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Towards Resource-Constrained Event Extraction: A Knowledge-Augmented Framework for Overcoming Challenges in Vietnamese NLP

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***Abstract*—Event Extraction (EE) is a crucial task in Natural Language Processing (NLP), instrumental in capturing meaningful activities and contributing to the tracking of narratives and developments within textual documents. Extensive research has been dedicated to improving the accuracy of event trigger identification and argument role classification, spanning from traditional machine learning to modern deep learning architectures. Recently, driven by the rapid advancements of Large Language Models (LLMs), these models have been applied to EE, primarily through data augmentation or fine-tuning approaches. However, the computational and resource overhead associated with LLMs remains a significant challenge. Furthermore, existing state-of-the-art methods predominantly focus on high-resource languages such as English and Chinese, leaving low-resource languages, like Vietnamese, largely under-explored due to their unique linguistic ambiguities. Consequently, our research direction focuses on leveraging a Small Language Model-based (SLM-based) approach, augmented with external knowledge, to address the EE task in Vietnamese. The ultimate objective is to develop a compact model capable of effectively addressing core EE challenges, such as rare events, semantic ambiguity, and long-range dependencies—thereby establishing an efficient and robust framework specifically tailored for the Vietnamese low-resource language domain.**

***Keywords*—Event Extraction, Small Language Model, Knowledge Integration, Vietnamese NLP**

I. INTRODUCTION

A variety of approaches have been proposed for the Event Extraction (EE) task, ranging from traditional machine learning algorithms to deep learning methods [1]. With the advancement of deep learning, numerous artificial neural network-based models have been introduced to address various facets of the EE problem [2]. The emergence of Large Language Models (LLMs) has demonstrated superior performance across almost all tasks in Natural Language Processing (NLP) [3]. The EE task is no exception, as evidenced by numerous recent studies leveraging LLMs for strategies such as data augmentation and model fine-tuning [4], [5], [6]. Despite the advancements in methods to address the EE problem, several persistent issues continue to challenge the scientific community:

- The non-uniform distribution of event triggers and event types constitutes a major obstacle. In the ACE 2005 dataset, 78.2% of event triggers appear fewer than five times in the training set [2]. This data scarcity leads to overfitting on frequent classes and poor performance on rare classes.
- In complex sentences, arguments and triggers can be separated by long spans of text, which diminishes the effectiveness of sequential models in capturing their relationship. This problem is known as long-range dependencies. While some graph-based methods have been proposed to address this, they often increase system complexity [7].
- Training and deploying LLMs for EE are costly in terms of computational resources. This is particularly unnecessary for events within specialized data domains and limits deployment on resource-constrained devices.

Beyond these general challenges, the focus on high-resource languages (like English and Chinese) has created a significant gap. Low-resource languages such as Vietnamese face compounded difficulties: the lack of dedicated, publicly available datasets and the presence of linguistic complexities. Specifically, Vietnamese, as a low-resource language, faces unique linguistic complexities, including: (a) pervasive word segmentation errors, which are a major source of significant span errors in both entity and trigger detection, and (b) highly complex and lengthy entity mentions, which frequently contribute to long-range dependencies and overlapping event contexts [8].

Our research will focus on solving the EE problem in specialized data domains and addressing the resource and cost issue by shifting the approach from LLM-based to Small Language Model-based (SLM-based). Concurrently, we propose to utilize external structural and semantic knowledge, such as Abstract Meaning Representation (AMR) and Knowledge Graph (KG) to compensate for the reduced model size. This strategic integration will effectively address the non-uniform distribution of event types and handle the issue of long-range dependencies, while also providing a robust framework to tackle the unique linguistic challenges posed by the Vietnamese language.

