

Joint Multimedia Event Extraction from Video and Article

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Abstract

Visual and textual modalities contribute complementary information about events described in multimedia documents. Videos contain rich dynamics and detailed unfoldings of events, while text describes more high-level and abstract concepts. However, existing event extraction methods either do not handle video or solely target video while ignoring other modalities. In contrast, we propose the first approach to jointly extract events from video and text articles. We introduce the new task of Video MultiMedia Event Extraction (VM²E²) and propose two novel components to build the first system towards this task. First, we propose the first self-supervised multimodal event coreference model that can determine coreference between video events and text events without any manually annotated pairs. Second, we introduce the first multimodal transformer which extracts structured event information jointly from both videos and text documents. We also construct and will publicly release a new benchmark of video-article pairs, consisting of 860 video-article pairs with extensive annotations for evaluating methods on this task. Our experimental results demonstrate the effectiveness of our proposed method on our new benchmark dataset. We achieve 6.0% and 5.8% absolute F-score gain on multimodal event coreference resolution and multimedia event extraction.

1 Introduction

Traditional event extraction methods target a single modality, such as text, images, or videos. However, real-world multimedia (e.g. online news) features content in multiple modalities which collectively convey a cross-modal narrative. As a consequence, components of events described by the document may lie jointly or solely in either the textual or visual modalities. By randomly watching 100 videos and associated articles from BBC Official YouTube

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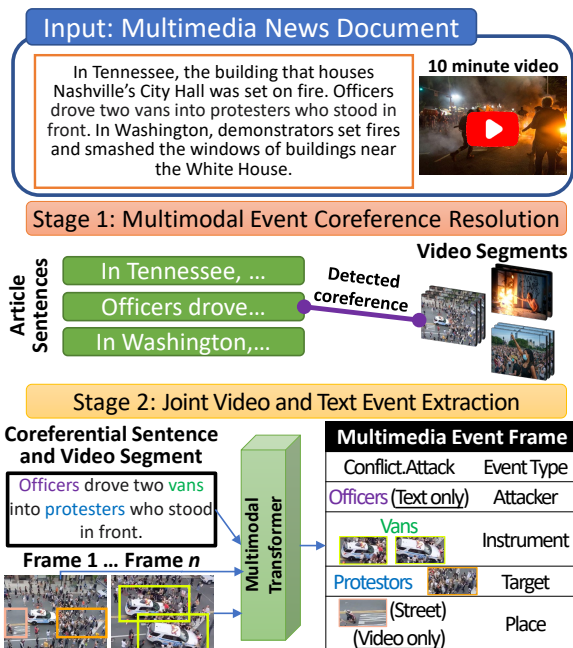


Figure 1: We introduce the problem of video multimedia event extraction. Given a multimedia document containing a text article and a video, the goal is to jointly extract events and arguments. Our method first performs multimodal event coreference resolution to identify which sentences and video segments refer to the same event. Our novel multimodal transformer then extracts multimedia event frames from coreferential sentence and video segment pairs. Our method is able to resolve coreference and extract multimodal event frames more accurately than existing approaches.

Channel, we find that 45% of videos contain event arguments that are not explicitly mentioned in the article.

Event extraction is a well-studied problem in the natural language processing community (Nguyen et al., 2016; Sha et al., 2018; Liu et al., 2019, 2020). Similarly, methods focusing on event argument extraction have likewise been proposed (Wang et al., 2019, 2020). However, all of these methods solely target the text modality and ignore the contribution of visual media. A related line of research

has emerged in the computer vision community focusing on the extraction of purely visual events (Yatskar et al., 2016; Li et al., 2017; Mallya and Lazebnik, 2017; Pratt et al., 2020). While a few methods have sought to transfer visual knowledge from images to improve text-only event extraction (Zhang et al., 2017; Tong et al., 2020), these do not detect multimodal events, whose arguments span multiple modalities.

Li et al. (2020) propose a method for extracting multimodal events from text and images jointly. However, Li et al. (2020)’s method does not handle videos. Extending Li et al. (2020) to the video domain is non-trivial because localizing events in videos requires first identifying temporal boundaries of the event, which is a challenging vision problem in its own right (Pardo et al., 2021; Huang et al., 2020; Lin et al., 2019). Moreover, while Li et al. (2020) transfer existing image and text event extraction resources to the multimodal domain, there are no datasets containing event argument localization in videos, thus Li et al. (2020)’s method cannot be directly trained for multimodal text and video event extraction as it was for images.

We argue that multimodal event extraction from videos is important for several reasons. For one thing, images contain snapshots of events, but may not capture all arguments or participants of the event in a single snapshot. In contrast, videos often contain more action events and may reveal additional event arguments that can be extracted as events evolve over time that may be missing from any single frame. Finally, we find some event argument *roles* are hard to determine from single images, while video provides additional context which helps disambiguate the roles different arguments play in the event.

In this paper, we propose the first model that extracts multimodal events and arguments from text and videos jointly. Specifically, we propose a new task called Video M²E² (Video MultiMedia Event Extraction). Given a document with an accompanying video, our goal is to jointly extract the events and argument roles appearing in both data modalities. Because of the lack of an existing dataset for this task, we introduce a new multimodal video-text dataset with extensive annotations covering event and argument role extraction, coreference resolution, and grounding of event arguments (bounding boxes).

We tackle this task in a two-stage manner: first

we find a coreferential sentence-segment pair and then we jointly extract events from it. For multimodal event coreference resolution, we propose a self-supervised model to find video segment-sentence pairs describing the same event. These coreferential cross-modal pairs are then used to perform event classification and argument role labeling. To do so, we propose a novel multimodal transformer architecture which learns to perform event and argument role prediction jointly from video and text. We show that this system substantially outperforms unimodal approaches, while allowing us to discover event arguments lying solely in one modality.

To summarize, we make the following contributions.

- We propose the novel problem of video multimodal event extraction and contribute a high-quality benchmark dataset for this task containing extensive annotations of event types, event arguments and roles, argument grounding, and cross-modal coreference resolution of events in text and videos.
- We propose a self-supervised training strategy which allows us to find coreferential sentence and video segment.
- We introduce a novel multimodal transformer architecture leveraging modality-specific decoders for joint text and video event and argument extraction.
- We present extensive experimental results demonstrating that our proposed approach significantly outperforms both unimodal and multimodal baselines for event coreference resolution, event extraction, and argument role labeling.

2 Related Work

Learning multimodal common space.

Instead of learning representations in single modalities (text, visual), there have been various works that tried to learning representation from textual and visual modalities jointly and acquire a common space where the features from different modalities are directly comparable (Miech et al., 2019, 2020; Chen et al., 2021). In the task such as weakly supervised grounding also tries to find a common space for text and visual where we can find the correct region given a text query (Akbari et al., 2019; Zhang et al., 2020; Gupta et al., 2020). These works usually learn in a weakly supervised

manner where human-annotated image/video caption pairs were given. In our multimodal event coreference resolution task, we try to learn in a self-supervised manner where only the video and its ASR were given.

