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A Unified Event Argument Extraction Framework with Layered Attention and Retrieval-Aware Prompting

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Abstract: Event argument extraction is a critical subtask of information extraction that aims to identify and classify entities that participate in specific events mentioned in unstructured text. Despite recent advancements in natural language processing, extracting arguments accurately remains challenging due to the complex syntactic structures of long sentences, the implicit relationships between event triggers and arguments, and the scarcity of high-quality annotated data. To address these persistent challenges, this paper proposes a novel, unified event argument extraction framework that synergistically integrates a layered attention mechanism with a retrieval-aware prompting strategy. The layered attention module is designed to capture hierarchical structural semantics from word-level to sentence-level representations, enabling the model to dynamically focus on contextually relevant spans while ignoring noisy syntactic artifacts. Concurrently, the retrieval-aware prompting module leverages a dense retrieval system to fetch structurally similar historical event templates from an external datastore. These retrieved instances are then seamlessly integrated into the prompt formulation process, providing explicit grounding and guiding the generative language model to produce accurate argument roles. Extensive evaluations on standard benchmark datasets demonstrate the superiority of the proposed framework over existing state-of-the-art baselines. Through comprehensive ablation studies and error analyses, we reveal that the combination of hierarchical context modeling and retrieval-augmented guidance significantly mitigates issues related to long-range dependencies and out-of-domain generalization.

Keywords: Event Argument Extraction, Information Extraction, Layered Attention, Retrieval-Augmented Generation, Prompt Tuning

INTRODUCTION

1.1 The Challenge of Event Argument Extraction

In the domain of natural language processing and information extraction, event extraction serves as a foundational pillar for understanding the dynamic occurrences described in textual data. The process is generally bifurcated into two sequential or parallel stages: event trigger detection, which identifies the word or phrase invoking the event, and event argument extraction, which locates the specific entities involved in the event and assigns them predefined semantic roles. The latter, event argument extraction, is widely recognized as the more formidable challenge [1]. The difficulty

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stems from the inherent flexibility and ambiguity of human language, where arguments can be scattered across lengthy sentences, nested within complex clauses, or separated from their corresponding triggers by significant distances [2]. Furthermore, a single entity might play multiple roles in different events within the same discourse, requiring the model to maintain a nuanced understanding of contextual boundaries [3]. Historically, the natural language processing community has approached event argument extraction through rigid, pipeline-based architectures that heavily rely on handcrafted linguistic features, such as dependency parse trees, part-of-speech tags, and named entity recognition outputs [4]. While these pipeline models establish a structured methodology for extracting information, they suffer from a well-documented phenomenon known as error propagation. When the upstream trigger detection or named entity recognition module makes a mistake, that error cascades down to the argument extraction phase, irreversibly capping the overall performance of the system [5]. To circumvent these limitations, the paradigm shifted toward joint modeling approaches that attempt to extract triggers and arguments simultaneously using shared representations [6]. Although joint models alleviate error cascading to some extent, they struggle with data sparsity and often fail to capture the complex, long-range dependencies required to correctly link arguments to multiple overlapping events in dense documents. The advent of large language models and prompt-based learning has recently revolutionized the information extraction landscape. By framing event argument extraction as a machine reading comprehension or generative sequence-to-sequence task, researchers can leverage the vast amounts of parameters and pre-trained knowledge embedded in models to directly generate event structures [7]. However, relying solely on parametric memory presents its own set of unique vulnerabilities. Generative models are prone to hallucination, where they confidently generate plausible but factually incorrect arguments that do not exist in the source text [8]. Moreover, zero-shot and few-shot generative prompting techniques often struggle to adapt to the highly specific, rigid schema constraints required by domain-specific event extraction tasks, such as those found in financial or biomedical texts, without extensive fine-tuning [9].

