Survey: Graph Neural Network for Abstract Meaning Representation

Sichang Tu
sichang.tu@emory.edu
Emory University
Atlanta, Georgia, USA

ABSTRACT

This survey aims to provide an overview of Graph Neural Networks (GNNs) for Abstract Meaning Representation (AMR). We first provide an introduction of the research problem, and illustrate the challenges of the current research. Then we review the graph construction in AMR. Then we focus on the existing works for graph representation learning in AMR. And last, we will propose the possible directions of the topic.

KEYWORDS

graph neural network, abstract meaning representation, natural language processing

1 INTRODUCTION

Representing the semantic content of language in a machine-interpretable way has always been an important research area in Natural Language Processing (NLP). As a broad-coverage semantic formalism, Abstract Meaning Representation [1] models the semantic meaning of a sentence as a rooted, labeled, directed acyclic graph (DAG). Figure 1 gives an example of the AMR graph. Each node in the graph is a concept labeled with a unique variable, representing events, objects, or features of the sentence (e.g., "d" stands for "dog"). And each edge between the nodes represents semantic relations (e.g., the dog is the ARG0/"wanter" of the bone). AMR has been applied to many downstream NLP tasks, including question answering [12, 13], machine translation [11, 15], information extraction [18, 21], and text summarization [7, 9]

Since AMR formalism contains various information, such as semantic roles, coreference, and named entities, the complexity of the AMR graph poses challenges for graph construction and graph representation learning. Traditional sequence-based, deep learning models, which are designed for euclidean data, may not benefit AMR and its downstream NLP tasks considerably. To leverage the power of neural networks (NNs), Graph Neural Networks (GNNs) [14], as an extension of NNs to the non-Euclidean domain, have been widely applied to AMR in recent years.

This survey aims to investigate the graph construction and graph representation learning methods in AMR. In Section 2, we will formulate the problems and examine challenges for the tasks. Section 3 elaborates graph construction methods for AMR. Section 4 focuses on the different graph representation learning techniques for AMR. At last, we will discuss the potential future directions, providing helpful insights for researchers who are interested in this research area.

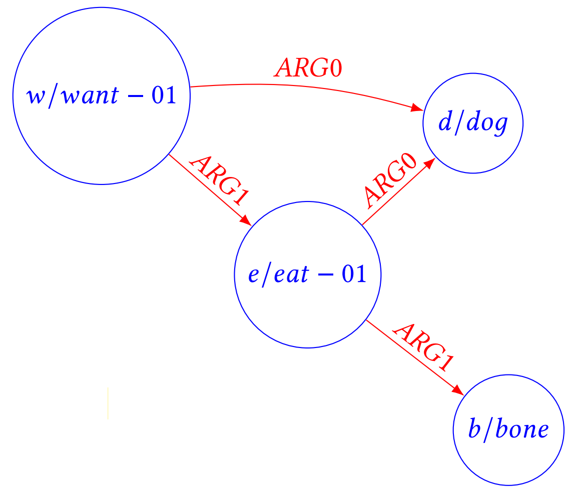

Figure 1: An example of AMR graph for the sentence "The dog wants to eat the bone."

2 BACKGROUND

In NLP, text sequences are always used as the model input. However, graph structure would be a better representation for many NLP problems like AMR since it provides more comprehensive semantic information than sequence input. Though deep learning methods have become ubiquitous in the NLP domain, graph-structured data has not taken full advantage of those techniques due to their euclidean nature. Hence, there is an increasing interest in developing graph-based models for AMR to address this gap.

Previous works on GNN for AMR can be divided into graph construction and graph representation learning. The former focuses on building AMR graphs from input text sequences, while the latter transduce graph structure into text sequences.

Graph Construction. Mathematically, for a given input sequence of text $W =< w_1, w_2, ..., w_n >$, the goal of the model is to generate an arbitrary graph $G =< V, E >$. Labels for vertices and edges are given from sets N, R. The first step of graph construction is identifying the concepts from the input sentence W, adding node v_i for each concept with a node type $n_i \in N$. And then, step two adds an edge e_i from node v_i to node v_j with an edge label $r_{i,j} \in R$. However, there are two profound challenges for the graph construction:

(1) The deficiency of the ground-truth alignment between the node in the graph and the word in the input sequence hinders the generation of training data from explicit alignment.

(2) The complicated structure of AMR graphs. For instance, the reentrancy property of AMR allows one concept to be referenced multiple times, thus differentiating AMR graphs from parsing trees.
(3) The annotated data is limited. Annotating AMR is time-consuming, and usually requires expert annotators.

