Abstract

We present a novel encoder-decoder architecture for graph-to-text generation based on Transformer, called the Graformer. With our novel graph self-attention, every node in the input graph is taken into account for the encoding of every other node – not only direct neighbors, facilitating the detection of global patterns. For this, the relation between any two nodes is characterized by the length of the shortest path between them, including the special case when there is no such path. The Graformer learns to weigh these node-node relations differently for different attention heads, thus virtually learning differently connected views of the input graph. We evaluate the Graformer on two graph-to-text generation benchmarks, the AGENDA dataset and the WebNLG challenge dataset, where it achieves strong performance while using significantly less parameters than other approaches.\footnote{We will make our code available upon publication.}

1 Introduction

A knowledge graph (KG) is a flexible data structure commonly used to store both general world knowledge (Auer et al., 2008) and highly specialized information, such as biomedical findings (Wishart et al., 2018) or formal representations of visual content (Krishna et al., 2016). Generating a natural language summarization of such a graph (KG→text) makes the stored information accessible to a broader audience of end users. It is therefore important for KG-based question answering (Bhowmik and de Melo, 2018), data-to-document generation (Moryossef et al., 2019; Koncel-Kedziorski et al., 2019) and interpretability of KGs in general (Schmitt et al., 2020).

Recent approaches to KG→text employ encoder-decoder architectures where the encoder first computes a vector representation of the graph’s nodes, which the decoder then uses to predict the text sequence. Typical encoder choices are graph neural networks based on message passing between direct neighbors in the graph (Kipf and Welling, 2017; Veličković et al., 2018) or variants of Transformer (Vaswani et al., 2017) that apply self-attention on all nodes together, whether they are directly connected or not.

We propose a flexible alternative to these two extreme approaches, a Transformer-based encoder that, by means of multi-head attention, dynamically learns different views of the input graph with differently weighed connection patterns. We combine this encoder with a Transformer-based decoder augmented with a copy mechanism. Allowing the model to directly copy from the source to the target side has been found beneficial in data to text generation (Wiseman et al., 2017) but only few Transformer-based architectures make use of it so far (Cai and Lam, 2020). We call our new architecture the Graformer.

Following previous work, we evaluate the Graformer on two benchmarks: (i) the AGENDA dataset (Koncel-Kedziorski et al., 2019), i.e., the generation of scientific abstracts from automatically extracted entities and relations specific to scientific text, and (ii) the WebNLG challenge dataset (Gardent et al., 2017), i.e., the task of generating text from DBPedia subgraphs. On both datasets, the Graformer achieves strong performance while using significantly fewer parameters than alternative models.

2 The Graformer Model

Our proposed architecture follows the general multi-layer encoder-decoder pattern known from the original Transformer (Vaswani et al., 2017). In the following, we describe our formalization of the KG input and how it is processed by Graformer.
2.1 Graph data structure

Knowledge graph. We formalize a knowledge graph (KG) as a directed, labeled multigraph
\[ G_{KG} = (V, A, s, t, l_V, l_A, L_V, R) \]
with \( V \) a set of vertices (the KG entities), \( A \) a set of arcs (the KG facts), \( s, t : A \rightarrow V \) functions assigning to each arc its source/target node (the subject/object of a KG fact), and \( l_V : V \rightarrow L_V, l_A : A \rightarrow R \) providing labels to vertices and arcs, where \( R \) is the set of KG-specific relations and \( L_V \) the set of entity names.

Token graph. Entity names usually consist of more than one token or subword unit. Hence, a
tokenizer \( t : L_V \rightarrow \Sigma^* \) is needed, which splits an entity’s label into its components. Following recent
work (Ribeiro et al., 2020), we mimic this compositionality of node labels in the graph structure by splitting each node into as many nodes as there are tokens in its label. We thus obtain a directed hypergraph
\[ G_T = (V_T, A, s_T, t_T, l_T, l_A, \Sigma, \text{same}) \]
where \( s_T, t_T : A \rightarrow \mathcal{P}(V_T) \) now assign a set of source (resp. target) nodes to each (hyper)arc and all nodes are labeled with only one token, i.e., \( l_T : V_T \rightarrow \Sigma \). Unlike Ribeiro et al. (2020), we additionally keep track of all token nodes’ origin:
\[ \text{same} : V_T \rightarrow \mathcal{P}(V_T \times \Sigma) \]
assigns to each node \( n \) all other nodes \( n’ \) stemming from the same entity together with the relative position of \( l_T(n) \) and \( l_T(n') \) in the original tokenized entity name. Figure 1b shows the corresponding token graph to the KG in Fig. 1a.

