MC^2: A Minimum-Coverage and Dataset-Agnostic Framework for Compositional Generalization of LLMs on Semantic Parsing

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Abstract

Compositional generalization is one of the important abilities that large language models (LLMs) need to have for semantic parsing. Previous research typically relies on dataset-specific designs or a large number of samples in demonstrations to improve the compositional generalization of LLMs on semantic parsing. We revisit this issue and find that when the number of samples in a demonstration is limited to a lower bound for achieving compositional generalization (minimum-coverage), current advanced LLMs cannot arbitrarily achieve good compositional generalization generically on different semantic parsing datasets without dataset-specific designs. To solve this problem, we propose Multi-level Component Composition (MC^2), a minimum-coverage and dataset-agnostic framework based on input primitives, which aims to generically help LLMs achieve compositional generalization by selecting and organizing samples from multiple compositional levels that satisfy the primitive coverage. Experiments and analysis show that MC^2 can effectively improve the compositional generalization of LLMs on different semantic parsing datasets in the minimum-coverage setting. Data and code are available at https://github.com/xzy-xzy/MC2.

1 Introduction

Compositional generalization (Lake et al., 2016) refers to the ability to correctly handle unseen or rare combinations formed by known primitives. It is one of the inherent linguistic abilities of humans (Hupkes et al., 2020). Due to the potentially infinite number of combinations in languages (Chomsky, 1965), language models often encounter new combinations formed by known primitives in real-world tasks and require the ability of compositional generalization to cope with them. Therefore, compositional generalization of language models has been studied on many natural language processing tasks (Hupkes et al., 2022).

Semantic parsing (Kamath and Das, 2019) is one of the fields that have received the most attention in the research on compositional generalization. Tasks in this field aim to transform natural language into a more formal language to express its meaning more precisely, such as syntactic structure generation (Kim and Linzen, 2020), text-to-SQL (Keysers et al., 2020), etc. Since target languages typically have a strong compositionality, language models intuitively require the ability of compositional generalization for semantic parsing tasks.

The emergence of large language models (LLMs) drives the emergence of the in-context learning (Dong et al., 2024) paradigm for compositional generalization research on semantic parsing. In this paradigm, LLMs are asked to achieve the correct processing of test samples containing unseen combinations after seeing the demonstrations formed by samples drawn from the training corpus. Many research works have considered how compositional generalization of LLMs on semantic parsing tasks can be improved under the in-context-learning paradigm (Levy et al., 2023; An et al., 2023a; Zhou et al., 2023; Drozdov et al., 2023). Limited by the performance of LLMs at the time, the methods used for improvement often rely on task-specific designs or a large number of samples in demonstrations, and thus have drawbacks in terms of generalizability or consumption. As the performance of LLMs improves, the question of *whether LLMs can generically achieve compositional generalization on different semantic parsing datasets with a rather limited number of samples in demonstrations and without dataset-specific designs* becomes a question worth revisiting.

To revisit this question, we introduce the minimum-coverage setting. This setting requires LLMs to achieve compositional generalization on semantic parsing tasks when the number of samples in a demonstration is limited to a lower bound for achieving compositional generalization. We

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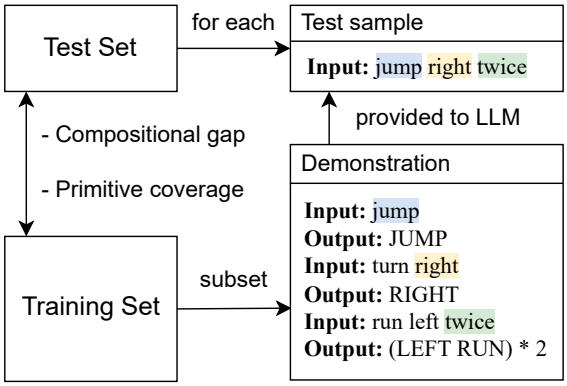

Figure 1: An illustration of compositional generalization of LLMs on the semantic parsing task in the in-context learning paradigm.

find that existing advanced LLMs cannot arbitrarily achieve good compositional generalization on various semantic parsing datasets generically in the minimum-coverage scenario without dataset-specific designs. This suggests that despite the continued development of LLMs, achieving *dataset-agnostic* compositional generalization on semantic parsing in the *minimum-coverage* setting remains a challenge currently.

