Graph Pre-training for AMR Parsing and Generation

Anonymous ACL submission

Abstract

Abstract meaning representation (AMR) highlights the core semantic information of text in a graph structure. Recently, pre-trained language models (PLMs) have advanced tasks of AMR parsing and AMR-to-text generation. However, PLMs are typically pre-trained on textual data, thus are sub-optimal for modeling structural knowledge. To this end, we investigate graph self-supervised training to improve the structure awareness of PLMs over AMR graphs. In particular, we introduce two graph auto-encoding strategies for graph-to-graph pre-training and four tasks to integrate text and graph information during pre-training. We further design a unified framework to bridge the gap between pre-training and fine-tuning tasks. Experimental results on both AMR parsing and AMR-to-text generation tasks show the superiority of our model. To our knowledge, we are the first to consider pre-training on AMR graphs.

1 Introduction

Abstract meaning representation (AMR; Banarescu et al. (2013)) is a semantic structure formalism. It represents the meaning of a text in a rooted directed graph, where nodes represent basic semantic units such as entities and predicates, and edges represent their semantic relations. One example is shown in Figure 1(a), with the corresponding sentence in Figure 1(b). Serving as a structural representation, AMR has been shown useful for NLP tasks such as text summarization (Liu et al., 2015; Liao et al., 2018), machine translation (Song et al., 2019), information extraction (Huang et al., 2016; Zhang and Ji, 2021) and dialogue systems (Bai et al., 2021).

There are two fundamental NLP tasks concerning AMR, namely AMR parsing (Flanigan et al., 2014; Konstas et al., 2017; Lyu and Titov, 2018; Guo and Lu, 2018; Zhang et al., 2019a; Cai and Lam, 2020; Bevilacqua et al., 2021) and AMR-to-text generation (Konstas et al., 2017; Song et al., 2018; Zhu et al., 2019; Zhao et al., 2020; Bai et al., 2020; Ribeiro et al., 2021a). As shown in Figure 1, the former transforms a textual input (e.g., a sentence) into a corresponding AMR structure, and the latter transforms an AMR input into a fluent and grammatical sentence that conveys the same meaning. A common challenge to both tasks is that AMR exists in the form of a graph structure, which is difficult for neural models to learn with limited human-curated data.

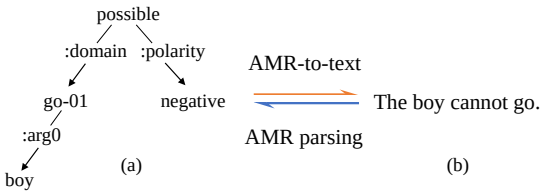


Figure 1: Illustration of AMR tasks: (a) an AMR graph; (b) a corresponding sentence.

Recently, large-scale pre-trained sequence-to-sequence (seq2seq) language models (Lewis et al., 2020; Raffel et al., 2020) have been shown useful for both tasks above. The basic idea is to linearize AMR structures into a sequence form, so that both AMR parsing and AMR-to-text generation can be solved as standard seq2seq tasks, using a pre-trained language model fine-tuned on task-specific data. In this way, semantic knowledge learned in self-supervised text-to-text (`t2t`) pre-training can benefit both text-to-graph (`t2g`) and graph-to-text (`g2t`) transformation.

Intuitively, structural knowledge about AMR can be a useful complement to semantic knowledge from text. A natural question that arises is whether similar self-supervision strategy can be useful for AMR graphs, so that graph-to-graph (`g2g`) denoise auto-encoder training can serve as effective addition to `t2t` pre-training, before a model is fine-tuned on `t2g` and `g2t` tasks. We investigate this problem in this paper. In particular, there are three

specific questions of interest. *First, as mentioned before, is g2g pre-training complementary to t2t pre-training? Second, what is the most effective way to combine t2t and g2g training? Third, is silver data useful for AMR self-supervision training, and what is the most effective way of making use of such data?*

Taking BART (Lewis et al., 2020) as the seq-to-seq model, we introduce two strategies for g2g pre-training and propose four tasks to combine t2t and g2g training. To reduce the gap among different pre-training tasks and between pre-training and fine-tuing, we unify all pre-training tasks and fine-tuning tasks in a general framework. Results on standard benchmarks show that 1) graph pre-training achieves significant improvements over the state-of-the-art systems; 2) silver data are useful for our pre-training framework; 3) our pre-training framework is a better way than fine-tuning to make use of silver data and; 4) our model is more robust than existing systems in unseen domains. Our final models give the best reported results on both parsing and generation tasks, with a large margin of improvement over the previous best results. To our knowledge, we are the first to consider graph-to-graph self-supervised training on AMR structures. We release code at xxx.

2 Related Work

AMR Parsing. Early AMR parsing systems use statistical methods (Flanigan et al., 2014, 2016; Wang et al., 2015a,b). With the advance in deep learning, various neural models are developed for AMR parsing. Those models can be categorized into: 1) neural transition-based parsers (Ballesteros and Al-Onaizan, 2017; Liu et al., 2018; Fernandez Astudillo et al., 2020; Zhou et al., 2021); 2) sequence-to-graph parsers (Zhang et al., 2019a; Lyu et al., 2020; Cai and Lam, 2020) and; 3) sequence-to-sequence parsers (Konstas et al., 2017; Peng et al., 2017, 2018; Zhang et al., 2019b; Xu et al., 2020; Bevilacqua et al., 2021). Recently, pre-training techniques have significantly boosted the performance of AMR parsing. For example, Lyu and Titov (2018), Zhang et al. (2019a,b) and Cai and Lam (2020) use BERT (Devlin et al., 2019) for sentence encoding; Bevilacqua et al. (2021) fine-tune BART for sequence-to-AMR generation. Xu et al. (2020) pre-train a model on three relevant seq2seq learning tasks before fine-tuning on AMR parsing. Similar to those methods, we consider using pre-trained models to improve the model capacity. However, while they use models pre-trained on text, we pre-train a seq2seq model also on AMR graphs. In addition, our method does not require information from external tasks.

AMR-to-Text Generation. On a coarse-grained level, we can categorize existing AMR-to-text generation approaches into two main classes: Graph-to-sequence models adopt a graph encoder to process an AMR graph and use a sequence decoder for generation (Song et al., 2018; Beck et al., 2018; Damonte and Cohen, 2019; Zhu et al., 2019), and sequence-to-sequence models linearize an AMR graph into a sequence and solve it as a seq2seq problem using randomly initialized (Konstas et al., 2017) or pre-trained models (Mager et al., 2020; Ribeiro et al., 2021a; Bevilacqua et al., 2021). This work follows a seq2seq manner, but we use a graph-aware encoder. The closest to our work, Ribeiro et al. (2021b) integrate AMR structures into pre-trained T5 (Raffel et al., 2020) by using adapters (Houlsby et al., 2019) for AMR-to-text generation. However, they do not pre-train AMR structures, and their method can not solve both parsing and generation tasks as they require full AMR structure in the encoder as the input.

Graph Self-supervised Learning. Kipf and Welling (2016) introduce a variational graph auto-encoder to allow self-supervised learning on graph-structured data. Hu et al. (2020a,b) propose local and global learning strategies to pre-train a graph neural network on large-scale protein ego-networks, academic graphs and recommendation data. Lu et al. (2021) enhance the graph learning strategies of Hu et al. (2020b) with dual adaptations. While existing work considers graph neural networks, we pre-train a seq2seq model on AMR graphs. In addition, we jointly pre-train on graphs and text for graph-text correlation modeling. In contrast, existing work pre-trains models on graphs and in isolation with text pre-training. To our knowledge, we are the first to consider AMR as a graph pre-training target.

