



Sherlock: Towards Multi-scene Video Abnormal Event Extraction and Localization via a Global-local Spatial-sensitive LLM

Junxiao Ma
20235227109@stu.suda.edu.cn
School of Computer Science and
Technology, Soochow University
Suzhou, China

Jingjing Wang*
djingwang@suda.edu.cn
School of Computer Science and
Technology, Soochow University
Suzhou, China

Jiamin Luo
20204027003@stu.suda.edu.cn
School of Computer Science and
Technology, Soochow University
Suzhou, China

Peiying Yu
20244227007@stu.suda.edu.cn
School of Computer Science and
Technology, Soochow University
Suzhou, China

Guodong Zhou
gdzhou@suda.edu.cn
School of Computer Science and
Technology, Soochow University
Suzhou, China

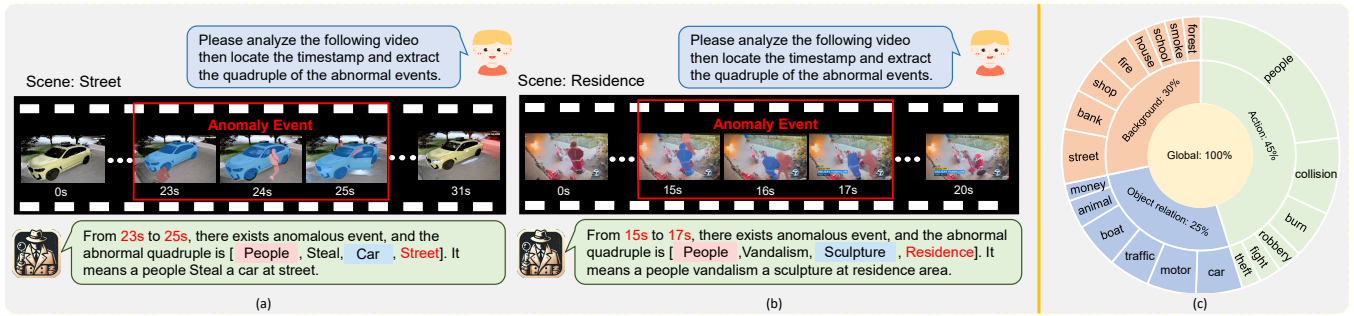


Figure 1: (a) and (b) illustrate two surveillance video examples for our M-VAE task and Sherlock model in two scenes (Street and Residence). Sherlock precisely generates the abnormal event quadruples and their corresponding timestamps. (c) presents a circular ratio diagram illustrating different spatial information. From (c), we observe that the global spatial information and the local spatial information (i.e., action, object relation, and background) in our M-VAE dataset are imbalanced.

Abstract

Prior studies on Video Anomaly Detection (VAD) mainly focus on detecting whether each video frame is abnormal or not in the video, which largely ignore the structured video semantic information (i.e., what, when, and where does the abnormal event happen). With this in mind, this paper propose a new chat-paradigm Multi-scene Video Abnormal Event Extraction and Localization (M-VAE) task, aiming to extract the abnormal event quadruples (i.e., subject, event type, object, scene) and localize such event. Further, this paper believes that this new task faces two key challenges, i.e., global-local spatial modeling and global-local spatial balancing. To this end, this paper proposes a Global-local Spatial-sensitive Large

Language Model (LLM) named Sherlock, i.e., acting like *Sherlock Holmes* to track down the criminal events, for this M-VAE task. Specifically, this model designs a Global-local Spatial-enhanced MoE (GSM) module and a Spatial Imbalance Regulator (SIR) to address the two challenges respectively. Extensive experiments on our M-VAE instruction dataset show the significant advantages of Sherlock over several advanced Video-LLMs. This justifies the importance of global-local spatial information for the M-VAE task and the effectiveness of Sherlock in capturing such information.

CCS Concepts

• Computing methodologies → Artificial intelligence.

Keywords

Multi-scene Video, Video Abnormal Event, Spatial-sensitive LLM

ACM Reference Format:

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*Corresponding Author: Jingjing Wang.

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1 Introduction

Video Understanding is a foundational task in artificial intelligence, which focuses on analyzing and interpreting the content of videos to enable various applications, including video classification, activity recognition, and scene understanding [40, 59, 60, 70]. As a critical branch of video understanding, Video Anomaly Detection (VAD) [21, 70], which aims to automatically detect abnormal videos, has garnered significant research attention due to its wide range of applications in criminal activity detection and disaster response [56]. Prior studies on VAD mainly focus on detecting whether each video frame is abnormal or not in the video [21, 30, 41, 56]. However, these studies overlook targeting at determining the underlying video semantic structure, i.e., “*what is the abnormal type, where they have occurred, which people or things are involved*” with a given video.

Motivated by these, this paper proposes a novel Multi-scene Video Abnormal Event Extraction and Localization (M-VAE) task, aiming at localizing abnormal events (i.e., starting and ending times of the anomaly) and extracting event quadruples (i.e. [subject of the event, event type, object of the event, scene of the event]) through a chat paradigm. Take an example of *Street* scene in Figure 1 (a), within 23s to 25s, a man bends down and pries the lock, then drives away from the street and the abnormal event quadruple is [*people, steal, car, street*]. Different scene (i.e., Residence scene) is also shown in Figure 1 (b). Within 15s to 17s, a man vandalizes a sculpture at one’s residence and the quadruple is [*people, Vandalism, Sculpture, Residence*]. This structured processing for abnormal videos can significantly improve the practicality and efficiency of video anomaly localization systems. In fields such as real-time abnormal event monitoring that require high reliability and precision monitoring, using such structured processing can quickly search and screen for the required abnormal elements, which provides more convenient and intuitive evidence for further processing. Therefore, it is worthwhile to address this new task. Nevertheless, we believe that this new task faces two key challenges.