To solve this problem, we propose *Multi-level Component Composition* (MC^2), which is a minimum-coverage and dataset-agnostic framework based on input primitives. By three steps of chunking-matching-ordering, the framework selects samples from multiple compositional levels for LLMs and organizes the samples in a way that potentially exhibits compositional paths, while satisfying the basic requirement of the minimum-coverage scenario. We show the effectiveness of the MC^2 framework through experiments on a variety of compositional generalization datasets of different types of semantic parsing tasks in the minimum-coverage scenario. We also experimentally analyze (1) the importance of introducing multiple compositional levels, which is the core idea of the MC^2 framework, (2) the effect of steps in the framework, and (3) the impact of choices on method components and implementation rules in the framework. The experiments and analysis further confirm the design motivation of the MC^2 framework and demonstrate the room for improvement of the framework.

2 Preliminaries

In this section, we first introduce the concept of compositional generalization. Then, we introduce the minimum-coverage and dataset-agnostic settings, describe the motivation for introducing the settings, and estimate the difficulty of the settings.

2.1 Compositional Generalization of LLMs

Before the advent of LLMs, compositional generalization is typically evaluated using the train-test paradigm (Finegan-Dollak et al., 2018). Researchers construct the training set V and the test set W with significantly different distributions of combinations. The model is asked to be trained (or fine-tuned) on V and its performance on W is used to evaluate the ability of compositional generalization. A basic requirement to be met by sets V and W is that every input primitive appearing in W also appears in V, since the model needs to know at least the representation of the input primitive in the target to complete the composition (Lake and Baroni, 2018). This requirement is known as primitive coverage of W by V.

The emergence of LLMs introduces the in-context learning paradigm of compositional generalization (Levy et al., 2023; An et al., 2023a). In this paradigm, the demonstration phase of in-context learning is regarded as the training phase. For each test sample s in W, a subset V' of samples in V that satisfy the primitive coverage of $\{s\}$ by V' is provided to the LLM as a demonstration, and then the LLM is asked to process the test sample. The testing of each test sample in W is independent. Figure 1 shows an illustration of compositional generalization of LLMs on the semantic parsing task in the in-context learning paradigm.

2.2 Minimum-Coverage

Based on the in-context learning paradigm, we introduce the minimum-coverage setting, which is a dynamic limit on the size of the subset V' (i.e., the number of samples in the demonstration). In the minimum-coverage setting, for a test sample containing n input primitives, at most n samples can be included in the demonstration. Even an ideal model (i.e., one that can achieve compositional generalization as long as the demonstration satisfies primitive coverage) must, in the extreme case, be provided with n samples in the demonstration to satisfy primitive coverage to achieve compositional generalization. Thus, the minimum-coverage setting is a lower bound for achieving compositional generalization. The main motivation for introducing minimum-coverage setting is that this setting minimizes the input consumption of

Model	$SCAN_1$	COGS	CFQ_1
DeepSeek-2.5	63.8	89.7	63.8
Qwen-plus	62.1	82.4	66.2
GPT-4o	70.2	81.5	73.4
SOTA	99.7	99.2	94.3

Table 1: Results of the pre-experiment. SOTA refers to state-of-the-art results using methods that have dataset-specific designs and are not minimum-coverage.

LLMs for compositional generalization.

2.3 Dataset-Agnostic

The dataset-agnostic setting requires the method to be independent of the dataset. This requirement implies that (1) the method needs to be based on input primitives only, since the output formal language is usually dataset-relevant, and (2) the method does not need to have any prior knowledge of the dataset beyond the identification of the input primitive (see Appendix A for details), such as knowledge of the dataset-specific input syntax. The motivation for introducing the dataset-agnostic setting is to ensure that the method can be generalized across different datasets without additional intervention.

2.4 Difficulty Estimation

To estimate the difficulty of the minimum-coverage and dataset-agnostic settings, we conduct a pre-experiment to test the performance of advanced LLMs DeepSeek-2.5 (DeepSeek-AI et al., 2024), Qwen-plus-0919 (Qwen et al., 2024) and GPT-4o-20240806 (OpenAI et al., 2024) The datasets and metrics of the pre-experiment are consistent with the main experiment (which we will describe in detail in Section 4). For a test sample containing n input primitives, we randomly select for each primitive a sample that covers it, for a total of n mutually exclusive samples for the demonstration.

