to refine the timestamp of the generated steps in Stage 2, resulting in extra training source for video-text alignment, named HowToStep.

consists of around 10 sentences. Next, we prompt Llama2- 7B [\[29\]](#page-9-8) to summarize the transcripts into concise steps describing the main action presented in the video. Additionally, we prompt LLM to filter the colloquial sentences in the speech. We refer the readers to the complete prompt in Appendix.

Formally, let Θ , κ refer to the large language model and the prompt texts, and the steps are generated separately:

$$
\mathcal{S} = \{\hat{G}_1, \dots, \hat{G}_M\}, \ \hat{G}_i = \Theta(G_i; \kappa), \ \forall i \in [1, M]
$$

where M is the number of separated ASR transcript segments. \hat{G}_i refers to the summarized procedure steps for each segment G_i , which consists of zero to four descriptive steps. S denotes the complete sequence of generated steps for one instructional video. As a result, we have transformed the ASR transcripts of around 370k videos (a subset of HowTo100M selected by [\[12\]](#page-8-3)) into approximately 7M descriptive steps. For comparison, the Wikihow knowledge base only contains 100k procedural steps from 14k instructional articles according to the statistics in [\[18\]](#page-8-5).

3.2.2 Temporal Grounding for Generated Steps

As a baseline method, we can simply get the desired steps grounding matrix between steps and video timestamps by directly computing $\mathbb{Y}_{\mathcal{SV}} = g(\mathcal{S}) \cdot f(\mathcal{V})^T$, where $f(\cdot), g(\cdot)$ is the corresponding visual-textual backbone (*e.g*., Intern-Video). However, in practice, such an approach performs poorly, as shown in the ablation study at Tab. [4.](#page-7-0)

Alternatively, after generating descriptive steps, we propose to acquire their corresponding temporal windows in the instructional videos, with a two-stage approach to determine the start/end timestamp.

Stage 1: Approximate estimation. As the procedural steps are summarized from transcript sentences, we first compute the similarity score between S generated steps and N narrations of the transcript from each video, *i.e.*, 'steps→transcript' matrix:

$$
\mathbb{T}_{\mathcal{SN}} = \text{softmax}(g(\mathcal{S}) \cdot g(\mathcal{N})^T / \nu, \text{dim} = 1)
$$

where ν is temperature, $\mathbb{T}_{\mathcal{SN}} \in \mathbb{R}^{S \times N}$ is the textual similarity matrix. The generated steps grounding matrix can then be computed by chaining the 'steps→transcript' and 'transcript→video' matrices, that has been defined in Sec. [3.1.](#page-2-0)

$$
\mathbb{Y}_{\mathcal{SV}} = \mathbb{T}_{\mathcal{SN}} \cdot \mathbb{Y}_{\mathcal{NV}}, \quad \mathbb{Y}_{\mathcal{SV}} \in \mathbb{R}^{S \times T}
$$

We select the timestamp of the maximal alignment score as the center time c_k for each step k,

$$
c_k = \operatorname*{argmax}_{t} \mathbb{Y}^{[k,t]}_{\mathcal{SV}}
$$

and then find start $/$ end time (s_k, e_k) towards left and right side of c_k until the alignment score $(\mathbb{Y}_{SV}^{[k,s_k]}, \mathbb{Y}_{SV}^{[k,e_k]})$ are lower than the percentage ζ of the score of the center time (*i.e.*, $\mathbb{Y}_{SV}^{[k,c_k]} \times \zeta$) following [\[18\]](#page-8-5). The step with the

maximal alignment score $\mathbb{Y}_{SV}^{[k,c_k]}$ lower than the threshold ϵ_1 will be regarded as unalignable and discarded.

Stage 2: Temporal refinement. In the first stage, the start / end time of the generated steps is completely obtained from weakly-aligned transcripts, which is naturally inaccurate, we further propose to refine the temporal windows with self-training. As shown in Fig. [2,](#page-3-0) we train the proposed video-text alignment network on the descriptive steps filtered after the first stage with their temporal windows as pseudo-labels. Then we use the trained model to do inference on the whole set of steps generated by LLM, to get new steps-to-video grounding matrix $\mathbb{Y}_{S\mathcal{V}}$ for each video, which might recycle some of the filtered steps back.