For one thing, it is challenging to model the global-local spatial information (named global-local spatial modeling challenge for short). Existing video understanding models [35, 38, 54] mainly focus on modeling the general global information (i.e., general representations of videos). However, the local spatial information in our M-VAE task is often crucial compared to general global information, which are highly discriminative and essential for precise identification. Taking Figure 1 (a) as an example, the local spatial information, such as action (bend down), object relations (<man, near, car>), and background (street), can help better identify abnormal events. However, those local spatial information (e.g., actions, object relations, backgrounds) have different heterogeneous representations (i.e., different model structures and encoders). Therefore, a single, fixed-capacity transformer-based model, often makes it difficult to capture those critical local spatial information in videos. Recently, the Mixture of Expert (MoE) [24, 25] paradigm has demonstrated scalability in multi-modal heterogeneous representation fusion tasks [19, 70]. Inspired by this, a well-behaved model for our M-VAE task should adopt the MoE paradigm to not only consider the global spatial information but also emphasize the importance of the local spatial information.

For another, a straightforward approach is to employ a basic Mixture of Expert (MoE) mechanism [24, 25] to treat global spatial information (i.e., general representations of videos) and local spatial information (e.g., actions) as the global expert and local experts for integrating those information. However, the data imbalance issue among local spatial information may lead to the basic MoE experts being biased towards the more frequently occurring spatial information in the dataset. The statistics in Figure 1 (c) can illustrate this imbalance. Certain frequently appearing local information (i.e., action at 45%), can lead to higher weight for the corresponding expert. However, in Figure 1 (a), the object relations information, with the smallest proportion (25%), but is the most discriminative for extracting and localizing *Theft* events. More seriously, global spatial information is the most frequent and our preliminary experiments in Figure 7 (a) reveal global expert is often more thoroughly trained and often have the highest weights. Therefore, a better-behaved MoE expert fusion mechanism should mitigate this data imbalance (named global-local spatial balancing challenge), ensuring all experts are sufficiently trained to highlight their importance.

To tackle above challenges, we propose a Global-local Spatial-sensitive LLM named Sherlock, i.e., acting like *Sherlock Holmes* to track down criminal events, for M-VAE. Specifically, this model designs a Global-local Spatial-enhanced MoE (GSM) module to address the global-local spatial modeling challenge, which includes four spatial experts to extract spatial information and an expert gate to weigh global and local spatial information. Furthermore, this model designs a Spatial Imbalance Regulator (SIR) to address the global-local spatial balancing challenge, which includes a Gated Spatial Balancing Loss (GSB) to further balance global and local experts. Particularly, we construct a M-VAE instruction dataset to better evaluate the effectiveness of our model. Detailed experiments show Sherlock can effectively extract and localize abnormal events and surpass advanced Video-LLMs in multiple evaluation metrics.

2 Related Work

• **Video Anomaly Detection.** Video Understanding is a rapidly evolving research field which encompasses several tasks, including video grounding [40, 59, 60], spatial-temporal detection [15] and so on. As an important branch of video understanding, previous studies on Video Anomaly Detection (VAD) can be categorized into unsupervised, weakly-supervised, and fully-supervised categories. Unsupervised approaches focus on leveraging reconstruction techniques to identify anomalies [21, 62]. Weakly-supervised methods have shown promising results in identifying abnormal frames [12, 71]. Fully-supervised methods are scarce due to the expensive frame-level annotations required [8, 11, 14, 53, 70], but they are unstructured video anomaly detection. Different from the above studies, our Sherlock model aims to target at determining the underlying video semantic structure, providing a structured quadruple that goes beyond previous methods, facilitating the rapid detection and early warning of abnormal events in real-time.

• **Event Extraction (EE)** focuses on extracting structured information from given types of information. Traditional EE methods mainly extract from text documents [5, 22, 26, 36, 37, 52, 57, 58]. Recently, many studies [2, 44, 65–67] generate similar event structures from visual image data. Different from all the above studies, we are

