# An Autoregressive Text-to-Graph Framework for Joint Entity and Relation Extraction

**Urchade Zaratiana[1,2], Nadi Tomeh[1], Pierre Holat[1,2], Thierry Charnois[1]**

[1] Fi Group, [2] Laboratoire d'Informatique de Paris-Nord, Université Sorbonne Paris Nord – CNRS
{zaratiana, tomeh, charnois}@lipn.fr, pierre.holat@fi-group.com

## Abstract

In this paper, we propose a novel method for joint entity and relation extraction from unstructured text by framing it as a conditional sequence generation problem. In contrast to conventional generative information extraction models that are left-to-right token-level generators, our approach is *span-based*. It generates a linearized graph where nodes represent text spans and edges represent relation triplets. Our method employs a transformer encoder-decoder architecture with pointing mechanism on a dynamic vocabulary of spans and relation types. Our model can capture the structural characteristics and boundaries of entities and relations through span representations while simultaneously grounding the generated output in the original text thanks to the pointing mechanism. Evaluation on benchmark datasets validates the effectiveness of our approach, demonstrating competitive results. Code is available at https://github.com/urchade/ATG.

## Introduction

Joint entity and relation extraction is a fundamental task in Natural Language Processing (NLP), serving as the basis for various high-level applications such as Knowledge Graph construction (Ye et al. 2022b) and question answering (Chen et al. 2017). Traditionally, this task was tackled via pipeline models that independently trained and implemented entity recognition and relation extraction, often leading to error propagation (Brin 1999). Deep learning has led to the creation of end-to-end models, allowing for the use of shared representations and joint optimization of loss functions for both tasks (Wadden et al. 2019; Wang and Lu 2020; Zhao et al. 2021; Zhong and Chen 2021; Yan et al.). Despite this advancement, these models essentially remain pipeline-based, with entity and relation predictions executed by separate classification heads, thereby ignoring potential interactions between these tasks.

Recent advancements have seen a shift towards "real" end-to-end solutions, where the prediction of entities and relations is intertwined, accomplished through autoregressive models. These models treat the joint entity-relation task as a process of generating plain text, employing *augmented languages* to encode and decode structural information (Paolini et al. 2021; Lu et al. 2022; Liu et al. 2022; Fei et al. 2022). While these models have achieved remarkable performance, we argue that they also expose room for improvement, especially in terms of grounding the output in the input text.

In this paper, we present an autoregressive transformer encoder-decoder model that generates a linearized graph instead of generating plain text. Our model makes use of a pointing mechanism (Vinyals, Fortunato, and Jaitly 2015) on a dynamic vocabulary of spans and relations, providing explicit grounding in the original text. In fact, without grounding, models can generate output that are semantically coherent but contextually detached from the input. Our pointing mechanism mitigates this issue by ensuring that the decoder's outputs, specifically the entity spans, are directly tied to the input text. Furthermore, by generating spans and relations directly from the text, rather than producing standalone plain text, our model encode the structural characteristics and boundaries of entities/spans more accurately, which can be missed by previous generative information extraction models. The cornerstone of our solution is the explicit enumeration of all spans[1] at the encoder's output, making them readily available to the decoder. Although the number of spans can be extensive, we note that when bounding the span size, our model's vocabulary is typically smaller than that of traditional language models (Devlin et al. 2019; Raffel et al. 2019), as discussed in subsequent sections.

Moreover, as previous generative IE models operate at the token level, they scatter the information regarding an entity's span and its boundaries over multiple decoding steps. In contrast, generating an entity and its type in our approach is accomplished in a single decoding step, resulting in shorter sequence (Table 5). Additionally, our method naturally ensures the well-formedness of the output while some generative IE models that produce text, often require non-regular constraints. As an example, in TANL (Paolini et al. 2021), if a portion of the generated sentence has an invalid format, that segment is discarded. Such issues are readily addressed in our model since the vocabulary can be fully controlled.

We evaluated our model on three benchmark datasets for joint entity and relation extraction: CoNLL 2004, SciERC, and ACE 05. Our model demonstrated competitive performance on all datasets. Our contributions can be summarized as follows:

Copyright © 2024, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

[1] Up to a certain length in practice.

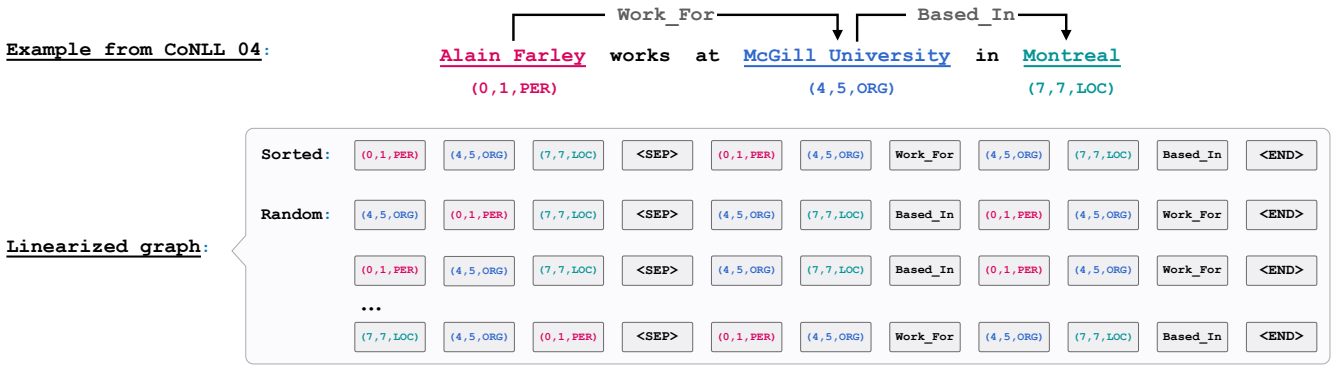



Figure 1: **Linearization for Information Graph Generation**. The input text is mapped into an information extraction graph. The graph consists of entities and relation triplets, which are generated sequentially by first producing entity spans (represented by start word, end word, and entity type) followed by relation triplets (head entity, tail entity, and relation type). We compare our linearization scheme with previous models in Table 5, highlighting the advantages of our approach (shorter output sequence and the ability to easily include constraints).

- We propose a novel method for joint entity and relation extraction by framing it as a conditional sequence generation problem. Our approach generates a linearized graph representation, where nodes represent entity spans and edges represent relation triplets.
- Our model employs a transformer encoder-decoder architecture with a pointing mechanism on a dynamic vocabulary of spans and relation types. This allows to capture the structural characteristics and boundaries of entities and relations while grounding the generated output in the original text.
- We demonstrate the effectiveness of our approach through extensive evaluations on benchmark datasets, including CoNLL 2004, SciERC, and ACE 05. Our model achieves state-of-the-art results on CoNLL 2004 and SciERC, surpassing previous comparable models in terms of Entity F1 scores and Relation F1 scores.

## Task definition

We address the task of joint entity and relation extraction from text as a graph generation approach. Our proposed model generates nodes and edges as a single sequence, effectively integrating both entity and relation extraction into a unified framework. Formally, the task can be defined as follows: Given an input text sequence $\boldsymbol{x} = \{x_1, x_2, ..., x_L\}$, where $x_i$ represents the $i$-th token in the sequence, our objective is to generate a linearized graph representation $\mathbf{y} = \{y_1, y_2, ..., y_M\}$, where $y_j$ represents a token in the generated sequence. As shown in Figure 1, in Each token $y_j$ can take one of three forms:

- **Entity Span**: The token $y_j$ represents an entity span, defined as $y_j = (s_j, e_j, t_j)$, where $s_j$ and $e_j$ denote the starting and ending positions of the entity span, and $t_j$ denotes the type of the entity.
- **Relation Type**: The token $y_j$ represents a relation type between two entities, such as `Work_For` relation.
- **Special Token**: The token $y_j$ represents special tokens used in the generation process, such as `<SEP>` to separate entities and relations or the `<END>` to stop the generation.

