AMR-to-text Generation with Synchronous Node Replacement Grammar

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Abstract

This paper addresses the task of AMR-to-text generation by leveraging synchronous node replacement grammar. During training, graph-to-string rules are learned using a heuristic extraction algorithm. At test time, a graph transducer is applied to collapse input AMRs and generate output sentences. Evaluated on SemEval-2016 Task 8, our method gives a BLEU score of 25.62, which is the best reported so far.

1 Introduction

Abstract Meaning Representation (AMR) (Banarescu et al., 2013) is a semantic formalism encoding the meaning of a sentence as a rooted, directed graph. AMR uses a graph to represent meaning, where nodes (such as “boy”, “want-01”) represent concepts, and edges (such as “ARG0”, “ARG1”) represent relations between concepts. Encoding many semantic phenomena into a graph structure, AMR is useful for NLP tasks such as machine translation (Jones et al., 2012; Tamchyna et al., 2015), question answering (Mitra and Baral, 2015), summarization (Takase et al., 2016) and event detection (Li et al., 2015).

AMR-to-text generation is challenging as function words and syntactic structures are abstracted away, making an AMR graph correspond to multiple realizations. Despite much literature so far on text-to-AMR parsing (Flanigan et al., 2014; Wang et al., 2015; Peng et al., 2015; Vanderwende et al., 2015; Pust et al., 2015; Artzi et al., 2015; Groschwitz et al., 2015; Goodman et al., 2016; Zhou et al., 2016), there has been little work on AMR-to-text generation (Flanigan et al., 2016; Song et al., 2016; Pourdamghani et al., 2016). Flanigan et al. (2016) transform a given AMR graph into a spanning tree, before translating it to a sentence using a tree-to-string transducer. Their method leverages existing machine translation techniques, capturing hierarchical correspondences between the spanning tree and the surface string. On the other hand, it suffers from error propagation since the output is constrained given a spanning tree due to the projective correspondence between them. Information loss in the graph-to-tree transformation step cannot be recovered. Song et al. (2016) directly generate sentences using graph-fragment-to-string rules. They cast the task of finding a sequence of disjoint rules to transduce an AMR graph into a sentence as a traveling salesman problem, using local features and a language model to rank candidate sentences. However, their method does not learn hierarchical structural correspondences between AMR graphs and strings.

We propose to leverage the advantages of hierarchical rules without suffering from graph-to-tree errors by directly learning graph-to-string rules. As shown in Figure 1, we learn a synchronous node replacement grammar (NRG) from a corpus of ⟨AMR, sentence⟩ pairs. At test time, we apply a graph transducer to collapse input AMR graphs and generate output strings according to the
learned grammar. Our system makes use of a log-linear model with real-valued features, tuned using MERT (Och, 2003), and beam search decoding. It gives a BLEU score of 25.62 on the SemEval-2016 Task 8 benchmark, which is the best result reported so far.

2 Synchronous Node Replacement Grammar

2.1 Grammar Definition

A synchronous node replacement grammar (NRG) is a rewriting formalism: \( G = (N, \Sigma, \Delta, P, S) \), where \( N \) is a finite set of nonterminals, \( \Sigma \) and \( \Delta \) are finite sets of terminal symbols for the source and target sides, respectively. \( S \in N \) is the start symbol, and \( P \) is a finite set of productions. Each instance of \( P \) takes the form \( X_i \to (\langle F, E \rangle, \sim) \), where \( X_i \in N \) is a nonterminal node, \( F \) is a rooted, connected AMR fragment with edge labels over \( \Sigma \) and node labels over \( N \cup \Sigma, E \) is a corresponding target string over \( N \cup \Delta \) and \( \sim \) denotes the alignment of nonterminal symbols between \( F \) and \( E \). A classic NRG (Engelfriet and Rozenberg, 1997, Chapter 1) also defines \( C \), which is an embedding mechanism defining how \( F \) is connected to the rest of the graph when replacing \( X_i \) with \( F \) on the graph. Here we omit defining \( C \) and allow arbitrary connections.

