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 are specifically effective when combined with pre-training, suggesting that they help unlock information acquired during the pre-training process.

Our approach is closely related to previous work on coarse-to-fine decoding (Dong and Lapata, 2018), intermediate representations (Guo et al., 2019; Suhr et al., 2020) and seq2seq2seq (Baziotis et al., 2019). Our main novelty is the focus

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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:¹

- We study the effect of intermediate representations on the compositional generalization in pretrained 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. shows an example utterance x and program yfor 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 people.person.nationality 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 <TABLE NAME>alias<N> for the Nth use of the same table in one program. Finally, we consider the instruction following formalism

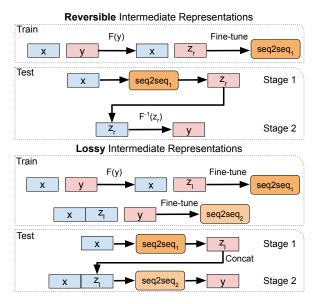


Figure 1: Our framework for parsing utterances (x) into programs (y) through reversible (z_r) and lossy (z_l) intermediate representations using seq2seq models.

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 $z = \mathcal{F}(y)$ where \mathcal{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 \mathcal{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 $\text{Seq2Seq}_1: x \leadsto z$ is trained to predict the IR z. Second, we map the predicted z to a program y, using one of the two methods depend-

¹Our code is available at https://github.com/google-research/language/tree/master/language/compir.

²Note that z is not necessarily shorter than the original program y, as z could carry additional structural cues.

```
(a) SPARQL
    What French actor of M1 married M2 and M3?
    SELECT DISTINCT ?x0 WHERE { ?x0 performance.character M1 . ?x0 person.nationality m_0f819c .
    ?x0 marriage.spouses M2 . ?x0 marriage.spouses M3 . }
    SELECT DISTINCT ?x0 WHERE { ( ?x0 character ( M1 ) ) . ( ?x0 nationality ( m\_0f819c ) ) .
    ( ?x0 spouses ( M2 , M3 ) ) . }
    SELECT DISTINCT {f var} WHERE { {f var} performance.character {f var} . {f var} person.nationality {f var} .
    var marriage.spouses var . var marriage.spouses var . }
(b) SQL
    Show me the airlines from SFO
    SELECT DISTINCT ALalias0.airline_code from AL as ALalias0 , AP as APalias0 ,
    FL as FLaliasO where APaliasO.airport code = "SFO" and FLaliasO.airline code =
    ALalias0.airline code and FLalias0.from airport = APalias0.airport code;
   SELECT DISTINCT ALO.airline_code from AL as ALO , AP as APO , FL as FLO where
    APO.airport code = "SFO" and FLO.airline code = ALO.airline code and
    FLO.from airport = APO.airport code;
   SELECT DISTINCT table.airline code from alias where table.airport code = "SFO";
(c) Instruction following
    jump opposite right and turn opposite left twice
    RTURN RTURN JUMP LTURN LTURN LTURN LTURN
    ( RTURN RTURN JUMP ) ( ( LTURN LTURN ) ( LTURN LTURN ) )
    RTURN ACTION JUMP LTURN ACTION ACTION ACTION
```

Figure 2: Examples for the different formalisms, of an utterance (x), program (y), reversible intermediate representation (z_l) and lossy intermediate representation (z_l) . For each formalism, tokens with the same color share their semantic role. Tokens in z_r and z_l 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.

ing on the reversibility of the transformation \mathcal{F} . If \mathcal{F} is reversible, then the IR z is a reversible IR and contains all information to reconstruct the program y. In this case, we can simply call the inverse transformation $\mathcal{F}^{-1}:z\to y$ to produce the final prediction (Figure 1, top). If \mathcal{F} is irreversible, the IR is said to be lossy. In this case we train an additional seq2seq model Seq2Seq2: $(x[SEP]z)\leadsto y$ that predicts a program y in the original formalism conditioned on both x and z (Figure 1, bottom). This process is similar to coarse-to-fine decoding (Dong and Lapata, 2018) if the lossy IR is designed to carry properties of a coarse sketch.

