Measuring Alignment Bias in Neural Seq2Seq Semantic Parsers

Davide Locatelli
Universitat Politècnica de Catalunya
Campus Nord, Barcelona
davide.locatelli@upc.edu

Ariadna Quattoni
Universitat Politècnica de Catalunya
Campus Nord, Barcelona
aquattoni@cs.upc.edu

Abstract

Prior to deep learning the semantic parsing community has been interested in understanding and modeling the range of possible word alignments between natural language sentences and their corresponding meaning representations. Sequence-to-sequence models changed the research landscape suggesting that we no longer need to worry about alignments since they can be learned automatically by means of an attention mechanism. More recently, researchers have started to question such premise. In this work we investigate whether seq2seq models can handle both simple and complex alignments. To answer this question we augment the popular GEO semantic parsing dataset with alignment annotations and create GEO-ALIGNED. We then study the performance of standard seq2seq models on the examples that can be aligned monotonically versus examples that require more complex alignments. Our empirical study shows that performance is significantly better over monotonic alignments.

1 Introduction

In semantic parsing, the goal is to map natural language (NL) sentences into machine-readable meaning representations (MR) which allow for automated reasoning. For example, consider the following pair:

NL : What is the population of Georgia?
MR : answer (population (state (georgia)))

Prior to deep learning models, a popular approach was to learn a grammar-based parser that explicitly models alignments between the NL and MR sequences (Wong and Mooney, 2006; Zettlemoyer and Collins, 2005, 2007; Lu et al., 2008; Kwiatkowski et al., 2010; Kwiatkowski et al., 2011). The emergence of sequence-to-sequence (seq2seq) semantic parsers with attention mechanisms changed the research landscape: one of the initial premises of seq2seq models is that alignments no longer need to be explicitly modeled because the attention mechanisms will automatically learn them (Bahdanau et al., 2015). More recently, researchers started to question such premise, having observed that seq2seq models fail to make proper generalizations on out-of-distribution test sets on which traditional grammar-based models excel (Liu et al., 2020, 2021; Wang et al., 2021).

In this paper we follow this line of research and ask the questions: Can standard seq2seq models handle arbitrary alignments? And if not, what kind of alignment bias do they have? To answer these questions, we augment the GEO semantic parsing benchmark (Zelle and Mooney, 1996) with alignment annotations and create GEO-ALIGNED. We then compare the performance of seq2seq models on examples that can be easily aligned with simple monotonic alignments to the performance of these models on examples that require word reordering. Our empirical study shows that seq2seq parsers perform significantly better over examples that can be monotonically aligned. In other words, the flexibility of not having to explicitly model alignments comes at a cost: seq2seq models have difficulties in learning complex alignments.

The main contributions of this paper are:

1. We introduce a new dataset: GEO-ALIGNED that augments the GEO semantic benchmark with alignment annotations. We used the English and German versions of the original dataset, and we additionally introduce a new Italian version.

2. Using GEO-ALIGNED we define new evaluation splits to distinguish parsing performance

---

1The code and data is publicly available at https://github.com/interact-erc/geo-aligned
over easier and harder examples.

3. Our empirical study shows that seq2seq parsers are significantly better in handling monotonic alignments, and quantifies the impact of using attention.

4. As a side contribution we offer a measure of the complexity of the GEO dataset, showing that more than half of the examples involve monotonic alignments.

2 The GEO-ALIGNED Benchmark

In this section we describe the GEO-ALIGNED dataset, an augmentation of the popular GEO semantic parsing benchmark first introduced by Zelle and Mooney (1996). We start by providing a brief formal definition of word alignments following standard notation from the statistical machine translation literature, and we define monotonic and non-monotonic alignments (Wu, 2010). We then detail how we augment the GEO dataset and provide statistics that measure the complexity of the dataset.