The template employed in our model, we refer to **ATG** (**A**utoregressive **T**ext-to-**G**raph), is depicted in Figure 1. It starts by generating the entities, followed by a `<SEP>` token, and ends with the relation triplets, each consisting of head node, tail node and edge/relation type. During training, we try two distinct orderings for the graph linearization: *sorted* and *random*. As shown in the Figure 1, the *sorted* linearization organizes entities and relations based on their positions in the original text, while the *random* linearization randomly shuffles entities and relations order.

## Model Architecture

Our model, ATG, employed an encoder-decoder architecture, which processes the input text sequence and produces a linearized graph as illustrated in the Figure 2.

### Encoder

The encoder in ATG utilizes a transformer layer that takes an input text sequence $\mathbf{x}$ and outputs token representations $\mathbf{H} \in \mathbb{R}^{L \times D}$, where $D$ is the model dimension.

### Vocabulary Construction

**Dynamic Vocabulary** To enable the pointing mechanism in our decoder, we construct a dynamic vocabulary matrix $\mathbf{E}$ that includes embeddings for spans, special tokens, and relation types. While special tokens and relation type embeddings are randomly initialized and updated during training, the span embeddings are dynamically computed, *i.e* their representations depend on the input sequence. More specifically, the embedding of a span $(\text{start}, \text{end}, \text{type})$ is computed as follows:

$$\mathbf{S}_{[\text{start,end,type}]} = \mathbf{W}^T_{\text{type}}[\mathbf{h}_{\text{start}} \odot \mathbf{h}_{\text{end}}] \quad (1)$$

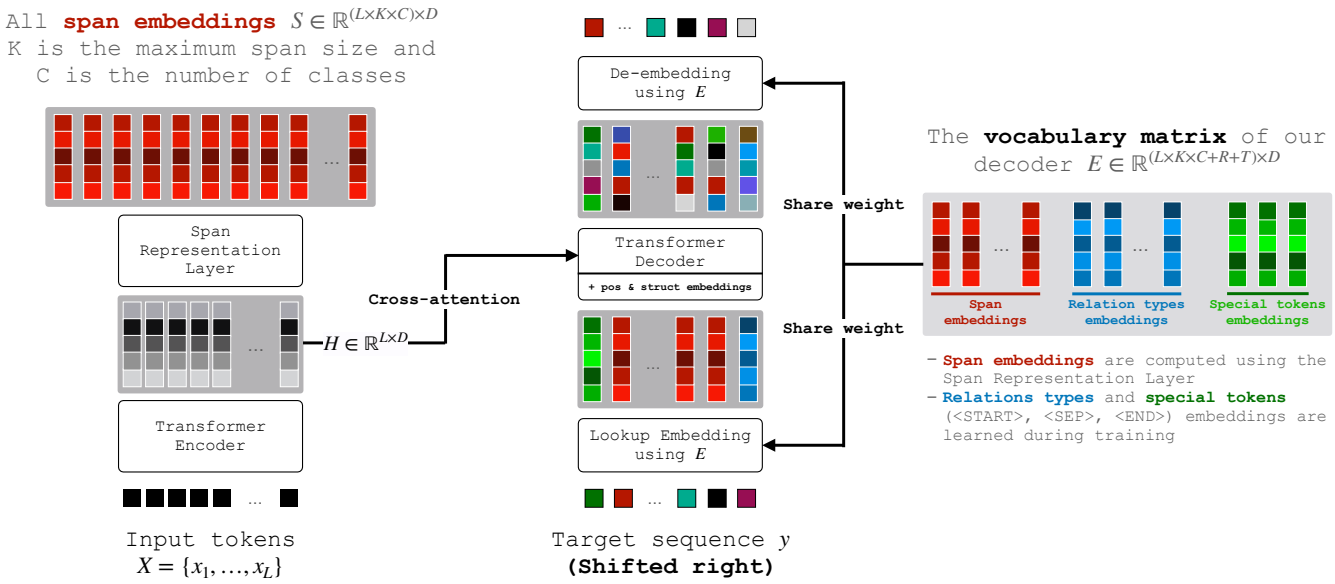



Figure 2: **Illustration of the architecture of our model, ATG**. (*left*) The Encoder takes in the input sequence $X$ and generates representations of the tokens $\boldsymbol{H}$ and spans $\boldsymbol{S}$. (*middle*) The Decoder then generates the next token conditioned on the previous tokens and the input representation $\boldsymbol{H}$. (*right*) The vocabulary matrix used for decoding consists of the concatenation of span embeddings $\boldsymbol{S}$, learned relation type embeddings, and special token embeddings.

In this equation, $[\odot]$ represents a concatenation operation; $\mathbf{h}_{\text{start}}$ and $\mathbf{h}_{\text{end}}$ denote the representations of tokens at the start and end positions, respectively. $\mathbf{W}_{\text{type}} \in \mathbb{R}^{2D \times D}$ is a weight matrix associated with the entity type (*i.e*, there is a $\mathbf{W}_{\text{type}}$ for each entity types in a datasets). Finally, the vocabulary embedding matrix $\mathbf{E}$ is formed by stacking all the span embeddings $\mathbf{S}$, special token embeddings $\mathbf{T}$, and relation type embeddings $\mathbf{R}$.

**Vocabulary Size** The size of the vocabulary matrix $\mathbf{E} \in \mathbb{R}^{V \times D}$ is $V = L \times K \times C + R + T$, where $L$ represents the sequence length, $K$ the maximum span size, $C$ the number of entity types, $R$ the number of relations, and $T$ the number of special tokens (<START>, <END>, and <SEP>). Let's take the CoNLL 2004 dataset as an example to illustrate this. This dataset has the following characteristics: $K = 12$, $C = 4$, $R = 5$, and $T = 3$. Considering a sentence of length 114 (which is the maximum length in the training set), the resulting vocabulary size would be 5480. This size is considerably smaller when compared with the vocabulary size of a typical language model, which usually hovers around 30,000 distinct tokens.

## Decoder

The decoder is a causal transformer trained to predict the next token in the sequence, akin to traditional language modeling. However, it is important to note that the vocabulary of our decoder consists of entity spans, relation types, and special tokens, rather than plain text. The decoder conditions its predictions on the previously generated tokens $y_{<j}$ using self-attention and on the input token representations $\mathbf{H}$ using cross-attention. This enables the decoder to attend to relevant information from both the previously generated tokens and the input text. Through attention visualizations, as depicted in Figure 10 and 11, we observed that the model effectively harnesses both sources of information. Finally, The training objective aims to maximize the following conditional probability:

$$p(\boldsymbol{y}|\boldsymbol{x}) = \prod_{j=1}^{M} p(y_j|\boldsymbol{y}_{<j}, \boldsymbol{H}) \tag{2}$$

This is achieved during the training by minimizing the negative log-likelihood of a reference sequence obtained by linearizing the reference IE graph. Details about the decoder input and output are given in the subsequent paragraphs.