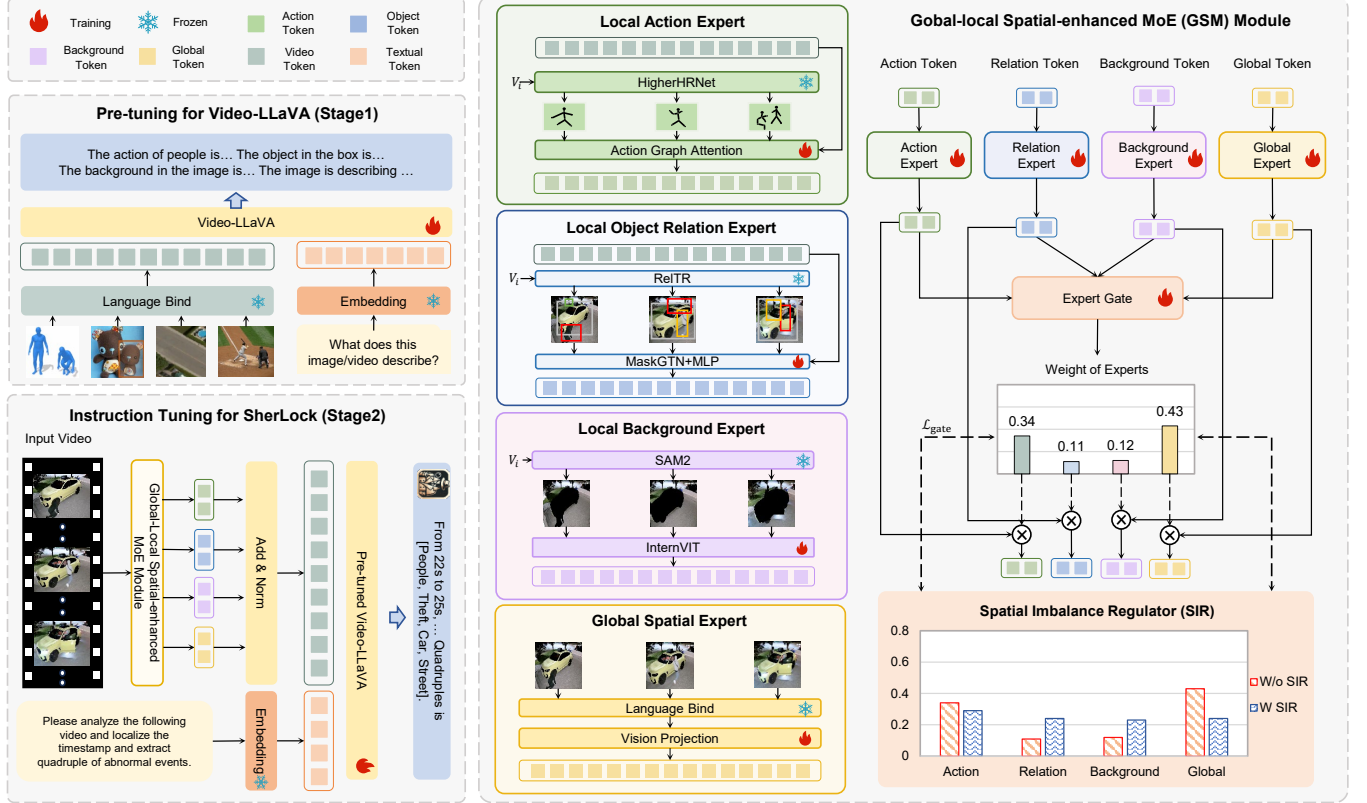


Figure 2: The overall framework of Sherlock. It consists of a Global-local Spatial-enhanced MoE (GSM) Module and a Spatial Imbalance Regulator (SIR). The SIR exerts a direct influence on the output weights of the expert gate.

the first to focus on extracting the abnormal event from videos and constructing a quadruple dataset, incorporating information from multiple spatial information, enriching the task of event extraction, and making it more practical for real-world applications.

• **Video-oriented Large Language Models.** The rise of ChatGPT [49] has stimulated the prosperity of Video Large Language Models which can be categorized into four major types: firstly, Video Chat [35] and Video LLaMA [68], which utilize BLIP-2 [34] and Q-Former to map visual representations onto Vicuna; secondly, models like Video ChatGPT [47], Otter [32], Valley [46], mPLUG-Owl [64], and Chat-UniVi [27], which leverage CLIP [51] to encode visual features; thirdly, PandaGPT [54], which adopts ImageBind [16] as its core architecture for video understanding; and fourthly, VideoLLaVA [38], which aligns video features into linguistic feature spaces using LanguageBind [72]. Recently, a few studies [28, 63, 70] incorporate spatial information in models. Besides, some studies, e.g., OneLLM [19] and Hawkeye [70] employ MoE to integrate various modalities into LLMs, but they fail to consider the balance between global-local representations. Different from all the above studies, we design a new Sherlock model, to address our M-VAE task, which includes a Global-local Spatial-enhanced MoE module and a Spatial Imbalance Regulator to address the challenges of global-local modeling and balancing.

3 Our Sherlock Model

In this paper, we propose a Sherlock model to address the M-VAE task. Figure 2 illustrates the framework of Sherlock, which is

composed of two core components (i.e., the Global-local Spatial-enhanced MoE (GSM) module (sec 3.1) for the global-local spatial modeling challenge and the Spatial Imbalance Regulator (SIR) (sec 3.2) for the global and local spatial balancing challenge). Subsequently, we present our training strategies to enhance the ability of understanding spatial information (sec 3.3).

Backbone. We choose Video-LLaVA [38] together with its visual encoder LanguageBind [72] as the core framework, since Video-LLaVA is optimized with large-scale images and videos, and demonstrates leading performance across most image and video benchmarks. We treat Video-LLaVA as the backbone of M-VAE to explore the potential of Video-LLMs in extracting and localizing abnormal events.

Task Formulation. Given a video V for M frames, each frame is labeled with 1 or 0, where 1 and 0 represent whether this frame conveys an abnormal event. The goal of M-VAE is to interactively generate the quadruple (sub , $type$, obj , sce) for each event along with the corresponding timestamp sta and end , where sub , $type$, obj , sce , sta and end are the subject, event type, object, scene, start time and end time of the abnormal event. As shown in Figure 1 (a), a man steals a car at street from 23s to 25s. Therefore, the output of our M-VAE task is {23s, 25s, (people, steal, car, street)}.

3.1 Global-local Spatial-enhanced MoE Module

As shown in Figure 2, we design a Global-local Spatial-enhanced MoE (GSM) Module for the global-local spatial modeling challenge. Inspired by Mixture-of-Experts (MoE) [25], we design three Local Spatial Experts (i.e., Local Action Expert, Local Object Relation

Expert and Local Background Expert) and a Global Spatial Expert to extract spatial information, detailed as follows.

Local Spatial Experts contain three local spatial experts (i.e., action, object relation, and background), detailed as follows.

• **Local Action Expert (Action Expert, AE).** We leverage HigherHRNet [7], a well-adopted bottom-up human pose estimation network to extract local spatial action information. HigherHRNet can generate local spatial action tokens $\mathbf{T}_a = \{t_1^a, \dots, t_i^a, \dots, t_m^a\}$, and each token consists of 17 human joint nodes for each individual in every frame of a video sequence. Here, i denotes the i -th frame. Next, following Hawkeye [70], we adopt Action Graph Attention to integrate \mathbf{T}_a with video tokens $\mathbf{T}_v = \{t_1^v, \dots, t_i^v, \dots, t_m^v\}$ generated by Video Encoder in Video-LLMs. Attention weight α_{kj} is computed for each node e_k in t_i^a relative to its neighboring node e_j :

$$\alpha_{kj} = \text{softmax} \left(\frac{1}{\sqrt{d}} (\mathbf{W}_a h_k) \cdot (\mathbf{W}_a h_j) \right) \quad (1)$$

