LAGr: Labeling Aligned Graphs for Improving Systematic Generalization in Semantic Parsing

Dóra Jámbor*  
Quebec Artificial Intelligence Institute (Mila)  
McGill University  
dora.jambor@mail.mcgill.ca

Dzmitry Bahdanau  
Element AI, a ServiceNow company  
Quebec Artificial Intelligence Institute (Mila)  
McGill University  
Canada CIFAR AI Chair

Abstract

Semantic parsing is the task of producing a structured meaning representation for natural language utterances or questions. Recent research has pointed out that the commonly-used sequence-to-sequence (seq2seq) semantic parsers struggle to generalize systematically, i.e., to handle examples that require recombining known knowledge in novel settings. In this work, we show that better systematic generalization can be achieved by producing the meaning representation (MR) directly as a graph and not as a sequence. To this end we propose LAGr, the Labeling Aligned Graphs algorithm that produces semantic parses by predicting node and edge labels for a complete multi-layer input-aligned graph. The strongly-supervised LAGr algorithm requires aligned graphs as inputs, whereas weakly-supervised LAGr infers alignments for originally unaligned target graphs using an approximate MAP inference procedure. On the COGS and CFQ compositional generalization benchmarks the strongly- and weakly-supervised LAGr algorithms achieve significant improvements upon the baseline seq2seq parsers.

1 Introduction

Deep learning has led to impressive advances in natural language processing (NLP), yet recent research points out that neural models still struggle to systematically (or compositionally) generalize to examples with unseen combinations of seen primitives and rules from the training set (Lake & Baroni (2018); Finegan-Dollak et al. (2018); Hupkes et al. (2019)). An important applied scenario in which systematic generalization can be especially desirable is semantic parsing, a task that requires models to produce a formal meaning representation (MR), such as a logical form or a database query, for natural utterances or questions. Systematic generalization of semantic parsers has been recently extensively studied on both synthetic (Bahdanau et al., 2019; Kim & Linzen, 2020; Keysers et al., 2020) and natural benchmarks (Finegan-Dollak et al., 2018; Shaw et al., 2020). Many approaches have recently been proposed to make semantic parsers generalize more compositionally, including but not limited to the use of meta-learning (Conklin et al., 2021), pretrained models (Furrer et al., 2020), and intermediate representations (Herzig et al., 2021).

With the exception of a few neural grammar methods like that of Herzig & Berant (2020), at the core of most recent semantic parsers is sequence-to-sequence learning (seq2seq, Sutskever et al., 2014; Bahdanau et al., 2015). A seq2seq neural semantic parser sequentially emits the serialized meaning representation token-by-token. This approach has two potential drawbacks in the context of semantic parsing. The first drawback is that seq2seq requires one to serialize the MR that could often be more parsimoniously represented as a graph or a tree. The arbitrary serialization choices can adversely impact generalization. The second drawback is that the autoregressive seq2seq decoder learns to predict the next token based on all other previous tokens, whereas in semantic parsing many aspects of meaning can be predicted independently, which can facilitate generalization.

In this work we show that systematic generalization gains can be achieved by building the MR directly as a graph instead of outputting the MR graph as a sequence. Specifically we construct the MR

*Corresponding author. Work partly done during an internship at Element AI, a ServiceNow company.
by labelling nodes and edges of a fully-connected multi-layer output graph that is aligned with the
input utterance, an approach we call LAGr (LAGr — Labeling Aligned Graphs). Our approach is
inspired by a work by Lyu & Titov (2018) who use a similar method to construct Abstract Meaning
Representation (AMR) graphs, however, to the best of our knowledge such a sequence-to-graph
method has not been considered in systematic generalization research\(^1\). Importantly, LAGr retains
most of the flexibility that seq2seq models have, without the complexity and rigidity that comes with
the grammar-based approaches.

We propose and evaluate two versions of the LAGr algorithm. The strongly-supervised version
of LAGr requires training examples in which the output graph is aligned to the input sequence.
Using the COGS dataset by Kim & Linzen (2020) as the testbed, we show how strongly-supervised
LAGr generalizes more systematically than the seq2seq baseline. For the common scenario where
the alignment between the MR graph and the input sequence is not known we propose a weakly-
supervised version of LAGr in which we treat the alignment as a latent variable. Using approximate
maximum-a-posteriori alignments for training the model, weakly-supervised LAGr significantly
improves upon comparable seq2seq parsers on two out of three Maximum Compound Divergence
(MCD) splits of the CFQ dataset by Keysers et al. (2020).

2 Semantic Parsing by Labeling Aligned Graphs

We propose LAGr, a framework for constructing semantic parses directly as graphs. When LAGr
is used to output logical forms, the graph nodes can be variables, entities, categories and predicates,
while graph edges mark Neo-Davidsonian (Parsons, 1990) style relations between the nodes e.g.
"is-agent-of", "is-theme-of", etc. LAGr can also in principle be used to output other kinds of graphs,
such as abstrax syntax tree parses of SQL queries, although we do not perform such experiments in
this paper. LAGr predicts the output by labelling the nodes and edges of a fully-connected multi-layer
output graph that is aligned with the input utterance. Illustrations of labeled aligned graphs with 1
and 2 layers respectively can be found in Figure 1. We label a multi-layer as opposed to a single-layer
graph because some meaning representation graphs can have more nodes than the number of input
tokens (see Section 4.2 for further discussion).