Text Event Extraction. Recognizing and extracting events in text is an important information extraction problem that has been thoroughly studied. Both document-level (Yang et al., 2018; Li et al., 2021) and sentence-level (Zeng et al., 2018) methods have been proposed. Classic work by Ahn (2006) and Ji and Grishman (2008) leverage manually designed features for the task and formulate event extraction as a classification problem. More recent event extraction methods have leveraged neural models such as recurrent networks (Nguyen et al., 2016; Sha et al., 2018), convolutional networks (Chen et al., 2015), graph networks (Liu et al., 2019; Zhang and Ji, 2021), joint neural model (Lin et al., 2020a), conditioned generation (Li et al., 2021) and transformers (Liu et al., 2020) to automatically learn task-relevant features.

A related line of work has focused on the problem of event argument extraction, where the goal is to predict event argument roles of entities in text to fill the roles of predicted event frames. Wang et al. (2019) propose a hierarchical event argument extraction model leveraging modular networks to exploit argument role concept correlation. Wang et al. (2020) propose a sampling-based method for jointly extracting events and arguments. Other methods have attempted to leverage zero-shot learning (Huang et al., 2018) and weak supervision (Chen et al., 2017) to further improve performance on both event and event argument extraction.

While impressive progress has been made in recent years, all of these methods exclusively focus on text and forego the oftentimes complex and complementary information found in visual media. In contrast, we propose to extract both events and event arguments from both text and video.

Visual event extraction. Event recognition has also been studied by the computer vision community, where it is commonly termed “situation recognition” (Yatskar et al., 2016; Pratt et al., 2020). Analogous to textual event extraction methods, the goal of visual situation recognition is detecting events occurring in an image, the objects and agents involved, and identifying their roles. Most work in this space (Yatskar et al., 2016; Li et al., 2017; Mallya and Lazebnik, 2017; Pratt et al., 2020) re-

lies on the FrameNet (Baker et al., 1998) ontology derived from text which defines frames for each verb, along with semantic roles of arguments.

Seminal work by Yatskar et al. (2016) introduced the *SituNet* dataset of images labeled with visual verbs and argument roles. Follow-up approaches have leveraged structured prediction mechanisms (Li et al., 2017; Suhail and Sigal, 2019) and attention (Cooray et al., 2020) to further improve performance on *SituNet*. Pratt et al. (2020) extend *SituNet* with bounding box annotations of event arguments and introduce a model for localizing event arguments in images. None of these target the video domain as we do or perform multimodal event extraction. More related to our work is Sadhu et al. (2021), which introduces the video semantic role labeling dataset and task, where the target is to extract events and generate language description for arguments. Unlike Sadhu et al. (2021), we propose to extract multimodal events and localize arguments, where components in the extracted event frame may appear in either modality.

Multimodal Event Extraction. Some prior work has leveraged multimodal information for text-only event extraction. Zhang et al. (2017) propose a method which learns to transfer visual knowledge from multimodal resources to text-only documents to improve event extraction. Tong et al. (2020) supplement existing event detection benchmarks with image data and show significant performance gains by leveraging multimodal information for trigger disambiguation.

Most relevant to our work is Li et al. (2020)’s method which introduces the task of multimedia event extraction, where event frames are comprised of both visual and textual arguments. Li et al. (2020) leverage single-modality training corpora and weak supervision to train a cross-modal method, without any annotations. Our work has several important differences from Li et al. (2020). First, we target the video modality, while Li et al. (2020) target images. This problem is significantly more challenging because video event extraction requires understanding the rich dynamics in videos. Additionally, because no datasets of video event argument role localization exist, we can not directly borrow existing image event extraction resources like Li et al. (2020). Finally, we propose a novel multimodal transformer architecture for this task.

Event Type	
CastVote (26)	Disaster.FireExplosion (60)
Contact.Broadcast (359)	Life.Injure (78)
Contact.Correspondence (75)	Justice.ArrestJail (31)
Contact.Meet (196)	ManufactureAssemble (44)
Conflict.Attack (147)	Movement.Evacuation(23)
Conflict.Demonstrate (242)	Movement.PreventPassage (43)
DamageDestroy (50)	Movement.Transport (287)
DetonateExplode (62)	Transcation.ExchangeBuySell (36)

Table 1: Event types in VM²E². Numbers in parentheses represent the counts of visual events.

3 VM²E²Dataset

3.1 Dataset Collection

We introduce the VM²E²dataset which labels (1) Multimodal event coreference (2) Events and argument roles from 860 video article pairs.

Event types. The Linguistic Data Consortium (LDC) has created document-level event ontology based on previous LDC-supported ontologies ERE and ACE. These have been made publicly available online¹. The event types covered by the LDC ontology focus on issues related to disasters, attacks and activities from international news. We found that this ontology provides good coverage of many events found in world news and thus adopt it for our system. Because not all event types in the ontology are visually detectable, we manually selected event types defined in the LDC ontology that are: (1) Visually detectable: events that can be visually seen, and (2) Frequent: events that have a frequency > 20 in our dataset. This resulted in a set of 16 event types, which we show in Table 1. The full event type and argument role definition are included in the supplementary.

Candidate Video/Article Filtering. Given the 16 event types, we build a data collection pipeline. First, we use the event types and news source names as keywords to search on Youtube. We harvest from VOA, BBC, and Reuters. We choose these sources because we they are trustworthy and usually contain articles under the video such that the content is about the same event as the video. Second, we filter out videos that are longer than 16 minutes to avoid extra-long videos. Third, we check each video to make sure it contains at least one visual event. Starting from 1.2K videos, we end up with 860 video article pairs containing multimodal events. For the dataset, we will release the YouTube URLs that contains the video and article

¹<https://tac.nist.gov/tracks/SM-KBP/2018/ontologies/SeedlingOntology>

Type	1-to-1	1-to-n	n-to-1	n-to-n	Total
Count	202	104	260	286	852

Table 2: Multimodal event coreference link types found in VM²E².

along with the annotations. We do not own the copyright of the video and the researcher shall use the data only for non-commercial research and educational purposes. More information about the Fair Use Notice will be included in the supplement.

3.2 Dataset Annotation Procedure

In order to collect annotations, we perform the following steps for videos and text. First, annotators watch the entire video to identify all event instances in the video. Next, for each event instance, the temporal boundary, event type, and co-referential text event (if existent) is annotated and three keyframes within the temporal boundary are selected. Then, for each selected keyframe all arguments are identified. Finally, for each argument, the argument role type, entity type, and co-referential text event (if existent) is annotated. We extensively annotate the videos and sampled keyframes with bounding boxes for argument roles to ensure none are missed.

3.3 Quality control

We train fourteen NLP and computer vision researchers to complete the annotation work with two independent passes. After annotation, two expert annotators perform adjudication. For the multimodal event coreference resolution, we sampled 10% of annotations and reached an Inter-Annotator Agreement (IAA) of 84.6%. For the event and argument role labeling, we sampled 10% of annotations and reached an Inter-Annotator Agreement (IAA) of 81.2%.