**Decoder Input Embedding** The embedding step feeds the previous decoder outputs $y_1, \ldots, y_{i-1}$ into the model using the vocabulary matrix $\mathbf{E}$, along with *positional* and *structural* embeddings as shown in Figure 3. This process can be expressed as follows:

$$\begin{aligned} \boldsymbol{z}_1, \ldots, \boldsymbol{z}_{i-1} = & \boldsymbol{E}[y_1, \ldots, y_{i-1}] \\ & + \boldsymbol{E}_{pos}[1, \ldots, i-1] \\ & + \boldsymbol{E}_{struct}[y_1, \ldots, y_{i-1}] \end{aligned} \tag{3}$$

Here, $\boldsymbol{E}[y_1, \ldots, y_{i-1}]$ corresponds to the token embeddings, which may corresponds to spans, relation types, or special tokens embeddings depending on the nature of $y_{<i}$. The matrix $\boldsymbol{E}_{pos}$ represents absolute positional embedding. It allows to capture the positional information of the decoder outputs from $y_1$ to $y_{i-1}$. Additionally, the structural embedding $\boldsymbol{E}_{struct}$ serve as indicators to guide the model in generating specific elements. In particular, they provide informa-

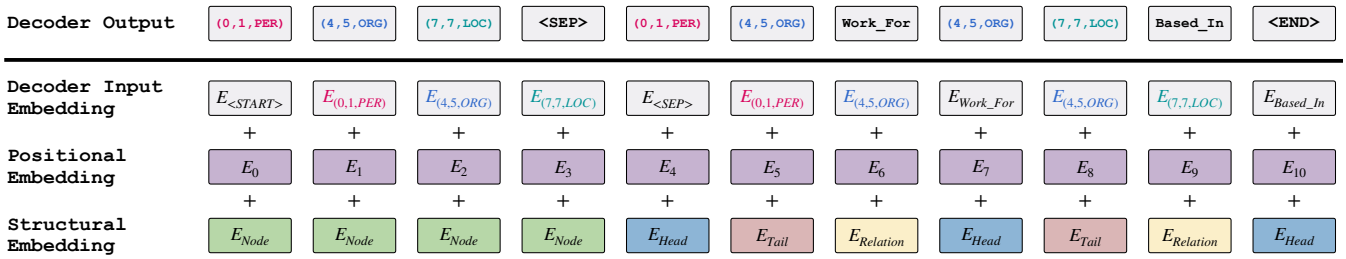



Figure 3: **Input/ouptut of the decoder**. The process starts with the special token **<START>** and continues until the **<END>** token is generated. To separate the generation of nodes and edges, a special token **<SEP>** is used. At each position, the decoder takes in the sum of the embedding of the current token, an absolute position embedding, and a structure embedding.

tion about whether the model should generate a Node (before <SEP> tokens), Tail, Head nodes, or Relation types (as illustrated in Figure 3). Both the absolute position encoding and the structural embedding are randomly initialized and updated during training. In summary, by combining these embeddings, ATG can capture the semantic, positional and structural information about the linearized graph.

**Decoder Output** We define $\tilde{\boldsymbol{z}}_i$ as the hidden state at the last position of the decoder output sequence obtained by feeding the previous output embedding and the encoder outputs $\boldsymbol{H}$ (for cross-attention) to the decoder, *i.e*,

$$\tilde{\boldsymbol{z}}_i = \mathcal{D}ecoder(\boldsymbol{z}_1, \ldots, \boldsymbol{z}_{i-1}; \boldsymbol{H})[-1] \tag{4}$$

Then, to compute the probability distribution over the dynamic vocabulary for generating the next token, $y_i$, our model employs the softmax function on the dot product between the dynamic vocabulary embedding matrix $\boldsymbol{E}$ and $\tilde{\boldsymbol{z}}_i$:

$$p(y_i|\boldsymbol{y}_{<i}, \boldsymbol{H}) = \frac{\exp \boldsymbol{E}^T \tilde{\boldsymbol{z}}_i}{\sum_{k=1}^{V} (\exp \boldsymbol{E}^T \tilde{\boldsymbol{z}}_i)_k} \tag{5}$$

The probabilities generated by this formulation allow the model to select the appropriate token from the vocabulary for generating a span, special token, or relation type.

**Constrained Decoding** During inference, we sample from the model by enforcing constraints that preserve the well-formedness of the output graph. More specifically, during inference, we feed our model with the <START> token, and the generation process is guided by state-transition constraints as outlined in Table 4. This structured approach ensures that each step in the generation aligns with the defined template, thereby maintaining the well-formedness of the output and allowing the production of valid IE graphs. All generations start with the start token **(Start)** state and continue until the <END> token is sampled. In practice, we also add other constraints: in state **1**, we prevent the repetition of already generated spans, and in state **3**, we ensure the tail span is different from the head. Furthermore, it is also possible to incorporate domain knowledge into the prediction. For instance, if the type of a head entity is PER and the tail entity is ORG, the relation can be constrained to be Work_For (CoNLL 04 dataset).

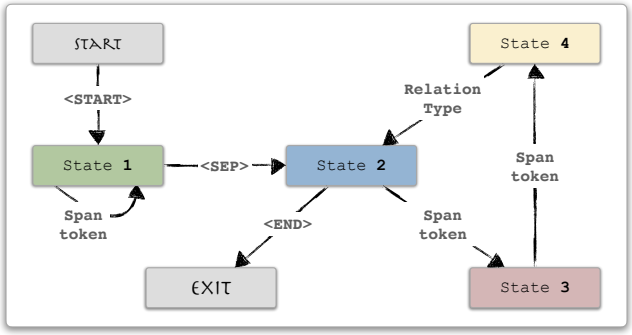



Figure 4: **State-Transition diagram for constrained decoding**. This diagram illustrates the state-based decision process used during the inference phase, which ensures the generation of a correct graph. Each state is represented by a node, and directed edges indicate valid actions. We use the same color code as the *structural embedding* in Figure 3.

## Training with Sentence Augmentation

In our work, we observed oversmoothing (Kulikov, Eremeev, and Cho 2022), where the model prematurely generates the <EOS>, *i.e* a bias towards short sequences (Murray and Chiang 2018; Xuewen et al. 2021). We found this bias to harm the recall of the tasks as the generation terminates before predicting all the entities/relations. To counteract this, we propose sentence augmentation, drawing inspiration from Pix2seq (Chen et al. 2022), who encounter a similar problem for their generative object detection model. This approach forms an augmented training sample $s_{\text{aug}}$ by randomly concatenating sentences from the training set $\mathcal{D} = \{s_1, s_2, ..., s_N\}$:

$$s_{\text{aug}} = \bigoplus_{k=1}^{n} s_{i_k}, \quad i_k \sim \mathcal{U}(1, N), n \sim \mathcal{U}(1, B) \tag{6}$$

Here, $\mathcal{U}$ denotes the uniform distribution, and $B$ is a hyperparameter indicating the maximum number of sentences that can be concatenated. By applying this sentence augmentation technique during training, the model is exposed to diverse input/output sequence lengths, reducing the risk of premature generation of the <EOS> token.