Incidence graph. For ease of implementation, our final data structure for the KG is the hypergraph’s
incidence graph, a regular bipartite graph where hyperarcs are represented as nodes and edges are unlabeled: \( G = (N, E, l, \Sigma, R, S) \) with the set of nodes \( N = V_T \cup A \), the set of directed edges \( E = \{ (n_1, n_2) \mid n_1 \in s_T(n_2) \lor n_2 \in t_T(n_1) \} \) and a label function \( l : N \rightarrow \Sigma \cup R \). We fully connect \( \text{same} \) clusters with special \( \text{SAME}_p \) edges:
\[
\text{SAME}_p = \{ (n_1, n_2) \mid (n_2, p) \in \text{same}(n_1) \}
\]
where \( p \) differentiates between different relative positions in the original entity string. See Fig. 1c for an example.

2.2 Graformer encoder

The initial graph representation \( h^0 \in \mathbb{R}^{|N| \times d} \) is a learned embedding \( W_{emb} \in \mathbb{R}^{|\Sigma| \times d} \) of the node labels: \( h^0 = l(i)W_{emb} \) where \( i \)’s label is used interchangeably with its one-hot-encoding.

The node representation \( h^L \) in the \( L \)th layer is then computed by multi-head self-attention
\[ \text{SelfAtt}_C \] with a residual connection and a layer normalization step \( LN \) followed by a feedforward layer \( FF \) similar to a regular transformer encoder:
\[
h^L = FF(LN(h^{L-1} + \text{SelfAtt}_C(h^{L-1}))) \quad (1)
\]

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Different representations of the same KG (types are omitted for clarity).}
\end{figure}
Analogously to self-attention on text, we define our structural graph self-attention as follows:

\[
\alpha_{ij} = \text{softmax}\left(\frac{h_i W_{enc}^Q (h_j W_{enc}^K + a_{ij}^V)^	op}{\sqrt{d}} + gpos(R_{ij})\right)
\]

Figure 2: \( R \)-matrix for the incidence graph in Fig. 1c with \( D_{\text{max}} = 3 \).

For \( W_{enc}^V, W_{enc}^K, W_{enc}^Q \in \mathbb{R}^{d \times d} \) are learnable matrices and \( gpos : \mathbb{Z} \rightarrow \mathbb{R} \) is a learnable embedding of the relative position \( R_{ij} \) between nodes \( i, j \).

We define \( R \) with respect to two factors: (i) the text relative position \( p \) in the original entity name if \( i \) and \( j \) stem from the same original entity, i.e., \( (i, j) \in \text{SAME}_p \) for some \( p \) and (ii) shortest path lengths otherwise:

\[
R_{ij} = \begin{cases} 
0, & \text{if } i \text{ unreachable from } j \\
\text{encode}(p), & \text{if } (i, j) \in \text{SAME}_p \\
-\delta(j, i), & \text{if } \delta(j, i) < \delta(i, j) \\
\delta(i, j) + 1, & \text{if } \delta(i, j) \leq \delta(j, i)
\end{cases}
\]

where \( \delta(i, j) \) is the length of the shortest path between \( i \) and \( j \) and \( \text{encode} \) maps text relative positions \( p \in \mathbb{Z} \setminus \{0\} \) to a certain range of \( R \) encodings to avoid clashes. Concretely, we use \( \text{encode}(p) := \text{sgn}(p) \cdot (D_{\text{max}} + 1) + p \) where \( D_{\text{max}} \) is the maximum value of \( \delta \) over all graphs in consideration, i.e., the maximum graph diameter.

Thus, graph relative position is modeled as the length of the shortest paths using either only forward edges \( (R_{ij} > 0) \) or only backward edges \( (R_{ij} < 0) \). Additionally, two special cases are considered: (i) nodes without any purely forward or purely backward path between them \( (R_{ij} = 0) \) and (ii) token nodes originating from the same entity. Here the relative position in the original entity string \( p \) is encoded outside the range of path length encodings (which are always in the interval \( [-D_{\text{max}}, D_{\text{max}}] \)).