As briefly described in Sec. [3.1,](#page-2-0) when feeding video and a set of descriptive steps as input, the proposed NSVA model outputs the alignment matrix (\hat{A}) . We take the timestamp of the maximal alignment score as the start time for each step, and the duration is a constant Δ_{sec} , following [\[8,](#page-8-19) [27\]](#page-9-7). Similarly, the generated step with the maximal alignment score lower than the threshold ϵ_2 will be discarded. Thus, we obtain a dataset consisting of aligned descriptive steps, named HowToStep. In practice, we observe that although our NSVA model is trained on noisy pseudo-labels (*i.e*., relying on weakly-aligned transcripts, and getting steps-transcript similarity from imperfect language model), the model tends to learn the alignment patterns from procedural step to videos before overfitting to the noises, as also being observed in [\[34\]](#page-9-9). More details for generating the dataset are presented in ablation studies in Sec. [4.3.1](#page-6-0) and **Appendix.**

Relation to existing work. Generally speaking, the proposed idea here is similar to the recent work [\[18\]](#page-8-5), but with one crucial difference, that is, [\[18\]](#page-8-5) aims to ground steps collected from the external knowledge base (*i.e*., Wikihow) as extra training source, while we try to align the descriptive steps summarized from the ASR transcript within the *same* video. This design brings two benefits for training the video-text alignment network: (i) the procedural steps generated per video are more diverse than those from Wikihow; (ii) the generated steps within the video are more likely to be alignable to the video itself than those externally sourced Wikihow steps.

3.3. Architecture

As shown in Fig. [3,](#page-4-1) we adopt a simple Transformer-based architecture, where visual features of each clip are individually encoded and treated as key-value pairs, the textual features of narrations or steps are treated as queries. The queries iteratively attend visual features with cross attention, and the alignment scores can be computed by textualvisual similarity, which emits high scores for any alignable sentences with their corresponding video timestamp. The

Figure 3. Schematic visualization of the proposed Transformerbased video-text alignment network termed NSVA. The visual features are treated as key-value pairs while textual features are treated as queries, to predict the alignment score matrix $\mathbb{\hat{A}}$ between video frames and texts.

following sections describe the full details.

3.3.1 Visual-Textual Features

As defined in Sec. [3.1,](#page-2-0) given an untrimmed long instructional video, 8-mins long in our case, with K associated texts (narrations or procedural steps), we compute the visual and textual features with pre-trained backbones, that can be denoted as:

$$
x_v = f(\mathcal{V}) \in \mathbb{R}^{T \times C}, \quad x_j = g(\mathcal{J}) \in \mathbb{R}^{K \times C}
$$

where x_v refers to features of a video sequence, and x_i denotes the textual features for narrations or procedural steps associated with the video. C is the dimension of the feature vector. Note that, the resulting feature dimensions depend on the pre-trained visual or textual backbone.

We consider three popular pre-trained visual-language models, namely, the S3D-G backbone trained with MIL-NCE [\[20,](#page-8-6) [32\]](#page-9-10), CLIP-ViT/L-14 trained with InfoNCE [\[22,](#page-8-20) [25\]](#page-9-0), and InternVideo-MM-L14 trained with masked video reconstruction and multi-modal contrastive loss [\[30,](#page-9-11) [31\]](#page-9-12). We follow the pre-processing procedure from corresponding models, as detailed below:

S3D-G. As for pre-processing, the video is decoded with 16 frames per second (fps). Each 16-frame video clip cropped by a non-overlapping temporal window is fed into the S3D-G architecture, resulting in one feature (512-d) per second.

Figure 4. Qualitative examples of manually annotated visually well-aligned text-to-video alignment matrix $\mathbb{Y} \in \{0,1\}^{K \times T}$ and the learned text-to-video alignment score matrix $\hat{A} \in \mathbb{R}^{K \times T}$ of the model output for samples from HTM-Align *(left)* and HT-Step *(right)*. Since HT-Step does not provide the ground truth timestamp for each step, we label it by ourselves.

For each sentence, it is encoded with the text encoder associated with the S3D-G video encoder [\[20\]](#page-8-6). Specifically, the sentence is first tokenized and converted into word vectors (300-d) through an embedding layer trained on Google News. Then, word vectors from the same sentence will be projected into 512-d vectors, and turned into one sentence vector through maxpooling.

CLIP. We decode the video into 1fps and extract one visual feature (768-d) per second with OpenAI's ViT/L-14 model [\[10\]](#page-8-21). The text feature (768-d) is encoded with CLIP's text encoder. The embedding of the \leq e \circ t \circ token is used as the feature for each sentence.