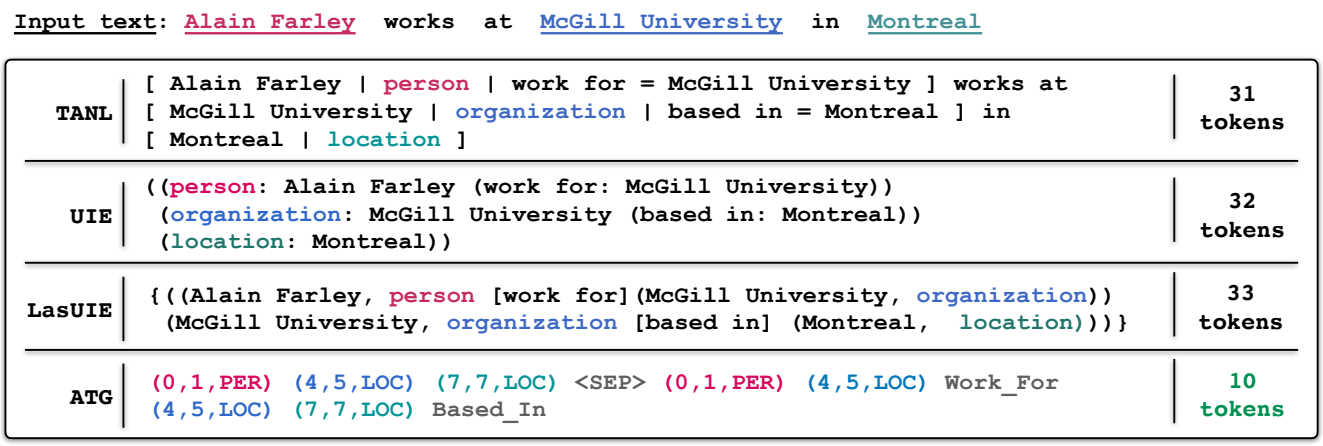



Figure 5: **Linearization for different models.** In contrast to other previous approaches (**TANL** (Paolini et al. 2021), **UIE** (Lu et al. 2022), **LasUIE** (Fei et al. 2022)), our proposed model, **ATG**, generates spans instead of text tokens, which allows for a shorter output sequence and a richer (span-level) representation.

## Experiments setup

### Datasets

We evaluated our model on three benchmark English datasets for joint entity-relation extraction, namely SciERC (Luan et al. 2018), CoNLL 2004 (Carreras and Màrquez 2004), and ACE 05 (Walker et al. 2006). The statistics of the dataset is reported on Table 1.

**ACE 05** is collected from a variety of domains, such as newswire, online forums and broadcast news. It provides a diverse set of entity types such as Persons (PER), Locations (LOC), Geopolitical Entities (GPE), and Organizations (ORG), along with intricate relation types that include ART (Artifact relationships), GEN-AFF (General affiliations), and PER-SOC (Personal social relationships). This dataset is particularly notable for its complexity and wide coverage of entity and relation types, making it a robust benchmark for evaluating the performance of IE models.

**CoNLL 2004** is an annotated corpus collected from newswires and focuses on general entities such as People, Organizations, and Locations, and relations like Work_For and Live_in.

**SciERC** is a dataset that comes with entity, coreference, and relation annotations for a collection of documents from 500 AI paper abstracts. The dataset defines scientific term types and relation types specifically designed for AI domain knowledge graph construction.

| Dataset | $\lvert\mathcal{E}\rvert$ | $\lvert\mathcal{R}\rvert$ | # Train | # Dev | # Test |
|---|---|---|---|---|---|
| ACE05 | 7 | 6 | 10,051 | 2,424 | 2,050 |
| CoNLL 04 | 4 | 5 | 922 | 231 | 288 |
| SciERC | 6 | 7 | 1,861 | 275 | 551 |

Table 1: The statistics of the datasets. We use ACE04, ACE05, SciERC, and CoNLL 04 for evaluating end-to-end relation extraction.

### Evaluation Metrics

For the NER task, we adopt a span-level evaluation requiring precise entity boundaries and type predictions. To evaluate relations, we use two metrics: (1) Boundaries evaluation (**REL**) necessitates the correct prediction of entity boundaries and relation types; (2) Strict evaluation (**REL+**) additionally require accurate entity type prediction. We report the micro-averaged F1 score.

### Baselines

We succinctly and briefly describe here the baseline that we compared with our model, which we separate into two categories: Span-based/table-filling and generative IE.

**Span-based and Table-filling** *DyGIE++* (Wadden et al. 2019) is a model that uses a pretrained transformer to compute contextualized representations and employs graph propagation to update the representations of spans for prediction. *Tab-Seq* (Wang and Lu 2020) tackles the task of joint information extraction by treating it as a table filling problem. *PURE* (Zhong and Chen 2021) is a pipeline model for the information extraction task that learns distinct contextual representations for entities and relations. *PFN* (Yan et al.) introduces methods that model two-way interactions between tasks by partitioning and filtering features. *UniRE* (Wang et al. 2021) proposes a joint entity and relation extraction model that eliminates the separation of label spaces for entity detection and relation classification. Their model uses a unified classifier to predict labels for each cell in a table of word pairs. In *TablERT* (Ma, Hiraoka, and Okazaki 2022), entities and relations are treated as tables, and the model utilizes two-dimensional CNNs to effectively capture and model local dependencies within these table-like structures.

**Generative IE** *HySPA* (Ren et al. 2021) is a model for text-to-graph extraction that has linear space and time complexity using a Hybrid span generator. *TANL* (Paolini et al.

| Models | SciERC | | | ACE 05 | | | CoNLL 2004 | | |
|---|---|---|---|---|---|---|---|---|---|
| | **ENT** | **REL** | **REL+** | **ENT** | **REL** | **REL+** | **ENT** | **REL** | **REL+** |
| DYGIE++ (Wadden et al. 2019) | 67.5 | 48.4 | – | 88.6 | 63.4 | – | – | – | – |
| Tab-Seq (Wang and Lu 2020) | – | – | – | 89.5 | – | 64.3 | 90.1 | 73.8 | 73.6 |
| PURE (Zhong and Chen 2021) | 66.6 | 48.2 | 35.6 | 88.7 | 66.7 | 63.9 | – | – | – |
| PFN (Yan et al.) | 66.8 | – | 38.4 | 89.0 | – | **66.8** | – | – | – |
| UniRE (Wang et al. 2021) | 68.4 | – | 36.9 | 89.9 | – | 66.0 | – | – | – |
| TablERT (Ma, Hiraoka, and Okazaki 2022) | – | – | – | 87.8 | 65.0 | 61.8 | **90.5** | 73.2 | 72.2 |
| GENERATIVE | | | | | | | | | |
| HySPA (Ren et al. 2021) | – | – | – | 88.9 | 68.2 | – | – | – | – |
| TANL (Paolini et al. 2021) | – | – | – | 89.0 | – | 63.7 | 90.3 | – | 70.0 |
| ASP (Liu et al. 2022) † | – | – | – | **91.3** | *72.7* | *70.5*† | 90.3 | – | *76.3* |
| UIE (Lu et al. 2022) | – | – | 36.5 | – | – | 66.6 | – | 75.0 | – |
| LasUIE (Fei et al. 2022) | – | – | – | – | – | 66.4 | – | 75.3 | – |
| ATG (*Our model*) | **69.7** | **51.1** | **38.6** | 90.1 | **68.7** | 66.2 | **90.5** | **78.5** | **78.5** |

Table 2: **Comparison of our proposed model with state-of-the-art methods**. Results are reported in terms of Entity (ENT) F1, Relation (REL) F1, and Strict Relation (REL+) F1 scores. The best scores are shown in bold, and the second-best scores are underlined. † *Italic scores use undirected evaluation for relation extraction and thus are not strictly comparable to our results.*

2021) solves the task of entity and relation extraction by framing it as translation from plain text to augmented natural languages by fine-tuning a T5 model (Raffel et al. 2019). This model has been further extended by *UIE* (Lu et al. 2022) and *LasUIE* (Fei et al. 2022), which both proposed better linearization and additional pretraining to enhance results. Finally, *ASP* (Liu et al. 2022) handles entity and relation extraction by encoding the target structure as a series of structure-building actions, using a conditional language model to predict these actions.

