Syntax-Aware Graph-to-Graph Transformer for Semantic Role Labelling

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Abstract

The goal of semantic role labelling (SRL) is to recognise the predicate-argument structure of a sentence. Recent models have shown that syntactic information can enhance the SRL performance, but other syntax-agnostic approaches achieved reasonable performance. The best way to encode syntactic information for the SRL task is still an open question. In this paper, we propose the Syntax-aware Graph-to-Graph Transformer (SynG2G-Tr) architecture, which encodes the syntactic structure with a novel way to input graph relations as embeddings directly into the self-attention mechanism of Transformer. This approach adds a soft bias towards attention patterns that follow the syntactic structure but also allows the model to use this information to learn alternative patterns. We evaluate our model on both dependency-based and span-based SRL datasets, and outperform all previous syntax-aware and syntax-agnostic models in both in-domain and out-of-domain settings, on the CoNLL 2005 and CoNLL 2009 datasets. Our architecture is general and can be applied to encode any graph information for a desired downstream task.

1 Introduction

The semantic role labelling (SRL) task provides a shallow semantic representation of a sentence and builds event properties and relations among relevant words. SRL graphs are defined in both dependency-based and span-based styles, as shown in Figure 1. SRL graphs enhance many NLP tasks including Question Answering (Yih et al., 2016; Shen and Lapata, 2007), Machine Translation (Kazemi et al., 2017; Wang et al., 2016), Natural Language Inference (Zhang et al., 2020).

Traditionally, syntactic structure was regarded as a pre-requisite for SRL models (Gildea and Palmer, 2002; Punyakanok et al., 2008), but new models outperform syntax-aware architectures by leveraging deep neural network architectures (Cai et al., 2018; Tan et al., 2017; He et al., 2017; Marcheggiani et al., 2017) without explicitly encoding syntactic structure.

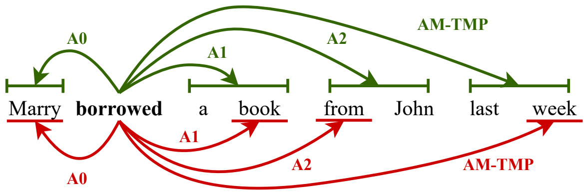

Figure 1: Example of SRL graphs. The upper structure is in the span-based style, and the lower one is in the dependency-based style.

However, some recent works (Zhou et al., 2020a; Strubell et al., 2018; He et al., 2017; Marcheggiani and Titov, 2017) claim that deep neural network models could benefit from using syntactic information, rather than discarding it. They suggest that syntax has the potential to improve the SRL predication by joint learning both syntactic and semantic structures (Zhou et al., 2020a), training one self-attention head in Transformer (Vaswani et al., 2017a) to attend to each token's syntactic parent (Strubell et al., 2018), or encoding syntactic structure with graph convolutional networks (Marcheggiani and Titov, 2017). But the question remains open as to the most effective way to incorporate the auxiliary syntactic information into deep learning architectures for SRL.

Recently Mohammadshahi and Henderson (2020a) proposed an architecture called Graph-to-Graph Transformer which allows the input and output of arbitrary graphs. They first applied it to transition-based dependency parsing, for conditioning on the partially constructed dependency graph (Mohammadshahi and Henderson, 2020a), and then to graph-based syntactic parsing with iterative refinement (Mohammadshahi and Henderson, 2020b), where predicted dependency graphs are iteratively corrected. The Graph-to-Graph Transformer architecture inputs graph relations as embeddings incorporated into the self-attention mechanism of Transformer (Vaswani et al., 2017b), inspired by the way Shaw et al. (2018) encode sequence order with relative position embeddings. In this way, it is easy for the self-attention mechanism to follow relations, but it can also learn to combine this information in more useful alternative soft attention patterns.

In this paper, we propose the Syntax-aware Graph-to-Graph Transformer (SynG2G-Tr) architecture for encoding syntactic structure, for predicting SRL structures. The model conditions on the sentence's dependency structure and jointly predicts both dependency-based and span-based SRL structures. Our architecture is different from the original Graph-to-Graph Transformer in the way in which it encodes the input graph structure. Inspired by Huang et al. (2020), our self-attention functions model the interaction of the graph relations with both the query and key vectors, instead of just the key. The second novelty is that our model builds two semantic graphs (dependency-based and span-based SRL) as the output, which is in a different domain than the encoded syntactic graph. For the SRL decoding, we use a joint scorer and decoder to build dependency-based and span-based SRL graphs at the same time (Li et al., 2019).

We show empirically that our model outperforms all previous work that leverages syntactic information. In an in-domain setting, the SynG2G-Tr model achieves 88.93(87.57) F1 score on the CoNLL 2005 dataset given the predicate (end-to-end), and 91.23(88.05) F1 on the CoNLL 2009 dataset given the predicate (end-to-end). In the out-of-domain setting, our model reaches 83.21(80.53) F1 score on the CoNLL 2005 dataset given the predicate (end-to-end), and 86.43(81.93) F1 scores on the CoNLL 2009 dataset given the predicate (end-to-end).