Table 1 shows the results of the pre-experiment. Near-perfect performance can be achieved using methods that have dataset-specific designs and are not minimum-coverage. In contrast, the performance of LLMs with randomly selected demonstration samples in the minimum-coverage setting is far from perfect. The results provide an estimate of the challenge of the minimum-coverage and dataset-agnostic settings, as the LLMs in the minimum-coverage setting are not yet able to achieve good compositional generalization on different semantic parsing datasets without dataset-specific designs under arbitrary choices for demonstration. This motivates us to conduct research on improvements.

3 MC^2 Framework

In this section, we introduce the Multi-level Component Composition (MC^2) framework for helping LLMs achieve compositional generalization on semantic parsing. The core idea of the design is to (1) compartmentalize the inputs of the test samples into compositional levels, (2) select the appropriate demonstration samples for the components of different compositional levels, and (3) demonstrate the path of thinking from low to high in the compositional levels. The design of the framework satisfies that (1) it is minimum-coverage and task-agnostic, and (2) it always satisfies the primitive coverage requirements. The framework consists of three steps: chunking, matching, and ordering. Figure 2 shows an illustration of the MC^2 framework.

3.1 Chunking

The chunking step aims at obtaining components from multiple compositional levels of the input and the relationships between the components as a basis for subsequent sample selection. In the chunking step, the input is decomposed compositionally to form a tree structure. Each node in the tree represents a component that is decomposed from the component represented by its parent node. For an input containing n input primitives, the final tree will contain n leaf nodes representing the primitives, and up to $n-1$ non-leaf nodes. The method of chunking is flexible, and any task-independent method capable of tree-like component decomposition can be chosen. We consider the following two methods of chunking:

PPL-based chunking. We use a small language model to compute the perplexity. For the component represented by each node, we enumerate the schemes that slice the component into two parts *L* / *R* and choose the scheme that minimizes the perplexity of the sentence "*Using / to split the sentence {component}. {L} / {R}*". According to the scheme, we split the components and recursively process the two child nodes formed. The method always results in binary trees. See Algorithm 1 for pseudo-code.

Off-the-shelf parser. The task of constituent parsing (Kitaev and Klein, 2018) aims at obtaining a tree-like constituent decomposition of the input sentence with constituent labels, which fits with the goal of the chunking step. Therefore, we can

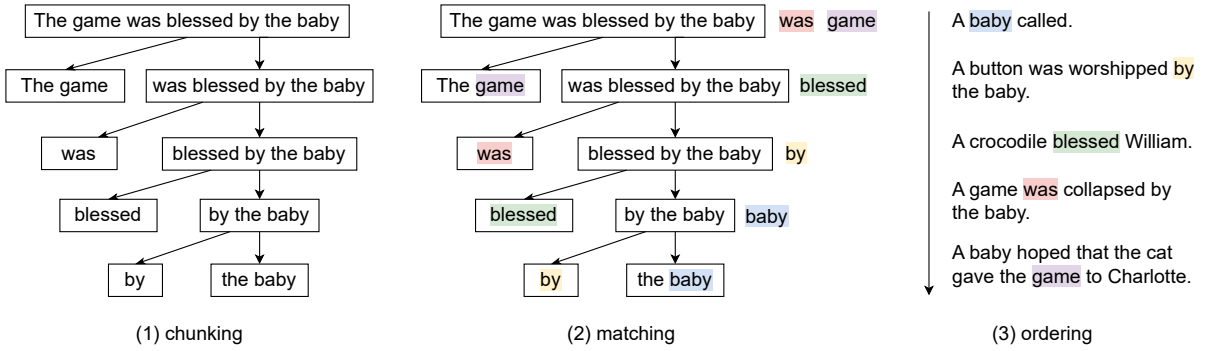

Figure 2: An illustration of the MC^2 framework. (1) Chunking: the input is component-wise chunked to form a tree structure. (2) Matching: each leaf node primitive (in color) corresponds to a non-leaf node, and the non-leaf node component matches the most similar sample in the training set that covers the corresponding primitive. (3) Ordering: samples matched by each non-leaf node are arranged in a specific order to form a demonstration.