Figure 2 shows an example derivation process for the sentence “the boy wants to go” given the rule set in Table 1. Given the start symbol \( S \), which is first replaced with \( X_1 \), rule (c) is applied to generate “X_2 to go” and its AMR counterpart. Then rule (b) is used to generate “X_3 wants” and its AMR counterpart from \( X_2 \). Finally, rule (a) is used to generate “the boy” and its AMR counterpart from \( X_3 \). Our graph-to-string rules are inspired by synchronous grammars for machine translation (Wu, 1997; Yamada and Knight, 2002; Gildea, 2003; Chiang, 2005; Huang et al., 2006; Liu et al., 2006).

2.2 Induced Rules

There are three types of rules in our system, namely induced rules, concept rules and graph glue rules. Here we first introduce induced rules, which are obtained by a two-step procedure on a training corpus. Shown in Algorithm 1, the first replaced with \( X_i \), nodes previously connected to \( F \) are re-connected to \( X_i \).

![Figure 2: The deduction procedure](image)

| ID | \( F \) | \( E \) |
|---|---|---|
| (a) | \( b \ / \ \text{boy} \) | the boy |
| (b) | \( w \ / \ \text{want-01} \) | \#X# wants |
| (c) | \( X \ / \ \#X# \) | :ARG1 (g / go-01 \#X# to go \:ARG0 X)) |
| (d) | \( w \ / \ \text{want-01} \) | \#X# to go |

Table 1: Example rule set
step is to extract a set of initial rules from training sentence, AMR pairs (Line 2) using the phrase-to-graph fragment extraction algorithm of (Peng et al., 2015) (Line 3). Here an initial rule contains only terminal symbols in both $F$ and $E$. As a next step, we match between initial rules $r_i$ and $r_j$ according to Cai and Knight (2013), and generate $r_{ij}$ by collapsing $r_i$ with $r_j$, if $r_i$ contains $r_j^E$ (Line 6-8). When collapsing $r_i$ with $r_j$, we replace the corresponding subgraph in $r_i$. $F$ with a new non-terminal node, and the sub-phrase in $r_i$. $E$ with a non-terminal. For example, we obtain rule (b) from rules (d) and (a) in Table 1. All initial and generated rules are stored in a rule list $R$ (Lines 5 and 9), which will be further normalized to obtain the final induced rule set.

2.3 Concept Rules and Glue Rules

In addition to induced rules, we adopt concept rules (Song et al., 2016) and graph glue rules to ensure existence of derivations. For a concept rule, $F$ is a single node in the input AMR graph, and $E$ is a morphological string of the node concept. A concept rule is used in case no induced rule can cover the node. We refer to the verbalization list for creating more complex concept rules. For example, one concept rule created from the verbalization list is “(k / keep-01 :ARG1 (p / peace)) ||| peacekeeping”.

Inspired by Chiang (2005), we define graph glue rules to concatenate non-terminal nodes connected with an edge, when no induced rules can be applied. Three glue rules are defined for each type of edge label. Taking the edge label “ARG0” as an example, we create the following glue rules:

$$\begin{align*}
    r_1 & : (X1 / X1# : ARG0 (X2 / X2#)) ||| X1# \# X2# \\
    r_2 & : (X1 / X1# : ARG0 (X2 / X2#)) ||| X2# \# X1# \\
    r_3 & : (X1 / X1# : ARG0 X1) ||| X1#
\end{align*}$$

where for both $r_1$ and $r_2$, $F$ contains two non-terminal nodes with a directed edge connecting them, and $E$ is the concatenation of the two non-terminals in either the monotonic or the inverse order. For $r_3$, $F$ contains one non-terminal node with a self-pointing edge, and $E$ is the non-terminal. With concept rules and glue rules in our final rule set, it is easily guaranteed that there are legal derivations for any input AMR graph.