Our architecture is general and can be used to encode any graph structure for the desired downstream task. Our contributions are as follows:

- We propose an improved version of the Graph-to-Graph Transformer architecture for conditioning on graph structures.
- We show that this architecture can effectively condition on the syntactic dependency graph for predicting both dependency-based and span-based semantic role labelling graphs.
- We improve the state-of-the-art accuracies on the CoNLL 2005 (span-based) and CoNLL 2009 (dependency-based) datasets.

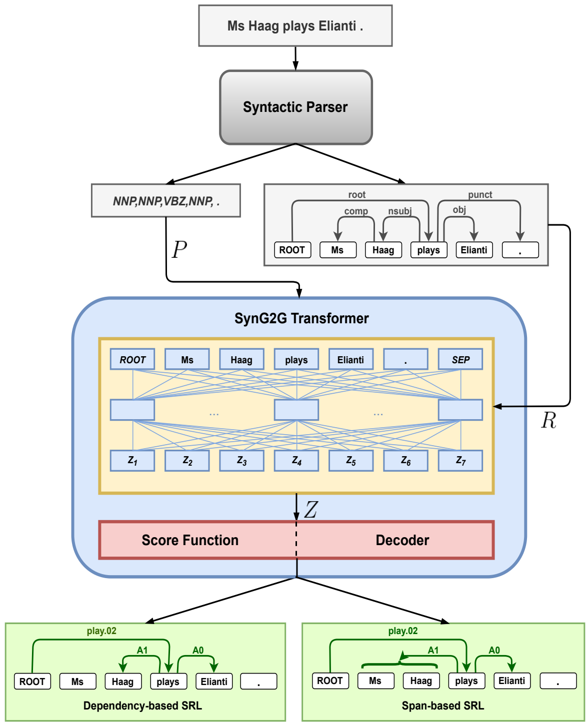

Figure 2: The framework of Syntax-aware Graph-to-Graph Transformer, applied to the SRL task.

2 Syntax-aware Graph-to-Graph Transformer

The Syntax-aware Graph-to-Graph Transformer architecture is illustrated in Figure 2, applied to the SRL task. The input to the model is tokenised text ($W = (w_1, w_2, ..., w_N)$), and these tokens are considered the nodes of all input and output graphs. The outputs are the dependency-based (G_{dep}) and span-based (G_{span}) SRL graphs. Initially, a syntactic parser predicts the dependency graph (G_{syn}), and Part-of-Speech (PoS) tags ($F = (f_1, f_2, ..., f_N)$), which can be any syntactic parser. Then our SynG2G-Tr model encodes both these sequences (W,F) and this dependency graph (G_{syn}) into contextualised representations for the graph nodes, which are used by the decoder to jointly predict both SRL graphs.

The Syntax-aware Graph-to-Graph Transformer architecture uses an improved way of inputting graph relations into the self-attention mechanism of Transformer (Vaswani et al., 2017b). Unlike the previously proposed version of Graph-to-Graph Transformer (Mohammadshahi and Henderson, 2020b), we modify the self-attention mechanism to have a more comprehensive interaction between graph relations, queries and keys.

The SynG2G-Tr model can be formalised in terms of an encoder E^{sg2g} and decoder D^{sg2g}:

$$\begin{cases} Z = \mathrm{E}^{\mathrm{sg2g}}(W,F,G_{syn}) \\ G_{span},G_{dep} = \mathrm{D}^{\mathrm{sg2g}}(Z) \end{cases} \quad (1)$$

where $Z = (z_1,z_2,...,z_N)$ is the sequence of output value embeddings which is conditioned on input sequences (W, F) and dependency graph (G_{syn}), and N is the sequence length.

The dependency graph is defined as:

$$\begin{cases} G_{syn} = \{(i,j,l_{in}),\, j = 2,...,N-1\} \\ \text{where } 1 \leq i \leq N-1,\, l_{in} \in L_{syn} \end{cases} \quad (2)$$

where the graph is the set of tuples (i, j, l_{in}), meaning that each token w_j has the parent as w_i with label l_{in}, where parent could be the ROOT node (w_1). We will discuss the input sequence in more detail in Section 2.1.

Inspired by Li et al. (2019), we define a span-based SRL graph as:

$$\begin{cases} G_{span} = \{(k,<i,j>,l_{out})\} \\ \text{where } 2 \leq i,j,k \leq N-1,\, l_{out} \in L_{srl} \end{cases} \quad (3)$$

where the span-based SRL graph is the set of predicate-argument tuples $(k, < i, j >, l_{out})$, k is the predicate, $<i,j>$ is the argument span starting from i and ending in j, and l_{out} is the SRL label. The dependency-based SRL graph is defined in the same way as Equation 3, with the only difference that i equals to j in the span argument.

In the remaining paragraphs, we will describe each element of our architecture in detail, and propose our baselines.

