

When and Where Did it Happen? An Encoder-Decoder Model to Identify Scenario Context

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Abstract

We introduce a neural architecture finetuned for the task of *scenario context* generation: The relevant location and time of an event or entity mentioned in text. Contextualizing information extraction helps to scope the validity of automated findings when aggregating them as knowledge graphs. Our approach uses a high-quality curated dataset of time and location annotations in a corpus of epidemiology papers to train an encoder-decoder architecture. We also explored the use of data augmentation techniques during training. Our findings suggest that a relatively small fine-tuned encoder-decoder model performs better than out-of-the-box LLMs and semantic role labeling parsers to accurately predict the relevant scenario information of a particular entity or event.

1 Introduction

We present an approach to contextualizing information extraction (IE) that focuses on enhancing events and entities with *scenario context*: the location and time relevant to extracted elements.

Knowing *when* and *where* an event occurs has become increasingly relevant due to the wide adoption of large-scale machine reading technology. Decision makers in high-stakes areas,¹ like epidemiology, public health or climate sciences, are increasingly turning to natural language processing (NLP) technologies to help guide their decision making through automatic evidence discovery and aggregation. In light of this, properly scoping automated IE becomes very valuable to the users of these tools.

One example of a domain when scenario context information is relevant is the modeling of epidemic dynamics, where the literature describes different outbreaks using different mathematical models, such as variations of the susceptible-infected-recovered (SIR) compartmental model. The dif-

ferent scenarios have different parameters and it is useful to contextualize the relevant event to have a better picture of the scenario described. Another example is the domain of climate and climate change, where changes in the climate of different geographical regions over time is studied by the geosciences community.

Scenario information is often explicitly found in the periphery of the text describing an extraction, but not necessarily in the same sentence—thus, it is a form of *inter-sentence* relation extraction (see Figure 1 for examples).

In this work, we tackle the problem as a *generative* task using an encoder-decoder transformer based on T5 (Raffel et al., 2019). Given the locations and temporal phrases in an input passage, we prompt the model to choose and generate the relevant scenario information with respect to a specific entity or event. The main contributions of this work are the following:

- (1) An encoder-decoder model finetuned for generating *scenario context*, i.e., the spatial and temporal context of a particular event or concept within a larger phrase.
- (2) A high-quality, hand-curated dataset of location and temporal relations with intra- and inter-sentence relations, used to train and evaluate the aforementioned model.
- (3) An error analysis of the predictions of the model, shedding light on potential future improvements to this method.

All artifacts used to train and evaluate the model are publicly available.²

2 Related Work

Annotating *when* and *where* an event occurs is closely related to semantic role labeling (SRL) (Levin and Hovav, 2005; Gardner et al.,

¹<https://www.darpa.mil/program/automating-scientific-knowledge-extraction-and-modeling>

²Code, data and artifacts available for download from <https://github.com/ml4ai/scenario-context>.

