Abstract

While a number of works showed gains from incorporating source-side symbolic syntactic and semantic structure into neural machine translation (NMT), much fewer works addressed the decoding of such structure. We propose a general Transformer-based approach for tree and graph decoding based on generating a sequence of transitions, inspired by a similar approach that uses RNNs by Dyer et al. (2016). Experiments with using the proposed decoder with Universal Dependencies syntax on English-German, German-English and English-Russian show improved performance over the standard Transformer decoder, as well as over ablated versions of the model.

1 Introduction

The use of structure (mostly syntactic structure) in machine translation has deep roots, dating back to the early days of the field (Lopez, 2008). While the focus has shifted more to string-to-string methods since the introduction of neural methods, considerable work has shown gains from integrating syntactic and semantic structure into NMT technologies, as well as in using similar architectures for other tasks, such as grammatical error correction and code generation (see §7).

Incorporating target-side structure into NMT decoders has been less frequently addressed than source-side structure, possibly due to the additional conceptual and technical complexity it entails, as it requires jointly generating the translation and its structure. In addition to linearizing the structure into a string, that allows easily incorporating source and target-side structure (Aharoni and Goldberg, 2017b; Nadejde et al., 2017), several works generated the nodes of the syntactic tree using RNNs, either in a top-down (Gü et al., 2018; Wang et al., 2018) or a bottom-up manner (Wu et al., 2017). Other works have shown gains from multi-task training of a decoder with a syntactic parser (Eriguchi et al., 2016). However, we are not aware of any Transformer-based NMT architectures to support the integration of target-side structure in the form of a tree or a graph. Addressing this gap, we propose a flexible architecture for integrating a variety of syntactic and semantic structures into a Transformer decoder.

Our approach is based on predicting the output tree/graph as a sequence of transitions (§3), following the transition-based tradition in parsing (Nivre, 2003, and much subsequent work). The method (presented in §4) is based on generating the generated structure as a sequence of transitions. As is customary in transition-based parsers, the parser uses an auxiliary stack in its predictions, and incrementally constructs the output graph. However, unlike standard linearization approaches, our proposed decoder re-encodes the intermediate graph (and not only the generated tokens), thus allowing the decoder to take advantage of the information embedded in the hitherto produced structure in its further predictions.

In §2, we discuss the possibilities offered by such decoders, that do not only auto-regress on their previous outputs, but also on (symbolic) structures defined by those outputs. Indeed, a decoder thus built can condition both on other types of information than the type it predicts (e.g., information from external knowledge bases) and information it predicted at a later stage. We introduce a bidirectional attention mechanism allowing the representation of each word to be dependent on the following words that were predicted. This is similar to the operation of the encoder, where every word can attend to every word, and not only to preceding words.

Our architecture is flexible, supporting decoding into any graph structure for which a transition
system exists. We test two architectures for incorporating the syntactic graph defined by the transitions. One inputs the graph into a Graph Convolutional Network (GCN; Kipf and Welling, 2016) and another dedicates an attention head to point at the syntactic head of each token.

We analyze in §6 the impact of different parts of the architecture, showing improved performance of the full model over its ablated versions, as well as over the vanilla Transformer decoder. Our findings show that the gating mechanism of the GCN is crucial for the results, but also that the contribution of the syntactic labels to the GCN is minor. Overall, we see that the proposed UD-based decoder outperforms the vanilla decoder on English-German (En-De), German-English (De-En) and English-Russian (En-Ru). Improved performance is further observed on the En-De and De-En challenge sets by Choshen and Abend (2019).

2 Decoding Approach

Attention-based models are characterized by being state-less. They can therefore be viewed as conditional language models, namely as models for producing a distribution for the next word, given the generated prefix and source sentence. Unlike RNNs, attention-based models do not inherently rely on past predictions in terms of inputs, weights and gradients (in contrast to methods such as backpropagation through time, standardly used in RNN training);¹ the only connection to past predictions is mediated through their re-encoding back into the decoder.

This architecture, therefore, allows more flexibility than in RNNs, where subsequent predictions are made by different cells of the same network. It is, therefore, possible to re-encode other information (not only the decoded output) into the decoder at each step. It is also possible to change the source sentence partially or completely (e.g., adding noise to increase robustness), condition on additional discrete or continuous information (§4) and change that information for different words, or even encode states given by the previous outputs. One can also predict only tokens of interest, rather than the complete sequence.