Formally, let \( x = x_1, x_2, \ldots, x_N \) denote a natural language utterance of \( N \) tokens. LAGr produces a
labeled output graph \( G \) by labeling the nodes and edges of a complete graph \( \Gamma_a \) with \( M = L \cdot N \)
nodes that are arranged in \( L \) layers. Each layer is aligned with the input sequence \( x \), meaning for each
input position \( i \) each layer has a unique corresponding output node. We will use a one-dimensional
indexing system to refer to the nodes of \( \Gamma_a \), namely by assigning the index \( j = (l - 1)N + i \) to refer
to the \( i \)-th node in the layer \( l \). We use \( z_j \in V_n \) and \( \xi_{jk} \in E_e \) to refer to the labels of node \( j \) and the
edge \((j, k)\), where \( V_n \) and \( E_e \) stand for the node and the edge label vocabularies respectively. We
will also use a notation \( \Gamma_a = (z, \xi) \) to reflect the fact that a complete labeled graph \( \Gamma_a \) is defined by
its node labels \( z \in V_n^M \) and edge labels \( \xi \in E_e^{M \times M} \). To produce the output graph \( G \) from the aligned

\(^1\)A concurrent systematic generalization study by Ontañon et al. (2021) that was put on ArXiv on August 5
features a “sequence tagging” approach that is similar to LAGr,
To label the nodes of $Γ_a = (z, ξ)$ we remove all the nodes $j$ labeled as $z_j = \emptyset \in V_n$ (null nodes), all the edges that are adjacent to the null nodes, and all the edges $(j, k)$ that are labeled as $ξ_{jk} = \emptyset \in V_e$ (null edges).

### 2.1 Labeling the Aligned Graph

To label the nodes of $Γ_a$ we encode the input utterance $x$ as a matrix of $N$ $d$-dimensional vectors $H = f_{enc}(x) \in \mathbb{R}^{N \times d}$, where the encoder $f_{enc}$ can be e.g. an LSTM (Hochreiter & Schmidhuber, 1997) or a Transformer (Vaswani et al., 2017) model. LAGR then defines the following factorized graph $Γ$:

In practice, the alignment between the graphical MR $Γ$ then defines the following factorized graph $Γ$:

In the equations above $O \in \mathbb{R}^{M \times |V_n|}$ contains concatenated logits for the nodes in all $L$ layers, $W^α_n, \ldots, W^L_n \in \mathbb{R}^{d \times |V_n|}$ are weight matrices, $b^α_n, \ldots, b^L_n \in \mathbb{R}^{|V_n|}$ are bias vectors. Here and in further equations $\text{softmax}()$ is applied to the last dimension of the input tensor.

Our edge labelling computation is reminiscent of the multi-head self-attention by Vaswani et al. (2017), with the key difference that softmax is applied across the edge label heads and not across positions:

In the equations above $H^α_q, H^α_k \in \mathbb{R}^{d \times |V_e|}$ contain concatenated key and query vectors for the label $α \in V_e$ for all $L$ layers, $W^α_k, W^α_q \in \mathbb{R}^{d \times d}$ are the weights matrices and $b^α_q, b^α_0 \in \mathbb{R}^d$ are the bias vectors for the edge label $α$ and the layer $l \in \{1; L\}$.

Given the factorized nature of the node and edge label distributions $p(z|x)$ and $p(ξ|x)$, the argmax inference $z^*, ξ^* = \arg\max p(z, ξ|x)$ is trivial to perform. When an aligned version $Γ_a$ of the ground-truth graph $G$ is available at the training time, LAGR can be trained by directly optimizing $\log p(z^*, ξ^*|x)$, where $z^*$ and $ξ^*$ are $Γ_a$'s node and edge labels. When $z$ and $ξ$ are available, we will refer to this training setting as strongly-supervised LAGR.

### 2.2 The Latent Alignment Model

In practice, the alignment between the graphical MR $G$, and the question $x$ is often unknown and the aligned graph $Γ_a$ is not readily available. To address this common scenario, we propose a weakly-supervised LAGR algorithm based on a latent alignment model. Similarly to the strongly-supervised case, we assume that the MR $G$ can be represented as a multi-layer complete labeled graph $Γ_m = (s \in V_n^M, e \in V_e^M \times M)$, with the difference that in this case the alignment between $x$ and $Γ_m$ is not known. We assume a generative process whereby $Γ_m$ is obtained by permuting the columns of the latent aligned graph $Γ_a$ with a random permutation $a$, where $a_j$ is the position in the input utterance $x$ that is mapped to the $j$-th column of $Γ_a$. For the rest of this section we focus on the single layer ($L = 1$) case to simplify the formulas. For this case our probabilistic model defines the following distribution over $Γ_m = (s, e)$:

In the equations above $H^α_q, H^α_k$ contain concatenated key and query vectors for the label $α \in V_e$ for all $L$ layers, $W^α_k, W^α_q \in \mathbb{R}^{d \times d}$ are the weights matrices and $b^α_q, b^α_0 \in \mathbb{R}^d$ are the bias vectors for the edge label $α$ and the layer $l \in \{1; L\}$.

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where \( p(a) = 1/N! \).