2.1 Input Embeddings

The input to the embedding layer of the SynG2G-Tr model contains the sequence of tokenised text (W) and predicted PoS tags (F). The input sequence starts with a ROOT node, followed by the tokenised sequence, and then we add a SEP token at the end of the sequence to make it compatible with BERT's token representation (Devlin et al., 2019). We sum several embeddings to build the input sequence representations: pre-trained embeddings of BERT (b_i), learned embeddings of PoS tags (f_i), and positional embeddings (o_i) to keep the order information:

$$x_i = b_i + f_i + o_i,\, i = 1,2,...,N \quad (4)$$

where x_i is the input embedding of token w_i.

2.2 Self-attention Mechanism

Encoding graph information into Transformer-based architectures is possible by inputting graph relations directly to the self-attention mechanism, as proposed by Mohammadshahi and Henderson (2020a,b), and inspired by Shaw et al. (2018) for relative position relations. Recently, Huang et al. (2020) proposed an improved way of inputting relative position relations for the input sequence of BERT (Devlin et al., 2019) by changing the self-attention functions. We propose a new version of the Graph-to-Graph Transformer architecture (Mohammadshahi and Henderson, 2020a,b) which incorporates these new self-attention functions.

The Transformer architecture consists of a stack of self-attention layers with multiple attention heads. We modify the attention mechanism of each head in each layer to input the dependency graph. These attention scores α_{ij} are calculated as a Softmax function over e_{ij} values:

$$e_{ij} = \frac{1}{\sqrt{d}}\Big[(x_i\boldsymbol{W^Q} + r_{ij}\boldsymbol{W^R})(x_j\boldsymbol{W^K} + r_{ij}\boldsymbol{W^R})^T - (r_{ij}\boldsymbol{W^R})(r_{ij}\boldsymbol{W^R})^T\Big] \quad (5)$$

where $\boldsymbol{W^Q}, \boldsymbol{W^K} \in \mathbb{R}^{d_x \times d}$ are learned query and key matrices. r_{ij} is a one-hot vector specifying both the label and direction of the dependency relation between token i and token j (id_{label} if $i \rightarrow j$, $id_{label} + |L_{syn}|$ if $j \leftarrow i$, or NONE, where $|L_{syn}|$ is the label set size). $\boldsymbol{W^R} \in \mathbb{R}^{2|L_{syn}|+1 \times d}$ is a matrix of learned relation embeddings. d is the attention head size, and d_x is the hidden size.

For better implementation, we re-formulate Equation 5 as below to calculate all terms in parallel:

$$e_{ij} = \frac{1}{\sqrt{d}}\Big[x_i\boldsymbol{W^Q}(x_j\boldsymbol{W^K})^T + x_i\boldsymbol{W^Q}(r_{ij}\boldsymbol{W^R})^T + r_{ij}\boldsymbol{W^R}(x_j\boldsymbol{W^K})^T\Big] \quad (6)$$

The output of the attention function is the value embedding (v_i), which we calculate as:[1]

$$v_i = \sum_j \alpha_{ij}(x_j\boldsymbol{W^V}) \quad (7)$$

[1]Mohammadshahi and Henderson (2020a,b) also incorporate the relation information r_{ij} into this value function, but in preliminary experiments, we found no advantage to doing so, so we also simplify the value function as shown.

By applying Equation 5, graph information is incorporated into the attention mechanism of Transformer with a soft bias, meaning the model can still use this encoded graph information to learn other structures.

2.3 Scorer and Training

Scorer: Inspired by Zhou et al. (2020a), we first define span representation (s_{ij}) as the difference between right and left end-points of the span $<i,j>$:

$$s_{ij} = s\vec{r}_j - s\overleftarrow{l}_i \tag{8}$$

where $s\vec{r}_j$ is defined as $[\overleftarrow{z_{j+1}}; \vec{z_j}]$, and $s\overleftarrow{l}_i$ is calculated as $[\vec{z}_i; \overleftarrow{z_{i+1}}]$. $\vec{z}_i$ is computed by dividing the output representation of Transformer (z_i) in half.

Argument (a_{ij}) and predicate (p_k) representations are defined as:

$$\begin{aligned} a_{ij} &= \mathrm{ReLU}(\boldsymbol{W^1_{srl}} s_{ij} + b^1_{srl}) \\ p_k &= z_k \end{aligned} \tag{9}$$

where $\boldsymbol{W^1_{srl}}$ and b^1_{srl} are learned parameters, and $\mathrm{ReLU}(.)$ is the Rectified Linear Unit function.

We predict semantic roles as defined in Zhou et al. (2020a):

$$\Phi_l(p,a) = \boldsymbol{W^3_{srl}}(\mathrm{LN}(\boldsymbol{W^2_{srl}}[a_{ij};p_k] + b^2_{srl})) + b^3_{srl} \tag{10}$$

where $\mathrm{LN}(.)$ is the layer normalisation function, and $\boldsymbol{W^2_{srl}}$, $\boldsymbol{W^3_{srl}}$, b^2_{srl}, and b^3_{srl} are learned parameters. The semantic role score for a specific label l_{out} is defined as:

$$\Phi_l(p,a,l_{out}) = [\Phi_l(p,a)]_{l_{out}} \tag{11}$$

Since the number of predicate-argument pairs is $O(n^3)$, we apply the pruning method proposed in Li et al. (2019); He et al. (2018a) by defining separate scorers for argument and predicate candidates (Φ_a and Φ_p), and pruning all but the top-ranked arguments and predicates based on their corresponding scores.