InternVideo. We decode the video into 8fps and feed it into the InternVideo-MM-L14 model with an 8-frame nonoverlapping temporal window, obtaining one visual feature (768-d) per second. The text encoder is the same as CLIP's but pre-trained on video-text datasets. Similarly, the embedding of the \leq e \circ t \circ token is feature of each sentence.

3.3.2 Video-Text Alignment Module

As shown in Fig. [3,](#page-4-1) after extracting the visual and textual features independently, we project both features into the same dimension, fuse multimodal information with Transformer, and then predict the alignment score matrix between video and texts.

Feature projection. After computing visual-textual features with pre-trained frozen models, we adopt one linear layer to project the features into the embedding with the same dimension D. In terms of positional encoding, we add sin/cos positional encoding to the visual features, while on the text side, we only add learnable positional embeddings to sentence features for the narration alignment task, but not in the step grounding task:

$$
h_v = \phi_v(x_v) + p_v, \quad h_j = \phi_j(x_j) + \mathbb{I}_{\mathcal{J} = \mathcal{N}} \cdot p_j
$$

where $h_v \in \mathbb{R}^{T \times D}, h_j \in \mathbb{R}^{K \times D}$. ϕ_v, ϕ_j refer to differ-

ent projection heads for the features of video and sentences. $\mathbb{I}_{\mathcal{J}=\mathcal{N}}$ is the indicator function which takes value 1 only when input texts $\mathcal J$ are ordered narrations $\mathcal N$, otherwise zero. p_v, p_j denote positional encoding for visual and textual features respectively.

Visual-textual feature fusion. The visual features are processed with a temporal aggregator, followed by a grounding module, expressed as:

$$
o_v = \Phi_{\text{temp-agg}}(h_v), \quad o_j = \Psi_{\text{temp-ground}}(o_v, h_j)
$$

where $o_v \in \mathbb{R}^{T \times D}$, $o_j \in \mathbb{R}^{K \times D}$, $\Phi_{\text{temp-agg}}(\cdot)$ refers to a temporal aggregator with three Transformer Encoder layers. $Φ_{temp-ground}(\cdot)$ denotes a temporal grounding module, consisting of three Transformer Decoder layers, where visual features act as key-value pairs and textual features act as queries.

Alignment prediction. In order to get the alignment score matrix between video and texts, we first project the output of the encoder and decoder into same dimension,

$$
z_v = \varphi_v(o_v) \in \mathbb{R}^{T \times d}, \quad z_j = \varphi_j(o_j) \in \mathbb{R}^{K \times d}
$$

and then compute the alignment score matrix:

$$
\hat{\mathbb{A}}^{[k,t]} = \frac{z_j^k \cdot {z_v^t}^T}{\|z_j\| \cdot \|z_v\|} \in [0,1]
$$

where $\hat{\mathbb{A}} \in \mathbb{R}^{K \times T}$ is the predicted alignment matrix. The higher value of $\hat{A}^{[k,t]}$ means the k-th sentence is more likely to align with the visual content of timestamp t .

Training Details. As introduced in Sec. [3.1,](#page-2-0) given the ground truth labels $\mathbb{Y}_{\mathcal{TV}}$, we train the video-text alignment network with a variant of the InfoNCE loss, which has been adopted for such video-text alignment problem [\[12,](#page-8-3) [18\]](#page-8-5):

$$
\mathcal{L} = -\frac{1}{K} \sum_{k=1}^{K} \log \frac{\sum_{t} \mathbb{Y}_{\mathcal{J}\mathcal{V}}^{[k,t]} \exp(\hat{\mathbb{A}}^{[k,t]}/\tau)}{\sum_{t} \exp(\hat{\mathbb{A}}^{[k,t]}/\tau)}
$$

ASR Transcripts	HT-Step \uparrow R@1	HTM-Align \uparrow R@1		
Youtube	36.1	60.4		
WhisperX	35.9	63.8		

Table 1. Ablation study for upgrading ASR systems. The visual-textual backbones are adopted from InternVideo-MM-L14.

where $\mathbb{Y}_{\mathcal{J} \mathcal{V}} \in \{0, 1\}^{K \times T}$ is the ground truth alignment matrix. τ is a temperature hyper-parameter, and k, t refer to k -th sentence and t -th timestamp in the video respectively.

4. Experiments

In this section, we start by describing the datasets used in this paper, then present the implementation details and results for the video-text alignment task.

