Grounding Partially-Defined Events in Multimodal Data

Kate Sanders[♠*] **Reno Kriz**[♠*] **David Etter**[♠*] **Hannah Recknor**[♠]
Alexander Martin[♠♡] **Cameron Carpenter**[♠] **Jingyang Lin**[♡] **Benjamin Van Durme**[♠]
[♠]Johns Hopkins University [♡]University of Rochester
`{ksande25, rkriz1, detter2, vandurme}@jhu.edu`

Abstract

How are we able to learn about complex current events just from short snippets of video? While natural language enables straightforward ways to represent under-specified, partially observable events, visual data does not facilitate analogous methods and, consequently, introduces unique challenges in event understanding. With the growing prevalence of vision-capable AI agents, these systems must be able to model events from collections of unstructured video data. To tackle robust event modeling in multimodal settings, we introduce a multimodal formulation for *partially-defined* events and cast the extraction of these events as a three-stage span retrieval task. We propose a corresponding benchmark for this task, MultiVENT-G, that consists of 14.5 hours of densely annotated current event videos and 1,168 text documents, containing 22.8K labeled event-centric entities. We propose a collection of LLM-driven approaches to the task of multimodal event analysis, and evaluate them on MultiVENT-G. Results illustrate the challenges that abstract event understanding poses and demonstrates promise in event-centric video-language systems.

1 Introduction

Event recognition is critical to how we understand the world. Evidence suggests that even prelinguistic infants demonstrate a capacity for recognizing discrete events in real-world stimuli (Wynn, 1996; Yates et al., 2022). Natural language reflects this cognitive inclination towards event modeling through the various linguistic structures tied to event representations (Pustejovsky, 2005; Bohnemeyer et al., 2007), and significant work considers how to model events conveyed through these structures formally (Schein, 2013) and through data-driven approaches (Li et al., 2022b).

In comparison, there is less work considering the relationship between these event models and the natural, temporal stimuli from which they are derived. A handful of tasks have been proposed, but rely on highly limited ontologies with events that can be fully depicted in seconds (Chen et al., 2021; Sadhu et al., 2021). In contrast, event modeling systems for text can operate at a seemingly arbitrary level of event complexity, an ability enabled by the event-centric structure of natural language; for example, we can simply write a sentence like

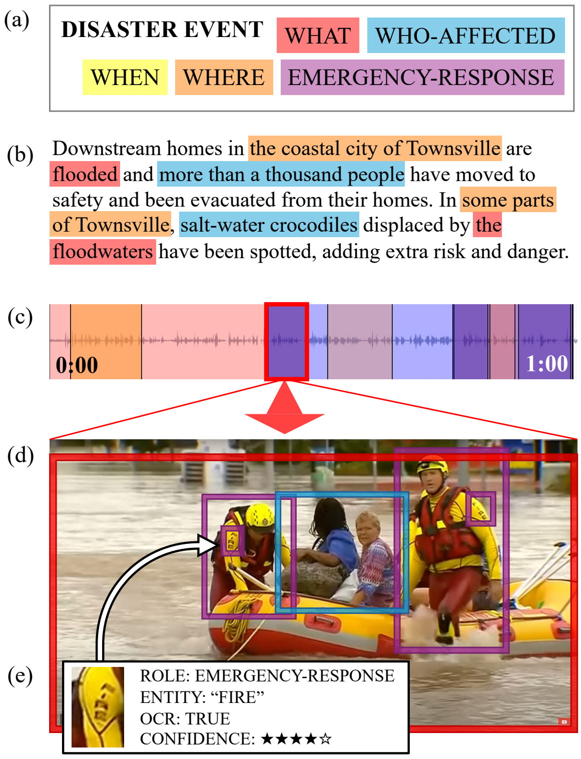

(a)
DISASTER EVENT
WHAT
WHO-AFFECTED
WHEN
WHERE
EMERGENCY-RESPONSE
(b)
Downstream homes in the coastal city of Townsville are flooded and more than a thousand people have moved to safety and been evacuated from their homes. In some parts of Townsville, salt-water crocodiles displaced by the floodwaters have been spotted, adding extra risk and danger.
(c)
0:00
1:00
(d)
(e)
ROLE: EMERGENCY-RESPONSE
ENTITY: "FIRE"
OCR: TRUE
CONFIDENCE: ★★★★☆

Figure 1: In MultiVENT-G every video-text pair is labeled with (a) an event template that guides the annotations, and annotations identifying entities that help fill these template roles at the (b) text, (c) temporal (video time stamps), and (d) spatial levels. Spatial annotations are also paired with (e) a natural language description of the visual content (or transcription of the readable text), a flag for whether the entity is natural language within the video, and confidence for how sure the annotator is that the entity relates to the event role in question.

Findings of the Association for Computational Linguistics: EMNLP 2024, pages 15905–15927
November 12-16, 2024 ©2024 Association for Computational Linguistics

"the War of 1812 lasted two years and eight months" while omitting the detail of what would theoretically be a two year and eight months-long video.

However, human understanding of most world events is founded in fractured snippets of this detailed, natural data. We regularly reason over intricate, recursive webs of multimodal information pieces, like visual-auditory data and language, to understand complicated situations. To work towards this same reasoning capability in AI systems, we consider the task of reasoning over noisy, multimodal data to extract information about events that are only partially shown in video content (temporally or spatially), or *partially-defined* events. By shifting the focus towards grounding conclusions in specific pieces of data, we are also able to work towards reliable, transparent reasoning systems.

To this end, we formally describe the relationship between pieces of multimodal data and a pre-specified event, and propose a three-stage retrieval task for empirically modeling this relationship: These stages are modeled in Figure 1 sections (b), (c), and (d+e). We introduce an extension to the MultiVENT multilingual video retrieval dataset (Sanders et al., 2024), MultiVENT-Grounded (MultiVENT-G), to serve as a benchmark for this task. MultiVENT-G consists of over 14.5 hours of densely annotated multilingual video footage and 1,168 paired text documents, consisting of 22.8K multimodal event entity annotations. Figure 1 depicts a sample data point from MultiVENT-G . We consider a collection of methods tackling each stage of this task, focusing on the employment of contemporary LLM and VLM models. We evaluate these approaches on our benchmark and provide an analysis of their comparative strengths and weaknesses.

In summary, we introduce:

1. MultiVENT-G, the first open dataset for partially-defined event extraction in multimodal data, including multilingual content annotated in detail by professional linguists.

2. Experiments comparing approaches to partially-defined event extraction on MultiVENT-G that demonstrate strong baseline results and illustrate the benefits and drawbacks of different contemporary modeling techniques on the task.

2 Related Work

2.1 Events in Video

Tzelepis et al. (2016) succinctly survey the scope of "event-based media processing" in machine learning in the 2000's and early 2010's, covering how events are defined and represented in text, audio, and vision. They reference the standard understanding of events being changes in state (Francois et al., 2005), distinguishing it from definitions of more complex events like group actions (Hakeem et al., 2004), news (Sayyadi et al., 2009), or social settings (Petkos et al., 2014). They go on to compare existing event models, differentiating them on the basis of relative and absolute temporal representation, relative and absolute spatial representation, and mereologic/causal/correlation inter-event relationship representation.

In the last decade, researchers have moved away from formal video event definitions, models, and extraction, instead focusing on downstream tasks that *involve* event understanding, but do not model it as a task or evaluate for models' ability to perform it. Action recognition (Herath et al., 2017), scene graph generation (Zhu et al., 2022), retrieval (Spolaôr et al., 2020), captioning (Amaresh and Chitrakala, 2019), Q&A (Zhong et al., 2022), and multipurpose benchmarks (Wang et al., 2024; Huang et al., 2020; Lin et al., 2023; Grauman et al., 2022; Patraucean et al., 2024) all involve events, but do not model them explicitly. In contrast to Tzelepis's organization of event models, Sanders and Van Durme (2024) argue that these implicit models generally diverge in terms of semantic and temporal complexity.

2.2 Event Extraction

Event extraction can be broadly defined as the identification of specific information in unstructured data relating to changes of state. Hogenboom et al. (2011) organize early event extraction work into data-driven approaches (Lei et al., 2005; Liu et al., 2008; Okamoto and Kikuchi, 2009), knowledge- (or expert-) driven approaches (Nishihara et al., 2009; Aone and Ramos-Santacruz, 2000; Capet et al., 2008), and hybrid approaches (Lee et al., 2003; Jungermann and Morik, 2008). Data-driven approaches resemble open-domain event extraction work, and knowledge-driven approaches resemble closed-domain work (Liu et al., 2021). They argue that data-driven methods do not sufficiently account for semantics, whereas knowledge-driven approaches are based on linguistic knowledge, but knowledge-driven methods introduce difficult modeling challenges stemming from the unstructured data involved. Meanwhile, hybrid approaches make up a large chunk of existing event extraction work: The structure of extracted events typically align with knowledge-driven methods, but the systems still take advantage of statistical approaches and the available data.

Multiple public event extraction challenges have been held over the years, including MUC (Chinchor and Robinson, 1997), NIST's TDT (Fiscus et al., 1999), and ACE (Doddington et al., 2004). These challenges involve extracting event "templates" from unstructured text documents to produce structured knowledge bases, or closed-domain event extraction tasks. Closed-domain tasks tend to break a text down into a "mention" span (describes the event), a "trigger" span (single word that best describes the event), and "argument" spans (entities that fill a specific event role). Following this setup, many closed-domain event extraction tasks like ACE are divided into four stages: Trigger detection, event identification, argument detection, and role identification. On the other hand, open-domain event extraction tasks are generally simpler, focusing on event detection and clustering. Text documents for both task types often focus on news articles and social media posts.

2.3 Video Event Extraction

While recent work in video understanding has generally avoided closed-ontology event extraction, there are a few notable exceptions: Chen et al. (2021) introduce the task of MMEE, in which a system must map news clips to passages from their corresponding text articles through a closed-domain event template. They introduce the VM2E2 dataset to facilitate the study of this task. The events considered in this task are relatively simple, generally spanning a few seconds.

Meanwhile, Sadhu et al. (2021) propose the task of VidSRL, which splits video clips into two-second segments and require models to (1) map the clips to event templates and (2) identify the relationships between the clips in terms of their event content. They introduce a corresponding dataset for this task consisting of movie clips. Again, these events typically span short time frames.

Our work differs from these efforts as it tackles partially-defined events depicted across multiple pieces of multimodal data, which as we explore in the paper, which introduces unique challenges that require new data and approaches to study effectively.

3 Partially-Defined Event Extraction

3.1 Partially-Defined Events

Generally, data collection for video benchmarks falls into one of two categories: (1) A class of events is selected and individual instantiations of those events in video are found and labeled, or (2) videos are retrieved, and then events are found and annotated within them. The events annotated in both categories are wholly defined by the videos themselves, as they do not exist outside this piece of data. On the other hand, the events in MultiVENT exist outside the data in which they are depicted. During the dataset construction process, individual current events were identified, and multiple video-text pairs were retrieved that each depict different pieces of the event, temporally and spatially, and therefore contribute different information.