Computing \( p(e, s|x) \) exactly is intractable. For this reason, we train LAGr by using an approximation of \( p(e, s|x) \) in which instead of summing over all possible alignments \( a \) we only consider the Maximum \( \text{A Posteriori (MAP)} \) alignment \( \hat{a} = \arg \max_a p(a|e, s, x) \). This approach is sometimes called the hard Expectation-Maximization algorithm in the literature on probabilistic models (Svensén & Bishop, 2007). The training objective thus becomes

\[
p(e, s|\hat{a}, x) = \prod_j p(z_{\hat{a}_j} = s_j|x) \prod_j \prod_k p(\xi_{\hat{a}_j, \hat{a}_k} = e_{jk}|x).
\]

(10)

To infer the MAP alignment, we need to solve the following inference problem:

\[
\hat{a} = \arg \max_a p(a|e, s, x) = \arg \max_a \frac{p(a, e, s, x)}{p(e, s, x)} = \arg \max_a \log p(s|a, x) + \log p(e|a, x) =
\]

(11)

\[
= \arg \max_a \left[ \sum_j \log p(z_{\hat{a}_j} = s_j|x) + \sum_j \sum_k \log p(\xi_{\hat{a}_j, \hat{a}_k} = e_{jk}|x) \right]
\]

(12)

We are not aware of an exact algorithm for solving the above optimization problem, however if the edge log-likelihood term \( \log p(e|a, x) \) is dropped in the equations above, maximizing the node label probability \( p(s|a, x) \) is equivalent to a standard minimum cost bipartite matching problem. This optimization problem can be solved by a polynomial-time Hungarian algorithm (Kuhn, 1955). We can thus use an approximate MAP alignment \( \hat{a} = \arg \max_a \sum_j \log p(z_{\hat{a}_j} = s_j|x) \). While dropping \( p(e|a, x) \) from Equation 11 is a drastic simplification, in situations where node labels \( s \) are unique and the model is sufficiently trained to output sharp probabilities \( p(z_j|x) \) we expect \( \hat{a} \) to often match \( a \). To further improve the MAP alignment approximation and alleviate the reliance on the above strong assumptions, we generate a shortlist of \( K \) candidate alignments by solving \( K \) noisy matching problems of the form \( \arg \max_a \sum_j \log p(z_{\hat{a}_j} = s_j|x) + \epsilon_{\hat{a}a_j} \), where \( \epsilon_{\hat{a}a_j} \sim N(0, \sigma) \). We then score the generated candidates with the full log-likelihood \( \log p(s|a, x) + \log p(e|a, x) \) and select the best one. We refer the reader to Algorithm 1 for a detailed presentation of the resulting weakly-supervised LAGr algorithm.

### Algorithm 1: Weakly-supervised training of LAGr

**Init:** Let \( K \) be the number of alignment iterations, \( T \) be the number of training steps, \( f_{enc} \) denote the encoder model, \( \theta_t \) be the model parameters after \( t \) steps.

1. **for** \( t = 1, \ldots, T \) **do**
2. 1. sample example \( (x, e, s) \)
3. 2. **for** \( k = 1, \ldots, K \) **do**
4. 3. \( \epsilon_{ji} \sim N(0, \sigma) \)
5. 4. \( \text{cost}_{ji} = -\log p(z_i = s_j|x) + \epsilon_{ji} \)
6. 5. \( a^k = \text{MinCostBipartiteMatching(cost)} \)
7. 6. \( J^k = \sum_j \log p(z_{a^*_j} = s_j|x) + \sum_j \sum_k \log p(\xi_{a^*_j, a^*_k} = e_{jk}|x) \)
8. 7. \( \hat{k} = \arg \max_k J^k \)
9. 8. \( \theta_{t+1} \leftarrow \text{Optimizer}(\theta_t, \nabla_a - J^k) \)
10. **return** \( \theta_{T+1} \)

### 3 Related Work

The LAGr approach is heavily inspired by graph-based dependency parsing algorithms (McDonald, 2006). In neural graph-based dependency parsers (Kiperwasser & Goldberg, 2016; Dozat & Manning, 2017) the model is trained to predict the existence and the label of each of the possible edges between the input words. The Abstract Meaning Representation (AMR) parser by Lyu & Titov (2018) brings similar methodology to the realm of semantic parsing, although they do not consider the systematic generalization implications of using a graph-based parser instead of a seq2seq one. Lyu & Titov (2018) only output single layer graphs which requires aggressive graph compression; in LAGr we allow the model to output a multiple layer graph instead. Lastly, the amortized Gumbel-Sinkhorn alignment inference used by Lyu & Titov (2018) is much more complex than the
Hungarian-algorithm-based approximate MAP inference that we employ here. Another important inspiration for LAGr is the UDepLambda method (Reddy et al., 2016) for converting dependency parses into graph-like logical forms. LAGr can be seen as an algorithm that produces the UDepLambda graphs directly with the neural model, side-stepping the intermediate dependency parsing step.