4.1. Datasets and Metrics

Following the previous work [\[12,](#page-8-3) [18\]](#page-8-5), we train our NSVA model on a subset of the HowTo100M dataset, with narrations from transcripts and steps generated in Sec. [3.2.](#page-2-1) As for evaluation, we conduct procedural step grounding on HT-Step [\[18\]](#page-8-5), narration alignment on HTM-Align [\[12\]](#page-8-3), and zero-shot action step localization on CrossTask [\[37\]](#page-9-1).

HTM-370K (Training). The HowTo100M dataset [\[19\]](#page-8-2) is a large-scale instructional dataset crawled from YouTube, consisting of approximately 1.2M videos with ASR transcripts. Following previous work [\[12,](#page-8-3) [18\]](#page-8-5), we use HTM-370K for training, it contains videos from the Food & Entertaining categories, consisting of 32% of the videos of the entire HowTo100M dataset.

HowToStep (Training). As introduced in Sec. [3.2,](#page-2-1) we construct this dataset for training, by transforming the original transcripts of HTM-370K into around 4M ordered instructional steps with start/end timestamps for almost 340K videos after filtering.

HTM-Align (Evaluation). This benchmark is proposed by [\[12\]](#page-8-3) for evaluating narration alignment. It contains 80 videos from the HTM-370K as a holdout testing set. The authors have manually labeled the alignability for each narration and further aligned them to the visual signal with start/end timestamps if alignable. The metric on this dataset is Recall@1 ($R@1$), which means if the maximally matched timestamp for each alignable sentence model predicted falls into the ground truth temporal window, it is regarded as being successfully recalled. The recall score is computed as the ratio of successfully recalled sentences to all the alignable sentences.

HT-Step (Evaluation). This benchmark [\[18\]](#page-8-5) aims to evaluate the procedural step grounding. It contains manual annotations for 600 videos, specifically, for each video, the authors first collect activity steps from the related Wiki-

Backbone	HT-Step ↑R@1	HTM-Align \uparrow R@1		
CLIP ViT/L-14 [25]	33.3	53.9		
MIL-NCE S3D-G [20]	29.1	56.4		
InternVideo ViT-L/14 [31]	35.9	63.8		

Table 2. Ablation for visual-textual backbones. The training texts are WhisperX ASR transcripts.

how article using the task name, *e.g*., Make Pumpkin Puree, and then annotates the temporal segment for steps alignable with the video. The metric on this dataset is same as HTM-Align, namely, R@1.

CrossTask (Evaluation). In addition to benchmarks based on HowTo100M, we also adopt this established instructional video benchmark for zero-shot step localization. The CrossTask Dataset [\[37\]](#page-9-1) contains 4800 videos, which can be divided into 18 primary tasks (cooking, DIY car, and shelf assembly) and 65 related tasks. The videos in the primary tasks are annotated as steps with temporal segments from a predefined taxonomy of 133 steps. The metric on this dataset is Average Recall@1 (Avg. R@1), which measures the recall over steps in videos for each task and averages the results. We take a random set of 1850 videos from 18 primary tasks as the evaluation set as previous work [\[18\]](#page-8-5).

4.2. Implementation Details

Overall, we investigate the effectiveness of three popular pre-trained visual-language models, namely, the S3D-G, CLIP-ViT/L-14, and InternVideo-MM-L14, as described in Sec. [3.3.](#page-4-0) While exploring other factors, for example, the effect of ASR transcripts, and the effect of incorporating descriptive steps during training, we use InternVideo-MM-L/14 by default, unless specified otherwise.

At training time, the temperature τ in our loss is 0.07. We use the AdamW [\[17\]](#page-8-22) optimizer and train the model with an initial learning rate 10^{-4} and cosine decay for 12 epochs. When determining the start/end time for generated steps, the hyper-parameters for the 2-stage are $\zeta = 0.7, \epsilon_1 = 0.15$, $\epsilon_2 = 0.8$, which is also discussed in ablation study. When training for narration alignment, we add learnable positional embeddings to the extracted textual features and keep the original order of texts, while training for procedural step grounding, we shuffle texts on the train set, with no positional embeddings being added. Complete implementation details are included in the appendix.

4.3. Results

4.3.1 Ablation Studies

We explore the effects of multiple design choices on narration alignment and procedural step grounding, and all models are evaluated on HTM-Align and HT-Step.