Training: The model is trained to optimise the probability $P(\hat{y}|W,F,G_{syn})$ of predicate-argument pairs, conditioned on input sequence (W), PoS tags (F), and predicated dependency graph (G_{syn}). This objective can be factorised as:

$$\begin{aligned} J(\theta) &= \sum_{y \in \Gamma} -log P_\theta(y|W,F,G_{syn}) \\ &= \sum_{\langle p,a,l_{out}\rangle \in \Gamma} -log \frac{\exp(\Phi(p,a,l_{out}))}{\sum_{\hat{l} \in L_{srl}} \exp(\Phi(p,a,\hat{l}))} \end{aligned} \tag{12}$$

where $\Phi(p,a,l_{out})$ is defined as $\Phi_p(p) + \Phi_a(a) + \Phi_l(p,a,l_{out})$, and θ is model parameters. Γ is the set of predicate-argument-relation tuples for all possible predicate-argument pairs and either the correct relation or NONE.

2.4 Decoders

Since we define a uniform representation for both types of SRL, we use a single dynamic programming algorithm with a non-overlapping constraint (Punyakanok et al., 2008) to find predicated graphs.

2.5 Baselines

Previous works proposed several approaches to use syntax information for the SRL task (Strubell et al., 2018; Roth and Lapata, 2016; Marcheggiani and Titov, 2017; He et al., 2019). As baselines, we define a syntax-agnostic BERT-based model, and an alternative method to encode the syntactic graph. Proposed baselines are as follows:

BERT: For this model, we use BERT (Devlin et al., 2019) as the encoder to build contextualised representations of tokens, and use the same scorer function and decoder as defined in Sections 2.3 and 2.4. This model is syntax-agnostic.

BERT+SynEmb: In this model, we add information about the syntactic graph to the embedding layer of the BERT model:

$$\begin{cases} x_i = b_i + f_i + d_i + r_i \boldsymbol{W_{emb}} \\ i = 1,2,\ldots,N \end{cases} \tag{13}$$

where b_i, f_i, and d_i are the same as Equation 4. r_i is the one-hot vector representing the dependency label for dependent i, and $\boldsymbol{W_{emb}} \in \mathbb{R}^{(|L_{syn}|+1)\times d}$ is the learned label embeddings matrix. The scorer and decoder are the same as Section 2.3 and Section 2.4.

2.6 Dependency Parser

The dependency parser jointly predicts a sequence of PoS tags and the dependency graph as follows:

$$\begin{cases} A = E^{syn}(W) \\ F = D^{pos}(A) \\ G_{syn} = D^{syn}(A) \end{cases} \tag{14}$$

where E^{syn} is the BERT encoder, A is the output contextualised token representations, and D^{pos} is the decoder for PoS tags. D^{syn} is a joint scorer and decoder for dependency and constituency graphs based on Head-driven phrase structure grammar

(HPSG) (Zhou and Zhao, 2019). We choose this decoder since it achieved state-of-the-art results in the dependency parsing task. More details about the architecture of decoders can be found in Zhou and Zhao (2019).

3 Experimental Setup

Our models are evaluated on two kinds of SRL graphs, dependency-based and span-based. For dependency-based graphs, we test our models on the CoNLL 2009 dataset (Hajič et al., 2009). For span-based SRL, we evaluate them on the CoNLL 2005 dataset (Carreras and Màrquez, 2005). For predicate disambiguation, we follow previous work (Roth and Lapata, 2016).

We define two strategies for SRL evaluation, *end-to-end*, and *pre-defined predicate*. For the former setting, our models jointly predict both predicates and their relations with predicted arguments. For the latter setting, predicates are defined in the dataset.

3.1 Datasets

CoNLL 2005: In this shared task (Carreras and Màrquez, 2005), the focus was on verbal predicates in English. The training data includes sections 2-21 of the Wall Street Journal (WSJ) dataset. Section 24 is considered as the development set. Section 23 is used for the in-domain test set, and 3 sections of the Brown corpus are used for the out-of-domain dataset.

CoNLL 2009: This shared task (Hajič et al., 2009) focused on the dependency-based SRL and is created by merging PropBank and NomBank treebanks. We evaluated our models on the English dataset with the same split as the CoNLL 2005 dataset.

3.2 Hyper-parameters Setting

Our models are initialised with BERT-large model (Devlin et al., 2019), specifically *bert-large-whole-word-masking*[2]. The implementation is based on Pytorch[3] framework, and HugginFace repository (Wolf et al., 2020). All hyper-parameters are specified in Appendix A.

Since the BERT tokeniser (Wu et al., 2016) differs from the one that was used to tokenise the SRL corpora, we apply BERT's wordpiece tokeniser to each word in the SRL corpus, and input all the resulting sub-words to the model. For decoding, we use the contextualised embedding of the first sub-word of each word as its encoded representation[4]. For inputting the dependency graph, the relation between two words is specified as a relationship between their respective first sub-words, and we define a new relationship between the non-first sub-words of each word and its corresponding first sub-word.

