Hierarchical Curriculum Learning for AMR Parsing

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Abstract

Abstract Meaning Representation (AMR) parsing aims to translate sentences to semantic representation with a hierarchical structure, and is recently empowered by pretrained sequence-to-sequence models. However, there exists a gap between their flat training objective (i.e., equally treats all output tokens) and the hierarchical AMR structure, which limits the model generalization. To bridge this gap, we propose a Hierarchical Curriculum Learning (HCL) framework with Structure-level (SC) and Instance-level Curricula (IC). SC switches progressively from core to detail AMR semantic elements while IC transits from structure-simple to -complex AMR instances during training. Through these two warming-up processes, HCL reduces the difficulty of learning complex structures, thus the flat model can better adapt to the AMR hierarchy. Extensive experiments on AMR2.0, AMR3.0, structure-complex and out-of-distribution situations verify the effectiveness of HCL.

1 Introduction

Abstract Meaning Representation (AMR) (Banarescu et al., 2013) parsing aims to translate a natural sentence into a directed acyclic graph. Figure 1(a) illustrates an AMR graph where nodes represent concepts, e.g., ‘die-01’ and ‘soldier’, and edges represent relations, e.g., ‘:ARG1’ and ‘:quant’. AMR has been exploited in the downstream NLP tasks, including information extraction (Rao et al., 2017; Wang et al., 2017; Zhang and Ji, 2021), text summarization (Liao et al., 2018; Hardy and Vlachos, 2018) and question answering (Mitra and Baral, 2016; Sachan and Xing, 2016).

The powerful pretrained encoder-decoder models, e.g., BART (Lewis et al., 2020), have been successfully adapted to the AMR parsing and became the mainstream and state-of-the-art methods (Bevilacqua et al., 2021). Through directly generating the linearized AMR graph (e.g., Figure 1(a)) from the sentence, these sequence-to-sequence methods (Xu et al., 2020b; Bevilacqua et al., 2021) circumvent the complex data processing pipeline and can be easily optimized compared with transition-based or graph-based methods (Naseem et al., 2019; Lee et al., 2020; Lyu and Titov, 2018; Zhang et al., 2019a,b; Cai and Lam, 2020; Zhou et al., 2021b). However, there exists a gap between the flat sentence-to-AMR training objective1 and AMR graphs, since sequence-to-sequence models deviate from the essence of graph representation. Therefore, it is difficult for sequential generators to learn the inherent hierarchical structure of AMR (Zhou et al., 2021b).

Humans usually adapt to difficult tasks by dealing with examples gradually from easy to hard, i.e., Curriculum Learning (Bengio et al., 2009; Platanios et al., 2019; Su et al., 2021; Xu et al., 2020a). Inspired by human behavior, we propose a hierarchy-

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1Flat means the objective equally treats all output tokens.
In each step of the $i$-th episode, the training scheduler samples a batch of examples from buckets $\{S_j : j \leq i\}$ to train the model. When parsing instances, we propose a hierarchical curriculum learning (HCL) framework to help the sequence-to-sequence model progressively adapt to the AMR hierarchy. (2) Extensive experiments on AMR2.0, AMR3.0, structure-complex and out-of-distribution situations verify the effectiveness of HCL.

2 Methodology

We formulate AMR parsing as a sequence-to-sequence transformation. Given a sentence $x = (x_1, \ldots, x_N)$, the model aims to generate a linearized AMR graph $y = (y_1, \ldots, y_M)$. As shown in Figure 1(a), following Bevilacqua et al. (2021), the AMR graph is linearized by the DFS-based linearization method with special tokens to indicate variables and parentheses to mark visit depth. Specifically, variables of AMR nodes are set to a series of special tokens $<RO>$, ..., $<RX>$ (more details of linearization are included in Appendix A). In this paper, we propose a hierarchical curriculum learning framework (Figure 2) with the structure- and instance-level curricula to help the flat model progressively adapt to the structured AMR graph.

2.1 Structure-level Curriculum

Motivated by learning core concepts first, we propose Structure-level Curriculum (SC). AMR graphs are organized in a hierarchy where the core semantic elements stay closely to the root node (Cai and Lam, 2019). As depicted in Figure 1, the concepts and relations that locate in the different layers of the AMR graph correspond to different levels of abstraction in terms of the semantic representation. Motivated by the human learning process, i.e., core concepts first, then details. SC enumerates all AMR sub-graphs with different depths, and deals with them in order from shallow to deep. (2) Instance-level Curriculum (IC). Our preliminary study in Figure 3 shows that the performance of the vanilla BART baseline would drop rapidly as the depth of AMR graph grows, which indicates that handing deeper AMR hierarchy is more difficult for pretrained models. Inspired by the human cognition, i.e., easy ones first, then hard ones, we propose IC which trains the model by starting from easy instances with a shallower AMR structure and then handling hard instances.

