Unlocking Compositional Generalization in Pre-trained Models Using Intermediate Representations

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Abstract

Sequence-to-sequence (seq2seq) models are prevalent in semantic parsing, but have been found to struggle at out-of-distribution compositional generalization. While specialized model architectures and pre-training of seq2seq models have been proposed to address this issue, the former often comes at the cost of generality and the latter only shows limited success. In this paper, we study the impact of intermediate representations on compositional generalization in pre-trained seq2seq models, without changing the model architecture at all, and identify key aspects for designing effective representations. Instead of training to directly map natural language to an executable form, we map to a reversible or lossy intermediate representation that has stronger structural correspondence with natural language. The combination of our proposed intermediate representations and pre-trained models is surprisingly effective, where the best combinations obtain a new state-of-the-art on CFQ (+14.8 accuracy points) and on the template-splits of three text-to-SQL datasets (+15.0 to +19.4 accuracy points). This work highlights that intermediate representations provide an important and potentially overlooked degree of freedom for improving the compositional generalization abilities of pre-trained seq2seq models.

1 Introduction

Compositional generalization is the desired ability for a semantic parser to generalize to new combinations of program components, where each component was seen at training time, but where the particular combination is out-of-distribution. For example, a parser trained on questions such as “Rivers crossing New York” and “What states border Texas?” should generalize to “Rivers that cross states bordering Washington” at test time.

While sequence-to-sequence (seq2seq) models dominate semantic parsing (Jia and Liang, 2016; Dong and Lapata, 2016; Wang et al., 2020), previous work found that they perform poorly on evaluation that requires compositional generalization (Finegan-Dollak et al., 2018; Lake and Baroni, 2018; Keysers et al., 2020). Both new architectures (Li et al., 2019; Lake, 2019; Nye et al., 2020; Chen et al., 2020, inter alia) and general-purpose pre-trained seq2seq models such as T5 (Raffel et al., 2020) have shown improvements on some evaluations of compositional generalization, but strong performance in general remains a significant challenge (Shaw et al., 2020; Furrer et al., 2020).

In this paper we posit that pre-trained seq2seq models struggle with compositional generalization in part due to a low structural correspondence between the natural language and its meaning representation. Thus, instead of training to directly map natural language to an executable form, we map to an intermediate representation designed to increase the structural correspondence with natural language: for example, omitting elements of the parse that cannot be easily aligned to natural language, and adding structural cues such as brackets to indicate nested scopes. Since the intermediate form is no longer executable and may not even contain all details necessary for execution, we then apply a second stage to convert the intermediate representation into an executable parse. This is done using either deterministic transformations or a second seq2seq model that conditions on both the intermediate representation and the original natural language utterance, as illustrated in Figure 1. Notably, we find that our intermediate representations provide an important and potentially overlooked degree of freedom for improving the compositional generalization abilities of pre-trained seq2seq models.

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on the context of compositional generalization and our model-agnostic design for two-stage decoding. Previous methods mostly targeted in-distribution generalization or did not find significant benefits in the compositional generalization setup (Furrer et al., 2020). Therefore, we believe our paper is a first thorough attempt to explore how intermediate representations can be combined with pre-training to improve compositional generalization.

The contributions of our paper are:

• We study the effect of intermediate representations on the compositional generalization in pre-trained seq2seq models, and identify key aspects for designing effective representations.

• We show that a well-designed intermediate representation is often synergistic with pre-training: when both are used together, the gains are bigger than the sum of each individually.

• We show that the best combinations of our intermediate representations with pre-trained seq2seq models obtain new state-of-the-art results on CFQ (Keysers et al., 2020) (+14.8 accuracy) and the template-splits of three text-to-SQL datasets (Finegan-Dollak et al., 2018) (+15.0 to +19.4 accuracy), outperforming previous work by a large margin while maintaining competitive performance on the i.i.d. (random) splits.