Another alternative to seq2seq semantic parsers are span-based parsers that predict span-level actions for building MR expressions from sub-expressions. (Herzig & Berant, 2020; Pasupati et al., 2019). A prerequisite for using a span-based parser is an MR that can be viewed as a recursive composition of MRs for subspans. While this strong compositionality assumption holds for the logical forms used in earlier semantic parsing research (e.g. Zettlemoyer & Collins (2005)), an intermediate MR would be required to produce other meaning representations, such as e.g. SPARQL or SQL queries, with a span-based parser. The designer for an intermediate MR for a span-based parser must think about MRs for spans and how they should be composed. This can sometimes lead to non-trivial corner cases, such as e.g. ternary grammar rules in Herzig & Berant (2020). On the contrary, a graph-based parser can in principle produce any graph, although in practice in our experiments we compress the raw graphs slightly to make the learning problem easier.

Other related semantic parsing approaches include the semantic labeling method by Zhong et al. (2020) and the structured reordering approach by Wang et al. (2021). Zhong et al. (2020) show that labelling the input sequence prior to feeding it to the seq2seq semantic parser improves compositional generalization. Compared to that study, our work goes one step further by adding edge labeling, which allows us to let go of the seq2seq model entirely. Wang et al. (2021) model semantic parsing as structured permutation of the input sequence followed by monotonic segment-level transduction. This approach achieves impressive results, but is considerably more complex than LAGr. Finally, Guo et al. (2020) achieve a very high performance on CFQ by combining the sketch prediction approach (Dong & Lapata, 2018) with an algorithm that outputs the MR as a directed acyclic graph (DAG). Unlike LAGr, their algorithm produces the DAG in a sequential left-to-right fashion. Notably, the non-hierarchical version of this algorithm without sketch prediction performs poorly.

4 Experiments

We demonstrate the effectiveness of LAGr using two compositional generalization benchmarks: Compositional Generalization for Semantic Parsing (COGS) for the strongly-supervised LAGr algorithm that takes aligned graphs as training data, and Compositional Freebase Questions (CFQ) for weakly-supervised LAGr that takes unaligned graphs and infers alignment during training.

4.1 Strongly-supervised LAGr on COGS

Dataset COGS (Kim & Linzen, 2020) is a semantic parsing benchmark that requires models to translate English sentences to lambda calculus logical forms (see Figure 1a). The out-of-distribution generalization set of COGS features novel combinations of words and syntactic structures from the training dataset. For example, while the word hedgehog is only observed as a subject during training (e.g. “the hedgehog sleeps”), the generalization set requires the model to understand it in the object role (e.g. “the hero painted the hedgehog”). For further examples on other linguistic phenomena used in COGS’s generalization set, we refer the reader to Appendix A.1.

Graph Construction To use COGS in our strongly-supervised LAGr experiments, we convert the logical forms to UDepLambda (Reddy et al., 2016) MR graphs. First, we create graph nodes for the one- and two-place predicates and definite articles. In the example shown in Figure 1a, this process yields the hedgehog, apple, eat and the * nodes. We do not create dedicated nodes for variables, because in COGS every variable is either an argument to just one 1-place predicate (e.g. $x_1$ for hedgehog($x_1$)) or the first argument for just one 2-place predicate (e.g. $x_2$ for eat in eat.agent($x_2$, $x_1$)); we let the respective predicate node represent the variables. To define the graph's labeled edges, we use the Neo-Davidsonian role predicates (i.e., agent, theme, recipient, ccomp, nmod.on, nmod.in, xcomp, nmod.beside). Thus the eat.agent($x_2$, $x_1$) conjunct results into an agent edge between the eat and hedgehog nodes. We add special article edges to connect definite article nodes (denoted by the * label) to their respective nouns (hedgehog in the considered example from Figure 1a).
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Table 1: Average exact match accuracy of reproduced seq2seq baselines and strongly-supervised LAGr results on COGS over 10 runs with a 95% confidence interval in brackets (bottom). Middle: Seq2seq baselines including the original results by Kim & Linzen (2020) ◊, the best reproduced Transformer by Conklin et al. (2021) •, and the best reproduced LSTM and a lexicon-based approach by Akyürek & Andreas (2021) ▽. Top: Prior work by Conklin et al. (2021), included for reference.

| Algorithm                      | train | test  | gen  |
|-------------------------------|-------|-------|------|
| Tree-MAML LSTM ▲              | -     | 99.7  | 41.0 (±4.9) |
| Tree-MAML Transformer ▲       | -     | 99.6  | 66.7 (±4.4) |
| LSTM+Attn ◇                   | -     | 99.5  | 58.6 (±3.7) |
| Transformer ◇                 | -     | 99.5  | 58.6 (±3.7) |
| LSTM + Lex: Simple ▽          | -     | -     | 82. (±1.) |
| LSTM + Lex: PMI ▽             | -     | -     | 82. (±0.) |
| LSTM + Lex: IBMMM2 ▽          | -     | -     | 82. (±0.) |
| LSTM+Attn (ours)              | 100 (±0.0) | 99.6 (±0.1) | 26.1 (±4.8) |
| Transformer (ours)            | 100 (±0.0) | 97.9 (±1.8) | 56.7 (±8.6) |
| LSTM_{sh} strongly-supervised LAGr | 100 (±0.0) | 99.9 (±0.1) | 39.0 (±6.5) |
| LSTM_{sep} strongly-supervised LAGr | 100 (±0.0) | 100 (±0.0) | 71.4 (±2.1) |
| Transformer_{sh} strongly-supervised LAGr | 100 (±0.0) | 99.8 (±0.3) | 77.4 (±2.8) |
| Transformer_{sep} strongly-supervised LAGr | 100 (±0.0) | 99.9 (±0.0) | 81.5 (±1.3) |

We align the constructed MR graphs with the input utterance using the indices from variable names (the variable corresponding to the $i$-th token is always called $x_i$ in COGS) and by looking up named entities. This process results in single-layer ($L = 1$) aligned graphs $\Gamma_a$ that are suitable for the strongly-supervised LAGr algorithm described in Section 2.1. The node and edge vocabularies for the aligned graphs contain 645 and 10 labels respectively, including the null labels.

