SNaRe 🥁: Domain-aware Data Generation for Low-Resource Event Detection

Anonymous ACL submission

Abstract

Event Detection (ED) – the task of identifying event mentions from natural language text – is critical for enabling reasoning in highly specialized domains such as biomedicine, law, and epidemiology. Data generation has proven to be effective in broadening its utility to wider applications without requiring expensive expert annotations. However, when existing generation approaches are applied to specialized domains, they struggle with label noise, where annotations are incorrect, and domain drift, characterized by a distributional mismatch between generated sentences and the target domain. To address these issues, we introduce SNaRe, a domain-aware synthetic data generation framework composed of three components: Scout, Narrator, and Refiner. Scout extracts triggers from unlabeled target domain data and curates a high-quality domain-specific trigger list using corpus-level statistics to mitigate domain drift. Narrator, conditioned on these triggers, generates high-quality domain-aligned sentences, and Refiner identifies additional event mentions, ensuring high annotation quality. Experimentation on three diverse domain ED datasets reveals how SNaRe outperforms the best baseline, achieving average F1 gains of 3-7% in the zero-shot/few-shot settings and 4-20% F1 improvement for multilingual generation. Analyzing the generated trigger hit rate and human evaluation substantiates SNaRe's stronger annotation quality and reduced domain drift.

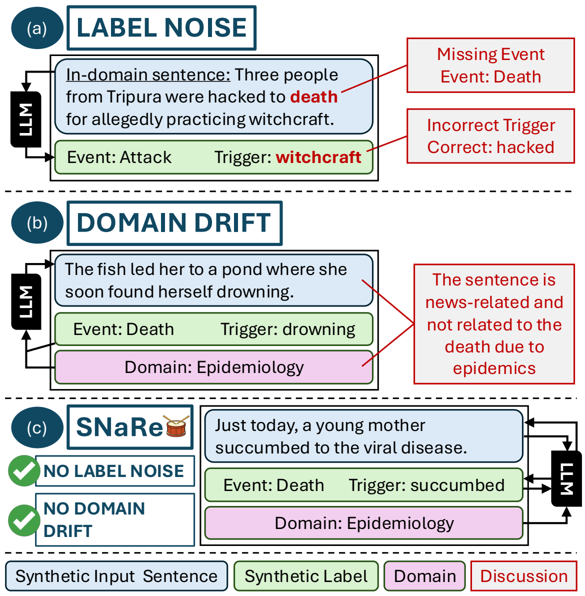

Figure 1: Highlighting the errors of existing data generation approaches. (a) Using LLMs to generate the labels from in-domain sentences leads to *label noise* owing to poor LLM reasoning. (b) Utilizing LLMs to generate sentences conditioned on event and domain causes *domain drift*, wherein the synthetic sentence is not aligned with the target domain. Finally, in (c), we illustrate how SNaRe minimizes both errors to generate higher quality synthetic data.

1 Introduction

Event Detection (ED) (Sundheim, 1992; Doddington et al., 2004) involves identifying and categorizing significant events from natural language text based on a pre-defined ontology. It has widespread applications in domains such as biomedicine (Pyysalo et al., 2012), epidemiology (Parekh et al., 2024b,c), law (Francesconi et al., 2010). Due to the high cost of expert-annotated data, synthetic data generation (Xu et al., 2023) (i.e., generating sentence and event annotations) has emerged as a promising alternative, particularly for practical use-cases in specialized domains.

However, existing generation approaches often focus on general-domain settings and fail to address the distinct challenges of specialized domains (Song et al., 2025). Weak supervision methods (He et al., 2021; Chia et al., 2022) that use LLMs to generate labels for unlabeled sentences frequently introduce *label noise* (Figure 1(a)), where incorrect or incomplete labels arise due to weak LLM reasoning (Huang et al., 2024) or limited domain knowledge (Song et al., 2025). Downstream training on such incorrect labels can cause spurious bias propagation. Conversely, recent generation approaches (Josifoski et al., 2023; Ma et al., 2024) that utilize LLMs' self-knowledge to jointly generate labels and sentences struggle with *domain drift* (Figure 1(b)), often synthesizing sentences that are misaligned with the target domain. This can be attributed to the lack of utilization of target domain information for generation and can drastically hamper model training as lexical and structural cues are highly influential for ED (Tong et al., 2022). Overall, *label noise* and *domain drift* reduce synthetic data quality, eventually leading to subpar supervised downstream model performance.

To this end, we propose SNARE, a novel domain-aware, three-stage data synthesis LLM pipeline comprising the **S**cout, **Na**rrator, and **Re**finer modules. Scout surveys unlabeled target domain data to identify salient triggers via prompt-based trigger extraction. Using corpus-level statistics for automated aggregation and filtering, Scout curates a list of high-quality domain-specific triggers per event type. Next, Narrator samples from these domain-specific triggers and utilizes LLMs to synthesize diverse sentences for each event type. Utilizing specialized and diverse domain information for conditional generation aids Narrator in generating more domain-aligned sentences, eventually reducing domain drift in the synthesized sentences. Since Narrator sentences could mention additional events apart from the input set, we design the Refiner to utilize LLM inference to annotate such missing events in these sentences. Narrator's conditional text generation and Refiner's missing label annotation aid in reducing the label noise and ensuring high data quality. We provide an illustration of SNARE's generation in Figure 1(c).

We benchmark SNARE on ED datasets from three domains: ACE (Doddington et al., 2004) (news), SPEED (Parekh et al., 2024c) (epidemiology), and GENIA2011 (Kim et al., 2011) (biomedical). For evaluation, we report the ED performance of DEGREE (Hsu et al., 2022) trained on the synthesized data. Across the zero-shot and few-shot settings, SNARE performs the best, outperforming the previous state-of-the-art baselines (Ding et al., 2023; Ma et al., 2024) by an average of 3-7% F1 points. Under multilingual generation for Arabic and Chinese, SNARE outshines even more, with improvements of 4-20% F1 over the best baseline. Our analysis reveals how SNARE's synthesized triggers overlap 4-11% more (relative to baselines) with the gold trigger set, demonstrating the reduction in domain drift. Finally, human evaluation provides qualitative evidence for SNARE's superior data annotation quality and domain alignment.[1]

2 Problem Definition

We focus on the task of Event Detection (ED) (Sundheim, 1992; Doddington et al., 2004) for this work. ED aims to extract mentions of any events of interest from natural language text. Following ACE 2005 (Doddington et al., 2004), we define an *event* as something that happens or describes a change of state and is labeled by a specific *event type*. The word/phrase that most distinctly highlights the occurrence of the event is defined as the *event trigger*, and the trigger-event type pair is known as the *event mention*. *Event Detection* requires extracting the event *triggers* from the sentence and classifying them into one of the pre-defined event types. We provide an illustration of this task below, where *arrested* and *campaigns* trigger the events of *Justice: Arrest-Jail* and *Conflict: Demonstrate*, respectively.

> Some 3,000 people have been **arrested** since the disobedience **campaigns** began last week.
> Conflict: Demonstrate — Justice: Arrest-Jail

In our work, we specifically focus on ED in diverse and specialized domains (e.g., biomedical), where procuring a training dataset D_T of annotated data points is expensive, but unlabeled data D'_T is available. We focus on two realistic low-resource data setups - **zero-shot** (zero labeled data) and **few-shot** (k labeled datapoints per event type) settings. Unlike domain transfer, we do not consider any labeled data for the source domain, and directly optimize model performance for the target domain.