3 Method

We take BART (Lewis et al., 2020) as the basic seq2seq model for both AMR parsing and generation (Section 3.1), adding graph pre-training (Section 3.2) and unified pre-training (Section 3.3).

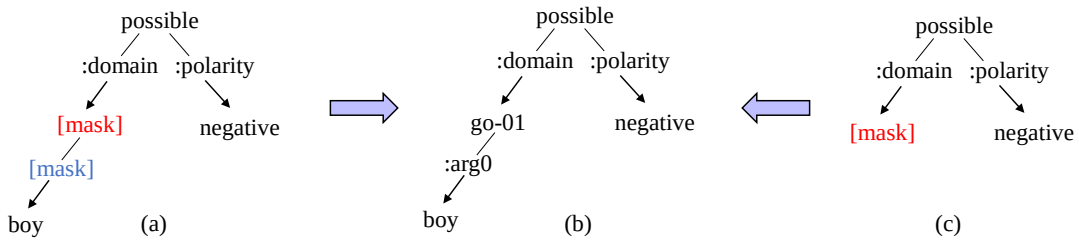


Figure 2: Illustration of two graph pre-training strategies: 1) node/edge level denoising (a→ b); 2) sub-graph level denoising (c→ b). Two transformations can be composed.

3.1 BART

Bidirectional and Auto-Regressive Transformers (BART) is a pre-trained denoising auto-encoder which is implemented as a sequence-to-sequence model based on the standard Transformer (Vaswani et al., 2017) architecture. BART is trained by learning to reconstruct the original text based on a corrupted text which is generated by several noising functions. Typically, BART has 5 noising functions: 1) Token Masking. Tokens are randomly replaced by `[mask]` elements; 2) Token Deletion. Tokens are randomly deleted from the input; 3) Text Infilling. Text spans are randomly replaced by a single `[mask]` token; 4) Sentence Permutation. Text is divided into segments and then shuffled; 5) Document Rotation. A document is rotated to start with a random token. In fine-tuning, BART takes a complete text as input and maps it into a task-specific output sequence.

We linearize an AMR graph into a sequence, so that both AMR parsing and AMR-to-text generation can be performed using a seq2seq model. In addition, it allows pre-training of AMR structures using BART. Following Konstas et al. (2017), we adopt the depth-first search (DFS) algorithm which is closely related to the linearized natural language syntactic trees (Bevilacqua et al., 2021). For instance, the AMR graph in Figure 1 is linearized into: `possible :domain ( go :arg0 ( boy ) ) :polarity ( negative ) .` To deal with the AMR symbols, we follow previous work (Bevilacqua et al., 2021) to expand the vocabulary by adding all relations and frames. In addition, to distinguish between text and AMR graphs, we add two special tokens <g> and </g> to mark the beginning and end of AMR graphs.

3.2 Pre-training on AMR graphs

We introduce two self-supervised training strategies to further pre-train a BART on AMR graphs. As shown in Figure 2(a), the node/edge level denoising strategy encourages the model to capture local knowledge about nodes and edges. The graph level denoising strategy (Figure 2(c)) enforces the model to predict a sub-graph, thus facilitating graph-level learning.

1) Node/edge level denoising. We apply a noise function on AMR nodes/edges to construct a noisy input graph. In particular, the noise function is implemented by masking 15% nodes and 15% edges in each graph. As shown in Figure 2(a), the node `[go-01]` and edge `[:arg0]` are replaced with two `[mask]` tokens.

2) Sub-graph level denoising. This task aims to predict the whole graph when giving part of the graph. We randomly remove a sub-graph[1] from the graph and replace it with a `[mask]` token (see Figure 2(c)). The masking probability is 0.35.

3.3 Unified Pre-training Framework

The above standard pre-training and fine-tuning strategy is shown in Table 1(a), by using <s> and <g> for differentiating text and graphic information and structural information during pre-training. However, the model does not fully learn the interaction between textual and AMR information during pre-training. To further address this issue, we consider a unified pre-training framework, which combines text and AMR sequences as input to the denoise auto-encoder. In such way, dynamic masking can be carried out on the text, AMR or both ends, so that the model can learn to make use of one source of information for inferring the other. This can benefit both a parser and a generation model by enforcing the learning of correspondence between text and AMR structures.

In addition, as shown in Table 1, there is a gap between standard pre-training and fine-tuning phase for AMR from/to text transduction. Specifically, the input and output formats are same in the pre-training phase (i.e., $\hat{t}$2t and $\hat{g}$2g) but different

[1] A sub-graph has at least one edge and one node.

Phase		Task	input	output
(a)	**Std. P.T.**	$\hat{\texttt{t}}$2t	<s> $x_1, ..$ [mask] $.., x_n$ </s>	<s> $x_1, x_2, ..., x_n$ </s>
		$\hat{\texttt{g}}$2g	<g> $g_1, ..$ [mask] $.., g_m$ </g>	<g> $g_1, g_2, ..., g_m$ </g>
	Std. F.T.	g2t	<g> $g_1, g_2, ..., g_m$ </g>	<s> $x_1, x_2, ..., x_n$ </s>
		t2g	<s> $x_1, x_2, ..., x_n$ </s>	<g> $g_1, g_2, ..., g_m$ </g>
(b)	**Unified P.T.**	$\hat{\texttt{t}}\overline{\texttt{g}}$2t	<s> $x_1, ..$ [mask] $.., x_n$ </s> <g> [mask] </g>	<s> $x_1, x_2, ..., x_n$ </s>
		$\overline{\texttt{t}}\hat{\texttt{g}}$2g	<s> [mask] </s><g> $g_1, ..$ [mask] $.., g_m$ </g>	<g> $g_1, g_2, ..., g_m$ </g>
		$\hat{\texttt{t}}$g2t	<s> $x_1, ..$ [mask] $.., x_n$ </s> <g> $g_1, g_2, ..., g_m$ </g>	<s> $x_1, x_2, ..., x_n$ </s>
		t$\hat{\texttt{g}}$2g	<s> $x_1, x_2, ..., x_n$ </s> <g> $g_1, ..$ [mask] $.., g_m$ </g>	<g> $g_1, g_2, ..., g_m$ </g>
		$\hat{\texttt{t}}\hat{\texttt{g}}$2t	<s> $x_1, ..$ [mask] $.., x_n$ </s> <g> $g_1, ..$ [mask] $.., g_m$ </g>	<s> $x_1, x_2, ..., x_n$ </s>
		$\hat{\texttt{t}}\hat{\texttt{g}}$2g	<s> $x_1, ..$ [mask] $.., x_n$ </s> <g> $g_1, ..$ [mask] $.., g_m$ </g>	<g> $g_1, g_2, ..., g_m$ </g>
	Unified F.T.	$\overline{\texttt{t}}$g2t	<s> [mask] </s> <g> $g_1, g_2, ..., g_m$ </g>	<s> $x_1, x_2, ..., x_n$ </s>
		t$\overline{\texttt{g}}$2g	<s> $x_1, x_2, ..., x_n$ </s> <g> [mask] </g>	<g> $g_1, g_2, ..., g_m$ </g>

Table 1: Different pre-training and fine-tuning strategies. P.T.=pre-training, F.T.=fine-tuning. t/g denotes the *original* text/graph. $\hat{\texttt{t}}/\hat{\texttt{g}}$ represents a *noisy* text/graph. $\overline{\texttt{t}}/\overline{\texttt{g}}$ means an *empty* text/graph.

in the fine-tuing phase (i.e., t2g and g2t). This gap restrains models to make the best use of "pre-trained knowledge" in the fine-tuning phase. The unified pre-training framework can also benefit task fine-tuning by drawing closer the input and output formats between pre-training and fine-tuning.