2 Review: Semantic Parsing Formalisms

We briefly describe the semantic parsing formalisms we explore in this work. Figure 2 shows an example utterance \( x \) and program \( y \) for each formalism. We first experiment with SPARQL programs from CFQ (Keysers et al., 2020). Each SPARQL program contains a set of conjuncts, each of which consists of a subject, relation, and object. For example, the conjunct \(?x0 \text{person.person.nationality} \text{m_0f819c}\) limits the possible values for the variable \(?x0\) to people of French nationality. Second, we experiment with SQL programs, canonicalized by Finegan-Dollak et al. (2018) to a consistent writing style where, e.g., table aliases are in the form \(<\text{TABLE NAME}_alias<N>\) for the \(N\)th use of the same table in one program. Finally, we consider the instruction following formalism in SCAN (Lake and Baroni, 2018), where natural language commands (e.g., “jump twice”) are mapped to action sequences (e.g., JUMP JUMP).

For all of these formalisms, there can be a significant degree of structural mismatch between an utterance and its corresponding program. We hypothesize that this structural mismatch contributes to poor generalization on out-of-distribution compositional examples, even for pre-trained models.

3 Intermediate Representations

We study intermediate representations (IRs) to improve compositional generalization for seq2seq models. For a program \( y \), an IR can be defined as \( z = F(y) \) where \( F \) is a deterministic transformation function. Example IRs (\( z \)) are shown in Figure 2. As we will explain in §3.1, we design IRs to simplify programs and increase their structural correspondence with the input utterance.\(^2\) Additionally, to make use of existing pre-trained models, our transformations \( F \) are model-agnostic and do not require any architecture change to the model.

As shown in Figure 1, our framework for incorporating IRs when parsing utterances \( x \) into programs \( y \) consists of two stages. First, instead of predicting \( y \) directly from the utterance \( x \), our seq2seq model \( \text{Seq2Seq} : x \rightarrow z \) is trained to predict the IR \( z \). Second, we map the predicted \( z \) to a program \( y \), using one of the two methods depend-
Figure 2: Examples for the different formalisms, of an utterance (x), program (y), reversible intermediate representation (z₁), and lossy intermediate representation (z₂). For each formalism, tokens with the same color share their semantic role. Tokens in z₁ and z₂ that are modified w.r.t. y are in bold. We abbreviate original SPARQL relations, and also abbreviate the SQL table names airline, airport, and flight to AL, AP and FL, respectively.

**3.2 Reversible Intermediate Representation**

We adapt the following reversible IRs for each formalism (z₁ in Figure 2).

**3.2.1 SPARQL**

A mismatch between SPARQL programs and utterances often occurs when relations are expressed in a distributive manner in language. For example, in Figure 2 (a), while marriage.spouses appears twice in the program y, it is manifested once in the utterance x ("married M2 and M3"). To alleviate this mismatch, we group conjuncts that share the same subject and relation; for example, given a SPARQL query with triples \{ (x₀, r₁, e₁), (x₁, r₁, e₂), (x₀, r₂, e₁), (x₁, r₂, e₂) \}, we modify it to \{ (x₀, r₁, \{ e₁, e₂ \}), (x₀, r₂, \{ e₁, e₂ \}) \}. We further shorten the IR by truncating relation...
names of the form \(<r_{prefix}><ns:><r_{suffix}>\) to \(<r_{suffix}>\) while ensuring the final relation name is still unique. Finally, to induce additional hierarchical structure, we add brackets around each conjunct. We find this IR to be more effective than those proposed by previous work (Furrer et al., 2020; Guo et al., 2020b). Later, in §5.2, we find each of our design decisions to individually assist performance.

**SQL** Previous work has proposed various IRs for SQL, such as SemQL (Guo et al., 2019), SQL\_UF (Suhr et al., 2020), and an extension of relational algebra (Rubin and Berant, 2020). However, these IRs are primarily developed for the Spider dataset (Yu et al., 2018), and their conversion procedures make various assumptions that can limit their applicability to other datasets. For example, unlike Spider, datasets such as ATIS contain SQL queries with self joins and multiple foreign key relations between a given pair of tables. Consequently, Suhr et al. (2020) note that less than 20% of the queries in ATIS can be successfully converted to their intermediate representations, SQL\_UF.

Therefore, we propose a simple IR aimed at omitting tokens in the program that do not align to any phrase in the utterance. By convention, the datasets we study use table aliases of the form \(<\text{TABLE NAME}>\text{alias}<\text{N}>\) for the \(N\)th use of the same table in a query. For the reversible IR, we simply remove the alias token, such that table alias names take the form of \(<\text{TABLE NAME}><\text{N}>\). We will further simplify the program using lossy IRs (§3.3).