**Training Details** Hyperparameter tuning on COGS is challenging since the performance on the in-distribution development set always saturates to near 100% level. For this reason we adopt the hyperparameter tuning procedure discussed in Conklin et al. (2021). Specifically, we create a “Gen Dev” dataset by sampling 1000 random examples from the generalization set and use them to find the best hyperparameter configuration. To measure performance, we use exact match accuracy, i.e., the percentage of examples for which the predicted graphs after serialization yielded the same logical form. We report the 95% confidence intervals for the generalization set exact match accuracy for each of our baselines and strongly-supervised LAGr models. For more details on our hyperparameter search, and best configurations, we refer the reader to Appendix A.2.

**Baselines** We compare LAGr to LSTM- and Transformer- based seq2seq semantic parsers that produce the COGS logical forms as sequences of tokens. In addition to training our own seq2seq baselines, we include the baseline results from the original COGS paper by Kim & Linzen (2020) and from follow-up works by Akyürek & Andreas (2021), and Conklin et al. (2021). The baseline seq2seq results for COGS vary highly from one implementation to another, hence we include results from several studies for a more rigorous assessment. We also compare LAGr to a lexicon-based seq2seq model “LSTM+Lex” by Akyürek & Andreas (2021). In that work, the authors propose an extension to the copy mechanism of seq2seq decoders that performs a lexical lookup to generate output tokens. Lastly, we include results by a Tree-MAML algorithm Conklin et al. (2021) that uses meta-learning to improve compositional generalization.

**Results** Table 1 shows that our best strongly-supervised LAGr model outperforms all vanilla sequence-to-sequence baselines, obtaining 81.5% (±1.3) exact match accuracy. LAGr achieves the best results with separate encoders for node and edge predictions. We reflect this distinction in the model names in Table 1 by adding the "_sep" subindex for separate encoders and "_sh" for shared encoders. With a shared Transformer used for both node and edge prediction, LAGr performs well above seq2seq baselines (77.4%). While having separate encoders significantly improves LAGr’s performance for both encoder types, it is crucial to get LAGr to work when an LSTM encoder is used (71.4% vs 39.0%).
When comparing LAGr to other methods that improve compositional generalization LAGr brings a higher improvement on top of seq2seq than meta-learning in Tree-MAML does. LAGr matches the performance of the LSTM+Lex approach by Akyürek & Andreas (2021) without using a lexicon (see Section 5 for a discussion of this result).

### 4.2 Weakly-supervised LAGr on CFQ

**Dataset** CFQ (Keysers et al., 2020) is a benchmark for compositional generalization in semantic parsing that requires models to translate English sentences to SPARQL database queries. We use CFQ’s Maximum Compound Divergence (MCD) splits, which were generated by making the distribution of compositional structures in the train and test sets as divergent as possible.

SPARQL queries contain two components: a SELECT and a WHERE clause. The SELECT clause is either of the form SELECT count(*) for yes/no questions or SELECT DISTINCT ?x0 for wh-questions (those starting with “which”, “what”, “who”, etc.). The WHERE clause can take on three forms: filter constraints ensuring two variables or entities are distinct (e.g. `FILTER ?x0 != M0`), 2-place predicates expressing a relation between two entities (e.g. `?x0 a ns:film.actor`), and 1-place predicates expressing if an entity belongs to a category (e.g. `?x0 a ns:film.actor`).

**Graph Construction** Before constructing the graphs, we compress the SPARQL queries by merging some of the triples in WHERE clauses similarly to prior work (Furrer et al., 2020; Guo et al., 2020). As an example, consider the question “Were M2 and M3 directed by a screenwriter that executive produced M1?” where the original MR contains both [M2 directed_by ?x0, M3 directed_by ?x0] conjuncts. To make SPARQL queries easier to align to the input question, we merge such triples by concatenating their subjects and objects. For the example above the resulting merged triple is [[M2, M3] directed_by ?x0]. Note that the compressed SPARQL queries can now have an arbitrary number of entities in the triples.

We convert the compressed SPARQL queries to graphs by first removing the SELECT clauses. To preserve the question type information, for wh-questions we replace the ?x0 variable in the WHERE clause with a special select_?x0 variable. As the example in Figure 1b shows, we define the graph nodes by taking the entities (including variables, e.g. `?x0`, `M1`) and all predicates (parent, sibling, actor) from the triples. For 1-place predicate triples, we connect the entity nodes to the predicate node with an edge label. For 2-place predicates, we connect the predicate to the left-hand side and right-hand side entities with the edge respectively. We add a FILTER edge between the variables or entities that participate in a filter constraint. The node and the edge vocabularies for our MR graphs contain 84 and 4 labels respectively, including the null labels in both cases.