Formally, denoting the text and linearized graph sequence as t and g where $\texttt{t} = \{x_1, x_2, ..., x_n\}$ and $\texttt{g} = \{g_1, g_2, ..., g_n\}$. $\hat{\texttt{t}}$ and $\hat{\texttt{g}}$ represent the *noisy* text and graph, respectively, and $\overline{\texttt{t}}$ and $\overline{\texttt{g}}$ refer to the *empty* text and graph, respectively. As shown in Table 1(b), we unify the input form for both pre-training and fine-tuning to tg. For consistency, all input sequences start with a text sequence and end with a graph sequence.

Joint Text and Graph Pre-training. We introduce 4 additional pre-training tasks to encourage information exchanging between graphs and text. As shown in Table 1(b), the additional tasks are:

1) graph augmented text denoising ($\hat{\texttt{t}}$g2t), where an AMR graph is taken as additional input to help masked text reconstruction;

2) text augmented graph denoising (t$\hat{\texttt{g}}$2g), where text helps masked graph reconstruction;

3) noisy graph augmented text denoising ($\hat{\texttt{t}}\hat{\texttt{g}}$2t), where the target text is generated based on a pair of masked text and masked graph;

4) noisy text augmented graph denoising ($\hat{\texttt{t}}\hat{\texttt{g}}$2g), where a target graph is generated based on a pair of masked text and masked graph.

Dynamic masking rate. Different from standard masking (Devlin et al., 2019) which uses a static masking rate, we adopt a dynamic masking rate p for task $\hat{\texttt{t}}$g2t and t$\hat{\texttt{g}}$2g. Formally, at each step t, we calculate the masking probability p according to the following function:

$$f(t) = max(1, 0.3 + t/T * 0.8), \quad (1)$$

where 0.3 is the initial masking rate and p increase with training step t. When p increases to 1.0, the pre-training tasks are identical to fine-tuning tasks.

Unified Pre-training and Fine-tuning. In our unified framework, fine-tuning tasks can be viewed as having an *empty* text (or AMR graph) in the original input, resulting in an input format of $\overline{\texttt{t}}$g2t for AMR-to-text generation and t$\overline{\texttt{g}}$2g for AMR parsing, respectively. In this way, pre-training and fine-tuning tasks share the same input format, thus facilitating knowledge transfer from pre-training to fine-tuning.

3.4 Training

For pre-training, we jointly optimize the sum of the following 6 objectives:

$$\begin{aligned}
\mathcal{L}_{\hat{\texttt{t}}\texttt{2t}} &= -logP(\texttt{t}|\hat{\texttt{t}}, \overline{\texttt{g}}), \\
\mathcal{L}_{\hat{\texttt{g}}\texttt{2g}} &= -logP(\texttt{g}|\overline{\texttt{t}}, \hat{\texttt{g}}), \\
\mathcal{L}_{\hat{\texttt{t}}\texttt{g2t}} &= -logP(\texttt{t}|\hat{\texttt{t}}, \texttt{g}), \\
\mathcal{L}_{\texttt{t}\hat{\texttt{g}}\texttt{2g}} &= -logP(\texttt{g}|\texttt{t}, \hat{\texttt{g}}), \\
\mathcal{L}_{\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2t}} &= -logP(\texttt{t}|\hat{\texttt{t}}, \hat{\texttt{g}}), \\
\mathcal{L}_{\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2g}} &= -logP(\texttt{g}|\hat{\texttt{t}}, \hat{\texttt{g}}), \\
\mathcal{L}_{total} &= \mathcal{L}_{\hat{\texttt{t}}\texttt{2t}} + \mathcal{L}_{\hat{\texttt{g}}\texttt{2g}} + \mathcal{L}_{\hat{\texttt{t}}\texttt{g2t}} \\
&\quad + \mathcal{L}_{\texttt{t}\hat{\texttt{g}}\texttt{2g}} + \mathcal{L}_{\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2t}} + \mathcal{L}_{\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2g}},
\end{aligned} \quad (2)$$

where $\mathcal{L}_{\hat{\texttt{t}}\texttt{2t}}$ and $\mathcal{L}_{\hat{\texttt{g}}\texttt{2g}}$ are standard pre-training loss on text (Section 3.1) and graph (Section 3.2), respectively. $\mathcal{L}_{\hat{\texttt{t}}\texttt{g2t}}$, $\mathcal{L}_{\texttt{t}\hat{\texttt{g}}\texttt{2g}}$, $\mathcal{L}_{\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2t}}$, and $\mathcal{L}_{\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2g}}$ denote 4 joint pre-training losses (Section 3.3).

For fine-tuning, the training objectives are:

$$\begin{aligned}
\mathcal{L}_{\texttt{amr2text}} &= -logP(\texttt{t}|\overline{\texttt{t}}, \texttt{g}), \\
\mathcal{L}_{\texttt{text2amr}} &= -logP(\texttt{g}|\texttt{t}, \overline{\texttt{g}}),
\end{aligned} \quad (3)$$

where $\mathcal{L}_{\texttt{amr2text}}$ and $\mathcal{L}_{\texttt{text2amr}}$ are training loss of AMR generation and AMR parsing, respectively.

Datasets	AMR2.0	AMR3.0	New3	TLP	Bio
Train	36521	55635	-	-	-
Valid	1368	1722	-	-	-
Test	1371	1898	527	1562	500

Table 2: Benchmark AMR datasets.

4 Experiments

We evaluate the effectiveness of our model on different benchmarks and compare the results with state-of-the-art systems on both AMR parsing and generation tasks. In addition to standard supervised training settings, we evaluate the robustness of our model on a zero-shot domain adaptation setting.

4.1 Datasets

Table 2 shows the statistics of datasets. Following Bevilacqua et al. (2021), we use the **AMR2.0** (LDC2017T10) and **AMR3.0** (LDC2020T02). We also evaluate the model performance on **New3**, *The Little Prince* (**TLP**) and *Bio AMR* (**Bio**) corpora. For pre-training, we additionally use 200k silver data parsed by SPRING (Bevilacqua et al., 2021). These data are randomly selected from Gigaword (LDC2011T07) corpus, which shares the same textual source with AMR data.[2]

4.2 Settings

We follow Bevilacqua et al. (2021) in pre-processing and post-processing AMR graphs, except for omitting the recategorization step which does not consistently improve model performance in our preliminary experiments. Our model is built based on a vanilla BART, available at *huggingface*[3] library. The best model and hyper-parameters are selected by performance on the validation set. The detailed hyper-parameters are given in Appendix A.