3.4 Dataset statistics

Overall, we annotated 852 multimodal event coreference links between video segments and sentences. Table 2 breaks down the annotations into relation categories: **1-to-1**, where one text event is only coreferential with a single video event, and **n-to-n**, where multiple text events and video events are coreferential. We also provide data statistics for the event extraction and argument role annotations in Table 3.

Document		Event Mention		Argument Role	
Sentence	Video	Textual	Visual	Textual	Visual
13,239	860	4,164	2,702	18,880	5,467

Table 3: Annotated VM²E² data event and argument role statistics.

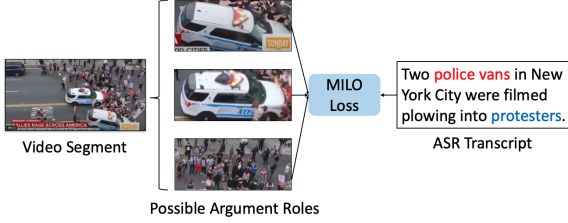


Figure 2: Self-supervised multimodal event coreference resolution by considering the possible argument roles that participate in the event.

4 Method

4.1 Problem Formulation

In Multimodal Event Coreference Resolution, given M sentences and N video segments in a multimedia document, the system is required to predict the coreference $c_{ij} \in \{0, 1\}$ between a sentence x_i and a video segment y_j . In Joint Multimodal Event Extraction and Argument Role Labeling, given a text sentence x_i and a video segment y_j , the system is required to predict the multimodal event type e , the text mention t_e , the text mention t_{a_k} and the bounding box $bbox_{a_k}$ for each argument role a_k .

4.2 Multimodal Event Coreference Resolution

We aim to learn a common space across the video and text modalities such that the embeddings across these modalities are close if they represent the same event. This is a particularly challenging task since in an unannotated multimodal document, we don't know which video segment aligns with which article sentence. Inspired by multimodal self supervised methods learning from instructional videos (Miech et al., 2019), we learn the common space across the two modalities from our unannotated video clips using their auto-generated ASR transcripts as supervision. To accomplish this, we use a standard noise contrastive loss (NCE) (Jozefowicz et al., 2016) \mathcal{L}_{NCE} :

$$\max_{f,g} \sum_{i=1}^n \log \left(\frac{e^{f(x_i)^\top g(y_i)}}{e^{f(x_i)^\top g(y_i)} + \sum_{(x',y') \sim \mathcal{N}_i} e^{f(x')^\top g(y')}} \right)$$

where x represents a sentence and y a video clip. f and g are the two learnable networks that project the two features into a common space. The loss learns to pull the positive pairs (x_i, y_i) that co-occur in time while pushing mis-matched pairs in the batch away.

Additionally, we find the region information (arguments that participate in the event) to be crucial in finding coreferential events between video and text. For example, when we see an *Attack* event in the text, we might find the objects “van” or “protester” in the video to be important since they participate in the event as shown in Figure 2. In order to learn such correspondences between text and object regions, we introduce the Multi-Instance Learning from Objects \mathcal{L}_{MILO} loss:

$$\max_{f,h} \sum_{i=1}^n \log \left(\frac{\sum_{(x,z) \in \mathcal{P}_i} e^{f(x)^\top h(z)}}{\sum_{(x,z) \in \mathcal{P}_i} e^{f(x)^\top h(z)} + \sum_{(x',z') \sim \mathcal{N}_i} e^{f(x')^\top h(z')}} \right)$$

where z represents the regions in the video clip and h is a projection layer. Given a specific video instance i , \mathcal{P}_i represents the *positive* region/sentence candidate pairs (i.e. the region and sentence co-occur in time, see Figure 2) while \mathcal{N}_i represents the set of negative region/narration pairs that were sampled from different time frames. The learning objective takes all possible region information into consideration by summing over all the pairs. The model learns in a multi-instance fashion to select the regions that are most important for multimodal event coreference resolution. Our final multimodal coreference loss combines both global and local constraints:

$$\mathcal{L}_{mmcoref} = \mathcal{L}_{NCE} + \mathcal{L}_{MILO} .$$

4.3 Joint Multimodal Event Extraction and Argument Role Labeling

Inspired by recent work (Lin et al., 2021) on leveraging multimodal transformers to jointly process text and visual information, we propose a joint multimodal transformer (JMMT) to extract events and arguments from a paired text sentence and video clip. The proposed JMMT has an encoder-decoder structure: the encoder extracts and fuses information from both modalities (text and video), while the decoder is more complex. The decoder consists of two heads: one for detecting trigger words, event types, and arguments from text, and the other for classifying video event types and predicting bounding boxes for visual arguments. With this joint

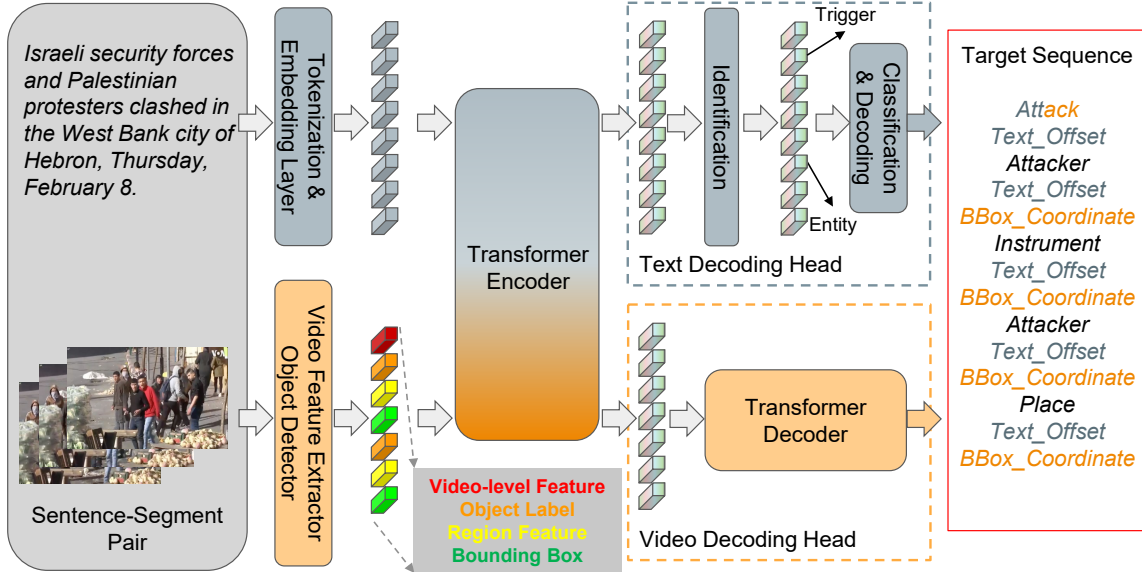


Figure 3: Multimodal transformer for joint event extraction and argument role labeling. In the target sequence, blue-gray and light orange are for textual and visual decoding heads, respectively.

encoder, JMMT can effectively leverage contextual information to extract events and label argument roles.