where h_k and h_j is the features of e_k and e_j respectively. \mathbf{W}_a denote the learnable weight matrix, and d is the feature dimension. Then, the feature \tilde{h}_k of node e_k is aggregated as: $\tilde{h}_k = \sum_{j \in \mathcal{V}(e_k)} h_j \alpha_{kj}$, where $\mathcal{V}(e_k)$ is neighboring nodes of e_k . Finally the feature of e_k is calculated by $\hat{h}_k = \text{ReLU}(\mathbf{W}_k [\tilde{h}_k, h_k])$, where \mathbf{W}_k donates learnable matrix parameter and $[\tilde{h}_k, h_k]$ is the concatenation of \tilde{h}_k and h_k . After graph attention, \mathbf{T}_a is enhanced using the attention mechanism with query \mathbf{Q}_v , key \mathbf{K}_a , and value \mathbf{V}_a calculation to obtain final action tokens: $\mathbf{T}'_a = \text{softmax}(\mathbf{Q}_v^\top \cdot \mathbf{K}_a) \cdot \mathbf{V}_a$.

• **Local Object Relation Expert (Object Relation Expert, ORE).** We leverage RelTR [10], a well-studied one-stage object relation graph generation method to extract local spatial object relation information. RelTR can generate an object relation token $t_i^o = (R_i, E_i)$, which represents the object relation graph of the i -th frame. Here, $R_i = \{(c_{i,1}, b_{i,1}), \dots, (c_{i,k}, b_{i,k})\}$ is a set of k detected objects, with class c and corresponding bounding box b . The set $E_i = \{c_{i,p}, r_{i(p,q)}, c_{i,q}\}$ consists of the directed edges in the graph, representing two directional edges from $c_{i,p}$ to $r_{i(p,q)}$ and from $r_{i(p,q)}$ to $c_{i,q}$, where $r_{i(p,q)}$ denotes a relationship category. For example, an object might be represented as $(man, <0.36, 0.24, 0.75, 1.62>)$, and an edge as $(man, near, car)$. Then, following Hawkeye [70], we perform object masking via Masked Graph Transformer Networks (MaskGTN) to fully mine object relations. Irrelevant object parts are masked based on bounding boxes and information is aggregated from neighbors using the graph transformer layer (GT). Given an input graph of region classes and edges, MaskGTN computes updated vectors for each region and edge. Assuming that we use L layers of GT, with \mathbf{H}^ℓ representing the features of the ℓ -th layer, the final forward propagation is computed as:

$$\mathbf{H}^{\ell+1} = \text{ReLU} \left(\sqrt{\hat{\mathbf{D}}} \cdot \hat{\mathbf{A}} \cdot \sqrt{\hat{\mathbf{D}}} \cdot \mathbf{H}^\ell \cdot \mathbf{W}^\ell \right) \quad (2)$$

where $\hat{\mathbf{A}}$ is the adjacency matrix of the object-relation graph, derived from E_i , and $\hat{\mathbf{D}}$ is its degree matrix, with $\hat{\mathbf{D}}_{i,i} = \sum_j \hat{\mathbf{A}}_{i,j}$. \mathbf{W}^ℓ is the trainable matrix parameter. ReLU is the activation function.

• **Local Background Expert (Background Expert, BE).** We leverage SAM2 [29], an advanced model for visual segmentation, to extract local spatial background information from videos. SAM2 can generate a background image for each frame of video. Then we

leverage InternVIT [6] to encode local spatial background information which is a large vision encoder extending the parameters of vision transformer (ViT) [4] to 6B, formally represented as:

$$\mathbf{T}_b = \text{InternVIT}(\text{SAM2}(v_i)) \quad (3)$$

where v_i is the i -th frame of video V . This process results in the local spatial background tokens $\mathbf{T}_b = \{t_1^b, \dots, t_i^b, \dots, t_m^b\}$ for the entire video sequence, with n representing the total number of the video frames.

Global Spatial Expert has a comprehensive understanding of the training data. Collaborate with local spatial experts to bring specialization and generalization capabilities to M-VAE tasks.

• **Global Spatial Expert (Global Expert, GE).** The weight assigned to the global spatial expert complements that of the local spatial experts. Consequently, the local spatial experts acquire specialized skills for specific tasks, whereas the global spatial expert develops a comprehensive understanding of the entire training corpus. The collaboration between these two types of experts provides both specialization and generalization for our M-VAE task. In this way, we leverage LanguageBind [72] in Video-LLaVA [38], which inherits the ViT-L/14 structure from CLIP and is equipped with powerful and universal visual encoding capabilities to extract global spatial information for our task. We subsequently leverage a pre-trained FFN layer by [38] to align the dimension with other spatial information, formally represented as:

$$\mathbf{T}_g = \text{FFN}(\text{LanguageBind}(v_i)) \quad (4)$$

where v_i is the i -th frame of video V . This process yields the full set of global tokens $\mathbf{T}_g = \{t_1^g, \dots, t_i^g, \dots, t_m^g\}$ for the entire video sequence, with n representing the total number of frames.

After designing four experts, we ensure that the four Spatial Experts can dynamically adjust the weights of the four heterogeneous types of spatial information inspired by Mixture-of-Experts (MoE) [19]. As shown in Figure 2, unlike methods that embed several FFNs within LLMs, our GSM put four experts outside the LLMs to adjust weights for global and local spatial information. Based on this, we introduce a dynamic Expert Gate (EG) [50], which controls the contribution of each expert by calculating gating weights as a soft gate. Finally, the output \mathbf{O} of GSM, based on four spatial experts and EG, is formally represented as:

$$\mathbf{g} = \text{softmax} \left(\mathbf{W}_g \cdot \sum_{i=1}^N (\mathbf{S}_i) \right) \quad (5)$$

$$\mathbf{O} = \text{LayerNorm} \left(\sum_{i=1}^N (\mathbf{g}_i \cdot \mathbf{S}_i) \right) \quad (6)$$

where $\text{LayerNorm}(\cdot)$ indicates layer normalization [1]. \mathbf{g}_i (the i -th entry in \mathbf{g}) represents the weight of the i -th expert. \mathbf{S}_i represents the outputs of the i -th Spatial expert. N is the total number of spatial expert, and \mathbf{W}_g being the trainable weight matrix.