1.2 Motivation for a Unified Framework

Given the respective strengths and weaknesses of structural attention models and generative large language models, there is a compelling motivation to bridge the gap between these two methodologies. A framework that can simultaneously understand the granular, hierarchical syntactic structures of a sentence while leveraging the expressive power of guided text generation represents a logical evolution in the field of event extraction [10]. This paper posits that the key to unlocking higher precision and recall in event argument extraction lies in dual enhancements: internal structural comprehension and external knowledge grounding. Internal structural comprehension can be achieved through advanced attention mechanisms. Standard self-attention, while powerful, often treats all tokens in a sequence democratically, which can dilute the focus when dealing with localized event arguments [11]. We propose a layered attention mechanism that processes the input text through multiple hierarchical stages, moving from fundamental token interactions to phrase-level amalgamations, and finally to sentence-level contextualization. This allows the model to build a robust syntactic and semantic scaffold, ensuring that the relationships between potential arguments and the event trigger are mathematically prioritized in the latent space before any extraction decisions are made [12]. External knowledge grounding addresses the hallucination and schema-conformance issues inherent in generative models. Instead of forcing the model to memorize the extraction schema or relying entirely on static prompts, we introduce

a retrieval-aware prompting strategy [13]. By treating a curated dataset of annotated events as a non-parametric datastore, our framework can dynamically retrieve the most similar historical extraction cases for any given input text [14]. These retrieved exemplars are injected directly into the prompt, serving as high-quality, structurally homologous demonstrations [15]. This retrieval-augmented approach essentially provides the generative model with a localized instruction manual on how to format its output and map specific entities to the correct roles, drastically reducing formatting errors and grounding the generated arguments in the provided text. The fusion of these two components into a single, unified, end-to-end differentiable framework constitutes the primary contribution of this research.

2. Literature Review

2.1 Evolution of Information Extraction

Information extraction has undergone several distinct evolutionary phases over the past three decades, transitioning from rule-based symbolic systems to statistical machine learning, and finally to deep neural networks. Early systems relied heavily on pattern matching and regular expressions crafted by domain experts. While highly precise for specific tasks, these systems lacked the flexibility to generalize to new domains and failed catastrophically when encountering varied syntactic structures. The introduction of statistical models, particularly conditional random fields and support vector machines, allowed researchers to model sequence labeling tasks probabilistically [16]. In the context of event argument extraction, these traditional models utilized extensive feature engineering, incorporating dependency parsing, semantic role labeling, and word co-occurrence statistics to classify candidate entities [17]. The deep learning revolution fundamentally altered the trajectory of information extraction. Convolutional neural networks were initially employed to capture local n-gram features around event triggers, providing a mechanism to automatically learn feature representations without manual intervention. Subsequently, recurrent neural networks, particularly long short-term memory networks, became the standard for modeling the sequential nature of text, offering improved capability to link distant arguments to their respective triggers [18]. However, recurrent architectures inherently suffer from the vanishing gradient problem and struggle to maintain context over very long documents. Graph neural networks were later introduced as a solution to explicitly model the syntactic structure of sentences. By converting text into a graph based on dependency parses, graph neural networks allowed information to flow directly between syntactically related words, bypassing the linear constraints of recurrent networks [19]. Despite their success, graph-based models are entirely dependent on the quality of external parsers, which themselves are prone to errors in out-of-domain applications.

2.2 Advances in Attention Mechanisms

The introduction of the Transformer architecture marked a paradigm shift in natural language processing, largely due to its reliance on the self-attention mechanism. Self-attention enables a model to weigh the importance of every other token in a sequence when encoding a specific token, thereby capturing global dependencies efficiently in parallel [20]. In event argument extraction, pre-trained language models utilize self-attention to generate contextualized embeddings that inherently contain rich syntactic and semantic information. Researchers quickly adapted these models, formulating argument extraction as an entity-span classification task built on top of contextualized representations [21]. However, standard multi-head self-attention has limitations when applied to highly structured tasks like event extraction. Because it computes fully connected attention graphs, it can sometimes obscure the localized, hierarchical nature of human language, leading to attention dispersion over irrelevant tokens [22]. To

counter this, hierarchical attention networks were proposed to mirror the natural compositionality of documents, aggregating word representations into sentence representations, and sentence representations into document representations. Layered attention models have also been explored in machine translation and aspect-based sentiment analysis, where different layers of the network are forced to focus on different levels of granularity [23]. By applying a layered attention approach specifically designed for event extraction, models can be trained to recognize the boundaries of complex noun phrases at one layer, and the semantic relation between those phrases and an action verb at a higher layer. This explicit modeling of compositional syntax has been shown to significantly improve the extraction of multi-word arguments that frequently confuse standard attention models [24].