**Hyperparameters** Our model, ATG, employs a transformer encoder-decoder (Vaswani et al. 2017) architecture. We train it for a maximum of 70k steps using AdamW (Loshchilov and Hutter 2017) optimizer. We use learning rate warmup for the first 10% of training and then decay to 0. The base learning rates are 3e-5 for the encoder, 7e-5 for the decoder, and 1e-4 for other projection layers. Unlike other generative IE models that utilize pretrained encoder-decoder architectures, often relying on large models such as T5 (Raffel et al. 2019), we initialize ATG's encoder with pretrained transformer encoders, while the decoder is randomly initialized. In our preliminary experiments, we observed that initializing ATG with a pretrained encoder-decoder led to suboptimal performance. We hypothesize that this is due to our decoder's utilization of a dynamic vocabulary, whereas existing pretrained encoder-decoder models have a fixed token vocabulary, which creates a large discrepancy. We use DeBERTa (He, Gao, and Chen 2021) for Conll-04 and ACE 05 and SciBERT (Beltagy, Lo, and Cohan 2019) for SciERC dataset. Across all configurations, the number of decoder layers is set to 6, though we noted that even a single layer can be enough in certain cases. The sentence augmentation hyperparameter $B$ is set to 5. We did our experiments on a server equipped with A100 GPUs.

## Main results

Table 2 presents the main results of our experiments, along with comparable approaches from the literature. ATG demonstrates strong performance across all datasets. On the SciERC dataset, ATG achieves the highest scores across all metrics. It outperforms the second-best result by 0.2 in **REL+** and surpasses the best generative approach, UIE (Lu et al. 2022), by 2.1 points. On ACE 05, ATG provide a competitive performance, securing the second-highest scores. The reported top-performing model, ASP (Liu et al. 2022), operates under a relaxed, undirected relation evaluation, thereby limiting a fair comparison of results (Taillé et al. 2021). On the CoNLL 2004 dataset, ATG exhibits its superiority by outperforming the second-best result by 2.2 in terms of **REL+**. Overall, across all three datasets, our proposed model either holds the top position or showcases strong competitive performance.

## Ablation studies

Here, we present a series of ablations to examine the impact of modelling choices on the performance of ATG, on **REL+**.

**Number of Decoder Layers** The number of decoder layers impact is illustrate on the Figure 6. It has a varying impact on performance across the datasets. In SciERC, increasing the number of decoder layers leads to a gradual improvement in the performance, reaching a peak of 38.6 at 6 layer. For ACE 05, the score shows a slight improvement from 65.3 to 66.2 as the number of decoder layers increases from 1 to 6. For the CoNLL 2004 dataset, the score fluctuates with different numbers of decoder layers, achieving already strong performance with only a single layer. Overall, the choice of the number of decoder layers can have a noticeable impact on **REL+** performance but the effect may vary across datasets.

Figure 6: **Number of decoder layers**

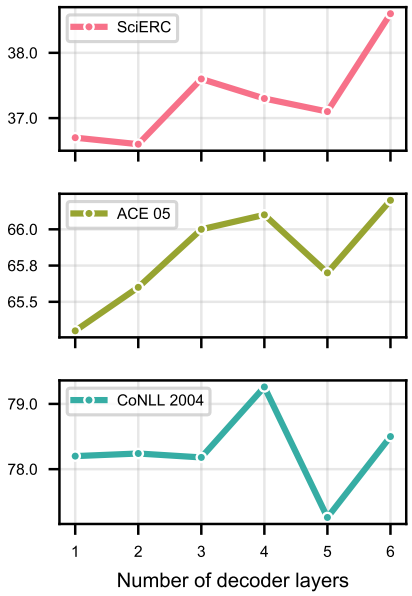



Figure 7: **Sentence augmentation**

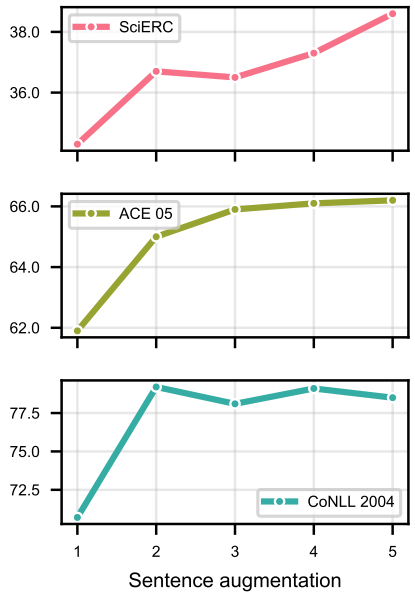
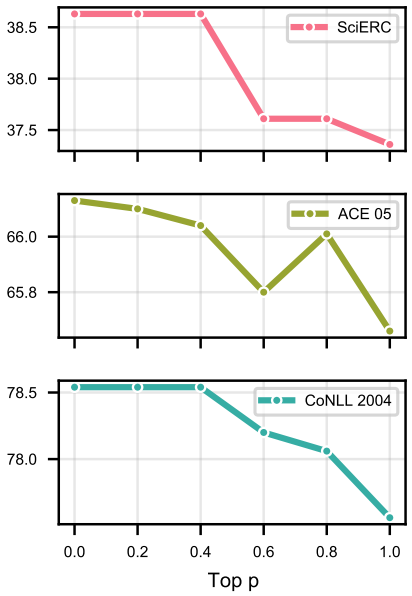



Figure 8: **Nucleus Sampling Top-p**




**Sentence Augmentation** The effect of sentence augmentation size on **REL+** performance is illustrated in Figure 7. The results reveal that increasing the number of sentence augmentations always improves performance across all datasets, except for CoNLL, where achieving state-of-the-art (SOTA) results is possible with just a size of 2. However, the absence of sentence augmentation leads to a significant decrease in **REL+**, proving its importance.

**Nucleus Sampling** The impact of different top p values in nucleus sampling (Holtzman et al. 2019) on the performance (REL+) is shown in Figure 8. The scores across all datasets demonstrate a relatively stable trend, with minor variations observed as the top p value changes. This can be attributed to the application of constrained decoding, which ensures that the output remains well-formed. However, the lowest values of top p, corresponding to greedy decoding, consistently deliver the best performance.

| | SciERC | ACE 05 | CoNLL 2004 |
|---|---|---|---|
| Full | **38.6** | **66.2** | **78.5** |
| - *Pos* | 36.4 | 66.0 | 78.3 |
| - *Struct* | 36.1 | 65.8 | 78.4 |
| - *Both* | 35.4 | 65.4 | 78.0 |

Table 3: **Effect of positional and structural embedding on REL+.**

**Positional and Structural Embeddings** Table 3 illustrates the importance of positional and structural encoding on the Relation F1 score. When employing both encoding, **ATG** achieves the best performance across all datasets (38.6 for SciERC, 66.2 for ACE 05, and 78.5 for CoNLL 2004). Excluding positional encoding causes only slight performance drops, since the span representations may contain some positional information. Omitting structural encoding leads to similar, but slightly larger drops. Finally, when both are removed, the scores decrease the most, indicating their importance for the task.

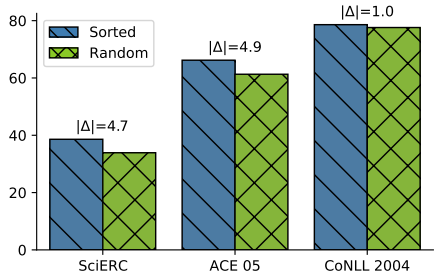



Figure 9: **Impact of sequence ordering on REL+.**

**Sequence Ordering** Figure 9 compares the effects of sorted and random sequence ordering across different datasets. The results clearly show that the sorted ordering approach consistently outperforms the random one. The difference in performance is particularly significant on SciERC and ACE 05, with improvements of 4.7 and 4.9, respectively. On the CoNLL 04 dataset, although the sorted approach still leads, the difference narrows to 1. Interestingly, we initially hypothesized that random ordering would deliver better performance, given that any generation errors in a sorted order could be difficult to rectify.