3 Related Works

Data Generation for Information Extraction LLM-powered synthetic data generation has been successful for various NLP tasks (Li et al., 2023b; Wang et al., 2023c; Wu et al., 2024; Shao et al., 2025). For information extraction, works have explored knowledge retrieval (Chen and Feng, 2023; Amalvy et al., 2023), translation (Parekh et al., 2024a; Le et al., 2024), data re-editing (Lee et al., 2021; Hu et al., 2023), and label extension (Zhang et al., 2024). Recent works utilize LLMs to generate labels for sentences (Chia et al., 2022; Ye

[1]We will release our code and data upon acceptance.

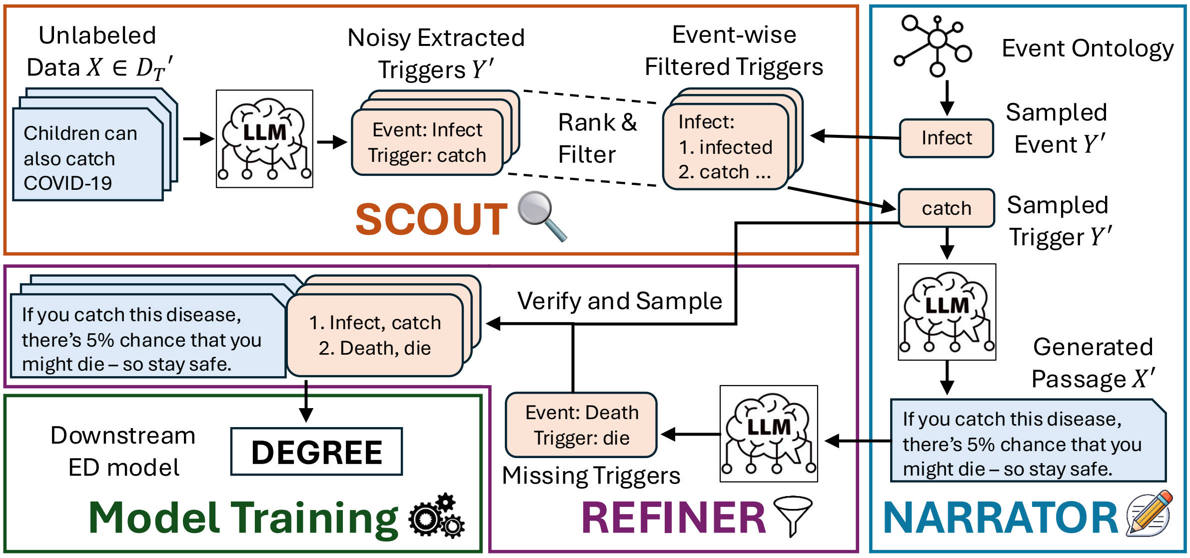

Figure 2: Model Architecture Diagram highlighting the various components of SNaRe. First, Scout extracts and filters domain-specific triggers, then Narrator generates passages conditioned on these triggers. Finally, Refiner adds any missing annotations and sample N data points per event for downstream training.

et al., 2022; Wang et al., 2023a; Tang et al., 2023), while some other works explore the generation of sentences from labels (Josifoski et al., 2023; Ma et al., 2024). Our work introduces SNaRe focused on infusing better domain-specific information for data generation.

Low-resource Event Detection Event Detection (ED) has been studied extensively (Sundheim, 1992; Grishman and Sundheim, 1996), leading to diverse datasets in news (Doddington et al., 2004; Song et al., 2015; Ellis et al., 2015), Wikipedia (Li et al., 2021; Pouran Ben Veyseh et al., 2022), and general domains (Wang et al., 2020; Parekh et al., 2023), as well as niche areas like biomedical (Pyysalo et al., 2012; Kim et al., 2011, 2013), multimedia (Li et al., 2020), cybersecurity (Satyapanich et al., 2020), epidemiology (Parekh et al., 2024b,c), and pharmacovigilance (Sun et al., 2022). To address the growing need for event detection across expanding domains, prior works have explored transfer learning via Abstract Meaning Representation (Huang et al., 2018), Semantic Role Labeling (Zhang et al., 2021), and Question Answering (Lyu et al., 2021). Reformulating ED as a conditional generation task has also aided low-resource training (Hsu et al., 2022, 2023b; Huang et al., 2022). Recently, LLM-based reasoning (Li et al., 2023a; Gao et al., 2023; Wang et al., 2023b) and transfer-learning (Cai et al., 2024) has been explored, but their performance remains inferior to supervised models (Huang et al., 2024). This motivates efforts in LLM-powered synthetic data generation for low-resource ED.

4 Methodology - SNaRe

In this work, we focus on domain-aware synthetic data generation using Large Language Models (LLMs) to alleviate the need for expert-annotated training data. By generating a large dataset $D_s = \{(X, Y)\}$, we can train domain-specific downstream ED models using minimal supervised data.

Existing weak-supervision approaches (Mintz et al., 2009; Wang et al., 2021) utilizing automatic methods to assign labels to unlabeled sentences often generate incorrect labels (*label noise*). This can be attributed to the domain-specific context understanding and deep reasoning requirement of ED, leading to poor automatic label quality, even when using recent LLMs (Huang et al., 2024). Another route of approaches that utilize LLMs to generate sentences conditioned on labels (Schick and Schütze, 2021; Josifoski et al., 2023), i.e., synthesize X for a designated Y, often curate sentences that are distributionally divergent from the target domain (*domain drift*). This is mainly since these approaches focus on the general domain and fail to utilize any target domain signals in their generation. Both label noise and domain drift hurt the synthetic data quality, in turn, diminishing the downstream supervised model performance.

To mitigate these issues, we propose SNaRe 🥁, a domain-aware high-quality data synthesizer, comprising three components: **S**cout, **Na**rrator, and **Re**finer. Scout studies unlabeled target domain data D'_T to curate domain-specific triggers, in turn, reducing domain drift. Narrator generates domain-specific sentences conditioned on Scout's curated triggers, while Refiner adds additional annotations to ensure high-quality labels. Overall, SNARE is a training-free LLM inference pipeline and easily deployable and scalable across domains. We provide our architectural diagram in Figure 2 and explain each component of our pipeline below.

4.1 Scout

Scout is tasked with the curation of domain-specific triggers that are later utilized for sentence generation. Events can assume a wide range of triggers depending on the domain and context. For example, an "Attack" event can be triggered by *war*, *killed* in news, or *breach*, *phish* in cybersecurity, or *infect*, *transmit* in epidemiology domains.

Thus, unlike past works (Ma et al., 2024) that utilize only LLMs' internal knowledge for trigger generation, we develop **Scout**, which extracts high-precision domain-specific triggers using unlabeled target domain data D'_T. Specifically, trigger extraction involves a two-stage prompt setup: (1) The first stage is tasked with identifying and filtering possible event types mentioned in the target domain sentence, and (2) The second stage aims to find the most appropriate trigger word from the unlabeled sentence for each filtered event type. We illustrate this setup in § A.