As shown in Figure 3, JMMT takes text and visual tokens as input. For text tokens, we follow Raffel et al. (2020) to embed text tokens. For visual tokens, we use four feature types to comprehensively represent both global and local information: 1) video-level features extracted from the whole video segment capture the global event context; 2) frame-level object labels produced by an object detector; 3) frame-level region features extracted from bounding boxes detected by the object detector provide fine-grained argument information; 4) frame-level object coordinates also provided by the object detector for localization of arguments. Note that we sample t frames and for each frame, we sample k objects with the highest confidence scores. The text and visual tokens are then stacked as a sequence and input to the encoder for joint processing.

Our encoder and decoder are initialized from transformers pretrained on text corpora (Raffel et al., 2020). Our decoding head for text event extraction is borrowed from Lin et al. (2020b)’s state-of-the-art text event extraction model. For text decoding, we take encoder outputs as input and first merge these multimodal contextualized embeddings of word pieces to obtain a representation for each word in the input sequence. Then we process these word representations for

identification, classification and decoding, following Lin et al. (2020b). For the video decoding head, we leverage the decoder from Raffel et al. (2020)’s pretrained text transformer and cast the task as a sequence-to-sequence prediction problem. We set the target sequence as $\{e, a_1, bbox, a_2, bbox, \dots, a_n, bbox\}$, which begins with event type e and then goes through each argument role a_i to produce the bounding box coordinates $bbox$ on the sampled key frames.

Each decoding head is supervised by its own loss term and the gradients are both back-propagated to the encoder. The text decoding head is supervised based on the objective \mathcal{L}_{text} proposed in Lin et al. (2020b) and the video decoding head is trained using a standard teacher-forcing strategy with cross-entropy loss (Raffel et al., 2020) \mathcal{L}_{video} . The overall objective is

$$\mathcal{L}_{JMMT} = \mathcal{L}_{text} + \mathcal{L}_{video}.$$

In this way, the proposed JMMT can effectively fuse multimodal information and jointly extract events and arguments.

5 Experiments

5.1 Dataset

Event coreference resolution. Our model is trained on our unannotated dataset, which contains 3K videos and corresponding automatically generated speech transcriptions. We test our model on

the annotated dataset, which contains 860 videos and their articles from YouTube.

Event extraction and argument role labeling. We split the annotated 860 video-article pairs into 645 and 215 for training and testing, respectively. To focus on joint multimedia event extraction, we sample all the coreference segment-sentence pairs for training and evaluation.

5.2 Evaluation Setting

Event coreference resolution. We evaluate our model on the annotated event coreference data by predicting whether every possible sentence-video segment pair from the same multimodal document is coreferential or not. We perform feature similarity between the text and video features within the learned joint space and predict the pair as coreferential if their similarity surpasses a threshold. We adopt traditional link prediction metrics, i.e. precision, recall, F_1 , and accuracy for evaluation.

Event extraction and argument role labeling. We evaluate models on text-only, video-only, and multimedia event mentions in the VM²E² dataset. We follow the common event extraction metrics, i.e. precision, recall, and F_1 . For a text event mention, we follow Li et al. (2020) to only consider it as correct if its trigger offsets and event type both match a reference trigger. Similarly, a textual argument is only considered as correct when its offsets, event type, and role type all match a reference argument. Analogously, a video event mention is considered correct if its segment and event type match a reference segment. A video argument is considered correct if its localization, event type and role type matches a reference argument. A visual argument is correctly localized if its Intersection over Union (IoU) with the ground truth bounding box is greater than 0.3. Finally, a multimedia event mention is considered correct if its event type and trigger offsets (or the video segment) match a reference trigger (or the reference segment). Arguments of multimedia events with either a correct textual or visual argument mention are considered correct.

5.3 Baseline methods

Event coreference resolution. We compare our method against several self-supervised models that learn a joint visual text space. Specifically, HowTo100m (Miech et al., 2019) learn a joint video-text space using a max-margin ranking loss (Karpathy et al., 2014). NCE loss (Jozefowicz et al., 2016) trains a classifier to discriminate be-

tween real instances and a generated noise distribution. MIL-NCE (Miech et al., 2020) further extends NCE by explicitly considering the misalignment of the video segment and ASR transcript to design a multi-instance loss. We do not compare to retrieval methods that require fine-tuning.

Event extraction and argument role labeling. 1) **Text-only baseline:** We re-implement a state-of-the-art method, OneIE (Lin et al., 2020b). For a fair comparison, we use the same text encoder (Raffel et al., 2020) as our JMMT. 2) **Video-only baseline:** As no existing method addresses the problem of event extraction and argument role labeling from videos, we adopt the state-of-the-art method for grounded image event extraction, JSL (Pratt et al., 2020), to extract events and arguments from each annotated key frame. 3) **Multimedia baseline:** As previous multimedia event extraction methods only consider image-text pairs, we borrow one of the best performing models on M²E² (Li et al., 2020), WASE (Li et al., 2020), as our baseline for multimedia event extraction. Note that we rebuild WASE to extend from its ontology to our ontology.

5.4 Implementation details

For the visual branch of the multimodal event coreference resolution model we follow Miech et al. (2019) and use pre-trained 2D features from a ResNet-152 model (He et al., 2016) trained on ImageNet (Deng et al., 2009) and 3D features from a ResNeXt-101 model (Hara et al., 2018) trained on Kinetics (Carreira and Zisserman, 2017). For the textual branch, a GoogleNews pre-trained Word2vec model (Mikolov et al., 2013) provides word embeddings, followed by a max-pooling over words in a given sentence to extract a sentence embedding. We use Faster R-CNN (Ren et al., 2015) pre-trained on the Visual Genome dataset (Krishna et al., 2017) as our object detector. For selecting the number of objects, we sort by the confidence score of each object and select the top 5 as possible argument roles. Also, we uniformly sample 3 frames in each video segment and end up with 15 objects for each segment. More details about the object selection can be found in the supplementary material.

For event extraction and argument role labeling, we use the same video-level feature and object detector. We use T5-base (Raffel et al., 2020) with pre-trained weights provided in HuggingFace (Wolf et al., 2020) for initialization. More

Input	Model	Text Evaluation						Video Evaluation						Multimedia Evaluation					
		Event Mention			Argument Role			Event Mention			Argument Role			Event Mention			Argument Role		
		<i>P</i>	<i>R</i>	<i>F</i> ₁	<i>P</i>	<i>R</i>	<i>F</i> ₁	<i>P</i>	<i>R</i>	<i>F</i> ₁	<i>P</i>	<i>R</i>	<i>F</i> ₁	<i>P</i>	<i>R</i>	<i>F</i> ₁	<i>P</i>	<i>R</i>	<i>F</i> ₁
Text	OneIE	38.5	52.1	44.3	16.6	21.8	18.8	-	-	-	-	-	-	-	-	-	-	-	-
Video	JSL	-	-	-	-	-	-	24.1	17.1	20.0	2.2	2.8	2.4	24.1	17.1	20.0	2.2	2.8	2.4
	JMMT _{Video}	-	-	-	-	-	-	26.6	29.2	27.8	8.9	10.1	9.5	26.6	29.2	27.8	8.9	10.1	9.5
Multimedia	WASE	33.6	53.8	41.4	15.2	22.1	18.0	20.4	14.0	16.6	2.8	1.3	1.7	34.0	54.0	41.8	15.3	22.1	18.1
	JMMT	39.7	56.3	46.6	17.9	24.3	20.6	32.4	37.5	34.8	9.2	10.6	9.9	41.2	56.3	47.6	18.8	24.7	21.3

Table 4: Event and argument extraction results (%). We evaluate three categories of models in three evaluation settings. By jointly leveraging multimodal context, JMMT significantly improves multimedia event extraction from video segments and sentences.