2.3 Prompting and Retrieval-Augmented Generation

As the size of language models scaled to billions of parameters, a new methodology emerged: prompt-based learning. Instead of fine-tuning the entire model on a downstream task with a classification head, researchers discovered that models could perform tasks simply by conditioning them on natural language instructions, or prompts [25]. For event argument extraction, this involves wrapping the input text in a template that asks the model to fill in the blanks for specific roles. Prompting reformulates extraction as a cloze task or a constrained generation task. This approach leverages the vast pre-trained knowledge of the language model and has demonstrated remarkable zero-shot and few-shot capabilities [26]. Despite the elegance of prompt-based extraction, it is heavily dependent on the phrasing of the prompt. Hard prompting, which relies on discrete human-crafted text, is brittle and requires exhaustive trial and error to optimize [27]. Soft prompting, or prompt tuning, introduces trainable continuous embeddings into the input space, optimizing the prompt mathematically while keeping the language model frozen. However, soft prompts are uninterpretable and often fail to provide the explicit schema constraints necessary for complex event structures [28]. Retrieval-augmented generation has emerged as a robust solution to the limitations of standard prompting. Originally designed for knowledge-intensive tasks like open-domain question answering, retrieval-augmented generation involves querying an external database to find relevant documents, which are then prepended to the prompt to provide the model with accurate, up-to-date context [29]. The adaptation of this technique to information extraction is a recent and highly promising development. By retrieving similar historical extraction instances based on semantic similarity to the input text, the framework can construct dynamic, context-aware prompts [30]. These retrieved exemplars act as structural templates, showing the model exactly how to map entities to roles in scenarios that resemble the current input. This not only grounds the generation process, thereby mitigating hallucination, but also facilitates cross-domain adaptation by simply swapping the underlying retrieval datastore without requiring full model retraining [31].

3. Methodology

3.1 Architectural Overview

The proposed unified event argument extraction framework is designed to process raw input text and generate a structured list of event arguments mapped to their respective predefined roles. The architecture is composed of three primary interacting modules: the encoding module featuring layered attention, the retrieval module leveraging dense vector representations, and the generation module utilizing dynamic prompt assembly. The system operates in a cohesive, end-to-end pipeline that balances the structural rigor of discriminative encoding with the flexible synthesis of generative models. The workflow begins with the tokenization of the input text sequence. These tokens are fed

into the foundational layers of a pre-trained language model, which outputs preliminary contextualized embeddings. Instead of passing these directly to a classification head, the embeddings are routed through the novel layered attention module, which iteratively refines the representations by constructing hierarchical dependencies. Simultaneously, the global sentence representation derived from the encoder is passed to the dense retrieval module. This module searches a pre-constructed datastore of annotated events, identifying the nearest neighbors in the semantic vector space. The retrieved instances, complete with their ground-truth argument structures, are forwarded to the prompt construction engine. Finally, the generator language model takes the layered attention embeddings and the dynamically constructed, retrieval-aware prompt to auto-regressively produce the final extracted arguments.