Nevertheless, the standard practice is to only re-encode past predictions.² Moreover, existing Transformer implementations impose a further architectural bias, namely not allowing the decoders’ representation of a given token to attend to future tokens. Transformer models for MT mask attention in the following manner (as explained in (Vaswani et al., 2017); we did not find any alternative methods that were explored): token embeddings attend only to previously generated tokens, even when the following tokens are already known. This practice “ensures that the predictions for position i can depend only on the known outputs at positions less than i.”

The Transformer encoder is seen as sequentially producing a sequence of “columns”, one for each token. Each column takes past embeddings into account and the gradients direct past embeddings to be useful also for the current column. In a sense, the Transformer is viewed as an unrolled RNN. While improving computational efficiency, doing so introduces a bias into the model, which is unwanted for our purposes here.

Consider this simple motivating example “The Jaguar drove off”. It seems plausible that a better representation of “Jaguar” may be computed if “drove” is taken into account. To reach this end, representation must be re-computed and improved, as further tokens are generated.

We propose to allow tokens to attend to any known token (see Fig. 1), as done on the encoder side. Due to the motivational resemblance to Bidirectional RNN, we name it Bidirectional Transformer. This is in symmetry to the encoder which is always bidirectional.

Formally, let $X$ be a source sequence and $O = o_1 \ldots o_n$ a predicted sequence. The attention in the vanilla Transformer decoder masks the attention of each token $o_i$ to attend to $o_1 \ldots o_{i-1}$, while our implementation attends to $o_1 \ldots o_n$. This change does not introduce any new parameters or hyperparameters, but still increases the expressivity of the model. We note, however, that this modification does prevent some commonly implemented speed-ups relying on unidirectionality (e.g., in NEMATUS; Sennrich et al., 2017).

¹Transformers do have gradients over-representation of past words, if they are fed into the network. But unlike backpropagation through time, the preceding tokens can be changed. Specifically, in our case, preceding tokens may have different representations at each generation step.

²This is true even in cases of bidirectional generation (e.g., Zhang et al., 2018).
Figure 1: Illustration of the information re-encoded into the decoder with each method. Left: Vanilla. Center: Bidirectional Decoder Right: Structural Decoder. At a given step Bidirectional Decoder attends to all predicted words and Syntactic Transformer predicts edges and receives both edges and graph as input.

3 Transition-based Structure Generation

After setting the stage for a more flexible approach to Transformer decoding, we turn to describe how we represent structure within the proposed decoder.

We take a transition-based approach to generate the target-side structure, motivated by the practical strength of such methods, as well as their sequential nature, which fits well with neural decoders. A similar architecture, based on RNNs, was developed by Dyer et al. (2016). The decoder operates by reintroducing the partial syntax built at a certain timestep as input at the next timestep. As edges and their tokens are not generated simultaneously (but rather by different transitions; see below), we rely on bidirectional attention to update the past embeddings when a new edge connects previously generated tokens. In this section, we will discuss the syntax we output and in the next §4 the ways we incorporate it back into the model.

In this work, we use Universal Dependencies (UD; Nivre et al., 2016) to represent the target-side structure, but note that the framework can be easily adapted to other syntactic and semantic formalisms that have transition-based parsers, including a wide variety of semantic formalisms (Hershcovich et al., 2018; Oepen et al., 2020). We select UD due to its support of a wide variety of languages (over 100 to date) and its status as the de facto standard for syntactic representation in NLP.

We use the arc-standard transition system (Nivre, 2003), which can produce any projective tree. The only difference from the regular arc-standard is that we replace the SHIFT transition (that reads a token from the buffer into the stack) with a generation operation, that generates a new token. When a sub-word is generated, further tokens are generated until a full word is formed.

Formally, assume Σ is a stack of full words created and pushed into it. The possible tokens in the transitions are: tokens from the vocabulary that generates a new sub-word from a dictionary (replaces SHIFT); \textsc{Left-ARC}:label makes the top word in the stack Σ the head of the second word and removes the second; \textsc{Right-ARC}:label makes the second word in the stack Σ the head of the top word and removes the top.

An example translation sequence might be:

Thrill@@ ing paper \textsc{Left-ARC}:amod indeed \textsc{Right-ARC}:advmod . \textsc{Right-ARC}:punct

That corresponds to the output:

\begin{center}
\quad
\end{center}

The transitions are added to the vocabulary of the network. This allows the network to select in the sequence when to create a new word and when to connect words in the graph. There are 45 labels and two directions of connections, summing up to 90 new tokens. This hardly affects the vocabulary size, which usually consists of tens of thousands of tokens. We treat both token and transition predictions in the same way, and do rescale their score as done in Stanojević and Steedman (2020).
It is possible to split the tokens to edges and labels (summing to 47), but this increases the length of the sentences unnecessarily, which is costly in terms of memory consumption. We did not experiment with other methods for encoding the transitions (e.g., embedding labels and edges separately, concatenating, and adding them as token embeddings).