**Instruction Following** Programs in SCAN consist of a sequence of actions with no explicit hierarchical (e.g., tree) structure that could indicate the scope of actions in the program. This lack of structure is conveyed by common errors we encounter when decoding reoccurring actions. For example, “turn opposite left twice” in Figure 2 (c) should be mapped to four consecutive LTURN actions. In this case the model often wrongly decodes LTURN more or less times than required. We induce a hierarchical structure into the reversible IR by adding brackets around repeated program components (e.g., each of the two occurrences that “turn opposite left twice” maps to) and around complex actions (e.g., the program component that “jump opposite right” maps to), which could assist the model in mapping language phrases to actions.\(^3\)

\(^3\)We use a synchronous CFG to add this bracketing, so for SCAN the transformation \(F\) is also a function of \(x\).

### 3.3 Lossy Intermediate Representations

The IRs suggested in §3.2 are required to be fully reversible such that we can recover the executable program in the original formalism without information loss. However, we find lossy IRs that omit or anonymize program components to be desired. For example, table names in SQL are frequently absent from utterances, such as airport and flight in Figure 2(b), and thus predicting them correctly can be difficult.

Figure 2 illustrates examples of the lossy IRs (\(z_i\)) we propose. For SPARQL, we anonymize entities and variables, replacing them with the placeholder \(\text{var}\), which increases the similarity between different \(z_i\) instances. For SQL, we adapt \(z_i\) to only contain components that are frequently manifested in the utterance (e.g., column names and values), which reduces the mismatch between utterances and their IR \(z_i\). Particularly, we omit the FORM clause, mask table names, and omit conditions that are only relevant for joining tables. For instruction following, we anonymize repeated single actions, except the first one. Formally, we replace strings \(C^n\) (action \(C\) repeating \(n > 1\) times) with \(C A^{n-1}\), where \(A\) represents an anonymized action. This IR increases the similarity of different \(z_i\) instances and targets common errors for SCAN (§3.2).

**Using lossy IRs** We experiment with two methods for predicting and utilizing lossy IRs. The first method is direct prediction, where we use \(\text{Seq2Seq}_1 : x \leadsto z_1\) to directly produce the IR \(z_1\), and then apply \(\text{Seq2Seq}_2 : (x[\text{SEP}] z_1) \leadsto y\) to predict the final program. Here, we hypothesize that mapping to IRs is an easier learning problem for \(\text{Seq2Seq}_1\), and in addition, that the joint encoding of the utterance \(x\) and the IR \(z_1\) provides a rich context for \(\text{Seq2Seq}_2\).

To isolate the two hypotheses, we experiment with a second method, indirect prediction, where \(\text{Seq2Seq}_1\) is trained to predict the original program instead of an IR. From the prediction \(y^* = \text{Seq2Seq}_1(x)\), we apply the lossy transformation to create the IR \(z_1 = F(y^*)\) before applying \(\text{Seq2Seq}_2 : (x[\text{SEP}] z_1) \leadsto y\).

### 4 Experiments

#### 4.1 Datasets

We evaluate performance on (1) CFQ (Keysers et al., 2020); (2) three text-to-SQL datasets curated by Finegan-Dollak et al. (2018), including GEO-
We first conduct a pilot study where we experiment with different IRs in §3 on all compositional splits to evaluate their potentials. Against the no-transformation baseline \((x \rightsquigarrow y)\), we consider using the reversible IR (RIR: \(x \rightsquigarrow z_l \rightsquigarrow y\)) and the lossy IR with either direct prediction (LIR_d: \(x \rightsquigarrow z_l \rightsquigarrow y\)) or indirect prediction (LIR_ind: \(x \rightsquigarrow y^* \rightarrow z_l \rightarrow y\))^1. As LIR and RIR are independent, we also experiment with pipelining them together (LIR_d+RIR: \(x \rightsquigarrow z_l \rightsquigarrow z_r \rightarrow y\) and LIR_ind+RIR: \(x \rightsquigarrow z^*_l \rightarrow z_l \rightarrow z_r \rightarrow y\), where \(z_l, r\) is the result of applying both the reversible and lossy transformations). We use T5-base as the seq2seq model.

