SemViQA: A Semantic Question Answering System for Vietnamese Information Fact-Checking

Nam V. Nguyen^{1,2,*}, Dien X. Tran^{2,*}, Thanh T. Tran², Anh T. Hoang^{2,4}, *Tai V. Duong*², *Di T. Le*², *Phuc-Lu Le*³

¹FPT Software AI Center, Viet Nam

²Faculty of Information Technology, Industrial University of Ho Chi Minh City, Viet Nam ³Faculty of Information Technology, University of Science, VNU-HCM, Viet Nam ⁴FPT Telecom, Viet Nam

Correspondence: lplu@fit.hcmus.edu.vn

Abstract

The rise of misinformation, exacerbated by Large Language Models (LLMs) like GPT and Gemini, demands robust fact-checking solutions, especially for low-resource languages like Vietnamese. Existing methods struggle with semantic ambiguity, homonyms, and complex linguistic structures, often trading accuracy for efficiency. We introduce SemViQA, a novel Vietnamese fact-checking framework integrating Semantic-based Evidence Retrieval (SER) and Two-step Verdict Classification (TVC). Our approach balances precision and speed, achieving state-of-the-art results with 78.97% strict accuracy on ISE-DSC01 and 80.82% on ViWikiFC, securing 1st place in the UIT Data Science Challenge. Additionally, SemViQA Faster improves inference speed 7× while maintaining competitive accuracy. SemViQA sets a new benchmark for Vietnamese fact verification, advancing the fight against misinformation. The source code is available at: https://github. com/DAVID-NGUYEN-S16/SemViQA.

1 Introduction

The rapid advancement of large language models (LLMs), such as OpenAI's ChatGPT, Google Gemini (Team et al., 2024), Llama3.1 (Touvron et al., 2023), Qwen2.5 (Qwen et al., 2025), DeepSeek V3, (DeepSeek-AI et al., 2024), Phi3.5 (Abdin et al., 2024) has significantly improved information retrieval and processing across various domains. However, a major challenge with these systems is their tendency to generate factually incorrect or hallucinated content seemingly plausible information that lacks factual grounding (Soleimani et al., 2020). This issue is particularly critical in domains requiring high accuracy, such as healthcare, law, and journalism, where misinformation can have

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serious consequences. Consequently, developing reliable fact-checking systems capable of retrieving and evaluating evidence from real-world sources has become an urgent need in Natural Language Processing (NLP).

Although fact verification has been extensively studied in high-resource languages like English, with a primary focus on datasets such as FEVER (Thorne et al., 2018), LIAR (Wang, 2017), PubHealthTab (Akhtar et al., 2022), and Tab-Fact (Chen et al., 2020), extending these methods to low-resource languages like Vietnamese remains a significant challenge. Transformer-based approaches, including BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), have shown strong performance in fact verification, yet their adaptation to Vietnamese is still underexplored. For Vietnamese fact verification, ViNSV (Tran et al., 2024) employs BM25 and SBERT (Reimers and Gurevych, 2019a) for evidence retrieval. However, SBERT's 256-token input limitation leads to information loss in long-context claims, making it particularly ineffective for complex cases requiring multi-sentence reasoning or cross-referencing distant evidence. As a result, the system struggles with hard samples that demand deeper contextual understanding, ultimately reducing fact verification accuracy. In contrast, graph-based reasoning methods in English (Zhong et al., 2020) have shown notable potential for semantic inference but are often hindered by high computational costs, restricting their real-world applicability. Moreover, traditional retrieval techniques like TF-IDF and BM25, though widely used, rely heavily on token frequency and exact keyword matching, making them less effective at capturing the nuanced semantics of complex claims. While some recent work employing large language models (LLMs) (Huo et al., 2023; Schimanski et al., 2024) has shown promise in addressing hard retrieval questions, these approaches typically require considerably more com-

Equal contribution.

puting resources and longer processing times compared to conventional methods. Thus, a trade-off persists: models offering high accuracy tend to operate slowly, whereas faster models often compromise on accuracy.

To address the challenges in fact verification, we introduce SemViQA, a system designed to optimize both accuracy and efficiency. It comes in two variants: SemViQA Standard, which prioritizes accuracy, and SemViQA Faster, which significantly improves inference speed while maintaining strong performance. The system is built upon three core components:

- 1. Data Processing: A specialized preprocessing pipeline designed to efficiently handle long-token sequences, a known limitation of Transformer-based models. Our approach preserves the semantic integrity of input claims while ensuring optimal tokenization for downstream processing.
- 2. Semantic-based Evidence Retrieval (SER): A hybrid retrieval framework combining TF-IDF for efficient keyword-based matching and a Question Answering Token Classifier (QATC) for semantic-based evidence selection. This approach balances speed and accuracy by prioritizing TF-IDF for common cases while activating QATC selectively for hard samples, significantly improving precision while maintaining computational efficiency.
- 3. Two-step Verdict Classification (TVC): A hierarchical classification strategy leveraging Focal Loss (Lin et al., 2018) and Cross-Entropy Loss to enhance claim verification accuracy. This approach first determines whether a claim is Supported, Refuted, or Not Enough Information (NEI) and subsequently refines the decision boundary for hard-to-classify cases, reducing misclassification and improving robustness.

We evaluate SemViQA on two of the largest Vietnamese fact verification datasets, ISE-DSC01 and ViWikiFC (Le et al., 2024). Our system achieves 78.97% strict accuracy on ISE-DSC01 ¹ and 80.82% on ViWikiFC, outperforming existing baselines. These results highlight SemViQA's

potential to improve the accuracy of fact verification in Vietnamese, contributing to misinformation mitigation and enhancing transparency in digital content.

The remainder of this paper is structured as follows: Section 2 discusses related work. Section 3 details our proposed methodology, including SER, TVC, and QATC. Section 4 presents experimental results and performance evaluation. Finally, Section 5 concludes the paper and outlines future research directions.

2 Related Works

Advancements in Natural Language Processing (NLP) have significantly improved information verification and evidence extraction. Early methods, such as the Neural Semantic Matching Network (NSMN) (Nie et al., 2018), leveraged BiLSTM (Graves and Schmidhuber, 2005) and WordNet-based features to enhance verification accuracy but struggled with complex sentence relations due to LSTM's sequential nature.

The introduction of transformer models, notably BERT (Devlin et al., 2019), transformed claim verification by enabling bidirectional contextual encoding (Soleimani et al., 2020; Zhou et al., 2019; Malon, 2018). While achieving state-of-the-art results on FEVER (Aly et al., 2021; Lin et al., 2024; Yuan and Vlachos, 2024; DeHaven and Scott, 2023), BERT's input length limitation makes it less effective for long-context fact-checking.

Graph-based models have further advanced multi-step reasoning. Approaches such as GCN-based reasoning (Zhong et al., 2020; Thorne et al., 2018) and AdMIRaL's logic-driven document retrieval (Aly and Vlachos, 2022) improve evidence sufficiency but demand high computational resources.

