Levi Graph AMR Parser using Heterogeneous Attention

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Abstract

Coupled with biaffine decoders, transformers have been effectively adapted to text-to-graph transduction and achieved state-of-the-art performance on AMR parsing. Many prior works, however, rely on the biaffine decoder for either or both arc and label predictions although most features used by the decoder may be learned by the transformer already. This paper presents a novel approach to AMR parsing by combining heterogeneous data (tokens, concepts, labels) as one input to a transformer to learn attention, and use only attention matrices from the transformer to predict all elements in AMR graphs (concepts, arcs, labels). Although our models [1] use significantly fewer parameters than the previous state-of-the-art graph parser, they show similar or better accuracy on AMR 2.0 and 3.0.

1 Introduction

Abstract Meaning Representation (AMR) has recently gained lots of interests due to its capability in capturing abstract concepts (Banarescu et al., 2013). In the form of directed acyclic graphs (DAGs), an AMR graph consists of nodes as concepts and edges as labeled relations. To build such a graph from plain text, a parser needs to predict concepts and relations in concord.

While significant research efforts have been conducted to improve concept and arc predictions, label prediction has been relatively stagnated. Most previous models have adapted the biaffine decoder for label prediction (Lyu and Titov, 2018; Zhang et al., 2019a; Cai and Lam, 2019; Zhou et al., 2020; Lindemann et al., 2020). These models assign labels from the biaffine decoder to arcs predicted by another decoder, which can be misled by incorrect arc predictions during decoding.

[1]Resources are publicly available at https://github.com/emorynlp/levi-graph-amr-parser.

The enhancement of message passing between decoders for arc and label predictions has shown to be effective. Among these works, Cai and Lam (2020) emerge with an iterative method to exchange embeddings between concept and arc predictions and feed the enhanced embeddings to the biaffine decoder for label prediction. While this approach greatly improves accuracy, it complicates the network architecture without structurally avoiding the error propagation from the arc prediction.

This paper presents an efficient transformer-based (Vaswani et al., 2017) approach that takes a mixture of tokens, concepts, and labels as inputs, and performs concept generation, arc prediction, and label prediction jointly using only attentions from the transformer without using a biaffine decoder. Its compact structure (§3.3) enables cross-attention between heterogeneous inputs, providing a complete view of the partially built graph and a better representation of the current parsing state. A novel Levi graph decoder (§3.4) is also proposed that reduces the number of decoder parameters by 45% (from 5.5 million to 3.0 million) yet gives similar or better performance. To the best of our knowledge, this is the first text-to-AMR graph parser that operates on the heterogeneous data and adapts no biaffine decoder.

2 Related Work

Recent AMR parsing approaches can be categorized into four classes: (i) transition-based parsing which casts the parsing process into a sequence of transitions defined on an abstract machine (e.g., a transition system using a buffer and a stack) (Wang et al., 2016; Damonte et al., 2017; Ballesteros and Al-Onaizan, 2017; Peng et al., 2017; Guo and Lu, 2018; Liu et al., 2018; Naseem et al., 2019; Fernandez Astudillo et al., 2020; Lee et al.,

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2020), (ii) seq2seq-based parsing [2] which transduces raw sentences into linearized AMR graphs in text form (Barzdins and Gosko, 2016; Konstas et al., 2017; van Noord and Bos, 2017; Peng et al., 2018; Xu et al., 2020; Bevilacqua et al., 2021), (iii) seq2graph-based parsing which incrementally and directly builds a semantic graph via expanding graph nodes without resorting to any transition system (Cai and Lam, 2019; Zhang et al., 2019b; Lyu et al., 2020). (iv) graph algebra parsing which translates an intermediate grammar structure into AMR (Artzi et al., 2015; Groschwitz et al., 2018; Lindemann et al., 2019, 2020).

Our work is most closely related to seq2graph paradigm while we extend the definition of node to accommodate relation labels in a Levi graph. We generate a Levi graph which is a linearized form originally used in seq2seq models for AMR-to-text (Beck et al., 2018; Guo et al., 2019; Ribeiro et al., 2019). Our Levi graph approach differs from seq2seq approaches in its attention based arc prediction, where arc is directly predicted by attention heads instead of brackets in the target sequence.