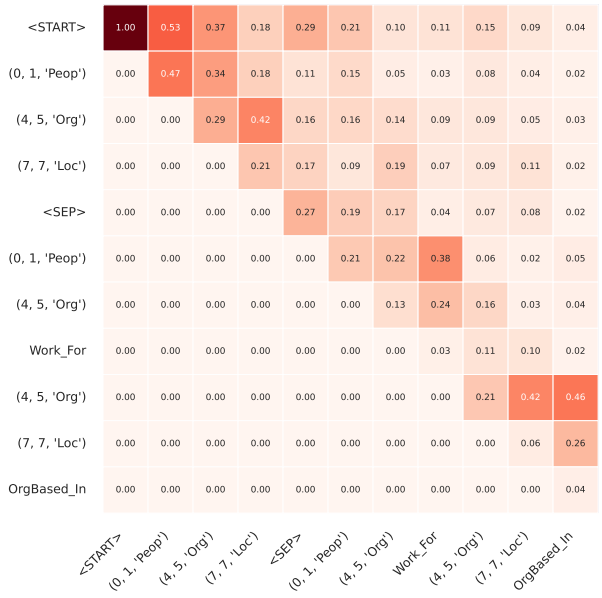



Figure 10: **Decoder Self-Attention Visualization**. This figure illustrates the attention patterns among elements in the generated sequence.

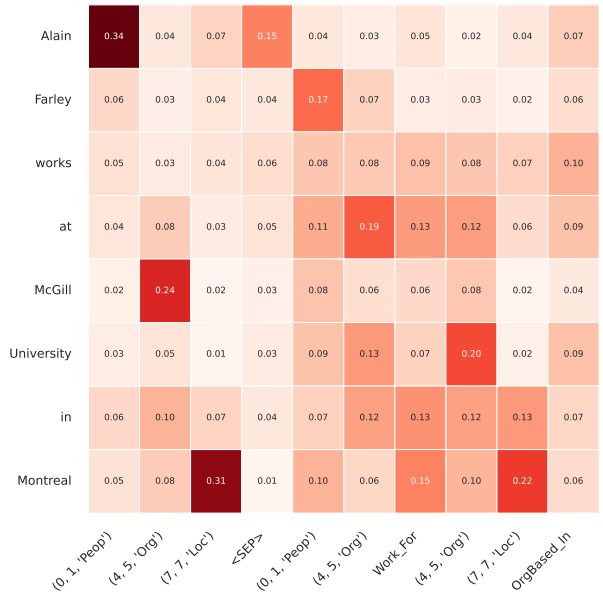



Figure 11: **Decoder Cross-Attention Visualization**. This detailed map displays how each target element in the decoder interacts with and utilizes the original input text.

# Interpretability Analysis

## Attention Analysis

Here we analyze the attention of the model during the decoding step, which allow us to explain some of the model's decision. We investigate both the self-attention (Fig. 10) and cross-attention (Fig. 11).

**Self-Attention** The self-attention map, shown in Figure 10, depicts the distribution of attention across preceding tokens during generation. One notable observation is the model's tendency to focus on the head and tail entities that comprise the relation when predicting relation types. For example, when predicting the `Work_For` relation, the model allocates most of its attention weight to the tokens `(0,1,Peop)` and `(4,5,Org)`.

**Cross-Attention** The cross-attention map in Figure 11 indicates the specific areas in the input sequence that the decoded tokens attend to during generation. For entity labels in the output sequence such as `(0,1,Peop)`, `(4,5,Org)`, and `(7,7,Loc)`, we can observe higher attention scores for the words `Alain`, `McGill`, and `Montreal`, respectively, in the input sequence. This indicates that the model tends to focuses on the beginning of each entity span when generating these entities in the output sequence. Furthermore, when predicting tail entities for relations, significant attention is directed toward the prepositions 'at' and 'in' in the input sequence. This suggests that the model has learned to associate these prepositions with specific relations between entities.

## Learned Structure Embedding

To investigate the impact of the learned structure embedding on model performance, we analyze the similarity between the structure embeddings learned during training, depicted in Figure 13. Notably, we observe a consistent pattern across datasets: the embeddings for the Head and Tail exhibit a high negative correlation. This finding may suggest that the model learns to differentiate between the Head and Tail entities, capturing their distinct characteristics. However, we do not have a clear interpretation of this phenomenon. Moreover, we also report structure embedding values (over the 512 embedding dimensions) in Figure 12. We observe that the structure embeddings $E_{Head}$ and $E_{Tail}$ exhibit higher values than the others, which may suggest that predicting the head and tail entities is the most challenging for the model.

# Related Works

**Non-Generative IE** In the field of information extraction (IE), traditional pipeline models have been used, consisting of separate stages for entity recognition and relation extraction (Roth and Yih 2004). Entity recognition is performed to identify mentioned entities (Chiu and Nichols 2015; Lample et al. 2016), followed by relation extraction to determine the relationships between these entities (Zelenko, Aone, and Richardella 2002; Bach and Badaskar 2007; Lin et al. 2016; Wu, Bamman, and Russell 2017). However, this approach suffers from error propagation, where mistakes in entity recognition can negatively impact the accuracy of relation extraction (Brin 1999; Nadeau and Sekine 2007). To address these challenges, there has been a shift towards end-to-end models that jointly optimize both entity recognition

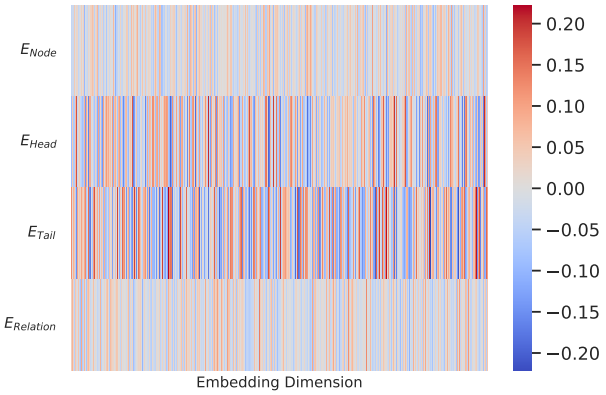



Figure 12: **Structure embedding values**. This shows the values taken by the learned structure embeddings over the 512 embedding dimensions.

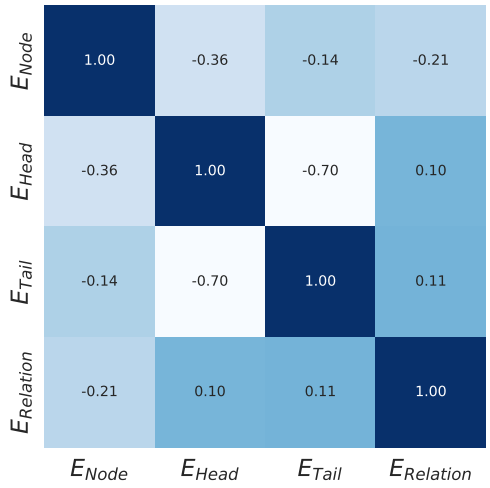



Figure 13: **Structure embedding similarity**. This map shows the cosine similarity between pairs of structure embedding.

and relation extraction. This joint optimization aims to harness the interplay between the two tasks, thereby enhancing overall performance (Sun et al. 2021; Zhao et al. 2021; Ye et al. 2022a). Noteworthy directions in this domain include table-filling methods (Wang and Lu 2020; Ma, Hiraoka, and Okazaki 2022), span pair classification (Eberts and Ulges 2019; Wadden et al. 2019), set prediction (Sui et al. 2020), augmented sequence tagging mechanisms (Ji et al. 2020), fine-grained triplet classification (Shang, Huang, and Mao 2022), and the use of unified labels for tasks (Wang et al. 2021).