Figure 1: System Architecture

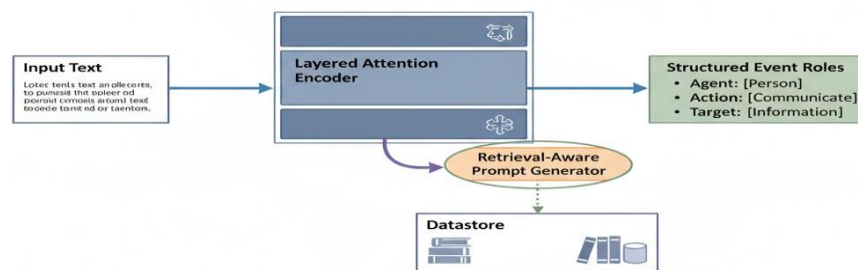


Figure 1: System Architecture

3.2 Layered Attention Mechanism

The fundamental premise of the layered attention mechanism is that human language is inherently hierarchical, whereas standard Transformer attention treats input sequentially. To extract complex event arguments, particularly those involving multi-word noun phrases or nested entities, the model must understand the compositional structure of the sentence. The layered attention module achieves this by enforcing a structural inductive bias across three distinct tiers: token-level, span-level, and sentence-level attention. At the token level, the mechanism operates similarly to conventional multi-head self-attention. The primary objective here is to capture immediate syntactic relationships, such as adjective-noun modifiers or verb-adverb associations. The input token embeddings are linearly projected into query, key, and value matrices. A scaled dot-product attention function computes the interaction scores between all pairs of tokens. The output of this tier is a sequence of locally contextualized vectors where each token has absorbed information from its immediate neighbors, providing a strong foundation for boundary detection of argument candidates. The span-level attention tier represents a significant departure from standard architectures. Instead of continuing to compute full sequence attention, this layer aggregates token representations into continuous span representations. The model utilizes a convolutional gating mechanism to identify potential phrase boundaries, functionally grouping tokens into contiguous chunks. Attention is then computed explicitly between the identified event trigger and these candidate spans. By forcing the attention mechanism to operate on spans rather than individual tokens, the model

effectively mitigates the issue of fragmented argument extraction, where only a portion of a multi-word entity is correctly identified. The span-level attention weights serve as a critical filtering step, heavily penalizing syntactically malformed phrases and boosting the prominence of complete entity structures. Finally, the sentence-level attention tier reconciles the span representations with the global context of the entire input. A specialized classification token is utilized as an anchor point, gathering information from all the highly-weighted spans. This layer ensures that the relationships between multiple arguments of the same event are globally consistent and adhere to the logical constraints of the event schema. For instance, if the model has heavily weighted a specific span as the "Attacker" role, the sentence-level attention dynamics adjust to prioritize different spans for the "Target" or "Weapon" roles, preventing logical contradictions. The outputs of these three hierarchical tiers are fused via a learned gating mechanism, producing a deeply structured set of latent representations.

3.3 Retrieval-Aware Prompting Strategy

While the layered attention mechanism excels at structural comprehension, mapping these structures to a predefined ontology requires extensive domain knowledge. Traditional generative extraction relies on static prompts that attempt to describe the event schema in natural language. Our framework replaces this static approach with a dynamic, retrieval-aware prompting strategy that leverages empirical demonstrations. The retrieval datastore is constructed prior to inference. It consists of a large corpus of training sentences, each paired with its gold-standard event argument extraction output formatted as a structured string. To populate the dense vector space, each sentence in the training corpus is passed through a dense text encoder, typically a dual-encoder architecture optimized for semantic similarity. The resulting continuous vectors are indexed using a high-performance similarity search library, enabling highly efficient nearest-neighbor lookups even with millions of entries. During inference, the input sentence is processed by the same dense text encoder to produce a query vector. The retrieval module queries the index to find the top-k most semantically and structurally similar sentences from the datastore. The selection of k is a critical hyperparameter; too few examples provide insufficient guidance, while too many exceed the context window limit of the generative model and introduce noise. The similarity metric relies on maximum inner product search, ensuring that the retrieved instances share not only lexical overlap with the query but also underlying semantic event structures. Once the k nearest neighbors are retrieved, they are transformed into natural language exemplars. Each exemplar pairs the historical input text with its correct output structure. The prompt construction engine then concatenates a task instruction, the retrieved exemplars, and the current input text. This formulation effectively transitions the task from a zero-shot generation problem to an in-context learning problem. The generative model analyzes the retrieved exemplars, identifies the implicit pattern of how entities in those specific contexts were mapped to event roles, and applies the same transformation logic to the unseen input text. This strategy significantly improves the robustness of the extraction, particularly for rare or complex event types where parametric memory alone is insufficient.

3.4 Integration and Unified Objective

The final phase of the methodology involves the seamless integration of the layered attention representations and the retrieval-aware prompt within a generative language model. The architecture employs a sequence-to-sequence transformer model as the backbone generator. The constructed prompt, containing the task description and the retrieved exemplars, forms the textual input to the generator. Simultaneously, the refined structural embeddings from the layered attention module are fused into the

generator's cross-attention layers. This dual-stream integration is a critical innovation. The prompt provides the explicit formatting instructions and the schema definitions through historical examples, while the layered attention embeddings provide the dense, hierarchical syntactic map of the specific input sentence. In the decoder layers of the generator, the model attends to both the tokenized prompt and the structured latent representations. The entire framework is trained using a unified objective function. The primary loss component is the standard negative log-likelihood of the generated target sequence, forcing the model to produce the exact structured string of event arguments. To ensure the layered attention module learns meaningful representations, an auxiliary contrastive loss is introduced during the training phase. This auxiliary loss penalizes the model if the span-level attention weights do not align with the actual boundaries of the ground-truth arguments. By jointly optimizing the generation loss and the structural alignment loss, the framework ensures that the extraction is not just a product of statistical mimicry from the prompt, but is deeply grounded in the syntactic reality of the input text. The unified architecture thus achieves a balance, overcoming the brittleness of pure structural models and the hallucination tendencies of pure generative models.