Graph Representation Learning. Contrary to the graph construction, the goal of graph representation learning is to generate a text sequence from a given graph $G =< V, E >$, where $|V| = N$ and $|E| = M$. We define that $e_{i,j,l}$ is an edge from node v_i to v_j with a label l. And the corresponding sentence of Graph G is $W =< w_1, w_2, ..., w_n >$. There are also challenges for the transduction from graphs to sentences, including how to appropriately choose graph representation methods, how to deal with non-sequential input, and how to better modeling complex graph structure.

3 GRAPH CONSTRUCTION

AMR graph construction approaches can be categorized into 4 types, namely transition-based methods, sequence to sequence models, graph algebra methods, and sequence to graph models. This survey only focuses on the graph neural network application for AMR graphs, omitting the first three approaches.

As defined in Section 2, graph construction models seek to transduce the input text sequence in to a directed, labeled DAG. Most recent research adopted sequence to graph (seq2graph) paradigm, which directly construct the AMR graph from plain text without using transition approaches. Zhang et al. [20] propose an attention-based neural transducer as an extension of their earlier two-stage AMR parser [19]. Their model simplifies the two-step graph construction (see Section 2) into one, adopting a deep biaffine graph-based parser with maximum spanning tree to build relations.

Meanwhile, Cai and Lam [3] presents a novel framework for AMR graph construction, Graph Spanning Based Parsing (GSP), which is the first top-down approach for AMR parsing. They utilize a graph transformer encoder together with sentence encoder to output node representations. This method produces a semantic graph incrementally at each step. Therefore, it could capture complex intra-graph interactions, and reduce the parsing steps. Following this incremental seq2graph approach, they later introduce an end-to-end AMR parser, which incorporates an interactive inference process between the sequence encoder and the graph encoder [4]. This dual decision process better abstracts the input sentences and expands the AMR graph node-by-node.

Based on the work of Cai and Lam [4], Na and Min [10] presents a simplified joint-model for interactive inference between graphs and sequences. Instead of using both concept solver to predict new concepts in graph and relation solver to connect nodes, they combine the two components into one joint state vector. The joint state vector is updated via applying attention mechanism to both sequence memory and graph memory.

Though the above works prove the advantages of utilizing the transformer, one limitation of the approach is that some models adopt two different decoders for label generation and arc generation. That is to say, if a wrong arc is generated, the corresponding label is prone to be misled. Hence, He and Choi [6] introduces a novel Levi graph decoder, which jointly generate concepts, edges and labels.

4 GRAPH REPRESENTATION LEARNING

Graph to sequence transduction is a significant intermediate step for many downstream NLP tasks.In the section, we will discuss various graph representation learning techniques that convert the AMR graph structure into natural language sentences. Recent works on graph to sentence models for AMR can be divided into two categories: variants of graph neural network, including ; and graph transformers.

4.1 Graph Neural Network

Since the emergence of the Graph Neural Network [14], it has been extensively explored by the researchers in the NLP domain. Due to limitation of sequence to sequence (seq2seq) models, Beck et al. [2] propose an encoder based on Gated Graph Neural Networks (GGNNs) [8]. Compared with previous seq2seq models, GGNNs carry the full AMR graph structure without losing key information. Furthermore, they present a Levi graph transformation which convert arcs into additional nodes, which solves the potential problem of potential parameter exploding.

Another problem of traditional seq2seq model is that the input must be sequential. To solve this problem, Song et al. [16] introduce a graph2seq model, utilizing a graph-state LSTM to directly encode the graph structure. Their model avoids the linearization of the AMR graph and can even capture the non-local information. Damonte and Cohen [5] later compare three AMR encoders, including the Graph Convolutional Network (GCN) encoder, proving the superiority of the GCN based encoder and achieving the state-of-the-art results.

4.2 Graph Transformer

Though GNN based graph2seq models outperform the seq2seq models, the difference is not significant. Wang et al. [17] adapt the transformer model and introduce a novel graph transformer. In order to enable the model to take non-sequential inputs, they exploit a stacked encoder-decoder architecture with attention mechanism. This architecture could obtain better semantic information in the graph, and thus outruns the previous works.

Cai and Lam [4] also present a transformer-based model to address the problem that GNNs lacks global communication when computing node representations. Adopting multi-head attention mechanism, their method can model the inter-node dependencies regardless to the distance between the two nodes. Besides, they use explicit relation encoding to avoid the problem that all graph would be considered as fully connected.

5 DISCUSSION

This proposal investigates the recent development of graph neural network for AMR. We first formulate the problem for both graph construction and graph representation learning, offering overview of the two major problem in the AMR graph. Then we review the existing works based on various approaches they adopt.

As a renascent research area that becomes popular in recent years, the development of GNN for AMR is promising. One potential direction could be the hybrid graph representation learning method, combined sequence-based and graph-based approaches. Since each method has its limitations, we could seek to find an approach that incorporates the advantages from both sides. Also, the AMR graph for large scale of data and for long text sequences would be worthwhile exploring.