3.1 Intermediate Representation Design

Our specific adaptation of each transformation \mathcal{F} is guided by common errors we encountered in preliminary experiments with seq2seq on the original utterance-program pairs. Overall, based on our observations, we synthesize the following principles for constructing intermediate representations.

First, reduce the mismatch between the formal and natural language. This can be implemented in two ways: omitting program elements that cannot be easily aligned to the utterance (e.g., the FROM clause in SQL), and rearranging the program struc-

ture (e.g., by grouping conjuncts in SPARQL). Second, *increase structural similarities among programs*. For example, anonymizing elements such as entities and variables in SPARQL can lead to different programs in the train and test sets having an identical IR, which improves generalization. Finally, *induce hierarchical structure into programs to indicate scoping*. For instance, we add brackets for different program components in SCAN.

3.2 Reversible Intermediate Representation

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

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 $\{(x_0, r_1, e_1), (x_0, r_1, e_2), (x_0, r_2, e_1), (x_0, r_2, e_2)\}$, we modify it to $\{(x_0, r_1, (e_1, e_2)), (x_0, r_2, (e_1, e_2))\}$. We further shorten the IR by truncating relation

names of the form $< r_{\tt prefix} > < ns: > < r_{\tt suffix} >$ to $< r_{\tt suffix} >$ 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 <TABLE NAME>alias<N> for the Nth 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 <TABLE NAME><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

3.3 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_l) we propose. For SPARQL, we anonymize entities and variables, replacing them with the placeholder var, which increases the similarity between different z_l instances. For SQL, we adapt z_l 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_l . Particularly, we omit the FROM 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 \mathbb{C}^n (action \mathbb{C} repeating n > 1 times) with $\mathbb{C} \mathbb{A}^{n-1}$, where A represents an anonymized action. This IR increases the similarity of different z_l 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 $\mathtt{Seq2Seq}_1: x \leadsto z_l$ to directly produce the IR z_l , and then apply $\mathtt{Seq2Seq}_2: (x[\mathtt{SEP}]z_l) \leadsto y$ to predict the final program. Here, we hypothesize that mapping to IRs is an easier learning problem for $\mathtt{Seq2Seq}_1$, and in addition, that the joint encoding of the utterance x and the IR z_l provides a rich context for $\mathtt{Seq2Seq}_2$.

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

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-

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

QUERY (Zelle and Mooney, 1996), ATIS (Dahl et al., 1994), and SCHOLAR (Iyer et al., 2017); and (3) SCAN (Lake and Baroni, 2018). The formalism for each dataset is described in §2, and the dataset sizes are given in Table 7 in the Appendix.

We consider multiple dataset splits that aim to assess compositional generalization. For CFQ and SCAN, we use the Maximum Compound Divergence (MCD) splits (Keysers et al., 2020), which are generated by making the distributions of compositional structures in the train and test sets as divergent as possible. For the text-to-SQL datasets, we use template splits (Finegan-Dollak et al., 2018), which ensure that the train and test set contain distinct SQL query "templates" (constructed by replacing values in the SQL queries with anonymized placeholders). Finally, for SCAN, we use two additional splits from Lake and Baroni (2018): the length split, which requires generalization to longer sequences, and the turn left split, where the "turn left" command is recombined with other elements of the training set in novel ways at test time.

4.2 Experimental Setup

Unless stated otherwise, each seq2seq in our model is a pre-trained T5 model (Raffel et al., 2020) fine-tuned on appropriate input-output pairs (e.g., $(x, z_r = \mathcal{F}(y))$) pairs for Seq2Seq1: $x \rightsquigarrow z_r$). We only tune the leaning rate for each dataset on the dev set, considering the values $[1e^{-3}, 5e^{-4}, 1e^{-4}]$. For SCAN, as no dev set is available, we tune the learning rate on the *around right* split (Loula et al., 2018), which we use as a held-out set. We use batch size of 128 and fine-tune all models for 30K steps. We evaluate our models on exact-match accuracy. For CFQ, we post-process predicted programs by sorting conjuncts alphabetically and removing duplicate conjuncts, similar to Guo et al. (2020b).