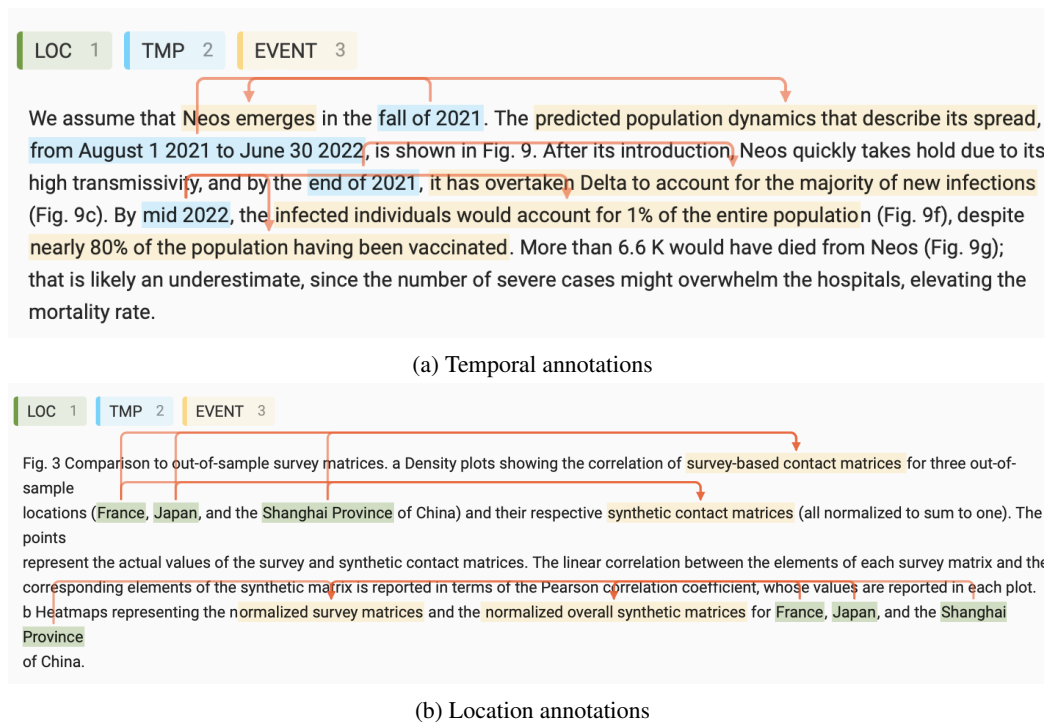


Figure 1: Example annotations in our dataset. Predicates highlighted in yellow represent ‘events’ with scenario context information assigned to them, text highlighted with cyan represents temporal context, and text in green location context. The arrows connect a context expression to an event they are associated with. The scenario context to event associations are effectively many-to-many relations. Figure 1a shows a passage with several temporal scenario contexts and Figure 1b shows several location scenario contexts.

2017) and document-level relation extraction (Sahu et al., 2019; Xu et al., 2022; Delaunay et al., 2023). An important distinction, however, is that SRL operates on parsing the structure of a sentence and assign roles to phrases within it. Our proposed approach is generative in nature, and is not constrained to the structural elements identified during parsing.

The typical approach for IE is finetuning a pre-trained transformer (Vaswani et al., 2017) such as T5 on the data of interest. We build upon the family of encoder-decoder architectures (Bahdanau et al., 2014) to map an input passage to the expected output that represents the relevant scenario information.

Recently, large language models (LLMs) (Brown et al., 2020; Jiang et al., 2023; Touvron et al., 2023) have gained traction, but concerns remain about their tendency to hallucinate. Our work relies on supervised learning via finetuning instead of attempting to mitigate hallucinations.

Contextualizing IE has been of interest to the research community for a while, particularly in the biomedical domain (Noriega-Atala et al., 2018; Sosa and Altman, 2022; Noriega-Atala et al., 2021).

In this work we focus instead on the more general class of *scenario information*: the relevant location and time of an entity or event.

3 Dataset

In order to train our model, we created a dataset that contains location and temporal context annotations at both intra- and inter-sentential levels. We focused on 22 epidemiology research articles, including ones that involve modeling the dynamics of infection and outbreak case-studies, published between 2020–2022.

These articles often describe parallel scenarios to compare and contrast the behavior of different outbreaks, making the inference of the scenario context of relevant concepts and events in these papers non-trivial. Correctly understanding the location and time period for specific events is important for the accuracy of any inference drawn from these studies. We excluded any temporal mentions that were abstract or relative, and any location mentions that were modifiers or adjectives. Figure 1 shows an example of an annotated passage of each kind.

The dataset comprises 383 passages, ranging in length from a single sentence to a couple of para-

graphs. A total of 1,382 relations were annotated with 833 (60.3%) location context relations and 549 (39.7%) temporal context relations.