Algorithm 1 PPL-based Chunking

function: chunking
Input: input primitives $p_1, p_2, ..., p_n$
Output: root node x of the tree structure
  $x \leftarrow$ new node $(p_1, p_2, ..., p_n)$
  if $n = 1$ **then**
    return x
  end if
  $m, v \leftarrow 0, \infty$
  for i from 1 to $n-1$ **do**
    sent $\leftarrow$ "Using / to split the sentence $\{p_1, p_2, ..., p_n\}$. $\{p_1, p_2, ..., p_i\}$ / $\{p_{i+1}, p_{i+2}, ..., p_n\}$"
    if PPL (sent) $< v$ **then**
      $m, v \leftarrow i$, PPL (sent)
    end if
  end for
  $l \leftarrow$ chunking $(p_1, p_2, ..., p_m)$
  $r \leftarrow$ chunking $(p_m, p_{m+1}, ..., p_n)$
  set l, r to be the left and right son nodes of x
  return x

Algorithm 2 Matching and Ordering

Input: tree structure T, training set V
Output: ordered list of samples L as the demonstration
  for all non-leaf node x in T **do**
    $D_x \leftarrow$ (the number of child nodes of x) $-$ ($x \neq$ root)
    $L_x \leftarrow$ empty list
  end for
  for all leaf node y in T in inverted BFS order **do**
    $p \leftarrow$ the primitive represented by y
    $x' \leftarrow$ parent node of y
    while $|L_{x'}| = D_{x'}$ **do**
      $x' \leftarrow$ parent node of x'
    end while
    $R \leftarrow \{s \mid s \in V \wedge (\forall x,\ s \notin L_x) \wedge s \text{ covers } p\}$
    $c \leftarrow$ the component represented by x'
    $L_{x'} \leftarrow L_{x'}$ + [the sample in R that is most similar to c]
  end for
  $L \leftarrow$ empty list
  for all non-leaf node x in T in inverted BFS order **do**
    $L \leftarrow L + L_x$
  end for
  return L

use an off-the-shelf constituent parser (based on a small language model) for the chunking step. The method may result in multinomial trees.

3.2 Matching

Based on the tree structure obtained from the chunking step, the matching step aims to select a total of n mutually exclusive samples from the training set that are similar to the components of the different compositional levels and satisfy the primitive coverage requirement.

For a non-leaf node x, we define the degree D_x as (the number of child nodes of x) $- 1$. It always holds that $\sum D_x = n - 1$. After increasing D_{root} by 1, we can select D_x samples for each non-leaf node x to get a total of n samples.

We visit each leaf node y in reverse order of breadth-first search (BFS). For y, we find the deepest ancestor node x' of y for which the number of samples selected is less than $D_{x'}$. Then, from the samples in the training set that have not been selected and cover the primitive represented by y, we will select a sample that is most similar to the component represented by x'. Finally, we will select n mutually exclusive samples that satisfy the primitive coverage requirement.

The method of finding the most similar sample is flexible and can be chosen from any method that estimates the text similarity. We consider two methods: the BM25 (Lù, 2024), and the cosine similarity of sentence vectors given by the small language model. See Algorithm 2 for pseudo-code.

3.3 Ordering

The ordering step aims to order the selected samples in a way that potentially presents compositional thinking paths. Based on the tree structure, we simply visit each non-leaf node in inverted BFS order and list the samples selected for each node in turn to form the demonstration. The BFS inverted order is the order of the compositional levels of the tree nodes from low to high, and to some extent characterizes the compositional thinking paths that are progressively from simple to complex components. See Algorithm 2 for pseudo-code.

4 Main Experiment

In this section, we conduct the main experiment to verify the effectiveness of the MC^2 framework on different semantic parsing tasks in the minimum coverage scenario and to verify the effect of the core idea of the framework and steps in it.

4.1 Datasets and Metrics

We conduct experiments on three representative datasets for compositional generalization research on semantic parsing: SCAN (Lake and Baroni, 2018), COGS (Kim and Linzen, 2020), and CFQ (Keysers et al., 2020). The three datasets correspond to three different semantic parsing tasks. Table 2 shows samples of the datasets.

SCAN. The SCAN dataset corresponds to the task of simplified natural language to action sequence translation. We use the maximum compound divergence (MCD) splits provided by Keysers et al. (2020), containing three training-test splits MCD1~MCD3. The MCD splits achieve high compositional divergence under similar atom distributions, which can effectively evaluate the ability of compositional generalization. The format follows Zhou et al. (2023).

COGS. The COGS dataset corresponds to the task of syntactic structure generation for natural language. We use the original training-test split containing five categories of compositional generalization. The format follows Ontañón et al. (2022).

CFQ. The CFQ dataset corresponds to the task of text-to-SPARQL. This dataset contains realistic natural language questions and corresponding SPARQL queries. We use the original MCD splits containing the three training-test splits MCD1~MCD3.