For Vietnamese fact verification, research remains limited. ViNSV (Tran et al., 2024) combined BM25 and SBERT (Reimers and Gurevych, 2019a) for evidence retrieval but struggled with complex reasoning due to static embeddings.

Building on prior work, SemViQA optimizes fact verification by integrating fast keyword-based retrieval (TF-IDF) with semantic reasoning (QATC) and a hierarchical classification strategy, ensuring high accuracy, fast inference, and scalability for real-world applications.

 $^{^{1}\}mbox{https://codalab.lisn.upsaclay.fr/competitions/}\ 15497\mbox{\#results}$

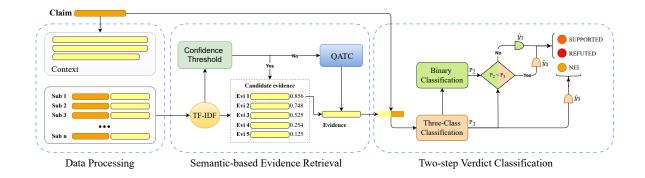


Figure 1: **SemViQA**: A Three-Stage Method for semantic-based evidence retrieval and two-step verdict classification, where P_2 and P_3 represent the probabilities of the two-class and three-class classifications, respectively, and \hat{y}_2 and \hat{y}_3 denote their corresponding predictions.

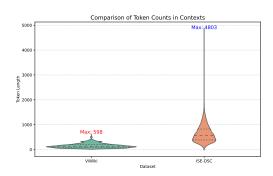


Figure 2: Graph representing the lengths of contexts.

3 SemViQA - Semantic Vietnamese Question Answering

Our proposed method, SemViQA, employs a three-stage pipeline to enhance fact verification, as illustrated in Figure 1. The process begins with a preprocessing stage, where input data is restructured to ensure compatibility with retrieval and classification models. Subsequently, evidence retrieval is performed using TF-IDF for straightforward cases, while the Question Answering Token Classifier (QATC) refines evidence selection for more complex claims. Finally, in the claim classification stage, a hierarchical approach integrates Cross-Entropy Loss and Focal Loss (Lin et al., 2018) to improve both accuracy and robustness.

3.1 Data Processing

Before implementing data processing solutions, we conducted a thorough analysis of the input data to understand its characteristics and challenges. One of the prominent issues we encountered is the token limit of current Vietnamese BERT models, as clearly illustrated in Figure 2.

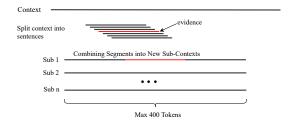


Figure 3: Long context processing solution.

During data processing, we observed that the input context has a considerable length, with the longest context extending up to 4803 tokens. This presents a challenge for data processing given the limitations of 256 tokens for classification and 512 tokens for the Question Answering model.

For the classification data: We start by segmenting the context into smaller passages and removing special characters such as ".,!?\n". We use the Underthesea library to tokenize the sentences. The tokens are then concatenated to form new phrases.

For the input data for the Question Answering model: We use pairs of claim and context. Due to the large length of the context, a solution for processing is necessary. First, we preprocess the data to remove newline characters ("\n"). However, for the Question Answering model, punctuation marks are not removed as was done in the classification process. This is based on experimental results, which repeatedly show that removing punctuation negatively impacts the quality of the Question Answering model's results.

From a long context, we proceed to split it into smaller segments. We then slide through each segment and check the number of tokens in each segment. If the token count does not exceed 400, we append the segment to the subcontext. When the subcontext has a token count greater than 400 (see Figure 3), we check if the evidence sentence is contained within the subcontext. If it is, then the subcontext is considered to contain that evidence. Otherwise, if it is not present, the evidence for that subcontext is assigned as an empty string. This process allows us to create new data samples with contexts containing fewer than 512 tokens, which is beneficial for training the model more effectively. This ensures that no segment is omitted, unlike stride-based cutting methods, which may result in evidence sentences being split between segments within a complete paragraph.

3.2 Semantic-based Evidence Retrieval (SER)

In addressing this problem, focusing on evidence retrieval is a crucial and decisive part. Accurate classification can only be performed when the evidence is correct. After analyzing and training on the data, we found that methods like TF-IDF and BM25 are effective for simpler samples but struggle with more complex samples.

Therefore, we have divided the evidence retrieval process into two parts:

Part 1: Using TF-IDF: We begin by segmenting the context into smaller passages and pairing each segment with the claim to generate structured data samples, which then undergo a preprocessing pipeline including noise removal and tokenization using ViTokenizer ² to standardize the input. A key observation is that TF-IDF performs well on simple claims, particularly those classified as refuted, but struggles with claims requiring deeper reasoning, as it relies solely on keyword matching without capturing semantic relationships. To address this limitation, we introduce an enhanced strategy to enrich contextual information, where segments containing fewer than 60% of the claim's token count are merged with the preceding segment to supplement missing information. This is particularly beneficial for short or incomplete sentences where crucial words may be absent from the claim, leading to improved evidence retrieval accuracy. After retrieving potential evidence using TF-IDF, we rank the retrieved segments and apply a Confidence Threshold to classify them into easy and challenging cases, as detailed in Appendix C. While simple cases can be resolved directly using

TF-IDF, more complex cases are forwarded to Part 2 for further analysis, ensuring higher classification accuracy.

Part 2: Using the Question Answering Token **Classifier Model:** The subcontext is also used for model QA inference instead of inferring the full context. In this process, three situations can occur: The first, when multiple subcontexts generate different responses, we interpret this as the model exhibiting confusion in handling evidence responses. In this case, we collect all retrieved evidence and apply TF-IDF to select the most appropriate one. The second, when only one piece of evidence appears across multiple subcontexts, we interpret this as the model being highly confident in its prediction. The third, when the model does not retrieve any evidence, we use TF-IDF to extract relevant evidence as input for our TVC method. By combining these methods, we have achieved the best results in accurately and reliably retrieving evidence.

3.3 Two-step Verdict Classification (TVC)

Our input data consists of claim-evidence pairs, where the claim is the statement that needs to be verified, and the evidence comprises information used to support (*supported*), refute (*refuted*), or indicate insufficient information (*NEI*) regarding the claim. To address this problem, we undertake two main tasks as follows:

Three-Class Classification: The first step involves categorizing each claim into one of three categories: Supported, Refuted, or Not Enough Information (NEI). Given a claim-evidence pair (C, E), we employ a classification function:

$$P_3 = f_{\text{Three-Class}}(C, E), \tag{1}$$

where

$$P_3 = [P_{SUP}, P_{REF}, P_{NEI}]$$

represents the predicted probabilities. Here, $f_{\rm Three-Class}$ denotes a neural network model based on an advanced BERT-based architecture, trained to classify each claim into one of the three categories. The model leverages a fine-tuned BERT-derived approach and is optimized using Cross Entropy Loss, ensuring that the predicted probability distribution closely aligns with the true labels.