A key aspect of the dataset is the presence of annotations for inter-sentential relations—i.e., relations where the event/concept of interest and its scenario context are in different sentences. These comprise 18% of scenario context relations. Approaches that rely on syntax, e.g., SRL, are not well suited for inter-sentential relations. Figure 2 shows the distribution of sentence distances for the inter-sentential subset of annotations.

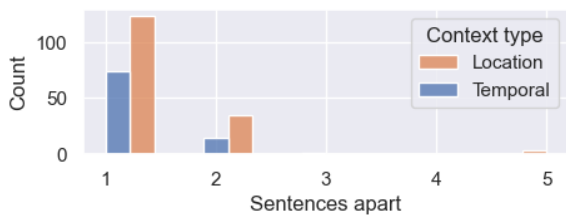


Figure 2: Number of sentences between the relevant entity/event and its corresponding context.

A random sample consisting of 13% of the relations was used to measure inter-annotator agreement using the Cohen’s Kappa method (Cohen, 1960), resulting in a score of $\kappa = 0.79$.³ Details about the annotation guidelines are found in Appendix A

3.1 Data Augmentation

Manually annotating data is time-consuming and labor-intensive. To address this challenge and scale up the amount of data available for the scenario context generation task, we explored two techniques for data augmentation using LLMs—paraphrasing and procedural generation. The details of prompts and generation procedures are provided in Appendix D.

Paraphrasing. To increase the lexical and syntactic diversity of the gold annotations, we generated variations of each passage in the dataset using GPT-4. Additionally, we substituted the temporal and location arguments with alternatives while keeping track of the relations present in them. This process resulted in 434 additional scenario context relations.

Procedurally generated relations. We used GPT-4 to procedurally generate passages containing one or more fictional events with temporal and loca-

tion context. We used the prompt to control the topic, role of the narrator, length, and number of scenario contexts in each passage. This procedure allows to scale up the amount of training data proportional to one’s budget. This approach resulted in an additional 1,361 scenario context relations.

4 Experiments and Results

We trained⁴ an encoder-decoder model (Sutskever et al., 2014; Vaswani et al., 2017) based on T5 to generate the location and temporal information relevant to a specific event from its surrounding context. For each relation in the dataset, we prompted (see Appendix B for details) the model to decode the context information of the specific event. Each event may have zero, one or more context relations of each type. The model decoded all of them simultaneously.

We held out a random sample of 20% of the annotations for testing and fine-tuning t5-base. Table 1 contains the main results averaged across three runs with different random seeds. Since a particular event may have zero or more annotations of each type, we compute precision, recall, and F1 individually for each and average them across the testing set. We report two variants of this evaluation: (i) span-level, and (ii) token-level. At the *span level*, a generation is considered correct only if it exactly matches the gold standard annotation. In order to ignore minor lexical variations, we applied a basic normalization procedure before comparing strings: converting to lowercase, trimming spaces on both ends, and removing commas. Nevertheless, having a partially correct prediction may still be useful (e.g., july 5 1987 vs july 1987), therefore the *token level* evaluation reports the precision, recall, and F1 scores at the token level, similar to SQuAD (Rajpurkar et al., 2016).

Table 1 contains the results of models trained (i) with manual annotations only and (ii) with the augmented dataset. In general, our approach achieves better results when predicting location than temporal context. Training only with the manual annotations results on the best performance for locations; training with the augmented data decreases the performance for location, but improves the per-

³Agreements over 0.61 are considered substantial and over 0.81 are considered almost perfect (Landis and Koch, 1977).

⁴The model was finetuned using a workstation with an RTX 3090Ti GPU, a Threadripper 3960X 24-Core CPU and 128 GB of system memory. Each model was finetuned from t5-base using HuggingFace’s Seq2SeqTrainer for 10,000 steps, 3e-5 learning rate, linear weight decay of 0.1 and batch size of 4.