3.2 Spatial Imbalance Regulator

After modeling the spatial information, we design a Spatial Imbalance Regulator (SIR) including a Gated Spatial Balancing Loss (GSB) for the global-local spatial balancing challenge, detailed as follows.

Table 2: Comparison of several Video-LLMs and Sherlock on our instruction dataset. The ↓ beside FNRs indicates the lower the metric, the better the performance. AE, ORE, BE, GE, and EG represent four Spatial Experts and Expert Gate respectively. Sub, Type, Obj, and Sce represent Subject, Event type, Object, and Scene respectively. For each task, Blue and Green donate the first and second place respectively.

| Models | Event Extraction | | | | | | | | | | | | Event Location | | | | Anomaly Cls. | |
|----------------|------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|----------------|--------------|--------------|--------------|--------------|--------------|
| | Single (F1) | | | | Pair (F1) | | | | Quadruple | | | | mAP@tIoU | | | | FNRs↓ | F2 |
| | Subject | Type | Object | Scene | Sub-Type | Obj-Type | Sub-Sce | Obj-Sce | F1 | T5-based | GPT-based | Average | 0.1 | 0.2 | 0.3 | Average | | |
| Video Chat | 73.14 | 71.35 | 64.28 | 71.76 | 70.12 | 58.69 | 71.55 | 61.18 | 40.95 | 61.68 | 53.94 | 62.6 | 77.28 | 74.93 | 66.26 | 72.82 | 38.79 | 65.88 |
| Video ChatGPT | 61.87 | 59.51 | 54.82 | 46.39 | 54.23 | 49.68 | 43.26 | 41.38 | 39.63 | 57.36 | 50.38 | 49.86 | 74.65 | 70.91 | 67.03 | 70.86 | 41.47 | 61.35 |
| Valley | 64.64 | 62.27 | 58.94 | 52.26 | 58.36 | 51.64 | 49.68 | 46.42 | 42.38 | 63.34 | 56.67 | 54.23 | 69.34 | 62.26 | 57.66 | 63.08 | 43.49 | 59.42 |
| Panda GPT | 73.09 | 75.45 | 68.42 | 61.93 | 71.96 | 59.92 | 59.79 | 59.45 | 41.17 | 54.36 | 48.55 | 60.37 | 76.64 | 62.69 | 57.21 | 65.51 | 35.62 | 69.16 |
| mPLUG-Owl | 52.86 | 37.54 | 40.24 | 37.68 | 31.97 | 28.89 | 33.9 | 27.87 | 22.12 | 30.68 | 32.41 | 34.1 | 61.42 | 53.21 | 46.46 | 53.69 | 56.98 | 51.66 |
| Chat-UniVi | 59.71 | 57.26 | 55.28 | 44.23 | 52.43 | 50.62 | 41.24 | 40.96 | 37.68 | 55.34 | 48.84 | 43.59 | 65.89 | 58.62 | 40.02 | 54.84 | 52.52 | 53.78 |
| Video-LLaVA | 77.85 | 73.68 | 65.67 | 75.91 | 69.32 | 59.21 | 73.25 | 62.24 | 41.32 | 52.94 | 56.74 | 64.37 | 78.31 | 74.79 | 64.92 | 72.67 | 41.34 | 64.96 |
| Sherlock | 87.97 | 82.12 | 74.99 | 92.15 | 77.06 | 66.28 | 85.16 | 73.17 | 57.57 | 75.46 | 67.52 | 75.22 | 94.03 | 82.59 | 76.12 | 84.24 | 17.24 | 83.59 |
| w/o AE | 83.15 | 77.64 | 71.28 | 90.16 | 72.36 | 63.47 | 80.52 | 70.39 | 52.48 | 60.61 | 62.02 | 71.18 | 92.24 | 81.21 | 75.38 | 82.94 | 21.82 | 80.45 |
| w/o ORE | 83.96 | 78.25 | 72.37 | 90.01 | 74.24 | 64.46 | 81.56 | 70.97 | 54.35 | 72.28 | 65.08 | 72.5 | 91.13 | 82.08 | 74.62 | 82.61 | 22.97 | 78.83 |
| w/o BE | 81.16 | 74.65 | 67.88 | 88.07 | 69.29 | 61.12 | 77.64 | 66.64 | 48.63 | 53.04 | 55.94 | 67.71 | 88.62 | 79.09 | 72.24 | 79.98 | 25.36 | 73.51 |
| w/o GE | 79.2 | 74.09 | 66.71 | 84.11 | 70.38 | 60.77 | 75.44 | 66.28 | 46.34 | 63.97 | 57.06 | 66.75 | 86.18 | 78.37 | 69.28 | 77.94 | 28.97 | 71.28 |
| w/o EG | 78.83 | 73.96 | 65.02 | 83.15 | 70.15 | 60.26 | 74.15 | 63.37 | 43.64 | 59.14 | 51.82 | 64.86 | 81.31 | 77.68 | 67.88 | 75.62 | 32.58 | 67.07 |
| w/o SIR | 84.47 | 80.14 | 71.94 | 92.34 | 75.58 | 64.84 | 83.21 | 70.06 | 55.73 | 72.87 | 65.18 | 73.3 | 83.41 | 78.49 | 68.37 | 76.75 | 30.64 | 70.97 |
| w/o pre-tuning | 78.24 | 74.44 | 64.22 | 82.21 | 68.55 | 57.74 | 72.62 | 62.91 | 42.51 | 57.22 | 50.54 | 63.74 | 79.58 | 75.32 | 65.07 | 73.32 | 34.87 | 66.64 |

each abnormal event. If they cannot reach an agreement, an expert will make the final decision to ensure annotation quality. The *Kappa* consistency check value of the annotation is 0.87. 2) For localization task, we use the timestamp in the CUA as labels for localization. Furthermore, we adhere to the split of CUA for training and inference videos and take 8 frames per second, resulting in **800K** frames from 1k videos and each video contains **1.68** abnormal event on average. The statistics of the number of events and the duration in seconds (s) of events for each scene are shown in Table 1. Finally, we obtain our M-VAE instruction dataset. Our instruction for the M-VAE task is: "Generate a quadruple and localize an abnormal event in the video. The quadruple includes subject, event type, object, and scene in abnormal events". Figure 1 (c) and Figure 3 show the top 20 quadruple elements, revealing the spatial imbalance.