Model	Development			Test		
	UAS	LAS	PoS	UAS	LAS	PoS
Syntactic parser	96.72	94.83	96.81	96.85	95.24	97.41

Table 1: Labelled and unlabelled attachment scores of the dependency parser on WSJ Penn Treebank, alongside with the PoS tagging accuracy.

Model	WSJ			Brown		
	P	R	F1	P	R	F1
End-to-End						
He et al. (2017)	85.0	84.3	84.6	74.9	72.4	73.6
He et al. (2018a)	81.2	83.9	82.5	69.7	71.9	70.8
Li et al. (2019)	-	-	83.0	-	-	-
Strubell et al. (2018)	85.53	84.45	84.99	75.8	73.54	74.66
+Pre-training						
He et al. (2018a)	84.8	87.2	86.0	73.9	78.4	76.1
Li et al. (2019)	85.2	87.5	86.3	74.7	78.1	76.4
Strubell et al. (2018)	87.13	86.67	86.9	79.02	77.49	78.25
BERT	86.4	87.79	87.08	78.76	80.06	79.40
BERT+SynEmb	86.46	88.02	87.23	79.2	80.98	80.08
SynG2G-Tr	86.86	88.3	**87.57**	80.01	81.07	**80.53**
Pre-defined predicate						
Tan et al. (2017)	84.5	85.2	84.8	73.5	74.6	74.1
He et al. (2018a)	-	-	83.9	-	-	73.7
Ouchi et al. (2018)	84.7	82.3	83.5	76.0	70.4	73.1
Strubell et al. (2018)	86.02	86.05	86.04	76.65	76.44	76.54
+Pre-training						
He et al. (2018a)	-	-	87.4	-	-	80.4
Ouchi et al. (2018)	88.2	87.0	87.6	79.9	77.5	78.7
Li et al. (2019)	87.9	87.5	87.7	80.6	80.4	80.5
BERT	88.67	88.36	88.52	83.84	82.09	82.56
BERT+SynEmb	88.97	88.34	88.65	83.48	82.18	82.82
SynG2G-Tr	89.11	88.74	**88.93**	83.93	82.50	**83.21**

Table 2: Comparing our models with previous state-of-the-art results on CoNLL 2005 (span-based) test sets.

4 Results and Discussion

First, we report SRL results on CoNLL 2005, and CoNLL 2009 datasets in both in-domain and out-of-domain settings[5]. Then, we analyse the distribution of errors made by the SynG2G-Tr and

[2]https://github.com/google-research/bert

[3]https://pytorch.org/

[4]Preliminary results show that using the embedding of the first sub-word achieves better or similar results than the last sub-word or averaging embeddings

[5]We exclude Zhou et al. (2020a); Cai and Lapata (2019) and Zhou et al. (2020b) from Table 2, and Table 3 because they trained syntactic (constituency and dependency) and SRL graphs jointly, while we use predicted syntactic graph, and don't combine constituency parsing to our approach. Zhou et al. (2020b) also used language modelling loss, and a huge amount of additional unlabelled corpora in the training time.

baselines, alongside storage and time complexities. Finally, we do an ablation study to understand the model better. The accuracy of the dependency parser is shown in Table 1.

4.1 CoNLL 2005 Results

Span-based SRL results are shown in Table 2. In the end-to-end setting, the SynG2G-Tr and BERT+SynEmb models outperform previous work with an F1 relative error reduction (RER) of 5.11%/2.52% for the in-domain dataset, respectively. Additionally, for the out-of-domain dataset, SynG2G-Tr and BERT+SynEmb models reach a better performance than previous works with an RER of 10.48%/8.41%. The better performance of the SynG2G-Tr model shows that injecting the graph information into the attention mechanism is more effective than adding it to the input embedding layer. Also, Both SynG2G-Tr and BERT+SynEmb models outperform syntax-agnostic BERT baseline, which demonstrates that encoding syntax is still beneficial even for the strong baseline that already outperforms previous works.

In the pre-defined predicate set-up, our SynG2G-Tr model again results in better performance than previous work, with 10% RER in the in-domain dataset. For the out-of-domain dataset, SynG2G-Tr and BERT+SynEmb models achieve 13.9%/11.89% RER compared to previous works, respectively. Better performance of the SynG2G-Tr model confirms the effectiveness of our model in encoding the dependency graph that provides global and between-edge views of the sentence.

4.2 CoNLL 2009 Results

Dependency-based SRL results are shown in Table 3. First, we consider the end-to-end setting. In in-domain data, the SynG2G-Tr model achieves better performance compared to previous works, and our baselines, while the BERT+SynEmb model does not improve the performance compared to syntax-agnostic BERT baseline. For out-of-domain data, both SynG2G-Tr and BERT+SynEmb models achieve better performance compared to the BERT baseline and outperform previous works with 29.96%/27.79% RER. The improvement of the SynG2G-Tr model, especially in out-of-domain data again shows the effectiveness and generality of the model.