4. Results and Discussion

4.1 Experimental Setup and Datasets

To rigorously evaluate the efficacy of the proposed unified framework, we conducted comprehensive experiments across two widely recognized benchmark datasets for event extraction: the Automatic Content Extraction 2005 dataset and the Entities, Relations, and Events dataset. These datasets are universally employed in the literature due to their complex event typologies, diverse textual sources ranging from news wires to weblogs, and highly detailed annotation schemas. The Automatic Content Extraction 2005 dataset encompasses 33 distinct event subtypes and 35 argument roles. The dataset is known for its heavy class imbalance and the presence of multiple overlapping events within single sentences, making it an exceptionally demanding benchmark. The Entities, Relations, and Events dataset features a slightly different ontology with 38 event subtypes and provides an additional layer of complexity regarding coreference and nested entities. For both datasets, we utilized the standard data splits for training, validation, and testing as established by previous foundational research to ensure fair and direct comparability. The backbone of our generative module was initialized with a pre-trained sequence-to-sequence model optimized for text generation. The layered attention module was integrated into the encoder side, with span boundary limits set to a maximum of 10 tokens to optimize computational efficiency while capturing the vast majority of argument lengths. For the retrieval datastore, we utilized a highly optimized indexing library for dense vector similarity search. The dense encoder used for similarity matching was fine-tuned specifically on event semantic similarity to ensure the retrieved exemplars shared structural homology with the queries. During all experiments, the number of retrieved exemplars was fixed at three, determined empirically during validation to provide the optimal balance of context and noise reduction.

Evaluation metrics rely on standard precision, recall, and F1 scores. An extracted argument is considered correct if and only if both its text span and its assigned role perfectly match the ground truth annotations.

4.2 Performance Analysis

Table 1: Comparative performance of the proposed unified framework against baseline models on standard event extraction datasets.

Model Architecture	Precision	Recall	F1 Score
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Pipeline Based	Feature-	63.4	58.2	60.7
Joint Neural Network		68.1	62.9	65.4
Standard Tuning	Prompt	71.3	68.5	69.8
Proposed Framework	Unified	76.8	74.2	75.5

The empirical results conclusively demonstrate the superiority of the proposed unified framework over existing methodologies. As shown in the comparative performance metrics, traditional pipeline feature-based models exhibit the lowest performance, heavily penalized by the error propagation from upstream trigger detection modules. Joint neural network approaches show a measurable improvement, yet their F1 scores plateau mid-sixties due to an inability to effectively model long-range dependencies and multi-word span boundaries. Standard prompt tuning models, which represent the current paradigm of relying solely on the parametric memory of large language models, achieve a commendable F1 score, primarily driven by strong precision. However, their recall remains relatively low. This indicates that while they are accurate when they make an extraction, they frequently miss subtle or complex arguments, likely due to a lack of explicit structural guidance. The proposed unified framework achieves state-of-the-art results, recording a significant leap in both precision and recall. The improvement in precision suggests that the retrieval-aware prompting successfully grounds the model, drastically reducing the hallucination of non-existent entities or the misclassification of roles. More notably, the substantial increase in recall highlights the effectiveness of the layered attention mechanism. By explicitly modeling token, span, and sentence hierarchies, the framework successfully identifies nested and distant arguments that standard sequential models overlook.