3 Approach

3.1 Text-to-Graph Transducer

Figure 1 shows the overview of our Text-to-Graph Transduction model. Let $W = \{w_0, w_1, \ldots, w_n\}$ be the input sequence where w_0 is a special token representing the target node and w_i is the i'th token. W is fed into a *Text Encoder* creating embeddings $\{e^w_0, e^w_1, \ldots, e^w_n\}$. In parallel, *NLP Tools* produce several features for w_i and pass them to a *Feature Encoder* to generate $\{e^f_0, e^f_1, \ldots, e^f_n\}$. Embeddings $\{e^w_i \oplus e^f_i : i \in [0, n]\}$ are put to a *Text Transformer*, which generates $E^t = \{e^t_0, e^t_1, \ldots, e^t_n\}$.[3]
Let $V = \{v_0, v_1, \ldots, v_m\}$ be the output sequence where v_0 is a special token representing the root and v_i is the i'th predicted node. V is fed into a *Graph Encoder* to create $E^v = \{e^v_0, e^v_1, \ldots, e^v_m\}$. Finally,

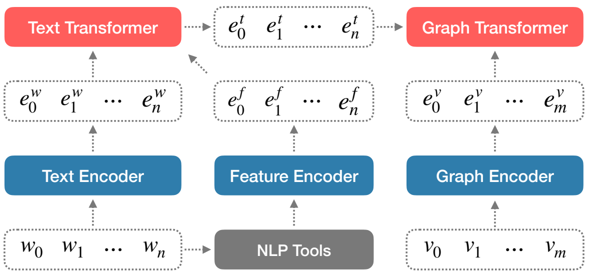


Figure 1: Overview of our Text-to-Graph Transducer.

E^t and E^v are fed into a *Graph Transformer* that predicts the target node as well as its relations to all nodes in V. The target node predicted by the *Graph Transformer* gets appended to V afterwards.[4]

3.2 Concept + Arc-Biaffine + Rel-Biaffine

Our first graph transformer generates $\{v_1, \ldots, v_m\}$ where v_i is a concept in the target graph, and predicts both arcs and labels using a biaffine decoder. Given E^t and E^v (§3.1), three matrices are created, $\mathcal{Q} = e^t_0 \in \mathbb{R}^{1\times d}, \mathcal{K}|\mathcal{V} = [e^t_1, .., e^t_n, e^v_0, e^v_1, .., e^v_m] \in \mathbb{R}^{k\times d}$ $(k = n+m+1)$. These matrices are put to multiple layers of multi-head attention (MHA) producing $\{\alpha^i : i \in [1, h]\}$ and $\{\beta^i : i \in [1, h]\}$ from the last layer, where h is the total number of heads in MHA ($\mathrm{W}^{\mathcal{Q}|\mathcal{K}|\mathcal{V}}_i \in \mathbb{R}^{d\times d}, \mathrm{W}^{\oplus} \in \mathbb{R}^{(h\cdot d)\times d}$):

$$\begin{aligned}
\alpha^i &= \mathrm{softmax}(\frac{(\mathcal{Q}\mathrm{W}^{\mathcal{Q}}_i)(\mathcal{K}\mathrm{W}^{\mathcal{K}}_i)^\top}{\sqrt{d}}) && \in \mathbb{R}^{1\times k} \\
\beta^i &= \alpha^i \cdot \mathcal{V} \cdot \mathrm{W}^{\mathcal{V}}_i && \in \mathbb{R}^{1\times d} \\
\alpha^{\oslash} &= [\alpha^1_j : j \in [1, n]] && \in \mathbb{R}^{1\times n} \\
\beta^{\oplus} &= (\beta^1 \oplus \ldots \oplus \beta^h) \cdot \mathrm{W}^{\oplus} && \in \mathbb{R}^{1\times d}
\end{aligned}$$