Binary Classification: If the three-class model does not predict *NEI*, an additional classification step is applied to further refine the decision between *Supported* and *Refuted*. In this step, we use another classification function:

²https://github.com/trungtv/pyvi

$$P_2 = f_{\text{Binary-Class}}(C, E), \tag{2}$$

where

$$P_2 = [P_{\text{SUP}}, P_{\text{REF}}]$$
.

Here, $f_{\rm Binary-Class}$ is a neural network based on an advanced BERT-based architecture, specifically trained to distinguish between *Supported* and *Refuted* claims. Unlike the three-class model, this binary classifier leverages a fine-tuned BERT-derived model and is trained using Focal Loss (Lin et al., 2018) to mitigate class imbalance and improve performance on challenging examples.

Finally, the predicted class \hat{y} is determined based on the following decision rule:

$$\hat{y} = \begin{cases} \text{NEI,} & \text{if } \hat{y}_3 = \text{NEI} \\ \hat{y}_2, & \text{if } P_2 > P_3 \text{ and } \hat{y}_3 \neq \hat{y}_2 \\ \hat{y}_3, & \text{if } P_3 \geq P_2 \text{ or } \hat{y}_3 = \hat{y}_2. \end{cases}$$
(3)

This method effectively balances the strengths of both classification models, ensuring improved accuracy for complex claims while maintaining high performance on straightforward cases.

3.4 Question Answering Token Classifier (QATC)

Typical QA models are trained only to predict the start and end positions of an answer. Here, we extend this by introducing a **Token Classification task**, where we assign a label of 1 to tokens within the answer and 0 otherwise. This enhances the model's ability to identify relevant tokens for answer extraction.

Procedure: We input the context and claim into the model, extract token features, and apply two linear layers to predict answer start and end probabilities. The default QA loss is the Cross Entropy loss:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{N} t_i \log(p_i), \tag{4}$$

where N is the number of classes, t_i is the true label, and p_i is the softmax probability for the i^{th} class.

3.4.1 Token Classification Task

Inspired by Rationale Tagging (Ju et al., 2019), we predict whether each token is part of the answer (label 1) or not (label 0). For NEI (Not Enough Information) cases, all tokens are labeled 0. To achieve

this, we introduce an additional fully connected (FC) layer that computes classification probabilities:

$$p_t^r = \sigma(w_2 \cdot \text{ReLU}(W_1 h_t)), \tag{5}$$

where h_t is the output representation of token t from RoBERTa (Zhuang et al., 2021; Aly et al., 2021). The loss for this task is the Binary Cross Entropy loss:

$$\mathcal{L}_{RT} = -\frac{1}{T} \sum_{t=1}^{T} \left[y_t^r \log(p_t^r) + (1 - y_t^r) \log(1 - p_t^r) \right].$$
(6)

3.4.2 Rationale Regularization Loss

To encourage sparsity and continuity in rationale predictions, we introduce a Rationale Regularization Loss \mathcal{L}_{RR} , which consists of:

1. **Sparsity Loss**: Encourages the model to minimize the number of tokens selected as rationales:

$$\mathcal{L}_{sparse} = \frac{1}{T} \sum_{t=1}^{T} m_t p_t^r, \tag{7}$$

where m_t is a mask ensuring that the loss is computed only on non-padding tokens.

2. **Continuity Loss**: Encourages smoother rationale selection by minimizing sudden jumps between selected tokens:

$$\mathcal{L}_{cont} = \frac{1}{T-1} \sum_{t=1}^{T-1} m_t m_{t+1} (p_t^r - p_{t+1}^r)^2. \quad (8)$$

The total rationale regularization loss is:

$$\mathcal{L}_{RR} = \lambda_{sparse} \mathcal{L}_{sparse} + \lambda_{cont} \mathcal{L}_{cont}. \tag{9}$$

3.4.3 Combined Loss Function

The final objective function integrates all components:

$$\mathcal{L} = \mathcal{L}_{CE} + \mathcal{L}_{RR} + \alpha \mathcal{L}_{RT}, \tag{10}$$

where α controls the weight of the rationale tagging loss, and λ_{sparse} , λ_{cont} are hyperparameters for regularization.

4 Experiments

4.1 Dataset

ISE-DSC01, used in the UIT Challenge 2023, is designed for AI evaluation in information extraction and verification. It comprises training, public test, and private test sets with diverse claim-context pairs, posing challenges in evidence retrieval and fact-checking.

ViWikiFC (Le et al., 2024) was developed to combat misinformation, featuring over 20,000 claims from Wikipedia. Unlike ISE-DSC01, it explicitly includes evidence for the "nei" (Not Enough Information) label, enhancing real-world applicability.

	ISE-DSC01	ViWikiFC
Train	37,967	16,738
Dev	4,794	2,090
Test	5,396	2,091

Table 1: Overview of the datasets used in our experiments

Table 1 summarizes the datasets. For ViWikiFC, experiments were conducted on all three sets: training, public test, and private test.

4.2 Experimental Setup

We optimized our model through extensive experiments on an NVIDIA A100 GPU, fine-tuning key hyperparameters while maintaining consistent settings across all runs. The final hyperparameters, selected via rigorous validation, improved both accuracy and strict accuracy on ISE-DSC01 and Vi-WikiFC. Details are provided in Appendix B. For evaluation, all methods were tested on an NVIDIA T4 instance in Kaggle to ensure fairness.

Additionally, the large language model was finetuned on a distributed setup with 4×H100 GPUs, utilizing a structured prompt reformulation process. The dataset, originally in raw text and labels, was transformed into a prompt-based format optimized for LLM fine-tuning. This ensured effective task-specific learning while aligning with pre-trained knowledge. Further details on training setup, prompt design, and preprocessing are in Appendix B.

4.3 Main Results

The results in Table 2 demonstrate that SemViQA outperforms previous methods in Vietnamese fact-checking tasks. Specifically, our model achieves the highest Strict Accuracy, reaching 80.82% on ViWikiFC and 78.97% on ISE-DSC01, establishing a new benchmark for automated fact-checking systems in Vietnamese language.

4.3.1 Performance Comparison

a) Handling Long Token Sequences in Fact-Checking One major limitation of conventional Question Answering (QA) models in fact verification tasks is their inability to process long-context claims due to token length constraints. Transformer-based models such as ViMRC_{large}, InfoXLM_{large} (Chi et al., 2021), and XLM-R_{large} (Conneau et al., 2020), Ernie-M_{large} (Ouyang et al., 2021) are restricted to a maximum input length of 512 tokens. However, real-world fact-checking datasets, such as ISE-DSC01, often contain contexts exceeding 4800 tokens, causing a significant drop in performance for QA-based approaches due to their inability to handle long-token sequences. This limitation prevents these models from effectively leveraging the full evidence available, leading to incomplete or inaccurate fact verification.

To address this issue, our proposed SemViQA model incorporates a retrieval-based approach capable of handling long-token sequences efficiently, as illustrated in Figure 3. On ISE-DSC01, where long contexts are essential for verification, SemViQA significantly outperforms traditional QA models by effectively capturing and utilizing extended contextual information. This demonstrates that the long-token issue is a critical bottleneck in fact verification tasks.