Method	Visual Model	TR	<i>P</i>	<i>R</i>	<i>F</i> ₁	<i>Acc</i>
HowTo100M	R152+RX101	N	32.2	62.8	44.3	55.2
NCE	R152+RX101	N	35.5	68.3	45.5	47.5
Ours	R152+RX101	N	38.4	76.4	51.5	59.6
MIL-NCE	S3D-G	Y	37.8	75.0	50.6	59.2

Table 5: Multimodal event coreference resolution results. Our method outperforms all baselines, including one with a more powerful and trainable visual backbone (indicated by TR).

details are in the supplementary material.

5.5 Quantitative Performance

Event coreference resolution. We first examine the results of the multimodal event coreference resolution task in Table 5. All the methods we compare share the same text feature extractor. For visual feature extraction, HowTo100M, NCE, and our method apply ResNet-152 (R152) and ResNeXt-152 (RX101) followed by Miech et al. (2019). MIL-NCE uses a more advanced video feature extraction backbone, S3D-G (Xie et al., 2018). Our model significantly outperforms all previous methods using the same architecture, as well as those models with a trainable (TR) and more powerful visual backbone (Miech et al., 2020).

Event extraction and argument role labeling. The proposed JMMT significantly improves the event extraction performance over baseline methods as shown in Table 4. Compared to text-only OneIE or video-only JSL baselines, the JMMT produces at most **74%** relative gain in event extraction, which demonstrates the importance of leveraging multimodal information for understanding complex events. Compared to previous methods on image-text multimedia event extraction, the superior performance of JMMT verifies 1) the effectiveness of the powerful transformer model for multimodal information fusion and 2) the importance of modeling dynamics in videos.

5.6 Qualitative Analysis

We visualize results from our event coreference resolution model in Fig 5. We observe that the model correctly selects the most appropriate sentence for a given video segment. Also, we find that the model learns to associate object regions to the words in the sentence. For example, the first sentence had a high similarity score with the object ‘Crane’ since it mentioned ‘building some new island’.

We also visualize results of event extraction. As shown in Fig. 4, the center frame is very hard to extract events from due to the occlusion of arguments. With only this image as input, WASE fails to extract events and arguments. However, our JMMT successfully recognizes the event and detects “Jailer” in the image with the help of video-level dynamics and the context of the previous and next frames. This example illustrates both the importance and difficulty of multimedia event extraction from videos and articles. We also observe that our JMMT fails to recognize the “Detainee” because of occlusion. This indicates the possibility of leverage entity tracking to further improve VM²E² which we leave as future work.

6 Limitation

Dataset. Our method was based on our collected dataset, which might contain unintended societal, gender, racial, and other biases when deploying models trained on this data. Also, our problem formulation assumes the video and article are about the same topic. This assumption leads our method to work on news videos and instructional videos. If we didn’t constrain the videos to these genres, we might collect videos without articles or videos with unrelated articles such as music videos and animated videos on YouTube.

Evaluation. Our proposed pipeline could be combined as a two-step approach, starting from raw videos and articles and then acquiring both modal-

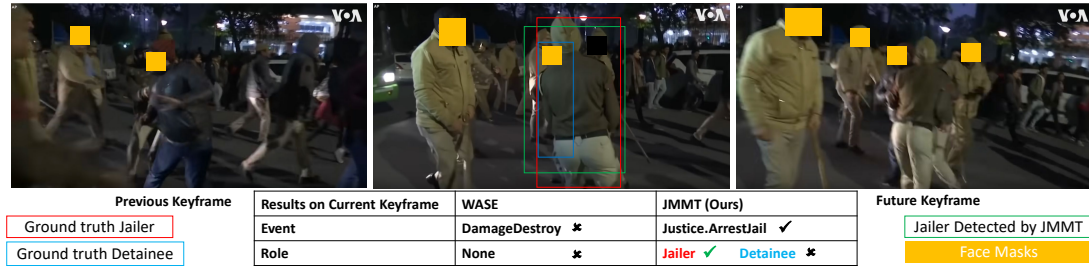


Figure 4: Visualization of event extraction results on one video segment. We mask faces (orange boxes) for privacy.

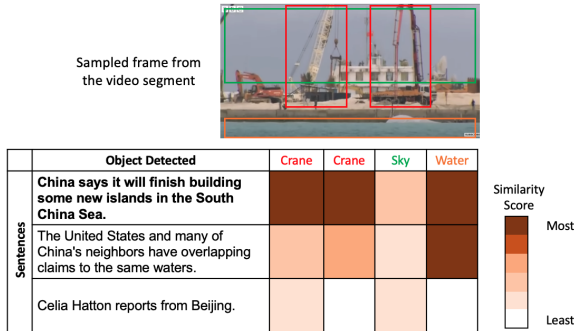


Figure 5: Event coreference resolution visualization. The bold sentence is correctly selected as coreferential within the article by the model.

ities’ event and argument roles. However, in our evaluation, we only evaluate the argument roles on annotated keyframes since we don’t have the annotation for every video frame due to the expense of annotation. End-to-end evaluation for all frames is not practical because the chosen frames from the multimodal event coreference resolution model are not guaranteed to be the ground truth frames on which we have annotations. Consequently, we cannot evaluate the predictions of our multimodal event extraction model (stage 2) when we use predicted frames as input since we do not have annotations on the frames on which predictions are made (thus, the results in those frames could be correct or incorrect).

7 Conclusions

We have introduced a novel task VM^2E^2 - given a video with a paired article, our first goal is to find coreferenced events across modalities. Also, our task requires extracting the event type and argument roles from both modalities. 860 video-article pairs were labeled to support this task. We developed a novel self-supervised multimodal network that learns a common embedding space by processing local (object region) and global (video level) se-

mantic relationships to perform multimodal event coreference resolution. In addition, we present a new architecture JMMT that jointly extracts events and arguments from both modalities using an encoder-decoder-based multimodal transformer. Our extensive experiments on multiple settings show that considering region information and a joint transformer for both modalities is essential for good performance on the two subtasks in VM^2E^2 . Our dataset collection pipeline and approach can be extended to more scenarios such as instructional videos and other videos that contain video-article pairs for extracting multimodal events across both modalities.