2.1 Bi-text alignments

Given an input sequence of \( N \) words \( x = x_1, \ldots, x_N \), and a target sequence of \( M \) words \( y = y_1, \ldots, y_M \), a bi-text is defined as the tuple \((x, y)\). A bi-text word alignment is a set of bi-symbols \( \mathcal{A} \), where each bi-symbol \((x_i, y_j)\) couples a word \( x_i \) in the input sequence at position \( i \) to a word \( y_j \) in the target sequence at position \( j \).

If a word \( x_i \) from the input sequence does not need an alignment to a word in the target, we introduce an \( \varepsilon \) in \( y \) at position \( i \). This bi-symbol \((x_i, \varepsilon)\) amounts to a deletion, i.e. mapping from input to target involves deleting a word from the input. Conversely, if a word \( y_j \) from the target does not require an alignment to a word in the input, we introduce an \( \varepsilon \) in \( x \) at position \( j \). This bi-symbol \((\varepsilon_j, y_j)\) amounts to an insertion, i.e. mapping from input to target involves inserting an extra word in the target. We refer to the number of insertions and deletions in an alignment as the gap length. Figure 1 shows examples of alignments from the GEO-ALIGNED dataset.

2.2 Monotonic and non-monotonic alignments

Monotonic alignments are bi-text alignments where \( \mathcal{A} \) contains bi-symbols of the forms \((x_i, y_j)\), \((x_i, \varepsilon)\) or \((\varepsilon_i, y_j)\) where \( i = j \). In other words, a monotonic alignment does not involve any reordering of the words. Conversely, non-monotonic alignments also include bi-symbols of the form \((x_i, y_j)\) where \( i \neq j \). Figure 1 shows an example of a monotonic alignment versus a non-monotonic one.

2.3 Alignment annotation

The original GEO dataset contains 880 English questions about US geography, paired with a meaning representation. Several MR formalisms have been introduced for this dataset, including a first-order logic as in Zelle and Mooney (1996), a variable-free functional language introduced by Kate et al. (2005) and SQL (Popescu et al., 2003; Giordani and Moschitti, 2013; Iyer et al., 2017). In GEO-ALIGNED, we use the variable-free functional language formalism. Similarly to Wang et al. (2021), we further simplify the MR by removing the brackets. This is done to avoid introducing numerous \( \varepsilon \) in the alignments, and also to better reveal the structural similarity between the NL and MR sequences. Similarly to Dong and Lapata (2016), we remove constants used to identify states, rivers, cities, places and countries by substituting them with their type.

Alignments were provided by four expert annotators. For each pair, the annotators were first asked to decide whether there was a monotonic or non-monotonic alignment. Secondly, annotators were asked to provide the actual alignment from NL to MR words. More specifically, two annotators aligned the entire dataset, while the other two each

![Figure 1: Examples alignments from the GEO-ALIGNED benchmark. Each bi-symbol is represented as a vertical line coupling words in the NL with words in the corresponding MR. The monotonic alignment (a) does not involve crossings of bi-symbols, while the non-monotonic alignment (b) involves considerable reordering.](image-url)
annotated fifty disjoint examples. Inter-annotation agreement was calculated by comparing the alignments provided. A first agreement metric is Cohen’s Kappa statistic (Cohen, 1960) to measure the agreement of monotonic versus non-monotonic labels: the average score obtained is 0.803, which corresponds to substantial agreement. We then calculated the average percentage of exact matches between the alignments of the two main annotators and each of the other three, which resulted in a 90% average match. Disagreements were resolved by keeping the annotation that best matched the alignment strategy taken by the majority.

Bi-text word alignments vary depending on the order in which the words appear both in the natural language and the meaning representation (Steedman, 2020). If we keep the MR fixed, a sentence in one language might be monotonically aligned, while the same sentence in another language might not be. To better understand the range of alignments between natural language utterances and meaning representations one should ideally consider multiple languages. With this objective in mind, we additionally annotated the German version (Jones et al., 2012) of GEO, and a new Italian version that we introduce, obtained by translations of the English sentences provided by an Italian native speaker.

The resulting dataset contains the NL and MR data pairs, augmented with

- a label indicating whether there is a monotonic alignment;
- the alignment that maps NL and MR words.