Effect of upgrading ASR system. To start with, we com-

Backbone	Text	HT-Step \uparrow R@1	HTM-Align \uparrow R@1	
CLIP-ViT/L-14	W	33.3	53.9	
CLIP-ViT/L-14	$W + S$	42.0	60.3	
$S3D-G$	W	29.1	56.4	
$S3D-G$	$W + S$	43.6	62.5	
InternVideo-ViT/L-14	W	35.9	63.8	
InternVideo-ViT/L-14	$W + S$	46.7	69.9	

Table 3. Ablation of ASR transformation into descriptive steps. W denotes transcripts from WhisperX, and S denotes HowToStep.

pare the original transcripts generated from YouTube, with that from the recent WhisperX $[3, 26]$ $[3, 26]$ $[3, 26]$, as the weaklyaligned labels for training. Qualitatively, we do observe that WhisperX generates fewer punctuation errors, and gives higher accuracy of temporal boundaries in the ASR transcripts. As shown in Tab. [1,](#page-6-1) upgrading the ASR system indeed leads to noticeable performance improvement in narration alignment. However, in procedural step grounding, it is not effective, showing a marginal performance decrease, we conjecture this is because the gap of text style between the train set (dense spoken narrations) and test set (concise activity steps) dominates the performance. In later sections, we use the WhisperX transcripts by default.

Effect of upgrading visual-textual backbone. Here, we explore different visual backbones with the corresponding text encoder. As shown in Tab. [2,](#page-6-2) S3D-G exceeds CLIP ViT/L-14 in narration alignment but is inferior to the latter in step grounding. In general, InternVideo ViT/L-14 shows significant advantages on both tasks, attributed to the large pre-trained dataset and effective supervision in video representation learning, which is our default choice.

Effect of ASR transformation. We validate the effectiveness of the proposed pipeline to transform noisy ASR transcripts into descriptive steps, with the post-determined temporal segments as an extra training source for video-text alignment. As shown in Tab. [3,](#page-7-1) on three backbones, we find that the generated dataset is effective for both narration alignment and step grounding. Notably, the average improvement exceeds 10% in HT-Step implies that the generated steps are indeed more descriptive, resembling a similar style as the instructions from the Wikihow knowledge base. For narration alignment, our generated steps add more diversity for training, thus leading to better performance.

Ablation of methods to generate dataset. We investigate the two-stage approach with hyper-parameters to generate the extra training dataset (HowToStep) as described in Sec. [3.2.](#page-2-1) As shown in Tab. [4,](#page-7-0) the difference between directly determining the timestamp of the generated steps by video-step similarity matrix and indirectly by chaining 'steps→transcript' similarity and 'transcript→video' labels is not obvious for the first stage, while becomes significant

	HT-Step				
Pesudo-label	ϵ_1	Self-training	ϵ_2	\uparrow R@1	
Step-Video Step-Video	0.15 0.15	х	0.8	37.2 37.4	
Step-ASR	0.15	х		35.1	
Step-ASR	0.35	х		36.9	
Step-ASR	0.15		0.7	42.4	
Step-ASR	0.15		0.8	43.0	
Step-ASR	0.35		0.7	41.5	
Step-ASR	0.35		0.8	42.5	

Table 4. Ablation of methods to generate new training dataset. As described in Sec. [3.2,](#page-2-1) Step-Video means to determine the start/end time directly by computing visual-textual similarity, while Step-ASR means indirectly by chaining 'steps→transcript' similarity and 'transcript→video' timestamp. The texts used for training the model here are only the generated steps (S).

Method	HT-Step \uparrow R@1	HTM-Align \uparrow R@1	CrossTask (ZS) \uparrow Avg. R@1		
$TAN*$ [12]	31.2	47.1			
VINA $[18]$	37.4	66.5	44.8		
Ours	46.7	69.9	49.5		

Table 5. Comparison with the state-of-the-art for narration alignment on HTM-Align, step grounding on HT-Step, and zeroshot action step localization on CrossTask. The results of TAN* are reproduced by [\[18\]](#page-8-5). 'ZS' refers to zero-shot.

when using the pseudo-label of the first stage for the selftraining in the second stage, there is a large gap between the two methods. We find that using the video-step similarity matrix directly will make the model learn a trivial solution (*i.e*., identity mapping), while indirectly obtained pseudo-label can let the model learn the alignment patterns as analyzed in Sec. [3.2.2.](#page-3-1) In addition, we choose the best thresholds to generate the final dataset according to Tab. [4.](#page-7-0)