$\alpha^{\oslash}_j$ indicates the probability of w_j being aligned to the target node, and $\beta^{\oplus}$ is the embedding representing the node. Let C be the list of all concepts in training data and L be the list of lemmas for tokens in W such that $|W| = |L|$. Given $X = C^\frown W^\frown L$, $\alpha^{\oslash}$ and $\beta^{\oplus}$ are fed into a *Node Decoder* estimating the score of each $x_i \in X$ being the target node:

$$\begin{aligned}
g(C|W|L) &= \mathrm{softmax}(\beta^{\oplus} \cdot \mathrm{W}^{C|W|L}) \\
p(x_i) &= g(C) \cdot [\mathrm{softmax}(\beta^{\oplus} \cdot \mathrm{W}^{G})]_i \\
&\quad + g(W) \sum_{j\in W(x_i)} \alpha^{\oslash}_j + g(L) \sum_{j\in L(x_i)} \alpha^{\oslash}_j
\end{aligned}$$

$g(C|W|L)$ is the gate probability of the target node being in $C|W|L$, respectively ($\mathrm{W}^{C|W|L} \in \mathbb{R}^{d\times 1}$).

[2]Seq2seq-based parsing is sometimes categorized into "translation-based methods" (Koller et al., 2019) possibly due to the prevalence of seq2seq model in Neural Machine Translation, while we believe that translation refers more to the transduction between languages while AMR is neither a language nor an interlingua.

[3]In our case, BERT (Devlin et al., 2019) is used as the *Text Encoder* and $\forall_i . e^f_i = e^{\text{LEMMA}}_i \oplus e^{\text{POS}}_i \oplus e^{\text{NER}}_i \oplus e^{\text{CHAR}}_i$ is created by the *Feature Encoder* using predictions (lemmas, part-of-speech tags and named-entities) from the *NLP Tools* and character level features from a Convolutional Neural Network. In this work, we use CoreNLP (Manning et al., 2014) for a fair comparison with existing approaches.

[4]*Graph Encoder* creates $\forall_i . e^v_i = \mathrm{transformer}(e^{\text{NODE}}_i \oplus e^{\text{CHAR}}_i)$.

$p(x_i)$ is estimated by measuring the probabilities of x_i being the target if $x_i \in C$ ($\mathrm{W}^G \in \mathbb{R}^{d \times |C|}$), and if $x_i \in W|L$ where $W|L(x_i) = \{j : (x_i = y_j) \wedge y_j \in W|L\}$, respectively. Finally, the output layer $o^{\text{node}} = [p(x_i) : x_i \in X] \in \mathbb{R}^{1\times(|C|+|W|+|L|)}$ gets created and $\arg\max_{x_i}(o^{\text{node}})$ is taken as the target.

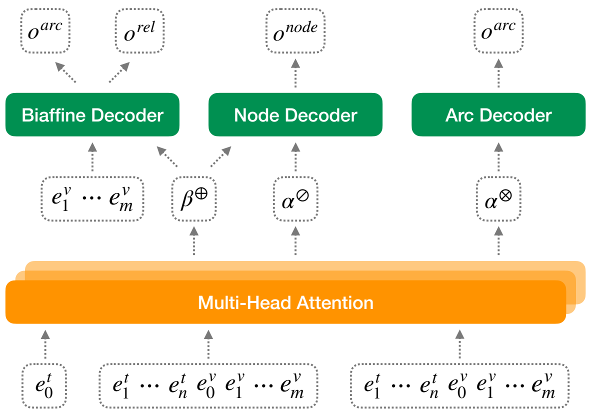


Figure 2: Overview of our Graph Transformer models. ND/BD/AD: node/biaffine/arc decoder. §3.2: ND for concept generation and BD for arc and label predictions; §3.3: ND for concept generation, AD for arc prediction, and BD for label prediction; §3.4: ND for concept and label generations and AD for arc prediction.

For arc and label predictions, the target embedding $\beta^{\oplus}$ is used to represent a head and the embeddings of previously predicted nodes, $\{e_1^v, \ldots, e_m^v\}$, are used to represent dependents in a *Biaffine Decoder*, which creates two output layers, $o^{\text{arc}} \in \mathbb{R}^{1\times m}$ and $o^{\text{rel}} \in \mathbb{R}^{1\times m\times|R|}$, to predict the target node being a head of the other nodes, where $|R|$ is the list of all labels in training data (Dozat and Manning, 2017).