Table 1 reports annotation statistics for GEO-ALIGNED. In general, it can be observed that across all languages the majority of the alignments are monotonic and the average gap length is less than three. For non-monotonic alignments the average number of reordered words is below three.

With respect to differences between the three languages, Figure 2 shows a histogram of the gap lengths of monotonic alignments. As we can see the distributions are quite similar, but slightly shifted towards longer gaps for German and Italian. In particular, there are significantly more alignments with no gap in English. The proportion of monotonic alignments reflects the structural similarity between the variable-free MRs and the NL sequences. It is highest in the case of English, after which the MR formalism was modeled. German

| Lang | Len | MP | MG  | M0 | NMR |
|------|-----|----|-----|----|-----|
| EN   | 7.67| 0.75| 2.52| 8.2| 2.14|
| DE   | 7.72| 0.65| 2.91| 0.55| 2.52|
| IT   | 7.92| 0.52| 2.54| 1.5 | 2.23|

Table 1: Alignment annotation statistics for different languages. Len is the mean length of input NL sentences, MP is the percentage of monotonic alignments, MG is the average gap in monotonic alignments, M0 is the percentage of monotonic alignments with no gap, and NMR is the average number of words reordered in the non-monotonic alignments.

![Figure 2](image-url) Figure 2: Distribution of gap lengths for the monotonic alignments.

is syntactically more similar to English than Italian and as a result it can be more easily aligned with the MR sequences. An exemplary syntactic difference is adjective placement: in English and German adjectives come before nouns, whilst in Italian they are usually placed after. When a superlative is used in the NL sentence, the MR, being modeled after English, places it before the noun. This creates a monotonic alignment with English and German sentences and a non-monotonic one with Italian ones. For example, if the question is What is the largest state? the corresponding MR will be answer(largest(state(all))). Because largest comes before state in both English and German as well as in the MR, the alignment will be monotonic. In Italian, largest comes after state and the alignment will require reordering.

3 Measuring Alignment Bias

3.1 Models and Experiments

The goal of our study is to compare the performance of neural seq2seq models over monotonic and non-monotonic alignments. Our hypothesis is
that seq2seq models can implicitly learn monotonic alignments more easily than non-monotonic alignments. To evaluate this hypothesis we compared the performance of two seq2seq architectures on GEO-ALIGNED.

**LSTM Seq2Seq** A standard seq2seq model based on a bidirectional-LSTM encoder (Hochreiter and Schmidhuber, 1997; Schuster and Paliwal, 1997), and a unidirectional LSTM decoder that uses attention (Bahdanau et al., 2015). We then ablate the decoder of the attention layer to investigate its impact on the performance for the different alignments.

**BART** A pre-trained seq2seq model based on a bidirectional encoder and a left-to-right decoder (Lewis et al., 2020). Since it was pre-trained on English corpora, we only used this model on the English version of the dataset.

For our experiment we use exact-match accuracy as the evaluation metric, i.e. the percentage of exact matches between the predicted and ground-truth MRs. The alignment labels in GEO-ALIGNED allow us to break down the accuracy score for the two classes of alignments and observe whether the seq2seq framework has an implicit bias towards monotonic alignments. Further implementation and experimental setup details can be found in Appendix A.

### 3.2 Results

Table 2 shows the performance for the different models and languages. As we can observe accuracy for all models is significantly lower over non-monotonic alignments and this is true for all languages. The difference in performance between monotonic and non-monotonic alignments is more pronounced for models with no attention, but it holds true for all of them.

The performance follows the same pattern across languages and models: accuracies are higher for monotonic sequences than for non-monotonic ones. For English and Italian the differences are quite similar: models with attention score 0.13 point higher for monotonic sequences; without attention the difference is 0.19 for English and 0.17 for Italian. German has a lower accuracy overall. One possible explanation (as shown in Figure 2) is that the monotonic gap distribution for these two languages has a slight shift towards shorter gaps and in particular the sequences with no gap could help the models to implicitly induce better alignments. Moreover, the difference between monotonic and non-monotonic performance is starker: the model scored 0.19 and 0.23 better on monotonic examples with and without attention respectively. This might be due to the fact that more words are reordered on average for German than for the other two languages (see Table 1). Figure 3 shows accuracy for monotonic sequences binned by gap length. We observe that for all languages there is a negative correlation between accuracy and gap length.