Metrics. We use a decoding beam size of 5 for generation. Following Bevilacqua et al. (2021), we evaluate on the AMR parsing benchmarks by using Smatch (Cai and Knight, 2013) and other fine-grained metrics.[4] Regarding AMR-to-text, we use three common Natural Language Generation measures, including BLEU (Papineni et al., 2002), CHRF++ (Popović, 2017) and METEOR (Banerjee and Lavie, 2005), tokenizing with the script provided with JAMR (Flanigan et al., 2014).

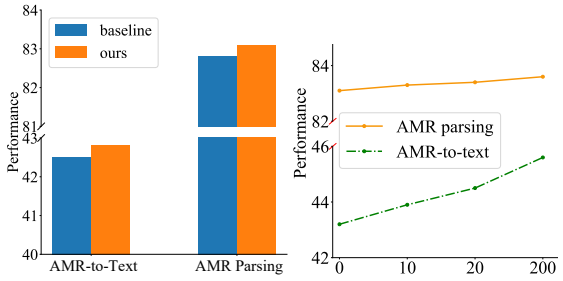
[2]The data are available at https://catalog.ldc.upenn.edu.

[3]https://github.com/huggingface/transformers.

[4]Please refer to Appendix B for more details.

Setting	Smatch	BLEU	Avg
baseline (BART)	82.7	42.5	62.6
+ $\hat{t}\bar{g}2t$	82.9	42.9	62.9
+ $\bar{t}\hat{g}2g$	83.1	42.6	62.9
+ $\hat{t}\bar{g}2t$, $\bar{t}\hat{g}2g$	83.1	42.8	63.0
+ $\hat{t}\bar{g}2t$, $\bar{t}\hat{g}2g$, $t\hat{g}2g$	83.4	42.8	63.1
+ $\hat{t}\bar{g}2t$, $\bar{t}\hat{g}2g$, $\hat{t}g2t$	83.1	45.3	63.2
+ $\hat{t}\bar{g}2t$, $\bar{t}\hat{g}2g$, $t\hat{g}2g$, $\hat{t}g2t$	83.3	45.0	63.2
+ $\hat{t}\bar{g}2t$, $\bar{t}\hat{g}2g$, $\hat{t}\hat{g}2g$	83.2	43.0	63.1
+ $\hat{t}\bar{g}2t$, $\bar{t}\hat{g}2g$, $\hat{t}\hat{g}2t$	83.1	44.2	63.7
+ $\hat{t}\bar{g}2t$, $\bar{t}\hat{g}2g$, $\hat{t}\hat{g}2g$, $\hat{t}\hat{g}2t$	83.2	44.0	63.6
+ ALL	83.6	45.6	64.1

Table 3: AMP parsing (Smatch) and AMR-to-text generation (BLEU) performance on AMR2.0.



(a) (b)

Figure 3: Development results: (a) comparison of standard pre-training and fine-tuning phase (baseline) and our unified frameworks; (b) impact of silver data.

4.3 Baselines

For **AMR parsing**, we consider the following baselines: 1) Lyu and Titov (2018; LyuT), a neural parser trained by jointly modeling alignments, concepts and relations; 2) Zhang et al. (2019b; Zhang+), a seq2seq approach which incrementally builds an AMR graph via predicting a sequence of semantic relations; 3) Zhou et al. (2020; Zhou+), an aligner-free parser (Zhang et al., 2019a) enhanced by explicit dependency and latent structures; 4) Cai and Lam (2020a; CaiL), a graph-based parser which enhances incremental sequence-to-graph model with a graph-sequence iterative inference mechanism; 5) Bevilacqua et al. (2021; Bevilacqua+), a fine-tuned BART model which predicts a linearized AMR graph from text.

For **AMR-to-text generation**, the baselines are: 1) Zhu et al. (2019; Zhu+), a Transformer-based model that enhances self-attention with graph relations; 2) Bai et al. (2020; Bai+), a graph encoder (Zhu et al., 2019) with a structural decoder that jointly predicts the target text and the input structure; 3) Mager et al. (2020; Mager+), a fine-tuned GPT that predicts text based on a PENMAN linearized AMR graph; 4) Bevilacqua et al. (2021; Bevilacqua+), a fine-tuned BART that predicts text

Model	Smatch	Unlab.	NoWSD	Con.	Wiki.	NER	Reent.	Neg.	SRL
AMR 2.0									
LyuT (2018)	74.4	77.1	75.5	85.9	75.7	86.0	52.3	58.4	69.8
Zhang+ (2019b)†	77.0	80.0	78.0	86.0	86.0	79.0	61.0	77.0	71.0
Zhou+ (2020)†	77.5	80.4	78.2	85.9	86.5	78.8	61.1	76.1	71.0
CaiL (2020a)†	80.2	82.8	80.0	88.1	86.3	81.1	64.6	78.9	74.2
Xu+ (2020)†	80.2	83.7	80.8	87.4	75.1	85.4	66.5	71.5	78.9
Bevilacqua+ (2021, base)†	82.7	85.1	83.3	89.7	82.2	90.0	70.8	72.0	79.1
Bevilacqua+ (2021, large)†	84.5	86.7	84.9	89.6	**87.3**	83.7	72.3	**79.9**	79.7
Bevilacqua+ (2021, large)†^{s}	84.3	86.7	84.8	90.8	83.1	90.5	72.4	73.6	80.5
Ours (base)†	83.7	86.8	84.1	90.2	78.0	90.4	71.1	73.3	79.4
Ours (large)†	**85.2**	88.0	**85.6**	**91.1**	80.9	**91.2**	73.2	74.4	81.3
Ours (large)†^{s}	**85.2**	**88.1**	**85.6**	90.8	80.9	90.9	**73.8**	75.7	**81.5**
AMR 3.0									
Bevilacqua+ (2021, large)†	83.0	85.4	83.5	89.8	**82.7**	87.2	70.4	**73.0**	78.9
Bevilacqua+ (2021, large)†^{s}	83.0	85.4	83.5	89.5	81.2	87.1	71.3	71.7	79.1
Ours (base)†	82.7	85.8	83.1	89.4	75.9	86.7	70.6	70.3	78.6
Ours (large)†	**83.9**	**86.9**	**84.3**	**90.2**	78.0	**88.4**	**71.8**	72.3	80.1
Ours (large)†^{s}	83.8	**86.9**	84.2	90.1	77.8	88.3	71.7	72.3	**80.2**

Table 4: AMR parsing results on AMR2.0 and AMR3.0. s means using 200k silver data for fine-tuning. Model marked with † rely on pre-trained models. The best result within each row block is shown in bold.

based on a DFS linearized AMR graph; 5) Ribeiro et al. (2021; Ribeiro+), a fine-tuned BART based on a PENMAN linearized AMR graph. For a fair comparison, we leave out baselines that rely on T5 (Ribeiro et al., 2021a,b), which has about two times more parameters than BART.

4.4 Development Experiments

Table 3 shows results on the validation set of AMR2.0 under different model settings, where we take a fine-tuned BART-based model (Bevilacqua et al., 2021) as our baseline.