3 Model

We adopt a log-linear model for scoring search hypotheses. Given an input AMR graph, we find the highest scored derivation $t^*$ from all possible derivations $t$:

$$
t^* = \arg\max_t \exp\left( \sum_i w_i f_i(g, t) \right),
$$

where $g$ denotes the input AMR, $f_i(\cdot, \cdot)$ and $w_i$ represent a feature and the corresponding weight, respectively. The feature set that we adopt includes phrase-to-graph and graph-to-phrase translation probabilities and their corresponding lexicalized translation probabilities (section 3.1), language model score, word count, rule count, re-ordering model score (section 3.2), and moving distance (section 3.3). The language model score, word count and phrase count features are adopted from SMT (Koehn et al., 2003; Chiang, 2005).

We perform bottom-up search to transduce input AMRs to surface strings. Each hypothesis contains the current AMR graph, translations of collapsed subgraphs, the feature vector and the current model score. Beam search is adopted, where hypotheses with the same number of collapsed edges and nodes are put into the same beam.

3.1 Translation Probabilities

Production rules serve as a basis for scoring hypotheses. We associate each synchronous NRG rule $n \rightarrow (\langle F, E \rangle, \sim)$ with a set of probabilities. First, phrase-to-fragment translation probabilities are defined based on maximum likelihood estimation (MLE), as shown in Equation 2, where $c(F, E)$ is the fractional count of $\langle F, E \rangle$.

$$p(F|E) = \frac{c(F, E)}{\sum_{F'} c(F', E)}
$$

In addition, lexicalized translation probabilities are defined as:

$$p_w(F|E) = \prod_{l \in F} \sum_{w \in E} p(l|w)
$$

Here $l$ is a label (including both edge labels such as “ARG0” and concept labels such as “want-01”) in the AMR fragment $F$, and $w$ is a word in the phrase $E$. Equation 3 can be regarded as a “soft” version of the lexicalized translation probabilities adopted by SMT, which picks the alignment yielding the maximum lexicalized probability for each translation rule. In addition to $p(F|E)$...
and $p_w(F|E)$, we use features in the reverse direction, namely $p(E|F)$ and $p_w(E|F)$, the definitions of which are omitted as they are consistent with Equations 2 and 3 respectively. The probabilities associated with concept rules and glue rules are manually set to 0.0001.

3.2 Reordering Model

Although the word order is defined for induced rules, it is not the case for glue rules. We learn a reordering model that helps to decide whether the translations of the nodes should be monotonic or inverse given the directed connecting edge label. The probabilistic model using smoothed counts is defined as:

$$p(M|h, l, t) = \frac{1.0 + \sum_h \sum_l c(h, l, t, M)}{2.0 + \sum_o \sum_h \sum_l c(h, l, t, o)}$$

$c(h, l, t, M)$ is the count of monotonic translations of head $h$ and tail $t$, connected by edge $l$.

3.3 Moving Distance

The moving distance feature captures the distances between the subgraph roots of two consecutive rule matches in the decoding process, which controls a bias towards collapsing nearby subgraphs consecutively.

4 Experiments

4.1 Setup

We use the dataset of SemEval-2016 Task8, which contains 16833 training, 1368 dev and 1371 test instances. Rules are extracted from the training data, and model parameters are tuned on the dev set. For tuning and testing, we filter out sentences with more than 30 words, resulting in 1103 dev instances and 1055 test instances. We train a 4-gram language model (LM) on gigaword (LDC2011T07), and use BLEU (Papineni et al., 2002) as the evaluation metric. MERT is used (Och, 2003) to tune model parameters on $k$-best outputs on the dev set, where $k$ is set 20.

We investigate the effectiveness of rules and features by ablation tests: “NoInducedRule” does not adopt induced rules, “NoConceptRule” does not adopt concept rules, “NoMovingDistance” does not adopt the moving distance feature, and “NoReorderModel” disables the reordering model. Given an AMR graph, if NoConceptRule cannot produce a legal derivation, we concatenate existing translation fragments into a final translation, and if a subgraph cannot be translated, the empty string is used as the output. We also compare our method with previous works, in particular JAMR-gen (Flanigan et al., 2016) and TSP-gen (Song et al., 2016), on the same dataset.