We consider the Davidsonian understanding of events (Davidson, 1969); namely that (1) events are unique spatio-temporal entities and (2) they can be uniquely defined by a collection of attributes, known in event extraction literature as templates or frames. Allen (1984) goes further and describes an event as a non-homogeneous entity that exists at some place for some interval of time, meaning that events can be broken up into sub-parts. As individual data pieces in MultiVENT depict different pieces of the event, we can conclude that each provides a partial observation of some possibly empty subset of the sub-events that make up the event in question. We illustrate this concept in Figure 2.

The idea of partial observations of sub-events is explored by Hwang et al. in their work on episodic logic (Hwang and Schubert, 1993). They argue that while an event can be *defined* by one sentence, it may be *described* by another. We adopt this formulation here: While videos in most benchmarks define events, the videos in MultiVENT describe and *partially* define them. We explore the different ways videos can deviate in their partial descriptions through examples in Figure 3.

3.2 Task Formulation

So, it doesn't make sense to formulate event understanding over collections of data as a traditional event extraction problem. Instead of modeling an event as it is defined by data, we want to model it

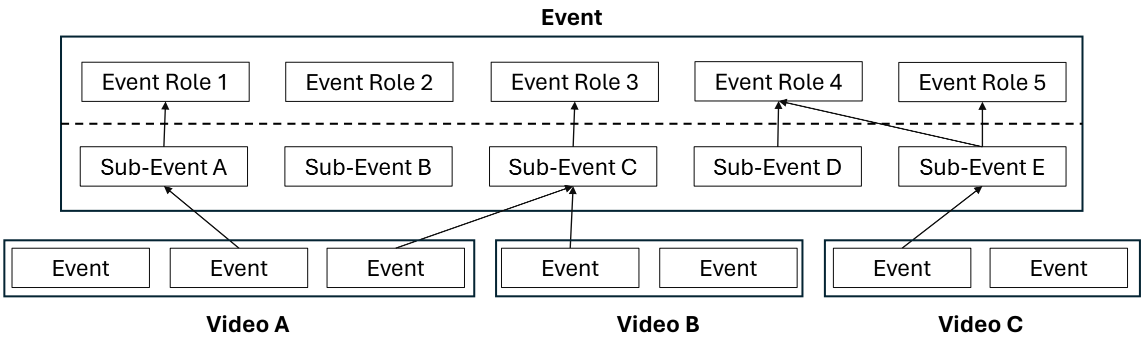
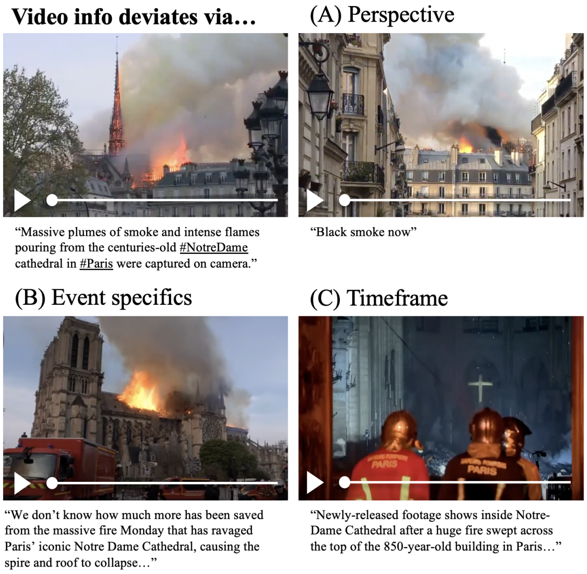


Figure 2: An illustration demonstrating the relationship between a pre-specified event and a collection of videos. Each role can simultaneously be defined by a set of event roles and by set of sub-events. Some subset of the sub-events characterize the role fillers, and some subset of the events depicted in a given video depict sub-events of the event.



"Massive plumes of smoke and intense flames pouring from the centuries-old #NotreDame cathedral in #Paris were captured on camera."

"Black smoke now"

"We don't know how much more has been saved from the massive fire Monday that has ravaged Paris' iconic Notre Dame Cathedral, causing the spire and roof to collapse…"

"Newly-released footage shows inside Notre-Dame Cathedral after a huge fire swept across the top of the 850-year-old building in Paris…"

Figure 3: Example video-description pairs depicting the Notre Dame Cathedral fire pulled from MultiVENT-G. These videos illustrate how a single event can be described differently by different video clips: (A) provides the same semantic and temporal information as the reference video, but from a different perspective. (B) shows different semantic details, such as the fire trucks pictured at the bottom of the video frame. (C) was taken later than the reference video, showing a separate temporal snippet from the event in question with changed event semantics.

as it is described by data. We cast this as a retrieval problem, where we aim to answer the question of how data influences our understanding of an event defined through the inputted template.

Input Specifically, our input is a collection of some sample of text and video data of nonzero size, and an event template which guides the event modeling. We treat the event template as the retrieval query - we query on a specific event type, defined by the template.

Output We aim to return the set of "descriptive spans" present in our input data that describe the event dictated by the inputted template. These spans are both textual and spatio-temporal, and so we explicitly decompose the event understanding task into three distinct stages:

1. Text span retrieval: Retrieve the set of descriptive spans within the text samples that describe the event under consideration, labeled with the event role they describe.
2. Temporal span retrieval: Retrieve the set of video intervals, described as start-end points, that describe the event under consideration, labeled by role.
3. Spatial span retrieval: Given an additional input variable of time point within a video, retrieve the set of spatial bounding boxes that mark the visual entities that describe the event. These should also be labeled with the template role they correspond to.

As shown above, we do not explicitly include template filling as part of the task. This is because, as the events are not defined by the input data, there is no meaningful function to map between input content and the true underlying labels that does not involve modeling for substantial unknowable noise. We instead focus on retrieving useful information within the provided data that can then be used by systems to make meaningful hypotheses about the underlying event, better matching how humans learn and understand partially-defined events.

3.3 Metrics

For this task, we consider five metrics: Precision, recall, F1, CEAF-RME, and IoU. We outline these and their implementations below.

Precision, recall, and F1 We first implement span-based generic retrieval scores, in which we consider the granular units of each domain (characters, seconds, and pixels) as the entities over which we are doing retrieval. Let R_f be the set of ground truth entities for role filler f, and S_f be the set of predicted entities. Then, our corresponding metrics can be formalized as

$$P_0 = \frac{1}{|F|} \sum_{f \in F} \frac{|R_f \cap S_f|}{|S_f|} \quad R_0 = \frac{1}{|F|} \sum_{f \in F} \frac{|R_f \cap S_f|}{|R_f|}$$

$$F_0 = \frac{2 P_0 R_0}{P_0 + R_0}$$

CEAF-RME For text evaluation, we implement Chen et al. (2022)'s modification to Du et al. (2020a)'s template filling metric CEAF-REE, CEAF-RME. CEAF-RME uses the Kuhn-Munkres maximum bipartite matching algorithm (Kuhn, 1955; Munkres, 1957) to map predicted spans to ground truth annotations and then report the resulting precision, recall, and F1 scores. However, it relaxes the definition of "map" to allow for partially overlapping entities.

Role-Filling IoU For temporal and spatial evaluations, we implement 2D and 3D versions of IoU at 0.5, 0.7, and 1, treating the temporal/spatial annotations for one role as a single entity annotation. We define our metric as

$$R\,(\text{IoU} = k) = \frac{1}{|F|} \sum_{f \in F} \min\left(1, \frac{|R_f \cap S_f|}{k\,|R_f \cup S_f|}\right)$$

4 MultiVENT-G

4.1 Videos

We select a 1,168 video subset of the MultiVENT dataset, a collection of multi-format, multilingual videos depicting 260 current events paired with natural language descriptions and aligned Wikipedia articles. The mean length of these videos is 83.7 seconds. Our selected videos are distributed across five languages (Arabic, Chinese, English, Korean, and Russian) and four news genres (emergencies, political content, social events, and science/business coverage). The videos are organically produced for speakers of these languages, and can include multiple videos (up to ten) depicting the same event.

Table 1: Examples of spatial entity labels before and after data cleaning using GPT, done with the goal of making long human-written labels concise and uniform with respect to the rest of the dataset.

Original label	**New label**
policeman, security, or another federal official dressed in similar attire	law enforcement
lights flickering, presumable due to shaking	flickering lights
residents of the area that was attacked going through the rubble	residents in rubble
grandson helping grandmother to safety	family evacuation
a firetruck plowing through a flood	firetruck in flood

4.2 Event Information

We first align each depicted event to the FrameNet template (Baker et al., 1998) that provides the best semantic match. We consolidate these templates into a set of seven categories that sufficiently covers the span of event types: Emergencies, elections, phenomenon launch or discovery, political development, political demonstrations, social events, and sports events. We adapt these templates to the visual domain by removing event roles that cannot be immediately shown in visual content, and occasionally adding roles that are important to understanding the events visually. For each text-video pair in our MultiVENT subset, we ground the corresponding event roles in three dimensions: Text, time, and space. Below, we describe this grounding in detail, and provide the full ontology in Table 10.

Textual annotations. We map each event role to the (possibly empty) subset of continuous spans within the text description string that provide information about the event role in question.

Temporal annotations. We identify time spans within the video content during which a visible entity, entities, or interaction between entities provides information about the event role. We identify the start and end times, and if the same entity reappears later in the video, we annotate that time point as a separate segment mapping to the same role. We map these time segments to their corresponding event role labels.

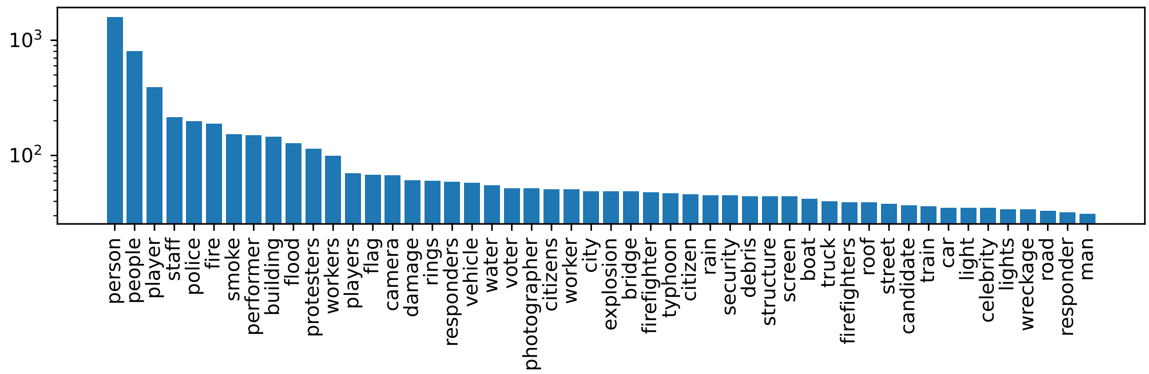


Figure 4: The distribution, using a logarithmic scale, of spatial entity labels (post-data cleaning) in MultiVENT-G. The labels reflect the domain of annotated content, e.g., as many videos depict emergencies, “police" and “fire" labels are common.