Now, consider the pre-defined predicate set-up. The SynG2G-Tr model again reaches better performance than the BERT+SynEmb model in

Model	WSJ			Brown		
	P	R	F1	P	R	F1
End-to-End						
Li et al. (2019)	-	-	85.1	-	-	-
+Pre-training						
He et al. (2018b)	83.9	82.7	83.3	-	-	-
Cai et al. (2018)	84.7	85.2	85.0	-	-	72.5
Li et al. (2019)	84.5	86.1	85.3	74.6	73.8	74.2
BERT	85.37	89.23	87.26	79.12	83.22	81.12
BERT+SynEmb	84.74	89.79	87.19	78.83	84.07	81.37
SynG2G-Tr	86.38	89.78	**88.05**	80.35	83.57	**81.93**
Pre-defined predicate						
Kasai et al. (2019)	89.0	88.2	88.6	78.0	77.2	77.6
+Pre-training						
He et al. (2018b)	89.7	89.3	89.5	81.9	76.9	79.3
Cai et al. (2018)	89.9	89.2	89.6	79.8	78.3	79.0
Li et al. (2019)	89.6	91.2	90.4	81.7	81.4	81.5
Kasai et al. (2019)	90.3	90.0	90.2	81.0	80.5	80.8
Lyu et al. (2019)	-	-	90.99	-	-	82.18
Chen et al. (2019)	90.74	91.38	91.06	82.66	82.78	82.72
BERT	90.13	91.24	90.68	85.11	86.33	85.72
BERT+SynEmb	90.97	91.17	91.07	86.14	86.25	86.20
SynG2G-Tr	91.31	91.16	**91.23**	86.40	86.47	**86.43**

Table 3: Comparing our models with previous state-of-the-art results on CoNLL 2009 (dependency-based) test sets.

both in-domain and out-of-domain datasets. For out-of-domain dataset, the SynG2G-Tr model substantially improves previous state-of-the-art models with 21.47% RER, which demonstrates the benefit of encoding the graph structure directly in the attention mechanism.

Finally, we confirm that encoding the syntactic graph into the attention mechanism of Transformer (SynG2G-Tr) is more effective than using it in the embedding layer (BERT+SynEmb) since it provides the global and interdependence information when each token captures information in the attention mechanism.

4.3 Ablation Study

In Table 4, we analyse the interaction of the dependency graph with key and query vectors in the attention mechanism, as defined in Equation 6. Excluding the key interaction results in a similar attention score mechanism as defined in Mohammadshahi and Henderson (2020b). This SynG2G-Tr-*key* model achieves similar results compared to the SynG2G-Tr model on the WSJ test dataset, but the SynG2G-Tr model outperforms it on the development set, and both types of out-of-domain datasets, confirming that key interaction is a critical part of the SynG2G-Tr model.

Then, we exclude both key and value interactions, which results in the BERT baseline. The SynG2G-Tr-*key* model achieves better performance compared to the BERT model in all settings, which demon-

Model	CoNLL 2005			CoNLL 2009		
	Dev	WSJ	Brown	Dev	WSJ	Brown
End-to-End						
BERT	86.65	87.08	79.40	86.40	87.26	81.12
SynG2G-Tr *-key*	86.82	87.27	80.33	86.85	87.50	81.51
SynG2G-Tr	**87.08**	**87.57**	**80.53**	**87.13**	**88.05**	**81.93**
Given pred.						
BERT	87.93	88.52	82.56	90.16	90.68	85.72
SynG2G-Tr *-key*	88.03	**88.91**	82.90	90.31	**91.22**	86.28
SynG2G-Tr	**88.17**	**88.93**	**83.21**	**90.66**	**91.23**	**86.43**

Table 4: Model comparison of SynG2G-Tr model, and other variants on in-domain and out-of-domain SRL evaluations sets based on F1 score.

strates the impact of query interaction in the modified attention mechanism of the SynG2G-Tr model.

So, we conclude that both key and query interactions with dependency graph relations are critical parts of the SynG2G-Tr model.

4.4 Error Analysis

As shown in Figure 3, we analyse the improvement derived from each method by measuring the F1 score based on the sentence length, and dependency length for the SynG2G-Tr model, and other baselines on CoNLL 2009 end-to-end setting, which is the harder situation than the given predicate setup[6].

In the left figure, we compute the F1 score based on the sentence length. The SynG2G-Tr and BERT+SynEmb models achieve better performance on all sentence lengths (except 20-29) compared to the BERT baseline, confirming that syntax could still benefit SRL models even for this powerful baseline. Also, The SynG2G-Tr model reaches better results in all sentence lengths, which confirms the effectiveness of the model in encoding the graph structure.

In the right figure, we measure the F1 score based on the dependency length, meaning the distance between the argument and predicate in the input sentence. Again, the SynG2G-Tr model performs better on all dependency lengths, which shows the benefit of encoding the dependency graph in the attention mechanism.

4.5 Complexity Analysis

In this section, we analyse the added parameters and run-time complexity of the SynG2G-Tr model, and baselines. Consider a Transformer model with m self-attention layers, $|L_{syn}|$ as the number of dependency labels, and a batch of size b with a maximum sequence length of N.

[6]F1 score numbers and CoNLL 2005 analysis are provided in Appendix B.