In contrast, on the ViWikiFC dataset, where the token length is closer to 512 tokens, QA-based models achieve competitive performance, further confirming that the long-token issue is a major factor in performance degradation. However, when the long-token limitation does not exist on the ViWikiFC dataset, integrating our SER approach into a QA-based model proves to be an effective solution. By leveraging SER, we achieve approximately 1.86% higher ER Accuracy on ViWikiFC, demonstrating its efficiency in optimizing fact verification when token constraints are minimized.

These results highlight that long-token constraints are a fundamental challenge in fact verification. Our approach not only mitigates this issue through retrieval-based processing in SemViQA but also enhances QA models with QACT when long-token constraints are less severe, ensuring improved performance across diverse datasets.

- b) Performance and Inference Time Optimization One of the key advancements of SemViQA over other methods is its significant reduction in inference time without compromising accuracy. Key observations include:
 - The average inference time of SemViQA on ISE-DSC01 is 5200s, whereas large

TF-IDF XL	$foXLM_{large}$	Parameter	Strict Acc								
TF-IDF XL	-		Strict Acc	VC Acc	ER Acc	Time (s)	Strict Acc	VC Acc	ER Acc	Time (s)	Avg Strict Acc
	- 1	560M	75.56	82.21	90.15	131	73.59	78.08	76.61	378	74.58
Erı	LM-R _{large}	560M	76.47	82.78	90.15	134	75.61	80.50	78.58	366	76.04
	rnie-M _{large}	560M	75.56	81.83	90.15	144	78.19	81.69	80.65	403	76.88
Inf	foXLM _{large}	560M	70.44	79.01	83.50	130	72.09	77.37	75.04	320	71.27
BM25 XL	LM-R _{large}	560M	70.97	78.91	83.50	132	73.94	79.37	76.95	333	72.46
En	rnie-M _{large}	560M	70.21	78.29	83.50	141	76.58	80.76	79.02	381	73.40
	foXLM _{large}	838M	74.99	81.59	89.72	195	71.20	76.59	74.15	915	73.10
	LM-R _{large}	838M	75.80	82.35	89.72	194	72.85	78.78	75.89	835	74.33
En	rnie-M _{large}	838M	75.13	81.44	89.72	203	75.46	79.89	77.91	920	75.30
QA-based approaches VC	С										
Inf	foXLM _{large}	1120M	77.28	81.97	92.49	3778	54.36	64.14	56.84	9798	65.82
ViMRC _{large} XL	LM-R _{large}	1120M	78.29	82.83	92.49	3824	53.98	66.70	57.77	9809	66.14
	rnie-M _{large}	1120M	77.38	81.92	92.49	3785	56.62	62.19	58.91	9833	67.00
	foXLM _{large}	1120M	78.14	82.07	93.45	4092	53.50	63.83	56.17	10057	65.82
	LM-R _{large}	1120M	79.20	83.07	93.45	4096	53.32	66.70	57.25	10066	66.26
	rnie-M _{large}	1120M	78.24	82.21	93.45	4102	56.34	62.36	58.69	10078	67.29
LLM										'	
Qwen2.5-1.5B-Instruct		1.5B	51.03	65.18	78.96	7665	59.23	66.68	65.51	19780	55.13
Qwen2.5-3B-Instruct		3B	44.38	62.31	71.35	12123	60.87	66.92	66.10	31284	52.63
LLM VC	С										
Inf	foXLM _{large}	2B	66.14	76.47	78.96	7788	64.40	68.37	66.49	19970	65.27
Qwen2.5-1.5B-Instruct XL	LM-R _{large}	2B	67.67	78.10	78.96	7789	64.66	69.63	66.72	19976	66.17
Ern	rnie-M _{large}	2B	66.52	76.52	78.96	7794	65.70	68.37	67.33	20003	66.11
	foXLM _{large}	3.5B	59.88	72.50	71.35	12246	65.72	69.66	67.51	31477	62.80
Qwen2.5-3B-Instruct XL	LM-R _{large}	3.5B	60.74	73.08	71.35	12246	66.12	70.44	67.83	31483	63.43
Ern	rnie-M _{large}	3.5B	60.02	72.21	71.35	12251	67.48	70.77	68.75	31512	63.80
SER Faster (ours) TV	VC (ours)										
TF-IDF + ViMRC _{large}	rnie-M _{large}	1680M	79.44	82.93	94.60	410	78.32	81.91	80.26	995	78.88
TF-IDF + InfoXLM _{large}	IIIIC-IVI _{large}	1680M	79.77	83.07	95.03	487	78.37	81.91	80.32	925	79.07
SER (ours) TV	VC (ours)										
Inf	foXLM _{large}	1680M	80.25	83.84	94.69	2731	75.13	79.54	76.87	5191	77.69
TF-IDF + ViMRC $_{large}$ XL	LM-R _{large}	1680M	80.34	83.64	94.69	2733	76.71	81.65	78.91	5219	78.53
	rnie-M _{large}	1680M	79.53	82.97	94.69	2733	78.97	82.54	80.91	5225	79.25
	foXLM _{large}	1680M	80.68	83.98	95.31	3860	75.13	79.60	76.87	5175	77.91
	LM-R _{large}	1680M	80.82	83.88	95.31	3843	76.74	81.71	78.95	5200	78.78
	rnie-M _{large}	1680M	80.06	83.17	95.31	3891	78.97	82.49	80.91	5297	79.52

Table 2: Performance comparison on the ViWikiFC test set and the ISE-DSC01 private-test dataset. The results highlight differences among models based on several criteria: Strict Accuracy (Strict Acc), Veracity Classification Accuracy (VC Acc), and Evidence Retrieval Accuracy (ER Acc). Time represents the total inference time required to generate the complete results. Parameter indicates the total number of parameters used in each task. The results highlighted in blue indicate that our SER Faster method achieves the highest performance among all methods, except for the standard SER method.

LLM-based models such as Qwen2.5-3B-Instruct (Qwen et al., 2024) require over 31,000s, making SemViQA at least **6 times faster** than these large language model approaches.

- Compared to ViMRC_{large}³ (9800s on ISE-DSC01), SemViQA reduces inference time by nearly 50% while maintaining higher performance in both Strict Accuracy and Veracity Classification Accuracy.
- Methods based on SBERT (Reimers and Gurevych, 2019b) or BM25 have lower infer-

ence times but fail to maintain high accuracy, particularly when dealing with multi-step reasoning tasks. SemViQA achieves a better balance between classification performance and processing speed, ensuring practical deployment in real-world environments.