**Training Details** To better accommodate the large MR graphs of CFQ we use L=2 graph layers. Using a single layer, as done in the COGS experiments, would not be possible because of examples such as

### Table 2: Weakly-supervised LAGr results on CFQ (bottom)

We report the graph accuracy average over 10 runs. Brackets show the 95% confidence interval. Middle: results by several seq2seq baselines from prior work (∇ Keysers et al. (2020), ◼ Furrer et al. (2020)). Top: for reference, results by Hierarchical Poset Decoding ▲ Guo et al. (2020), and a pretrained T5-small seq2seq model with intermediate representations (IR) ◊ Herzig et al. (2021) (both not directly comparable to LAGr).

| Metric | Random | Mean MCD | MCD1 | MCD2 | MCD3 |
|--------|--------|----------|------|------|------|
|        |        | train    | test | train | test |
| LSTM + Attn ▼ | - | 97.4 (+0.3) | 14.9 (+1.1) | 28.9 (+1.1) | 5.0 (+0.8) | 10.8 (+0.6) |
| Transformer ▼ | - | 98.5 (+0.2) | 17.9 (+0.9) | 34.9 (+1.1) | 8.2 (+0.3) | 10.6 (+1.1) |
| Universal Transformer ▼ | - | 98.0 (+0.3) | 18.9 (+1.4) | 37.4 (+2.2) | 8.1 (+1.6) | 11.3 (+0.3) |
| Evol. Transformer ▲ | - | 20.8 (+0.7) | 42.4 (+1.0) | 93.0 (+0.8) | 10.8 (+0.2) |
| LSTM + Simpler SPARQL ▲ | - | 26.1 | 42.2 | 14.5 | 21.5 |
| Transformer + Simpler SPARQL ▲ | - | 31.4 | 53.0 | 19.5 | 21.6 |
| T5-small from scratch ◼ | - | 29.8 | - | - | - |
| T5-small from scratch + IR ◊ | - | 22.6 | - | - | - |
| Transformer ▲ weakly sup. LAGr, k=1 | 99.6 (+0.1) | 98.5 (+0.5) | 29.2 (+5.9) | 50.9 (+37.) | 18.3 (+1.2) | 18.4 (+0.9) |
| Transformer ▲ weakly sup. LAGr, k=5, σ = 10 | 100 (+0.1) | 99.7 (+0.1) | 34.9 (+6.9) | 57.9 (+2.4) | 26.0 (+2.2) | 20.9 (+0.9) |
Table 3: The effect of the number of alignment candidates $K$ and noise level $\sigma$ on the performance of weakly-supervised LAGr on the random split of CFQ. We report the average graph accuracy over 5 runs with the 95% confidence interval. We show the best configuration in bold.

"Who married M1’s female German executive producer?" that contains 8 tokens, but induces the following 10 nodes: ?x1, executive_produced, M1, gender, ns:m.02zsn, nationality, ns:m.0345h, select_?x0, spouses, person.

In all our CFQ experiments we use a shared Transformer encoder for both node and edge prediction. For hyperparameter tuning, we follow Keysers et al. (2020) and use CFQ’s in-distribution random split to find the best model configuration. We do this by first fixing the number of candidate alignments at $K = 1$ to search for the best hyperparameters, then fixing the best configuration and varying $K$ and $\sigma$. To assess performance, we use exact graph accuracy, which we define as the percentage of examples where the predicted and true graphs are isomorphic. Since graphs can be serialized into SPARQL queries based on the alphabetical order of triples — a common practice in evaluating seq2seq models for CFQ (Guo et al., 2020) — exact graph accuracy can be compared to the exact match accuracy. Once the best configuration is obtained, we report the average graph accuracy and 95% confidence intervals from 10 runs of weakly-supervised LAGr on the out-of-distribution splits MCD1, MCD2, and MCD3 as well as the random one. Some training runs of weakly-supervised LAGr diverged; we discarded the runs that reached less than 98% graph accuracy on the training set, while making sure that we have 10 converged runs of each configuration. For further details on our CFQ experiments we refer the reader to Appendix A.4.

Results We compare LAGr to seq2seq semantic parsing results reported in prior work (Keysers et al., 2020; Furrer et al., 2020), including results obtained with compressed SPARQL queries (Guo et al., 2020; Herzig et al., 2021). As shown in Table 2, weakly-supervised LAGr outperforms all such baselines on the MCD1 and MCD2 splits. On MCD3, we match the compressed SPARQL results reported by Guo et al. (2020). Our best performing model is obtained with $K = 5$ and $\sigma = 10$, confirming that that considering several alignment candidates leads to performance gains, when compared to using best one based on the node-loss only ($K = 1$). For reference, in Table 2 we also include state-of-the-art CFQ results by the Hierarchical Poset Decoding (HPD, Guo et al., 2020) method (see 3 for more details on HPD), which arguably is not a fair baseline to LAGr because of its use of sketch prediction and lexicons. Notably, LAGr performs much better than the base poset decoding algorithm that does not use the extra techniques mentioned above.