3.3 Concept + Arc-Attention + Rel-Biaffine

Our second graph transformer is similar to the one in §3.2 except that it uses an *Arc Decoder* instead of the *Biaffine Decoder* for arc prediction. Given $A = \{\alpha^1, \ldots, \alpha^h\}$ in §3.2, $\alpha^{\otimes} \in \mathbb{R}^{1\times(m+1)}$ is created by first applying dimension-wise maxpooling to A and slicing the last $m+1$ dimensions as follows:

$$\alpha^{\otimes} = [\max(\alpha_j^1, \ldots, \alpha_j^h) : j \in [n+1, n+m+1]]$$

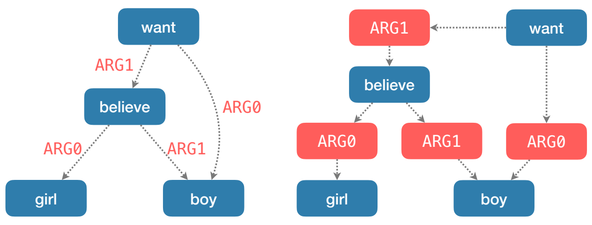
Notice that values in $\alpha^{\otimes}$ are derived from multiple heads; thus, they are not normalized. Each head is expected to learn different types of arcs. During decoding, any $v_i \in V$ whose $\alpha_i^{\otimes} \geq 0.5$ is predicted to be a dependent of the target node. During training, the negative log-likelihood of $\alpha^{\otimes}$ is optimized.[5]

[5]This model still uses the *Biaffine Decoder* for label prediction.

The target node, say v_t, may need to be predicted as a dependent of v_i, in which case, the dependency is reversed (so v_t becomes the head of v_i), and the label is concatenated with the special tag `_R` (e.g., $\texttt{ARG0}(v_i, v_t)$ becomes $\texttt{ARG0\_R}(v_t, v_i)$).

3.4 Levi Graph + Arc-Attention

Our last graph transformer uses the *Node Decoder* for both concept and label generations and the *Arc Decoder* for arc prediction. In this model, $v_i \in V'$ can be either a concept or a label such that the original AMR graph is transformed into the Levi graph (Levi, 1942; Beck et al., 2018) (Figure 3).



(a) AMR graph (b) Levi graph

Figure 3: AMR and Levi graphs for the input, "*The boy wants the girl to believe him*".

Unlike the node sequence containing only concepts in the AMR graph ordered by breadth-first traverse, used as the output sequence for the models in §3.2 and §3.3, the node sequence in this model is derived by inserting the label of each edge after head concept during training. This concepts-labels alternation has two advantages over a strict topological order: (i) it can handle erroneous cyclic graphs, (ii) it is easier to restore relations as each label is connected to its closest concept. The heterogeneous nature of node sequences from Levi graphs allows our Graph Transformer to learn attentions among 3 types of input, tokens, concepts, and labels, leading to more informed predictions.

Let V' be the output sequence consisting of both predicted concepts and labels. Let C' be the set of all concepts and labels in training data. Compared to V and C in §3.2, V' is about twice larger than V because every concept has one or more associated labels that indicate relations to its heads. However, C' is not so much larger than C because the addition from the labels is insignificant to the number of concepts that are already in C. By replacing $V|C$ with $V'|C'$ respectively, the *Node Decoder* in §3.2 can generate both concepts and labels. $\alpha^{\otimes}$ in §3.3 then gives attention scores among concepts and labels that can be used by the *Arc Decoder* to find arcs among them.