4.2 Results

The results are shown in Table 2. First, All outperforms all baselines. NoInducedRule leads to the greatest performance drop compared with All, demonstrating that induced rules play a very important role in our system. On the other hand, NoConceptRule does not lead to much performance drop. This observation is consistent with the observation of Song et al. (2016) for their TSP-based system. NoMovingDistance leads to a significant performance drop, empirically verifying the fact that the translations of nearby subgraphs are also close. Finally, NoReorderingModel does not affect the performance significantly, which can be because the most important reordering patterns are already covered by the hierarchical induced rules. Compared with TSP-gen and JAMR-gen, our final model All improves the BLEU from 22.44 and 23.00 to 25.62, showing the advantage of our model. To our knowledge, this is the best result reported so far on the task.

5 Conclusion

We showed that synchronous node replacement grammar is useful for AMR-to-text generation by developing a system that learns a synchronous NRG in the training time, and applies a graph transducer to collapse input AMR graphs and generate output strings according to the learned grammar at test time. Our method outperforms the previous state-of-the-art, empirically proving the advantages of our graph-to-string rules.
References

[Artzi et al.2015] Yoav Artzi, Kenton Lee, and Luke Zettlemoyer. 2015. Broad-coverage CCG semantic parsing with AMR. In Conference on Empirical Methods in Natural Language Processing (EMNLP-15), pages 1699–1710.

[Banarescu et al.2013] 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.

[Chiang2005] David Chiang. 2005. A hierarchical phrase-based model for statistical machine translation. In Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL-05), pages 263–270, Ann Arbor, Michigan.

[Engelfriet and Rozenberg1997] J. Engelfriet and G. Rozenberg. 1997. Node replacement graph grammars. In Grzegorz Rozenberg, editor, Handbook of Graph Grammars and Computing by Graph Transformation, pages 1–94. World Scientific Publishing Co., Inc., River Edge, NJ, USA.

[Flanigan et al.2014] 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 (ACL-14), pages 1426–1436.

[Flanigan et al.2016] Jeffrey Flanigan, Chris Dyer, Noah A. Smith, and Jaime Carbonell. 2016. Generation from abstract meaning representation using tree transducers. In Proceedings of the 2016 Meeting of the North American chapter of the Association for Computational Linguistics (NAACL-16), pages 731–739.

[Gildea2003] Daniel Gildea. 2003. Loosely tree-based alignment for machine translation. In Proceedings of the 41th Annual Conference of the Association for Computational Linguistics (ACL-03), pages 80–87, Sapporo, Japan.

[Goodman et al.2016] James Goodman, Andreas Vlachos, and Jason Naradowsky. 2016. Noise reduction and targeted exploration in imitation learning for abstract meaning representation parsing. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL-16), pages 1–11, Berlin, Germany.

[Groschwitz et al.2015] Jonas Groschwitz, Alexander Koller, and Christoph Teichmann. 2015. Graph parsing with s-graph grammars. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics (ACL-15), pages 1481–1490, Beijing, China.

[Huang et al.2006] Liang Huang, Kevin Knight, and Aravind Joshi. 2006. Statistical syntax-directed translation with extended domain of locality. In Proceedings of Association for Machine Translation in the Americas (AMTA-2006), pages 66–73.

[Jones et al.2012] Bevan Jones, Jacob Andreas, Daniel Bauer, Karl Moritz Hermann, and Kevin Knight. 2012. Semantics-based machine translation with hyperedge replacement grammars. In Proceedings of the International Conference on Computational Linguistics (COLING-12), pages 1359–1376.

[Koehn et al.2003] Philipp Koehn, Franz Josef Och, and Daniel Marcu. 2003. Statistical phrase-based translation. In Proceedings of the 2003 Meeting of the North American chapter of the Association for Computational Linguistics (NAACL-03), pages 48–54.

[Li et al.2015] Xiang Li, Thien Huu Nguyen, Kai Cao, and Ralph Grishman. 2015. Improving event detection with abstract meaning representation. In Proceedings of the First Workshop on Computing News Storylines, pages 11–15, Beijng, China.