4.3 Pilot Study

We first conduct a pilot study where we experiment with the different IRs in §3 on all compositional splits to evaluate their potentials. Against the no-transformation baseline $(x \leadsto y)$, we consider using the reversible IR (RIR: $x \leadsto z_r \to y$) and the lossy IR with either direct prediction (LIR_d: $x \leadsto z_l \leadsto y$) or indirect prediction (LIR_{ind}: $x \leadsto y^* \to z_l \leadsto y$)⁴. As LIR and RIR are independent, we also experiment with pipelining them

together (LIR_d+RIR: $x \rightsquigarrow z_{l,r} \rightsquigarrow z_r \rightarrow y$ and LIR_{ind}+RIR: $x \rightsquigarrow z_r^* \rightarrow z_{l,r} \rightsquigarrow z_r \rightarrow y$, 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 $seq2seq_1$ on MCD1 is only 47.2, suggesting that anonymizing variables and entities might hide relevant information that could assist $seq2seq_1$ 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 LIRd 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-

⁴Note that the predicted y^* from the first seq2seq can be different from the final prediction y, as described in §3.3.

Model	CFQ			Text-to-SQL			SCAN				
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	15.2	14.3	10.6
RIR	86.3	49.1	46.8	36.3	81.3	19.4	54.7	100.0	100.0	100.0	75.3
LIR_d	48.1	40.3	35.3	44.4	83.5	20.6	14.2	83.5	15.7	13.2	17.5
LIR _d +RIR	72.5	61.1	51.2	47.8	83.0	20.0	56.4	100.0	100.0	100.0	75.1
LIRind	57.6	41.4	34.7	38.3	80.8	16.5	13.5	65.7	15.0	13.8	10.6
LIR _{ind} +RIR	85.8	64.0	53.6	41.5	81.9	16.5	54.4	100.0	100.0	100.0	75.0

Table 1: Results on the test set for all approaches and all compositional splits with T5-base.

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. \diamondsuit	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
Baseline (T5-base)	58.5	27.0	18.4	34.6
Baseline (T5-large)	65.1	32.3	25.4	40.9
Baseline (T5-3B)	65.0	41.0	42.6	49.5
RIR (T5-base)	86.3	49.1	46.8	60.8
RIR (T5-large)	88.7	62.2	57.1	69.3
RIR (T5-3B)	88.7	72.6	63.5	75.0
LIR _{ind} +RIR (T5-base)	85.8	64.0	53.6	67.8
LIR _{ind} +RIR (T5-large)	88.6	79.2	72.7	80.2
LIR _{ind} +RIR (T5-3B)	88.4	85.3	77.9	83.8

Table 2: CFQ test set results for different model sizes and in comparison with previous work: \clubsuit (Keysers et al., 2020), \diamondsuit (Furrer et al., 2020), \spadesuit (Guo et al., 2021) and \heartsuit (Guo et al., 2020b).

ent Transformer variants (Vaswani et al., 2017; Dehghani et al., 2018; So et al., 2019). 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 LIRind gives further improvements that also compound with model capacity. With T5-large and T5-3B, the models surpass state-of-the art, yielding accuracy of 80.2 and 83.8, respectively.

Text-to-SQL results are in Table 3. We compare with general seq2seq architectures (Seq2Seq and Transformer), GECA (Andreas, 2020) — a data augmentation method evaluated by Zheng and Lapata (2020), and with ST (semantic tagging) which targets compositional generalization. We further find that for T5-base, the no-transformation base-

Model	ATIS	GEOQUERY	SCHOLAR
Seq2Seq ♣	32.0	20.0	5.0
GECA ♦	24.0	52.1	-
Seq2Seq ♠	28.0	48.5	-
Transformer •	23.0	53.9	-
Seq2Seq+ST ♠	29.1	63.6	-
Transformer+ST ♠	28.6	61.9	-
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 _d +RIR (T5-base)	47.8	83.0	20.0
LIR _d +RIR (T5-large)	43.2	79.7	22.0
LIR _d +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).

line is already on-par with (ATIS) or surpasses (GEOQUERY and SCHOLAR) the state-of-the-art. LIR_d+RIR yields additional gains and achieves new state-of-the-art on all three datasets. For both our T5 baseline and LIR_d+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

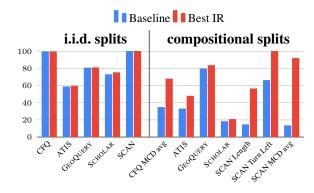


Figure 3: Compared to Baseline (T5-base), the best IR of each split maintains the baseline accuracy for i.i.d. splits while giving large gains for compositional splits.