Model	Span-level						Token-level					
	Location			Temporal			Location			Temporal		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Annotations	0.81	0.80	0.80	0.76	0.73	0.74	0.84	0.84	0.83	0.76	0.80	0.77
+paraphrases	0.80	0.79	0.78	0.78	0.76	0.76	0.83	0.82	0.82	0.79	0.81	0.79
+synthetic	0.78	0.77	0.76	0.79	0.78	0.78	0.81	0.81	0.80	0.79	0.81	0.79
+para & synth	0.77	0.76	0.75	0.71	0.70	0.7	0.81	0.81	0.80	0.74	0.75	0.74

Table 1: Scenario context evaluation results. P = Precision, R = Recall.

Method	Location			Temporal		
	P	R	F1	P	R	F1
GPT-4o	0.29	1	0.22	0.33	0.89	0.24
Mistral-7B	0.25	1	0.20	0.23	0.98	0.19
SRL	0.09	0.01	0.01	0.08	0.05	0.03

Table 2: SRL and LLM baseline results. P = Precision, R = Recall, Mistral-7B = Mistral 7B Instruct v0.2.

formance for temporal context. We hypothesize that this is a consequence of the differences between expressing named locations vs. temporal expressions. There is less variance in how locations are written; they are usually proper nouns or adjectives, whereas time expressions are much more varied—they could be expressed as a standalone year, full date, date range, season, relative temporal phrase, etc. Data augmentation may help increase the diversity of temporal context phrases shown during training, leading to less overfitting to the lexicon compared to location.

Baselines We compare our methods with a decoder-based LLM approach and an SRL system. Table 2 contains the baselines’ results. For the LLM baseline, we tested GPT-4o (OpenAI, 2023) and Mistral 7B (Jiang et al., 2023). We asked the models⁵ to generate the scenario context for each event and computed the span level results. We find that the LLMs successfully identify time spans and locations relevant to concepts and events, but also tend to predict spurious relations that are not related to the focus of the query. This is reflected in the high recall and low precision exhibited by the LLMs. These observations support the use of supervised learning approaches when feasible.

SRL assigns roles between the clauses in a sentence. We used it as an alternative baseline to the other generative approaches. To test for scenario context detection, we used AllenNLP’s struc-

ture prediction pre-trained model⁶ to parse the sentences containing events in each passage of the ground truth dataset. We considered a scenario context relation ‘extracted’ if the appropriate context is contained within a predicted modifier argument (ARGM-LOC, ARGM-TMP) and the text of the event is contained in the union of another argument with the predicate. We found that SRL is not well-suited for this task—it often failed to select the event of focus within an argument.

Error Analysis We performed an error analysis on a sample of the testing predictions of the model trained only with human annotations. Table 3 contains different types of prediction errors broken down by scenario context type. *Spurious predictions* occur when there is no context annotation, but the model generates a prediction; conversely, a *Missing prediction* happens when there is a gold annotation but no prediction from the model. *Mistaken predictions* are when there is both a gold annotation and a prediction, but the model was outright wrong about it. *Partial predictions* occur when the generated text is properly contained in the annotation’s text, but is not an exact match—e.g., an event with a location context annotation of “Western and Northern Europe, United Kingdom” where the model predicted “Western and Northern Europe” is a partial prediction; *Overprediction* errors are the opposite. These instances are considered false positives for the span-level results in Table 1, however their partial, accurate predictions are accounted for in the token-level evaluations. *Other* errors are artifacts of the generative nature of the task. Consider the gold annotation “California, Indiana, New York” and the prediction of “California (CA), Indiana (IN), New York (NY)” —clearly the prediction is correct; however, the model decoded state acronyms

⁶<https://storage.googleapis.com/allennlp-public-models/structured-prediction-srl-bert.2020.12.15.tar.gz>

⁵Prompting details in Appendix C

Error Type	Context Type	
	Location	Temporal
Spurious	11	12
Missing	10	7
Mistaken	4	6
Partial	7	3
Over	8	7
Other	3	4
Total	49	39

Table 3: Prediction error types.

alongside the names, which fail an exact string match. The token-level evaluation is able to pick up the full state names. For temporal context, *Mistaken* predictions mostly stem from the variety of ways time intervals can be expressed in text and the inability of the model to abstract that information, e.g., the gold annotation “between 2009 and 2014” was predicted as “2009, 2014”, which correctly includes the endpoints of the range, but fails to specify the crucial detail that this is an inclusive range including the years between them.