SemViQA Faster: We introduce an optimized version of SemViQA that achieves up to 7× faster inference while maintaining high accuracy. As shown in Figure 4, the inference speed of SER-Faster closely matches that of traditional methods while still outperforming competing solutions in both efficiency and accuracy. To achieve this speed improvement, we process all subcontexts within a sample as a batch, enabling batch inference (see

 $^{^3}$ https://huggingface.co/nguyenvulebinh/vi-mrc-large



Figure 4: Comparison of method performance, balancing accuracy and inference time. Each retrieval method is evaluated based on its highest achieved score, while the total inference time across both datasets is reported to highlight efficiency. Further details can be found in Table 2.

Section 3.1 for details on subcontexts). While this approach results in a slight performance drop compared to the standard SemViQA model, the trade-off is minimal considering the significant reduction in processing time. This efficiency enhancement makes SemViQA Faster highly suitable for real-world deployment, allowing seamless integration into large-scale fact-checking applications.

4.3.2 Analysis of Confidence Threshold in SemViQA

The confidence threshold plays a crucial role in balancing accuracy and inference time in SemViQA's evidence retrieval process. Analysis from Figure 5 indicates that as the threshold increases from 0.0 to 0.5, evidence retrieval accuracy improves significantly, particularly on ViWikiFC (95%) and ISE-DSC01 (80.8%). However, beyond 0.5, accuracy gains plateau, while inference time decreases sharply due to the system filtering out low-confidence evidence more aggressively. Setting an optimal threshold in the range of 0.4 – 0.5 achieves a trade-off between efficiency and accuracy, ensuring that SemViQA operates swiftly while maintaining precise evidence retrieval.

4.3.3 Comparison with other results in the competition

The results presented in Table 3 indicate that our SemViQA approach outperforms other competing teams, achieving the highest Strict Accuracy and demonstrating exceptional effectiveness in information processing and verification. This achievement highlights SemViQA's capability to deliver

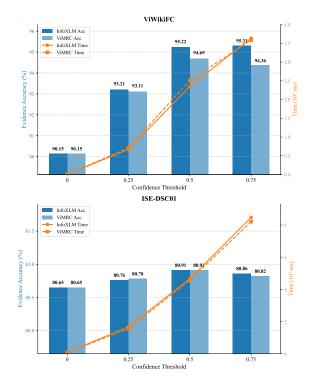


Figure 5: Impact of confidence threshold on evidence retrieval accuracy in SemViQA.

Methods	Strict Acc	VC Acc	ER Acc
SemViQA	78.97	82.54	80.91
DS@UIT Dynasty	78.05	84.76	80.13
URA_FNU	77.87	83.71	79.96
Plain Sailing	77.09	82.33	78.31
ViNSV	76.33	81.67	78.11

Table 3: Comparison of results with the top 5 teams in the competition

significantly more accurate and reliable results.

5 Conclusion and Future Works

We introduced SemViQA, a Vietnamese fact-checking framework that integrates Semantic-based Evidence Retrieval (SER) and Two-step Verdict Classification (TVC) to enhance claim verification. Our approach outperforms existing methods, including LLMs, TF-IDF, BM25, SBERT, and QA-based models, particularly in handling long-token sequences and complex reasoning tasks. Extensive experiments demonstrated SemViQA's state-of-the-art performance on ISE-DSC01 and ViWik-iFC. Additionally, the SemViQA Faster variant accelerates inference by up to 7×, improving its practicality for real-world applications. By addressing key challenges such as semantic ambiguity and multi-step reasoning, SemViQA lays the ground-

work for advancing Vietnamese NLP, with potential applications in misinformation detection and low-resource language fact-checking.

Limitations

While SemViQA demonstrates strong performance in Vietnamese fact verification, several limitations remain. First, our reliance on TF-IDF for initial evidence retrieval, while efficient, limits the model's ability to capture deep semantic relationships and retrieve implicit evidence. To mitigate this, we employ a threshold-based mechanism to identify hard samples and process them with a more advanced retrieval model. However, this approach relies on manually defined thresholds, which may not generalize well across different datasets, underscoring the need for adaptive and data-driven retrieval strategies in future work. Second, our Two-step Verdict Classification (TVC) framework improves claim verification accuracy but requires multiple classification stages, increasing inference time compared to single-step approaches. This additional computational cost is particularly significant in three-class classification tasks, where optimizing model efficiency without compromising accuracy remains a key challenge. Future work should focus on refining retrieval mechanisms and classification strategies to enhance efficiency and robustness, ensuring broader applicability of SemViQA in real-world fact verification scenarios.

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Kwak, Victor Ähdel, Sujeevan Rajayogam, Travis Choma, Fei Liu, Aditya Barua, Colin Ji, Ji Ho Park, Vincent Hellendoorn, Alex Bailey, Taylan Bilal, Huanjie Zhou, Mehrdad Khatir, Charles Sutton, Wojciech Rzadkowski, Fiona Macintosh, Konstantin Shagin, Paul Medina, Chen Liang, Jinjing Zhou, Pararth Shah, Yingying Bi, Attila Dankovics, Shipra Banga, Sabine Lehmann, Marissa Bredesen, Zifan Lin, John Eric Hoffmann, Jonathan Lai, Raynald Chung, Kai Yang, Nihal Balani, Arthur Bražinskas, Andrei Sozanschi, Matthew Hayes, Héctor Fernández Alcalde, Peter Makarov, Will Chen, Antonio Stella, Liselotte Snijders, Michael Mandl, Ante Kärrman, Paweł Nowak, Xinyi Wu, Alex Dyck, Krishnan Vaidyanathan, Raghavender R, Jessica Mallet, Mitch Rudominer, Eric Johnston, Sushil Mittal, Akhil Udathu, Janara Christensen, Vishal Verma, Zach Irving, Andreas Santucci, Gamaleldin Elsayed, Elnaz Davoodi, Marin Georgiev, Ian Tenney, Nan Hua, Geoffrey Cideron, Edouard Leurent, Mahmoud Alnahlawi, Ionut Georgescu, Nan Wei, Ivy Zheng, Dylan Scandinaro, Heinrich Jiang, Jasper Snoek, Mukund Sundararajan, Xuezhi Wang, Zack Ontiveros, Itay Karo, Jeremy Cole, Vinu Rajashekhar, Lara Tumeh, Eyal Ben-David, Rishub Jain, Jonathan Uesato, Romina Datta, Oskar Bunyan, Shimu Wu, John Zhang, Piotr Stanczyk, Ye Zhang, David Steiner, Subhajit Naskar, Michael Azzam, Matthew Johnson, Adam Paszke, Chung-Cheng Chiu, Jaume Sanchez Elias, Afroz Mohiuddin, Faizan Muhammad, Jin Miao, Andrew Lee, Nino Vieillard, Jane Park, Jiageng Zhang, Jeff Stanway, Drew Garmon, Abhijit Karmarkar, Zhe Dong, Jong Lee, Aviral Kumar, Luowei Zhou, Jonathan Evens, William Isaac, Geoffrey Irving, Edward Loper, Michael Fink, Isha Arkatkar, Nanxin Chen, Izhak Shafran, Ivan Petrychenko, Zhe Chen, Johnson Jia, Anselm Levskaya, Zhenkai Zhu, Peter Grabowski, Yu Mao, Alberto Magni, Kaisheng Yao, Javier Snaider, Norman Casagrande, Evan Palmer, Paul Suganthan, Alfonso Castaño, Irene Giannoumis, Wooyeol Kim, Mikołaj Rybiński, Ashwin Sreevatsa, Jennifer Prendki, David Soergel, Adrian Goedeckemeyer, Willi Gierke, Mohsen Jafari, Meenu Gaba, Jeremy Wiesner, Diana Gage Wright, Yawen Wei, Harsha Vashisht, Yana Kulizhskaya, Jay Hoover, Maigo Le, Lu Li, Chimezie Iwuanyanwu, Lu Liu, Kevin Ramirez, Andrey Khorlin, Albert Cui, Tian LIN, Marcus Wu, Ricardo Aguilar, Keith Pallo, Abhishek Chakladar, Ginger Perng, Elena Allica Abellan, Mingyang Zhang, Ishita Dasgupta, Nate Kushman, Ivo Penchev, Alena Repina, Xihui Wu, Tom van der Weide, Priya Ponnapalli, Caroline Kaplan, Jiri Simsa, Shuangfeng Li, Olivier Dousse, Fan Yang, Jeff Piper, Nathan Ie, Rama Pasumarthi, Nathan Lintz, Anitha Vijayakumar, Daniel Andor, Pedro Valenzuela, Minnie Lui, Cosmin Paduraru, Daiyi Peng, Katherine Lee, Shuyuan Zhang, Somer Greene, Duc Dung Nguyen, Paula Kurylowicz, Cassidy Hardin, Lucas Dixon, Lili Janzer, Kiam Choo, Ziqiang Feng, Biao Zhang, Achintya Singhal, Dayou Du, Dan McKinnon, Natasha Antropova, Tolga Bolukbasi, Orgad Keller, David Reid, Daniel Finchelstein, Maria Abi Raad, Remi Crocker, Peter Hawkins, Robert Dadashi, Colin Gaffney, Ken