To ensure high-precision of the triggers, we develop an aggregation and filtering mechanism by incorporating corpus-level statistics. Specifically, for each event type, we aggregate the counts of the triggers at the corpus level and filter out the top $t = 10$ triggers as the curated list of high-quality domain-specific event-indexed triggers. These triggers carry important target domain signals that help in generating domain-specific sentences (§ 4.2), in turn reducing domain drift of our synthetic data.

4.2 Narrator

Narrator is tasked with the synthesis of domain-specific sentences for our synthetic dataset. Existing works (Josifoski et al., 2023; Ma et al., 2024) do not utilize any target domain information, which causes domain drift in their synthesized sentences. Instead, in our work, we condition the Narrator to utilize the rich and diverse domain-specific triggers from Scout to synthesize domain-specific sentences, which, in turn, reduce domain drift.

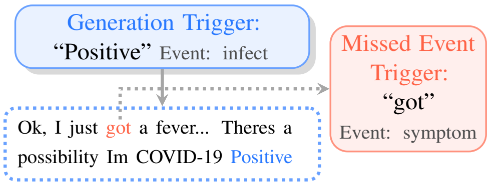

Figure 3: Illustration of how inverse generation can produce unannotated event mentions. Blue box = target event mention, red box = unannotated event mention.

Specifically, Narrator samples 1-2 event types per synthetic data instance and corresponding domain-specific triggers from Scout's curated trigger list – constituting the label Y. Next, it prompts the LLM with the task instructions and the event definitions, and asks it to generate a passage X' that mentions the sampled events using the sampled triggers (Y). We illustrate this prompt in Figure 8. The generated sentences are naturally more aligned with the target domain owing to the conditioning on the domain-specific triggers (qualitative examples shown in § 7.6). Further domain-specific adaptations are possible by fine-tuning the LLM on unlabeled domain-specific data (analysis in § 7.5).

4.3 Refiner

While the Narrator ensures the sampled triggers are mentioned in the passage, it could potentially introduce new unknown events in the passage, leading to under-annotated (X', Y) data instances. We illustrate this in Figure 3 where the sampled trigger *positive* for *infect* event is mentioned, but the sentence also mentions the missing *symptom* event triggered by *got*.

To account for such missing annotations, we introduce **Refiner** - tasked to annotate missing events in the generated sentence. Here, we simply prompt the LLM to find all event mentions in the generated sentence (illustrated in Figure 9) and append them to the original sampled Y. To avoid adding noisy labels, we only add annotations for newly discovered events. To further improve data quality, we apply an automated rule to remove passages that do not mention the target trigger. Additionally, we standardize trigger annotations by correcting variations in trigger word forms. Such normalization and conservative filtering further aid in ensuring high data quality. Finally, we apply a greedy sampling algorithm to sample $N = 50$ instances (X', Y) per event type to create our final synthetic dataset D_s.

Base LLM	Method	Unlabeled Data Source	ACE Eve-I	ACE Tri-C	SPEED Eve-I	SPEED Tri-C	GENIA Eve-I	GENIA Tri-C	Average Eve-I	Average Tri-C
Llama3-8B	Inference	-	30.2	23.8	39.8	25.4	21.9	17.2	30.6	22.1
	STAR	-	44.9	35.0	21.0	10.1	25.9	19.0	30.6	21.4
	Weak Sup	train	41.7	37.8	45.6	31.5	26.9	21.4	38.1	30.2
	SNaRe (ours)	train	57.4	50.2	44.6	31.5	**35.2**	**28.9**	45.7	**36.9**
	SNaRe (ours)	external	**57.7**	**52.6**	**47.8**	**32.9**	33.6	24.6	**46.4**	36.7
Llama3-70B	Inference	-	46.9	41.3	46.9	35.6	34.2	28.2	42.7	35.0
	STAR	-	50.0	42.3	18.3	13.8	23.3	16.9	30.5	24.3
	Weak Sup	train	53.2	48.0	**52.8**	**39.6**	36.2	29.1	47.4	38.9
	SNaRe (ours)	train	58.1	53.8	49.9	38.7	38.0	29.7	48.7	40.7
	SNaRe (ours)	external	**59.7**	**55.6**	50.1	39.2	**39.2**	**31.5**	**49.7**	**42.1**
GPT-3.5	Inference	-	33.0	26.2	44.2	32.9	31.2	24.7	36.1	27.9
	STAR	-	45.0	36.6	21.3	14.6	21.8	14.3	29.4	21.8
	Weak Sup	train	49.7	44.6	**50.7**	**37.5**	37.7	30.1	46.1	37.4
	SNaRe (ours)	train	**54.8**	48.3	50.3	36.8	**39.3**	**31.1**	**48.1**	**38.7**
	SNaRe (ours)	external	54.0	**48.5**	50.1	36.1	38.7	29.4	47.6	38.0
(Upper Bound)	Gold Data	-	64.6	61.6	64.0	53.5	51.3	44.0	60.0	53.0

Table 1: Zero-shot results comparing SNaRe with other baselines across three datasets and three base LLMs. Except for Inference, all other evaluations are performances of downstream DEGREE (Hsu et al., 2022) model trained on data generated by each technique (50 datapoints per event type).

Downstream Model Training: The final component utilizes the generated synthetic data D_s to train downstream ED models in a supervised manner. The trained ED models are then used to infer on the test set and for eventual evaluation. Since we use small BART-based language models for inference, our inference time computation is negligible compared to LLM inference methods.

5 Experimental Setup

Datasets: We consider three ED datasets from diverse domains for our experiments: (1) ACE (Doddington et al., 2004), in the news domain, (2) SPEED (Parekh et al., 2024c), in the social media domain, and (3) GENIA (Kim et al., 2011), in the biomedical domain. We simplify GENIA by converting the original document-level annotations to sentence-level annotations. We consider the Arabic and Chinese versions of ACE for cross-lingual experiments. For the few-shot setting, we sample k few-shot examples from the training data.

For our unlabeled data, we consider two sources: (1) **Train** - annotation-free training splits (i.e., only the text) of each dataset and (2) **External** - unlabeled data from other external sources. For this external data source, for ACE, we utilize News Category Dataset (Misra, 2022) comprising Huffpost news articles from 2012-2022. We filter articles corresponding to political, financial, and business articles. For SPEED, we utilize COVIDKB (Zong et al., 2022), comprising tweets from the Twitter COVID-19 Endpoint. Finally, we utilize GENIA2013 (Kim et al., 2013). We provide statistics about these datasets in Table 10.

Baseline methods: We consider three LLM-based techniques for low-resource ED as the baselines for our work. (1) Inference (Gao et al., 2023): LLMs are used to directly infer on the target test data using their reasoning capability. (2) STAR (Ma et al., 2024): The state-of-the-art generation model for ED utilizing LLMs for trigger and passage generation without using any unlabeled data, (3) Weak Supervision (Weak Sup) (Ding et al., 2023): LLMs are utilized to synthesize labels for unlabeled data. For an upper bound reference, we also include a Gold Data generation baseline wherein we sample from the gold training data of each dataset to train the downstream ED model.

Base models: For our base LLMs, we consider three instruction-tuned LLMs of varying sizes, namely Llama3-8B-Instruct (8B model), Llama3-70B-Instruct (70B model) (Dubey et al., 2024), and GPT-3.5 (175B model) (Brown et al., 2020). For our downstream ED model, we consider a specialized low-resource model DEGREE (Hsu et al., 2022), a generative model prompted to fill event templates powered by a BART-large pre-trained language model (Lewis et al., 2020).