[Liu et al.2006] Yang Liu, Qun Liu, and Shouxun Lin. 2006. Tree-to-string alignment template for statistical machine translation. In Proceedings of the 44th Annual Meeting of the Association for Computational Linguistics (ACL-06), pages 609–616, Sydney, Australia.

[Mitra and Baral2015] Arindam Mitra and Chitta Baral. 2015. Addressing a question answering challenge by combining statistical methods with inductive rule learning and reasoning. In Proceedings of the National Conference on Artificial Intelligence (AAAI-16).

[Och2003] Franz Josef Och. 2003. Minimum error rate training in statistical machine translation. In Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics (ACL-03), pages 160–167, Sapporo, Japan.

[Papineni et al.2002] 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 (ACL-02), pages 311–318.

[Peng et al.2015] Xiaochang Peng, Linfeng Song, and Daniel Gildea. 2015. A synchronous hyperedge replacement grammar based approach for AMR parsing. In Proceedings of the Nineteenth Conference on Computational Natural Language Learning (CoNLL-15), pages 731–739.
[Pourdamghani et al.2016] Nima Pourdamghani, Kevin Knight, and Ulf Hermjakob. 2016. Generating English from abstract meaning representations. In *International Conference on Natural Language Generation (INLG-16)*, pages 21–25, Edinburgh, UK.

[Pust et al.2015] Michael Pust, Ulf Hermjakob, Kevin Knight, Daniel Marcu, and Jonathan May. 2015. Parsing English into abstract meaning representation using syntax-based machine translation. In *Conference on Empirical Methods in Natural Language Processing (EMNLP-15)*, pages 1143–1154.

[Song et al.2016] Linfeng Song, Yue Zhang, Xiaochang Peng, Zhiguo Wang, and Daniel Gildea. 2016. Amr-to-text generation as a traveling salesman problem. In *Conference on Empirical Methods in Natural Language Processing (EMNLP-16)*, pages 2084–2089, Austin, Texas.

[Takase et al.2016] Sho Takase, Jun Suzuki, Naoaki Okazaki, Tsutomu Hirao, and Masaaki Nagata. 2016. Neural headline generation on abstract meaning representation. In *Conference on Empirical Methods in Natural Language Processing (EMNLP-16)*, pages 1054–1059, Austin, Texas.

[Tamchyna et al.2015] Aleš Tamchyna, Chris Quirk, and Michel Galley. 2015. A discriminative model for semantics-to-string translation. In *Proceedings of the 1st Workshop on Semantics-Driven Statistical Machine Translation (S2MT 2015)*, pages 30–36, Beijing, China.

[Vanderwende et al.2015] Lucy Vanderwende, Arul Menezes, and Chris Quirk. 2015. An AMR parser for English, French, German, Spanish and Japanese and a new AMR-annotated corpus. In *Proceedings of the 2015 Meeting of the North American chapter of the Association for Computational Linguistics (NAACL-15)*, pages 26–30.

[Wang et al.2015] Chuan Wang, Nianwen Xue, and Sameer Pradhan. 2015. A transition-based algorithm for AMR parsing. In *Proceedings of the 2015 Meeting of the North American chapter of the Association for Computational Linguistics (NAACL-15)*, pages 366–375.

[Wu1997] Dekai Wu. 1997. Stochastic inversion transduction grammars and bilingual parsing of parallel corpora. *Computational linguistics*, 23(3):377–403.

[Yamada and Knight2002] Kenji Yamada and Kevin Knight. 2002. A decoder for syntax-based statistical mt. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL-02)*, pages 303–310, Philadelphia, Pennsylvania, USA.

[Zhou et al.2016] Junsheng Zhou, Feiyu Xu, Hans Uszkoreit, Weiguang QU, Ran Li, and Yanhui Gu. 2016. Amr parsing with an incremental joint model. In *Conference on Empirical Methods in Natural Language Processing (EMNLP-16)*, pages 680–689, Austin, Texas.