To sum up: (1) Inspired by the human learning process, i.e., core concepts first and easy instances first, we propose a hierarchical curriculum learning (HCL) framework to help the sequence-to-sequence model progressively adapt to the AMR hierarchy. (2) Extensive experiments on AMR2.0, AMR3.0, structure-complex and out-of-distribution situations verify the effectiveness of HCL.
We use the SMATCH work on two popular AMR benchmarks, AMR2.0, which is for AMR full graphs. (LDC2017T10) and AMR3.0 (LDC2020T02). Following Bevilacqua et al. (2021), we use the SMATCH scores (Cai and Knight, 2013) and the fine-grained evaluation metrics (Damonte et al., 2017) to evaluate the performances.

Experiment Setups Our implementation is based on Huggingface’s transformers library (Wolf et al., 2020) and the open codebase of Bevilacqua et al. (2021). We use BART-large as our sequence-to-sequence model the same as Bevilacqua et al. (2021). We utilizes RAdam (Liu et al., 2020) as our optimizer with the learning rate 3e-5. The batch size is 2048 graph linearization tokens with the gradient accumulation 10. Dropout is set to 0.25 and beam size is 5. The training steps $T_{sc}$ is 1000 and $T_{ic}$ is 500. After the curriculum training, the model is trained for 30 epochs on the training set. We use cross-entropy as our loss function. We train our model on a single NVIDIA TESLA V100 GPU with 32GB memory. We adopt the same post-processing process as Bevilacqua et al. (2021). Our code and model are available at https://github.com/Wangpeiyi9979/HCL-Text2AMR.

Table 1: SMATCH and fine-grained F1 scores on the AMR 2.0 and 3.0 test set. Our results are the average of 3 runs with different random seeds. Models\textsuperscript{G} indicate models with graph re-categorization (a data processing method that may hurt the model generalization ability Bevilacqua et al. (2021)).

3 Experiments

Datasets and Evaluation Metrics We evaluate our hierarchical curriculum learning framework on two popular AMR benchmarks, AMR2.0 (LDC2017T10) and AMR3.0 (LDC2020T02). Please refer to the Appendix B for details of two benchmarks. Following Bevilacqua et al. (2021), we use the SMATCH scores (Cai and Knight, 2013) and the fine-grained evaluation metrics (Damonte et al., 2017) to evaluate the performances.

| Model                | SMATCH   | Structure-independent | Structure-dependent |
|----------------------|----------|-----------------------|---------------------|
|                      | NoWSD | Conc. | NER | Neg. | Wiki. | Unll. | Reen. | SRL |
| Lyu and Titov (2018) | 74.4   | 75.5 | 85.9 | 86.0 | 58.4 | 75.7 | 77.1 | 52.3 | 69.8 |
| Zhang et al. (2019a) | 76.3   | 76.8 | 84.8 | 77.9 | 75.2 | 85.8 | 79.0 | 60.0 | 69.7 |
| Cai and Lam (2020)   | 78.7   | 79.2 | 88.1 | 87.1 | 66.1 | 81.3 | 81.5 | 63.8 | 74.5 |
| Cai and Lam (2020)\textsuperscript{G} | 80.2 | 80.8 | 88.1 | 81.1 | 78.9 | 86.3 | 82.8 | 64.6 | 74.2 |
| Fernandez Astudillo et al. (2020) | 80.2 | 80.7 | 88.1 | 87.5 | 64.5 | 78.8 | 84.2 | 70.3 | 78.2 |
| Zhou et al. (2021a)  | 81.7   | 82.3 | 88.7 | 88.5 | 69.7 | 78.8 | 85.5 | 71.1 | 80.8 |
| Bevilacqua et al. (2021) | 83.8 | 84.4 | 90.2 | 90.6 | 74.4 | 84.3 | 86.1 | 70.8 | 79.6 |
| HCL (Ours)           | 84.3   | 85.0 | 90.2 | 91.6 | 75.9 | 84.0 | 87.7 | 74.5 | 83.2 |

| Model                | SMATCH   | Structure-independent | Structure-dependent |
|----------------------|----------|-----------------------|---------------------|
|                      | NoWSD | Conc. | NER | Neg. | Wiki. | Unll. | Reen. | SRL |
| Cai and Lam (2020)   | 78.0   | 78.5 | 88.5 | 83.7 | 68.9 | 75.7 | 81.9 | 63.7 | 73.2 |
| Cai and Lam (2020)\textsuperscript{G} | 76.7 | 77.2 | 86.5 | 74.7 | 72.6 | 77.3 | 80.6 | 62.6 | 72.2 |
| Zhou et al. (2021a)  | 80.3   | -    | -   | -    | -    | -    | 85.4 | 70.4 | 78.9 |
| Bevilacqua et al. (2021) | 83.0 | 83.5 | 89.8 | 87.2 | 73.0 | 82.7 | 85.4 | 70.4 | 78.9 |
| HCL (Ours)           | 83.7   | 84.2 | 89.5 | 89.0 | 73.0 | 82.6 | 86.9 | 73.9 | 82.4 |

a sentence into a sub-graph with the depth $d$, we append a special string “parse to $d$ layers” to the input sentence, and replace the start token of the decoder with an artificial token $< d >$, so the model can perceive layers that need to be parsed.