4.3.2 Comparison with State-of-the-art

Based on the conducted ablation studies, we compare our best model with existing state-of-the-art approaches, to present a strong, yet simple baseline on video-text alignment for future research. As shown in Tab. [5,](#page-7-2) on the challenging HT-Step task, that aims to ground unordered procedural steps in videos, our model achieves 46.7% R@1, leading to an absolute improvement of 9.3%, over the existing state-of-the-art (37.4%) achieved by VINA [\[18\]](#page-8-5); On HTM-Align [\[12\]](#page-8-3), which aligns narrations in the video, our method exceeds sota model by 3.4%; On CrossTask [\[37\]](#page-9-1), where we need to align video frames and task-specific steps without finetuning, our method outperforms existing the state-ofthe-art approach by 4.7%, demonstrating our model learns stronger joint video-text representation.

5. Conclusion

To conclude, we have established a simple Transformerbased architecture for video-text alignment in large-scale instructional videos. We have investigated the factors that can potentially affect the performance, for example, upgrading the ASR system, exploring various visual-language backbones, including CLIP, S3D, InterVideo, transforming the noisy ASR transcript into descriptive steps with post-determined temporal windows as extra training source. When evaluating on three different public benchmarks, our method surpassing the existing state-of-the-art methods by a significant margin.

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Appendix

A. Additional Implementation Details

A.1. Architecture

In this section, we provide more details on the visual-language backbones, and the alignment module, as introduced in Sec. 3.3 (main paper).

Visual Backbone. We adopt S3D-G pre-trained with MIL-NCE, CLIP ViT/L-14 pre-trained with InfoNCE and InternVideo-MM-L-14 pre-trained with reconstruction and contrastive loss. For S3D-G, the original video is first resized to have a shorter side equal to 256 pixels, and then the frames are center-cropped with 224×224 resolution before feeding into the S3D-G. For CLIP and InternVideo, the original video is first center cropped to a shorter side and then resized to 224×224 resolution.

Textual Backbone. The text encoder associated with S3D-G adopts a Bag-of-word (BoW) model based on Word2Vec embeddings pre-trained on GoogleNews. Each sentence is tokenized and truncated under 32 tokens. After the embedding layer, each word vector is further projected by fully-connected layers, and a max-pooling layer is applied to get one sentence embedding. For the text encoder of CLIP and InternVideo, it takes a maximum of 77 tokens for each sentence. Each token is passed to an embedding layer and added with positional encoding. After being encoded by the Transformer blocks, we take sentence features from the \leq eot $>$ embedding for each sequence.

Alignment Modules. For video-text alignment modules in our proposed model, we use 3-layer Transformer encoder blocks and 3-layer decoder blocks with 8-head attention. The model dimension D equals 256, and the projection dimension d to compute the cosine similarity equals 64. At training time, we will truncate the videos whose duration is longer than 1200 seconds and set the batch size as 8. Our model is trained on a single GPU (NVIDIA GeForce RTX 3090) for approximately 20 hours on the full training data (Whisper $X + HowToStep$).

A.2. Dataset Details

HowToStep (Training). For our final HowToStep, the average steps (sentences) per video is 10.6 and the average words per step is 8.0. As shown in Fig. [5a](#page-11-0) and Fig. [5b,](#page-11-0) we plot the distribution of steps per video and words per step. In addition, we present a word cloud to show the descriptions of the summarized steps in HowToStep (Fig. [5c\)](#page-11-0).

HTM-Align (Evaluation). Given an instructional video from HowTo100M with its narrations with start-end timestamps from the Youtube ASR transcript, the annotator determines whether each narration is alignable with the video (*i.e*., visually related) and adjusts the ground truth temporal window to cover the visual content if the narration is alignable. The metric is Recall@1, which evaluates whether the predicted timestamp of the *narrations that are alignable* with the video falls into the ground truth temporal window [\[12\]](#page-8-3).

HT-Step (Evaluation). Given the video from HowTo100M with the task name (*e.g*., Make Pumpkin Puree) and the recipe steps from the corresponding Wikihow article, the annotator decides whether the video is relevant to the task. If the video is relevant to the task of steps, the annotator will mark all the instances of the steps with a temporal window. The test set contains 600 videos, with 5 videos per task and the metric is Recall@1 as well. The complete statistics for this dataset can be found in [\[18\]](#page-8-5).