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References

David Ahn. 2006. *The stages of event extraction*. In *Proceedings of the Workshop on Annotating and Reasoning about Time and Events*, pages 1–8, Sydney, Australia. Association for Computational Linguistics.

Hassan Akbari, Svebor Karaman, Surabhi Bhargava, Brian Chen, Carl Vondrick, and Shih-Fu Chang. 2019. *Multi-level multimodal common semantic space for image-phrase grounding*. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*, pages 12476–12486. Computer Vision Foundation / IEEE.

- 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*.
- João Carreira and Andrew Zisserman. 2017. [Quo vadis, action recognition? A new model and the kinetics dataset](#). In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 4724–4733. IEEE Computer Society.
- Brian Chen, Andrew Rouditchenko, Kevin Duarte, Hilde Kuehne, Samuel Thomas, Angie Boggust, Rameswar Panda, Brian Kingsbury, Rogerio Feris, David Harwath, et al. 2021. [Multimodal clustering networks for self-supervised learning from unlabeled videos](#). *ArXiv preprint*, abs/2104.12671.
- Yubo Chen, Shulin Liu, Xiang Zhang, Kang Liu, and Jun Zhao. 2017. [Automatically labeled data generation for large scale event extraction](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 409–419, Vancouver, Canada. Association for Computational Linguistics.
- Yubo Chen, Liheng Xu, Kang Liu, Daojian Zeng, and Jun Zhao. 2015. [Event extraction via dynamic multi-pooling convolutional neural networks](#). In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 167–176, Beijing, China. Association for Computational Linguistics.
- Thilini Cooray, Ngai-Man Cheung, and Wei Lu. 2020. [Attention-based context aware reasoning for situation recognition](#). In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 4735–4744. IEEE.
- Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Fei-Fei Li. 2009. [Imagenet: A large-scale hierarchical image database](#). In *2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2009), 20-25 June 2009, Miami, Florida, USA*, pages 248–255. IEEE Computer Society.
- Tanmay Gupta, Arash Vahdat, Gal Chechik, Xiaodong Yang, Jan Kautz, and Derek Hoiem. 2020. [Contrastive learning for weakly supervised phrase grounding](#). In *Computer Vision—ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16*, pages 752–768. Springer.
- Kensho Hara, Hirokatsu Kataoka, and Yutaka Satoh. 2018. [Can spatiotemporal 3d cnns retrace the history of 2d cnns and imagenet?](#) In *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018*, pages 6546–6555. IEEE Computer Society.
- Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. [Deep residual learning for image recognition](#). In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 770–778. IEEE Computer Society.
- Lifu Huang, Heng Ji, Kyunghyun Cho, Ido Dagan, Sebastian Riedel, and Clare Voss. 2018. [Zero-shot transfer learning for event extraction](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2160–2170, Melbourne, Australia. Association for Computational Linguistics.
- Yifei Huang, Yusuke Sugano, and Yoichi Sato. 2020. [Improving action segmentation via graph-based temporal reasoning](#). In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 14021–14031. IEEE.
- Heng Ji and Ralph Grishman. 2008. [Refining event extraction through cross-document inference](#). In *Proceedings of ACL-08: HLT*, pages 254–262, Columbus, Ohio. Association for Computational Linguistics.
- Rafal Jozefowicz, Oriol Vinyals, Mike Schuster, Noam Shazeer, and Yonghui Wu. 2016. [Exploring the limits of language modeling](#). *ArXiv preprint*, abs/1602.02410.
- Andrej Karpathy, Armand Joulin, and Fei-Fei Li. 2014. [Deep fragment embeddings for bidirectional image sentence mapping](#). In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 1889–1897.
- Diederik P. Kingma and Jimmy Ba. 2015. [Adam: A method for stochastic optimization](#). In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*.
- Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. 2017. [Visual genome: Connecting language and vision using crowdsourced dense image annotations](#). *International journal of computer vision*, 123(1):32–73.
- Manling Li, Alireza Zareian, Qi Zeng, Spencer Whitehead, Di Lu, Heng Ji, and Shih-Fu Chang. 2020. [Cross-media structured common space for multimedia event extraction](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2557–2568, Online. Association for Computational Linguistics.
- Ruiyu Li, Makarand Tapaswi, Renjie Liao, Jiaya Jia, Raquel Urtasun, and Sanja Fidler. 2017. [Situation](#)

- recognition with graph neural networks. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 4183–4192. IEEE Computer Society.
- Sha Li, Heng Ji, and Jiawei Han. 2021. Document-level event argument extraction by conditional generation. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 894–908, Online. Association for Computational Linguistics.
- Tianwei Lin, Xiao Liu, Xin Li, Errui Ding, and Shilei Wen. 2019. BMN: boundary-matching network for temporal action proposal generation. In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 3888–3897. IEEE.
- Tianwei Lin, Xu Zhao, Haisheng Su, Chongjing Wang, and Ming Yang. 2018. Bsn: Boundary sensitive network for temporal action proposal generation. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 3–19.
- Xudong Lin, Gedas Bertasius, Jue Wang, Shih-Fu Chang, Devi Parikh, and Lorenzo Torresani. 2021. Vx2text: End-to-end learning of video-based text generation from multimodal inputs. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7005–7015.
- Ying Lin, Heng Ji, Fei Huang, and Lingfei Wu. 2020a. A joint end-to-end neural model for information extraction with global features. In *Proc. The 58th Annual Meeting of the Association for Computational Linguistics (ACL2020)*.
- Ying Lin, Heng Ji, Fei Huang, and Lingfei Wu. 2020b. A joint neural model for information extraction with global features. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7999–8009, Online. Association for Computational Linguistics.
- Jian Liu, Yubo Chen, Kang Liu, Wei Bi, and Xiaojiang Liu. 2020. Event extraction as machine reading comprehension. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1641–1651, Online. Association for Computational Linguistics.
- Jian Liu, Yubo Chen, Kang Liu, and Jun Zhao. 2019. Neural cross-lingual event detection with minimal parallel resources. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 738–748, Hong Kong, China. Association for Computational Linguistics.
- Arun Mallya and Svetlana Lazebnik. 2017. Recurrent models for situation recognition. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 455–463. IEEE Computer Society.
- Antoine Miech, Jean-Baptiste Alayrac, Lucas Smaira, Ivan Laptev, Josef Sivic, and Andrew Zisserman. 2020. End-to-end learning of visual representations from uncurated instructional videos. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 9876–9886. IEEE.
- Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. 2019. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 2630–2640. IEEE.
- Tomás Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. In *1st International Conference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings*.
- Thien Huu Nguyen, Kyunghyun Cho, and Ralph Grishman. 2016. Joint event extraction via recurrent neural networks. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 300–309, San Diego, California. Association for Computational Linguistics.
- Alejandro Pardo, Humam Alwassel, Fabian Caba, Ali Thabet, and Bernard Ghanem. 2021. Refinelo: Iterative refinement for weakly-supervised action localization. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 3319–3328.
- Sarah Pratt, Mark Yatskar, Luca Weihs, Ali Farhadi, and Aniruddha Kembhavi. 2020. Grounded situation recognition. In *European Conference on Computer Vision*, pages 314–332. Springer.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.
- Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun. 2015. Faster R-CNN: towards real-time object detection with region proposal networks. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 91–99.
- Arka Sadhu, Tanmay Gupta, Mark Yatskar, Ram Nevatia, and Aniruddha Kembhavi. 2021. Visual semantic role labeling for video understanding. In *The*

- IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Lei Sha, Feng Qian, Baobao Chang, and Zhifang Sui. 2018. [Jointly extracting event triggers and arguments by dependency-bridge RNN and tensor-based argument interaction](#). In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018*, pages 5916–5923. AAAI Press.
- Haisheng Su, Weihao Gan, Wei Wu, Yu Qiao, and Junjie Yan. 2021. [Bsn++: Complementary boundary regressor with scale-balanced relation modeling for temporal action proposal generation](#).
- Mohammed Suhail and Leonid Sigal. 2019. [Mixture-kernel graph attention network for situation recognition](#). In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 10362–10371. IEEE.
- Meihan Tong, Shuai Wang, Yixin Cao, Bin Xu, Juanzi Li, Lei Hou, and Tat-Seng Chua. 2020. [Image enhanced event detection in news articles](#). In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 9040–9047.
- Xiaozhi Wang, Shengyu Jia, Xu Han, Zhiyuan Liu, Juanzi Li, Peng Li, and Jie Zhou. 2020. [Neural Gibbs Sampling for Joint Event Argument Extraction](#). In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing*, pages 169–180, Suzhou, China. Association for Computational Linguistics.
- Xiaozhi Wang, Ziqi Wang, Xu Han, Zhiyuan Liu, Juanzi Li, Peng Li, Maosong Sun, Jie Zhou, and Xiang Ren. 2019. [HMEAE: Hierarchical modular event argument extraction](#). In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5777–5783, Hong Kong, China. Association for Computational Linguistics.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. [Transformers: State-of-the-art natural language processing](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.
- Saining Xie, Chen Sun, Jonathan Huang, Zhuowen Tu, and Kevin Murphy. 2018. [Rethinking spatiotemporal feature learning: Speed-accuracy trade-offs in video classification](#). In *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part XV*, volume 11219 of *Lecture Notes in Computer Science*, pages 318–335. Springer.
- Hang Yang, Yubo Chen, Kang Liu, Yang Xiao, and Jun Zhao. 2018. [DCFEE: A document-level Chinese financial event extraction system based on automatically labeled training data](#). In *Proceedings of ACL 2018, System Demonstrations*, pages 50–55, Melbourne, Australia. Association for Computational Linguistics.
- Mark Yatskar, Luke S. Zettlemoyer, and Ali Farhadi. 2016. [Situation recognition: Visual semantic role labeling for image understanding](#). In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 5534–5542. IEEE Computer Society.
- Ying Zeng, Yansong Feng, Rong Ma, Zheng Wang, Rui Yan, Chongde Shi, and Dongyan Zhao. 2018. [Scale up event extraction learning via automatic training data generation](#). In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018*, pages 6045–6052. AAAI Press.
- Tongtao Zhang, Spencer Whitehead, Hanwang Zhang, Hongzhi Li, Joseph G. Ellis, Lifu Huang, Wei Liu, Heng Ji, and Shih-Fu Chang. 2017. [Improving event extraction via multimodal integration](#). In *Proceedings of the 2017 ACM on Multimedia Conference, MM 2017, Mountain View, CA, USA, October 23-27, 2017*, pages 270–278.
- Zhu Zhang, Zhou Zhao, Zhijie Lin, Xiuqiang He, et al. 2020. [Counterfactual contrastive learning for weakly-supervised vision-language grounding](#). *Advances in Neural Information Processing Systems*, 33:18123–18134.
- Zixuan Zhang and Heng Ji. 2021. [Abstract Meaning Representation guided graph encoding and decoding for joint information extraction](#). In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 39–49, Online. Association for Computational Linguistics.

The appendix is organized as follows:

- A. We include more experimental settings.
- B. We demonstrate our proposal generation component for selecting video segments with events.
- C. We list argument roles for each event type.
- D. We provide more details of our baseline.
- E. We show our annotation interface for the dataset.
- F. We state our Fair Use Notice.

A Implementation details

Multimodal event coreference resolution. For each feature extraction branch (text, video, object), we apply separate fully-connected layer and a gated unit for projection to common space. We use an Adam optimizer (Kingma and Ba, 2015) with a learning rate of $1e-4$. The batch size is set to 256 video clips. The model is trained for 50 epochs on one NVIDIA TITAN RTX for about 2 hours. We further split the 860 video data into 200 video article pairs for the validation set and 660 for testing the performance. The parameter search for the threshold was done in the validation set by selecting the highest F1 score, and the similarity score above 0.13 will be viewed as positive pairs for prediction.

Multimodal event extraction and argument role labeling. For video-level features and region features, we separately use a fully-connected layer to project them into 768-D space to be aligned with text embeddings. We directly use text embedding layer to embed bounding box coordinates. For the text decoding head, we borrow implementations from the official implementation² of OneIE and use the same hyper-parameters. The video decoding head uses Beam Search for decoding in inference, with a beam width of 5. During training and evaluation, we sample annotated $t = 3$ frames and extract $k = 15$ objects for each frame. We use a batch size of 6 examples per GPU, and distribute the training over 4 NVIDIA V100 GPUs. We use Adam with a learning rate of $1e-4$ to optimize our models. We train our models for 150 epochs.

B Event Proposal Generation

To acquire the temporal boundary of the video event, we use the Boundary Sensitive Network (Lin et al., 2018) for temporal proposal generation in the video clips. We fine-tune the network with the VM²E² training set to better capture the action

²<http://blender.cs.illinois.edu/software/oneie>

semantics within the dataset. Table 6 shows the proposal generation results for VM²E² test set. Similar to (Lin et al., 2018; Su et al., 2021), we evaluate the improvement in the ability of BSN to generate proposals which have high temporal overlap with ground truth proposals. To quantify this improvement, we measure the recall (AR) over multiple temporal-IoU thresholds (0.5 to 0.95 with an increment of 0.05) for a fixed number of proposals (N). We also measure the area under (AUC) average recall (AR) at different number of proposals (N) curve.

Although we use ground truth proposals for event extraction and argument role labelling section of the experiments in the current work, our method can be extended to work with automatically generated proposals. Hence, our method combined with any proposal generation technique, can be considered as an end-to-end solution to multimedia event extraction given a video-article pair.

Training	AR		AUC
	@1	@100	
ActivityNet	0.11	0.52	38.52
ActivityNet + VM ² E ²	0.18	0.67	54.94

Table 6: Fine-tuning the BSN pipeline with VM²E² shows significant improvement in proposal generation and retrieval performance.

C Event type

The event type along with its argument roles are shown in Table 7. We followed The Linguistic Data Consortium (LDC) ontology defined for the AIDA program. These have been made publicly available online³.