II. BACKGROUND

A. Event Extraction Task

The EE task is a sub-problem within the field of Information Extraction. The objective of the task is to extract event occurrences from a given sentence or document. EE is widely applied in Question Answering systems and, significantly, in the construction of Knowledge Bases. The applications of this task are diverse, including automatic event detection in news feeds and decision support for financial investors [9]. An example sentence from a news article is provided as follows: "Trước đó, ngày 03/12/2019, Vingroup đã kí thỏa thuận nguyên tắc về việc sát nhập công ty VinCommerce và công ty con VinEco vào Masan Consumer Holdings." (Translation: "Previously, on December 3, 2019, Vingroup signed a principle agreement regarding the merger of VinCommerce and its subsidiary VinEco into Masan Consumer Holdings."). 0illustrates the resulting event extraction output for this sentence.

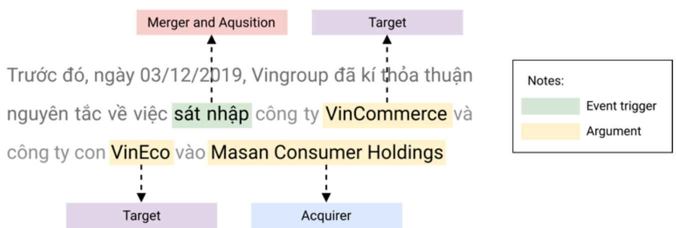

Fig. 1. Example of Event Extraction Task Result

The research methods applied to the sentence can extract a "Merger and Acquisition" event, with the trigger being "sát nhập" (merger). The involved parties are *Masan Consumer Holdings*, which takes on the role of the "Acquirer Company", and *VinCommerce* and *VinEco*, classified as the "Target Company".

B. Subtasks of Event Extraction

The Event Extraction task is typically decomposed into four subtasks to improve the accuracy of result prediction:

1. Event Trigger Identification (TI): Identifying the *trigger* (the word or phrase that activates the event) in the text. Triggers are typically verbs denoting actions or occurrences. As shown in 0the trigger is the word "sát nhập" (merger).
2. Event Type Classification (TC): Determining the event type corresponding to the identified trigger, based on a predefined classification scheme. For instance, the event type in Fig. 1. is "Merger and Acquisition".
3. Event Argument Identification (AI): After the trigger and event type are confirmed, the next step is to locate the *arguments* (the entities participating in the event). 0shows three event arguments: VinCommerce, VinEco, and Masan Consumer Holdings.
4. Event Argument Classification (AC) (or Argument Role Classification): This final task assigns the specific semantic role of each detected argument with respect to the activated event. For instance, the example assigns the roles of "Acquirer" and "Target".

Regarding model design, there has been an evolution in modeling approaches. Initially, research commonly employed a pipeline model, where Event Detection (ED) (subtasks 1 and 2) was performed independently, and the results were then passed to the Event Arguments Extraction (EAE) task (subtasks 3 and 4). However, this approach is susceptible to error propagation during model training. Specifically, a high error rate from the ED stage negatively affects the performance of EAE. Consequently, recent studies have shifted towards *joint* models (simultaneous processing of subtasks) to mitigate error cascading and more explicitly capture the correlation between the trigger and its arguments.

III. RELATED WORK

A. Dataset

Commonly used datasets to measure the effectiveness of Event Extraction models, such as ACE 2005 [10] (featuring 33 event types and 22 argument roles) and Rich ERE [11], have been influential for a long period. These datasets are constructed primarily in English and focus on general life events such as: Life, Conflict, and Transaction.

In the last five years, several domain-specific datasets in English have been released, including CASIE [12] for cybersecurity-related events and PHEE [13] for drug safety events.

Similarly, domain-specific datasets in Chinese have emerged, such as the legal event dataset LEVEN [14] and financial event datasets like FEED [15] and CFinDEE [16].

For the Vietnamese language, two datasets have been publicly announced as of 2024: BKEE [8], which focuses on general life events, and VHE [17], which addresses the specific domain of historical events. The construction process for BKEE relied entirely on manual human annotation. In contrast, VHE employed a semi-automatic approach, utilizing a GPT model for initial annotation followed by human review and quality control.

Compared to English and Chinese, the quantity of Vietnamese datasets for the EE task remains limited. The urgent need to develop more datasets, particularly in the specific domains of legal and financial events, is critical for advancing EE model development for the Vietnamese language.