We performed a qualitative analysis of the predictions by categorizing errors based on how many steps are needed to correct the mistake. Simpler errors are those where the correct MR can be recovered by inserting, deleting or changing at

| Lang | Model     | Acc | MAcc | NMAcc |
|------|-----------|-----|------|-------|
| EN   | LSTM      | 0.83| 0.87 | 0.74  |
|      | LSTM-attn | 0.75| 0.80 | 0.61  |
|      | BART      | 0.85| 0.87 | 0.80  |
| DE   | LSTM      | 0.63| 0.73 | 0.54  |
|      | LSTM-attn | 0.57| 0.69 | 0.46  |
| IT   | LSTM      | 0.77| 0.84 | 0.71  |
|      | LSTM-attn | 0.71| 0.80 | 0.63  |

Table 2: Summary of results for the different models and languages: LSTM is the seq2seq model based on a bidirectional LSTM encoder and an LSTM decoder with attention. LSTM-attn ablates the attention layer in the decoder. Acc reports the overall accuracy for each model, MAcc and NMAcc are the accuracy over sequences with monotonic and non-monotonic alignments respectively.

![Figure 3: Accuracy for monotonic examples as a function of gap length.](image-url)
Table 3: Statistics of qualitative analysis on prediction errors. Align indicates the type of alignment: M stands for monotonic, NM for non-monotonic. 1T is the proportion of examples requiring a one-token correction without reordering. Similarly, 2T is for two-token corrections without reordering. Other is the proportion of examples requiring more complex corrections of three or more tokens, occasionally with reordering.

| Lang | Align | Model | 1T | 2T | Other |
|------|-------|-------|----|----|-------|
| EN   | M     | LSTM  | 0.46 | 0.19 | 0.32  |
|      | NM    | LSTM  | 0.24 | 0.15 | 0.61  |
|      | M     | BART  | 0.67 | 0.25 | 0.08  |
|      | NM    | BART  | 0.29 | 0.17 | 0.54  |
| DE   | M     | LSTM  | 0.72 | 0.08 | 0.20  |
|      | NM    | LSTM  | 0.32 | 0.27 | 0.41  |
| IT   | M     | LSTM  | 0.72 | 0.05 | 0.23  |
|      | NM    | LSTM  | 0.43 | 0.18 | 0.39  |

More recently, neural seq2seq models were proposed for semantic parsing in Dong and Lapata (2016); Jia and Liang (2016); Iyer et al. (2017). The seq2seq approach aims to relax the reliance upon high-quality lexicons, i.e. domain-specific word alignments. Most seq2seq systems implement an attention mechanism such as those proposed by Bahdanau et al. (2015); Luong et al. (2015); Xu et al. (2015), which can be seen as a strategy to learn soft alignments (Dong and Lapata, 2016).

Recently there has been an interest in testing the generalization abilities of neural semantic parsers, which resulted in the creation of several new benchmarks (Bastings et al., 2018; Lake and Baroni, 2018; Loula et al., 2018; Ruis et al., 2020; Keysers et al., 2020; Kim and Linzen, 2020) on which recent work has shown improved performance by introducing more alignment bias in the models either explicitly (Liu et al., 2021), or implicitly (Wang et al., 2021).

5 Conclusion

In this paper we introduced the Geo-Aigned dataset that offers an evaluation framework for testing the performance of semantic parsers over examples of varying alignment complexity. Our experiments have shown that seq2seq neural parsers perform significantly better over simpler monotonic alignments, suggesting that they have an implicit bias. We hope that Geo-Aigned can be used by other researchers to further test alignment biases.