We first study the effectiveness of pre-training only on text and graphs. As shown in Table 3, both pre-training on the text ($\hat{\texttt{t}}\overline{\texttt{g}}\texttt{2t}$) and graph ($\overline{\texttt{t}}\hat{\texttt{g}}\texttt{2g}$) leads to better results, and combining them can give better results on both tasks. Also, adding joint pre-training tasks improves the performance. In particular, $\texttt{t}\hat{\texttt{g}}\texttt{2g}$ gives a Smatch improvement of 0.7 for AMR paring, and $\hat{\texttt{t}}\texttt{g2t}$ reaches a BLEU of 45.3 for AMR generation, which is 2.8 points higher than baseline. Adding $\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2g}$ gives a Smatch of 83.2 for AMR parsing, and $\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2t}$ improves the baseline by 1.7 BLEU points for generation. By combining $\texttt{t}\hat{\texttt{g}}\texttt{2g}$ and $\hat{\texttt{t}}\texttt{g2t}$, the performance increase by 0.6 and 2.5 points on AMR parsing and generation, respectively. Similar trend can be observed by combining $\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2g}$ and $\hat{\texttt{t}}\hat{\texttt{g}}\texttt{2t}$. Finally, using all 6 pre-training tasks, our model reach a result of 83.6 Smatch and 45.6 BLEU, respectively. We also study the impact of two graph self-supervised training strategies, please refer to Appendix C.1.

Figure 3(a) compares the performance of standard pre-training ($\hat{\texttt{t}}\texttt{2t}$, $\hat{\texttt{g}}\texttt{2g}$) and fine-tuning ($\texttt{t2g}$, $\texttt{g2t}$) with our unified pre-training framework. The unified framework gives better results than standard versions on both tasks. This confirms our assumption that our unified framework is helpful for reducing the gap between pre-training and fine-tuning phases. Besides, by unifying pre-training and fine-tuning format, our model converges faster than baseline during fine-tuning (See Appendix C.2).

Figure 3(b) shows the model performance regarding different scales of silver data. Even without silver data, the performance of our model is better than the baseline, indicating that graph pre-training is beneficial for downstream tasks by providing a rich format of training data and more training objectives. When silver data are available, the performance of both AMR parsing and generation tasks increase with the scale of silver data, with a BLEU increase by about 2 points.

4.5 Main Results

AMR parsing. Table 4 lists the result of different models on AMR2.0 and AMR3.0. Among previous works, Bevilacqua+ (2021, large) achieves the best results, consistently outperforming other systems. Compared with the system of Bevilacqua et al. (2021), our model obtains significantly (p<0.01) better Smatch scores in both *base* and *large* settings on both datasets. In particular, our

base model outperforms the Bevilacqua+ (2021, base) by 1.0 Smatch point on AMR2.0, and our *large* model obtains a Smatch of 85.2 and 83.9 on AMR2.0 and AMR3.0, respectively. To our knowledge, these are the best-reported results, showing the effectiveness of our method.

Besides, Bevilacqua+ (2021, large)^s uses silver data for fine-tuning, yet does not lead to consistent improvement over Bevilacqua+ (2021, large). In contrast, our large model gives 0.9 higher Smatch than Bevilacqua+ (2021, large)^s. This indicates that our pre-training framework is a better way than fine-tuning to make use of silver data. The main reason is that our models are pre-trained using a denoising auto-encoding manner, which is less sensitive to silver (or noisy) data than fine-tuning.

AMR-to-text generation. We report the results of different systems on AMR2.0 and AMR3.0 in Table 5. With the help of BART, Bevilacqua+ (2021, large) obtains significantly better results than previous graph-to-sequence and GPT-based models. Compared with the system of Bevilacqua et al. (2021), our models (*base* and *large*) give significantly (p<0.001) better results in terms of all evaluation metrics. In particular, our *base* model achieves comparable or better performance than Bevilacqua+ (2021, large). Compared with Bevilacqua+ (2021, large)^s, our large model improves the performance by 3.2 and 2.7 points on AMR2.0 and AMR3.0, respectively. In addition, using silver data (same with pre-training) for fine-tuning leads to further improvements over our *large* model. This indicates that our pre-training methods are complementary to fine-tuning on AMR generation task.

Zero-shot Domain Adaption. We use the model trained on AMR2.0 to get predictions on out-of-domain testsets. Table 6 shows the results on AMR parsing and AMR-to-text generation tasks. Similar to in-domain experiments, our models achieve better results than existing methods. In particular, our *base* model can give comparable performance than Bevilacqua+ (2021, large), and our *large* model obtains the best-reported results. This indicates that our model is more robust to new domains, thanks to joint graph and text pre-training. Regarding different domains, our method achieves bigger improvements on New3 than the other two domains. This is intuitive, as New3 is close to the domain of AMR training data, pre-training strengthens the model representation power on the domain.

In addition, Bevilacqua+ (2021, large)^s gives lower results than Bevilacqua+ (2021, large) in New3 (both tasks) and TLP (only AMR-to-text generation). In contrast, our model gives consistent improvements on all 3 domains. This can be because fine-tuning leads to catastrophic forgetting of distributional knowledge (Kirkpatrick et al., 2017).

Model	BLEU	CH.	MET.
AMR 2.0			
Zhu+ (2019)	31.8	64.1	36.4
Bai+ (2020)	34.2	65.7	38.2
Mager+ (2020)†	33.0	63.9	37.7
Ribeiro+ (2021)†	43.5	-	42.9
Bevilacqua+ (2021, base)†	42.7	72.2	40.7
Bevilacqua+ (2021, large)†	45.3	73.5	41.0
Bevilacqua+ (2021, large)^s†	45.9	74.2	41.8
Ours (base)†	46.4	74.1	41.2
Ours (large)†	49.1	75.8	42.5
Ours (large)†^{s}	**49.5**	**76.1**	**42.8**
AMR 3.0			
Bevilacqua+ (2021, large)†	44.9	72.9	40.6
Bevilacqua+ (2021, large)^s†	46.5	73.9	41.7
Ours (base)†	46.7	73.8	41.2
Ours (large)†	49.2	75.4	42.3
Ours (large)†^{s}	**49.7**	**75.8**	**42.6**

Table 5: AMR-to-text results on AMR 2.0 and AMR 3.0. CH.=CHRF++. MET.=METEOR. Model marked with † rely on pre-trained models. The best result within each row block is shown in bold.

Model	New3	TLP	Bio
AMR Parsing			
Bevilacqua+ (2021, large)	73.7	77.3	59.7
Bevilacqua+ (2021, large)^s	71.8	77.5	59.5
Ours (base)	74.9	77.8	59.5
Ours (large)	**76.4**	**79.2**	**62.0**
AMR-to-Text			
Bevilacqua+ (2021, large)	38.8	25.4	18.7
Bevilacqua+ (2021, large)^s	38.2	25.1	19.4
Ours (base)	40.6	25.7	17.4
Ours (large)	**45.2**	**27.5**	**21.1**

Table 6: Out of distribution performance on AMR parsing (Smatch) and AMR-to-text (BLEU).

4.6 Impact of Graph

Table 7 shows the effects of the graph size, graph diameter and reentrancies on the performance. We split the testset of AMR2.0 into different groups and report the performance improvement of over the system of Bevilacqua et al. (2021). All models are trained on AMR2.0. We first consider graph size, which records the number of nodes in an AMR graph. Our model consistently outperforms the baseline model on both tasks, with the performance gap growing on larger graphs. This indicates that

Graph Size	1-10 (522)	11-20 (556)	>20 (293)
AMR parsing	+0.3	+1.0	+0.8
AMR-to-text	+0.9	+3.2	+2.1
Graph Depth	1-3 (422)	4-6 (667)	>6 (282)
AMR parsing	+0.8	+0.9	0.0
AMR-to-text	+1.2	+2.3	+2.8
Reentrancies	0 (622)	1-3 (712)	>4 (37)
AMR parsing	+1.1	+0.6	0.0
AMR-to-text	+2.0	+2.7	+0.4

Table 7: Performance improvements on AMR parsing (Smatch) and AMR-to-text (BLEU).

our system is more powerful in dealing with larger graphs. The main reason is that our joint text and graph pre-training mechanism enhances the model with the ability to capture word or span level correlation between text and graph, which is helpful for dealing with long sequence and large graphs.