The results in Table 1 show that for CFQ, RIR improves baseline performance significantly, from an average of 34.6 to 60.8. Combining RIR with LIR_ind further boosts average performance on the MCD splits to 67.8. While LIR_d performs much better than the baseline on average, it lags behind other transformations on MCD1, e.g., 9.5 point worse than LIR_ind (48.1 vs 57.6). A closer look shows that exact-match accuracy of \(z_l\) predicted by seq2seq on MCD1 is only 47.2, suggesting that anonymizing variables and entities might hide relevant information that could assist seq2seq to predict the correct lossy IR.

For text-to-SQL datasets, even our simple RIR, where some tokens are omitted from the program, yields improvements across all datasets. Combining RIR with LIR_d further achieves significant improvements over the baseline, especially for ATIS (from 32.9 to 47.8).

On SCAN, RIR significantly improves baseline accuracy, achieving perfect accuracy for the turn left, MCD1 and MCD2 splits. On the length split, RIR yields a boost of 40 accuracy points even though generalizing to longer programs is a known challenge for seq2seq models (Newman et al., 2020). This shows that by injecting a small amount of additional information about the hierarchical structure of the output programs, we can outperform previous results for seq2seq models, and match the results of specialized architectures such as LANE (Liu et al., 2020) across most splits. As for LIRs, except for LIR_d we do not observe major improvements over the baseline and RIR. This is reasonable, as program elements in SCAN have overall close alignment to phrases in the utterance.

4.4 Main Results

Following our pilot study, we further experiment with the most promising IRs on CFQ and the text-to-SQL datasets, and compare performance across different model capacities (base, large and 3B).

The CFQ results are in Table 2. In line with Furrer et al. (2020), we find that our T5 baseline already performs better than general seq2seq architectures with no pre-training, including LSTM with attention (Bahdanau et al., 2015) and differ-
### Table 1: Results on the test set for all approaches and all compositional splits with T5-base.

| Model               | MCD1 | MCD2 | MCD3 | ATIS | GEOQUERY | SCHOLAR | Length | Turn Left | MCD1 | MCD2 | MCD3 |
|---------------------|------|------|------|------|----------|---------|--------|-----------|------|------|------|
| Baseline            | 58.5 | 27.0 | 18.4 | 32.9 | 79.7     | 18.1    | 14.5   | 66.1      | 18.1 | 14.5 | 10.6 |
| RIR                 | 86.3 | 49.1 | 46.8 | 36.3 | 81.3     | 19.4    | 54.7   | 100.0     | 100.0 | 75.3 |      |
| LIR<sub>d</sub>     | 48.1 | 40.3 | 35.3 | 44.4 | 83.5     | 20.6    | 14.2   | 83.5      | 13.2 | 17.5 |      |
| LIR<sub>d</sub>+RIR | 72.5 | 61.1 | 51.2 | 47.8 | 83.0     | 20.0    | 56.4   | 100.0     | 100.0 | 75.1 |      |
| LIR<sub>ind</sub>   | 57.6 | 41.4 | 34.7 | 38.3 | 80.8     | 16.5    | 13.5   | 13.8      | 10.6 |      |      |
| LIR<sub>ind</sub>+RIR| 85.8 | 64.0 | 53.6 | 41.5 | 81.9     | 16.5    | 54.4   | 100.0     | 100.0 | 75.0 |      |

Table 2: CFQ test set results for different model sizes and in comparison with previous work: ♣ (Keysers et al., 2020), ♦ (Furrer et al., 2020), ♠ (Guo et al., 2021) and ♦ (Guo et al., 2020b).