We made two practical choices when creating the graph. First, we deleted the root edge, as the root is not a word in the translation. Second, we train only on projective parses. This choice reduces noise due to the low reliability of current non-projective parsers (Fernández-González and Gómez-Rodríguez, 2018), while not losing many training sentences. We do note, however, that this choice is not without its problems: it might be less fitting for some languages in which non-projective sentences are common.

4 Regressing on Generated Structure

As discussed in §2, the state-less nature of the Transformer allows re-encoding not only the previous predictions, but any information that can be computed based on the previous predictions. So far we proposed a network to predict syntax as a sequence. Converting the output sequence to a graph could be done deterministically, so there is no point training a network to do so. Before generating the next transition, we generate the intermediate graph based on the transitions hitherto generated. The graph is then added as input to a designated architecture. Overall, the input to the network at each step is the source sentence, the predicted tokens, and the intermediate labeled graph. We employ a tree/graph encoder for re-encoding the intermediate graph into the network.

The graph terminals are not only tokens but also the transition tokens. The transition tokens are not connected by edges, which may result in sub-optimal representations for them. Hence, for each edge created by a transition token, the transition token mediates between the head and the dependent, creating new edges between each of them and the transition token. For each transition token $p$ that generates a new edge $(h, d, t)$, an edge $(h, p, t)$ and an edge $(p, d, t)$ are added to the graph. This allows better use of the transition tokens and embedding of the edges and types. Overall, the graph input takes the shape of a sparse matrix $W \in \mathbb{R}^{T \times T}$, where $T$ is the number of terminals.

Another issue with the parse graph is that edges connect words and not tokens. During preprocessing, some words are split into subwords. Hence, given an edge $(h, d, t)$, we duplicate edges and connect every subword $h_i \in h$ to every subword $d_j \in d$ by an edge $(h_i, d_j, t)$, forming a complete bipartite graph between the sub-words.

Our approach is modular and allows for any graph encoding method that is compatible with the Transformer architecture to be used. We here report experiments with two prominent methods for introducing a graph structure to the source side.

GCN Encoder. Graph Convolutional Networks (GCN; Kipf and Welling, 2016) are a type of graph neural network that aims at embedding a graph in a network. GCNs were used effectively to encode source-side syntactic and semantic structure for NMT (Bastings et al., 2017; Marcheggiani et al., 2018). The network learns weights for each type of edge and edge label, and applies them only on the embeddings from the previous layer that are connected to the currently embedded token by the edge of the relevant type and label. The network also contains gates allowing less emphasis or even partially ignoring the syntactic cue if the network chooses so. This is assumed to help in the case of noisy edges which we expect to be generated in our setting more than in regular parsing scenarios. We conduct ablation experiments to assess its impact in §6.2.

Following Kipf and Welling (2016), we introduce three types of edges into the GCN. Self typed edges are edges from each token to itself, while Left and Right are edges to and from the parent tokens respectively. Left and Right encode the directionality of the edges and Self the representation of the token itself in the previous layer.

For a GCN layer over input layer $h$, a node $v$ and a graph $G$ containing nodes of size $d$, with activation function $\rho$, edge directions $\text{dir}$, labels $\text{lab}$, and a function $N$ from a node in the graph to its neighbors is

$$\text{gcn}(h, v, G) = \rho \left( \sum_{u \in N(v)} g_{u,v} \cdot f_{u,v} \right)$$

where $f_{u,v}$ are graph weighted embedding:

$$f_{u,v} = (W_{\text{dir}(u,v)} h_u + b_{\text{lab}(u,v)})$$
and $g_{u,v}$ is the applied gate:

$$g_{u,v} = \sigma \left( h_u \cdot \hat{w}_{\text{dir}}(u,v) + \hat{b}_{\text{lab}}(u,v) \right)$$

where $\sigma$ is the logistic sigmoid function and $\hat{w}_{\text{dir}}(u,v) \in \mathbb{R}^d$, $W \in \mathbb{R}^{d \times d}$, $\hat{b}_{\text{lab}}(u,v) \in \mathbb{R}$, $b \in \mathbb{R}^d$ are the learned parameters for the GCN.