Table 3 zooms in on the differences in performance on the random split when using a different number of alignment candidates, $K$, and noise levels $\sigma$. Results show that choosing the best alignment out of $K$ candidates is indeed helpful, and that noise of sufficiently high magnitude ($\sigma \leq 10$) should be added to the cost for best improvement. The positive effect of a larger $K$ is in line with our expectation since 3.7 - 5.7% of examples in each CFQ split have at least two predicates with identical node labels, which can make it hard to align the MR graph to the input by looking at node labels only. Interestingly, in contrast to our intuition, when using ten candidate alignments, the random split test performance is slightly worse than when using five. We show examples of the node labels that weakly-supervised LAGr predicts in the learned aligned CFQ graphs as well as the corresponding SPARQL triples in Figure 2.
Example 1: Wrong edge predictions

Layer 2
- ?x0 actor
- ?x0 director
- ?x1 cinematographer
- ?x2 cinematographer
- M3 influenced
- M3 spouse
- M2 influenced

Layer 1
- Input
  - What French film editor that M1 influenced influenced a company’s founder and was influenced by M2

Target
- ?x1 actor
- ?x0 director
- ?x2 cinematographer
- M2 influenced
- M3 spouse

Predicted
- ?x0 actor
- ?x0 director
- ?x1 cinematographer
- ?x2 cinematographer
- M3 influenced
- M3 spouse

Example 2: Missing node

Layer 2
- select_?x0 ns:m.0f8l9c editor
- influenced_by
- ?x1 employer
- organizations_founded
- M2

Layer 1
- Input
  - Which male Dutch film editor that influenced a company’s founder was influenced by M2

Target
- ?x0 actor
- ?x0 director
- ?x2 cinematographer
- M2 influenced
- M3 spouse

Predicted
- ?x0 actor
- ?x0 director
- ?x2 cinematographer
- M2 influenced
- M3 spouse

Example 3: Correct prediction

Layer 2
- select_?x0 ns:m.05zppz ns:m.059j2
- editor
- director

Layer 1
- Input
  - Which male Dutch film editor that influenced a Spanish actor was influenced by M2

Predicted
- ?x0 actor
- ?x0 influenced
- ?x1 actor
- select_?x0 actor
- select_?x0 influenced
- select_?x0 influenced
- select_?x0 influenced
- select_?x0 person
- select_?x0 nationality ns:m.059j2

Example 4: Correct prediction

Layer 2
- select_?x0 ns:m.06mkj actor

Layer 1
- nationality
- person

Input
- Who was a Spanish actor that influenced an English actor

Predicted
- ?x0 actor
- ?x0 influenced
- ?x1 actor
- select_?x0 actor
- select_?x0 influenced
- select_?x0 influenced
- select_?x0 influenced
- select_?x0 person
- select_?x0 nationality ns:m.06mkj

Figure 2: Predicted nodes of aligned graphs and resulting queries produced by the best weakly-supervised LAGr with k=5, σ = 10 on the development set of CFQ. Top two rows show common errors with missing edge labels and missing nodes, and bottom rows show the inferred alignments for correct examples.

5 Discussion & Future Work

In this work we have shown that performing semantic parsing by Labeling Aligned Graphs (LAGr) brings significant gains in compositional generalization. In our COGS and CFQ experiments, LAGr significantly improves upon sequence-to-sequence baselines in both strongly and weakly-supervised settings. Specifically, on COGS LAGr outperforms all vanilla seq2seq baselines and performs similarly to LSTMs that leverage lexicons. Use of lexicons can be integrated into LAGr although we do not expect this to improve LAGr performance on COGS, as our best performing LAGr model already predicts node labels almost perfectly. Adoption of lexicons, however, brings its own challenges of dealing with context-dependency and ambiguity, hence it is notable that LAGr matches the performance of a lexicon-equipped model while making less assumptions about the nature of the input-to-output mapping. For CFQ LAGr outperforms all seq2seq baselines on 2 out of 3 MCD splits. Based on our error analysis (see Figure 2 and Appendix A.3), we believe that a modification of LAGr that conditions edge predictions on node labels could bring further improvements. Importantly, our alignment inference algorithm would not need to be changed for this new LAGr version. Another straightforward direction to improve LAGr performance is by using a pretrained encoder. Lastly, while the current alignment inference algorithm is effective, applying more advanced discrete-optimization-based or amortized inference methods could be another interesting direction for future work.

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A Appendix

A.1 Further COGS examples

| Case                                      | Training                                      | Generalization                        |
|-------------------------------------------|-----------------------------------------------|----------------------------------------|
| Subject → Object                         | A hedgehog ate the cake.                      | The baby liked the hedgehog.           |
| Object → Subject                         | Henry liked a cockroach.                     | The cockroach ate the bat.             |
| Primitive → Object                       | Paula                                        | The child helped Paula.                |
| Depth generalization                      | Ava saw the ball in the bottle on the table. | Ava saw the ball in the bottle on the table on the floor. |
| Active → Passive                         | Emma blessed William.                        | A child was blessed.                   |

Table 4: Example from Kim & Linzen (2020) that show various linguistic phenomena included in the COGS generalization set.

A.2 COGS Hyperparameter Tuning

COGS does not include an out-of-distribution development set, which makes it challenging to find the best model configuration. To overcome this problem, we followed the same hyperparameter tuning procedure as proposed by Conklin et al. (2021). We sampled 1000 examples from the generalization set as a "Gen Dev" set which was used to pick the best hyperparameter configuration. We tested 0.001, 0.004, 0.0001 and 0.0004 for learning rates, 64, 128 and 256 for batch sizes, and 0.1 versus 0.4 for dropout. We tested an embedding size of 256 versus 512. Furthermore, for the Transformer baselines and for LAGr with a Transformer encoder, we also tested 2 versus 4 layers, and 4 versus 8 attention heads.

