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...
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-tuning, 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).
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 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 denoising 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., \( \tilde{t}_2 \) and \( \tilde{g}_2 \)) but different

\(^1\) A sub-graph has at least one edge and one node.
| Phase     | Task                           | input                                                      | output                                                  |
|-----------|--------------------------------|------------------------------------------------------------|---------------------------------------------------------|
| Std. P.T. | $t2t$                          | $<s>x_1, ..., \text{[mask]} ..., x_n</s>$                  | $<s>x_1, x_2, ..., x_n</s>$                            |
|           | $g2g$                          | $<g>g_1, ..., \text{[mask]} ..., g_m</g>$                  | $<g>g_1, g_2, ..., g_m</g>$                            |
| Std. F.T. | $g2t$                          | $<g>g_1, g_2, ..., g_m</g>$                                | $<s>x_1, x_2, ..., x_n</s>$                            |
|           | $t2g$                          | $<s>x_1, x_2, ..., x_n</s>$                                | $<g>g_1, g_2, ..., g_m</g>$                            |
| Unified P.T. | $t\bar{g}2t$                  | $<s>x_1, ..., \text{[mask]} ..., x_n</s>\langle g\rangle$  | $<s>x_1, x_2, ..., x_n</s>$                            |
|           | $\bar{g}2g$                    | $<\text{[mask]} \rangle <g>g_1, ..., \text{[mask]} ..., g_m</g>$ | $<g>g_1, g_2, ..., g_m</g>$                            |
| Unified F.T. | $t\bar{g}2g$                  | $<s>x_1, x_2, ..., x_n</s>\langle g\rangle$               | $<g>g_1, g_2, ..., g_m</g>$                            |

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

in the fine-tuning 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 $t = \{x_1, x_2, ..., x_n\}$ and $g = \{g_1, g_2, ..., g_m\}$, $\bar{t}$ and $\bar{g}$ represent the noisy text and graph, respectively, and $\emptyset$ and $\bar{\emptyset}$ 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 $t\bar{g}$. 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 ($t\bar{g}2t$), where an AMR graph is taken as additional input to help masked text reconstruction;
2) text augmented graph denoising ($t\bar{g}2g$), where text helps graph reconstruction;
3) noisy graph augmented text denoising ($\bar{t}\bar{g}2t$), where the target text is generated based on a pair of masked text and masked graph;
4) noisy text augmented graph denoising ($\bar{t}\bar{g}2g$), 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 $t\bar{g}2t$ and $t\bar{g}2g$. Formally, at each step $t$, we calculate the masking probability $p$ according to the following function:

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

where 0.3 is the initial masking rate and $p$ increases 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 $t\bar{g}2t$ for AMR-to-text generation and $t\bar{g}2g$ 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:

$$L_{t2t} = -\log P(t|\bar{t}, \bar{g}),$$
$$L_{g2g} = -\log P(g|\bar{t}, \bar{g}),$$
$$L_{\bar{t}2t} = -\log P(t|\bar{t}, g),$$
$$L_{\bar{g}2g} = -\log P(g|\bar{t}, \bar{g}),$$
$$L_{\bar{t}2\bar{g}} = -\log P(t|\bar{t}, \bar{g}),$$
$$L_{\bar{g}2\bar{g}} = -\log P(g|\bar{t}, \bar{g}),$$

where $L_{t2t}$ and $L_{g2g}$ are standard pre-training loss on text (Section 3.1) and graph (Section 3.2), respectively. $L_{\bar{t}2\bar{g}}, L_{\bar{g}2\bar{g}}, L_{\bar{t}2\bar{g}}$, and $L_{\bar{g}2\bar{g}}$ denote 4 joint pre-training losses (Section 3.3).

For fine-tuning, the training objectives are:

$$L_{amr2text} = -\log P(t|\bar{g}, g),$$
$$L_{text2amr} = -\log P(g|t, \bar{g}),$$

where $L_{amr2text}$ and $L_{text2amr}$ are training loss of AMR generation and AMR parsing, respectively.
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 https://github.com/huggingface/transformers.