**Attending to Parent Token.** An alternative re-encoding method operates by dedicating one of the attention heads to attend only to the parent(s) of the given token. In common approaches, the parent is given by an external parser (Hao et al., 2019) or learned locally, learning to predict the identity of the parent for each token in each layer, by assigning it most of the attention weight (Strubell et al., 2018). Unlike such approaches, we rely on the predicted graph to provide the parents. A parent might not be unique as discussed at the beginning of this section. Moreover, at a given time, a parent may have not yet been generated. Therefore, we mask all but the parent(s) and the token itself. By attending the token, the network can ignore the parent when preferable.

Parent attention differs from GCN encoders considerably. On the one hand, they require minimal changes to the Transformer architecture. They require much fewer hyperparameters than GCNs and they affect all layers of the network, serving as an attention head rather than an additional embedding. On the other hand, parent attention does not represent labels, uses the Transformer architecture rather than introduces a dedicated one, and represents the parents rather than the whole graph, specifically children. Considering both architectures shows how most suggestions to improve the Transformer encoder (Bastings et al., 2017) may be easily adapted to apply to the decoder. It thus demonstrates the flexibility of the proposed framework for exploring methods for structure-aware NMT.

## 5 Experimental Setup

We experimented on three target languages using De-En, En-De and En-Ru pairs. We used WMT16 data (Bojar et al., 2016) for En-De pair, and either News commentary or Wmt20 data (Barrault et al., 2020) for En-Ru. As test sets, we used newstest 2013, 2014 and 2015 for German and Russian. For development, we used newstest 2012. We used UDPipe English and German over UD 2.0 and Russian with 2.5 with syntagrus version.

We report results with both BLEU and chrF+, and carry out evaluation both on the complete test sets, as well as on the challenge sets extracted by Choshen and Abend (2019). The challenge sets focus on sentences that contain **lexical long-distance dependencies**, cases where two or more words that are not contiguous in the source sentence are translated into a single word. For example, “trat” in German translates to “stepped”, but “trat ... entgegen” translates to “confronted” (and there may be an unbounded number of intervening tokens between the two parts). The challenge sets consist of three test sets for English as the source language, and two for German as the source language. For each phenomenon, they extract a large test set from the sizable books corpus (Tiedemann, 2012), and a smaller one from the news domain (Barrault et al., 2020). Improving the automatic measures on one such challenge set indicates better performance on a specific phenomenon, while better overall performance implies better handling of lexical long-distance dependencies.

Networks are all trained with batch size 128, embedding size 256, 4 decoder and encoder blocks, 8 attention heads (one of which might be a parent head §4), 90K steps (where empirically some saturation is achieved), a learning rate of $1e^{-4}$ with 4K warm-up steps. Optimizing through Adam (Kingma and Ba, 2015) with beta 0.9 and 0.999 for the first and second moment and epsilon of $1e^{-8}$. We use the standard (structure-unaware) Transformer encoder in all our experiments. Each model was trained on 4 NVIDIA Tesla M60 or RTX 2080Ti GPUs for approximately a week. The code is adapted from the NEMATUS code repository (Sennrich et al., 2017).

Preprocessing includes truecasing, tokenization as implemented by Moses (Koehn et al., 2007) and byte pair encoding (Sennrich et al., 2016b) without tying. Empty source or target sentences were dropped. In training, the maximum target sentence length is 40 non-transition tokens (BPE).

Whenever noisy and crawled data is used (WMT20 and Opus corpora) we have found filtering to be crucial for even the baselines to show reasonable results. Specifically, we filter sentences not recognized as belonging to the relevant language by langID (Lui and Baldwin, 2012) or aligned by FastAlign (Dyer et al., 2013) with probability -180 or less. Overall, about half the sentences were filtered by those measures or by...
length.

We use \texttt{chrF++-\textit{py}} with 0 words and beta of 3 to obtain the chrF+ (Popovic, 2017) score as in WMT19 (Ma et al., 2019) results and detokenized BLEU (Papineni et al., 2002) as implemented in Moses. We use two automatic metrics: BLEU as the standard measure and chrF+ as it was shown to better correlate with human judgments, while still being simple and understandable (Ma et al., 2019). Both metrics rely on n-gram overlap between the source and reference, where BLEU focuses on word precision, and chrF+ balances precision and recall and includes characters, as well as word n-grams.