In practice, we use two thresholds, \( n_\delta \) and \( n_p \). All values of \( \delta \) exceeding \( n_\delta \) are set to \( n_\delta \) and analogously for \( p \). This limits the number of different
2.4 Graformer decoder
2.4.1 Hidden decoder representation
The initial decoder representation \( z^0 \in \mathbb{R}^{M \times d} \) embeds the partially generated target text \( t \in \mathbb{R}^{M \times |\Sigma|} \), i.e., \( z^0 = tW_{emb} \). A decoder layer \( L \) then obtains a contextualized representation via self-attention \( v^L = \text{SelfAtt}_T(z^{L-1}) \). \text{SelfAtt}_T \) differs from \text{SelfAtt}_G \) by using different position embeddings in Eq. (6) and, obviously, \( \tau_{ij} \) is defined in the usual way for text.

Then \( v \) is modified via multi-head attention on the last layer of the graph encoder. As in the original Transformer, we employ a residual connection around this attention sub-layer, followed by layer normalization \( LN \) and a feedforward layer to obtain the final representation:

\[
\begin{align*}
    u &= M\text{HAtt}(v, h^L) + v \quad (8) \\
    z &= LN(FF(LN(u)) + LN(u)) \quad (9)
\end{align*}
\]

where

\[
M\text{HAtt}(x, h)_i = \sum_{j=1}^{N} \alpha_{ij}(h_jW^V_{dec})
\quad (10)
\]

\[
\alpha_{ij} = \text{softmax}(\frac{x_iW^Q_{dec}(h_jW^K_{dec})^\top}{\sqrt{d}})
\quad (11)
\]

2.4.2 Copy Mechanism
We employ the copy mechanism from (Zhu et al., 2020). The copy scores \( c \) are taken from the attention mechanism in the last decoder layer, i.e., \( c = \alpha \) from Eq. (11) averaged over heads. The probability \( P_{copy} \) of copying the next word vs. generating it from the vocabulary is computed in terms of the final representation \( z^D \) of the last decoder layer \( D \):

\[
P_{copy} = \sigma(z^D W_{copy} + b_{copy})
\quad (12)
\]

2.4.3 Final generation distribution
The final representation \( z^D \) is equally used to compute \( g \in \mathbb{R}^{T \times |\Sigma|} \), the probabilities for generating a word from the vocabulary \( \Sigma \) as in the original transformer:

\[
g = \text{softmax}(z^D W_{emb}^\top)
\quad (13)
\]

The final probability of generating word \( w_j \) at time step \( i \) is:

\[
p(y_i = w_j) = \text{softmax}(\gamma_{ij})
\quad (14)
\]

where

\[
\gamma_{ij} = (1 - P_{copy})g_{ij} + P_{copy} \sum_{k \in N} c_{ik}
\quad (15)
\]

2.5 Training
We train the Graformer with the standard negative log-likelihood loss \( \mathcal{L}_{\text{NLL}} \) based on the likelihood estimations described in Section 2.4.3. As it is important to cover the whole graph input, we additionally introduce a coverage loss \( \mathcal{L}_{\text{cov}} \) inspired by the coverage penalty from (Wu et al., 2016). It penalizes decoders that – averaged over layers and summed over decoding steps – put less attention than 1.0 on some of their input nodes.

\[
\alpha^\mu = \frac{1}{D} \sum_{L=1}^{D} \alpha^L
\quad (16)
\]

\[
\mathcal{L}_{\text{cov}} = -\frac{1}{|N|} \sum_{j} \log(\min(1.0, \sum_{i} \alpha^\mu_{ij}))
\quad (17)
\]

The final loss is then defined as follows:

\[
\mathcal{L} = \mathcal{L}_{\text{NLL}} + \lambda_{\text{cov}} \mathcal{L}_{\text{cov}}
\quad (18)
\]

3 Experiments
3.1 Datasets
We evaluate our new architecture on two popular benchmarks for KG-to-text generation, AGENDA (Koncel-Kedziorski et al., 2019) and WebNLG (Gardent et al., 2017). While the latter contains crowd-sourced texts corresponding to subgraphs from various DBPedia categories, the former was automatically created by applying an information
We also report statistics that depend on the tokeniz- 
ation protocol of the original challenge by convert-
ing all characters to lowercased ASCII and separat-
ing all punctuation from alphanumeric characters 
during tokenization.

For both datasets, we train a BPE vocabulary 
using sentencepiece (Kudo and Richardson, 2018) 
on the whole training data, i.e., a concatenation 
of node labels and target texts. See Table 1 for 
vocabulary sizes.