REFERENCES

[1] 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*. Association for Computational Linguistics, Sofia, Bulgaria, 178–186. https://aclanthology.org/W13-2322

[2] Daniel Beck, Gholamreza Haffari, and Trevor Cohn. 2018. Graph-to-Sequence Learning using Gated Graph Neural Networks. arXiv:1806.09835 [cs.CL]

[3] 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)*. Association for Computational Linguistics, Hong Kong, China, 3799–3809. https://doi.org/10.18653/v1/D19-1393

[4] 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*. Association for Computational Linguistics, Online, 1290–1301. https://doi.org/10.18653/v1/2020.acl-main.119

[5] Marco Damonte and Shay B. Cohen. 2019. Structural Neural Encoders for AMR-to-text Generation. arXiv:1903.11410 [cs.CL]

[6] Han He and Jinho D. Choi. 2021. Levi Graph AMR Parser using Heterogeneous Attention. arXiv:2107.04152 [cs.CL]

[7] Fei-Tzin Lee, Chris Kedzie, Nakul Verma, and Kathleen McKeown. 2021. An analysis of document graph construction methods for AMR summarization. arXiv:2111.13993 [cs.CL]

[8] Yujia Li, Daniel Tarlow, Marc Brockschmidt, and Richard Zemel. 2017. Gated Graph Sequence Neural Networks. arXiv:1511.05493 [cs.LG]

[9] Kexin Liao, Logan Lebanoff, and Fei Liu. 2018. Abstract Meaning Representation for Multi-Document Summarization. arXiv:1806.05655 [cs.CL]

[10] Seung-Hoon Na and Jinwoo Min. 2020. JBNU at MRP 2020: AMR Parsing Using a Joint State Model for Graph-Sequence Iterative Inference. In *Proceedings of the CoNLL 2020 Shared Task: Cross-Framework Meaning Representation Parsing*. Association for Computational Linguistics, Online, 83–87. https://doi.org/10.18653/v1/2020.conll-shared.8

[11] Long HB Nguyen, Viet H Pham, and Dien Dinh. 2021. Improving neural machine translation with AMR semantic graphs. *Mathematical Problems in Engineering* 2021 (2021).

[12] Geetanjali Rakshit and Jeffrey Flanigan. 2021. ASQ: Automatically Generating Question-Answer Pairs using AMRs. arXiv:2105.10023 [cs.CL]

[13] 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)*. Association for Computational Linguistics, Berlin, Germany, 486–492. https://doi.org/10.18653/v1/P16-2079

[14] Franco Scarselli, Marco Gori, Ah Chung Tsoi, Markus Hagenbuchner, and Gabriele Monfardini. 2009. The Graph Neural Network Model. *IEEE Transactions on Neural Networks* 20, 1 (2009), 61–80. https://doi.org/10.1109/TNN.2008.2005605

[15] 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 (Mar 2019), 19–31. https://doi.org/10.1162/tacl_a_00252

[16] Linfeng Song, Yue Zhang, Zhiguo Wang, and Daniel Gildea. 2018. A Graph-to-Sequence Model for AMR-to-Text Generation. arXiv:1805.02473 [cs.CL]

[17] Tianming Wang, Xiaojun Wan, and Hanqi Jin. 2020. AMR-To-Text Generation with Graph Transformer. *Transactions of the Association for Computational Linguistics* 8 (01 2020), 19–33. https://doi.org/10.1162/tacl_a_00297 arXiv:https://direct.mit.edu/tacl/article-pdf/doi/10.1162/tacl_a_00297/1923107/tacl_a_00297.pdf

[18] Yanshan Wang, Sijia Liu, Majid Rastegar-Mojarad, 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* (Boston, Massachusetts, USA) *(ACM-BCB '17)*. Association for Computing Machinery, New York, NY, USA, 36–43. https://doi.org/10.1145/3107411.3107426

[19] Sheng Zhang, Xutai Ma, Kevin Duh, and Benjamin Van Durme. 2019. AMR Parsing as Sequence-to-Graph Transduction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 80–94. https://doi.org/10.18653/v1/P19-1009

[20] Sheng Zhang, Xutai Ma, Kevin Duh, and Benjamin Van Durme. 2019. 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)*. Association for Computational Linguistics, Hong Kong, China, 3786–3798. https://doi.org/10.18653/v1/D19-1392

[21] Zixuan Zhang, Nikolaus Parulian, Heng Ji, Ahmed Elsayed, Skatje Myers, and Martha Palmer. 2021. Fine-grained Information Extraction from Biomedical Literature based on Knowledge-enriched Abstract Meaning Representation. 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)*. 6261–6270.