The graph depth is defined as the longest distance between the AMR node and root node. A graph with deeper depth has more long-range dependencies. For AMR parsing, the proposed model gives a better Smatch than the baseline on the first two groups of graphs, and a comparable score on graphs with a depth bigger than 6. For AMR generation, our model consistently improves over the baseline on all graphs, and the improvements are bigger on deeper graphs. This shows that our model is better for learning more complex graphs. A possible reason is that our graph masking strategies train the model to learn the relationships between a sub-graph and the remaining graph context, making it easier to understand deep graphs.

Reentrancy is the number of nodes which has multiple parents. According to previous work (Damonte and Cohen, 2019; Szubert et al., 2020), reentrancies pose difficulties to both AMR parsing and AMR-to-text tasks. The more reentrancies, the harder the graph is to be understood. Our method gives significantly (p<0.01) better results on both tasks when the input graphs have less than 4 reentrancies. For graphs with more than 4 reentrancies, the proposed model is 0.4 better on AMR-to-text generation task and comparable than baseline on AMR parsing task. This means that our system has an overall better ability on learning reentrancies.

4.7 Case study

Table 8 presents two examples for AMR parsing and generation tasks, respectively. We take the base model of Bevilacqua et al. (2021) as the baseline. Although generating a fluent sentence, the baseline model omits important semantic unit "*have-purpose-91*" in the first example. Also, in the second, the concept "*hard*" is ignored by baseline in the generated AMR graph. In contrast, our system preserves all semantic information from the input. This shows that our model generates more faithful output than baseline. The reason can be attributed to the modeling of correspondence between text and AMR graph during pre-training. We give more examples for both tasks in Table 11 and Table 12, please refer to Appendix C.3 for more details.

AMR: (h / have-purpose-91 :ARG1 (t / thing :ARG1-of (e / expend-01 :ARG2 (t2 / transport-01))) :ARG2 (a / amr-unknown))
Gold: What is the purpose of transportation-related expenditures? **Baseline:** What are the transportation expenses? **Ours:** What is the purpose of transportation expenses?
Text: It's getting hard to keep strong and keep carrying on with life.
Gold: (g / get-03 :ARG1 (a / and :op1 (k / keep-02 :ARG1 (s / strong-02)) :op2 (k2 / keep-02 :ARG1 (c / carry-on-02 :ARG1 (l / live-01)))) :ARG2 (h / hard-02)) **Baseline:** (z0 / get-03 :ARG1 (z1 / and :op1 (z2 / keep-02 :ARG1 (z3 / strong-02)) :op2 (z4 / carry-on-02 :ARG1 (z5 / life)))) **Ours:**(z0 / get-03 :ARG1 (z1 / and :op1 (z2 / keep-02 :ARG1 (z3 / strong-02)) :op2 (z4 / keep-02 :ARG1 (z5 / carry-on-02 :ARG1 (z6 / life)))) :ARG2 (z7 / hard-02 :ARG1 z1))

Table 8: Outputs generated by baseline and our model.

5 Conclusion

We investigated pre-training of AMR graphs as a complement to text pre-training for AMR parsing and generation tasks, considering a novel unified framework with dual graph and text masking. Results showed that graph pre-training is highly effective for both parsing and generation, and is a more effective way of making use of silver data compared with fine-tuning. Our methods give the best results on multiple benchmarks.

References

Xuefeng Bai, Yulong Chen, Linfeng Song, and Yue Zhang. 2021. Semantic representation for dialogue modeling. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4430–4445, Online. Association for Computational Linguistics.

Xuefeng Bai, Linfeng Song, and Yue Zhang. 2020. Online back-parsing for AMR-to-text generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1206–1219, Online. Association for Computational Linguistics.

Miguel Ballesteros and Yaser Al-Onaizan. 2017. AMR parsing using stack-LSTMs. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1269–1275, Copenhagen, Denmark. Association for Computational Linguistics.

Laura Banarescu, Claire Bonial, Shu Cai, Madalina Georgescu, Kira Griffitt, Ulf Hermjakob, Kevin Knight, Philipp Koehn, Martha Palmer, and Nathan Schneider. 2013. Abstract meaning representation for sembanking. In *Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse*.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Daniel Beck, Gholamreza Haffari, and Trevor Cohn. 2018. Graph-to-sequence learning using gated graph neural networks. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 273–283, Melbourne, Australia. Association for Computational Linguistics.

Michele Bevilacqua, Rexhina Blloshmi, and Roberto Navigli. 2021. One spring to rule them both: Symmetric amr semantic parsing and generation without a complex pipeline. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(14):12564–12573.

Deng Cai and Wai Lam. 2020. AMR parsing via graph-sequence iterative inference. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1290–1301, Online. Association for Computational Linguistics.

Shu Cai and Kevin Knight. 2013. Smatch: an evaluation metric for semantic feature structures. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 748–752, Sofia, Bulgaria. Association for Computational Linguistics.

Marco Damonte and Shay B. Cohen. 2019. Structural neural encoders for AMR-to-text generation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3649–3658, Minneapolis, Minnesota. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Ramón Fernandez Astudillo, Miguel Ballesteros, Tahira Naseem, Austin Blodgett, and Radu Florian. 2020. Transition-based parsing with stack-transformers. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1001–1007, Online. Association for Computational Linguistics.

Jeffrey Flanigan, Chris Dyer, Noah A. Smith, and Jaime Carbonell. 2016. CMU at SemEval-2016 task 8: Graph-based AMR parsing with infinite ramp loss. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 1202–1206, San Diego, California. Association for Computational Linguistics.

Jeffrey Flanigan, Sam Thomson, Jaime Carbonell, Chris Dyer, and Noah A. Smith. 2014. A discriminative graph-based parser for the Abstract Meaning Representation. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1426–1436, Baltimore, Maryland. Association for Computational Linguistics.

Zhijiang Guo and Wei Lu. 2018. Better transition-based AMR parsing with a refined search space. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1712–1722, Brussels, Belgium. Association for Computational Linguistics.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In *Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA*, volume 97 of *Proceedings of Machine Learning Research*, pages 2790–2799. PMLR.

Weihua Hu, Bowen Liu, Joseph Gomes, Marinka Zitnik, Percy Liang, Vijay S. Pande, and Jure Leskovec.

2020a. Strategies for pre-training graph neural networks. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.

Ziniu Hu, Yuxiao Dong, Kuansan Wang, Kai-Wei Chang, and Yizhou Sun. 2020b. GPT-GNN: generative pre-training of graph neural networks. In *KDD '20: The 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, CA, USA, August 23-27, 2020*, pages 1857–1867. ACM.

Lifu Huang, Taylor Cassidy, Xiaocheng Feng, Heng Ji, Clare R. Voss, Jiawei Han, and Avirup Sil. 2016. Liberal event extraction and event schema induction. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 258–268, Berlin, Germany. Association for Computational Linguistics.