### 3.3 Hyperparameters and training details

We train the Graformer with the Adafactor optimi-
zizer (Shazeer and Stern, 2018) and use the model 
yielding the best validation performance measured 
in corpus-level BLEU (Papineni et al., 2002). For 
hyperparameter optimization, we use a combina-
tion of manual tuning and a limited number of 
randomly sampled runs. For the latter we apply 
optuna (Akiba et al., 2019) with TPE-sampling 
(Bergstra et al., 2011) and median pruning, i.e., af-
ter each epoch of a particular hyperparameter run 
we check if its so-far best performance is worse 
than the median performance of previous runs at 
the same epoch and if so, abort it.

We apply a data loading scheme inspired by the 
bucketing approach by Koncel-Kedziorski et al. 
(2019) and length-based curriculum learning (Pla-
tanios et al., 2019): We sort the train set by target 
text length and split it into four buckets of two times 
40% and two times 10% of the data. After each 
training epoch, the buckets are shuffled internally 
but their global order stays the same from shorter 
target texts to longer ones. This reduces padding 
during batching as texts of similar lengths stay to-
gether and introduces a mini-curriculum from pre-
sumably easier examples (i.e., shorter targets) to 
more difficult ones for each epoch.

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### Table 1: Statistics of AGENDA and the original dataset from the WebNLG challenge as used in our experiments.

|                | AGENDA | WebNLG |
|----------------|--------|--------|
| #instances in train | 38,719 | 18,102 |
| #instances in val   | 1,000  | 872    |
| #instances in test  | 1,000  | 971    |
| #relation types     | 7      | 373    |
| avg #entities in KG | 13.4   | 4.0    |
| avg #graph components | 2.2   | 1.0    |
| % connected graphs  | 31.3   | 99.9   |
| avg #token nodes in graph | 98.0  | 36.0   |
| avg #tokens in text | 157.9  | 31.5   |
| avg % text tokens in graph | 42.7  | 56.1   |
| avg % graph tokens in text | 48.6  | 49.0   |
| Vocabulary size     | 24,100 | 2,100  |

### Table 2: Experimental results on AGENDA. GT (Graph Transformer) from (Koncel-Kedziorski et al., 2019); GT+RBS from (An et al., 2019); PGE-LW and CGE-RP from (Ribeiro et al., 2020). Number of parameters in millions.

|                | BLEU | METEOR | CHRF++ | #P |
|----------------|------|--------|--------|----|
| Ours           | 17.33±0.94 | 21.43±0.85 | 44.53±1.50 | 21.2|
| GT             | 14.30±1.01 | 18.80±0.28 | –      | –  |
| GT+RBS         | 15.1±0.97  | 19.5±0.29 | –      | –  |
| PGE-LW         | 17.40±0.08 | 22.06±0.09 | 46.19±0.16 | 67.7|
| CGE-RP         | 17.81±0.15 | 21.75±0.55 | 46.76±0.12 | 66.9|
Table 3: Experimental results on the WebNLG test set with seen categories. CGE from (Ribeiro et al., 2020); Adapt, Melbourne and UPF-FORGe from (Gardent et al., 2017); Graph Conv. from (Marcheggiani and Perez-Beltrachini, 2018); GTR-LSTM from (Trisedya et al., 2018); E2E GRU from (Castro Ferreira et al., 2019). Number of parameters in millions.

| Model          | BLEU   | METEOR | CHRF++ | #P  |
|----------------|--------|--------|--------|-----|
| CGE-RP         | 62.30  | ±0.27  | 43.51  | ±0.18| 75.49 ±0.34 | 13.9 |
| CGE-LG         | 63.10  | ±0.13  | 44.11  | ±0.09| 76.33 ±0.10 | 12.8 |

Table 3: Experimental results on the WebNLG test set.

4 Results and Discussion

Table 2 shows our evaluation on AGENDA in terms of BLEU, METEOR (Banerjee and Lavie, 2005), and CHRF++ (Popović, 2017) scores. Like the models we compare with, we report the average and standard deviation of 4 runs with different random seeds.

Our model outperforms previous Transformer-based models that only consider first-order neighborhoods per encoder layer (Koncel-Kedziorski et al., 2019; An et al., 2019). Compared to the very recent models by Ribeiro et al. (2020), the Graformer shows similar performance. Ribeiro et al. (2020) use a combination of two graph encoders, one of which sees a fully connected version of the input graph. This allows their models to combine information from very distant nodes but at the same time needs extra parameters for the second encoder. The Graformer is more efficient, using less than one third of their parameters, while achieving similar performance.

The results on the test set of seen categories of WebNLG (Table 3) show a similar picture. Our model shows a very competitive performance compared to both the original challenge participants and more recent work. Only the very strong Adapt model (Gardent et al., 2017) leveraging subword information and minimum risk training (Shen et al., 2016), as well as the corresponding models by Ribeiro et al. (2020) perform better. Compared to the latter, the Graformer is again more efficient in its use of parameters, using only about 60% of their parameter count, but does not perform on par on this dataset.