Unable to identify a preexisting implementation, we implemented labeled sparse GCNs with gating in Tensorflow. Implementation mostly focused on memory considerations, and was optimized for runtime when possible.

6 Experiments

We now proceed to assess the contribution of the different parts of the architecture. We start by assessing the contribution of bidirectional attention, experimenting with En-De and De-En translations (§6.1). Then, the contribution of the component parts of the system is assessed in §6.2 through ablation experiments.

6.1 Results on En-De and De-En

Our main results on En-De and De-En are presented in Table 1. Results show that both on En-De and De-En (see also En-RU in §6.3), the UD-based decoders (GCN and Parent rows) show better performance over the vanilla decoder. We also see a slight advantage to the GCN decoder on De-En, and an advantage to Parent on En-De.

Table 2 presents results on the challenge sets. We find that in all German to English and 9 of 12 cases in English-German the syntactic variants improve over the non-syntactic variants (whether unidirectional or not).

When considering the syntactic variants together, they invariably outperform the vanilla decoder, one of which scores best in most challenges and test sets.

6.2 Ablation Experiments

In order to better understand the contribution of different parts of the architecture and to compare them, we consider various ablated versions. In one, we train the Transformer over a series of transitions. This is reminiscent of the approach taken by (Aharoni and Goldberg, 2017b; Nadejde et al., 2017), albeit with a different type of linearization. This variant corresponds to the \textit{Linearized} in Tables 1 and 2.

The results of this experiment are mixed. Overall results are not better than bi/unidirectional Transformer. In terms of BLEU, they are also lower, while on all syntactic challenge sets it does improve. That shows that while overall cases did not improve, the network did manage to better cope with the challenging syntactic sentences. Moreover, it shows that improvement in the average score does not guarantee improvement over the challenge sets, which target rare but potentially important phenomena in the long tail.

We turn to experimente with ablated versions of the GCN decoder, and compare them against the full GCN decoder. The ablated versions are denoted \textit{Unlabeled}, which ignores the labels of the graph, and relies only on the graph structure. The last, denoted \textit{Ungated}, also relies solely on the graph structure but does not include the gating in the architecture. Gating was hypothesized to be important to avoid over-reliance on the graph in cases of errors (Bastings et al., 2017; Hao et al., 2019). As our graphs are generated by the network, rather than fed into it by an external parser, this is a good place to check this hypothesis.

We find that labels hardly contribute to the results, accounting for a 0.09 BLEU change on average in En-De and none on De-En. We note, that interpreting this result is not trivial, and one should not conclude, based on these results alone that syntactic labels are redundant. There are two technical points to consider. First, the labels are still found as tokens from past predictions, and hence have token embeddings which might compensate for the GCN architecture’s disregard of labels. Second, the role of the labels in GCNs is small, as they contribute a large number of hyperparameters while only changing a bias term, it is likely that this is an inefficient way of using labels which should be addressed in future work.

Unlike labels, gating appears to be crucial to the results. The Ungated models achieve lower results than the Unlabeled variants in 8/10 cases in both directions and an overall lower BLEU. This might indirectly support the hypothesis that when the parse contains errors, it is important to allow
|          | 2013 BLEU | 2014 chrF+ | 2015 BLEU | 2015 chrF+ | Average BLEU | Average chrF+ |
|----------|-----------|------------|-----------|------------|--------------|---------------|
| Vanilla  | 18.82     | 45.57      | 19.38     | 47.37      | 20.99        | 47.56         |
| BiTrans  | 18.88     | 45.67      | 19.47     | 47.60      | 20.82        | 47.65         |
| Parent   | **18.99** | **46.55**  | 20.99     | **47.56**  | **21.56**    | **48.97**     |
| GCN      | 18.91     | 46.23      | 19.59     | 48.25      | 21.37        | 48.68         |
| -Gates   | 18.70     | 45.93      | 19.20     | 47.92      | 20.98        | 48.40         |
| -Labels  | 18.86     | 46.21      | 19.51     | 48.09      | 20.94        | 48.51         |

(a) Test sets for English-German translation

|          | 2013 BLEU | 2014 chrF+ | 2015 BLEU | 2015 chrF+ | Average BLEU | Average chrF+ |
|----------|-----------|------------|-----------|------------|--------------|---------------|
| Vanilla  | 22.90     | 47.93      | 22.72     | 48.22      | 22.93        | 47.89         |
| BiTrans  | 23.02     | 48.21      | 22.75     | 48.65      | 22.94        | 48.35         |
| Parent   | **23.36** | 48.80      | 22.68     | 49.07      | 23.08        | 48.93         |
| GCN      | 23.28     | 48.85      | **22.79** | **49.39**  | **23.51**    | **49.39**     |
| -Gates   | 23.19     | 48.87      | 22.78     | 49.31      | 22.94        | 49.03         |
| -Labels  | 23.20     | **49.04**  | 22.59     | 49.39      | 23.14        | 49.20         |