Table 2: Distribution of annotated video types in MultiVENT-G, partitioned by language and semantic domain. As shown, the most videos are English, but this set still makes up a minority of the dataset in total.

Template	**AR**	**ZH**	**EN**	**KO**	**RU**	**Total**
Emergency	99	69	121	118	81	487
Election	0	17	23	20	5	65
Political	17	34	60	33	33	177
Demonstration	9	30	31	18	29	117
Social	0	33	58	20	21	132
Sports	0	6	50	0	5	61
Discovery	0	45	71	0	13	129
Total	**125**	**234**	**414**	**208**	**187**	**1168**

Table 3: Statistics corresponding to the raw annotations before and after post-processing (but after quality filtering).

Annotation	**25%**	**50%**	**75%**	**Max**
Annotation Counts per Video				
Text	2	5	9	105
Temporal	2	4	10	223
Spatial (Vis)	1	2	7	249
Spatial (OCR)	0	2	7	72
Text + Spatial	**7**	**14**	**23**	**251**
Span Sizes				
Text (char)	5	9	17	180
Temporal (sec)	2	4	8	186
Spatial width (%)	11	27	59	100
Spatial height (%)	22	42	70	100
OCR (char)	4	7	13	182
Post-Processed Statistics				
Temporal count	1	3	6	32
Temporal length (sec)	4	7	19	186

Spatial annotations. To spatially ground the event-relevant visual entities, for every temporal span-event role pair we select one representative frame from the temporal span in which the visual entity or entities are clearly visible, and draw a bounding box around the relevant content. If two entities corresponding to the same role contain negligible minimal space between them, they may occupy the same bounding box.

Entity metadata. For each spatial entity annotated in the previous section, alongside the event role name we assign a set of corresponding metadata labels to provide additional semantic information. Specifically, we include (1) a short, natural language description of the entity. This is recorded in English unless the entity is OCR content, in which case it is written as a direct transcription in the language it appears in. (2) We then note whether or not the entity in question is OCR content. (3) We include a human confidence score indicating how certain a human is that the entity in question is related to the corresponding event role. We include this confidence score because visual content is often ambiguous, and work suggests that human confidence scores are often a sound method for quantifying the clarity of such data (Sanders et al., 2022). This way, we avoid producing overly conservative annotations that miss key information that could help a model to identify an event.

4.3 Annotations

We recruit a team of professional linguists to annotate the video content. First, we train annotators through an hour-long seminar describing the task, and then another hour-long tutorial session during which annotators annotate a test video-text pair with “gold" annotations determined by the authors. This test annotation task is returned to the authors to be scored, and feedback is provided. Once annotators annotate the test task with a sufficient overall F1 score compared to the gold annotations, they are granted access to begin annotating videos in their preferred language. Annotators are encouraged to ask each other and the authors questions, and they are provided with a 20-page annotation manual and tutorial videos as reference material. Main instructions from the manual describing the task are included in Appendix C. All videos are annotated up to the 60-second mark.

4.4 Data Cleaning

The natural language descriptions labeling spatial spans have different levels of detail depending on the annotator. After stripping whitespace and converting characters to lowercase, there are 1964 distinct labels for 8299 visual entities. The 90th percentile length is 23 characters, but the maximum is 168 characters. The 90th percentile word count is 2, but the maximum is 29. To adjust these longer descriptions to better serve as entity labels for classification, we use GPT-3.5 to reduce the length of each description over 3 words, accounting for 487 distinct labels. We take the first phrase returned by GPT. We include a sample of the replaced descriptions in Table 1. The resulting set consists of 2484 distinct labels. The distribution of spatial labels is illustrated in Appendix B, and we include the prompt used for cleaning in Figure 6.

We also aggregate timeline annotations such that, for any label, two overlapping or adjacent timeline annotations are merged into a single segment.

4.5 Dataset Statistics

In total, our dataset consists of 8.4K textual annotations, 4.9K temporal annotations, and 14.4K spatial annotations (8.3K purely visual and 6.1K OCR) for a total of 27.6K labels, or 22.8K labeled event-relevant entity instances. We include details regarding annotated video categories and annotation statistics in Table 2 and Table 3.

5 Experiments

The three-stage task introduced in Section 3 is depicted in Figure 5. The task is difficult, as it requires extracting complex information from multiple modalities across highly varied domains. Therefore, we propose a collection of approaches that leverage the generalizability and high-level reasoning abilities of LLMs and VLMs to the three stages of the task. Below we provide an overview of their implementation and differences, as well as quantitative results comparing them on the three task stages using MultiVENT-G.

Table 4: Performance of various models evaluated on the text span retrieval task. We report precision, recall, and F1 scores and the CEAF-RME metrics as described in section 3. ‡ indicates the model was prompted with an in-context learning prompt created independently of the MultiVENT-G dataset.

Method	**P$_0$**	**R$_0$**	**F$_0$**	**P$_C$**	**R$_C$**	**F$_C$**
LLaMA 2	79.1	13.8	23.4	56.3	13.3	21.6
GPT-3.5	83.3	43.7	57.2	74.7	38.2	50.6
GPT-4o	83.3	**56.4**	**67.2**	77.1	**51.5**	**61.8**
LLaMA 2‡	66.7	21.3	32.3	43.3	20.4	27.8
GPT-3.5‡	77.8	46.4	58.1	72.0	42.6	53.5
GPT-4o‡	**84.1**	51.6	63.9	**79.1**	48.1	59.8

Table 5: Performance of various models evaluated on the temporal span retrieval task.

	P$_0$	**R$_0$**	**F$_0$**	**IoU$_{.5}$**	**IoU$_{.7}$**
TC	45.67	28.77	27.53	37.07	29.73
TC-C	**50.51**	**32.38**	**33.36**	**47.37**	**37.44**
TC-VG	47.50	24.72	25.66	35.00	27.25

Table 6: Performance of the detected entity mapping and caption grounding approaches on the spatial span retrieval task. We report Role Filling IoU as described in section 3, and additionally the modified CEAF-RME metrics described in subsection 5.3, P$_{C*}$/R$_{C*}$/F$_{C*}$. IV denotes InternVL, L denotes LLaVA, D denotes Grounding-DINO, and G denotes GLIP. P, R, and F scores do not change with grounding models as they only measure the quality of the captioners.

Method	**P$_{C*}$**	**R$_{C*}$**	**F$_{C*}$**	**IoU$'_{.3}$**	**IoU$'_{.5}$**	**IoU$'_{.7}$**
IV2B+D	**78.1**	14.9	25.0	3.5	3.0	2.6
IV2B+G	**78.1**	14.9	25.0	8.5	7.3	6.4
IV4B+D	58.8	30.3	**40.0**	7.9	6.7	5.8
IV4B+G	58.8	30.3	**40.0**	15.2	13.1	11.4
L7B+D	52.9	**31.4**	39.5	15.2	13.4	12.0
L7B+G	52.9	**31.4**	39.5	**27.2**	**23.8**	**21.1**

5.1 Text Span Retrieval

We cast the span extraction problem as an instance of the original dataset annotation task. Provided with the text description and the template, we ask the model to retrieve each segment of text that helps to answer the provided template role. [1] We attempt a zero-shot and in-context learning versions

---

[1] We include all LLM prompts in the appendix.

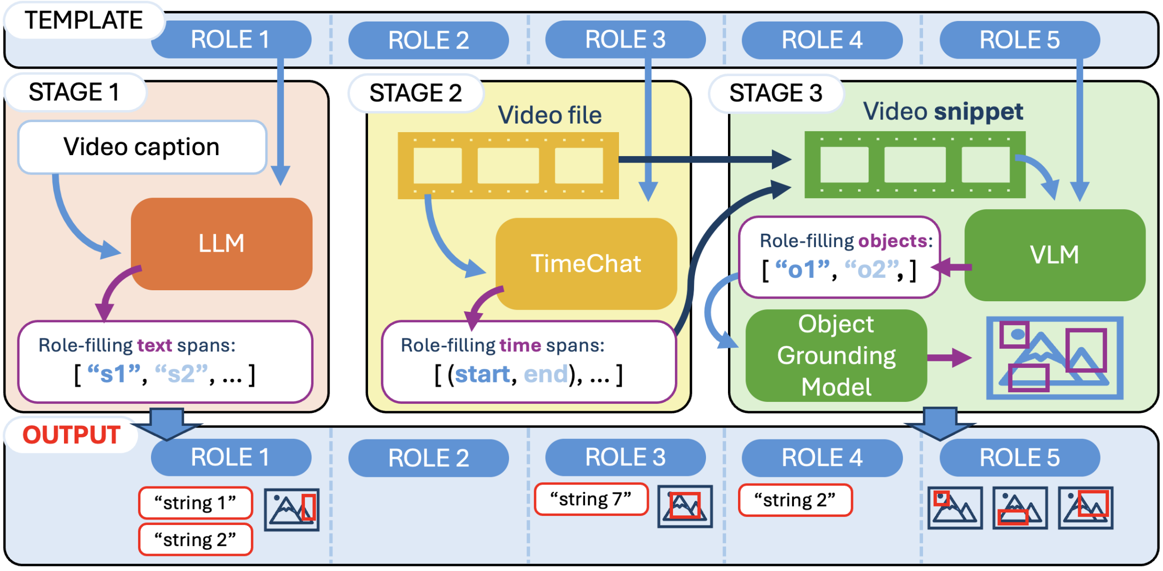


Figure 5: The complete partially-defined event understanding task, broken down into three stages. Stage 1 retrieves relevant text spans, stage 2 retrieves relevant temporal spans, and stage 3 retrieves relevant spatial spans. The output of computing these sub-tasks in sequence is a filled event template using both textual and spatio-temporal evidence from the video-language data.

Table 7: OCR results. Reported numbers are the retrieval rates for 50%+ and 100% of the relevant strings annotated in the videos, partitioned by writing system.

	AR	**EN**	**KO**	**RU**	**ZH**
			IoU$^*_{0.5}$		
Paddle	4.59	78.94	47.68	25.66	84.81
EasyOCR	74.23	75.27	76.20	69.45	73.51
			IoU$^*_{1.0}$		
Paddle	0.	60.17	36.09	08.33	55.69
EasyOCR	51.03	55.44	52.96	41.10	47.85

of the task. For the in-context learning task, for each queried event template role we provide two sample outputs taken from data not included in MultiVENT-G. For this approach, we test GPT-3.5, GPT-4o (Achiam et al., 2023), and LLaMA 2 7B (Touvron et al., 2023).