| Model                 | MCD1 | MCD2 | MCD3 | Ave. |
|-----------------------|------|------|------|------|
| LSTM+A                | 28.9 | 5.0  | 10.8 | 14.9 |
| Transformer           | 34.9 | 8.2  | 10.6 | 17.9 |
| Univ. Trans.          | 37.4 | 8.1  | 11.3 | 18.9 |
| Evol. Trans.          | 42.4 | 9.3  | 10.8 | 20.8 |
| IBT                   | 64.8 | 57.8 | 64.6 | 62.4 |
| HPD                   | 79.6 | 59.6 | 67.8 | 69.0 |

| Model                  | ATIS | GEOQUERY | SCHOLAR |
|------------------------|------|----------|---------|
| Baseline (T5-base)     | 32.9 | 79.7     | 18.1    |
| Baseline (T5-large)    | 31.4 | 81.9     | 17.5    |
| Baseline (T5-3B)       | 29.7 | 79.7     | 16.2    |
| LIR<sub>d</sub> (T5-base) | 47.8 | 83.0     | 20.0    |
| LIR<sub>d</sub>+RIR (T5-large) | 43.2 | 79.7     | 22.0    |
| LIR<sub>d</sub>+RIR (T5-3B) | 28.5 | 75.8     | 12.4    |

Table 3: Text-to-SQL test set results on the template splits, for different model sizes and in comparison with previous work: ♣ (Finegan-Dollak et al., 2018), ♦ (Andreas, 2020), and ♠ (Zheng and Lapata, 2020).

Our IRs then significantly improve upon the baseline performance, and this improvement compounds with model capacity. With T5-large, simply using RIR already yields 0.3 accuracy points over HPD (Guo et al., 2020b), the current state-of-the-art that utilizes a specialized architecture tailored for CFQ. We further note that an IR proposed by Furrer et al. (2020) for CFQ, that differently than ours, groups by subjects and objects, was only found to improve a T5 baseline by 1.2 points. Jointly applying RIR and LIR<sub>ind</sub> yields additional gains and achieves new state-of-the-art on all three datasets. For both our T5 baseline and LIR<sub>d</sub>+RIR, further increasing model capacity beyond T5-base does not give further improvements, which is consistent with previous work on similar tasks with small train set sizes (Shaw et al., 2020; Furrer et al., 2020).

### 4.5 Performance on i.i.d. Splits

While our proposed IRs substantially improve the performance of T5 on compositional splits, we wish to verify they do not hurt performance on i.i.d. splits. To this end, we test our approaches with T5-base on the random splits of SCAN and CFQ, and on the standard i.i.d. splits of the text-to-SQL datasets. As shown in Figure 3 (see Table 8 for full results), we find that IRs indeed maintain the baseline accuracy on these i.i.d. splits.

## 5 Analysis

### 5.1 Interaction with Pre-Training

To further inspect whether improvements from IRs occur due to T5 pre-training, we fine-tune a line is already on-par with (ATIS) or surpasses (GEOQUERY and SCHOLAR) the state-of-the-art. LIR<sub>d</sub>+RIR yields additional gains and achieves new state-of-the-art on all three datasets. For both our T5 baseline and LIR<sub>d</sub>+RIR, further increasing model capacity beyond T5-base does not give further improvements, which is consistent with previous work on similar tasks with small train set sizes (Shaw et al., 2020; Furrer et al., 2020).
Figure 3: Compared to Baseline (T5-base), the best IR of each split maintains the baseline accuracy for i.i.d. splits while giving large gains for compositional splits.

Table 4: Impact of adding pre-training and intermediate representations (LIR_{cat}+RIR for CFQ; LIR_{ind}+RIR for text-to-SQL) over a baseline model. The results are averaged over different test sets.

| Model                  | CFQ  | Text-to-SQL |
|------------------------|------|--------------|
| T5-small w/o pre-training | 20.8 | 33.7         |
| +Pre-training           | 28.0 | +7.2         |
| +IRs                   | 22.6 | +1.8         |
| +Pre-training+IRs      | 47.9 | +27.1        |

T5-small model without loading the pre-trained weights. Table 4 shows that for a model with no pre-training, IRs only give modest improvements or even hurt the accuracy. This suggests that our proposed IRs specifically assist T5 to unlock information it has acquired during pre-training.

5.2 Ablation on Reversible IR

Results in §4 show that RIR has a large impact on compositional generalization, particularly for CFQ. To understand the impact of each design decision, we ablate aspects of our RIR for SPARQL on CFQ. Table 5 shows that all ablations hurt performance. The largest drop in performance (60.8 to 38.7) comes from removing the merging of conjuncts with shared relations and objects.