(b) Test sets for German-English translation

Table 1: Results on English to German (Top) and German to English (Bottom) translation systems. Results are reported on newstest 2013-15. Ablated models include the Transformer decoder with linearized syntax (Linearized), GCN without labels or gating (-Gates) and GCN without labels (-Labels). The syntactic variants consistently outperform the vanilla and ablated variants, and the Bidirectional Transformer (BiTrans) slightly outperforms Vanilla Transformer.

In the network not to rely on it. It also hints at a possible improvement for the Parent model, by introducing similar mechanisms to it.

A small but consistent improvement is observed when using the bidirectional attention alone (see also En-RU in §6.3). Indeed, the bidirectional attention model outperforms the vanilla Transformer in two of the three En-De datasets and in the three De-En ones in terms of BLEU scores, and in all datasets in terms of chrF+.

We observe a similar trend in the challenge sets (Table 2): bidirectional attention improves results in fifteen of twenty syntactic challenge set scores across both translation directions. We may conclude and say that bidirectionality by itself is beneficial to some extent, in general, and specifically for aggregating the syntactically correct context tokens.

As a next step, we compare GCN and its ablated versions to Parent attention. Like unlabeled GCNs, Parent does not rely on the labels and provides a different way to incorporate the graph, which is shown to be successful without the labels. We remind that while labels are not incorporated, they are still found as input tokens, and are attended to by the attention heads. Comparing the two architectures, Parent attention shows significant gains over Unlabeled GCN. Despite being easier to implement and being much lighter in terms of memory, time and hyperparameters, Parent outperforms Unlabeled GCN in both performance and specific challenges. It outperforms Unlabeled GCN in terms of BLEU in most test sets on English-German and all chrF+. On English-German Parent is slightly better but it is slightly worse in German-English. It improves 3 out of the 5 German-English phenomena and non of the English-German when compared to the GCN variant.

These results paint a rough picture of a precedence: where Parent fares bests, then GCNs, then bidirectional attention, and finally the vanilla uni-
Table 2: Results on the syntactic challenge sets, both on the large challenges from book domain and the smaller ones from news. Models include Vanilla and Bidirectional Transformer baselines (top) and the GCN and Parent syntactic variants (middle). Ablated models (bottom) include the Transformer decoder with linearized syntax (Linearized), GCN without labels or gating (-Gates) and GCN without labels (-Labels). Among the baselines, BiTrans is better. It is inconclusive which syntactic method is best, but they are clearly superior to the baselines.

|                    | Books BLEU | Books chrF+ | News BLEU | News chrF+ | Books BLEU | Books chrF+ | News BLEU | News chrF+ |
|--------------------|------------|-------------|-----------|-------------|------------|-------------|-----------|-------------|
| Vanilla            | 5.95       | 25.19       | 5.37      | 23.93       | 5.32       | 23.98       | 5.71      | 25.38       |
| BiTrans            | 5.30       | 25.67       | 10.56     | 37.61       | 6.07       | 25.21       | 10.21     | 39.07       |
| Parent             | 6.21       | 27.34       | 11.17     | 40.49       | 5.47       | 24.83       | 11.93     | 40.40       |
| GCN                | 6.21       | 26.45       | 11.31     | 40.07       | 5.51       | 24.60       | 10.35     | 39.20       |
| -Gates             | 5.29       | 25.09       | 11.64     | 40.16       | 5.30       | 24.11       | 10.01     | 37.87       |
| -Labels            | 5.83       | 26.36       | 8.62      | 37.90       | 5.41       | 24.70       | 11.98     | 41.13       |

(a) Syntactic challenge sets for German-English

|                    | Books BLEU | Books chrF+ | News BLEU | News chrF+ | Books BLEU | Books chrF+ | News BLEU | News chrF+ |
|--------------------|------------|-------------|-----------|-------------|------------|-------------|-----------|-------------|
| Vanilla            | 7.15       | 26.54       | 17.79     | 44.20       | 6.83       | 25.73       | 19.68     | 44.31       |
| BiTrans            | 7.02       | 26.51       | 18.58     | 44.35       | 6.80       | 25.84       | 19.87     | 45.16       |
| Parent             | 7.82       | 27.25       | 19.66     | 45.48       | 7.49       | 26.55       | 20.97     | 46.22       |
| GCN                | 7.32       | 26.57       | 20.13     | 46.06       | 7.11       | 26.11       | 20.68     | 46.36       |

(b) Syntactic challenge sets for English-German

6.3 Results on English-Russian

We evaluate the Parent syntactic architecture on English-Russian translation, comparing it to the vanilla Transformer. We select Russian as it is typologically more distant to English than German, and because relatively high-quality parallel data and UD parsers are available.