We evaluate these methods on the task of text evidence retrieval, and report results in Table 4. We find that most of the LLMs perform relatively well on the task, and do not benefit substantially from few-shot prompting. For some of the models, few-shot prompting hurts performance. High recall possibly indicates longer retrieved spans, potentially full sentences, whereas precision indicates that single-word spans were likely more frequent.

5.2 Temporal Span Retrieval

Temporal span retrieval is difficult in that it requires the model to return time stamps, which is challenging for most systems. We introduce a suite of finetuned video language models based on the TimeChat (Ren et al., 2024) architecture. We train TimeChat on a variety of settings: TimeChat Base (TC) – the original model from (Ren et al., 2024), TimeChat Charades (TC$_c$) – the original checkpoint tuned on Charades (Zhang et al., 2019), and TimeChat Video Grounding (TC$_{vg}$), tuned on four temporal video grounding datasets (Hendricks et al., 2017; Zhang et al., 2019; Oncescu et al., 2021; Zala et al., 2023).

We evaluate these methods on the task of temporal retrieval using the MultiVENT-G dataset. We report results in Table 5. We find that VideoLLMs are capable of generalizing to the temporal retrieval task when it matches the task of temporal video grounding observed during instruction tuning. We see the best model in performance when the VideoLLM undergoes additional instruction tuning for the Charades (Zhang et al., 2019). However, when the VideoLLM is tuned further on additional temporal video grounding data, it loses its ability to generalize to MultiVENT-G. Traditional temporal video grounding focuses on entity-specific tasks, but the MultiVENT-G ontology covers a broader event spectrum, some of which are not human-centric and out-of-distribution from the training data. We offer a further breakdown of the performance of the temporal retrieval task across the languages and template types in subsection A.1.

5.3 Spatial Span Retrieval

We employ a two-step process for spatial span retrieval. (1) Given a frame from the video and an event template, we instruct a VLM to identify short phrases within the image that help to answer the template questions. We test LLaVA 1.5 7B (Liu et al., 2023) and two sizes of InternVL (Chen et al., 2024) for this step. (2) Then, given the descriptive phrases output by the VLM, we use a phrase grounding model to bound the relevant entities in the image. For this, we use MM-Grounding-DINO (Zhao et al., 2024) and a GLIP architecture (Li et al., 2022a) trained on a collection of detection datasets (Shao et al., 2019; Kamath et al., 2021; Sharma et al., 2018; Ordonez et al., 2011).

Through the annotation protocol, one frame is annotated per entity, but not all entities are annotated in the same frame. Therefore, not all relevant information is necessarily labeled in any individual frame. To account for this, for this evaluation we modify our role-filling IoU metric such that the IoU is computed per mapped bounding box, mapping from the top-3 bounding box predictions, and denote this as IoU'. In addition to the role-filling metric, for the captioning models we additionally compute a similarity-based retrieval metric, similar to CEAF-RME, that for each role in a video computes how similar the retrieved entity captions are to the ground truth natural language entity captions across all frames. For this, we compute the CEAF-RME for the retrieved labels, but replace the span similarity metric ϕ with the output of a distilled NLU model trained on sentence pairs that computes the semantic similarity between labels.

Results are shown in Table 6. Compared to the precision and recall scores of the more traditional textual information extraction task, the VLM captioners lag slightly behind in performance. The performance drop is noticable when shifting to object grounding—this is unsurprising as the models are both smaller than VLMs and generally trained on a more limited collection of datasets.

5.4 OCR Analysis

As an additional experiment, in an attempt to identify how well relevant OCR information in the videos can be extracted by contemporary systems we evaluate PaddleOCR (Du et al., 2020b) and EasyOCR (Shi et al., 2015; Baek et al., 2019) on the annotated frames of MultiVENT-G. We compute the recall for all retrieved strings that (1) overlap in bounding boxes with the ground truth and (2) correctly retrieve either at least 50% ($\text{IoU}^*_{0.5}$) or all ($\text{IoU}^*_{1.0}$) of the ground truth string. As OCR for multiple languages can appear in the same video, we only compare the predictions against strings written with the same writing system.

Results are reported in Table 7. EasyOCR is able to retrieve approximately 50% of the full relevant strings per language, indicating that current OCR systems are capable of retrieving a significant amount of event-centric text, and that there is still room for improvement.

6 Conclusion

In this paper we explore the problem of partially-defined event extraction in noisy, multimodal content, and propose a multimedia event formulation for tackling it. We subsequently introduce MultiVENT-G, a corresponding three-stage event extraction benchmark consisting of densely annotated news content building on the MultiVENT dataset, and a set of potential methods for peforming the task stages. We report method performance on this benchmark, comparing zero-shot/few-shot LLM based methods to more traditional fine-tuned approaches. This paper marks an important step towards robust AI agents that can synthesize complex amalgamations of natural stimuli and processed information with human-level ability.

In future work, we hope to develop comprehensive systems that can address each stage of the event extraction task in tandem, allowing the outputs for each stage to be conditioned on the intermediate states and outputs of the other two stages. We believe that incorporating multilingual OCR systems into our pipeline would also improve performance, especially for videos not taken in predominantly English-speaking countries. Finally, while we introduce a preliminary exploration of partially-defined events in visual data, there is a wide range of ideas left to explore further on this topic, with the goals of better performance on event-centric vision benchmarks and a better understanding of human event understanding.

Limitations

Below, we consider limitations and ethical considerations within the paper.

Dataset The MultiVENT-G dataset has been carefully annotated by speakers of the five target languages, but annotators are not immune to human error. Ideally, we would include multiple rounds of quality checks to ensure that all annotations are accurate. Furthermore, some aspects of the annotation task are subjective in nature, as complex visual data is inherently noisy. We attempt to account for this by including confidence judgments for spatial annotations. The MultiVENT-G dataset is smaller than some contemporary video datasets, due to the intensive time and monetary costs of annotating a dataset at a sufficient level of detail. We argue that as foundational models continue to grow in prominence, small, well-annotated evaluation datasets will become critical for analyzing the performance of such systems on complex tasks.

Experiments VideoLLMs, like TimeChat (Ren et al., 2024), were selected as the baseline for temporal span retrieval due to their strong ability to generalize to unseen data. However, it is common consensus in the literature that LLMs struggle with the tokenization of numeric data (Golkar et al., 2023; Singh and Strouse, 2024; Spathis and Kawsar, 2023). Ren et al. (2024) also report the difference in performance between TimeChat and task-specific and video-centric models between 5-7 pts in R@1 IoU. We leave the exploration of stronger video grounding of VideoLLMs and task-specific models to future work.

The experiments of the three task stages were conducted independently due to the complexity and general difficulty of the task. In future work, we hope to develop end-to-end systems that can simultaneously address these three task stages.

As with any task involving real-world content, there is potential for abuse. We strongly encourage researchers to be mindful of AI system biases that may arise when evaluating on or using this dataset to build systems.

The original MultiVENT dataset is licensed under CC-BY 4.0. Our work builds on the ideas introduced in the MultiVENT publication, in the same spirit of multilingual, multimodal information retrieval and extraction.

Acknowledgments

We thank Frank Ferraro for his contributions to the task formulation. Alexander Martin was also supported in part by the Goergen Institute for Data Science at the University of Rochester. We would also like to thank the many annotators who contributed to the dataset.

References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

James F Allen. 1984. Towards a general theory of action and time. *Artificial intelligence*, 23(2):123–154.

M. Amaresh and S. Chitrakala. 2019. Video captioning using deep learning: An overview of methods, datasets and metrics. In *2019 International Conference on Communication and Signal Processing (ICCSP)*, pages 0656–0661.

Chinatsu Aone and Mila Ramos-Santacruz. 2000. Rees: a large-scale relation and event extraction system. In *Sixth applied natural language processing conference*, pages 76–83.

Youngmin Baek, Bado Lee, Dongyoon Han, Sangdoo Yun, and Hwalsuk Lee. 2019. Character region awareness for text detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 9365–9374.

Collin F Baker, Charles J Fillmore, and John B Lowe. 1998. The berkeley framenet project. In *COLING 1998 Volume 1: The 17th International Conference on Computational Linguistics*.

Jürgen Bohnemeyer, Nicholas J Enfield, James Essegbey, Iraide Ibarretxe-Antuñano, Sotaro Kita, Friederike Lüpke, and Felix K Ameka. 2007. Principles of event segmentation in language: The case of motion events. *Language*, pages 495–532.

Philippe Capet, Thomas Delavallade, Takuya Nakamura, Agnes Sandor, Cedric Tarsitano, and Stavroula Voyatzi. 2008. A risk assessment system with automatic extraction of event types. In *Intelligent Information Processing IV: 5 th IFIP International Conference on Intelligent Information Processing, October 19-22, 2008, Beijing, China 5*, pages 220–229. Springer.

Brian Chen, Xudong Lin, Christopher Thomas, Manling Li, Shoya Yoshida, Lovish Chum, Heng Ji, and Shih-Fu Chang. 2021. Joint multimedia event extraction from video and article. *arXiv preprint arXiv:2109.12776*.

Yunmo Chen, William Gantt, Weiwei Gu, Tongfei Chen, Aaron Steven White, and Benjamin Van Durme. 2022. Iterative document-level information extraction via imitation learning. *arXiv preprint arXiv:2210.06600*.

Zhe Chen, Jiannan Wu, Wenhai Wang, Weijie Su, Guo Chen, Sen Xing, Muyan Zhong, Qinglong Zhang, Xizhou Zhu, Lewei Lu, et al. 2024. Internvl: Scaling up vision foundation models and aligning for generic visual-linguistic tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 24185–24198.

Nancy Chinchor and Patricia Robinson. 1997. Muc-7 named entity task definition. In *Proceedings of the 7th Conference on Message Understanding*, volume 29, pages 1–21.

Donald Davidson. 1969. The individuation of events. In *Essays in honor of Carl G. Hempel: A tribute on the occasion of his sixty-fifth birthday*, pages 216–234. Springer.

George R Doddington, Alexis Mitchell, Mark A Przybocki, Lance A Ramshaw, Stephanie M Strassel, and Ralph M Weischedel. 2004. The automatic content extraction (ace) program-tasks, data, and evaluation. In *Lrec*, volume 2, pages 837–840. Lisbon.

Xinya Du, Alexander M Rush, and Claire Cardie. 2020a. Grit: Generative role-filler transformers for document-level event entity extraction. *arXiv preprint arXiv:2008.09249*.

Yuning Du, Chenxia Li, Ruoyu Guo, Xiaoting Yin, Weiwei Liu, Jun Zhou, Yifan Bai, Zilin Yu, Yehua Yang, Qingqing Dang, et al. 2020b. Pp-ocr: A practical ultra lightweight ocr system. *arXiv preprint arXiv:2009.09941*.

Jon Fiscus, George Doddington, John Garofolo, and Alvin Martin. 1999. Nist's 1998 topic detection and tracking evaluation (tdt2). In *Proceedings of the 1999 DARPA broadcast news workshop*, pages 19–24.