2.2 Instance-level Curriculum

Inspired by learning easy instances first, we propose Instance-level Curriculum (IC). Figure 3 shows AMR graphs with deeper layers can be regarded as harder instances for the flat pretrained model, thus IC divides all AMR graphs into $M$ buckets according to their depths $\{I_i : i = 1, ..., M\}$, where $I_i$ contains AMR graphs with the depth $i$. As shown in Figure 2(b), IC has $M$ training episodes, and each episode consists of $T_{ic}$ steps. In each step of the $i$-th episode, the training scheduler samples a batch of examples from buckets $\{I_j : j \leq i\}$ to train the model. Specifically, we first use SC and then IC to train the model, since SC (follows learning core semantics first) is for AMR sub-graphs, which can be regarded as a warming-up stage of IC (obeys learning easy instances first), which is for AMR full graphs.
Table 2: The effect of our proposed curricula on the test set of AMR2.0 and AMR3.0. ‘w/o’ denotes without.

| Model                        | AMR2.0 | AMR3.0 |
|------------------------------|--------|--------|
| Ours                        | 84.3   | 83.7   |
| w/o instance curriculum      | 84.1   | 83.5   |
| w/o structure curriculum     | 84.0   | 83.3   |
| w/o curricula                | 83.8   | 83.0   |

Table 3: Results on out-of-distribution data.

| Model                          | BIO   | TLP   | News3 |
|--------------------------------|-------|-------|-------|
| Bevilacqua et al. (2021)       | 59.7  | 77.3  | 73.7  |
| HCL (Ours)                     | 61.1  | 78.2  | 75.3  |

4 An intuitive case study for the hard instance parsing is included in Appendix D.
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References

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, pages 178–186, Sofia, Bulgaria. Association for Computational Linguistics.

Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. 2009. Curriculum learning. In Proceedings of the 26th Annual International Conference on Machine Learning, ICML 2009, page 41–48, New York, NY, USA. Association for Computing Machinery.

Michele Bevilacqua, Rexhina Blloshmi, and Roberto Navigli. 2021. One spring to rule them both: Symmetric amr semantic parsing and generation without a complex pipeline. In Proceedings of the Thirty-Fifth AAAI Conference on Artificial Intelligence.

Deng Cai and Wai Lam. 2019. Core semantic first: A top-down approach for AMR parsing. 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 3799–3809, Hong Kong, China. Association for Computational Linguistics.

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, Shay B. Cohen, and Giorgio Satta. 2017. An incremental parser for abstract meaning representation. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 536–546, Valencia, Spain. 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.

Hardy Hardy and Andreas Vlachos. 2018. Guided neural language generation for abstractive summarization using Abstract Meaning Representation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 768–773, Brussels, Belgium. Association for Computational Linguistics.

Young-Suk Lee, Ramón Fernandez Astudillo, Tahira Naseem, Revanth Gangi Reddy, Radu Florian, and Salim Roukos. 2020. Pushing the limits of AMR parsing with self-learning. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 3208–3214, Online. Association for Computational Linguistics.

Mike Lewis, Yinhui 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.

Liyuan Liu, Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. 2020. On the variance of the adaptive learning rate and beyond. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.

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.

Arindam Mitra and Chitta Baral. 2016. Addressing a question answering challenge by combining statistical methods with inductive rule learning and reasoning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 30.
Tahira Naseem, Abhishek Shah, Hui Wan, Radu Florian, Salim Roukos, and Miguel Ballesteros. 2019. Rewarding Smatch: Transition-based AMR parsing with reinforcement learning. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4586–4592, Florence, Italy. Association for Computational Linguistics.

Emmanouil Antonios Platanios, Otilia Stretcu, Graham Neubig, Barnabas Poczos, and Tom Mitchell. 2019. Competence-based curriculum learning for neural machine translation. 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 1162–1172, Minneapolis, Minnesota. Association for Computational Linguistics.

Sudha Rao, Daniel Marcu, Kevin Knight, and Hal Daumé III. 2017. Biomedical event extraction using Abstract Meaning Representation. In BioNLP 2017, pages 126–135, Vancouver, Canada., Association for Computational Linguistics.