Thomas Kipf and Max Welling. 2016. Variational graph auto-encoders. *ArXiv*, abs/1611.07308.

James Kirkpatrick, Razvan Pascanu, Neil C. Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A. Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, Demis Hassabis, Claudia Clopath, Dharshan Kumaran, and Raia Hadsell. 2017. Overcoming catastrophic forgetting in neural networks. *Proceedings of the National Academy of Sciences*, 114:3521 – 3526.

Ioannis Konstas, Srinivasan Iyer, Mark Yatskar, Yejin Choi, and Luke Zettlemoyer. 2017. Neural AMR: Sequence-to-sequence models for parsing and generation. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 146–157, Vancouver, Canada. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.

Kexin Liao, Logan Lebanoff, and Fei Liu. 2018. Abstract Meaning Representation for multi-document summarization. In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 1178–1190, Santa Fe, New Mexico, USA. Association for Computational Linguistics.

Fei Liu, Jeffrey Flanigan, Sam Thomson, Norman Sadeh, and Noah A. Smith. 2015. Toward abstractive summarization using semantic representations. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1077–1086, Denver, Colorado. Association for Computational Linguistics.

Yijia Liu, Wanxiang Che, Bo Zheng, Bing Qin, and Ting Liu. 2018. An AMR aligner tuned by transition-based parser. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2422–2430, Brussels, Belgium. Association for Computational Linguistics.

Yuanfu Lu, Xunqiang Jiang, Yuan Fang, and Chuan Shi. 2021. Learning to pre-train graph neural networks. In *AAAI*.

Chunchuan Lyu, Shay B. Cohen, and Ivan Titov. 2020. A differentiable relaxation of graph segmentation and alignment for AMR parsing. *CoRR*, abs/2010.12676.

Chunchuan Lyu and Ivan Titov. 2018. AMR parsing as graph prediction with latent alignment. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 397–407, Melbourne, Australia. Association for Computational Linguistics.

Manuel Mager, Ramón Fernandez Astudillo, Tahira Naseem, Md Arafat Sultan, Young-Suk Lee, Radu Florian, and Salim Roukos. 2020. GPT-too: A language-model-first approach for AMR-to-text generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1846–1852, Online. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Xiaochang Peng, Linfeng Song, Daniel Gildea, and Giorgio Satta. 2018. Sequence-to-sequence models for cache transition systems. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1842–1852, Melbourne, Australia. Association for Computational Linguistics.

Xiaochang Peng, Chuan Wang, Daniel Gildea, and Nianwen Xue. 2017. Addressing the data sparsity issue in neural AMR parsing. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 366–375, Valencia, Spain. Association for Computational Linguistics.

Maja Popović. 2017. chrF++: words helping character n-grams. In *Proceedings of the Second Conference on Machine Translation*, pages 612–618, Copenhagen, Denmark. Association for Computational Linguistics.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text

transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Leonardo F. R. Ribeiro, Martin Schmitt, Hinrich Schütze, and Iryna Gurevych. 2021a. Investigating pretrained language models for graph-to-text generation. In *Proceedings of the 3rd Workshop on Natural Language Processing for Conversational AI*, pages 211–227, Online. Association for Computational Linguistics.

Leonardo F. R. Ribeiro, Yue Zhang, and Iryna Gurevych. 2021b. Structural adapters in pretrained language models for amr-to-text generation. In *EMNLP*.

Linfeng Song, Daniel Gildea, Yue Zhang, Zhiguo Wang, and Jinsong Su. 2019. Semantic neural machine translation using AMR. *Transactions of the Association for Computational Linguistics*, 7:19–31.

Linfeng Song, Yue Zhang, Zhiguo Wang, and Daniel Gildea. 2018. A graph-to-sequence model for AMR-to-text generation. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1616–1626, Melbourne, Australia. Association for Computational Linguistics.

Ida Szubert, Marco Damonte, Shay B. Cohen, and Mark Steedman. 2020. The role of reentrancies in Abstract Meaning Representation parsing. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2198–2207, Online. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008.

Chuan Wang, Nianwen Xue, and Sameer Pradhan. 2015a. Boosting transition-based AMR parsing with refined actions and auxiliary analyzers. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 857–862, Beijing, China. Association for Computational Linguistics.

Chuan Wang, Nianwen Xue, and Sameer Pradhan. 2015b. A transition-based algorithm for AMR parsing. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 366–375, Denver, Colorado. Association for Computational Linguistics.

Dongqin Xu, Junhui Li, Muhua Zhu, Min Zhang, and Guodong Zhou. 2020. Improving AMR parsing with sequence-to-sequence pre-training. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2501–2511, Online. Association for Computational Linguistics.

Sheng Zhang, Xutai Ma, Kevin Duh, and Benjamin Van Durme. 2019a. AMR parsing as sequence-to-graph transduction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 80–94, Florence, Italy. Association for Computational Linguistics.

Sheng Zhang, Xutai Ma, Kevin Duh, and Benjamin Van Durme. 2019b. Broad-coverage semantic parsing as transduction. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3786–3798, Hong Kong, China. Association for Computational Linguistics.

Zixuan Zhang and Heng Ji. 2021. Abstract Meaning Representation guided graph encoding and decoding for joint information extraction. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 39–49, Online. Association for Computational Linguistics.

Yanbin Zhao, Lu Chen, Zhi Chen, Ruisheng Cao, Su Zhu, and Kai Yu. 2020. Line graph enhanced AMR-to-text generation with mix-order graph attention networks. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 732–741, Online. Association for Computational Linguistics.

Jiawei Zhou, Tahira Naseem, Ramón Fernandez Astudillo, and Radu Florian. 2021. AMR parsing with action-pointer transformer. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5585–5598, Online. Association for Computational Linguistics.

Qiji Zhou, Yue Zhang, Donghong Ji, and Hao Tang. 2020. AMR parsing with latent structural information. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4306–4319, Online. Association for Computational Linguistics.

Jie Zhu, Junhui Li, Muhua Zhu, Longhua Qian, Min Zhang, and Guodong Zhou. 2019. Modeling graph structure in transformer for better AMR-to-text generation. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5459–5468, Hong Kong, China. Association for Computational Linguistics.

Param. Name	Value
Pre-training	
Batch Size	32
Optimizer	AdamW
Learning Rate (lr)	5e-5
Lr Scheduler	inverse_sqrt
Warmup Step	2,500
Total Step	100,000
Extended Vocabulary Size	53,843
Max Sequence Length	512
Mix Precision	fp16 (O1)
Number of Parameters	142M (base), 409M (large)
Training Time	13h (base), 70h (large)
Fine-tuning (AMR parsing)	
Batch Size	8
Optimizer	AdamW
Learning Rate (lr)	3e-5 (base), 1e-5 (large)
Lr Scheduler	constant
Warmup Step	0
Total Epoch	20
Early Stop	5
Max Sequence Length	512
Beam Size	5
Length Penalty	1.0
Label Smoothing	0
Mix Precision	fp16 (O1)
Training Time	6h (base), 12h (large)
Fine-tuning (AMR2text)	
Batch Size	8
Optimizer	AdamW
Learning Rate (lr)	1e-5 (base), 3e-6 (large)
Lr scheduler	constant
Warmup Step	0
Total Epoch	20
Early Stop	5
Max Sequence Length	512
Beam Size	5
Length Penalty	1.0
Label Smoothing	0
Mix Precision	fp16 (O1)
Training Time	3h (base), 6h (large)

Table 9: Hyper-parameters of our models on Pre-training and Fine-tuning.