Each configuration was evaluated on 5 seeds. Once the best configuration was found, we retrained all models on 10 new seeds. We trained all models for 70,000 steps with validating at every 3000 steps, with no early stopping. We used the same procedure for tuning the original sequence-to-sequence baselines, except we only trained models for 50,000 steps, evaluating at every 1000 steps and early stopping when models stopped improving on the Gen Dev set for more than 20 validation steps. The best configurations for COGS are shown in Table 5.

| Reproduced baselines | Strongly-supervised LAGr with different encoders |
|----------------------|-----------------------------------------------|
|                       | LSTM | Transformer | LSTM | LSTM | Transformer | Transformer |
| batch_size            | 256  | 64          | 256  | 64   | 256         | 256         |
| learning_rate         | 0.004| 0.0004      | 0.0001| 0.0004| 0.0001      | 0.0001      |
| scheduler             | linear with warmup of 1000 steps | linear with warmup of 1000 steps | linear with warmup of 1000 steps | 2 | 2 | 2 | 2 |
| layers                | 2    | 2           | 2    | 2    | 2           | 2           |
| enc_dim               | 256  | 256         | 256  | 256  | 512         | 512         |
| train_steps           | 50000| 50000       | 70000| 70000| 70000       | 70000       |
| validate_every (step) | 1000 | 1000        | 3000 | 3000 | 3000        | 3000        |
| early_stopping (valid steps) | 20  | 20           | -    | -    | -           | -           |
| dropout               | 0.4  | 0.1         | 0.1  | 0.4  | 0.1         | 0.1         |
| attention heads       | 8    | 8           | -    | -    | 4           | 4           |

Table 5: Best hyperparameters in the COGS experiments
A.3 COGS Error Analysis

Below we show some commonly encountered errors on COGS with strongly-supervised LAGr. In all examples, the model predicted the correct set of nodes. However, even when all nodes are correctly predicted, some may not show up in the final logical form, if it has no connecting edges to other nodes (see the “dog” node in example 4.).

Example 1: wrong edge label, between right nodes

In
A cockroach sent Sophia the sandwich beside the yacht.

Out
sandwich (x_5) ; yacht (x_8) ; cockroach (x_1) AND send .

Pred
sandwich (x_5) ; yacht (x_8) ; cockroach (x_1) AND send .

Example 2: Right edge label, but between wrong nodes

In
The girl beside the bed lended the manager the leaf.

Out
girl (x_1) ; bed (x_4) ; manager (x_7) ; leaf (x_9) ; girl . nmod . beside (x_1 , x_4) AND lend .

Pred
girl (x_1) ; bed (x_4) ; manager (x_7) ; leaf (x_9) ; lend .

Example 3: Mistaking edge labels

In
The dog noticed that a hippo juggled.

Out
dog (x_1) ; notice . agent (x_2 , x_1) AND notice . ccomp (x_2 , x_6) AND hippo (x_5) AND juggle .

Pred
dog (x_1) ; notice . agent (x_2 , x_1) AND notice . ccomp (x_2 , x_6) AND hippo (x_5) AND juggle .

Example 4: Correct nodes, but incorrect edges predicted

In
A dog beside a chair said that a melon on the bed was liked.

Out
dog (x_1) ; chair (x_4) ; say . agent (x_5 , x_1) AND melon (x_8) AND bed . nmod . in (x_11 , x_13) AND like .

Pred
dog (x_1) ; chair (x_4) ; say . agent (x_5 , x_1) AND melon (x_8) AND bed . nmod . in (x_11 , x_13) AND like .

Table 6: Incorrectly predicted logical forms for COGS with strongly-supervised LAGr. Errors are highlighted in bold.

A.4 CFQ Hyperparameter Tuning

We performed hyperparameter tuning on CFQ’s random split, and chose the best configuration based on the development exact graph accuracy. For LAGr with both shared and separate Transformer encoders, we tested learning rates of 0.0001, 0.0004, 0.0006, 0.0008 and 0.001, with a linear warmup of 1000 versus 5000 steps, with dropout of 0.1 and 0.4, batch sizes of 64, 128 and 256, and 2 versus 4 Transformer layers. For LAGr with a separate LSTM encoder, we tested learning rates of 64, 128, and 256, with a linear warmup of 1000 versus 5000 steps, a dropout of 0.1 and 0.4, and embedding size of 256 versus 512. Our best configurations are reported in Table 7.

| CFQ                  | Weakly-supervised LAGr |
|----------------------|------------------------|
|                      | LSTM<sub>sep</sub> | Transformer<sub>sh</sub> |
| batch_size           | 64                     | 256                     |
| learning_rate        | 0.001                  | 0.0004                  |
| scheduler            | linear with warmup of 1000 steps | linear with warmup of 1000 steps |
| layers               | 2                      | 4                       |
| enc_dim              | 512                    | 256                     |
| train_steps          | 200000                 | 200000                  |
| validate_every (step) | 10000                  | 10000                   |
| early_stopping (valid steps) | 5                      | 5                       |
| dropout              | 0.4                    | 0.1                     |
| attention heads      | -                      | 8                       |

Table 7: Best configuration for CFQ weakly-supervised LAGr.