5 Conclusions and Future Work

In this work, we introduced an encoder-decoder model finetuned to generate location and temporal context associated with a particular concept or event. We are releasing a dataset of hand-curated annotations from a collection of academic papers in the epidemiology domain that describe the dynamics of outbreaks in different locations and times. We found that our method more accurately recognizes the relevant context than out-of-the-box LLMs or SRL. We also explored the use of data augmentation methods, finding that they resulted in modest improvements in temporal context extraction.

There are at least two promising avenues for future work. The first is expanding the dataset to include more curated annotations from additional domains. This will foster the development of more accurate models with better generalization capabilities. The second is exploring other network architectures, such as span-prediction or decoder-only models. The former is useful for attributing the source of the context prediction and the latter can benefit from the transfer learning potential exhibited by open-source LLMs.

6 Limitations and Ethical Considerations

While the methods described in the paper are not specific to a particular domain, the annotations focus on scientific literature in the domain of epidemiology. The evaluations carried out in this work did not test for generalization capabilities on different domains. Additionally, all of the information used in this work was written solely in English, limiting the potential impact and applications of our contributions. While we evaluated the performance of LLMs for this task, we only tested two different models: GPT-4o and Mistral-Instruct. We recognize that the landscape of LLMs changes quickly and that the state-of-the-art is fleeting. Due to this, our baseline results may be rendered obsolete in the near future.

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A Annotation Guidelines

We used LabelStudio⁷ to manually annotate scientific articles with scenario context information. LabelStudio was set up with 383 tasks, where each contains a section of the article’s text containing either location or temporal scenario information of a specific event. At least one annotator carefully read each passage, selecting all the events with a designated location and/or temporal information. The annotator then proceeded to select and link each piece of scenario context information to the relevant event. Figure 1 displays two examples of the user interface of LabelStudio with different types of scenario context and event information.

Two other independent annotators worked in a sample comprising 13% of the tasks. Using these additional annotations, we computed an inter-annotator agreement metric using Cohen’s Kappa of $\kappa = 0.79$.

B Model Inputs and Outputs

Figure 3 shows the format of the prompt used as input to the scenario context model. Fields between double curly braces are substituted with the text containing the entity or event of focus in `{{event}}` and the complete passage from which relevant scenario context will be retrieved in `{{context}}`.

Figure 4 shows the output format produced by the model. The model will generate zero or more relevant locations and time expressions per input. Double curly braces are placeholders for the actual predicted values decoded by the model.

⁷<https://labelstud.io>

```
Text: {{event}}

Context: {{passage}}
```

Figure 3: Input prompt format used by the scenario context encoder-decoder model.

```
location: {{loc 1}}, ..., {{loc n}};
time: {{tmp 1}}, ..., {{tmp n}}
```

Figure 4: Output sequence format decoded by the scenario context encoder-decoder model.

C LLM Baseline Prompt Template

The prompt template shown in Figure 5 was to generate the scenario context predictions from both LLMs in § 4. At run-time, {{event}} was substituted by the entity/event of focus and {{pre_context}} and {{post_context}} were substituted by the passage’s text before and after it, respectively.

The output of the LLMs was parsed as a JSON object and used to compute the baseline scores.

For the following phrase, look at the event or concept surrounded by `` and tell me the locations and time periods that relevant to the element surrounded by ``.

The output format should be a json object with an array of strings for type of context. If there is not any element of a specific type, you will put an empty array in its value.