Evaluation: Our primary evaluation metric is supervised model performance trained on the synthesized data. We consider two low-resource settings

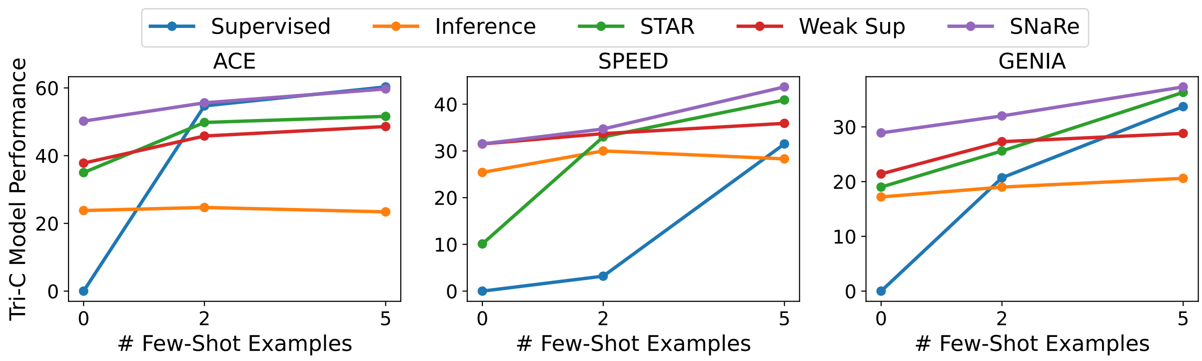

Figure 4: Few-shot results comparing SNARE with other baselines across three datasets using Llama3-8B-Instruct as the base LLM. Except for Inference, all other evaluations are performances of the downstream DEGREE (Hsu et al., 2022) model trained on data generated by each technique. Tri-C: Trigger Classification F1, #: Number of.

- zero-shot (no labeled data) and few-shot (k datapoints per event type are used). For Inference baseline, the LLM is directly run on the test set to procure model predictions. We report the F1 scores for two metrics (Ahn, 2006): (1) Event Identification (Eve-I) - correct identification of events, and (2) Trigger Classification (Tri-C) - correct identification of trigger-event pairs.

Implementation Details: We follow STAR for the implementation of the baseline models and most hyperparameter settings. For SNARE's passage generation, we select the top $t = 10$ triggers (except $t = 8$ for GENIA) for passage generation. We generate $N = 50$ datapoints per event type for each generation strategy. All our experimental results are reported over an average of three runs. Additional details are provided in Appendix C.

6 Results

We present the results for our zero-shot, few-shot settings, and cross-lingual experiment below.

6.1 Zero-shot Results

We present the main zero-shot results comparing the baselines across different LLMs and datasets in Table 1 and discuss our findings below.

SNARE performs the best: On average, SNARE beats STAR by 17.3% Eve-I F1 and 16.3% Tri-C F1 points – demonstrating how domain-specific cues from unlabeled data aid in tackling domain drift. Compared to Weak Sup, SNARE provides average gains of 3.6% Eve-I F1 and 3.3% Tri-C F1, suggesting how cleaner label quality can help improve model performance.

LLM	Method	Arabic		Chinese	
		EI	TC	EI	TC
Llama3-8B	Inference	21.5	13.4	15.0	11.8
	STAR	11.5	10.5	19.7	16.0
	Weak Sup	21.5	16.2	26.3	19.1
	SNARE (ours)	**40.1**	**33.6**	**35.9**	**31.1**
Llama3-70B	Inference	37.5	27.7	32.0	29.1
	STAR	37.1	30.9	26.0	22.0
	Weak Sup	30.0	20.4	28.1	26.3
	SNARE (ours)	**47.5**	**44.0**	**40.4**	**33.1**

Table 2: Comparing SNARE with zero-shot inference for other powerful LLMs for the ACE dataset.

External data source is effective: Assuming access to the training data as the unlabeled data source can be a strong assumption and bias for SNARE. To verify the robustness of our approach, we also evaluate SNARE with external data sources. Surprisingly, as seen in Table 1, SNARE with external data provides similar gains of 4% Eve-I F1 and 3.4% Tri-C F1 over the best baseline. We posit that the higher volume of external data leads to the extraction of cleaner domain-specific triggers, which eventually aids in better downstream performance.

6.2 Few-shot Results

We also study the various methods in the presence of small annotated data as part of our few-shot experiments. Specifically, we study the $k = 2$ and $k = 5$ few-shot settings, where k annotated examples per event type are utilized. We utilize the k-shots as in-context examples in the LLM prompts and append these few-shot examples to the synthesized training data as well. Additionally, we consider another baseline (Supervised) of downstream models trained only on the k-shot examples. We present the Tri-C results for all the datasets for the

Method	ACE	SPEED	GENIA
SNARE	50.2	31.5	28.9
– Scout	43.2	27.8	28.2
– Refiner	47.4	23.3	22.0

Table 3: Ablation study for SNARE's Scout and Refiner measured as Tri-C F1 performance across datasets.

LLM + Method	Eve-I	Tri-C
Llama3-70B + Inference	46.9	41.3
Llama3.3-70B + Inference	48.9	43.0
Qwen2.5-72B + Inference	40.9	34.2
GPT4o-mini + Inference	34.5	28.8
GPT4o + Inference	51.4	47.7
QwQ-32B + Inference	49.7	43.5
Deepseek-R1-L3-70B + Inference	41.8	36.6
Llama3-70B + SNARE (train)	**58.1**	**53.8**
Llama3-70B + SNARE (external)	**59.7**	**55.6**

Table 4: Comparing SNARE with zero-shot inference for other powerful LLMs for the ACE dataset.

Llama3-8B model in Figure 4. Similar to zero-shot results, we observe that SNARE consistently beats all other baseline models. On average, SNARE outperforms STAR and Weak Sup by 5.4% Tri-C F1 and 7% Tri-C F1 respectively.

6.3 Zero-shot Multilingual Results

To highlight the utility of our work, we apply our work across languages, specifically Arabic (ar) and Chinese (zh). We used multilingual ACE data (Doddington et al., 2004) for this experiment and utilized TagPrime (Hsu et al., 2023a), powered by XLM-Roberta-large (Conneau et al., 2019), as the downstream ED model. We present our results for Llama3-8B-Instruct and Llama3-70B-Instruct LLMs in Table 2. Surprisingly, SNARE performs the best out-of-the-box, with improvements ranging 10-20% F1 for Arabic and 4-12% F1 for Chinese, highlighting the broader impact of our work.

7 Analysis

In this section, we study the superior performance of SNARE through various analyses. Unless specified, we use Llama3-8B-Instruct as the base LLM.

7.1 Ablation study

Table 3 shows the ablation study for Scout and Refiner. For ablating Scout, we replace it by prompting LLM to directly generate triggers. We observe how both Scout and Refiner are critical, with average performance reductions of 3.8% F1 and 6% F1 upon removing the respective components.

Method	ACE		SPEED		GENIA	
	EI	TC	EI	TC	EI	TC
SNARE	**57.4**	**50.2**	**44.6**	**31.5**	**35.2**	**28.9**
Weak Sup + STAR	46.9	38.9	44.5	29.5	30.2	24.3

Table 5: Comparing SNARE with data-mixing of synthesized data from previous works.