B. *Deep Learning Methods*

The methods for the EE task can be categorized into groups as shown in the Fig. 2.

1) *Word-Sequence based Methods*

Approaches in this category typically employ deep learning networks such as CNNs, RNNs, or standard Transformers to sequentially encode the input words and perform sequence labeling to extract event triggers and arguments. This approach reduces the effort of manual feature engineering compared to machine learning, simplifying input processing. Notable models in this group include DMCNN [18], which uses a CNN, and JRNN [19], which uses an RNN. However, this group of methods is generally unable to effectively handle the problem of long-range dependencies.

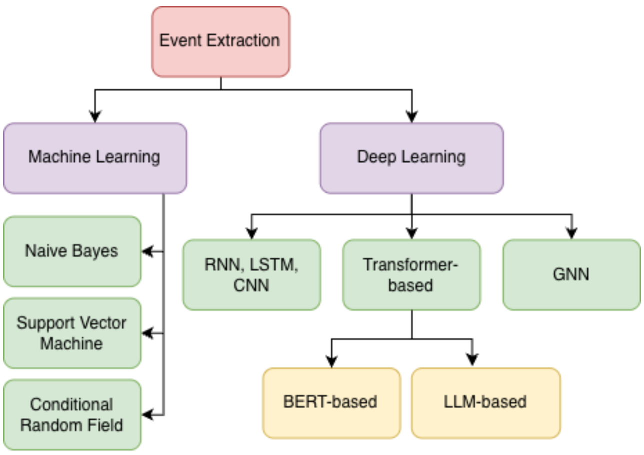

Fig. 2. Overview of Approaches to Event Extraction

2) *Graph-based Neural Network Methods*

Methods in this category transform the sentence into a syntactic graph and apply Graph Neural Networks (GNNs) for processing. The advantage of this group is its ability to learn context-rich representations, making them effective for resolving long-range dependency issues. Nevertheless, these methods heavily rely on the quality of the upstream tool used to convert the sentence into a graph structure. Prominent models in this group include JMEE [20] and MOGANED [21].

3) *External Knowledge-based Methods*

Approaches in this group leverage the ability to learn from external knowledge to enhance the model's generalization capability, particularly for handling rare events. The drawback of these methods is the complexity of the training process. For example, the work by J. Liu *et al.* [22] transferred open-domain knowledge related to event triggers, allowing smaller models to eliminate dependency on auxiliary tools during the inference stage. The work by Tong *et al.* also proposed integrating external knowledge to handle rare events [23].

C. *Generative Extraction Methods*

Models within the generative methods group can be divided into two sub-categories: models that generate output strictly in the required Event Extraction format, and models that generate the output in the form of natural language containing the extracted event information.

Following the direction of generating Formal Structure Templates, models in this group use Constrained Decoding techniques to ensure the structural validity of the output. Notable works in this direction include the Text2Event model [24] and the UIE model [25].

The direction of generating Natural Language Generation is the most natural for generative models, as the inherent nature of the model is preserved. However, generating natural language risks producing output that deviates from the expected format of the event extraction task. Prominent research works following this direction include the DEGREE model [26], BART-Gen [27], and AMPERE [28].

Furthermore, LLMs have recently emerged as a form of generative model applied to the Event Extraction task. Several studies have utilized LLMs for data augmentation [5], [6] or employed the LLMs themselves to directly predict EE results [4], [29]. LLMs represent a major research trend for EE, indicated as a future development direction in the survey by J. Xie *et al.* [2]. However, the same work also points out that training and fine-tuning LLMs require substantial memory resources.

Current efforts in Vietnamese EE, such as BKEE [8], primarily rely on the OneIE [30] framework built upon PhoBERT [31] and XLM-RoBERTa [32], without incorporating external structural or domain-specific knowledge. Similarly, the VHE [17] evaluation focuses on benchmarking open-source and closed-source LLMs in zero-shot or few-shot settings, without fine-tuning or integrating specialized knowledge. Our research direction aims to address these gaps by exploring the integration of AMR or KG representations into a generative-based SLM architecture, with the goal of improving semantic reasoning for Vietnamese while maintaining resource efficiency.