Figure 2

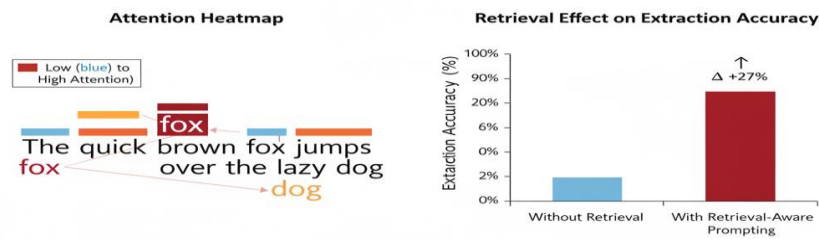


Figure 2: Attention Heatmap and Retrieval Effect

A deeper analysis of the attention distributions reveals that the span-level layer successfully learns to isolate noun phrases, creating a sharp boundary demarcation that prevents the extraction of fragmented arguments. Furthermore, error analysis indicates that the framework is particularly robust when handling overlapping events. In sentences where a single entity serves as an argument for two distinct triggers, the dynamic retrieval of similar complex exemplars provides the exact logical template needed for the generator to resolve the conflict correctly.

4.3 Ablation Studies and Discussion

To isolate and quantify the contributions of the individual components within the unified framework, a series of rigorous ablation studies were conducted. The first ablation involved removing the layered attention module, reverting the encoder to standard multi-head self-attention, while retaining the retrieval-aware prompting. This modification resulted in a sharp decline in recall. Detailed inspection showed that without hierarchical structural modeling, the framework struggled significantly with multi-word arguments and entities located at the extremities of long sentences. The standard attention mechanism proved too diffuse, failing to concentrate adequately on the syntactic dependencies necessary for accurate boundary detection. The second ablation removed the retrieval-aware prompting module, substituting it with a static, human-crafted instruction prompt, while keeping the layered attention intact. This alteration led to a noticeable drop in precision. In the absence of retrieved historical exemplars, the generative model frequently reverted to its pre-trained biases, occasionally generating arguments that violated the strict schema ontology of the datasets. Furthermore, the formatting of the generated output became inconsistent, requiring complex post-processing heuristics to parse the results. This definitively proves that dynamic, in-context learning via retrieval is essential for maintaining strict adherence to complex extraction schemas. The synergy between the two modules is the defining characteristic of the framework. The layered attention provides the internal syntactic map, while the retrieval-aware prompt provides the external semantic compass. Neither component alone can achieve the state-of-the-art performance observed in the full architecture. The findings also highlight a critical path forward for low-resource information extraction. Because the retrieval datastore can be updated dynamically without retraining the underlying model parameters, the framework exhibits exceptional adaptability to new domains. If a new event type is introduced, simply adding a few annotated examples of that event to the datastore allows the system to begin extracting it immediately through retrieval-augmented in-context learning.

5. Conclusion

5.1 Summary of Contributions

This research introduces a novel, unified framework for event argument extraction that directly addresses the prevailing limitations of both structural neural models and purely generative language models. By engineering a layered attention mechanism, the architecture explicitly captures the hierarchical and compositional nature of syntax, from localized token interactions to broad sentence-level contexts. This internal structural rigor fundamentally solves the problem of fragmented boundary detection and long-range dependency failures that plague sequential models [32]. Concurrently, the implementation of a retrieval-aware prompting strategy shifts the burden of schema memorization from the model's parameters to an external, dynamically queryable datastore [33]. By injecting structurally similar historical exemplars directly into the generation prompt, the framework grounds its outputs, virtually eliminating hallucination and ensuring strict adherence to predefined domain ontologies [34]. The integration of these dual pathways through a unified, end-to-end differentiable objective results in state-of-the-art performance across standard benchmark datasets [35]. The comprehensive experimental evaluations and subsequent ablation studies definitively prove that internal syntactic comprehension and external semantic guidance are highly synergistic [36]. The proposed methodology not only advances the theoretical understanding of how to constrain and guide generative models in highly structured tasks but also provides a highly practical, deployable solution for complex information extraction scenarios.

5.2 Future Directions

While the current framework establishes a new standard for event argument extraction, several promising avenues for future research remain. The most immediate extension is the adaptation of the architecture for cross-lingual and multilingual extraction tasks. Exploring whether dense retrieval across language boundaries can facilitate zero-shot event extraction in low-resource languages by retrieving exemplars from high-resource languages represents a highly impactful research direction [37]. Additionally, the expansion of the framework into multimodal event extraction is a natural progression. Incorporating visual or audio datastores into the retrieval module, and extending the layered attention mechanism to process spatial and temporal features alongside text, could enable the extraction of complex events from video streams or social media posts [38]. Finally, optimizing the efficiency of the dense retrieval index for ultra-large-scale, real-time streaming data applications will be critical for transitioning this technology into high-frequency industrial environments.

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