Franko, Anna Bulanova, Rémi Leblond, Shirley Chung, Harry Askham, Luis C. Cobo, Kelvin Xu, Felix Fischer, Jun Xu, Christina Sorokin, Chris Alberti, Chu-Cheng Lin, Colin Evans, Alek Dimitriev, Hannah Forbes, Dylan Banarse, Zora Tung, Mark Omernick, Colton Bishop, Rachel Sterneck, Rohan Jain, Jiawei Xia, Ehsan Amid, Francesco Piccinno, Xingyu Wang, Praseem Banzal, Daniel J. Mankowitz, Alex Polozov, Victoria Krakovna, Sasha Brown, MohammadHossein Bateni, Dennis Duan, Vlad Firoiu, Meghana Thotakuri, Tom Natan, Matthieu Geist, Ser tan Girgin, Hui Li, Jiayu Ye, Ofir Roval, Reiko Tojo, Michael Kwong, James Lee-Thorp, Christopher Yew, Danila Sinopalnikov, Sabela Ramos, John Mellor, Abhishek Sharma, Kathy Wu, David Miller, Nicolas Sonnerat, Denis Vnukov, Rory Greig, Jennifer Beattie, Emily Caveness, Libin Bai, Julian Eisenschlos, Alex Korchemniy, Tomy Tsai, Mimi Jasarevic, Weize Kong, Phuong Dao, Zeyu Zheng, Frederick Liu, Fan Yang, Rui Zhu, Tian Huey Teh, Jason Sanmiya, Evgeny Gladchenko, Nejc Trdin, Daniel Toyama, Evan Rosen, Sasan Tavakkol, Linting Xue, Chen Elkind, Oliver Woodman, John Carpenter, George Papamakarios, Rupert Kemp, Sushant Kafle, Tanya Grunina, Rishika Sinha, Alice Talbert, Diane Wu, Denese Owusu-Afriyie, Cosmo Du, Chloe Thornton, Jordi Pont-Tuset, Pradyumna Narayana, Jing Li, Saaber Fatehi, John Wieting, Omar Ajmeri, Benigno Uria, Yeongil Ko, Laura Knight, Amélie Héliou, Ning Niu, Shane Gu, Chenxi Pang, Yeqing Li, Nir Levine, Ariel Stolovich, Rebeca Santamaria-Fernandez, Sonam Goenka, Wenny Yustalim, Robin Strudel, Ali Elgursh, Charlie Deck, Hyo Lee, Zonglin Li, Kyle Levin, Raphael Hoffmann, Dan Holtmann-Rice, Olivier Bachem, Sho Arora, Christy Koh, Soheil Hassas Yeganeh, Siim Põder, Mukarram Tariq, Yanhua Sun, Lucian Ionita, Mojtaba Seyedhosseini, Pouya Tafti, Zhiyu Liu, Anmol Gulati, Jasmine Liu, Xinyu Ye, Bart Chrzaszcz, Lily Wang, Nikhil Sethi, Tianrun Li, Ben Brown, Shreya Singh, Wei Fan, Aaron Parisi, Joe Stanton, Vinod Koverkathu, Christopher A. Choquette-Choo, Yunjie Li, TJ Lu, Abe Ittycheriah, Prakash Shroff, Mani Varadarajan, Sanaz Bahargam, Rob Willoughby, David Gaddy, Guillaume Desjardins, Marco Cornero, Brona Robenek, Bhavishya Mittal, Ben Albrecht, Ashish Shenoy, Fedor Moiseev, Henrik Jacobsson, Alireza Ghaffarkhah, Morgane Rivière, Alanna Walton, Clément Crepy, Alicia Parrish, Zongwei Zhou, Clement Farabet, Carey Radebaugh, Praveen Srinivasan, Claudia van der Salm, Andreas Fidjeland, Salvatore Scellato, Eri Latorre-Chimoto, Hanna Klimczak-Plucińska, David Bridson, Dario de Cesare, Tom Hudson, Piermaria Mendolicchio, Lexi Walker, Alex Morris, Matthew Mauger, Alexey Guseynov, Alison Reid, Seth Odoom, Lucia Loher, Victor Cotruta, Madhavi Yenugula, Dominik Grewe, Anastasia Petrushkina, Tom Duerig, Antonio Sanchez, Steve Yadlowsky, Amy Shen, Amir Globerson, Lynette Webb, Sahil Dua, Dong Li, Surya Bhupatiraju, Dan Hurt, Haroon Qureshi, Ananth Agarwal, Tomer Shani, Matan Eyal, Anuj Khare, Shreyas Rammohan Belle, Lei Wang, Chetan Tekur, Mihir Sanjay Kale, Jinliang Wei, Ruoxin Sang, Brennan Saeta, Tyler Liechty, Yi Sun, Yao Zhao, Stephan Lee, Pandu Nayak, Doug Fritz, Manish Reddy Vuyyuru, John Aslanides, Nidhi Vyas, Martin Wicke, Xiao Ma, Evgenii Eltyshev, Nina Martin, Hardie Cate, James Manyika, Keyvan Amiri, Yelin Kim, Xi Xiong, Kai Kang, Florian Luisier, Nilesh Tripuraneni, David Madras, Mandy Guo, Austin Waters, Oliver Wang, Joshua Ainslie, Jason Baldridge, Han Zhang, Garima Pruthi, Jakob Bauer, Feng Yang, Riham Mansour, Jason Gelman, Yang Xu, George Polovets, Ji Liu, Honglong Cai, Warren Chen, Xiang-Hai Sheng, Emily Xue, Sherjil Ozair, Christof Angermueller, Xiaowei Li, Anoop Sinha, Weiren Wang, Julia Wiesinger, Emmanouil Koukoumidis, Yuan Tian, Anand Iyer, Madhu Gurumurthy, Mark Goldenson, Parashar Shah, MK Blake, Hongkun Yu, Anthony Urbanowicz, Jennimaria Palomaki, Chrisantha Fernando, Ken Durden, Harsh Mehta, Nikola Momchev, Elahe Rahimtoroghi, Maria Georgaki, Amit Raul, Sebastian Ruder, Morgan Redshaw, Jinhyuk Lee, Denny Zhou, Komal Jalan, Dinghua Li, Blake Hechtman, Parker Schuh, Milad Nasr, Kieran Milan, Vladimir Mikulik, Juliana Franco, Tim Green, Nam Nguyen, Joe Kelley, Aroma Mahendru, Andrea Hu, Joshua Howland, Ben Vargas, Jeffrey Hui, Kshitij Bansal, Vikram Rao, Rakesh Ghiya, Emma Wang, Ke Ye, Jean Michel Sarr, Melanie Moranski Preston, Madeleine Elish, Steve Li, Aakash Kaku, Jigar Gupta, Ice Pasupat, Da-Cheng Juan, Milan Someswar, Tejvi M., Xinyun Chen, Aida Amini, Alex Fabrikant, Eric Chu, Xuanyi Dong, Amruta Muthal, Senaka Buthpitiya, Sarthak Jauhari, Nan Hua, Urvashi Khandelwal, Ayal Hitron, Jie Ren, Larissa Rinaldi, Shahar Drath, Avigail Dabush, Nan-Jiang Jiang, Harshal Godhia, Uli Sachs, Anthony Chen, Yicheng Fan, Hagai Taitelbaum, Hila Noga, Zhuyun Dai, James Wang, Chen Liang, Jenny Hamer, Chun-Sung Ferng, Chenel Elkind, Aviel Atias, Paulina Lee, Vít Listík, Mathias Carlen, Jan van de Kerkhof, Marcin Pikus, Krunoslav Zaher, Paul Müller, Sasha Zykova, Richard Stefanec, Vitaly Gatsko, Christoph Hirnschall, Ashwin Sethi, Xingyu Federico Xu, Chetan Ahuja, Beth Tsai, Anca Stefanoiu, Bo Feng, Keshav Dhandhania, Manish Katyal, Akshay Gupta, Atharva Parulekar, Divya Pitta, Jing Zhao, Vivaan Bhatia, Yashodha Bhavnani, Omar Alhadlaq, Xiaolin Li, Peter Danenberg, Dennis Tu, Alex Pine, Vera Filippova, Abhipso Ghosh, Ben Limonchik, Bhargava Urala, Chaitanya Krishna Lanka, Derik Clive, Yi Sun, Edward Li, Hao Wu, Kevin Hongtongsak, Ianna Li, Kalind Thakkar, Kuanysh Omarov, Kushal Majmundar, Michael Alverson, Michael Kucharski, Mohak Patel, Mudit Jain, Maksim Zabelin, Paolo Pelagatti, Rohan Kohli, Saurabh Kumar, Joseph Kim, Swetha Sankar, Vineet Shah, Lakshmi Ramachandruni, Xiangkai Zeng, Ben Bariach, Laura Weidinger, Tu Vu, Alek Andreev, Antoine He, Kevin Hui, Sheleem Kashem, Amar Subramanya, Sissie Hsiao, Demis Hassabis, Koray Kavukcuoglu, Adam Sadovsky, Quoc Le, Trevor Strohman, Yonghui Wu, Slav Petrov, Jeffrey Dean, and Oriol Vinyals. 2024. 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A Strict Accuracy in Fact-Checking