For each split in each dataset, we sample 1,000 samples from the test set for testing. The metric is the accuracy under exact matching. Since sometimes the correct answer is not unique, we convert the model output and the standard answer to ensure correct matching. The details of the conversion are shown in Appendix B.

Dataset: SCAN (action sequence generation) **Input:** turn opposite left thrice and run around right twice **Output:** (LEFT LEFT) * 3 (RIGHT RUN RIGHT RUN RIGHT RUN RIGHT RUN) * 2
Dataset: COGS (syntactic structure generation) **Input:** Olivia believed that a donut was drawn by a girl. **Output:** believe (olivia, none, none) ccomp draw (girl, donut, none)
Dataset: CFQ (text-to-SPARQL) **Input:** What female person did M2 's employee and founder influence? **Output:** SELECT DISTINCT ?x0 WHERE { ?x0 a person . ?x0 influenced_by ?x1 . ?x0 has_gender female . ?x1 founded M2 . ?x1 employed_by M2 }

Table 2: Samples of the three semantic parsing datasets used in the experiments.

4.2 Settings

The small language models we use in our experiments include GPT-2-large (0.8B) (Radford et al., 2019) for PPL-based chunking, T5-large (0.8B) (Raffel et al., 2020) as a base model for the off-the-shelf parser BENEPAR (Kitaev and Klein, 2018), and all-mpnet-base-v2 (0.1B) (Song et al., 2020) for generating sentence vectors in the matching step. To verify the overall effect of the MC^2 framework and the effect of steps in it, our main experiment contains the following four settings:

Random. For each input primitive in turn, we randomly select a sample that is unselected and covers that primitive, and arrange the samples in the order of selection to form a demonstration.

Global Matching. Based on the previous setting, the random selection is replaced by the selection of the sample that is most similar to the whole input, using the same similarity estimation method as in the Matching step.

Chunking + Matching (C + M). The chunking and matching steps in the framework are used. The samples are arranged in the order that the covered primitives are in the input, consistent with the previous two settings.

Model	Setting	$SCAN_1$	$SCAN_2$	$SCAN_3$	COGS	CFQ_1	CFQ_2	CFQ_3
DeepSeek	Random	63.8	65.2	55.9	89.7	63.8	68.0	68.7
	Global Matching	68.1	79.2	50.1	92.9	77.8	69.9	72.1
	C + M	74.1	81.1	51.1	**95.4**	78.7	75.0	77.3
	Complete MC^2	**76.6**	**88.4**	**57.5**	95.2	**79.8**	**76.4**	**77.6**
Qwen-plus	Random	62.1	66.7	56.1	82.4	66.2	68.4	69.3
	Global Matching	69.4	89.7	59.1	87.8	79.2	72.5	70.7
	C + M	73.6	92.0	58.5	88.5	79.8	77.4	74.6
	Complete MC^2	**78.2**	**94.9**	**59.4**	**89.1**	**79.9**	**77.5**	**74.7**
GPT-4o	Random	70.2	71.7	64.5	81.5	73.4	71.9	72.7
	Global Matching	72.4	84.5	58.9	86.8	80.6	78.3	77.9
	C + M	81.9	87.8	64.8	88.7	81.3	81.1	78.9
	Complete MC^2	**82.4**	**90.8**	**67.1**	**89.3**	**83.3**	**83.7**	**80.8**

Table 3: Results of the main experiment in the minimum coverage scenario. For SCAN and CFQ, numerical subscripts indicate the corresponding MCD split.

Complete MC^2. The complete MC^2 framework is used, consisting of three steps.

In the main experiment, we fix the use of the off-the-shelf parser method in the chunking step and the vector method in the matching step. A comparative analysis of the different methods will be shown in Section 5.

4.3 Results

Table 3 shows the results of the main experiment in the minimum coverage scenario. We analyze the effect of the core idea of the MC^2 framework and steps in it by comparing the results in different settings adjacent to each other.

Random vs. **Global Matching**. Matching using similarity metrics is intuitively a better selection strategy than random selection. In most comparisons, using Global Matching indeed leads to better performance than Random. However, we find that in some cases Global Matching brings a significant performance degradation (DeepSeek and GPT-4o on $SCAN_3$). This suggests that global-level selection based on certain similarity metrics may instead lead to weaker compositional generalization for some tasks or models.