Method	ACE	SPEED	GENIA
STAR	9.6%	15.3%	15.1%
Weak Sup	19.1%	38.4%	44.8%
SNARE	**23.2%**	**49.4%**	**52.5%**

Table 6: Reporting the hit rate of synthesized data triggers relative to gold test triggers.

7.2 Comparison with Powerful LLMs

To further highlight the efficacy of SNARE, we compare it with zero-shot inference using more powerful recent LLMs for the ACE dataset in Table 4. As seen, Llama3-70B with SNARE significantly outperforms stronger LLMs like GPT4o and thinking-based models like QwQ-32B by 8-10% Eve-I F1 and 8-12% Tri-C F1 scores, respectively. This highlights the strong efficacy of synthetic generation SNARE over zero-shot inference even when using more powerful LLMs.

7.3 Comparison with Data mixing

Data-mixing (Hoffmann et al., 2022; Xie et al., 2023) is a widely used technique to leverage complementary information across datasets to promote robust downstream model training. We mix data from our two baselines of Weak Sup and STAR as a hybrid baseline to compare with SNARE. To keep the comparisons fair, we consider $N/2 = 25$ data instances per event type from each dataset. Results from Table 5 demonstrate how SNARE beats the data-mixing based hybrid model by 5-6% F1, underlining the significance of our three-stage model design over simpler data-mixing.

7.4 Analyzing domain drift and label quality

ED models have a strong tendency to over-rely on lexical relations between triggers and events (Tong et al., 2022). Thus, we compare the synthetic data triggers with the gold test triggers as a raw study of the domain drift of triggers in the synthesized data. Specifically, we extract triggers per event type in the synthetic datasets and measure the hit rate/overlap of the synthesized triggers with the gold set of triggers, as reported in Table 6. STAR's

Dataset	Event	Method	Trigger	Sentence
ACE	Attack	STAR	raid	As the rebels embarked on a daring trek across the desert, they launched a surprise **raid** on the heavily guarded fortress, catching the enemy off guard.
		SNARE	shooting	As the rival businessman signed the contract, a sudden **shooting** erupted outside, causing chaos in the midst of the transaction.
SPEED	Death	STAR	asphyxiation	The hiker's life was tragically cut short as **asphyxiation** occurred after she became stuck in the narrow cave crevice.
		SNARE	killed	The patient's feverish state was triggered when they tested positive for the virus, which ultimately led to their being **killed** by the rapidly spreading infection.
GENIA	Binding	STAR	merge	The regulatory protein's ability to activate a specific region of the DNA triggers the **merge** of two proteins, leading to the modification of gene expression.
		SNARE	bound	During the phosphorylation of the enzyme, it **bound** to the DNA sequence, initiating the transcription process.

Table 7: Qualitative examples demonstrating STAR and SNARE's trigger and sentence generation quality.

Method	Naturalness	Event Relevance	Annotation Quality
STAR	3.1	3.4	3.1
Weak Sup	**4.2**	-	2.9
SNARE	3.6	**4.0**	**3.6**

Table 8: Human evaluation for sentence naturalness, relevance of event in generated sentence, and the annotation quality. 1 = worst, 5 = best.

Method	ACE		SPEED		GENIA	
	EI	TC	EI	TC	EI	TC
SNARE	**57.4**	50.2	44.6	31.5	35.2	28.9
+ SFT LLM	55.2	**51.7**	**46.9**	**35.8**	**36.7**	**29.1**

Table 9: Measuring performance improvement by fine-tuning an LLM on unlabeled train data for SNARE.

low hit rate indicates the poor overlap with the gold triggers, which is a primary reason for its domain drift. Furthermore, the consistently stronger coverage of SNARE explains its lower domain drift.

To further study the quality and relevance of the label, we performed a human evaluation. Specifically, a human expert in ED is tasked with scoring generations (between 1-5) on the naturalness of the sentence specific to the target domain, the relevance of the event to the semantic actions described in the generated sentence, and the annotation quality evaluating the selection of triggers (details in § D.3). We provide the averaged scores across the three datasets for 90 samples in Table 8.[2] Weak Sup has high sentence quality but poor label annotations; STAR suffers from poor event relevance indicating domain drift. Overall, SNARE performs the best with high annotation quality and event relevance.

[2]Since Weak Sup annotates the unlabeled target domain sentences, event relevance is analogous to annotation quality and we do not explicitly evaluate it.

7.5 Domain-adapted LLM Fine-tuning

We fine-tune the base LLM for Narrator on the unlabeled target domain train data D'_T to better align the generated passages. Naturally, this can be applied only for smaller LLMs owing to fine-tuning costs. We present the results of fine-tuning Llama3-8B-Instruct on the unlabeled train data in Table 9. On average, we observe that target data fine-tuning additionally improves SNARE by 0.5-2% F1. Qualitative studies indicate that the generated passages are distributionally closer to the target domain, further reducing domain drift.

7.6 Qualitative analysis of generated data

We provide qualitative evidence for SNARE's reduction in domain drift by Scout's domain-specific triggers in Table 7 (more examples in Table 19). We compare with STAR, which uses LLM's internal knowledge to generate the triggers. Lack of domain grounding often results in STAR's triggers and sentences being misaligned (e.g. *asphyxiation* for *death* event related to pandemics) relative to the target domain. In contrast, SNARE's triggers are better aligned to the target domain corpus, resulting in better quality data and reduced domain drift.

8 Conclusion and Future Work

We introduce SNARE, a domain-aware synthetic data generation approach composed of Scout, Narrator, and Refiner. Utilizing Scout's domain-specific triggers for synthesizing sentences, along with Narrator's conditional generation and Refiner's annotations, helps reduce domain drift and label noise. Experiments on three diverse datasets in zero-shot, few-shot, and multilingual settings demonstrate the efficacy of SNARE, establishing SNARE as a strong data generation framework.

Limitations

We consider only Event Detection (ED) as the main task for data generation, but our method can be extended to other structured prediction tasks as well. We leave this exploration for future works. We consider three specialized domains of news, social media, and biomedical to provide a proof-of-concept of our work. There are other specialized domains for ED as well which can be explored as part of future work. Finally, our proposed method SNARE makes a practical assumption of access to unlabeled data to procure target domain cues to guide the data generation. However, for specific super-specialized domains or if data has privacy concerns, this may not be possible and our method may not be applicable here. We assume such cases to be super rare and beyond the scope of our work.

Ethical Considerations

The theme of our work is to generate high-quality domain-specific data using Large Language Models (LLMs). The inherent LLMs can have certain biases, which can lead to potentially harmful or biased generations. Furthermore, the LLM can introduce potential hallucinations in the annotations, which can hurt the model's performance. We do not check or consider any bias/hallucination detection method as part of our work, as it is beyond the scope. Future works should take due consideration of this vulnerability.

Our proposed method SNARE utilizes unlabeled data as a basis to procure domain-specific cues. If there are any biases in this data, it can propagate to the downstream model as well. We provide a proof-of-concept about our method in this work, but do not detect or rectify such biases.

SNARE's Narrator utilizes LLMs to generate sentences/passages. However, as noticed in past work, LLMs can potentially copy these sentences from the pre-training data on which it has been trained. This can potentially lead to copyright infringements, and we do not consider any such violations under consideration for our method. Users should consider this vulnerability before usage in commercial applications.