4.2 Baseline Models

In this paper, we select several advanced Video-LLMs as baselines which are introduced as follows. **VideoChat** [47] employs Q-Former [34] to map visual representations to Vicuna [9]. **VideoChatGPT** [47] integrates LLMs with CLIP [51] for video representations. **Valley** [46] employs a temporal modeling module to bridge visual and textual modes. **PandaGPT** [54] utilizes ImageBind [16] to demonstrate cross-modal capabilities. **mPLUG-Owl** [64] introduces a visual abstractor module to align different modes. **Chat-UniVi** [27] merges visual tokens with semantic meanings. **Video-LLaVA** [38] conducts joint training on images and videos. To ensure a fair comparison, we re-implement these models using their released codes in our experiments, with all LLMs sized at 7B.

4.3 Evaluation Metrics

M-VAE focuses on extracting event quadruples and locating abnormal events from videos, requiring evaluation metrics in three aspects (i.e., extract event quadruples, locate abnormal events, and classify abnormal events). **For the extraction performance**, we measure our model through three perspectives. 1) Single: performance of generating each individual element. 2) Pair: performance of generating the element pair, i.e., Subject-Type pair, Object-Type pair, Subject-Scene pair, Object-Scene pair. 3) Quadruple Generation: performance of generating the complete event quadruple.

Following the prior works [31], the performance is evaluated with Macro-F1. Furthermore, we use T5-based and GPT-based metrics based on Video-bench [48] especially for LLM. **For localization performance**, we use the mAP@tIoU metric [69], calculated by mean Average Precision (mAP) at different IoU thresholds from 0.1 to 0.3 with 0.1 intervals. **For classification performance**, we refer to the traditional anomaly classification task [18, 45, 61] for anomaly classification metric, which mainly determines whether each video frame is abnormal or not in the video. We prefer Recall over Precision and report F2 [69] as another classification metric. Furthermore, our model focuses on accurately distinguishing abnormal events. Following Hawkeye [70], it's better to mark all timestamps as abnormal than to miss any. So we prioritize false negative rates (FNRs): $FNRs = \frac{\text{num of false-negative frame}}{\text{num of positive frame}}$, which is the rate of mislabeling an abnormal event frame as normal. In addition, *t*-test [13] is used to evaluate the significance of the performance.

4.4 Implementation Details

In our experiments, we utilize open-source codes to obtain experimental results of all the baselines in Table 2. The hyper-parameters of these baselines remain the same setting reported by their public papers. For both Stage 1 and 2 of our M-VAE approach, we use a batch size of 16 and train for 1 epoch with the AdamW [43] optimizer and a cosine learning rate decay schedule with a warm-up period. The initial learning rate is $2e-5$. The hyper-parameter α in \mathcal{L} is tuned to 0.4. We tune the Video-LLaVA model using LoRA [23]. The LoRA matrix dimension, dropout rate, and dropout rate are 16, 64, and 0.05 respectively. Experiments are run on a single NVIDIA A100 GPU with 40GB memory. Stage 1 training takes about 16 hours, Stage 2 takes 60 hours, and inference takes about 8 hours.

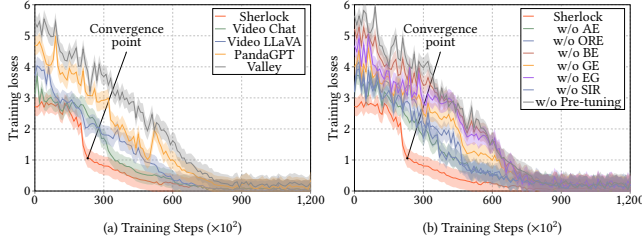
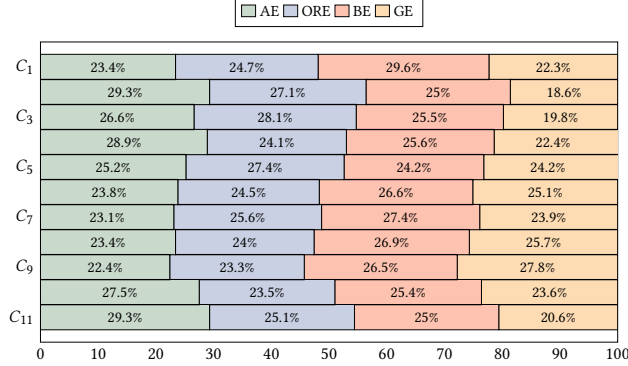
5 Results and Discussions

5.1 Experimental Results

Table 2 and Table 4 shows the performance comparison of different models on our M-VAE task, and we can see that: **For extraction performance**, our **Sherlock** model outperforms all baselines, with an average improvement of 10.85 (p -value < 0.05) over the second performance. Specifically, our **Sherlock** model surpasses the second

Table 3: Comparison of several advanced Video-LLMs and Sherlock on the 14 scenes of the M-VAE dataset with FNRs.