IV. RESEARCH METHODOLOGY

The most significant drawback of LLMs is the substantial computational cost and immense memory footprint required for usage and deployment. This critical limitation mandates a necessary transition toward SLMs for practical, domain-specific applications.

The potential of this transition is supported by the hypothesis that integrating structural knowledge can compensate for the limited parameter scale of compact models. For instance, Guo *et al.* [33] explored encoding KG into Transformer-based frameworks to improve event participant identification. Similarly, the AMPERE framework [28] utilized AMR as structural prefixes to guide generative-based architectures. These successes in generative architectures demonstrate a significant potential for incorporating external structural priors into a targeted SLM-based framework to effectively resolve long-range dependencies in Vietnamese.

To the best of our knowledge, the integration of SLM-based frameworks with external knowledge sources remains under-explored in the context of Vietnamese EE.

Our research follows the systematic workflow presented in Fig. 3.

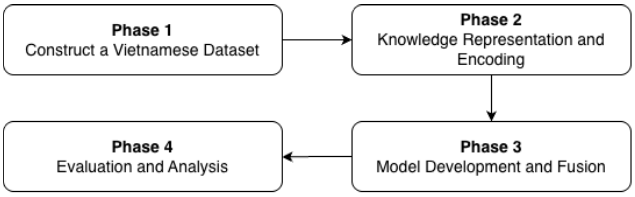

Fig. 3. Proposed Research Methodology Workflow

- *Phase 1 – Construct a Vietnamese Dataset:* To address the scarcity of resources, Phase 1 focuses on constructing a specialized Vietnamese dataset for the financial domain. The dataset will cover key financial events, such as M&A, executive changes, and earnings announcements, among others. We will implement a manual annotation process where event triggers and participants are cross-verified by multiple annotators to ensure high data reliability. The finalized dataset will be publicly released as a benchmark to advance event extraction research in the Vietnamese financial sector.
- *Phase 2 – Knowledge Representation and Encoding:* In this phase, we transition from raw external knowledge to continuous vector representations or symbolic formats designed for generative-based architectures. Knowledge sources such as AMR or KG are transformed into structural embeddings, encoded prefixes, or symbolic representations like linearized AMR strings or KG triplets. For integration, we will consider approaches such as using these formats as augmented input representations or as learned vectors injected into the internal layers during the fine-tuning process. This deep integration is expected to serve as a structural prior to help the generative model resolve long-range dependencies and mitigate challenges from rare events, thereby achieving high generalization in resource-constrained Vietnamese scenarios.
- *Phase 3 – Model Development and Fusion:* The core result is the development of a compact and lightweight EE model that significantly reduces the computational burden compared to LLM-based methods. We will focus exclusively on generative-based SLM architectures with fewer than 4B parameters, such as Qwen3-4B or Llama-3.2-3B, to leverage their superior reasoning and text generation capabilities. These models will integrate the encoded knowledge or prefixes from Phase 2 into their internal layers or input prompts. By fine-tuning these SLMs with structural priors, we aim to analyze the trade-off between performance and computational efficiency, ensuring the model is optimized for high-precision event extraction in Vietnamese while remaining deployable in resource-constrained environments.
- *Phase 4 – Evaluation and Analysis:* Finally, we will conduct a rigorous evaluation using F1-score to measure extraction performance, and inference latency and VRAM usage to assess resource efficiency. The framework will be compared with diverse baselines, including OneIE [30] (representing joint extraction frameworks), Text2Event [24] (generative architectures), and zero-shot or few-shot LLMs. To validate our specific contributions, ablation studies will be performed by systematically removing AMR/KG features and prefix-tuning components to isolate their individual impacts on model performance. Efficiency will be measured by averaging processing time per document and monitoring peak GPU memory consumption to ensure suitability for resource-constrained environments.