Strict Accuracy: This metric is a stringent measure that requires both the verdict and the evidence to be predicted correctly compared to the ground truth sample.

Verdict (v and v'): refers to the verdict of the sample and the predicted verdict (supported, refuted, nei). Evidence (e and e'): refers to the evidence of the sample and the predicted evidence.

$$StrAcc = f(v, v').f(e, e')$$
(11)

Where:

$$f(v, v') = \begin{cases} 1 & \text{if } v = v' \\ 0 & \text{otherwise} \end{cases}$$
 (12)

$$f(e, e') = \begin{cases} 1 & \text{if } e = e' \\ 0 & \text{otherwise} \end{cases}$$
 (13)

Strict accuracy is the average of all StrAcc values.

B Hyperparameter and LLM Training Configuration

In this section, we present the detailed hyperparameter settings and training configurations for both our SemViQA models and the Large Language Model (LLM) fine-tuning process. Table 4 consolidates all hyperparameters used across different models, including Binary Classification (BC), Three-Class Classification (TC), Question Answering Token Classifier (QATC), and LLM fine-tuning.

Hyperparameter	BC	TC	QATC	LLM
Epochs	20	20	20	1
RT Loss	-	-	\checkmark	-
Cross-Entropy Loss	-	\checkmark	\checkmark	-
Focal Loss	✓	-	-	-
Learning Rate	$1e^{-5}$	$1e^{-5}$	$2e^{-6}$	$5e^{-5}$
Batch Size	104	104	36	2
Gradient Accumulation	1	1	2	1
Optimizer (AdamW)	✓	\checkmark	\checkmark	\checkmark
Max Token Length	256	256	512	4096
GPUs	A100	A100	A100	$4 \times H100$
Zero	-	-	-	Zero3
LR Schedule	Linear	Linear	Cyclic	Cosine
Mixed Precision	-	-	-	bf16

Table 4: Consolidated hyperparameter and training configuration for SemViQA models and LLM fine-tuning.

We fine-tune a Large Language Model (LLM) using a restructured version of the original datasets, ViWikiFC and ISE-DSC01, as detailed in Figure 5. These datasets have been carefully adapted for training to improve performance and ensure compatibility with our model. For training, we utilize the official Qwen LLM implementation from the QwenLM repository⁴. Our training setup follows the full configuration outlined in Table 4, ensuring optimal efficiency and alignment with best practices.

 $^{^4} https://github.com/QwenLM/Qwen$

Question: You are tasked with verifying the correctness of the following statement.

- We provide you with a claim and a context. Please classify the claim into one of three labels: "SUPPORTED", "REFUTED", or "NEI" (Not Enough Info).
- Your answer should include the classification label and the most relevant evidence sentence from the context.
- Remember, the evidence must be a full sentence, not part of a sentence or less than one sentence.