Model	Parameter size	
	General	BERT-large
BERT	Θ	340M
BERT+SynEmb	+$(\|L_{syn}\|+1)d_x$	+49K
SynG2G-Tr	+$(2\|L_{syn}\|+1)md$	+145K

Table 5: Amount of additional parameters for the SynG2G-Tr model and other alternatives.

Model	Run-time	
	Train(sec/epoch)	Dev(sec)
BERT	637	12
BERT+SynEmb	909	21
SynG2G-Tr	1010	24

Table 6: Run-time performance of the SynG2G-Tr model and other alternative models. All models are trained with GeForce RTX 3090.

The number of parameters for the SynG2G-Tr model and baselines is calculated in Table 5. For the BERT+SynEmb baseline, the number of added parameters is $(|L_{syn}|+1)d_x$, since the graph information is added to the input embedding layer. For the SynG2G-Tr model, we share the relation embeddings across multiple attention heads in each layer, so the number of added parameters is computed as $(2|L_{syn}|+1)md$. The number of additional parameters is negligible compared to the baseline model (BERT-large), which has 340M parameters.

The run-time performance of our models is shown in Table 6. The time complexity of the self-attention mechanism for the Transformer architecture is calculated as $\mathcal{O}(bmn^2d)$. Two new terms in Equation 6 for the modified attention mechanism add a time complexity of $\mathcal{O}(bmn^2d)$, which doesn't change the total time complexity. Also, each term in Equation 6 can be calculated in parallel during training, which keeps the speed the same as for the BERT+SynEmb model. The difference between the BERT and BERT+SynEmb baselines can be considered as the time required to parse the dependency graph, and create the relation vectors r_i, which could be moved to pre-processing for the training time.

5 Related Work

Semantic role labelling was introduced by Gildea and Jurafsky (2000). In early works, most approaches focus on developing rich linguistic

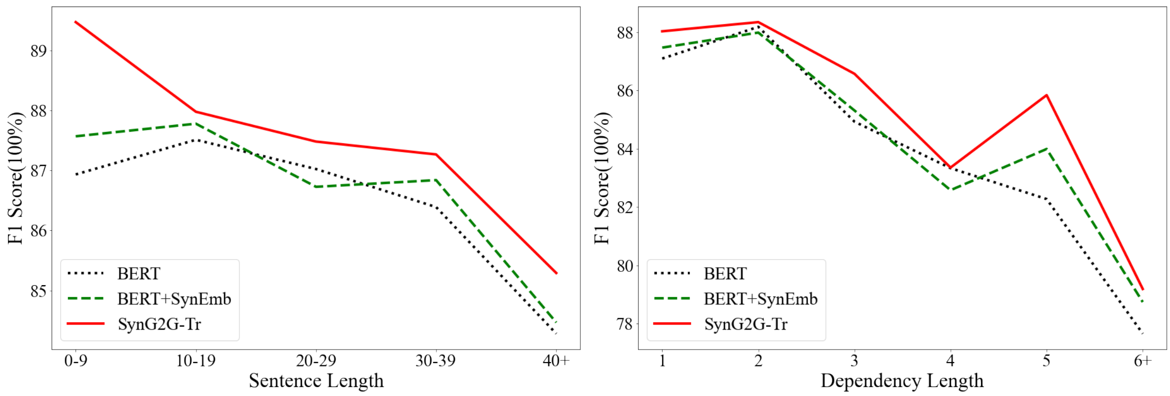

Figure 3: Error analysis of SynG2G-Tr, and baseline models on the development set of CoNLL 2009 dataset.

features as an input to their model (Pradhan et al., 2005; Surdeanu et al., 2007; Johansson and Nugues, 2008; Toutanova et al., 2008). Then Sutton and McCallum (2005) jointly modelled SRL and syntactic parsing. Lewis et al. (2015) also jointly modelled SRL and CCG parsing.

With the remarkable success of deep neural networks, a series of these models have been proposed for SRL task (FitzGerald et al., 2015; He et al., 2018b, 2017; Cai et al., 2017; Qin et al., 2017; Zhang et al., 2016; Henderson et al., 2013). More recent models are syntax-agnostic that achieve considerable results (Peters et al., 2018; He et al., 2018a; Zhou and Xu, 2015; Marcheggiani et al., 2017; He et al., 2017; Tan et al., 2017). However, there are several approaches that use syntactic information to improve the performance (Roth and Lapata, 2016; Marcheggiani and Titov, 2017; Strubell et al., 2018; Li et al., 2018; He et al., 2019). Marcheggiani and Titov (2017) encodes the predicted syntactic structure with GCN network, and outperforms previous models in dependency-based SRL. Roth and Lapata (2016) uses syntactic information by embedding dependency path. Strubell et al. (2018) incorporates dependency graph by training one attention head of Transformer to attend to syntactic parents for each token in a multi-task setting. Additionally, some works focus on joint learning of both SRL and syntax (Zhou et al., 2020a,b; Strubell et al., 2018; Cai and Lapata, 2019). Zhou et al. (2020a) defines a Transformer-based model to learn dependency-based, and span-based SRL, dependency and constituency syntactic graphs, and POS tags in multi-task fashion. Zhou et al. (2020b) also adds language modelling task to their previous model to build a structure-aware BERT model.