**Generative IE** Recent advancements in generative Information Extraction (IE) emphasize the use of language models to produce entities and relations, either as text or as a sequence of actions (Paolini et al. 2021; Lu et al. 2022; Nayak and Ng 2020; Liu et al. 2022; Fei et al. 2022). Typically, these models employ pretrained encoder-decoder architectures, such as T5 (Raffel et al. 2019) or BART (Lewis et al. 2020), to encode an input text and subsequently decode it into a structured output. Their primary advantage over non-generative methods is their ability to seamlessly integrate tasks by treating them as a unified generation process. A comprehensive review of this approach is available in (Ye et al. 2022b). Beyond entity and relation extraction, generative models have also found applications in other IE tasks, including entity linking (Cao et al. 2021), event extraction (Li, Ji, and Han 2021), and document-level relation extraction (Giorgi, Bader, and Wang 2022).

## Conclusion

In conclusion, our autoregressive text-to-graph framework for joint entity and relation extraction has demonstrated its effectiveness in achieving state-of-the-art or competitive results on multiple benchmark datasets. By directly generating a linearized graph representation instead of plain text, ATG successfully captures the structural characteristics, boundaries, and interactions of entities and relations. Moreover, the pointing mechanism on dynamic vocabulary provide robust grounding in the original text.

## Acknowledgments

This work was granted access to the HPC/AI resources of IDRIS under the allocation AD011014472 made by GENCI.

## References

Bach, N.; and Badaskar, S. 2007. A Review of Relation Extraction.

Beltagy, I.; Lo, K.; and Cohan, A. 2019. SciBERT: A Pretrained Language Model for Scientific Text. In *Conference on Empirical Methods in Natural Language Processing*.

Brin, S. 1999. Extracting Patterns and Relations from the World Wide Web. In Atzeni, P.; Mendelzon, A.; and Mecca, G., eds., *The World Wide Web and Databases*, 172–183. Berlin, Heidelberg: Springer Berlin Heidelberg. ISBN 978-3-540-48909-2.

Cao, N. D.; Izacard, G.; Riedel, S.; and Petroni, F. 2021. Autoregressive Entity Retrieval. In *International Conference on Learning Representations*.

Carreras, X.; and Màrquez, L. 2004. Introduction to the CoNLL-2004 Shared Task: Semantic Role Labeling. In *Proceedings of the Eighth Conference on Computational Natural Language Learning (CoNLL-2004) at HLT-NAACL 2004*, 89–97. Boston, Massachusetts, USA.

Chen, D.; Fisch, A.; Weston, J.; and Bordes, A. 2017. Reading Wikipedia to Answer Open-Domain Questions. In Barzilay, R.; and Kan, M.-Y., eds., *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*.

Chen, T.; Saxena, S.; Li, L.; Fleet, D. J.; and Hinton, G. 2022. Pix2seq: A Language Modeling Framework for Object Detection. In *International Conference on Learning Representations*.

Chiu, J. P. C.; and Nichols, E. 2015. Named Entity Recognition with Bidirectional LSTM-CNNs. *Transactions of the Association for Computational Linguistics*, 4: 357–370.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics.*, 4171–4186. Minneapolis, Minnesota.

Eberts, M.; and Ulges, A. 2019. Span-based Joint Entity and Relation Extraction with Transformer Pre-training. *ArXiv*, abs/1909.07755.

Fei, H.; Wu, S.; Li, J.; Li, B.; Li, F.; Qin, L.; Zhang, M.; Zhang, M.; and Chua, T.-S. 2022. LasUIE: Unifying Information Extraction with Latent Adaptive Structure-aware Generative Language Model. In Oh, A. H.; Agarwal, A.; Belgrave, D.; and Cho, K., eds., *Advances in Neural Information Processing Systems*.

Giorgi, J.; Bader, G. D.; and Wang, B. 2022. A sequence-to-sequence approach for document-level relation extraction. In *Workshop on Biomedical Natural Language Processing*.

He, P.; Gao, J.; and Chen, W. 2021. DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing. *ArXiv*, abs/2111.09543.

Holtzman, A.; Buys, J.; Forbes, M.; and Choi, Y. 2019. The Curious Case of Neural Text Degeneration. *ArXiv*, abs/1904.09751.

Ji, B.; Yu, J.; Li, S.; Ma, J.; Wu, Q.; Tan, Y.; and Liu, H. 2020. Span-based Joint Entity and Relation Extraction with Attention-based Span-specific and Contextual Semantic Representations. In *Proceedings of the 28th International Conference on Computational Linguistics*, 88–99. Barcelona, Spain (Online): International Committee on Computational Linguistics.

Kulikov, I.; Eremeev, M.; and Cho, K. 2022. Characterizing and addressing the issue of oversmoothing in neural autoregressive sequence modeling. In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*.

Lample, G.; Ballesteros, M.; Subramanian, S.; Kawakami, K.; and Dyer, C. 2016. Neural Architectures for Named Entity Recognition. In *North American Chapter of the Association for Computational Linguistics*.

Lewis, M.; Liu, Y.; Goyal, N.; Ghazvininejad, M.; Mohamed, A.; Levy, O.; Stoyanov, V.; and Zettlemoyer, L. 2020. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 7871–7880.

Li, S.; Ji, H.; and Han, J. 2021. Document-Level Event Argument Extraction by Conditional Generation. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 894–908.

Lin, Y.; Shen, S.; Liu, Z.; Luan, H.; and Sun, M. 2016. Neural Relation Extraction with Selective Attention over Instances. In *Annual Meeting of the Association for Computational Linguistics*.

Liu, T.; Jiang, Y. E.; Monath, N.; Cotterell, R.; and Sachan, M. 2022. Autoregressive Structured Prediction with Language Models. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, 993–1005. Abu Dhabi, United Arab Emirates.

Loshchilov, I.; and Hutter, F. 2017. Decoupled Weight Decay Regularization. In *International Conference on Learning Representations*.

Lu, Y.; Liu, Q.; Dai, D.; Xiao, X.; Lin, H.; Han, X.; Sun, L.; and Wu, H. 2022. Unified Structure Generation for Universal Information Extraction. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 5755–5772. Dublin, Ireland: Association for Computational Linguistics.

Luan, Y.; He, L.; Ostendorf, M.; and Hajishirzi, H. 2018. Multi-Task Identification of Entities, Relations, and Coreferencefor Scientific Knowledge Graph Construction. In *Proc. Conf. Empirical Methods Natural Language Process. (EMNLP)*.

Ma, Y.; Hiraoka, T.; and Okazaki, N. 2022. Joint Entity and Relation Extraction Based on Table Labeling Using Convolutional Neural Networks. In *Proceedings of the Sixth Workshop on Structured Prediction for NLP*, 11–21.

Murray, K.; and Chiang, D. 2018. Correcting Length Bias in Neural Machine Translation. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, 212–223. Brussels, Belgium.

Nadeau, D.; and Sekine, S. 2007. A survey of named entity recognition and classification. *Lingvisticae Investigationes*, 30: 3–26.

Nayak, T.; and Ng, H. T. 2020. Effective Modeling of Encoder-Decoder Architecture for Joint Entity and Relation Extraction. In *The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, New York, NY, USA, February 7-12, 2020*, 8528–8535. AAAI Press.