We would also like to mention and acknowledge that we have utilized AI chatbots to help with the writing of the work.

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A Additional details about SNARE

We provide illustrations of the various prompts used in SNARE. For Scout, we consider a two-prompt approach. The first prompt aims to identify whether events of interest are mentioned in the passage, as illustrated in Figure 6. This prompt comprises the task statement, full event ontology with definitions, the task instructions, and the query sentence. The second prompt identifies the trigger corresponding to the event of interest, as illustrated in Figure 7. Here, we specify the task definition, the event ontology details, and the query text with the task instructions.

For Narrator, we prompt the LLM with the task definition, the event ontology with event definitions, and the query comprising the sampled target structure. The LLM is asked to generate a sentence using the specified trigger words while mentioning the events of interest. We illustrate this prompt in Figure 8.

Finally, we provide the Refiner prompt in Figure 9. This prompt aims to identify any missing event mentions from the passage.

B Data Statistics

We discuss details about our dataset in § 5. Our test target domain data includes the test data splits of (1) ACE (Doddington et al., 2004) in the news domain, (2) SPEED (Parekh et al., 2024c) in the social media domain, and (3) GENIA (Kim et al., 2011) in the biomedical domain For unlabeled data, we utilize the training data of each dataset as one data source. For the other data source, we utilize data from external sources, specifically: (1) News Category Dataset (HuffPost) (Misra, 2022) comprising Huffpost news articles from 2012-2022 for ACE. We filter articles corresponding to political, financial, and business articles, (2) COVIDKB (Zong et al., 2022) mining tweets from the Twitter COVID-19 Endpoint released in April 2020 as the external data source, (3) GENIA2013 dataset (Kim et al., 2013) as the external data for GENIA. Finally, we also provide some statistics about the multilingual splits of the ACE dataset utilized for the Arabic and Chinese zero-shot experiments.[3] We provide statistics about this data in Table 10.

[3]For Chinese, the average length indicates the average number of characters.

Data Source	# Sents	# Event Mentions	Average Length
Test Data			
ACE - test	832	403	22.9
SPEED - test	586	672	28.1
GENIA - test	2,151	1,805	29.7
Unlabeled Train Data			
ACE - train	17,172	-	15.6
SPEED - train	1,601	-	33.5
GENIA - train	6,431	-	30.1
Unlabeled External Data			
HuffPost	43,350	-	17.4
COVIDKB	7,311	-	30.6
GENIA2013	6,542	-	17.4
Multilingual Test Data			
ACE - Arabic	313	198	24.6
ACE - Chinese	486	211	44.2
Unlabeled Multlingual Train Data			
ACE - Arabic	3,218	-	26.1
ACE - Chinese	6,301	-	45.5

Table 10: Data Statistics for the various test and unlabeled datasets used in our work. # = Number of.

C Implementation Details

Here, we provide detailed implementation details for each component and the models used in our work. We run most of our experiments on NVIDIA RTX A6000/A100 machines with support for 8 GPUs, while for GPT3.5, we make API calls through OpenAI using Curator (Marten et al., 2025).

C.1 LLM-based Generation

We provide details on the various hyperparameters for using LLMs in all the components of STAR and SNARE. For Llama3-8B-Instruct and Llama3-70B-Instruct, we present the hyperparameters in Table 11; while Table 12 presents the hyperparameters for GPT3.5.

Batch Size	32
Temperature	0.6
Top-p	0.9
Max Generation Length	250

Table 11: Hyperparameters for decoding using Llama3-8B/70B model.

C.2 Few-shot Implementation Details

For the few-shot setting, we can access additional k datapoints per event type to aid better performance.

Base LLM	gpt-3.5-turbo-0125
Temperature	1.0
Top-p	1.0
Max Generation Length	500

Table 12: Hyperparameters for decoding using GPT3.5 model.

For LLM-based prompting, we simply add these examples in the prompt as in-context examples to help the model do better reasoning/generation. For STARand SNARE, we do not add the k triggers to the trigger list, as it led to a drop in model performance. This can be attributed to the presence of duplicate information, as the trigger generation/extraction already accounts for these gold triggers. We also append the k datapoints to the synthetically generated data to provide signals from the gold data.

C.3 Downstream Model Training

We choose DEGREE (Hsu et al., 2022) as our downstream model for evaluation, a generation-based prompting model that utilizes natural language templates. We implemented the DEGREE model under the TextEE framework (Huang et al., 2024). Table 13 presents the primary hyperparameters for this model.

Pre-trained LM	BART-Large
Training Epochs	25
Warmup Epochs	5
Training Batch Size	32
Eval Batch Size	32
Learning Rate	0.00001
Weight Decay	0.00001
Gradient Clipping	5
Beam Size	1
Negative Samples	15
Max Sequence Length	250
Max Output Length	20

Table 13: Hyperparameters for DEGREE model.

C.4 LLM Fine-tuning

We discuss domain-adapted passage generation through LLM fine-tuning in § 7.5. Specifically, we conduct a low-rank finetuning (LoRA) (Hu et al., 2021) to reduce computational overhead to fine-tune Llama3-8B-Instruct. We implement LoRA using the `peft` and `trl` packages (Mangrulkar et al., 2022; von Werra et al., 2020). We choose the task of causal language modeling (i.e., continual pre-training) to perform domain adaptation on unlabeled in-domain sentences. We utilize cross-entropy loss on the dev split of the unlabeled data to select the best model. We provide additional details about the hyperparameters for this fine-tuning for each dataset in Table 14 below.

ACE	
Lora Rank	32
Lora Alpha	16
Lora Dropout	0.1
Learning Rate	0.0001
Weight Decay	0.05
Training Batch Size	32
Training Epochs	3
Eval Steps	20
SPEED	
Lora Rank	32
Lora Alpha	16
Lora Dropout	0.1
Learning Rate	0.00008
Weight Decay	0.05
Training Batch Size	32
Training Epochs	10
Eval Steps	20
GENIA	
Lora Rank	32
Lora Alpha	16
Lora Dropout	0.1
Learning Rate	0.00008
Weight Decay	0.05
Training Batch Size	32
Training Epochs	6
Eval Steps	20

Table 14: Hyperparameters for LoRA fine-tuning Llama3-8B-Instruct.

D Additional analyses

In this section, we provide additional analyses to support our main experiments.

D.1 STAR with domain-specific prompt

A simple way to infuse domain-specific information in past works like STAR would be to add domain-related information in the prompts to the LLM. We experiment with two such methods: (1) domain-mention, where we provide the target domain information in the prompt and ask the model to generate accordingly, and (2) domain-reference, where we use some examples from the unlabeled data in the prompt as reference sentences to better guide the passage generation. We provide results for these explorations using the Llama3-8B-Insturct model in Table 15. As observed, the results are generally poor, with an average drop of 0.1-0.6% F1 for domain-mention and

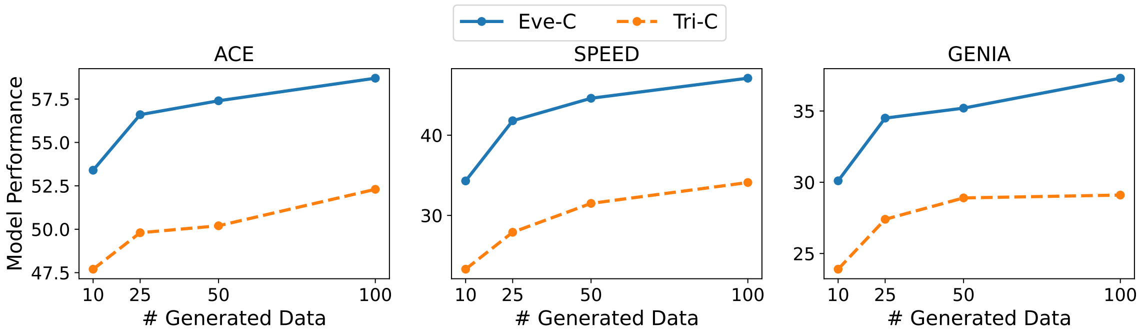

Figure 5: Model performance for SNARE as keep change the number of generated datapoints N using Llama3-8B-Instruct for the three datasets.