CrossTask (Evaluation). The CrossTask dataset consists of 4800 videos from 18 primary activities and 65 related activities. The videos of primary activities are annotated with steps from a predefined taxonomy of 133 atomic steps (*e.g*., add onion, add taco) and the corresponding temporal windows in the video. For the step localization task on this dataset, the metric is Average Recall@1, which means computing Recall@1 for steps of videos from each primary activity and averaging the results of different activities. Following previous work [\[18\]](#page-8-5), we report the average results over 20 random sets of 1850 videos from 18 primary activities.

A.3. Task Details

For the narration alignment task, the texts are in the form of narrations in videos, with strong temporal correlations. The consecutive sentences in narrations typically follow a temporal order. However, in procedural step grounding, the texts are in the form of steps collected from a knowledge base, namely, WikiHow. Due to the discrepancy between the knowledge base and the instructional videos, the order of steps in the knowledge base may differ from the order of actions in the videos.

(c) The keyword cloud of HowToStep.

Figure 5. Statistics visualization of HowToStep. We provide various statistics for a qualitative overview of the dataset.

Therefore, the temporal order of consecutive sentences is not fixed. Due to the different temporal attributes of the texts in the two tasks, we employ distinct training techniques for each task. As described in Sec. 3.3.2, during training for the narration alignment task, we add learnable positional embeddings to textual features and input all the texts of one video into the alignment module with a temporal order, which is determined differently for WhisperX texts (based on the ASR recognition time order) and HowToStep texts (based on temporal windows determined in the 2-stage temporal grounding). However, for the procedural step grounding task, we do not add positional embeddings, and input the texts of one video into the alignment module after shuffling their sequential order in training.

B. Extra Ablations

Ablation on prompts for LLM on dataset construction. Due to the excessive resources required for conducting prompt ablations on the complete HTM-370K dataset, which contains 370k videos, we perform the prompt ablations on approximately 16% of the total 370k videos, amounting to 61k videos. We use the same hyper-parameters in the 2-stage temporal grounding procedure for generated steps and then train on the same model to get the results on HT-Step. In Tab. [6,](#page-12-0) we experiment with various prompts to guide the LLM in generating descriptive steps for ablation. The first row in Tab. [6](#page-12-0) represents the basic prompt, which introduces the background of the task, a brief description of the task, and the general format requirements for output. Subsequently, by incorporating key phrases like "each step should be a short and concise phrase", "Do not output colloquial sentences in the speech" and "The number of steps in your output should range from zero to four steps", the LLM is guided to distill concise steps from the redundant ASR transcripts, thereby leading to performance improvement. Hence, we ultimately choose the prompt in the fourth row of Tab. [6](#page-12-0) to generate descriptive steps.

Ablation on temporal grounding. As mentioned in Sec. 3.2.2, we propose a two-stage method to determine the start/end timestamp for each generated descriptive step. Here, we conduct more ablation studies on the filtering thresholds used for temporal grounding, *i.e.* ϵ_1 and ϵ_2 . We choose the best thresholds ($\epsilon_1 = 0.15$ and $\epsilon_2 = 0.8$) to generate the final dataset. In Tab. [7](#page-12-1) we ablate the complete design choices for the two-stage temporal grounding approach, including the filtering threshold, the position of maximal alignment score in each step segment, and the duration of time allocated to each step. We can observe that setting the maximum similarity as the starting timestamp of the step with a constant duration brings the best performance.

Prompt	HT-Step \uparrow R@1
$\langle x1 \rangle$: I will give you an automatically recognized speech with timestamps from a video segment that is cut from a long video. $\langle x2 \rangle$: The speaker in the video is teaching the audience to do something. $\langle x3 \rangle$: Your task is to summarize the key steps in order. $(x6)$: Output only the numbered key steps without timestamps. $(x8)$: Here is this automatically recognized speech: $\langle ASR \ transcript \rangle$	38.8
$\langle x1 \rangle$ $\langle x2 \rangle$ $\langle x3 \rangle$ $\langle x4 \rangle$: Each step should be short and concise phrase. $\langle x6 \rangle$ $\langle x8 \rangle$	38.8
$\langle x1 \rangle$ $\langle x2 \rangle$ $\langle x3 \rangle$ $\langle x4 \rangle$ $\langle x5 \rangle$: Do not output colloquial sentences in the speech. $\langle x6 \rangle$ $\langle x8 \rangle$	39.5
$\langle x1\rangle$ $\langle x2\rangle$ $\langle x3\rangle$ $\langle x4\rangle$ $\langle x5\rangle$ $\langle x6\rangle$ $\langle x7\rangle$: The number of steps of your output should be between zero step and four steps. $\langle x8 \rangle$	40.3

Table 6. Ablation of prompts. We experiment with various prompts to guide the LLM in generating descriptive steps on a 61k subset of HTM-370K videos for training. We apply an identical temporal grounding approach, train the model only on the resulting subset, and then evaluate on HT-Step. $\langle xi \rangle$ refers to different prompt contents (with the specific contents being indicated in the form of $\langle xi \rangle$:...., when $\langle xi \rangle$ first appears), where i ranges from 1 to 8.