We expect that the proposed SLM-based framework strategically integrates the advantages of existing paradigms to address their critical flaws. We adopt the superior generative capability of LLM-based approaches but implement it within a resource-efficient SLM architecture, thereby resolving the high computational overhead. Furthermore, to combat long-range dependencies effectively, we incorporate the core principle of structural modeling found in Graph-based approaches by directly augmenting the SLM with AMR and KG principles. This targeted augmentation aims to bridge the performance gap between SLMs and LLMs in terms of generalization, while providing graph-level structural awareness at a significantly lower computational cost. This ensures robustness and scalability for low-resource environments like Vietnamese.

V. RESEARCH QUESTIONS

Based on the challenges identified and the proposed research direction, the following research questions will be addressed during my doctoral study:

Question 1: How can an SLM-based framework be effectively augmented with external relational knowledge to address data sparsity and rare event types in Vietnamese EE while maintaining computational efficiency?

- *Theoretical Anchor:* To address the resource constraints of LLMs, we adopt an external knowledge integration approach [2] to compensate for the limited internal capacity of SLMs.
- *Proposed Approach:* We will incorporate knowledge from external KGs as augmented input representations or symbolic formats. This integration serves as a structural prior that compensates for limited training data, enabling the SLM to more robustly recognize rare event triggers and types by leveraging pre-existing semantic relationships.
- *Validation Strategy:* The approach will be evaluated using EE performance metrics (e.g., F1-score) and ablation studies to isolate the impact of the integrated external knowledge.

Question 2: How can the integration of structural semantic knowledge (AMR or KG) into a generative SLM architecture address long-range dependencies and complex relational structures in Vietnamese sentences?

- *Theoretical Anchor:* Drawing on concepts from prior studies, including [28] and [33], this question investigates the explicit integration of structural knowledge to address limitations in existing Vietnamese EE baselines.
- *Proposed Approach:* We will encode AMR and KG structures as structural embeddings or learned prefixes injected into the model's internal layers. By providing a graph-based structural prior, this approach enables the generative SLM to better connect distant triggers and arguments, thereby addressing long-range dependencies that are often lost in purely sequential processing.
- *Validation Strategy:* The approach will be evaluated through targeted experiments on long-range dependency cases, along with ablation studies to assess the effectiveness of the structural components.

Question 3: To what extent can the proposed framework mitigate language-specific ambiguities, such as word segmentation errors and complex entity boundaries, by leveraging linguistically informed features?

- *Theoretical Anchor:* This question is motivated by analyses in BKEE [8] and VHE [17], which identify word segmentation ambiguity and complex morphology as key challenges for Event Extraction in Vietnamese.
- *Proposed Approach:* We propose incorporating Vietnamese-specific external knowledge into the SLM framework. This integration enables the model to better handle boundary ambiguities and structural complexities without relying solely on potentially error-prone automated segmenters.
- *Validation Strategy:* The approach will be validated by benchmarking the framework on standard Vietnamese EE datasets. In addition, ablation studies will be conducted to quantify the performance gains contributed by the Vietnamese-specific external knowledge compared to a baseline SLM.

VI. FUTURE RESEARCH PLANS

Building upon the proposed knowledge-augmented SLM framework, our future work will proceed in three critical directions to establish a robust Event Extraction solution for Vietnamese:

1. We plan to conduct a comprehensive survey of recent LLM-based EE approaches, including those identified in our literature review (e.g., [4], [5], [6], [29]) and other relevant studies utilizing LLMs. This will systematically analyze their strengths and weaknesses, and provide a solid comparative baseline and justifying the definitive shift toward SLM-based method.
2. To address the critical data scarcity, a key focus will be the construction of new Vietnamese domain-specific EE datasets, with an emphasis on financial sector. We will establish comprehensive annotation guidelines and conduct manual labeling, ensuring dataset reliability through rigorous Inter-Annotator Agreement (IAA) evaluation.
3. Finally, we will experiment with and refine the framework by optimizing knowledge-aware prompting or the injection of structural embeddings into the SLM. This involves testing how to best integrate AMR/KG-based structural priors to mitigate Vietnamese-specific challenges, such as word segmentation ambiguities. Our goal is to empirically determine the most effective configuration that maintains a strong balance between extraction performance and computational efficiency.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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