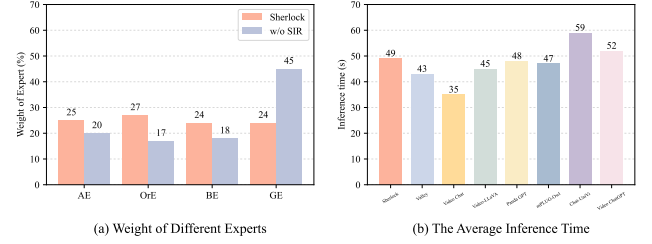
| Models | School | Shop | Underwater | Street | Road | Boat | Wild | Forest | Residence | Bank | Commercial | Factory | Lawn | Other |
|-----------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|--------------|-------------|
| Video Chat | 39.57 | 39.47 | 37.3 | 36.81 | 27.41 | 35.32 | 33.27 | 33.36 | 35.95 | 40.59 | 38.97 | 45.52 | 35.26 | 49.04 |
| Video Chatgpt | 45.91 | 41.98 | 39.36 | 41.41 | 30.11 | 38.19 | 36.32 | 37.73 | 37.54 | 44.5 | 42.96 | 40.78 | 36.28 | 52.33 |
| Valley | 46.68 | 43.76 | 41.37 | 44.24 | 35.66 | 42.15 | 46.78 | 39.25 | 42.15 | 48.35 | 48.31 | 47.21 | 37.11 | 53.09 |
| Pandagpt | 34.56 | 35.65 | 34.47 | 36.48 | 24.42 | 35.85 | 31.78 | 32.37 | 34.18 | 38.55 | 37.89 | 41.46 | 31.17 | 44.24 |
| mPLUG-Owl | 54.13 | 54.41 | 53.21 | 47.34 | 36.51 | 45.02 | 58.37 | 46.31 | 45.63 | 57.94 | 56.88 | 53.14 | 54.74 | 59.56 |
| Chat-UniVi | 52.51 | 48.82 | 47.52 | 48.68 | 35.53 | 44.41 | 59.88 | 45.96 | 44.34 | 54.92 | 55.66 | 51.12 | 52.22 | 55.48 |
| Video-llava | 45.27 | 37.43 | 34.63 | 38.84 | 27.76 | 32.54 | 26.41 | 30.29 | 31.45 | 21.19 | 29.84 | 20.08 | 30.72 | 28.31 |
| Sherlock | 16.35 | 21.91 | 15.16 | 24.24 | 14.63 | 20.96 | 17.29 | 18.48 | 20.43 | 11.21 | 23.43 | 8.96 | 21.44 | 13.6 |

**Figure 5: Convergence analysis of other baselines, Sherlock, and its variant without specific components.****Figure 6: The visualization of balanced spatial expert weights calculated in Eq.(5). The length of the bar in different colors represents the weights for the corresponding expert. C_1 to C_{11} is different Event types in quadruples.**

performance by an average of 9.9 (p -value < 0.05), 8.59 (p -value < 0.05), and 9.52 (p -value < 0.05) in average Single, Pair, and Quadruple metrics, justifying the effectiveness of **Sherlock** on extraction task. **For localization performance**, our **Sherlock** model exceeds the second performance by 11.42 (p -value < 0.01) in average $mAP@tIoU$ metric, justifying the effectiveness of **Sherlock** on localization task. Furthermore, **for classification performance**, in FNRs and F2 metric, **Sherlock** surpasses the second performance in 18.38 (p -value < 0.01) and 14.43 (p -value < 0.01). This implies the importance of our global and local information and justifies the effectiveness of our **Sherlock** model on our task.

5.2 Effectiveness Study for Main Modules

In order to further investigate the contributions of different modules of **Sherlock**, we conduct an ablation study on our **Sherlock** model. As shown in Table 2, w/o AE, w/o ORE, w/o BE, w/o GE, w/o EG, and w/o pre-tuning represent without four Spatial Experts, Expert Gate, and pre-tuning stage in sec 3.2 respectively.

**Figure 7: (a) is the visual comparison of our SIR and (b) is the comparison of the average inference time for a one-minute video between Sherlock and other Video-LLMs.****Table 4: Comparison of localization and anomaly classification task with several well-performing non-LLM models.**

| Models | Anomaly Location | | | | Anomaly CIs. | |
|-----------------|------------------|--------------|--------------|--------------|--------------|--------------|
| | $mAP@tIoU$ | | | Average | FNRs↓ | F2 |
| | 0.1 | 0.2 | 0.3 | | | |
| BiConvLSTM[20] | 52.74 | 37.31 | 31.12 | 40.39 | 68.05 | 44.48 |
| SPIL[55] | 53.28 | 38.89 | 32.91 | 41.69 | 67.84 | 46.87 |
| FlowGatedNet[8] | 53.64 | 39.64 | 33.18 | 42.15 | 67.24 | 46.55 |
| X3D[53] | 54.52 | 40.05 | 34.96 | 43.17 | 65.08 | 48.65 |
| HSCD[14] | 56.14 | 42.87 | 35.28 | 44.76 | 60.36 | 52.28 |
| Sherlock | 94.03 | 82.59 | 76.12 | 84.24 | 17.24 | 83.59 |

Effectiveness Study of Global and Local Spatial Expert. From Table 2, we can see that: The performance of **w/o AE**, **w/o ORE**, **w/o BE** and **w/o GE** degrades in all metrics, with an average decrease of 7.54 (p -value < 0.01), 7.57 (p -value < 0.01), 4.37 (p -value < 0.01), and 5.68 (p -value < 0.01) in FNRs, F2, average $mAP@tIoU$, and average event extraction metrics. This confirms the importance of global and local information in extracting and localizing abnormal events, and **Sherlock** can better model those information well.