Paolini, G.; Athiwaratkun, B.; Krone, J.; Ma, J.; Achille, A.; ANUBHAI, R.; dos Santos, C. N.; Xiang, B.; and Soatto, S. 2021. Structured Prediction as Translation between Augmented Natural Languages. In *International Conference on Learning Representations*.

Raffel, C.; Shazeer, N. M.; Roberts, A.; Lee, K.; Narang, S.; Matena, M.; Zhou, Y.; Li, W.; and Liu, P. J. 2019. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. *ArXiv*, abs/1910.10683.

Ren, L.; Sun, C.; Ji, H.; and Hockenmaier, J. 2021. HySPA: Hybrid Span Generation for Scalable Text-to-Graph Extraction. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, 4066–4078.

Roth, D.; and Yih, W.-t. 2004. A Linear Programming Formulation for Global Inference in Natural Language Tasks. In *Proceedings of the Eighth Conference on Computational Natural Language Learning (CoNLL-2004) at HLT-NAACL 2004*, 1–8. Boston, Massachusetts, USA.

Shang, Y.-M.; Huang, H.; and Mao, X.-L. 2022. OneRel: Joint Entity and Relation Extraction with One Module in One Step. In *AAAI Conference on Artificial Intelligence*.

Sui, D.; Chen, Y.; Liu, K.; Zhao, J.; Zeng, X.; and Liu, S. 2020. Joint Entity and Relation Extraction with Set Prediction Networks. *IEEE transactions on neural networks and learning systems*, PP.

Sun, K.; Zhang, R.; Mensah, S.; Mao, Y.; and Liu, X. 2021. Progressive Multi-task Learning with Controlled Information Flow for Joint Entity and Relation Extraction. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(15): 13851–13859.

Taillé, B.; Guigue, V.; Scoutheeten, G.; and Gallinari, P. 2021. Let's Stop Incorrect Comparisons in End-to-end Relation Extraction! arXiv:2009.10684.

Vaswani, A.; Shazeer, N. M.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is All you Need. In *NIPS*.

Vinyals, O.; Fortunato, M.; and Jaitly, N. 2015. Pointer Networks. In Cortes, C.; Lawrence, N.; Lee, D.; Sugiyama, M.; and Garnett, R., eds., *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc.

Wadden, D.; Wennberg, U.; Luan, Y.; and Hajishirzi, H. 2019. Entity, Relation, and Event Extraction with Contextualized Span Representations. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*.

Walker, C.; Strassel, S.; Medero, J.; and Maeda, K. 2006. ACE 2005 Multilingual Training Corpus.

Wang, J.; and Lu, W. 2020. Two are Better than One: Joint Entity and Relation Extraction with Table-Sequence Encoders. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.

Wang, Y.; Sun, C.; Wu, Y.; Zhou, H.; Li, L.; and Yan, J. 2021. UniRE: A Unified Label Space for Entity Relation Extraction. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 220–231.

Wu, Y.; Bamman, D.; and Russell, S. J. 2017. Adversarial Training for Relation Extraction. In *Conference on Empirical Methods in Natural Language Processing*.

Xuewen, S.; Heyan, H.; Ping, J.; and Yi-Kun, T. 2021. Reducing Length Bias in Scoring Neural Machine Translation via a Causal Inference Method. In *Proceedings of the 20th Chinese National Conference on Computational Linguistics*, 874–885. Huhhot, China: Chinese Information Processing Society of China.

Yan, Z.; Zhang, C.; Fu, J.; Zhang, Q.; and Wei, Z. ???? A Partition Filter Network for Joint Entity and Relation Extraction. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 185–197. Association for Computational Linguistics.

Ye, D.; Lin, Y.; Li, P.; and Sun, M. 2022a. Packed Levitated Marker for Entity and Relation Extraction. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 4904–4917. Dublin, Ireland: Association for Computational Linguistics.

Ye, H.; Zhang, N.; Chen, H.; and Chen, H. 2022b. Generative Knowledge Graph Construction: A Review. In Goldberg, Y.; Kozareva, Z.; and Zhang, Y., eds., *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, 1–17. Abu Dhabi, United Arab Emirates: Association for Computational Linguistics.

Zelenko, D.; Aone, C.; and Richardella, A. 2002. Kernel Methods for Relation Extraction. In *Journal of machine learning research*.

Zhao, T.; Yan, Z.; Cao, Y.; and Li, Z. 2021. A Unified Multi-Task Learning Framework for Joint Extraction of Entities and Relations. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(16): 14524–14531.

Zhong, Z.; and Chen, D. 2021. A Frustratingly Easy Approach for Entity and Relation Extraction. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.

# Appendix

## Additional notes

**Main motivation** In our paper, we propose a new paradigm for generative entity and relation extraction. Instead of directly generating text, our model generates typed entity spans. The main advantages are as follows: 1) Our model generates each entity in a single step, while text-based models require generating multiple tokens for a single entity and their types (since an entity may consist of multiple words). This significantly reduces the output sequence length, which is beneficial as the attention mechanism is quadratic in sequence length. 2) In our approach, it is trivial to maintain a valid output because the vocabulary can be controlled. In contrast, it is harder for text-based models to always produce a valid structure as they may hallucinate due to a lack of control.

**About sentence augmentation** The primary goal of sentence augmentation is to prevent the early generation of [EOS], which harms recall as the model finishes generation before generating all the entities/relations. By exposing the decoder to longer sequences during training, it biases our model towards longer outputs and thus improve recall (See Table 4). A similar technique has been applied in generative object detection by Pix2Seq (Chen et al. 2022) (see Section 2.3 of their paper).

| Sentence augmentation | Prec | Rec | F1 |
|---|---|---|---|
| Without (n=1) | 78.4 | 63.7 | 70.3 |
| With (n=2) | 80.6 (+2.2) | **77.7 (+14)** | 79.1 (+8.8) |

Table 4: Effect of sentence augmentation (CoNLL 04)

**Complexity of span enumeration** The span enumeration can be of high complexity, when applied to very long sequence. However, in our work, we set a maximum length ($K$) for the spans allowing to reduce complexity form quadratic to linear in sequence length. Furthermore, our implementation computes span representation in parallel making the overall process quite fast.

**Difference with pointer Network** Our approach is highly inspired by the pointer network (Vinyals, Fortunato, and Jaitly 2015), with the difference that our model points to *typed spans* instead of *input sequence elements*. The main advantage of our approach is as follows: pointing to the input sequence directly would considerably increase the length of the output, as the start, end and entity type would have to be generated separately, whereas our approach allows this to be done in a single decoding step. As a result, we reduce the sequence length by 3x, which is advantageous considering that the complexity of each transformer generation is quadratic.

**Why not treating relation as span of entities ?** Our model uses the whole sentence (and previous tokens) to understand and predict relationships between entities, rather than *just looking at the entities alone* (eg. by concatenation). This may avoid missing out on important information that can be lost when only focusing on entity pairs.

**Is our model still relevant in the current paradigm ?** The current paradigm is to employ Large language models (LLMs) for many tasks through natural language instruction. However, these models have several billions of parameters and are thus hard to deploy in limited compute environments. Although some of these models are accessible via APIs (e.g., ChatGPT), their availability is limited, and scaling up their usage can result in substantial costs. In contrast, our model has a more moderate size (at most 400 million parameters). Furthermore, these LLMs are not without their issues, such as hallucination, which makes them difficult to control. In contrast, our approach offers full control and the ability to impose constraints, ensuring the generation of valid structures. Taking these factors into account, we believe that our model can still offer value to the community.