Global Matching vs. **C + M**. Compared to Global Matching, C + M introduces the idea of multiple compositional levels. Unlike simply matching on the global input, C + M decomposes the components of different compositional levels with the help of the chunking step, and then matches the most similar samples for each component. As can be seen from the results, this hierarchical matching improves performance in most cases, and significantly in some comparisons. In the only exception where performance drops (Qwen-plus on $SCAN_3$), the drop is not significant. Overall, the chunking and matching steps that introduce the idea of multiple compositional levels effectively improve generic compositional generalization.

C + M vs. **Complete MC^2**. The complete MC^2 adds a a final ordering step compared to C + M, which changes the sample ordering from input order by matched primitive to order by matched tree nodes from lower to higher level. The results are similar to the previous set of comparisons. In most cases, the added ordering step improves performance, and the improvement is significant in some comparisons. In the only exception where performance drops (DeepSeek on COGS), the performance drop is also not significant. The results indicate that the addition of the ordering step overall improves generic compositional generalization.

From the results and analysis, we find that each step is important for performance improvement. The core idea of multiple compositional levels, which serves as the basis for component matching and sample ordering, plays an important role in generic improvement.

5 Analytical Experiments

In this section, we conduct analytical experiments on DeepSeek-2.5 and Qwen-plus on choices in the MC^2 framework, including the choice of method components and the choice of implementation rules. The purpose of the experiments is to analyze the impact of various choices on performance and to provide insight into the room for further improvement of the framework.

Model	Method	SCAN_1	SCAN_2	SCAN_3	COGS	CFQ_1	CFQ_2	CFQ_3
DeepSeek	PPL + BM25	67.9	84.2	56.4	92.2	79.3	75.7	74.4
	PPL + Vector	**78.4**	**93.4**	56.5	94.6	76.2	74.6	73.8
	Parser + BM25	69.3	83.1	**58.4**	91.7	78.2	75.7	**77.8**
	Parser + Vector	76.6	88.4	57.5	**95.2**	**79.8**	**76.4**	77.6
Qwen-plus	PPL + BM25	68.4	84.6	57.2	86.6	78.5	75.8	75.5
	PPL + Vector	72.3	93.3	56.4	**89.5**	76.9	75.2	73.7
	Parser + BM25	68.5	83.9	57.0	88.1	**80.0**	76.1	**76.2**
	Parser + Vector	**78.2**	**94.9**	**59.4**	89.1	79.9	**77.5**	74.7

Table 4: Results of experiments on choice combinations of method components in the minimum coverage scenario.

5.1 Method Components

In the MC^2 framework, the method of tree structure acquisition in the chunking step, and the method of finding the most similar samples in the matching step, are components that can be flexibly changed. As described in Section 3, we consider two methods, PPL and Parser, in the chunking step, and two methods, BM25 and Vector, in the matching step. We conduct experiments on the combination of method choices for the two steps.

Table 4 shows the results of experiments. Of the four combinations, Parser + Vector demonstrates the best performance in most cases, while Parser + BM25 and PPL + Vector also perform best in some cases. For different LLMs, the combinations that show the best performance under the same split of the same task are different; for the same LLMs, the combinations that show the best performance under different tasks are not exactly the same. Overall, there is no combination that presents an absolute performance advantage.

For the performance of the framework, the impact of the chosen combination of method components is significant in some cases, reflected in the large performance difference between the best and worst performing combinations (e.g., SCAN_1 and SCAN_2). In addition, the performance of the framework may be limited by the performance of the method components in a particular case, e.g., the performance improvement of DeepSeek using Parser + Vector on SCAN_3 is relatively limited due to the performance of the Vector method. Therefore, finding task-independent method components and combinations that have better generic performance is one of the potential room for further performance improvement of the framework.

5.2 Implementation Rules

The MC^2 framework contains several implementation rules with multiple choices without altering the underlying design purpose. In each of the following implementation rules, we experiment with a choice different from the one in Section 3.

Visiting rule. In the matching and ordering steps, we use the BFS inverted order as the visiting order with the purpose of demonstrating the potential compositional paths. In the choice of visiting rule, any order that potentially demonstrates compositional paths can be taken into account. We experiment with the inverse order of depth-first search (DFS) as the visiting order, which characterizes another typical bottom-up compositional pattern.