Acknowledgments

The authors would like to thank the reviewers as well as the other members of the INTERACT group at Universitat Politècnica de Catalunya for their helpful feedback and suggestions. This work is supported by the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation program (grant agreement No.853459).
References

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Jasmijn Bastings, Marco Baroni, Jason Weston, Kyunghyun Cho, and Douwe Kiela. 2018. Jump to better conclusions: SCAN both left and right. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 47–55, Brussels, Belgium. Association for Computational Linguistics.

Stephen Clark and James Curran. 2003. Log-linear models for wide-coverage CCG parsing. In Proceedings of the 2003 Conference on Empirical Methods in Natural Language Processing, pages 97–104.

Jacob Cohen. 1960. A coefficient of agreement for nominal scales. Educational and Psychological Measurement, 20(1):37–46.

Li Dong and Mirella Lapata. 2016. Language to logical form with neural attention. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 33–43, Berlin, Germany. Association for Computational Linguistics.

Alessandra Giordani and Alessandro Moschitti. 2013. Automatic generation and reranking of sql-derived answers to nl questions. In Trustworthy Eternal Systems via Evolving Software, Data and Knowledge, pages 59–76, Berlin, Heidelberg. Springer Berlin Heidelberg.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9:1735–80.

Srinivasan Iyer, Ioannis Konstas, Alvin Cheung, Jayant Krishnamurthy, and Luke Zettlemoyer. 2017. Learning a neural semantic parser from user feedback. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 963–973, Vancouver, Canada. Association for Computational Linguistics.

Robin Jia and Percy Liang. 2016. Data recombination for neural semantic parsing. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 12–22, Berlin, Germany. Association for Computational Linguistics.

Bevan Jones, Mark Johnson, and Sharon Goldwater. 2011. Formalizing semantic parsing with tree transducers. In Proceedings of the Australasian Language Technology Association Workshop 2011, pages 19–28, Canberra, Australia.

Bevan Jones, Mark Johnson, and Sharon Goldwater. 2012. Semantic parsing with Bayesian tree transducers. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 488–496, Jeju Island, Korea. Association for Computational Linguistics.

Rohit Kate, Yuk Wong, and Raymond Mooney. 2005. Learning to transform natural to formal languages. volume 3, pages 1062–1068.

Daniel Keysers, Nathanael Schärf, Nathan Scales, Hylke Buisman, Daniel Furrer, Sergii Kushabin, Nikola Momchev, Danila Sinopalnikov, Lukasz Stańki, Tibor Tihon, Dmitry Tsarkov, Xiao Wang, Marc van Zee, and Olivier Bousquet. 2020. Measuring compositional generalization: A comprehensive method on realistic data. In International Conference on Learning Representations.

Najoung Kim and Tal Linzen. 2020. COGS: A compositional generalization challenge based on semantic interpretation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 9087–9105, Online. Association for Computational Linguistics.

Tom Kwiatkowski, Luke Zettlemoyer, Sharon Goldwater, and Mark Steedman. 2010. Inducing probabilistic CCG grammars from logical form with higher-order unification. In Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing, pages 1223–1233, Cambridge, MA. Association for Computational Linguistics.

Tom Kwiatkowski, Luke Zettlemoyer, Sharon Goldwater, and Mark Steedman. 2011. Lexical generalization in CCG grammar induction for semantic parsing. In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, pages 1512–1523, Edinburgh, Scotland, UK. Association for Computational Linguistics.

Brenden Lake and Marco Baroni. 2018. Generalization without systematicity: On the compositional skills of sequence-to-sequence recurrent networks. pages 2873–2882. PMLR.

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

Chenyao Liu, Shengnan An, Zeqi Lin, Qian Liu, Bei Chen, Jian-Guang Lou, Lijie Wen, Nanning Zheng, and Dongmei Zhang. 2021. Learning algebraic recombination for compositional generalization. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 1129–1144, Online. Association for Computational Linguistics.
Qian Liu, Shengnan An, Jian-Guang Lou, Bei Chen, Zeqi Lin, Yan Gao, Bin Zhou, Nanning Zheng, and Dongmei Zhang. 2020. Compositional generalization by learning analytical expressions. In NeurIPS.