A Model Hyper-Parameters

Table 9 lists all model hyper-parameters used for our experiments. We implement our model based on *Pytorch* and *Huggingface Transformers*. The pre-processed data, source code and pre-trained models will be released at xxx.

B Fine-grained Evaluation Metric for AMR Parsing

The Smatch score (Cai and Knight, 2013) measures the degree of overlap between the gold and the prediction AMR graphs. It can be further broken into different sub-metrics, including:

- Unlabeled (Unlab.): Smatch score after removing edge-labels
- NoWSD: Smatch score after ignoring Propbank senses (e.g. go-01 vs go-02)
- Concepts (Con.): F-score on the concept identification task
- Wikification (Wiki.): F-score on the wikification (`:wiki` roles)
- Named Entity Recognition (NER): F-score on the named entities (`:name` roles).
- Reentrancy (Reen.): Smatch score on reentrant edges.
- Negation (Neg.): F-score on the negation detection (`:polarity` roles).
- Semantic Role Labeling (SRL): Smatch score computed on `:ARG-i` roles.

Setting	AMR parsing	AMR-to-text
Full Model	83.6	45.6
- Node/edge masking	83.4	45.1
- Sub-graph masking	83.1	44.7

Table 10: Comparison of two masking strategies.

C More Experimental Results

C.1 Ablation Study of Graph Masking Strategies

Table 10 shows an ablation study on two graph masking strategies (in Section 3.2). We use our base model as the baseline and evaluate the performance after removing the node/edge masking or the sub-graph masking task. Without the node/edge masking task, the performance decreases on both AMR parsing and AMR-to-text generation tasks. The performance drop is larger when removing the sub-graph masking task, with a decrease of by 0.5 Smatch and 0.9 BLEU, respectively.

C.2 The effect of our pre-training framework

Figure 4 compares the learning curve between our system (fine-tuning from our pre-trained model) and baseline (fine-tuning from vanilla BART) on AMR2.0 devset.[5] It can be observed that our system has a initial BLEU score of 26.0, which is significantly (p< 0.001) better than the baseline. This confirm that our unified framework can reduce the gap between pre-training and fine-tuning. In addition, the training curve of the proposed model

[5]We use the same learning rate and optimizer.

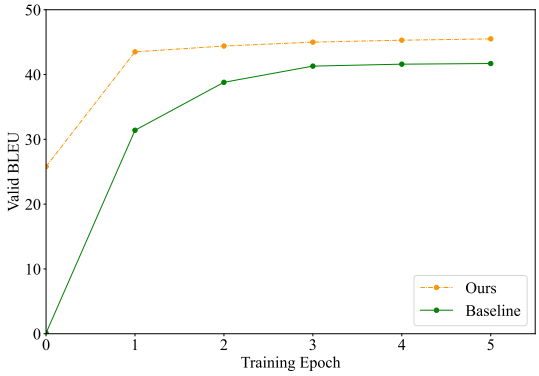


Figure 4: The learning curve of baseline and our system on AMR-to-text generation task.

converges faster while the BLEU score is better than the baseline. This indicates that our model has a larger capacity than baseline.

C.3 Case Study

Table 11 presents two cases of AMR parsing. We compare the model generated outputs (*base* model of (Bevilacqua et al., 2021) and our *base* model model) and the gold output given the same input sentence. As shown in the first example, the baseline model omits the semantic unit "*hard*", thus generates an incomplete AMR graph of a different meaning compared with the input sentence. In contrast, our system successfully preserves the concept "*hard*" and transfer the semantic relations correctly. In the second example, the clause "*they can help you*" in the input text is a modification of "*if*". We see that in the output AMR graph of the baseline model, clause "*they can help you*" is misconnected with "*tell*", resulting in the meaning of "they tell you they can help you". In contrast, our system preserves all semantic units and connects nodes with correct relations. This shows that our method is better than baseline in "translating" core semantics, thank to the modeling of correspondence between text and graph during pre-training.

Table 12 lists two AMR graphs and the corresponding outputs of two different AMR-to-text systems. In the first example, although the baseline generates a fluent sentence, it ignores the concept "*have-purpose-91*", resulting in that the generated sentence is of a different meaning compared with the input graph. Regarding to the second AMR graph, "*before*" modifies the phrase "*won many championships*". However, "*before*" is used to modified the phrase "*participating in international competitions*" in the baseline output. Compared

Text#1: It's getting hard to keep strong and keep carrying on with life.
Gold: (g / get-03 :ARG1 (a / and :op1 (k / keep-02 :ARG1 (s / strong-02)) :op2 (k2 / keep-02 :ARG1 (c / carry-on-02 :ARG1 (l / live-01)))) :ARG2 (h / hard-02))
Baseline: (z0 / get-03 :ARG1 (z1 / and :op1 (z2 / keep-02 :ARG1 (z3 / strong-02)) :op2 (z4 / carry-on-02 :ARG1 (z5 / life))))
Ours: (z0 / get-03 :ARG1 (z1 / and :op1 (z2 / keep-02 :ARG1 (z3 / strong-02)) :op2 (z4 / keep-02 :ARG1 (z5 / carry-on-02 :ARG1 (z6 / life)))) :ARG2 (z7 / hard-02 :ARG1 z1))
Text#2: If you tell people they can help you.
Gold: (p / possible-01 :ARG1 (h / help-01 :ARG0 (p2 / person) :ARG1 (y / you)) :condition (t / tell-01 :ARG0 y :ARG2 p2))
Baseline: (z0 / have-condition-91 :ARG2 (z1 / tell-01 :ARG0 (z2 / you) :ARG1 (z3 / possible-01 :ARG1 (z4 / help-01 :ARG0 (z5 / they) :ARG1 z2)) :ARG2 (z6 / person)))
Ours: (z0 / possible-01 :ARG1 (z1 / help-01 :ARG0 (z2 / they) :ARG1 (z3 / you)) :condition (z4 / tell-01 :ARG0 z3 :ARG2 (z5 / person)))

Table 11: Case study for AMR parsing.

with the baseline, our system recovers all concepts and maps the modification relationship from the AMR graph to text correctly. This indicates that our model generates more faithful sentences than baseline.

AMR#1:

```
(h / have-purpose-91
   :ARG1 (t / thing
      :ARG1-of (e / expend-01
         :ARG2 (t2 / transport-01)))
   :ARG2 (a / amr-unknown))
```

Gold: What is the purpose of transportation-related expenditures?
Baseline: What are the transportation expenses?
Ours: What is the purpose of transportation expenses?

AMR#2:

```
(w / win-01
   :ARG0 (p2 / person :wiki - :name (n / name :op1 "Fengzhu" :op2 "Xu"))
   :ARG1 (c / championship-02
      :ARG0 p2
      :quant (m / many))
   :time (b / before)
   :part-of (c2 / compete-01
      :mod (i / international)))
```

Gold: Fengzhu Xu has won many championships in international competitions before.

Baseline: Fengzhu Xu won many championships before participating in international competitions.

Ours: Fengzhu Xu has won many championships in international competitions before.

Table 12: Case study for AMR-to-text generation.