Degree rule. In the matching step, the degree rule specifies the number of samples D_x matched by each non-leaf node x. The rule is to satisfy the requirement that the total number of samples in the minimum coverage scenario cannot exceed n. Any positive integer assignment to D_x that satisfies the sum of n can be used as a degree rule. We experiment with another rule that concentrates D_x on the root. Under this rule, $D_x = 1$ for non-root and non-leaf nodes x, and $D_{root} =$ ($n -$ number of non-root and non-leaf nodes).

Primitive coverage rule. In the matching step, each sample matched for a non-leaf node must cover the primitive corresponding to the corresponding leaf node. This rule is to ensure that each input primitive is covered after the sample matching is completed. We experiment with the rule of adding a branch to the original rule: when the primitive represented by the corresponding leaf node has already been covered by a sample that has been selected, the sample selected this time does not have to cover the primitive. This new rule still satisfies the primitive coverage requirement,

Model	Rule	$SCAN_1$	$SCAN_2$	$SCAN_3$	COGS	CFQ_1	CFQ_2	CFQ_3
DeepSeek	Original	76.6	88.4	57.5	95.2	79.8	76.4	77.6
	* Visiting	77.4	88.7	56.2	95.1	79.4	75.4	78.0
	* Degree	76.9	89.0	57.2	95.6	79.5	76.3	77.6
	* Primitive	76.9	87.3	57.7	95.4	80.2	75.9	76.4
Qwen-plus	Original	78.2	94.9	59.4	89.1	79.9	77.5	74.7
	* Visiting	79.2	94.0	60.1	90.5	82.0	77.1	77.8
	* Degree	77.9	94.8	59.9	89.6	80.9	76.2	75.1
	* Primitive	78.2	94.2	59.0	87.7	81.4	77.0	76.9

Table 5: Results of experiments on the choice of implementation rules in the minimum coverage scenario. In the Rule column, Original indicates that the implementation rules described in Section 3 are used, and other rows with * indicate that one of the corresponding rules in 5.2 is modified. Compared to Original, the performance improved by the modification is marked in red, and the performance degraded is marked in blue.

potentially trading a reduction in the number of primitives in the demonstration for a larger sample selection space.

Table 5 shows the results of experiments. From the results, we find that there is no one implementation rule choice that exhibits an absolute performance advantage, similar to the results for method components. Although LLMs may exhibit some preference for the choice of implementation rules (e.g., Qwen-plus prefers the DFS visiting rule), it does not appear that implementation rules before and after modification exhibit the same comparative results on all splits of an LLM.

While some of the modifications result in slightly larger performance changes (e.g., visiting rule on CFQ_3 for Qwen-plus), most of the modifications result in small performance changes. This implies that the framework is relatively insensitive to modifications to a single implementation rule without changing the underlying design purpose. However, better choices of implementation rules remain to be investigated, especially considering that the internal combinations of implementation rules and their combinations with other elements of the framework are still under-explored.

6 Related Work

For compositional generalization of LLMs on semantic parsing in the in-context learning paradigm, many works have proposed different methods for improvement. Levy et al. (2023) proposes Cover-LS. This method first defines the task-specific local structure that the output has. Then, pairs of (input, output local structures) in the training set are used to train a prediction model. Finally, the prediction model predicts the local structures corresponding to the test input and selects the demonstration samples that cover more of the predicted local structures. An et al. (2023a) consider improvement based on the parsing tree on COGS. They consider structural similarity, diversity, and complexity to select the demonstration samples with the best matching parsing tree for the test sample. An et al. (2023b) utilizes dataset-specific examples to enable LLMs to generate descriptions for sample selection. Drozdov et al. (2023) proposes least-to-most prompting to improve the performance of LLMs on SCAN. They divide the task into two subproblems, decomposition and mapping, provide LLMs with manually written samples of decomposition and mapping, and then ask LLMs to solve the two subproblems sequentially. On COGS and CFQ, which are more difficult to decompose subproblems, Drozdov et al. (2023) proposes dynamic last-to-most prompting. They manually write specific decomposition rules and examples for COGS and CFQ, and ask LLMs to decompose the problem. Then, they perform the selection of demonstration samples for the decomposed subproblems and ask LLMs to solve the subproblems step-by-step. As distinct from related work, the MC^2 framework does not rely on dataset-specific design such as guidance from manual annotations, and can always satisfy the requirement of the minimum-coverage setting.