	SMATCH		Fine-grained Evaluation						
	Labeled	Unlabeled	No WSD	Concept	SRL	Reent.	Neg.	NER	Wiki
Lindemann et al. (2019)	75.3	-	-	-	-	-	-	-	-
Naseem et al. (2019)	75.5	80	76	86	72	56	67	83	80
Zhang et al. (2019a)	76.3	79.0	76.8	84.8	69.7	60.0	75.2	77.9	85.8
Zhang et al. (2019b)	77.0	80	78	86	71	61	77	79	86
Cai and Lam (2020)	80.2	82.8	80.8	88.1	74.2	64.6	78.9	81.1	86.3
Xu et al. (2020)†	80.2	83.7	80.8	87.4	78.9	66.5	71.5	85.4	75.1
Lee et al. (2020)‡	81.3	85.3	81.8	88.7	88.7	66.3	79.2	71.9	79.4
Bevilacqua et al. (2021)§	84.5	86.7	84.9	89.6	79.7	72.3	79.9	83.7	87.3
CL20	**80.0**±0.2	82.5±0.3	**80.5**±0.3	88.0±0.1	73.7±0.4	63.8±0.7	79.2±0.3	**81.1**±0.3	**86.2**±0.1
ND + BD + BD	79.4±0.1	82.3±0.1	80.0±0.2	87.9±0.2	73.1±0.2	62.5±0.2	**79.8**±0.3	80.7±1.0	85.8±0.5
ND + AD + BD	**80.0**±0.1	**82.6**±0.1	**80.5**±0.1	**88.2**±0.1	73.6±0.4	63.3±0.4	79.4±1.0	80.8±0.8	**86.2**±0.3
ND + AD + LV	**80.0**±0.1	82.2±0.2	**80.5**±0.1	87.7±0.2	**74.5**±0.2	**64.1**±0.3	78.4±1.0	80.5±0.8	**86.2**±0.3

(a) Results on AMR 2.0 results. Supervised†/unsupervised§ pre-training and self-learning‡ are orthogonal to our work.

	SMATCH		Fine-grained Evaluation						
	Labeled	Unlabeled	No WSD	Concept	SRL	Reent.	Neg.	NER	Wiki
Lyu et al. (2020)	75.8	-	-	**88.0**	72.6	-	-	-	-
CL20	76.8±0.2	79.9±0.2	77.3±0.2	86.3±0.2	73.2±0.2	63.4±0.2	72.3±1.4	73.0±0.5	79.5±0.2
ND + BD + BD	75.8±0.2	79.0±0.1	76.2±0.1	84.6±0.2	72.1±0.3	61.7±0.4	72.6±0.7	71.6±0.3	78.7±0.2
ND + AD + BD	76.8±0.1	**80.1±0.1**	77.3±0.1	86.5±0.2	73.1±0.2	**63.6±0.2**	**73.2±0.9**	73.0±0.2	**79.6±0.1**
ND + AD + LV	**77.0±0.2**	79.8±0.2	**77.5±0.2**	86.1±0.1	**73.6±0.3**	62.6±0.6	71.3±0.4	**73.3±0.7**	79.5±0.3

(b) Results on AMR 3.0.

Table 1: Averages ± standard deviations on AMR 2.0 and 3.0 . CL20: results by running the original implementation of Cai and Lam (2020) 3 times, ND+BD+BD: §3.2, ND+AD+BD: §3.3, ND+AD+LV: §3.4.

4 Experiments

4.1 Experimental Setup

All models are experimented on both the AMR 2.0 (LDC2017T10) and 3.0 datasets (LDC2020T02). AMR 2.0 has been well-explored by recent work, while AMR 3.0 is the latest release about 1.5 times larger than 2.0 that has not yet been explored much. The detailed data statistics are shown in Table A.1.2. The training, development, and test sets provided in the datasets are used, and performance is evaluated with the SMATCH (F1) (Cai and Knight, 2013) as well as fine-grained metrics (Damonte et al., 2017). The same pre- and post-processing suggested by Cai and Lam (2020) are adapted. Section A.2 gives the hyper-parameter configuration of our models.

4.2 Results

All our models are run three times and their averages and standard deviations are reported in Table 1. Compared to CL20 using 2 transformers to decode arcs & concepts then apply attention across them, our models use 1 transformer for the *Node Decoder* achieving both objectives simultaneously. All models except for ND+BD reaches the same SMATCH score of 80% on AMR 2.0. ND+AD+LV shows a slight improvement over the others on AMR 3.0, indicating that it has a greater potential to be robust with a larger dataset. Considering that this model uses about 3M fewer parameters than CL20, these results are promising. ND+BD+BD consistently shows the lowest scores, implying the significance of modeling concept generation and arc prediction coherently for structure learning. ND+AD+LV shows higher scores for SRL and Reent whereas the other models show advantage on Concept and NER on AMR 2.0, although the trend is not as noticeable on AMR 3.0, implying that the Levi graph helps parsing relations but not necessarily tagging concepts.