Mrinmaya Sachan and Eric Xing. 2016. Machine comprehension using rich semantic representations. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), Berlin, Germany. Association for Computational Linguistics.

Yixuan Su, Deng Cai, Qingyu Zhou, Zibo Lin, Simon Baker, Yunbo Cao, Shuming Shi, Nigel Collier, and Yan Wang. 2021. Dialogue response selection with hierarchical curriculum learning. 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 1740–1751, Online. Association for Computational Linguistics.

Yanshan Wang, Sijia Liu, Majid Rastegar-Mojarrad, Liwei Wang, Feichen Shen, Fei Liu, and Hongfang Liu. 2017. Dependency and amr embeddings for drug-drug interaction extraction from biomedical literature. In Proceedings of the 8th acm international conference on bioinformatics, computational biology, and health informatics, pages 36–43.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Phu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Benfeng Xu, Licheng Zhang, Zhendong Mao, Quan Wang, Hongtao Xie, and Yongdong Zhang. 2020a. Curriculum learning for natural language understanding. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6095–6104, Online. Association for Computational Linguistics.

Dongxin Xu, Junhui Li, Muhua Zhu, Min Zhang, and Guodong Zhou. 2020b. 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.

Jiawei Zhou, Tahira Naseem, Ramón Fernandez Astudillo, and Radu Florian. 2021a. 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.

Jiawei Zhou, Tahira Naseem, Ramón Fernandez Astudillo, Young-Suk Lee, Radu Florian, and Salim Roukos. 2021b. Structure-aware fine-tuning of sequence-to-sequence transformers for transition-based AMR parsing. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 6279–6290, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
A Linearization

DFS Linearization:
( <R0> tell -01  :ARG0  ( <R1> you ) :ARG1 ( <R3> wash -01 : ARG0 <R2> :ARG1 ( <R4> dog ) ) :ARG2 ( <R2> I ) )

Figure 5: The linearization for the AMR graph of the sentence “You told me to wash the dog”.

As shown in Figure 5, following Bevilacqua et al. (2021), the AMR graph is linearized by the DFS-based linearization method according to the edge order (’:ARG0’→’:ARG1’→’:ARG2’). Variables of the AMR graph are set to a series of special tokens <R0>, <R1>, <R2>, <R3>, <R4>, and the depth is marked by parentheses.

B Datasets

B.1 In-domain Distribution

AMR2.0 (LDC2017T10) contains 36,521, 1,368 and 1,371 sentence-AMR pairs in training, development and testing sets, respectively.

AMR3.0 (LDC2020T02) is larger than AMR2.0 in size, which contains 55,635, 1,722 and 1,898 sentence-AMR pairs for training development and testing set, respectively. AMR3.0 is a superset of AMR2.0.

B.2 Out-domain Distribution

BIO is a test set of the Bio-AMR corpus, consisting of 500 instances.

TLP is a AMR dataset annotated on the children’s novel The Little Prince (version 3.0), consisting of 1,562 instances.

New3 is a sub-set of AMR3.0, which is not included in the AMR2.0 training set, consisting of 527 instances.

C Fine-grained Metric Division

There are 8 fine-grained AMR metrics: (1) Unlabeled: Smatch score computed on the predicted graphs after removing all edge labels. (2) No WSD.: Smatch score while ignoring Propbank senses (e.g., duck-01 vs duck-02). (3) Named Ent.: F-score on the named entity recognition (:name roles). (4) Wikification: F-score on the wikification (:wiki roles). (5) Negation: F-score on the negation detection (:polarity roles). (6) Concepts: F-score on the concept identification task. (7) Reentrancy: Smatch computed on reentrant edges only, e.g., the edges of node ‘I’ in Figure A. (8) SRL: Smatch computed on :ARG-i roles only.

We only regard Unlabeled, Reentrancy and SRL as "structure-dependent" metrics, since: (1) Unlabeled does not consider any edge labels, and only considers the graph structure. (2) Reentrancy is a typical structure feature for the AMR graph. Without reentrant edges, the AMR graph is reduced to a tree. (3) SRL denotes the core-semantic relation of the AMR, which determines the core structure of the AMR. (4) As described above, all other metrics have little relationship with the structure.

D Case Study

Figure 6 shows a case study (we omit some details of AMR graphs for a more clear description). As is illustrated, our method achieves the right AMR, while the baseline model (i.e., SPRING (Bevilacqua et al., 2021)) gets a shallower and wrong structure AMR.

Figure 6: A specific case from the test set of AMR2.0. For the input sentence, our method achieves the right AMR, while the baseline model (i.e., SPRING (Bevilacqua et al., 2021)) gets a shallower and wrong structure AMR.