Alexandre RJ Francois, Ram Nevatia, Jerry Hobbs, Robert C Bolles, and John R Smith. 2005. Verl: an ontology framework for representing and annotating video events. *IEEE multimedia*, 12(4):76–86.

Siavash Golkar, Mariel Pettee, Michael Eickenberg, Alberto Bietti, Miles Cranmer, Geraud Krawezik, Francois Lanusse, Michael McCabe, Ruben Ohana, Liam Parker, Bruno Régaldo-Saint Blancard, Tiberiu Tesileanu, Kyunghyun Cho, and Shirley Ho. 2023. xval: A continuous number encoding for large language models. *Preprint*, arXiv:2310.02989.

Kristen Grauman, Andrew Westbury, Eugene Byrne, Zachary Chavis, Antonino Furnari, Rohit Girdhar, Jackson Hamburger, Hao Jiang, Miao Liu, Xingyu Liu, Miguel Martin, Tushar Nagarajan, Ilija Radosavovic, Santhosh Kumar Ramakrishnan, Fiona Ryan, Jayant Sharma, Michael Wray, Mengmeng Xu, Eric Zhongcong Xu, Chen Zhao, Siddhant Bansal, Dhruv Batra, Vincent Cartillier, Sean Crane, Tien Do, Morrie Doulaty, Akshay Erapalli, Christoph Feichtenhofer, Adriano Fragomeni, Qichen Fu, Abrham Gebreselasie, Cristina González, James Hillis, Xuhua Huang, Yifei Huang, Wenqi Jia, Weslie Khoo, Jáchym Kolář, Satwik Kottur, Anurag Kumar, Federico Landini, Chao Li, Yanghao Li, Zhenqiang Li, Karttikeya Mangalam, Raghava Modhugu, Jonathan Munro, Tullie Murrell, Takumi Nishiyasu, Will Price, Paola Ruiz, Merey Ramazanova, Leda Sari, Kiran Somasundaram, Audrey Southerland, Yusuke Sugano, Ruijie Tao, Minh Vo, Yuchen Wang, Xindi Wu, Takuma Yagi, Ziwei Zhao, Yunyi Zhu, Pablo Arbeláez, David Crandall, Dima Damen, Giovanni Maria Farinella, Christian Fuegen, Bernard Ghanem, Vamsi Krishna Ithapu, C. V. Jawahar, Hanbyul Joo, Kris Kitani, Haizhou Li, Richard Newcombe, Aude Oliva, Hyun Soo Park, James M. Rehg, Yoichi Sato, Jianbo Shi, Mike Zheng Shou, Antonio Torralba, Lorenzo Torresani, Mingfei Yan, and Jitendra Malik. 2022. Ego4d: Around the world in 3,000 hours of egocentric video. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 18995–19012.

Asaad Hakeem, Yaser Sheikh, and Mubarak Shah. 2004. Caseˆ e: a hierarchical event representation for the analysis of videos. In *AAAI*, pages 263–268.

Lisa Anne Hendricks, Oliver Wang, Eli Shechtman, Josef Sivic, Trevor Darrell, and Bryan Russell. 2017. Localizing moments in video with natural language. *Preprint*, arXiv:1708.01641.

Samitha Herath, Mehrtash Harandi, and Fatih Porikli. 2017. Going deeper into action recognition: A survey. *Image and vision computing*, 60:4–21.

Frederik Hogenboom, Flavius Frasincar, Uzay Kaymak, and Franciska De Jong. 2011. An overview of event extraction from text. *DeRiVE@ ISWC*, pages 48–57.

Qingqiu Huang, Yu Xiong, Anyi Rao, Jiaze Wang, and Dahua Lin. 2020. Movienet: A holistic dataset for movie understanding. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part IV 16*, pages 709–727. Springer.

Chung Hee Hwang and Lenhart K Schubert. 1993. Episodic logic: A comprehensive, natural representation for language understanding. *Minds and machines*, 3:381–419.

Felix Jungermann and Katharina Morik. 2008. Enhanced services for targeted information retrieval by event extraction and data mining. In *Natural Language and Information Systems: 13th International Conference on Applications of Natural Language to Information Systems, NLDB 2008 London, UK, June 24-27, 2008 Proceedings 13*, pages 335–336. Springer.

Aishwarya Kamath, Mannat Singh, Yann LeCun, Gabriel Synnaeve, Ishan Misra, and Nicolas Carion. 2021. Mdetr-modulated detection for end-to-end multi-modal understanding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1780–1790.

Harold W Kuhn. 1955. The hungarian method for the assignment problem. *Naval research logistics quarterly*, 2(1-2):83–97.

Chang-Shing Lee, Yea-Juan Chen, and Zhi-Wei Jian. 2003. Ontology-based fuzzy event extraction agent for chinese e-news summarization. *Expert Systems with Applications*, 25(3):431–447.

Zhen Lei, Ling-da Wu, Ying Zhang, and Yu-chi Liu. 2005. A system for detecting and tracking internet news event. In *Advances in Multimedia Information Processing-PCM 2005: 6th Pacific Rim Conference on Multimedia, Jeju Island, Korea, November 13-16, 2005, Proceedings, Part I 6*, pages 754–764. Springer.

Liunian Harold Li, Pengchuan Zhang, Haotian Zhang, Jianwei Yang, Chunyuan Li, Yiwu Zhong, Lijuan Wang, Lu Yuan, Lei Zhang, Jenq-Neng Hwang, Kai-Wei Chang, and Jianfeng Gao. 2022a. Grounded language-image pre-training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10965–10975.

Qian Li, Jianxin Li, Jiawei Sheng, Shiyao Cui, Jia Wu, Yiming Hei, Hao Peng, Shu Guo, Lihong Wang, Amin Beheshti, et al. 2022b. A survey on deep learning event extraction: Approaches and applications. *IEEE Transactions on Neural Networks and Learning Systems*.

Jingyang Lin, Hang Hua, Ming Chen, Yikang Li, Jenhao Hsiao, Chiuman Ho, and Jiebo Luo. 2023. Videoxum: Cross-modal visual and textural summarization of videos. *IEEE Transactions on Multimedia*.

Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. 2023. Improved baselines with visual instruction tuning. *arXiv preprint arXiv:2310.03744*.

Jiangwei Liu, Liangyu Min, and Xiaohong Huang. 2021. An overview of event extraction and its applications. *arXiv preprint arXiv:2111.03212*.

Mingrong Liu, Yicen Liu, Liang Xiang, Xing Chen, and Qing Yang. 2008. Extracting key entities and significant events from online daily news. In *Intelligent Data Engineering and Automated Learning–IDEAL 2008: 9th International Conference Daejeon, South Korea, November 2-5, 2008 Proceedings 9*, pages 201–209. Springer.

James Munkres. 1957. Algorithms for the assignment and transportation problems. *Journal of the society for industrial and applied mathematics*, 5(1):32–38.

Yoko Nishihara, Keita Sato, and Wataru Sunayama. 2009. Event extraction and visualization for obtaining personal experiences from blogs. In *Human Interface and the Management of Information. Information and Interaction: Symposium on Human Interface 2009, Held as part of HCI International 2009, San Diego, CA, USA, July 19-24, 2009, Proceedings, Part II*, pages 315–324. Springer.

Masayuki Okamoto and Masaaki Kikuchi. 2009. Discovering volatile events in your neighborhood: Local-area topic extraction from blog entries. In *Information Retrieval Technology: 5th Asia Information Retrieval Symposium, AIRS 2009, Sapporo, Japan, October 21-23, 2009. Proceedings 5*, pages 181–192. Springer.

Andreea-Maria Oncescu, Joao F Henriques, Yang Liu, Andrew Zisserman, and Samuel Albanie. 2021. Queryd: A video dataset with high-quality text and audio narrations. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 2265–2269. IEEE.

Vicente Ordonez, Girish Kulkarni, and Tamara Berg. 2011. Im2text: Describing images using 1 million captioned photographs. *Advances in neural information processing systems*, 24.

Viorica Patraucean, Lucas Smaira, Ankush Gupta, Adria Recasens, Larisa Markeeva, Dylan Banarse, Skanda Koppula, Mateusz Malinowski, Yi Yang, Carl Doersch, et al. 2024. Perception test: A diagnostic benchmark for multimodal video models. *Advances in Neural Information Processing Systems*, 36.

Georgios Petkos, Symeon Papadopoulos, Vasileios Mezaris, and Yiannis Kompatsiaris. 2014. Social event detection at mediaeval 2014: Challenges, datasets, and evaluation. In *MediaEval*.

James Pustejovsky. 2005. The syntax of event structure.

Shuhuai Ren, Linli Yao, Shicheng Li, Xu Sun, and Lu Hou. 2024. Timechat: A time-sensitive multimodal large language model for long video understanding. *Preprint*, arXiv:2312.02051.

Arka Sadhu, Tanmay Gupta, Mark Yatskar, Ram Nevatia, and Aniruddha Kembhavi. 2021. Visual semantic role labeling for video understanding. *Preprint*, arXiv:2104.00990.

Kate Sanders, David Etter, Reno Kriz, and Benjamin Van Durme. 2024. Multivent: Multilingual videos of events and aligned natural text. *Advances in Neural Information Processing Systems*, 36.

Kate Sanders, Reno Kriz, Anqi Liu, and Benjamin Van Durme. 2022. Ambiguous images with human judgments for robust visual event classification. *Advances in Neural Information Processing Systems*, 35:2637–2650.

Kate Sanders and Benjamin Van Durme. 2024. A survey of video datasets for grounded event understanding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7314–7327.

Hassan Sayyadi, Matthew Hurst, and Alexey Maykov. 2009. Event detection and tracking in social streams. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 3, pages 311–314.

Barry Schein. 2013. 8 event semantics. In *Routledge Companion to Philosophy of Language*, pages 300–314. Routledge.

Shuai Shao, Zeming Li, Tianyuan Zhang, Chao Peng, Gang Yu, Xiangyu Zhang, Jing Li, and Jian Sun. 2019. Objects365: A large-scale, high-quality dataset for object detection. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 8430–8439.

Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. 2018. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2556–2565.

Baoguang Shi, Xiang Bai, and Cong Yao. 2015. An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. corr abs/1507.05717 (2015). *URL: http://arxiv.org/abs/1507.05717*.

Aaditya K. Singh and DJ Strouse. 2024. Tokenization counts: the impact of tokenization on arithmetic in frontier llms. *Preprint*, arXiv:2402.14903.

Dimitris Spathis and Fahim Kawsar. 2023. The first step is the hardest: Pitfalls of representing and tokenizing temporal data for large language models. *Preprint*, arXiv:2309.06236.