João Loula, Marco Baroni, and Brenden Lake. 2018. Rearranging the familiar: Testing compositional generalization in recurrent networks. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 108–114, Brussels, Belgium. Association for Computational Linguistics.

Wei Lu, Hwee Tou Ng, Wee Sun Lee, and Luke S. Zettlemoyer. 2008. A generative model for parsing natural language to meaning representations. In Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing, pages 783–792, Honolulu, Hawaii. Association for Computational Linguistics.

Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1412–1421, Lisbon, Portugal. Association for Computational Linguistics.

Ana-Maria Popescu, Oren Etzioni, and Henry Kautz. 2003. Towards a theory of natural language interfaces to databases. In Proceedings of the 8th International Conference on Intelligent User Interfaces, IUI ’03, page 149–157, New York, NY, USA. Association for Computing Machinery.

Laura Ruis, Jacob Andreas, Marco Baroni, Diane Bouchacourt, and Brenden M Lake. 2020. A benchmark for systematic generalization in grounded language understanding. Advances in neural information processing systems, 33:19861–19872.

M. Schuster and K.K. Paliwal. 1997. Bidirectional recurrent neural networks. IEEE Transactions on Signal Processing, 45(11):2673–2681.

Mark Steedman. 1996. Surface structure and interpretation. MIT press.

Mark Steedman. 2000. The syntactic process. MIT press.

Mark Steedman. 2020. A formal universal of natural language grammar. Language, 96:618–660.

Bailin Wang, Mirella Lapata, and Ivan Titov. 2021. Structured reordering for modeling latent alignments in sequence transduction. In Advances in Neural Information Processing Systems.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. 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.

Yuk Wah Wong and Raymond Mooney. 2006. Learning for semantic parsing with statistical machine translation. In Proceedings of the Human Language Technology Conference of the NAACL, Main Conference, pages 439–446, New York City, USA. Association for Computational Linguistics.

Deukai Wu. 2010. Alignment. In Nitin Indurkhya and Fred Damerau, editors, Handbook of Natural Language Processing, Chapman Hall/CRC.

Kelvin Xu, Jimmy Lei Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Bengio. 2015. Show, attend and tell: Neural image caption generation with visual attention. In Proceedings of the 32nd International Conference on International Conference on Machine Learning - Volume 37, ICML, page 2048–2057. JMLR.org.

John M. Zelle and Raymond J. Mooney. 1996. Learning to parse database queries using inductive logic programming. In Proceedings of the Thirteenth National Conference on Artificial Intelligence - Volume 2, AAAI’96, page 1050–1055. AAAI Press.

Luke Zettlemoyer and Michael Collins. 2007. Online learning of relaxed CCG grammars for parsing to logical form. In Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), pages 678–687, Prague, Czech Republic. Association for Computational Linguistics.

Luke S. Zettlemoyer and Michael Collins. 2005. Learning to map sentences to logical form: Structured classification with probabilistic categorial grammars. In Proceedings of the 21st Conference on Uncertainty in Artificial Intelligence, UAI, page 658–666, Arlington, Virginia, USA. AUAI Press.

A Implementation and training details

We based our LSTM-based seq2seq model on Bahdanau et al. (2015). We use a one-layer bidirectional LSTM for our encoder and a one-layer unidirectional LSTM for our decoder. At training we minimize the cross entropy loss between the predictions and the ground-truth MR sequences. We use a batch size of 32, Adam optimizer and learning rate of 0.001. We manually tune the hyperparameters, and train for 100 epochs on one NVIDIA TESLA V100 16GB GPU.
For BART, we used the pre-trained BART-base model provided by the HuggingFace transformers library (Wolf et al., 2020). We fine-tune for 100 epochs with a learning rate of 0.00001 on one NVIDIA TESLA V100 16GB GPU. Fine-tuning took approximately 1h30mins.