Our work is different from previous works, since we propose an alternative way of encoding graph structure, which can encode both sequences and graphs in one general encoder, and the syntactic information is directly added to the attention mechanism with a soft bias that helps the model learn any structure.

6 Conclusion

In this paper, we propose the Syntax-aware Graph-to-Graph Transformer architecture, effectively incorporating syntactic information by inputting the predicted syntactic dependency graph to the self-attention mechanism of Transformer (Vaswani et al., 2017b). Our mechanism for inputting graph relation embeddings differs from the original Graph-to-Graph Transformer (Mohammadshahi and Henderson, 2020a) in that it models the complete interaction between the dependency relation, query vector and key vector. Also, it excludes the graph interaction with value vectors while keeping the performance. We have evaluated our model on the CoNLL 2005 (span-based) and CoNLL 2009 (dependency-based) SRL datasets and achieved state-of-the-art results on both in-domain and out-of-domain datasets. We showed that our model adds a negligible number of parameters relative to the BERT baseline. We also demonstrated the effectiveness of our models based on sentence length and dependency length.

Our model is an alternative way of encoding the graph structure into the Transformer-based models and can be applied to any NLP task which requires encoding the graph structure.

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Appendix A Hyper-parameters Setting

We apply different optimisers for pre-trained parameters and randomly initialised ones. We use bucket batching, grouping sentences by their lengths to the same batch to speed up the model. Early stopping is used to mitigate over-fitting. In pre-defined predicate setting, we use different dynamic programming decoders to find SRL graphs, since predicates are not necessarily the same in dependency-based and span-based SRL graphs. Here is the list of hyper-parameters for SynG2G-Tr model:

Component	Specification
Optimiser	BertAdam
Base Learning rate	1.5e-3
BERT Learning rate	1e-5
Adam Betas(b_1,b_2)	(0.9,0.999)
Adam Epsilon	1e-5
Weight Decay	0.01
Max-Grad-Norm	1
Warm-up	0.001
Self-Attention	
No. Layers	24
No. Heads	16
Embedding size	1024
Max Position Embedding	512

Component	Specification
Feed-Forward layers (SRL)	
Span Hidden size	512
Label Hidden size	250
Feed-Forward layers (PoS)	
Hidden size	250
Pruning (SRL)	
λ_{verb}	0.6
λ_{span}	0.6
Max No. Span	300
Max No. Verb	30
Epoch	100

Table 1: Hyper-parameters for training SynG2G-Tr and baselines.

For the dependency parser, we apply the same hyper-parameters as Zhou and Zhao (2019). We use the base learning rate of $2e-3$, and BERT learning rate of $1.5e-5$.

Appendix B Error Analysis

B.A Sentence Length

Model	0-9	10-19	20-29	30-39	40+
BERT	86.93	87.51	87.02	86.39	84.28
BERT+SynEmb	87.57	87.78	86.73	86.84	84.47
SynG2G-Tr	89.47	87.98	87.48	87.27	85.29

Table 2: F1 scores based on the sentence length for the SynG2G-Tr model, and baselines on the development set of CoNLL 2009 dataset.

B.B Dependency Length

Model	1	2	3	4	5	6+
BERT	87.08	88.17	84.92	83.33	82.27	77.66
BERT+SynEmb	87.46	87.97	85.31	82.57	83.98	78.74
SynG2G-Tr	88.02	88.33	86.56	83.35	85.83	79.19

Table 3: F1 scores based on the dependency length for the SynG2G-Tr model, and baselines on the development set of CoNLL 2009 dataset.

B.C Sentence Length on span-based SRL

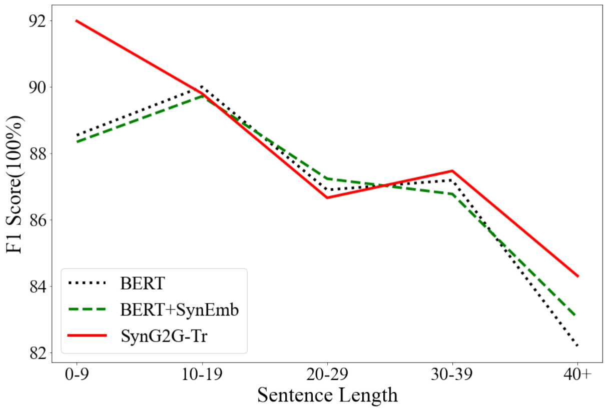

Figure 4: Error analysis of the SynG2G-Tr model, and other alternative models on the development set of CoNLL 2005 dataset.

Model	0-9	10-19	20-29	30-39	40+
BERT	88.54	89.99	86.89	87.18	82.20
BERT+SynEmb	88.34	89.71	87.23	86.77	83.04
SynG2G-Tr	91.98	89.80	86.66	87.47	84.2

Table 4: F1 scores based on the sentence length for the SynG2G-Tr model, and baselines on the development set of CoNLL 2005 dataset.