Effectiveness Study of Spatial Imbalance Regulator. From Table 2, we can see that: 1) Compared with **Sherlock**, **w/o EG** shows poorer performance in all metrics, with a decrease of FNRs, F2, average $mAP@tIoU$, and average extraction performance by 15.34 (p -value < 0.01), 16.52 (p -value < 0.01), 8.62 (p -value < 0.05) and 10.36 (p -value < 0.01), respectively. This demonstrates the effectiveness of GSM in global-local spatial modeling and encourages us to consider handling heterogeneity issues between spatial information in the manner of MoE. 2) From Table 2, we can see that compared to performance of **w/o SIR**, the performance of **w/o MG** is poorer, with FNRs, F2, average $mAP@tIoU$, and average event extraction metrics decreasing by 1.94 (p -value < 0.05), 3.9 (p -value < 0.05), 1.13 (p -value < 0.05) and 4.84 (p -value < 0.05), respectively. This further demonstrates the effectiveness of \mathcal{L}_{gate} in global-local

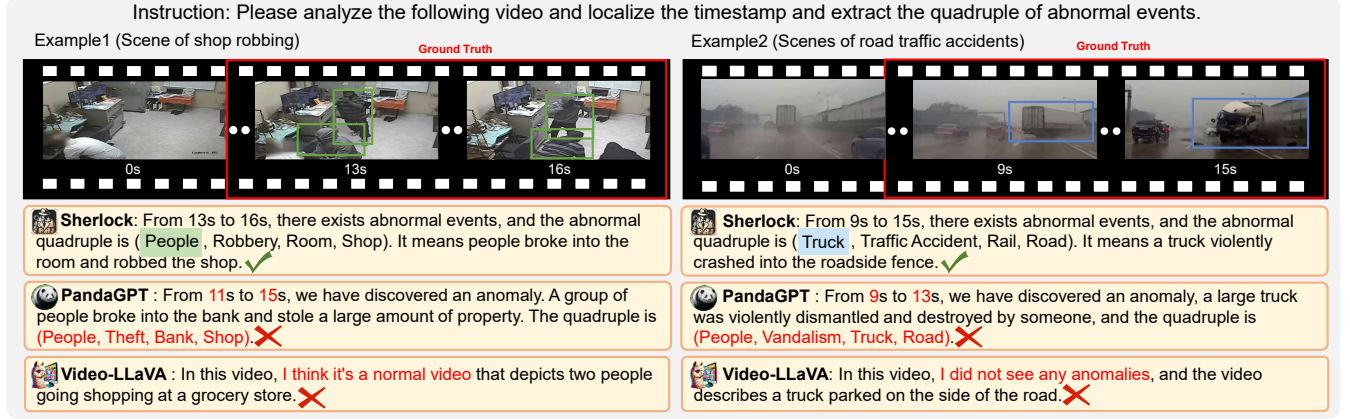


Figure 8: Two Visualized samples to compare Sherlock with other Video-LLMs.

spatial balancing and encourages us to consider using SIR to better balance spatial information. 3) In addition, we record the weights of four spatial experts after training in Figure 6 and Figure 7 (a). We can see that the weights of all experts have been relatively balanced, and each expert has demonstrated outstanding professional abilities when facing different types of abnormal videos.

Effectiveness Study of Pre-tuning. From Table 2, we can see that **w/o pre-tuning**, the performance is inferior to **Sherlock**. FNRs, F2, average map@tIoU, and average event extraction metrics have decreased by 17.63 (p -value < 0.01), 16.95 (p -value < 0.01), 10.92 (p -value < 0.01) and 11.48 (p -value < 0.01), respectively. This further justifies the effectiveness of pre-tuning, as well as encourages us to use more high-quality datasets to enhance the spatial understanding ability of Video-LLMs before instruction-tuning.

5.3 Convergence Analysis and Practical Assessment for Sherlock

In order to analyze the convergence of Sherlock, we record the loss of baseline Video-LLMs, Sherlock, and its variant without specific components. The results are shown in Figure 5 and we can see that: 1) **Sherlock** shows the fastest convergence compared to other Video-LLMs. At the convergence point, the loss of Sherlock is 1.05, while Video-LLaVA is 2.06. This underscores the high efficiency of Sherlock over other Video-LLMs. 2) **Sherlock** shows the fastest convergence compared to its variant in Figure 5. This justifies that the spatial information along with GSM and SIR can accelerate the convergence, which encourages us to consider the spatial information in the M-VAE task.

To assess practicality, we analyze the FNRs of Sherlock for each scene. As shown in Table 3, we can observe that in every scene, Sherlock outperforms other Video-LLMs. This indicates that the possibility of misclassifying abnormal events as normal events is minimized, thereby demonstrating the importance of global and local spatial modeling of Sherlock. We also analyze the average inference time in seconds for a one-minute video. As shown in Figure 7 (b), Sherlock does not perform much differently from the other models in terms of inference time. This is reasonable, as some studies confirm that the MoE architecture can improve efficiency [11, 28]. This suggests that introducing more information along with a MoE module for the M-VAE task does not increase the inference time and Sherlock can maintain good inference efficiency.

5.4 Qualitative Analysis for Sherlock

As shown in Figure 8, we visualize and compare **Sherlock** with other Video-LLMs. We randomly select two samples from our dataset and ask these models to *Analyze the following video and localize the timestamp and extract the quadruple of the abnormal events*. From the figure, we can see that: 1) Accurately localizing abnormal events and extracting correct quadruples is a huge challenge. For instance, example 2 captures a segment from 9s to 15s, where identifying the collision of the truck at road is challenging. 2) Compared with other advanced Video-LLMs, **Sherlock** shows excellent performance in localizing abnormal events. In example 1, **Sherlock** outperforms other models in terms of accuracy. In example 2, it outperforms PandaGPT in terms of accuracy and can generate a correct quadruple. This further demonstrates the effectiveness of **Sherlock** in precisely extracting and localizing abnormal events.

6 Conclusion

In this paper, we firstly propose a new M-VAE task and a constructed instruction dataset, making a significant contribution to future research. Secondly, we propose a Global-local Spatial-sensitive LLM named Sherlock to assist in localizing and extracting abnormal event. This model includes a Global-local Spatial-enhanced MoE module and Spatial Imbalance Regular to model and balance spatial information. Finally, our experimental results demonstrate the outstanding performance of Sherlock. In future work, we hope to consider the relationships between events and enrich our tasks with event inference to improve the performance of extraction. In addition, we also hope to improve the interpretability of our model by providing explanations for abnormal events.

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