Newton Spolaôr, Huei Diana Lee, Weber Shoity Resende Takaki, Leandro Augusto Ensina, Claudio Saddy Rodrigues Coy, and Feng Chung Wu. 2020. A systematic review on content-based video retrieval. *Engineering Applications of Artificial Intelligence*, 90:103557.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

Christos Tzelepis, Zhigang Ma, Vasileios Mezaris, Bogdan Ionescu, Ioannis Kompatsiaris, Giulia Boato, Nicu Sebe, and Shuicheng Yan. 2016. Event-based media processing and analysis: A survey of the literature. *Image and Vision Computing*, 53:3–19.

Yi Wang, Yinan He, Yizhuo Li, Kunchang Li, Jiashuo Yu, Xin Ma, Xinhao Li, Guo Chen, Xinyuan Chen, Yaohui Wang, Conghui He, Ping Luo, Ziwei Liu, Yali Wang, Limin Wang, and Yu Qiao. 2024. Internvid: A large-scale video-text dataset for multimodal understanding and generation. *Preprint*, arXiv:2307.06942.

Karen Wynn. 1996. Infants' individuation and enumeration of actions. *Psychological Science*, 7(3):164–169.

Tristan S Yates, Lena J Skalaban, Cameron T Ellis, Angelika J Bracher, Christopher Baldassano, and Nicholas B Turk-Browne. 2022. Neural event segmentation of continuous experience in human infants. *Proceedings of the National Academy of Sciences*, 119(43):e2200257119.

Abhay Zala, Jaemin Cho, Satwik Kottur, Xilun Chen, Barlas Oğuz, Yasher Mehdad, and Mohit Bansal. 2023. Hierarchical video-moment retrieval and step-captioning. *Preprint*, arXiv:2303.16406.

Jingran Zhang, Fumin Shen, Xing Xu, and Heng Tao Shen. 2019. Temporal reasoning graph for activity recognition. *Preprint*, arXiv:1908.09995.

Xiangyu Zhao, Yicheng Chen, Shilin Xu, Xiangtai Li, Xinjiang Wang, Yining Li, and Haian Huang. 2024. An open and comprehensive pipeline for unified object grounding and detection. *arXiv preprint arXiv:2401.02361*.

Yaoyao Zhong, Junbin Xiao, Wei Ji, Yicong Li, Weihong Deng, and Tat-Seng Chua. 2022. Video question answering: Datasets, algorithms and challenges. *Preprint*, arXiv:2203.01225.

Guangming Zhu, Liang Zhang, Youliang Jiang, Yixuan Dang, Haoran Hou, Peiyi Shen, Mingtao Feng, Xia Zhao, Qiguang Miao, Syed Afaq Ali Shah, and Mohammed Bennamoun. 2022. Scene graph generation: A comprehensive survey. *CoRR*, abs/2201.00443.

A Additional Results

A.1 Supplementary Temporal Evaluations

In this section we discuss the results of the experiments across the multiple languages of MultiVENT-G.

Language In Table 8, there is not a large variety in deviation in scores across the language types (with the exception of Korean performing 3-5 points worse than other languages). These results are consistent across each trained model. We interpret this result to signal that the visual content of the videos must be similar across languages.

Event Type In Table 9, we do not observe the same consistency between event types that we do with languages. The best result across each model is the social split including social and sporting events. This result is intuitive as sporting and social events are human-centric activities often occurring in the training data. Meanwhile, science and technology news videos tend to involve highly abstract visual content paired with OCR information. More investigation into incorporating OCR into temporal modeling methods may provide further insight.

B LLM and VLM prompts

In this section, we provide the collection of prompts used for data cleaning and experiments outlined in section 5. The prompts listed are:

1. Figure 6: Entity label cleaning
2. Figure 7: Text span labeling
3. Figure 8: Temporal span labeling
4. Figure 9: Spatial span labeling (VLM prompt)

		TC	TC_c	TC_{vg}
EN	F1	30.32	33.73	26.57
	$\text{IoU}_{0.5}$	41.67	48.51	37.15
	$\text{IoU}_{0.7}$	34.04	38.93	29.09
RU	F1	28.83	33.31	26.76
	$\text{IoU}_{0.5}$	37.34	46.41	35.97
	$\text{IoU}_{0.7}$	29.98	35.95	27.79
CH	F1	25.74	34.03	25.07
	$\text{IoU}_{0.5}$	35.59	48.41	34.34
	$\text{IoU}_{0.7}$	27.80	38.03	26.47
KO	F1	23.07	30.83	23.11
	$\text{IoU}_{0.5}$	30.08	42.70	30.31
	$\text{IoU}_{0.7}$	23.63	33.07	23.76
AR	F1	36.65	35.38	26.34
	$\text{IoU}_{0.5}$	34.69	51.04	35.17
	$\text{IoU}_{0.7}$	28.04	41.13	27.44

Table 8: Temporal Span Results By Language

		TC	TC_c	TC_{vg}
P	F1	23.85	34.76	23.27
	$\text{IoU}_{0.5}$	49.43	48.51	32.04
	$\text{IoU}_{0.7}$	38.69	38.93	24.55
S	F1	33.39	36.69	30.07
	$\text{IoU}_{0.5}$	52.09	46.41	41.11
	$\text{IoU}_{0.7}$	42.03	35.95	32.84
E	F1	29.17	32.61	26.47
	$\text{IoU}_{0.5}$	46.14	48.41	35.60
	$\text{IoU}_{0.7}$	36.34	38.03	27.59
T	F1	22.98	26.79	22.63
	$\text{IoU}_{0.5}$	32.31	27.94	31.71
	$\text{IoU}_{0.7}$	26.00	24.76	24.84

Table 9: Temporal Span Results By Event Type. P - Political, S - Social, E- Emergency, T - Technology

Entity label cleaning

You are a data cleaning system that takes in natural language descriptions of images and shortens them to labels of visual entities for an object classification model to train on. Keeping as much meaning from the original descriptions as possible, shorten the following passages to one- to three-word image labels. Return your labels in list format.

1. <original label 1>

2. <original label 2>

3. <original label 3>

Figure 6

Text span retrieval

You are generating labels for a SQuAD style dataset, a question-answer dataset where the answers are short snippets from one of a collection of multilingual text documents about a activity. The label generation process involves two steps: Identifying potential answers to the question, and then comparing against other documents to select the most accurate answer. You are working on step one: You are provided with a question and a text document, and your job is to identify all potential answers in the text.

Your answers should only contain text from the original passage. It is good to be as concise as possible - select the smallest passages that still contain the necessary information. The text should generally be a complete phrase, e.g. write “the president” instead of “president”. For additional prepositional phrases, only include these if they add information relevant to the template, e.g. “the president of the United States”.

If there are no suitable potential answers in the text document, write N/A. Unless your response is N/A, write your answer in list format, i.e.

1. [”Answer 1”, ”Answer 2”, ...]
2. N/A
3. [”Answer 1”]
4. ...

TEXT PASSAGE: "<text passage>”

QUESTIONS: <template questions>

ANSWERS:

Figure 7

Temporal content retrieval

Localize the visual content described by the given textual query Event: <event type>, Query: <template question> in the video, and output the start and end timestamps in seconds. The output format of the predicted timestamp should be like: ’start - end seconds’. A specific example is : 20.8 - 30.0 seconds’ .

Figure 8

Spatial content retrieval

You are generating candidate answer labels for a visual QA dataset that a human will quality-check. Given the image of a <event type> and the following question, provide any answer candidates you can see in the image in list format and nothing else. If you cannot use the image to answer the question, write N/A.

Question: "<template question>”

Figure 9

C MultiVENT-G annotation instructions

C.1 Introduction

When learning about a new current event, we often search for information that helps us answer specific questions about it. For example, if learning about a recent wildfire, we might ask questions like “where was the fire”, “when did the fire take place”, and “who was affected by the fire”. Notably, the type of current event we consider will influence the set of questions we wish to answer— for instance, the sort of questions we care about when learning about a press conference are not the same as those we’d care about when learning about a wildfire.

Internet videos and their corresponding descriptions (e.g. YouTube videos) often contain rich information about current events and are used by many to keep up-to-date with news. In this task, we are interested in annotating exactly how videos and text help us answer event-based questions like those described above. You will be provided with a set of video-text pairs in a language you are an expert in via an annotation interface. Each video-text pair has already been assigned a set of relevant event-based questions called a template. **Your goal is to identify the text and visual content that would help a person answer these questions in the template.** In the following sections, we will walk you through how to annotate a video and text description to achieve this goal.

C.2 Task Overview

As mentioned in the introduction, the goal in this task is to identify the text and visual content that would help a person answer the questions in the provided template. Each video-text pair will have a corresponding template (set of relevant questions) that will be used to annotate it. Each template typically has around six questions, or template fields. In the annotation interface, these template fields are referred to with a short name such as “what”, “where”„ or “who-affected”, but each of these corresponds to a full question that can be found in the template guide located at the end of this document. You are recommended to review the template guide often and use it as a reference when you are annotating.

But, you may be asking: What sort of text and visual content are we annotating, and how do we decide whether or not it “would help” a person answer event-based questions?

We can divide our general task into three subtasks based on the three modalities of data we will be identifying and annotating:

1. Phrases in text documents
2. Segments of time in videos
3. Bounding boxes in video frames

For each modality, the general question is the same: What [text phrases/video segments/objects in this image] provide information pertaining to each template field? Sometimes, a piece of data will clearly answer a question covered by a template field. For example, in a video of a protest, you will likely see people holding signs and marching - these people clearly provide information about the “WHO" field of the “DEMONSTRATION" template (see the template guide at the end of the document).

Other times, a piece of data will provide more implicit information pertaining to a template field that can nevertheless help answer the relevant event-based question. For example, in a news report of a hurricane, the text description may include the phrase “Hurricane last Monday". While this phrase does not directly give a complete answer to the question “when did the emergency occur" (corresponding to the “WHEN" field of the ‘DISASTER" template), we would still want to label this text phrase as providing information pertaining to the “WHEN" field.

Depending on the video you are annotating, much of the visual content may be confusing, and it might not always be clear whether or not visual content is salient to a template field or not. We will cover this case in detail in the frame annotation section, but generally, you will want to annotate ambiguous content if you feel there is a nonzero chance that it pertains to a template field. This is generally not as much of an issue with text, which tends to be more direct and unambiguous.

Now we are ready to work through the full annotation pipeline, which is detailed over the next few sections of the guide.

C.3 Step 0: Review the template and data

Before annotating, in addition to reviewing the template guide, you should also review the data by reading the provided text description and watching the video (with sound). Even though we do not explicitly annotate audio in this task, hearing it yourself while reviewing the video is important for obtaining all the context necessary to interpret the data accurately.

C.4 Step 1: Text annotation

After familiarizing yourself with the data, the first annotation step is to identify all phrases in the text document that help answer any of the provided template fields. To annotate text,

1. First click on the template field that you want to label a text section with.
2. Then, just highlight the section of text that provides information about that template field. It is good to be as concise as possible - select the smallest passage that still contains all the relevant information associated with that template field. Note: the text should generally be a complete phrase, e.g. annotating “the president” instead of “president”. For additional prepositional phrases, only include these if they add information relevant to the template, e.g. “the president of the United States”.