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.\footnote{Please refer to Appendix B for more details.} 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).

Table 2: Benchmark AMR datasets.

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

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

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

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.
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 (tg2t) and graph (tg2g) 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, tg2g gives a Smatch improvement of 0.7 for AMR paring, and tg2t reaches a BLEU of 45.3 for AMR generation, which is 2.8 points higher than baseline. Adding tg2g gives a Smatch of 83.2 for AMR parsing, and tg2t improves the baseline by 1.7 BLEU points for generation. By combining tg2g and tg2t, the performance increases by 0.6 and 2.5 points on AMR parsing and generation, respectively. Similar trend can be observed by combining tg2g and tg2t. Finally, using all 6 pre-training tasks, our model reaches 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 (tg2t, tg2g) and fine-tuning (t2g, 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) 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). 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), 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 generate 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) 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).

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

Table 8: Outputs generated by baseline and our model.

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

| 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.

- 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.

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. 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

5We use the same learning rate and optimizer.
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

![Figure 4: The learning curve of baseline and our system on AMR-to-text generation task.](image)

Text#1: It’s getting hard to keep strong and keep carrying on with life.

Gold:

\[ (g / \text{get-03}) :\text{ARG1} (a / \text{and}) \]

\[ :\text{op1} (k / \text{keep-02}) :\text{ARG1} (s / \text{strong-02})) \]

\[ :\text{op2} (k2 / \text{keep-02}) :\text{ARG1} (c / \text{carry-on-02}) \]

\[ :\text{ARG1} (1 / \text{live-01})) \]

\[ :\text{ARG2} (h / \text{hard-02}) \]

Baseline:

\[ (z0 / \text{get-03}) :\text{ARG1} (z1 / \text{and}) \]

\[ :\text{op1} (z2 / \text{keep-02}) :\text{ARG1} (z3 / \text{strong-02})) \]

\[ :\text{op2} (z4 / \text{carry-on-02}) :\text{ARG1} (z5 / \text{life})) \]

Ours:

\[ (z0 / \text{get-03}) :\text{ARG1} (z1 / \text{and}) \]

\[ :\text{op1} (z2 / \text{keep-02}) :\text{ARG1} (z3 / \text{strong-02})) \]

\[ :\text{op2} (z4 / \text{keep-02}) :\text{ARG1} (z5 / \text{carry-on-02}) \]

\[ :\text{ARG1} (z6 / \text{life})) \]

\[ :\text{ARG2} (z7 / \text{hard-02}) \]

\[ :\text{ARG1} (z1)) \]

Text#2: If you tell people they can help you.

Gold:

\[ (p / \text{possible-01}) \]

\[ :\text{ARG1} (h / \text{help-01}) :\text{ARG0} (p2 / \text{person}) \]

\[ :\text{ARG1} (y / \text{you}) \]

\[ :\text{condition} (t / \text{tell-01}) :\text{ARG0} y :\text{ARG2} p2)) \]

Baseline:

\[ (z0 / \text{have-condition-91}) \]

\[ :\text{ARG2} (z1 / \text{tell-01}) :\text{ARG0} (z2 / \text{you}) :\text{ARG1} (z3 / \text{possible-01}) \]

\[ :\text{ARG1} (z4 / \text{help-01}) :\text{ARG0} (z5 / \text{they}) \]

\[ :\text{ARG1} (z2)) \]

\[ :\text{ARG2} (z6 / \text{person})) \]

Ours:

\[ (z0 / \text{possible-01}) \]

\[ :\text{ARG1} (z1 / \text{help-01}) :\text{ARG0} (z2 / \text{they}) \]

\[ :\text{ARG1} (z3 / \text{you}) \]

\[ :\text{condition} (z4 / \text{tell-01}) :\text{ARG0} z3 \]

\[ :\text{ARG2} (z5 / \text{person})) \]

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.