To see if RIR increases structural similarity between programs, we calculate the percentage of new structures (defined as the result of anonymizing entities and variables in $z_r$) that appear in the dev set with respect to the train set. We also calculate the average length (number of word-pieces) of programs in the dev set to see if RIR helps reduce program complexity. Table 5 shows that performance correlates with having fewer novel structures and shorter programs. This suggests that our design choices for RIR, discussed in §3.1, contribute to compositional generalization.

5.3 Ablation on Lossy IR

We analyze two variations to our proposed usage of LIR_{cat}. (1) LIR_{cat}, where instead of using two separate models for predicting the IR $z_l$ and the program $y$, we only use one model that predicts $z_l$ concatenated with $y$. This differs from LIR_{ind} and LIR_{cat} in terms of model capacity and in how the model attends to the context when generating program tokens. (2) VARIified Baseline, where we use a single model to predict the program like in the baseline, but the generated program should have an additional var token before each variable and entity to indicate the similar role they share (e.g., ?x0 marriage.spouses M2 becomes var ?x0 marriage.spouses var M2). This is to see if the usage of var in our LIR can be effective without explicitly predicting an IR.

In addition, we run an oracle experiment LIR-ORACLE where we use the gold LIR as input to Seq2Seq during inference, instead of using the prediction from Seq2Seq.

Table 6 indicates that both LIR_{cat} and VARified Baseline achieve lower performance than LIR. However, while VARIified Baseline still improves upon the baseline performance from 34.2 to 38.8, LIR_{cat} performs worse than the baseline. This could be partially explained by the fact that 7.4% of the targets for LIR_{cat} exceed the maximal 512 tokens length after concatenation. Results for our oracle experiment, LIR-ORACLE, show that hav-
5.4 Example predictions

We compare the predictions from the T5 baseline and LIR₄₊RIR (with T5-base) on the text-to-SQL development sets. Figure 4 shows several examples where LIR₄₊RIR helps produce correct programs.

We can think of an SQL query as composed of two parts. The semantic part are clauses that express information from the utterance, such as the SELECT clause and the WHERE filters (e.g., airport = "SFO"). This part tends to follow the compositional structure in the query. In contrast, the structural part are additional clauses that make the query valid, such as the FROM clauses and the join clauses (e.g., writes.paperid = paper.paperid). The structural part usually depends on the semantic part, and generating them correctly requires schema reasoning.

The first example from Figure 4 shows how LIR₄₊RIR helps with compositional reasoning in the semantic part. T5 generates the common pattern of having two cities and forces in the argument values. By contrast, LIR₄₊RIR first predicts a shorter coarse program that only focuses on how the specified values are used as SQL filters. This makes the model less susceptible to blindly following common patterns found during training.

The second example shows how LIR₄₊RIR helps with schema reasoning in the structural part. The baseline T5 generates the program from left to right, so it is more susceptible to creating structural inconsistencies. In contrast, LIR₄₊RIR first generates the coarse structure, which outlines the semantic part, then conditions on them to generate the final program. As such, the structural part is more likely to agree with the semantic part.

5.5 Limitations

Our approach suggests designing IRs for improving the compositional generalization abilities of the semantic parser. While we observe substantial gains in doing so, our approach requires customizing new IRs for each new formalism. While this entails manual work, it should be done only once per formalism (for example we are able to apply the same IRs for three different text-to-SQL datasets). Furthermore, the design choices needed for constructing IRs are similar to those needed when designing a coarse structure in coarse-to-fine decoding (Dong and Lapata, 2018), prompts when describing unsupervised tasks (Brown et al., 2020), or task specific cloze-style patterns to help language models understand a given task (Schick and Schütze, 2020). Finally, our principles in §3.1 may assist in reducing the time needed for designing IRs to a minimum.

6 Related Work

Compositional Generalization In contrast to our work combining intermediate representation with pre-trained models, many other approaches have been pursued to improve compositional generalization in semantic parsing. These include new or modified model architectures (Li et al., 2019; Russin et al., 2019; Gordon et al., 2020; Liu et al., 2020; Nye et al., 2020; Chen et al., 2020; Zheng and Lapata, 2020; Oren et al., 2020; Herzig and Berant, 2020), hybrid models (Shaw et al., 2020), meta-learning (Lake, 2019), and compositional data augmentation (Andreas, 2020). Also, Furrer et al. (2020) compare pre-trained models vs specialized architectures for compositional generalization.