If two phrases both help answer the same field but describe two different entities, both should be separately highlighted. Similarly, if two sections of text describe the same relevant entity but are separated by other text describing a separate entity, both sections should be highlighted separately. It is likely that you’ll come across a phrase that provides information about multiple template fields. In this case, you should highlight it multiple times (once per relevant template field).

For hashtags (e.g. #NewYork, #BTS, etc.): Please include the hashtag symbol (#) in your spans when they precede a relevant text span.

C.5 Step 2: Timeline annotation

The goal of this step is to identify and record what portions of the video provide information about the template fields. We call these video portions “time segments”, and they can each be defined as a pair of “start” and “end” time points. Specifically, you will identify a segment that contains visual information pertinent to a question, mark the start and end points that this information appears on-screen, and then label it with the template field it provides information for. Even though you’re shown the audio information in this module, you should not annotate any audio information - in this subtask, we only want to annotate visual data that appears in the video. To annotate the timeline,

1. Pause the video where you want to mark the starting point.

2. Click on the question field that matches the visual content.

3. Drag from this starting point on the timeline to the approximate endpoint.

4. To pinpoint the exact endpoint, you can then pause at the precise endpoint, and then re-drag the right side of the segment to this endpoint.

C.6 Step 3A: Frame selection

For each timeline segment that you created in step 2, you should find a frame within it that clearly displays the salient visual content that you annotated that segment for. If two segments overlap, it is fine to select one frame that satisfies both, as long as the visual content for both segments is clearly pictured in the frame. The frame can be from any point within the segment as long as it is between the identified start and end points.

C.7 Step 3B: Drawing bounding boxes

After selecting a frame that clearly depicts the relevant visual information of one or more annotated timeline segments, the final step is to draw one bounding box on that frame per timeline segment the frame corresponds to. The box should contain the entire relevant visual entity (e.g. if the visual information is a person, the entire visible portion of the person in that frame should be contained within the drawn bounding box, not just the face, etc.). Similarly, the box should not be larger than what is required to contain the visual content (e.g. if only the person's face is visible, the box should not try to contain what portion of the person's body isn't visible in the frame). You should draw one box for each time segment the frame was chosen for, so after drawing each bounding box, there should be one (or, rarely, multiple) box for each time segment you annotated. To draw a bounding box,

1. First, go to your selected frame and drag over the video player to draw a box bounding a relevant entity.

2. Letting go of the cursor will produce a gray square. Click inside it to reveal bounding box-specific options. First, if you have the frame-level timeline toggled, you will see a diamond with a line attached to it here:

3. You will want to remove this line for each box you make, which can be done by clicking on the "toggle interpolation" button here while the corresponding box is selected.

4. Then, click on the question field below the frame timeline that corresponds to the bounding box.

C.8 Step 3C: Annotating bounding box details

After drawing these boxes, you will be asked to answer three questions about each bounded entity:

1. ENTITY DESCRIPTION: Give a short description of the bounded content, ideally one or two words. When you have typed the description, click the "Add" button to save it. This is the one annotation in the task that must be manually saved. If you feel that more than one description is necessary (for example, if the bounded entity is a doctor who has a visible nametag, you ideally will add "doctor" as well as their name) then after "Add"ing the first description, type in a second description and click "Add" again.

2. IS THIS TEXT: Select "Yes" if your bounding box is an image of text, e.g. the words on a street sign. Here are examples of text that would be labeled as such in a video:

3. CONFIDENCE SCORE: Rate your confidence that the bounding box helps answer the question field you selected. More information on confidence scores can be found in the next section of the guide.

4. ADDITIONAL NOTES: This section is optional and can be used to add any additional notes that you think are important to log about the bounded entity. Feel free to leave this blank most of the time, if not always.

C.9 Confidence scores

Visual data is difficult to annotate in that there is often uncertainty about what a visual entity is and what its relationship to the event is. In this task, we consider this uncertainty in terms of saliency. Given any visual entity in a video, there is an underlying probability that the entity answers a given template question (who,what,where…).

This is the purpose of the confidence scoring for individual bounding boxes. Given a bounding box and the template question it answers, you will rate how confident you are that the bounded entity does actually help to answer the template field question on a scale from 1 to 5.

This scale roughly aligns with the probability that the bounded entity is salient. Giving a boxed entity a confidence score of 2 means that you believe there is roughly a 40% chance that the entity helps answer the template field question. This system can be considered in terms of gambling - if you had \$5, and were aiming to earn/keep as much money as possible, how many dollars would you bet that the entity answers the template question? If you were 100% certain, you would bet \$5 (and mark your confidence as 5). If you thought that it was likely, but not certain, you might bet \$4 (and give a 4/5 rating). If you thought there was a low chance, but was still possible, you might bet \$1 (1/5).

Because we are interested in collecting confidence scores, this means that you should annotate visual content that you are not certain about in the videos. Anything that looks like it may be salient should be annotated and rated accordingly. However, if you are pretty certain that something is not salient (less than 20% sure), you do not need to annotate it. This is why there is no "0" on the confidence scale.

These ratings are subjective, and so your confidence may be different than another annotator's. As long as you are rating your own confidence that the bounded content helps answer the corresponding template question, your annotation is correct.

C.10 Confidence score examples

Below, we have included some examples of confidence ratings. Note that these confidence scores are based on still images, whereas you will have the full context of the video and text, and so there is a slight difference in how you may make your certainty decisions compared to these examples.

Pretend I am annotating a video of a protest. I know the video is of a protest, but I am only provided with this single frame from the video (Figure 10).

I am confident that the people dressed in black are law enforcement officers present at the protest. Therefore, I can box them, tag them with the "LAW-ENFORCEMENT" field, and mark my confidence as 5/5.

However, I am less certain about whether the figure in the bottom left is a protester (or even a person?). I think it is fairly likely, since it looks like the shape of a person and the law enforcement officers are surrounding them, and so I'd tag

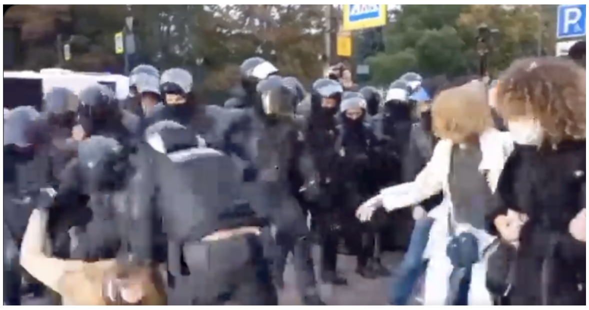


Figure 10: An example video frame used to explain confidence judgements in the annotation instructions manual.

them as a "WHO" and would probably rate my confidence as 3/5. Possibly 4/5, but definitely not 5/5 or 1/5.

Lastly, my best guess is that the people on the right of the frame are protesters, since they are near the other person I think is a protester being arrested. However, I am even less certain about these people. Perhaps the demonstration was being conducted by a single person, and these were just onlookers. Therefore, I'd tag these people as "WHO" with a confidence score of 2/5.

As you can see, all of these decisions are made based on personal knowledge and reasoning, and so they may vary slightly from person to person. This variance is perfectly okay.

C.11 Frequently asked questions

- **What language should I use for labeling bounding boxes?** If the bounded entity is a piece of actual text, please transcribe it in the original language. Otherwise, please write a brief description in English. When transcribing, you do not need to also translate the text.
- **If I want to draw bounding boxes for a group of people, should I draw one large box or individual boxes?** For groups of objects in general, unless they (a) answer different template field questions, (b) they have distinct identities that are clear from the video, and/or (c) they are significantly separated by other entities in the frame, please draw one bounding box for all of them. Otherwise, it might be preferable to draw individual bounding boxes, unless there is a significantly large number of objects present (e.g. more than 6).
- **When writing multiple labels for a bounding box, does the order that they are entered matter?** No.
- **What do I do if a single bounding box applies to multiple questions/template fields?** In this case, you should make multiple bounding boxes over the same area and tag each with a different field. This also applies for text and time segments.
- **Some text implies that an entity that would answer a template field exists, but does not directly state it. Should I annotate this text and label it with that field?** Yes. This also applies to other visual data that implies things that would answer template fields.
- **What if there isn't any text for a video-text pair?** In that case, please leave the text annotation field blank and move on to the next section.

D Ontology

Here we provide the MultiVENT-G ontology in Table 10.

E LLM Samples

We provide (a) a collection of sample outputs from the text labeling task in Figure 11 and (b) the few-shot samples provided for ICL prompting in section 5:

1. Figure 12: Disasters
2. Figure 13: Elections
3. Figure 14: Political developments
4. Figure 15: Social events
5. Figure 16: Sports
6. Figure 17: Discoveries/launches
7. Figure 18: Demonstrations

Input prompt

```
QUESTIONS:
1. ”What emergency/disaster is occurring/has occurred?”
2. ”Where is the emergency/disaster occurring?”
3. ”When did the emergency/disaster occur?”
4. ”Who was affected by the emergency/disaster?”
5. ”Who is responding to assist those affected by the emergency/disaster?”

TEXT PASSAGE: ”The opening of the floodgates of the Ross River dam in Queensland created what
Australia’s weather bureau called ”dangerous and high velocity flows”. With the dam at more than 300
percent capacity, engineers said they had no option.

Downstream homes in the coastal city of Townsville are flooded and more than a thousand people have
moved to safety and been evacuated from their homes.
In some parts of Townsville, salt-water crocodiles displaced by the floodwaters have been spotted,
adding extra risk and danger.

Al Jazeeraś Bernard Smith reports.

- Subscribe to our channel: http://aje.io/AJSubscribe
- Follow us on Twitter: https://twitter.com/AJEnglish
- Find us on Facebook: https://www.facebook.com/aljazeera
- Check our website: https://www.aljazeera.com/

#AlJazeeraEnglish #Australia #Floods”

ANSWERS:
```

GPT-3.5

```
1. [”floods”, ”dangerous and high velocity flows”]
2. [”coastal city of Townsville”]
3. N/A
4. [”more than a thousand people”]
5. [”engineers”, ”Al Jazeera’s Bernard Smith”]
```

GPT-4o

```
1. [”The opening of the floodgates of the Ross River dam”, ”floodwaters”]
2. [”Queensland”, ”the coastal city of Townsville”, ”Townsville”]
3. N/A
4. [”Downstream homes in the coastal city of Townsville”, ”more than a thousand people”, ”people have
moved to safety and been evacuated from their homes”]
5. N/A
```

GPT-4

```
1. [”floods”, ”dangerous and high velocity flows”]
2. [”coastal city of Townsville”]
3. N/A
4. [”more than a thousand people”]
5. [”engineers”, ”Al Jazeera’s Bernard Smith”]
```