D Multimodal event extraction and argument role labeling Baselines

SWiG (Situations with Grounding) dataset provides the annotations corresponding to the visually groundable verbs and the nouns associated with them. To evaluate the JSL (Lin et al., 2020b) model on VM²E² dataset, we map the SWiG verb classes onto the VM²E² event classes as described in Table 8. Note that some classes in SWiG do not have any verb corresponding to the VM²E² event. Hence, these events are never predicted by the JSL model. For fair comparison, we calculate the precision and recall with respect to the remaining classes only.

³<https://tac.nist.gov/tracks/SM-KBP/2018/ontologies/SeedlingOntology>

Event Type	Argument Role
CastVote	Voter,Candidate,Ballot,Result,Place
Contact.Broadcast	Communicator, Recipient, Instrument, Topic, Place
Contact.Correspondence	Participant, Instrument, Topic, Place
Contact.Meet	Participant, Topic, Place
Conflict.Attack	Attacker, Target, Instrument, Place
Conflict.Demonstrate	Demonstrator, Demonstrator, VisualDisplay, Topic, Target, Place
Damage.Destroy	Damager, Artifact, Instrument, Place
Detonate.Explode	Attacker, Target, Instrument, ExplosiveDevice, Place
Disaster.FireExplosion	FireExplosionObject, Instrument, Place
Life.Injure	Victim, Injurer, Instrument, BodyPart, MedicalCondition, Place
Justice.ArrestJail	Jailer, Detainee, Crime, Place
Manufacture.Assemble	ManufacturerAssembler, Artifact, Components, Instrument, Place
Movement.Evacuation	Transporter, PassengerArtifact, Vehicle, Origin, Destination
Movement.PreventPassage	Transporter, PassengerArtifact, Vehicle, Preventer, Origin, Destination
Movement.Transport	Transporter, PassengerArtifact, Vehicle, Origin, Destination
Transaction.ExchangeBuySell	Giver, Recipient, AcquiredEntity, PaymentBarter, Beneficiary, Place

Table 7: Event types and argument roles in VM²E².

In a similar manner, we reformulate the mappings used in WASE (Li et al., 2020) to extend the ontology of Image M²E² (Li et al., 2020) to the VM²E² ontology and retrain WASE as our baseline.

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E Annotation interface

Our data annotation interface for video is shown in Figure 6. Each annotator needs to walk through the whole video and corresponding articles. As shown in the figure, we have a list of event types for the annotators to label the start time and end time. The same event can appear multiple times in the same video. We also allow overlap between different events.

F Fair Use Notice

Our dataset and this paper contain copyrighted material the use of which has not always been specifically authorized by the copyright owner. We make such material available in an effort to advance understanding of technological, scientific, and cultural issues. We believe this constitutes a ‘fair use’ of any such copyrighted material as provided for in section 107 of the US Copyright Law. In accordance with Title 17 U.S.C. Section 107, the materials in this paper are distributed without profit to those who have expressed a prior interest in receiving the included information for non-commercial research and educational purposes. If you wish to use copyrighted material from this paper or in our dataset for purposes of your own that go beyond non-commercial research and academic purposes,

VM ² E ² Event Type	SWiG Verb Class
CastVote	Voting
Contact.Broadcast	Speaking
Contact.Correspondence	Calling, Dialing, Phoning, Telephoning
Contact.Meet	Communicating, Interviewing, Talking, Discussing, Shaking
Conflict.Attack	Attacking, Punching, Kicking, Striking, Shooting
Conflict.Demonstrate	Protesting, Marching, Displaying, Gathering
DamageDestroy	Breaking, Destroying
DetonateExplode	-
Disaster.FireExplosion	Flaming, Erupting, Burning
Life.Injure	-
Justice.ArrestJail	Detaining, Restraining, Arresting
ManufactureAssemble	Assembling
Movement.Evacuation	-
Movement.PreventPassage	Blocking, Guarding
Movement.Transport	Driving, Boating, Disembarking, Landing, Piloting, Steering, Taxiing, Commuting, Riding, Boarding, Biking
Transaction.ExchangeBuySell	Paying, Selling

Table 8: Mapping used to convert the SWiG verbs to VM²E²events. Note that 3 events do not have any mapping. We do not evaluate the JSL baseline over these events.

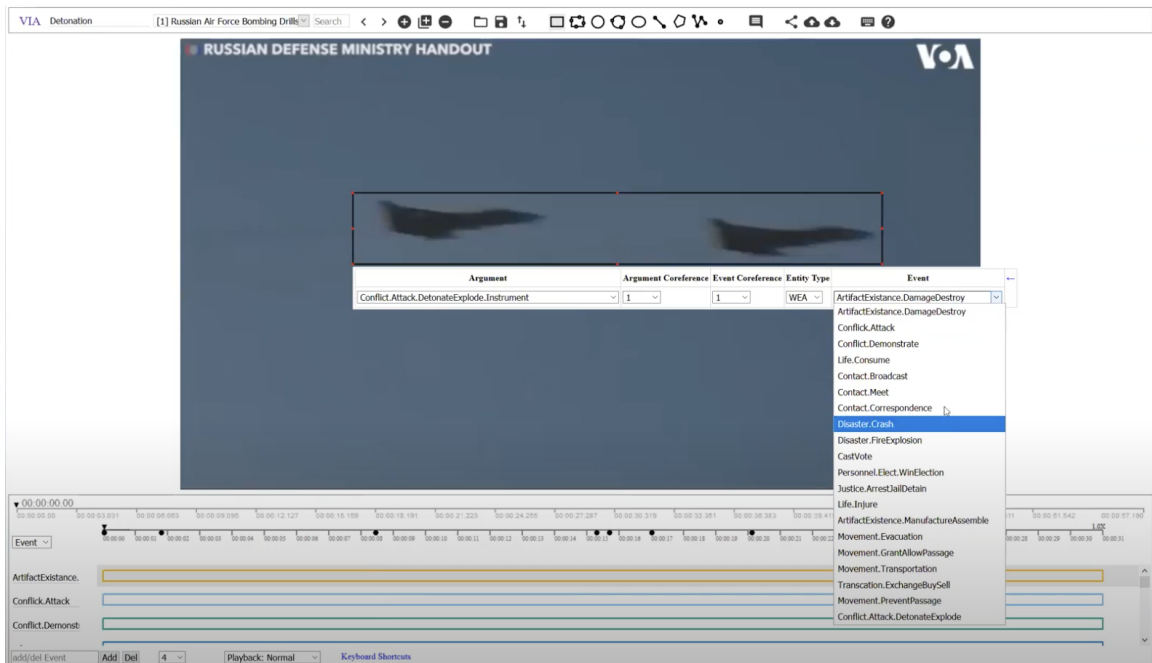


Figure 6: Annotation interface of the video. We annotate the event temporal of each video event. Also, we will annotate the multimodal event coreference between the video event and text event. For the argument role, we select 3 frames to annotate the bounding box.