Model	CFQ		Text-to-SQL	
T5-small w/o pre-training	20.8		33.7	
+Pre-training	28.0	+7.2	41.8	+8.1
+IRs	22.6	+1.8	21.9	-11.8
+Pre-training+IRs	47.9	+27.1	46.5	+12.8

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

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

Model	MCD average		% New structures	Ave. length (word pieces)	
Baseline	34.2		91.7	161	
RIR -shorter relations -brackets -merge conjuncts	60.8 58.2 57.2 38.7	-2.6 -3.6 -22.1	80.9 80.9 80.9 91.7	104 128 96 147	

Table 5: CFQ dev accuracy for RIR ablations.

Model choice	MCD average
Baseline	34.2
LIR _d	41.9
LIR _{cat}	30.8
VARified Baseline	38.8
LIR-ORACLE	80.7

Table 6: CFQ dev accuracy for LIR_d alternatives.

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_d. (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_d and LIR_{ind} in terms of model capacity and in how the model attends to the context when generating program tokens. (2) VARified 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 $Seq2Seq_2$ during inference, instead of using the prediction from $Seq2Seq_1$.

Table 6 indicates that both LIR_{cat} and VARified Baseline achieve lower performance than LIR. However, while VARified 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-

```
x how about arrivals for airline_code0 in city_name0
    select distinct FLalias0.flight id from AS as ASalias0, CT as CTalias0, FL as FLalias0
     where (CTalias0.city_code = ASalias0.city_code
and CTalias0.city_name = "city_name0"
and FLalias0.airline_code = "airline_code0"
     and FLalias0.to airport = ASalias0.airport code)
and FLalias0.from_airport = ASalias0.airport_code;
    select distinct table.flight_id from alias
where table.city_name = "city_name0"
and table.airline_code = "airline_code0";
     select distinct FLO.flight_id
    where CTO.city_code = ASO.city_code
and CTO.city_name = "city_name0"
and FLO.airline_code = "airline_code0"
and FLO.to_airport = ASO.airport_code;
x What papers does authorname0 have in venuename0 ?
     select distinct paperalias0.paperid
     from author as authoralias0, venue as venuealias0, writes as writesalias0 where authoralias0.authorname = "authorname0
     and venuealias0.venueid = paperalias0.venueid and venuealias0.venuename = "venuename0" and writesalias0.authorid = authoralias0.authorid
     and writesalias0.paperid = paperalias0.paperid ;
    select distinct table.paperid from alias
where table.authorname = "authorname0"
and table.venuename = "venuename0";
     select distinct paper0.paperid
     from author as author0, paper as paper0, venue as venue0, writes as writes0
     where ... (the rest is identical to T5)...
```

Figure 4: Example cases where LIR_d+RIR produces correct programs whereas the baseline T5 does not. SQL table names were shortened here for brevity.

ing the gold LIR during inference boosts performance from $41.9 \rightarrow 80.7$. This shows that the model can effectively utilize the LIR as context when generating the actual program.

5.4 Example predictions

We compare the predictions from the T5 baseline and LIR_d+RIR (with T5-base) on the text-to-SQL development sets. Figure 4 shows several examples where LIR_d+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 LIR_d+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, LIR_d+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 LIR_d+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, LIR_d+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 om 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.⁵ 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
	iid	95K	12K	12K
CEO	MCD1	95K	12K	12K
CFQ	MCD2	95K	12K	12K
	MCD3	95K	12K	12K
ATIS	iid	4347	447	486
AHS	Template	4812	121	347
CaaOwarry	iid	549	49	279
GeoQuery	Template	539	159	182
Cabalan	iid	499	100	218
Scholar	Template	408	94	315
	iid	16782	-	4182
	Length	11990	-	3920
CCAN	Turn Left	21890	-	1208
SCAN	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
LIR _d	99.3	58.4	79.6	73.9	100.0
LIR _d +RIR	99.3	59.3	79.2	74.3	100.0
LIR _{ind}	99.4	58.8	81.0	75.2	100.0
LIR _{ind} +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.