Method	ϵ_2 pos Δ_{sec}	center	center	center $\begin{array}{c cccccc}\nX & X & 6 & 8 & 10 & 6 & 8\n\end{array}$	start start	start	center	center	0.8 center
HT-Step \uparrow R@1				36.0 35.7 37.6 42.6 43.0 44.0 35.8 35.6					36.6

Table 7. Ablation of choices in further refinement. We use Step-ASR relation to obtain pseudo-labels. The texts used for training the model here are only HowToStep (S). X means we do not fix the duration for each generated step, but find the start-end timestamp from the center point as we do in the approximate estimation stage.

C. Qualitative Results

C.1. ASR Transformation Example

In Fig. [6,](#page-13-0) we provide an example of using an LLM with the prompt to transform ASR transcripts into descriptive steps. Comparing ASR transcripts with descriptive steps, we can observe that even ASR transcripts with completely accurate recognition can have issues of semantic ambiguity and redundancy. For instance, in Fig. 2a, sentences in orange are irrelevant to the task at hand, while those highlighted in blue exhibit issues with unclear references. Additionally, a segment of speech recognized by the ASR system often contains many important actions corresponding to different time intervals in the video, which is a significant source of misalignment between text and video. Conversely, the descriptive steps generated by the LLM are more concise and clear, eliminating the redundant information in the ASR transcripts and articulating the action procedure a unified form.

C.2. Alignment Visualization

In Fig. [7,](#page-14-0) we provide a visualization example of alignment for texts from various sources, including narrations from WhisperX transcripts, procedural steps from Wikihow, and descriptive steps in HowToStep. Fig. [7](#page-14-0) clearly shows that narrations often suffer from severe misalignment with video content, while the steps in Wikihow are very generic and frequently inconsistent with the activities shown in the video, as color-coded with yellow. However, our proposed HowToStep not only describes actions highly relevant to the video content using concise language but also demonstrates better temporal alignment after going through the two-stage temporal grounding process. From Fig. [7,](#page-14-0) it is evident that the majority of steps in the HowToStep are harmoniously aligned with the video content. However, the temporal misalignment of the sentences "Remove toast from the oven." and "Toast bread on the other side." in Fig. 3b arises due to obstructions, coupled with the challenge of distinguishing between fine-grained action such as taking out toast and flipping toast over.

(a) Narrations

- 1. Bring water to a boil and make simple syrup.
- 2. Dissolve granulated white sugar in water.
- 3. Slice and juice lemons.
- 4. Whisk mixture well.
- 5. Add simple syrup to taste, making the lemonade sweeter or less sweet as desired.
- 6. Add lemon juice and pink Moscato to a mixture.
- 7. Pour in Moscato lemonade.

(b) HowToStep

Figure 6. A complete example of the ASR transformation. (a) The ASR transcript recognized by WhisperX. (b) Descriptive steps transformed from the ASR transcript by the LLM.

D. Limitations and Ethical Concerns

As a proposal-free method for video-text alignment, we do not explicitly generate the temporal window for each narration or procedural step, and only obtain it via post-processing the alignment score matrix. In addition, we pay more attention to whether the most possible timestamp for each text falls into the ground truth temporal window since the start-end boundary of the text is not used under the Recall@1 metric compared with Recall@IoU metrics. For ethical concerns, we are aware that the public instructional video dataset and the knowledge of large language models may have gender, age, geographical, or cultural bias.

Figure 7. Examples of alignment visualization. *(Left)*: The temporal distribution of descriptive steps in HowToStep and narrations in ASR transcripts, as well as their alignment with video frames. *(Right)*: The procedural steps collected from an external knowledge base (Wikihow) to complete the task in the video without timestamps. For procedural steps in Wikihow, green timelines indicate the steps that can be aligned with the visual signals, while yellow timelines represent steps that are not visually alignable.