Results show similar trends to those observed on En-De and De-En. We find that the bidirectional Transformer slightly improves over the vanilla Transformer and the Parent syntactic variant further improves, achieving a 1.11 BLEU and 2.42 chrF+ improvement. In summary, we find that adding syntax to the decoder improved results in all three target languages that we experimented with.

7 Related Work

While there are indications that Transformers implicitly learn some syntactic structure when trained as language models or as NMT systems given sufficient training data (e.g., Jawahar et al., 2019; Manning et al., 2020), it is not at all clear whether such information replaces the utility of incorporating syntactic structure. Indeed, a considerable body of work suggests the contrary.

Much previous work tested RNN-based and attention-based systems for their ability to make syntactic generalizations. They showed that systems face difficulties when tested on their ability to generalize when generalizations based on syntactic structure is required of them (Ravfogel et al., 2019; McCoy et al., 2019). Moreover, while in
Table 3: Results on English-Russian. Results are reported on newstest 2013-15. Models include Vanilla and Bidirectional Transformer as well as Parent syntactic variant. The syntactic architectures improve over all datasets and on average.

|            | BLEU 2013 | chrF+ 2013 | BLEU 2014 | chrF+ 2014 | BLEU 2015 | chrF+ 2015 | Average |
|------------|-----------|------------|-----------|------------|-----------|------------|---------|
| Vanilla    | 13.20     | 38.71      | 17.17     | 43.88      | 14.19     | 40.90      | 15.12   |
| BiTrans    | 13.13     | 39.04      | 17.63     | 44.81      | 14.59     | 41.58      | 15.12   |
| Parent     | 13.61     | 40.60      | 18.53     | 46.57      | 15.75     | 43.58      | 15.96   |

many cases NMT systems do succeed in correctly translating sentences containing inter-dependent albeit linearly distant words, their performance is unstable: the same systems may well fail on other “obvious” cases of the same phenomena (Isabelle et al., 2017; Belinkov and Bisk, 2017; Choshen and Abend, 2019). This evidence provides motivation for efforts such as ours, to incorporate linguistic knowledge into the architecture.

Syntactic structure was used to improve various tasks, including code generation (Chakraborty et al., 2018), question answering (Bogin et al., 2020), automatic proof generation (Gontier et al., 2020) and grammatical error correction (Harer et al., 2019). Such approaches, however, may not be readily used in machine translation. For example, the latter makes very strong conditional independence assumptions, and seems less suitable for MT where the source and target side syntax may diverge considerably.

In NMT, some works aimed to use structural cues by reinforcement learning (Wieting et al., 2019), but the gain from such methods seems to very much constrained by the performance presented by the pre-trained model (Choshen et al., 2020). Aharoni and Goldberg (2017a) proposed to linearize constituency parsing and replace the source and target tokens by the linearized graph. Nadejde et al. (2017) proposed a similar approach using CCG parses. Eriguchi et al. (2016) proposed a recursive neural network architecture to encode the source syntax. Some works suggested modifications to the RNN architecture for NMT that encodes source-side syntax (Chen et al., 2017, 2018; Li et al., 2017). Song et al. (2019) used a graph recurrent network to encode source-side AMR structures. Few works suggested changes in the Transformer to incorporate source-side syntax: Nguyen et al. (2020) and Bugliarello and Okazaki (2020) proposed a tree-based attention mechanism to encode source syntax, while Zhang et al. (2019) incorporated the first layers of a parser in addition to the source-side token embeddings.

A parallel line of work used syntactic information in order to preprocess the data, improving results. Zhou et al. (2019a) used word order typological features and syntactic parses in order to create training data that is syntactically similar to the target language. Ponti et al. (2018) used rule-based manipulations of the UD structure of the input, so as to make it less divergent with the target side.