Figure 11

Few-shot samples: DISASTERS

```
QUESTIONS:
1. "What emergency/disaster is occurring/has occurred?"
2. "Where is the emergency/disaster occurring?"
3. "When did the emergency/disaster occur?"
4. "Who was affected by the emergency/disaster?"
5. "Who is responding to assist those affected by the emergency/disaster?"

TEXT PASSAGE: "Europe’s most active Campi Flegrei volcano experienced its largest seismic swarm in 40
years, with 150 earthquakes shaking southern Italy on the evening of May 20. Engineers are responding
to infrastructural damage in the area."

Join the Community https://bit.ly/godmembership

#volcano #naples #supervolcano"

ANSWERS:
1. ["its largest seismic swarm", "150 earthquakes", "#volcano", "#supervolcano"]
2. ["Europe’s most active Campi Flegrei volcano", "southern Italy", "#naples"]
3. ["40 years", "the evening of May 20"]
4. N/A
5. ["engineers"]
```

Figure 12: Prompt adapted from text in https://www.youtube.com/watch?v=svsmOvbXAPQ

Few-shot samples: ELECTIONS

```
QUESTIONS:
1. "What place/population does the election pertain to?"
2. "What is the position of the elected leader?"
3. "Who is the elected leader?"
4. "Who is the elected leader replacing?"
5. "Who is electing the new leader?"
6. "When does the election take place?"
7. "Where does the voting take place?"
8. "Who is running as a candidate in the election?"

TEXT PASSAGE: "Climate scientist and former Mexico City mayor Claudia Sheinbaum is projected to be
Mexico’s presidential election winner, making her the country’s first female president. Election day
was on June 2, 2024, and her main opponent was former Senator Xóchitl Gálvez. Sheinbaum has long been
an ally of the incumbent president, Andrés Manuel López Obrador.

CBS Mornings airs weekdays at 7 a.m. on CBS and stream it at 8 a.m. ET on the CBS News app."

ANSWERS:
1. ["Mexico", "the country", "Mexico City"]
2. ["president"]
3. ["Climate scientist", "former Mexico City mayor Claudia Sheinbaum", "Sheinbaum"]
4. ["Andrés Manuel López Obrador"]
5. N/A
6. ["June 2, 2024"]
7. N/A
8. ["Climate scientist", "former Mexico City mayor Claudia Sheinbaum", "former Senator Xóchitl Gálvez",
"Sheinbaum"]
```

Figure 13: Prompt adapted from text in https://sg.news.yahoo.com/mexico-elects-1st-female-president-following-deadliest-election-campaign-in-countrys-modern-history-heres-what-to-know-184442748.html

Few-shot samples: POLITICAL DEVELOPMENT

QUESTIONS:
1. "What is the development?"
2. "What has caused the development?"
3. "What is the effect of the development?"
4. "Who participated in causing the development?"
5. "Where does the development affect?"
6. "When does the development take place?"

TEXT PASSAGE: "Thaksin Shinawatra, the former prime minister of Thailand and still the most influential figure in the ruling Pheu Thai Party, has been indicted on lèse-majesté charges, revealing the latest twist in the country’s fragile political landscape."

ANSWERS:
1. ["indicted on lèse-majesté charges"]
2. ["the country’s fragile political landscape"]
3. ["the latest twist in the country’s fragile political landscape"]
4. ["Thaksin Shinawatra", "the former prime minister of Thailand", "the most influential figure in the ruling Pheu Thai Party"]
5. ["Thailand", "the country"]
6. N/A

Figure 14: Prompt adapted from text in https://www.cfr.org/blog/has-king-thailand-split-thaksin

Few-shot samples: SOCIAL EVENTS

QUESTIONS:
1. "Who has come to participate in the event?"
2. "What is the event?"
3. "Where does the event take place?"
4. "When is the event taking place?"
5. "What physical entities have been constructed or are presented on behalf of the event?"
6. "Who is working or presenting on behalf of the event?"

TEXT PASSAGE: "Watch as stars walk the 2024 Met Gala carpet and leave The Mark Hotel in New York.
Notable names include Zendaya, Doja Cat, and Anna Wintour.

#metgala #metgala2024"

ANSWERS:
1. ["stars", "Zendaya", "Doja Cat", "Anna Wintour"]
2. ["the 2024 Met Gala"]
3. ["The Mark Hotel", "New York"]
4. ["2024"]
5. ["the 2024 Met Gala carpet"]
6. N/A

Figure 15: Prompt adapted from text in https://www.youtube.com/watch?v=JIGkDU7Z39c

Few-shot samples: SPORTS

QUESTIONS:
1. "What competition is it?
2. "Who is participating in the competition?"
3. "Where is the competition taking place?"
4. "When does the competition take place?"
5. "What scores/results occur during the competition?"
6. "Who comes to watch the competition?"
7. "What sports are played in the competition?"

TEXT PASSAGE: "The Orioles led MLB with 41 home runs in the month of April. Reigning Rookie of the Year Gunnar Henderson led the team with nine homers, with outfielder Colton Cowser following close behind with six homers.

Subscribe to the YT Channel: https://bit.ly/2SYEQEV

#BaltimoreOrioles #Birdland"

ANSWERS:
1. ["MLB"]
2. ["The Orioles", "Gunnar Henderson", "Colton Cowser", "#BaltimoreOrioles"]
3. N/A
4. ["the month of April"]
5. ["41 home runs", "nine homers", "six homers"]
6. N/A
7. ["MLB"]

Figure 16: Prompt adapted from text in https://www.youtube.com/watch?v=672-6MK6Xu8

Few-shot samples: DISCOVERY/LAUNCH

QUESTIONS:
1. "Who has developed/discovered the concept?"
2. "What is being launched/discovered?"
3. "Where was the concept developed/discovered?"
4. "When was the concept developed/discovered?"
5. "What is the use case of this concept?"
6. "Where was the concept launched/presented?"

TEXT PASSAGE: "A team of researchers from South Korea created a lightweight structure to improve the energy density of lithium-ion batteries, which will enable them to remain stable for longer, Tech Xplore reported. Their results were published in the journal Advanced Science in April."

ANSWERS:
1. ["A team of researchers from South Korea"]
2. ["a lightweight structure"]
3. ["South Korea"]
4. ["April"]
5. ["to improve the energy density of lithium-ion batteries", "enable them to remain stable for longer"]
6. ["the journal Advanced Science"]

Figure 17: Prompt adapted from text in https://www.yahoo.com/tech/ev-battery-researchers-unveil-lightweight-003000555.html

Table 10: MultiVENT-G ontology, as written in the annotation instructions manual.

Field Name	Field Description	Examples
	Disasters	
What	What emergency/disaster is occurring/has occurred?	fire, earthquake, hurricane
Where	Where is the emergency/disaster occurring?	Australia, USA, movie theater
When	When did the emergency/disaster occur?	morning, last week, 2020
Outcome-Occurred	What was the outcome of the emergency/disaster?	burned trees, collapsed buildings
Who-Affected	Who was affected by the emergency/disaster?	people huddled together, animals running for cover, person interviewed
Emergency-Response	Who is responding to assist those affected by the emergency/disaster?	firefighters, doctors attending to wounded, politicians at the scene
	Elections	
Body	What place/population does the election pertain to?	Taiwan, US soccer federation
Role	What is the position of the elected leader?	President, senator
New-Leader	Who is the elected leader?	Barack Obama
Old-Leader	Who is the elected leader replacing?	George W. Bush
Selector	Who is electing the new leader?	Ukrainian citizens
When	When does the election take place?	Morning, last week, 2020
Where	Where does the voting take place?	US, polling center, online
Candidate	Who is running as a candidate in the election?	Joe Biden, Ted Cruz
	Political Developments	
Development	What is the development?	Sanctions, leader death
Cause	What has caused the development?	Trade war, protests
Effect	What is the effect of the development?	Economy collapse, new leader
Agent(s)	Who participated in causing the development?	Biden, ambassadors, citizens
Affected-Place	Where does the development affect?	Russia, international waters
Time	When does the development take place?	Morning, last week, 2020
	Social Events	
Attendees	Who has come to participate in the event?	Children, people, senators
Social-Event	What is the event?	Coachella, Ramadan
Place	Where does the event take place?	Taiwan, a hotel
Time	When is the event taking place?	Morning, last week, 2020
Event-Artifact	What physical entities have been constructed or are presented on behalf of the event?	Art exhibit, information stand
Performer/Staff	Who is working or presenting on behalf of the event?	Rihanna, speaker, staff
	Sports	
Competition	What competition is it?	World Cup 2022
Participants	Who is participating in the competition?	Players, Brazil, Yankees
Place	Where is the competition taking place?	Qatar, stadium, Lusail
Time	When does the competition take place?	Morning, last week, 2020
Result	What scores/results occur during the competition?	4-5, won, tie
Spectators	Who comes to watch the competition?	People, Yankees fans
Sport	What sports are played in the competition?	Soccer, pole vault, marathon
	Discoveries/Launches	
Developer	Who has developed/discovered the concept?	Amazon, an archaeologist
What	What is being launched/discovered?	Black hole image, iPhone 92
Place	Where was the concept developed/discovered?	Cupertino, US, a volcano
Time	When was the concept developed/discovered?	Morning, last week, 2020
Use	What is the use case of this concept?	Self-driving car, a physics theory
Presentation-Location	Where was the concept launched/presented?	A conference, Thailand
	Demonstrations	
Who	Who are the protesters?	Teenagers, people, veterans
Where	Where is the protest occurring?	Moscow, the street, the white house
When	When did the protest occur?	Lasted for 12 minutes, March 2020
Organization	What organizations are involved with the protest?	Truckers association, ANTIFA
Issue	What issue does the protest concern?	Taxes, war, climate change
Law-Enforcement	What law enforcement was involved at the protest?	Security guards, OMON

Few-shot samples: DEMONSTRATIONS

QUESTIONS:
1. "Who are the protesters?"
2. "Where is the protest occurring?"
3. "When did the protest occur?"
4. "What organizations are involved with the protest?"
5. "What issue does the protest concern?"
6. "What law enforcement was involved at the protest?"

TEXT PASSAGE: "BRUSSELS, June 4 (Reuters) - Farmers and others from European agricultural groups in Brussels on Tuesday protested against the European Union's environmental policies, but the action was shunned by mainstream farming groups who said it did not reflect their members' concerns.

A few days before the European Parliament election, farmers from the Netherlands travelled to Brussels to protest against EU green policies that organisers said undermine the competitiveness of European farmers."

ANSWERS:
1. ["Farmers", "others", "farmers from the Netherlands", "European farmers"]
2. ["Brussels"]
3. ["June 4", "Tuesday", "A few days before the European Parliament election"]
4. ["European agricultural groups", "mainstream farming groups"]
5. ["the European Union's environmental policies", "EU green policies"]
6. N/A

Figure 18: Prompt adapted from text in https://www.reuters.com/world/europe/main-farming-groups-shun-brussels-protest-against-eu-green-policies-2024-06-04/