Given a claim and context as follows:

Context: The actress revealed her secrets to maintaining a youthful appearance as follows: Eating three balanced meals a day. For dinner, Ivy Chen usually eats early to ensure her body has enough time to digest food, metabolize energy, and avoid putting pressure on the stomach and other organs. A recent study published in *Frontiers in Nutrition* suggests that eating dinner earlier can lead to a longer lifespan, with the ideal time being 7 PM. If this is not possible, experts recommend having the last meal of the day 2-3 hours before bedtime. Drinking ginger tea: To keep her body warm, promote blood circulation, and enhance circulation, Ivy Chen drinks ginger tea daily. Her ginger tea is typically made with ground ginger, black tea, turmeric powder, and brown sugar. This drink is a natural remedy that not only boosts the immune system and reduces inflammation but also fights oxidation, supports weight loss, improves skin health, and helps maintain a youthful look. Regular exercise: Ivy Chen is a fitness enthusiast who loves physical activities and exercises daily, even during pregnancy. The Taiwanese actress shared that if she is not busy with work, she runs for at least 30 minutes every day. Even when traveling abroad, she maintains her running habit. A recent study published in *Progress in Cardiovascular Disease* found that regular runners live three years longer than non-runners. Running significantly helps with weight loss, maintaining a balanced physique, toning muscles, relaxing the mind, and benefiting heart health. Besides running, Ivy Chen also swims, practices yoga, and hikes to maintain physical fitness and endurance. Skincare: Regarding her skincare routine, the actress emphasized the importance of hydration. The Taiwanese beauty revealed that she always carries a facial mist to ensure her skin stays hydrated while outdoors.

Claim: Even when traveling abroad, Ivy Chen maintains her running habit.

Answer: This claim is classified as **SUPPORTED**. The evidence is: *Even when traveling abroad, she maintains her running habit.*

Table 5: Example of a fact-checking task prompt used for LLM training. Note: Some parts of the Context and Claim were originally in Vietnamese. In this paper, we have translated them into English for better readability. Sentences highlighted in blue indicate the evidence.

We present the complete training progress of the LLM models and QATC in Figure 7 and Figure 6, respectively. Figure 7 illustrates the training dynamics of Qwen 1.5B and Qwen 3B, supporting the results presented in Table 2. Notably, the Qwen 1.5B model demonstrates more stable training dynamics compared to the Qwen 3B model during the initial stage. Meanwhile, Figure 6 showcases the completion of QATC training, depicting the loss curves of ViMRC_{large} and InfoXLM_{large}. These results highlight the convergence behavior of QATC training across different architectures, further supporting the robustness of our approach.

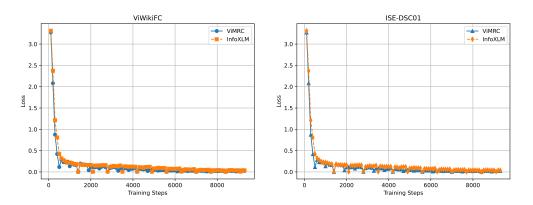


Figure 6: Training progress of the $ViMRC_{large}$ and $InfoXLM_{large}$ models.

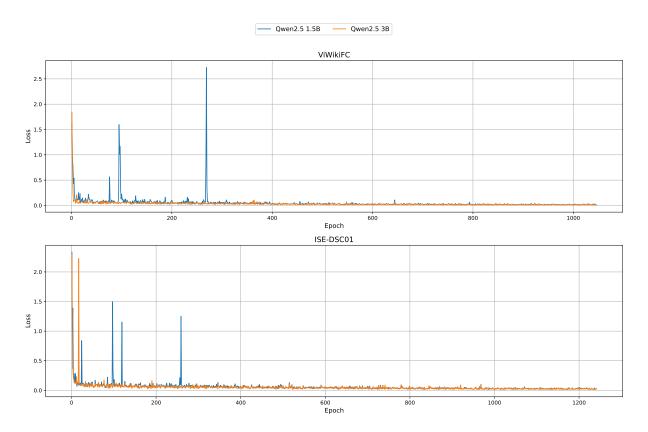


Figure 7: Training progress of the Qwen 1.5B and Qwen 3B models.

C Comparison of TF-IDF and QATC in Fact-Checking: Examples of Incorrect vs. Correct Evidence Selection

Claim	Evidence	TF-IDF	QATC
Du lịch Triều Tiên là	Theo nguyên tắc, bất	Khách du lịch không	Theo nguyên tắc, bất
điều mà chỉ có một số	kỳ ai cũng được phép	được đi thăm thú bên	kỳ ai cũng được phép
người được đi đến.	du lịch tới Triều Tiên,	ngoài vùng đã được	du lịch tới Triều Tiên,
(Traveling to North	và những ai có thể	cho phép trước mà	và những ai có thể
Korea is something	hoàn thành quá trình	không được hướng dẫn	hoàn thành quá trình
only a few people can	làm thủ tục thì đều	viên người Triều Tiên	làm thủ tục thì đều
do.)	không bị Triều Tiên từ	cho phép nhằm tránh	không bị Triều Tiên từ
	chối cho nhập cảnh.	các điệp viên nằm	chối cho nhập cảnh.
	(In principle, anyone is	vùng.	(In principle, anyone is
	allowed to travel to	(Tourists are not	allowed to travel to
	North Korea, and those	allowed to visit areas	North Korea, and those
	who complete the	outside of the	who complete the
	process are not denied	designated zones	process are not denied
	entry.)	without a North	entry.)
		Korean guide to	
		prevent undercover	
		spies.)	
Nó có độ nóng chảy ở	Nó là một kim loại	Nó là nguyên tố có độ	Nó là một kim loại
mức gần 30 độ C.	kiềm mềm, màu bạc,	âm điện thấp thứ hai	kiềm mềm, màu bạc,
(It has a melting point	và với điểm nóng chảy	sau franci, và chỉ có	và với điểm nóng chảy
of about 30°C.)	là 28 °C (83 °F) khiến	một đồng vị bền là	là 28 °C (83 °F) khiến
	cho nó trở thành một	caesi-133.	cho nó trở thành một
	trong các kim loại ở	(It is the second least	trong các kim loại ở
	dạng lỏng tại hay gần	electronegative	dạng lỏng tại hay gần
	nhiệt độ phòng.	element after francium,	nhiệt độ phòng.
	(It is a soft, silvery	and has only one stable	(It is a soft, silvery
	alkali metal with a	isotope, cesium-133.)	alkali metal with a
	melting point of 28°C		melting point of 28°C
	(83°F), making it one of the metals that is		(83°F), making it one of the metals that is
	liquid at or near room		liquid at or near room
	temperature.)		temperature.)

Table 6: Comparison of TF-IDF and QATC in Fact-Checking: TF-IDF selects irrelevant evidence (Incorrect), while QATC selects accurate evidence (Correct).