We hypothesize that this is due to the different properties of the two datasets. While the graphs in WebNLG are human-authored subgraphs of DBpedia, the graphs in AGENDA were automatically extracted. This leads to a higher number of graph components without any connections between them. Table 1 shows that nearly all WebNLG graphs consist of a single connected component, i.e., are connected graphs, whereas for AGENDA this is only the case for less than a third. The Graformer can distinguish between distant but connected nodes and those without any paths between them while the global encoder in (Ribeiro et al., 2020) cannot. This ability might be more helpful on AGENDA than WebNLG.

5 Related Work

Graph encoder. Most recent approaches to graph-to-text generation employ a graph neural network (GNN) based on message passing through the input graph’s topology (Kipf and Welling, 2017; Veličković et al., 2018) as encoder in their encoder-decoder architectures (Marcheggiani and Perez-Beltrachini, 2018; Koncel-Kedziorski et al., 2019; Ribeiro et al., 2019; Guo et al., 2019). As one layer of these encoders only considers immediate neighbors, a large number of stacked layers can be necessary to learn about distant nodes, which in turn also makes an encoder more prone to propagate noise (Li et al., 2018).

Other approaches (Zhu et al., 2019; Cai and Lam, 2020) base their encoder on the Transformer architecture (Vaswani et al., 2017) and thus, in each layer, compute self-attention on all nodes, not only direct neighbors, facilitating the information flow between distant nodes. Like our Graformer, these approaches incorporate information about the graph topology with some variant of relative position embeddings (Shaw et al., 2018). They, however, assume that there is always a path between any pair of nodes, i.e., there are no unreachable nodes or disconnected subgraphs. Thus they can learn a relation embedding using the edge or node labels along this path. In contrast to AMR graphs, however, KGs are frequently disconnected. The Graformer is more flexible and makes no such assumption. Furthermore it purely models structural information in its relative position embeddings instead of mixing it with label information. It thus effectively learns differently connected views of its
input graph.

Deficiencies in modeling long-range dependencies in graph neural networks have been considered a serious limitation before. Various solutions orthogonal to our approach have been proposed in recent work: By incorporating a connectivity score into their GAT network, Zhang et al. (2020) manage to increase the attention span to k-hop neighborhoods but, finally, only experiment with \( k = 2 \). Our graph encoder efficiently handles dependencies between much more distant nodes. Pei et al. (2020) define an additional neighborhood based on euclidean distance in a continuous node embedding space. As in our work, a node can thus receive information from theoretically any other node, given their embeddings are close enough. However, Pei et al. (2020) compute these embeddings only once before training, whereas in our approach node similarity is based on the learned hidden representation in each encoder layer. This allows our model to dynamically learn how nodes can interact in a graph.

A very recent approach (Ribeiro et al., 2020) uses two GNN encoders – one using the original topology and one with a fully connected version of the graph – and combines their output in various ways for graph-to-text generation. Our approach is more flexible as it cannot only see two extreme versions of the graph (direct neighbors and full connection) but dynamically learns a different view per attention head. It is also more parameter-efficient as our multi-view encoder does not need a separate set of parameters for each view.

**Copy mechanism.** Copy mechanisms were first introduced for recurrent neural networks in order to produce output sequences that entirely consist of elements from the input sequence, e.g., to sort sequences of variable length (Vinyals et al., 2015). Gu et al. (2016); See et al. (2017) then combined this idea with traditional sequence generation for tasks like text summarization.

The first approach to incorporating a copy mechanism into a Transformer architecture (Vaswani et al., 2017) randomly chooses one head and reuses its attention weights as copy scores (Gehrmann et al., 2018). Zhu et al. (2020) – like our Graformer – instead average attention weights over all heads. Other approaches compute their copy scores independently from encoder-decoder attention weights – either based on the output (Cai and Lam, 2020) or an intermediate representation of the last decoder layer (Ive et al., 2019).

### 6 Conclusion

We presented a new encoder-decoder architecture for graph-to-text generation based on Transformer, called the Graformer. The Graformer encoder uses a novel type of self-attention for graphs based on shortest path lengths between nodes, allowing it to detect global patterns by automatically learning appropriate weights for higher-order neighborhoods. In our experiments on two popular benchmarks for text generation from knowledge graphs, the Graformer achieved competitive results while using much fewer parameters than alternative models.

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