Case Study We study the effect of our proposed two improvements: heterogeneous Graph Transformer and Levi graph, from the view of attention in Figure 4. Figure 4a shows that the core verb "*wants*" is heavily attended by every token, suggesting that our Graph Transformer successfully grasps the core idea. Figure 4b presents the soft alignment between nodes and tokens, which surprisingly overweights " *boy*", "*girl*" and "*believe*" possibly due to their dominance of semantics. Figure 4c illustrates the arc prediction, which is a lower triangular matrix obtained by zeroing out the upper triangle of stacked $\alpha^{\otimes}$. Its diagonal suggests that self-loop is crucial for representing each node.

5 Conclusion

We presented two effective approaches which achieve comparable (or better) performance comparing with the state-of-the-art parsers with significantly fewer parameters. Our text-to-graph trans-

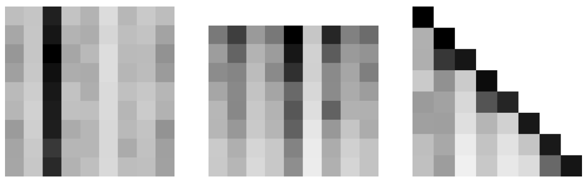

(a) Token⇆token (b) Node⇆token (c) Node⇆node

Figure 4: Self- and cross-attention for tokens "*The boy wants the girl to believe him*" and nodes "*want believe* `ARG1` *boy* `ARG1` `ARG0` *girl* `ARG0`".

ducer enables self- and cross-attention in one transformer, improving both concept and arc prediction. With a novel Levi graph formalism, our parser demostrates its advantage on relation labeling. An interesting future work is to preserve benefits from both approaches in one model. It is also noteworthy that our Levi graph parser can be applied to a broad range of labeled graph parsing tasks including dependency trees and many others.

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A Appendix

A.1 Datasets and Pre/Post-Processing

Table 2 describes statistics of the AMR 2.0[6] and the AMR 3.0[7] datasets used in our experiments.

	Sentences	Tokens	Concepts	Relations
TRN	36,521	624,750	422,655	426,712
DEV	1,368	27,713	19,890	20,111
TST	1,371	28,279	26,513	27,175

(a) AMR 2.0.

	Sentences	Tokens	Concepts	Relations
TRN	55,635	965,468	656,123	667,577
DEV	1,722	34,696	25,171	25,568
TST	1,898	37,225	34,903	35,572

(b) AMR 3.0.

Table 2: Statistics of AMR 2.0 and 3.0. TRN/DEV/TST: training/development/evaluation set.

Tokenization, lemmatization, part-of-speech and named entity annotations are generated by the Stanford CoreNLP tool (Manning et al., 2014). Most frequent word senses are removed and restored during pre- and post-processing. The same graph recategorization is performed to assign specific subgraphs to a single node as in Cai and Lam (2020). Wikification is done using the DBpedia Spotlight (Daiber et al., 2013) during post-processing.

A.2 Hyper-Parameter Configuration

The hyper-parameters used in our models are described in Table 3.

Embeddings	
lemma	300
POS tag	32
NER tag	16
concept	300
char	32
Char-level CNN	
#filters	256
ngram filter size	[3]
output size	128
Text Encoder	
#transformer layers	4
Graph Encoder	
#transformer layers	2
Transformer Layer	
#heads	8
hidden size	512
feed-forward hidden size	1024
Graph Transformer	
feed-forward hidden size	1024
Biaffine	
hidden size	100

Table 3: Hyper-parameters settings.

[6]AMR 2.0: https://catalog.ldc.upenn.edu/LDC2017T10

[7]AMR 3.0: https://catalog.ldc.upenn.edu/LDC2020T02