Method	ACE		SPEED		GENIA	
	EI	TC	EI	TC	EI	TC
STAR	**44.9**	**35.0**	**21.0**	10.1	25.9	19.0
+ mention	44.1	32.9	17.1	**10.3**	**28.7**	**20.4**
+ references	35.5	27.3	19.0	9.2	25.8	18.1

Table 15: Measuring model performance improvement providing domain-specific cues in the form of domain-mention (mention) or domain sentence references (references) to the LLM for STAR. EI: Event Identification F1, TC: Trigger Classification F1.

3.1-3.8% F1 for domain-reference. This is mainly because LLMs over-compensate, producing longer and more stereotypical information in their generations, which hurts the naturalness of the sentence and causes further domain drift. Furthermore, the LLM makes more errors in mentioning the event as a part of its reasoning, which is utilized to make the generation in the domain style. We provide some qualitative examples for such generations in Table 16. In some ways, it also puts into light and amplifies the gains obtained by doing target domain SFT for SNARE as discussed in § 7.5.

D.2 Impact of different number of training samples

We perform a small analysis to study the impact of changing the number of generated samples on the downstream model performance for SNARE. We present the results for Llama3-8B-Instruct in Figure 5. As observed, performance continues to increase as we increase the data from $N = 10$ to $N = 100$ datapoints per event type. This promises that data generation will provide continued improvements by practicing greater and better control over the data distribution.

Task Definition

You are an event detection system, looking to decide whether a sentence mentions or discusses an event from a specific list of events.

Full Event Ontology

Events of interests:
[infect, spread, symptom, prevent, control, cure, death]
An "infect" event is the process of a disease or pathogen invading host(s).
......

Query

Does the following sentence discuss or mention any of the events of interest?

sentence: "If health officials tell people to wear masks to help stop the spread and save lives ......"

Figure 6: Prompt for stage 1 of Scout.

D.3 Human Evaluation Details

We conduct a small human evaluation to judge the quality of the synthetic data in § 7.4. Here, we provide additional details about the human study and evaluation. Since the evaluation is conducted on three diverse and niche domains, we only utilize a single human annotator who is an ED expert and has previously worked on all three datasets as the primary annotator.

We majorly evaluate on three dimensions: (1) Sentence naturalness (SN): This metric judges whether the sentence seems grammatical, natural, and fits the domain of the target data. (2) Event Relevance (ER): This metric is computed only for generation methods that generate sentences from labels. This evaluation judges whether the sampled event and trigger are appropriately used to generate a sensible alignment with the target domain.

ACE
A 35-year-old cyclist was hit by a speeding car while riding to work, leaving her with severe injuries, while in a separate incident, a local retail giant filed a petition to restructure its debt, sparking concerns about its financial stability. As the war on terror raged on, the Mujahideen Advisory Council distributed a statement inviting Arab and foreign media reporters to enter Fallujah and cover the battles, while simultaneously, the ownership of the ancient artifacts was transferred to the museum, with the landlord demanding rent on the premises.
SPEED
As the influencer's viral challenge went viral, her followers were suddenly struck with a mysterious illness after the splash of a contaminated drink, leading to a shocking explosion of fatalities on social media. As the community struggled to come to terms with the devastating accident that had claimed the lives of several residents, the authorities swiftly implemented a strict quarantine to prevent the spread of the infectious disease, hoping to mitigate the tragedy.
GENIA
The specific transcription factor was elevated by the presence of the hormone, thereby increasing the expression of the target gene, while the inhibitory protein curbed the activity of a competing transcription factor, preventing the expression of a repressor gene. The binding of PEBP2/CBF to the promoter region boosts the expression of the gene, which turns on the production of a crucial cytokine in response to the immune response.

Table 16: Example passages of overly long and more stereotypical sentences generated when the domain is mentioned or references are added to the LLM prompt for STAR.

Furthermore, it is verified if the right event definition is used. (3) Annotation Quality (AQ): This metric judges if the right trigger is used for each event mentioned in the synthetic output. If there are any missing events, then this score is penalized. For each metric, a score is given on a Likert scale (Likert, 1932) from 1 (worst) to 5 (best). We also provide event definitions for each event in each dataset as a reference for better judgment. We illustrate the annotation interface in Figure 10 and provide some sample examples in Table 17.

D.4 Analysis in low-resource unlabeled data settings

In rare cases of hyper-specialized domains or domains with privacy concerns, there is a possibility of having super-low availability of unlabeled data. We believe that our current experimentation already simulates this setting, where we use only 773 documents for GENIA and 1.6k tweets for SPEED.

Task Definition

You are a writer, looking to extract a potential event trigger from a given sentence. Event trigger is the word that most clearly expresses the occurrence of the given event in the sentence. Event trigger is often only a single word in length.

Related Event Ontology

Event of interest: "spread"
A "spread" event is the process of a disease spreading/prevailing massively at a large scale.

Query

Given that the sentence mentions the event "spread", extract the trigger word in the sentence corresponding to this event type.

sentence: "If health officials tell people to wear masks to help stop the spread and save lives ......"

Figure 7: Prompt for stage 2 of Scout.

Secondly, by providing strong efficacy of external data relative to in-distribution data, we demonstrate how even mildly related unlabeled data can also work well for SNARE. Finally, we provide a deeper study of varying the amount of unlabeled data for the ACE dataset for Llama3-70B-Instruct as an ablative study to further substantiate the efficacy of our method in Table 18. Lowering the number of unlabeled data reduces the model performance relative to using higher number of data samples. However, even with 5% unlabeled training data (∼850 samples), SNARE still outperforms the other baselines, showing the efficacy of our method.

D.5 Additional Qualitative Examples

In § 7.6, we discussed how SNARE improves domain drift qualitatively relative to STARand provided some examples. Here, we provide more examples to further support that study in Table 19. This table further demonstrates how STAR can have a domain drift owing to a lack of domain-specific cues, while SNARE is better grounded in the target domain.

Task Definition

You are an writer, looking to write sentences that contain specific events and event triggers. An event is a specific occurrence involving participants. An event is something that happens. An event can frequently be described as a change of state. Event trigger is the word that most clearly expresses its occurrence. Event triggers are often only a few words in length.

Related Event Ontology

An "infect" event is the process of a disease/pathogen invading host(s).
A "death" event signifies the end of life of individuals due to infectious disease.

Query

Generate a new sentence using trigger 'fumble' for event infect, trigger 'drowning' for event death.