Intermediate Representations Unlike the formalisms we focus on in this work such as SQL,
previous approaches to semantic parsing have often leveraged formal representations that were explicitly designed with correspondence to natural language in mind, such as FunQL (Kate et al., 2005), DCS (Liang et al., 2011), and variants of typed lambda calculus (Carpenter, 1997; Zettlemoyer and Collins, 2005). Unlike our IRs, these formalisms typically require manual annotation. Guo et al. (2020a) compares performance of semantic parsers across several such formalisms as well as SQL. Other work has focused on developing IRs that are domain independent (Kwiatkowski et al., 2013; Herzig and Berant, 2018). We also discuss prior work (Guo et al., 2019; Suhr et al., 2020; Furrer et al., 2020; Guo et al., 2020b) developing reversible IRs for the formalisms we study in §3.2.

The use of lossy IRs proposed in this work is closely related to the coarse-to-fine method of Dong and Lapata (2018). However, their work did not consider pre-trained models, and they propose a specialized architecture. Such approaches commonly refer to the lossy IR as a sketch. The use of sketches as an IR has also been explored for program synthesis (Solar-Lezama, 2008; Zhang and Sun, 2013; Nye et al., 2019).

7 Conclusion

In this paper, we study simple yet effective strategies for constructing intermediate representations to improve compositional generalization abilities of pre-trained seq2seq models. We conduct extensive experiments on varied datasets and formalisms and our approaches consistently outperform state-of-the-art models by a large margin. We also demonstrate that our intermediate representations synergize well with pre-training, showing bigger gains than the sum of either alone when used together.

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Appendix

Datasets Size We include the sizes of all datasets and splits we experimented with in Table 7.

Performance on i.i.d. Splits Full results are in Table 8.

Training Details We fine-tune T5-Large and smaller on 32 Cloud TPU v3 cores, and use 128 cores for T5-3B. Fine-tuning takes approximately 48 hours for T5-3B, and less than 16 hours for T5-Large and smaller.

Model Sizes We experiment with T5-small (60 million parameters), T5-base (220 million parameters), T5-large (770 million parameters) and T5-3B (3 billion parameters).

| Dataset | Split | train | dev | test |
|---------|-------|-------|-----|------|
| CFQ     | iid   | 95K   | 12K | 12K  |
|         | MCD1  | 95K   | 12K | 12K  |
|         | MCD2  | 95K   | 12K | 12K  |
|         | MCD3  | 95K   | 12K | 12K  |
| ATIS    | iid   | 4347  | 447 | 486  |
|         | Template | 4812 | 121 | 347  |
| GeoQuery| iid   | 549   | 49  | 279  |
|         | Template | 539  | 159 | 182  |
| Scholar | iid   | 499   | 100 | 218  |
|         | Template | 408  | 94  | 315  |
| SCAN    | iid   | 16782 | -   | 4182 |
|         | Length | 11990 | -   | 3920 |
|         | Turn Left | 21890 | -   | 1208 |
|         | MCD1  | 8365  | -   | 1045 |
|         | MCD2  | 8365  | -   | 1045 |
|         | MCD3  | 8365  | -   | 1045 |

Table 7: Sizes of all datasets and splits.

5https://cloud.google.com/tpu/
|               | CFQ  | ATIS | GEOQUERY | SCHOLAR | SCAN |
|---------------|------|------|----------|---------|------|
| Baseline      | 99.5 | 58.6 | 80.6     | 72.9    | 100.0|
| RIR           | 99.4 | 58.6 | 80.6     | 72.9    | 100.0|
| LIRd          | 99.3 | 58.4 | 79.6     | 73.9    | 100.0|
| LIRd+RIR      | 99.3 | 59.3 | 79.2     | 74.3    | 100.0|
| LIRind        | 99.4 | 58.8 | 81.0     | 75.2    | 100.0|
| LIRind+RIR    | 99.4 | 59.5 | 80.6     | 72.9    | 100.0|

Table 8: Results on the test set for the for all approaches and all i.i.d. splits with T5-base.