7 Conclusion

In this work, we revisit the question of whether LLMs can achieve dataset-agnostic compositional generalization on semantic parsing in the minimum-coverage setting, and find that achieving this remains a challenge for current advanced LLMs. We propose a minimum-coverage and dataset-agnostic

framework, MC^2, to improve the compositional generalization of LLMs on semantic parsing. We illustrate the effectiveness and room for improvement of the framework and confirm the validity of the design ideas through experiments and analysis.

Limitations

This work investigates compositional generalization on semantic parsing in minimum-coverage and dataset-agnostic settings. The settings introduce potential limitations from a practical perspective, as the use of dataset-specific designs or larger sample sizes of the demonstration is fully allowed in real-world scenarios to improve performance. From the results, even with the MC^2 framework, there is still a gap between the performance demonstrated by LLMs and the state-of-the-art performance using methods that have dataset-specific designs and are not minimum-coverage. This represents a trade-off between the performance and input consumption as well as generalizability. Although this work performs experiments in the minimum-coverage setting, MC^2 can still be applied to looser coverage conditions (see Appendix C for a discussion).

Another limitation is the problem of data contamination. As LLMs evolve, data contamination becomes an unavoidable problem when performing compositional generalization experiments on already open-source datasets, and it is difficult to analyze their impact. Our experiments focus on comparisons of the same model in different settings, and there are no contamination-induced confidence issues for cross-model comparisons. However, contamination can still have an impact on the analysis of the source of improvement of the method on a given model. We will continue to follow up on related work on how to deal with the impact of data contamination on the results of compositional generalization tests.

Sample selection for compositional generalization has two directions of improvement: similarity and diversity. Our work focuses on improvements in the similarity direction and does not explore the diversity direction. A discussion on diversity can be found in Appendix D.

Ethics Statement

We comply with the license to use language models for scientific research purposes only. The datasets we use do not contain any information that names or uniquely identifies individual people or offensive content.

The AI assistant we use in our work is Copilot (for simple code completion).

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A Primitive Identification

For input, we mostly simply use spaces as separators to identify primitives and ignore cases when matching primitives. In the following cases, we perform special identification to avoid redundant or unusual primitives: (1) articles (e.g., the, a, an) are not considered as primitives, (2) punctuation marks are separated from the word and are not considered as primitives, and (3) for the SCAN dataset, opposite and around, which act as special ideograms, are combined with the directional adverbs that follow them to form a single primitive.

B Conversion Details

We match the model outputs and standard answers after a uniform conversion. The purpose of the conversion is to unify all possible correct answers to a unique one, which is consistent with the result of the conversion of the standard answer. For all datasets, we ignore redundant spaces and information other than answers. For the SCAN dataset, we expand the parentheses with multipliers by the number of repetitions shown by the multipliers to get the only correct answer without parentheses. For the COGS dataset, we ignore all case issues. For the CFQ dataset, following Drozdov et al. (2023), we uniquely orient the bidirectional relation and perform iterative sorting and normalization to ensure the uniqueness of the answer.

C Applying MC^2 in Looser Settings

MC^2 can simply be applied to settings that are looser (allow a larger number of demonstration samples) than the minimum-coverage setting by simply increasing D_x. For example, when allowing $2n$ demonstration samples, applying MC^2 only requires that D_x becomes twice as large. Table 6 shows the results of experiments on Qwen-plus in this looser setting ($2n$). The application of MC^2 still brings some performance improvement compared to random selection. This suggests that MC^2 can be somewhat practically useful even if the trade-off favors performance over input consumption.

D Discussion on Diversity

MC^2 is mainly improved based on the similarity direction. In the diversity direction, we supplement our experiments with a strategy: under the Global Matching strategy, we select samples with the smallest average similarity to the currently selected samples from the top 10% most similar samples to improve diversity. The results presented in Table 7 show that this strategy does not lead to performance improvement. In addition, we find a decrease in the average similarity between samples selected using the MC^2 framework compared to random. How to incorporate diversity into the framework and bring about performance gains remains to be explored.

	SCAN$_1$	**COGS**	**CFQ$_1$**
Random	80.7	90.8	74.9
MC^2	85.5	91.8	86.2

Table 6: Results of Qwen-plus when $2n$ demonstration samples are allowed.

	SCAN$_1$	**COGS**	**CFQ$_1$**
w/o Diversity	69.4	87.8	79.2
w/ Diversity	68.8	87.1	78.5

Table 7: Results of Qwen-plus without/with increasing diversity strategy when using Global Matching.