Figure 8: Prompt for Narrator.

Sentence	Score
The sudden crash of the ambulance sent shockwaves through the hospital as medical staff rushed to the scene to monitor the patient's life signs, but it was too late, as the patient succumbed to the infectious disease.	SN: 2 ER: 1 AQ: 1
The wealthy entrepreneur transferred ownership of the struggling tech company to her trusted business partner, relinquishing control and financial responsibility	SN: 5 ER: 5 AQ: 5
Taken together, these data suggest that Id1 could be a possible target gene for mediating the effects of BMP-6 in human B cells, whereas Id2 and Id3 not seem to be involved.	SN: 4 ER: 3 AQ: 2

Table 17: Illustration examples for the human evaluation metrics. SN: sentence naturalness, ER: event relevance, AQ: annotation quality.

Task Definition

This is an event extraction task where the goal is to extract structured events from the text. A structured event contains an event trigger word and an event type.

Full Event Ontology

Events of interests:
An "infect" event is the process of a disease or pathogen invading host(s).
......

Query

Below is a sentence from which you need to extract the events if any. Only output a list of tuples in the form [(\"event_type_1\", \"event_trigger_word_1\"), (\"event_type_2\", \"event_trigger_word_2\"), ...] for each event in the sentence.

sentence: "If health officials tell people to wear masks to help stop the spread and save lives ......"

Figure 9: Prompt for Refiner.

Method	# Unlabeled Data	Eve-I	Tri-C
Inference	-	46.9	41.3
STAR	-	50.0	42.3
Weak Sup	100% train	53.2	48.0
Weak Sup	20% train	51.4	46.1
Weak Sup	5% train	50.1	44.9
SNARE	100% train	58.1	53.8
SNARE	20% train	55.9	52.1
SNARE	5% train	**55.1**	**51.2**

Table 18: Ablating the amount of unlabeled data utilized for the ACE dataset by the different data generation methods using Llama3-70B-Instruct and its impact on downstream model performance.

Rate all the metrics from 1-5. Use the filters on top to group by dataset and assign the scores
Naturalness = Is the snetence natural and grammatical?
Event Relevance = Based on event definitons (other sheet), figure if the event mentioned in this sentence seems correct
Annotation Quality = Check if all events are correctly annotated and there are no missing annotations.

Sentence	**Annotation**	**Dataset**	**Naturalness of Sentence**	**Event Relevance**	**Annotation Quality**
As the riot police stormed the square, they were met with an assault, and in the chaos, a protester's clothes caught fire, causing them to burn.	[{'event': 'Conflict:Attack', 'trigger': 'assault'}, {'event': 'Life:Injure', 'trigger': 'burn'}]	ACE			
The couple's marriage was annulled, ending their union after a tumultuous relationship.	[{'event': 'Life:Divorce', 'trigger': 'annulled'}]	ACE			
The court's decision was reconsider by the higher court after the losing party filed a petition to review the ruling.	[{'event': 'Justice:Appeal', 'trigger': 'reconsider'}]	ACE			
A dispute over a disputed contract led to a court proceeding being initiated, but the accused party was ultimately cleared of all charges.	[{'event': 'Justice:Sue', 'trigger': 'disputed'}, {'event': 'Justice:Sue', 'trigger': 'dispute'}, {'event': 'Justice:Acquit', 'trigger': 'cleared'}]	ACE			
The manager dial the CEO to discuss the quarterly sales report and provide an update on the marketing strategy.	[{'event': 'Contact:Phone-Write', 'trigger': 'dial'}]	ACE			
The entrepreneur's long-held vision was finally realized with the launch of her innovative startup, marking the beginning of a new chapter in her professional journey.	[{'event': 'Business:Start-Org', 'trigger': 'launch'}]	ACE			
As the company's financial struggles mounted, the CEO announced the exit of the firm, while the truck driver shifted gears and hit the road, hauling away the last remaining assets.	[{'event': 'Movement:Transport', 'trigger': 'shifted'}, {'event': 'Business:End-Org', 'trigger': 'exit'}]	ACE			
The accused was exonerate by the court, clearing their name of all charges, after a lengthy trial, and later, the two former colleagues met to chat and clear the air about their past misunderstanding.	[{'event': 'Justice:Acquit', 'trigger': 'exonerate'}, {'event': 'Contact:Meet', 'trigger': 'chat'}]	ACE			
The police officer arrested the suspect, initiating a court proceeding to determine the liability of the accused for the alleged crime.	[{'event': 'Justice:Sue', 'trigger': 'arrested'}]	ACE			
The candidate was chosen to lead the team after being selected by the majority of voters in the competitive election.	[{'event': 'Personnel:Elect', 'trigger': 'selected'}]	ACE			

Figure 10: Illustration of the interface for the human evaluation of the synthetically generated data. Short instructions are provided at the top. Each query comprises the sentence, annotation, and dataset. The human annotator is expected to score 1-5 for each of the three metrics on the right.

Dataset	Event	Method	Trigger	Sentence
ACE	Attack	STAR	raid	As the rebels embarked on a daring trek across the desert, they launched a surprise **raid** on the heavily guarded fortress, catching the enemy off guard.
			siege	The government issued fines to the rebel group, while the city was under **siege**, with gunfire erupting throughout the streets.
			slay	The wealthy businessman filed a complaint against his former partner, leading to a court proceeding, just as the rival gang leader **slays** his arch-nemesis in a brutal battle.
		SNARE	shooting	As the rival businessman signed the contract, a sudden **shooting** erupted outside, causing chaos in the midst of the transaction.
			bombing	As the city was rocked by a devastating **bombing**, thousands of protesters took to the streets to demand justice and peace.
			fight	The rival gangs engaged in a brutal **fight**, sparking a wave of gunfire that left several people injured and buildings damaged.
SPEED	Death	STAR	asphyxiation	The hiker's life was tragically cut short as **asphyxiation** occurred after she became stuck in the narrow cave crevice.
			overdose	A young musician's **overdose** became the tragic finale of a life cut short in the midst of chaos.
			drowning	As she struggled to stay afloat, her heart stopped beating, and she succumbed to **drowning** in the icy waters.
		SNARE	killed	The patient's feverish state was triggered when they tested positive for the virus, which ultimately led to their being **killed** by the rapidly spreading infection.
			lost	As the pandemic spread rapidly across the globe, thousands of people **lost** their lives due to the deadly virus.
			died	The elderly man, who had been suffering from a severe case of tuberculosis, **died** in his sleep.
GENIA	Binding	STAR	merge	The regulatory protein's ability to activate a specific region of the DNA molecule triggers the **merge** of two proteins, leading to the modification of gene expression.
			fuse	When the proteins **fuse** together, the activity of the transcription factor is inhibited, preventing the gene expression from proceeding.
			snap	When the two proteins **snap** together, the binding of the complex inhibits the expression of the target gene by deactivating a specific region of the DNA molecule.
		SNARE	bound	During the phosphorylation of the enzyme, it **bound** to the DNA sequence, initiating the transcription process.
			translocation	The protein **translocation** to the nucleus triggers the induction of gene expression.
			binds	When the enzyme **binds** to the substrate, it activates the addition of a phosphate group to the target molecule, marking a crucial change in its function.

Table 19: Comparison of generated triggers and sentences from STAR and SNARE methods