Output format:

```
{
  "locations": [],
  "time periods": []
}
```

Phrase:

```
{pre_context} `` {event} `` {post_context}
```

Figure 5: Prompt used to elicit scenario context using an LLM.

D Data Augmentation Procedures

D.1 Paraphrasing Annotations

We used GPT-4 to generate paraphrases of the annotated dataset. Each passage was used as a seed

to generate multiple paraphrases using the prompts listed in Figure 6.

- Please give me a location that is either close or similar in nature with: ``{location}``.

Please do not return any additional information.

- Please give me a date that is either close or similar in nature with: ``{date}``. Please do not return any additional information.

- Please rephrase the following text, while keeping the following the following phrase fixed: ``{phrase}`` and maintaining the overall message and length

```
{text}
```

- Please rephrase the following text, maintaining the overall message and length

```
{text}
```

- Please replace word ``{word}`` and its derivatives with the word ``{replacement}`` and its appropriate derivatives the following text:

```
{text}
```

Figure 6: Prompts used for paraphrasing sequences in the original dataset

D.2 Procedurally Generated Data

We used GPT-4 to procedurally generate synthetic data.

First, we seed the procedure with a set of event types. In our experiments we defined these to be historical events, tech conferences, and public health emergencies. Then, for each event type, we repeat the following steps:

1. For each event type, we ask the LLM to generate ten different *fictional* event names.
2. We ask the LLM to generate five different *narrator roles*—e.g., news reporter, high school student, historian, etc.

3. We prompt the LLM to narrate each event, assuming each of the roles using a predefined set of numbers of paragraphs.

Figure 7 contains a code snippet from a Jupyter notebook used to generate the synthetic data.


```

1 # Get the number different types of events to develop context for
2
3 events_prompt = ChatPromptTemplate.from_messages([
4     ("user", "Generate a list of 10 different fictional {event_type} names.\
5     Don't any include details, locations, names or dates. You must provide a comma-separated\
6     list as a result.")
7 ])
8
9 narrator_prompt = ChatPromptTemplate.from_messages([
10    ("user", "Generate a list of 5 different narrator roles that describe {event_type}.\
11    For example, if we are describing a political event, a narrator role could be\
12    a news reporter; if it is a historical event, the narrator could be a historian\
13    writing a book, a highschool student writing a homework assignment or a PhD\
14    scholar writing a dissertation. You must provide a comma-separated list as the output.\
15    Don't include the event type, just the narrator role")
16 ])
17
18 generation_prompt = ChatPromptTemplate.from_messages([
19    ("system", "You are a {role} describing {event_type}"),
20    ("user", ""Write {length} about {event}.
21     Whenever you mention the event or refer, either explicitly or through pronouns, you
22     must wrap between <evt></evt> markup tags. You must include one location context in
23     your description. This location context represents where the event took place and
24     it could be a geographical region, country, city or location coherent with your
25     argument. Any mention of the geographical context must be wrapped between
26     <loc></loc> markup tags. You must include {loc_distractors} other distractor
27     locations that are not related to the location context. It must be unambiguous, but
28     subtle, that these distractor locations are not where the event took place.
29     The distractor locations must be wrapped by <nloc></nloc> markup tags. You must
30     also include one temporal context in your description. This temporal context
31     represents the specific time or time frame in which the event took place. Any
32     mention of the temporal context must be wrapped between <tmp></tmp> markup tags.
33     You must include {tmp_distractors} other distractor times that are not when the
34     event took place. It must be unambiguous, but subtle, that these distractor times
35     are not when the event happened. The distractor times be wrapped
36     by <ntmp></ntmp> markup tags.""").strip())
37 ])
38
39 events_chain = events_prompt | llm | list_parser
40 roles_chain = narrator_prompt | llm | list_parser
41 generation_chain = generation_prompt | llm | str_parser

```

Figure 7: Python code snippet with the prompts used to narrate a fictional event in order to procedurally generate data.