Much fewer works focused on structure-based decoding. Eriguchi et al. (2017), building on Dyer et al. (2016), train a decoder in a multi-task setting of translation and parsing. We note that unlike in the method we propose here, the generated translation in their case is not constrained by the parse during the decoding, but rather the two tasks are not related through their joint training. Few works proposed alternating between two connected RNNs one translating and one creating a linearized graph using a tree-based RNN (Wang et al., 2018) or transition-based parsing (Wu et al., 2017). Gü et al. (2018) both parse and generate, using a recursive RNN representation.

Somewhat similar to the bidirectional attention we employ is non-monotonic translation in which translation is not done left-to-right (Welleck et al., 2019; Emelianenko et al., 2019; Chan et al., 2020). In such works, the network receives a position and a context of other positions and tokens, and predicts a token for the given position. However, such work mainly focuses on selecting the order of prediction, not on what is the network learning and representing. Another related line of work use two separate decoders, and combines their results in various ways (Liu et al., 2016; Sennrich et al., 2016a; Zhang et al., 2018). Recently, Zhou et al. (2019b) proposed to have two unidirectional decoders, one of which is decoding in reverse order (rightmost token first), and uses both, where the beam search alternates between predicting a token...
from the end or the start.

Other work changed the RNN (Tai et al., 2015) or Transformer architecture to include structural inductive biases, but without explicit syntactic information. Wang et al. (2019) suggested an unsupervised way to train Transformers that learn treelike structures following the intuition that such representations are more similar to syntax than unrestricted self-attention. Shiv and Quirk (2019) altered the positional embeddings to allow encoding tree-structured data.

8 Discussion

Several motivations drive us towards this work, which aims to combine linguistic representation and improvements to the Transformer decoder. Expert human translators are native in the target language, but don’t have to be so in the source language. This makes one wonder, why most effort ignores the role of decoders for translation.

The second motivation is that Transformers for Machine Translation (MT) are trained in the same way that former sequence to sequence models are trained (e.g., RNNs) and to many, they are just a better architecture for the same task. We challenge this view, and emphasize the possibility of conditional training using Transformers; namely, Transformers should be able to predict the third token given the first two, even without previously predicting them. Although mostly not implemented as such, Transformers are already conditional networks, and allow for flexibility not found in RNNs.

Another motivation for conditional Transformers is the finding that MT quality differs between beginnings and ends of predicted sentences both in recurrent networks and in attention-based ones (Liu et al., 2016; Zhou et al., 2019b). This is often explained by lack of context and disregard to the future tokens. This future context is used by humans (Xia et al., 2017) and may help translations (Tu et al., 2016; Mi et al., 2016). The encoded input is the same throughout the prediction, so the varying performance is likely due to the decoder. Attending to all predictions, as we propose here, aims to provide more of this required information.4

Finally, previous work raised questions about the reasons for which incorporating source syntax help RNNs (Shi et al., 2018) and Transformers (Pham et al., 2019; Sachan et al., 2020) systems. These works failed to see improvement between incorporating (source) syntax and using a similar architecture without doing so, i.e., incorporating a non-syntactic predefined tree/graph structure. A hypothesis followed, that graph-like architectures are helpful, but the syntactic information is redundant. In our experiments, we observed that the Parent architecture achieves gains over the bidirectional decoding without further architectural changes. These benefits from syntactic information challenge this hypothesis.

9 Conclusion

We presented a novel flexible method for constructing decoders capable of outputting trees and graphs. While there have been several works on source-side tree and graph encoding, much fewer works addressed target-side structure, especially using an attention-based architectures. Our work addresses this gap.

Our proposal is based on two main modifications to the standard Transformer decoder: (1) autoregression on structure; (2) bidirectional attention in the decoder, which allows recomputing token embeddings in light of newly decoded tokens. In both cases, the system presented superior results over the vanilla Transformer decoder, as well as over ablated versions of the decoder. The method is flexible enough to allow outputting a wide variety of graph and tree structures.

This work opens many avenues for future work. One direction would be to focus on conditional networks, training with (intentionally) noisy prefixes, randomly masking "predicted" spans during training (as done in masked language models, Devlin et al., 2019) and data augmentation through hard words or phrases rather than full sentences. Another might focus and enhance bidirectionality by allowing regretting and changing past predictions. Finally, the work opens possibilities for better incorporating structure into language generators, of incorporating semantic structure and of enforcing meaning preservation (thus targeting hallucinations, Wang and Sennrich, 2020), by incorporating source and target structure together.

4We do note, that for the very first generated tokens, bidirectional attention will not help, as there is nothing to attend to.
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