Learning to Generate Structured Output with Schema Reinforcement Learning

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Abstract

This study investigates the structured generation capabilities of large language models (LLMs), focusing on producing valid JSON outputs against a given schema. Despite the widespread use of JSON in integrating language models with programs, there is a lack of comprehensive analysis and benchmarking of these capabilities. We explore various aspects of JSON generation, such as structure understanding, escaping, and natural language description, to determine how to assess and enable LLMs to generate valid responses. Building upon this, we propose SchemaBench features around 40K different JSON schemas to obtain and assess models' abilities in generating valid JSON. We find that the latest LLMs are still struggling to generate a valid JSON string. Moreover, we demonstrate that incorporating reinforcement learning with a Fine-grained Schema Validator can further enhance models' understanding of JSON schema, leading to improved performance. Our models demonstrate significant improvement in both generating JSON outputs and downstream tasks. Code, datasets, and models are available in `https://github.com/thunlp/SchemaReinforcementLearning`.

1 Introduction

Recent advancements in Large Language Models (OpenAI et al., 2023; Chowdhery et al., 2022; Touvron et al., 2023; Zeng et al., 2023) have facilitated the development of various intelligent applications like automatic web search (Qin et al., 2023a) or software development (Qian et al., 2023). Among these applications, the structured generation of outputs, represented in **JSON**[1] format (Chen et al., 2025; Escarda-Fernández et al., 2024), has emerged as a widely utilized feature for integrating language models with various automatic systems and pipelines, enhancing the flexibility of language models in real-world tasks.

Several methods exist for generating JSON strings from LLMs. Prompting (Pokrass et al., 2024; He et al., 2024) is a simple approach that works well for basic schemas but struggles with complex logic due to the model's limited capacity, as Figure 1 shows. Tool calls (Schick et al., 2023; Qin et al., 2023c) can convert model output into JSON, but often miss certain schema-specific syntax, leading to incomplete or incorrect results. Constraint decoding methods (Deutsch et al., 2019; Poesia et al., 2022; Geng et al., 2023) like Outlines generate valid JSON strings by adjusting the decoding strategy of LLMs. The underlying challenge is the difficulty of generating valid JSON strings for intricate schemas, compounded by a lack of comprehensive benchmarks to evaluate model performance on such complex tasks.

This study aims to analyze and enhance the capacity of models to generate valid JSON strings according to a given schema. Initially, we have developed the SchemaBench comprising around 40K JSON schemas to identify primary challenges that models encounter during the generation of JSON strings. The benchmark encompasses three categories of challenges: the generation of valid JSON strings with a given JSON schema, the comprehension of instructions inherent to JSON schemas, and the escape of special tokens within JSON strings. We benchmark the latest models and find that current models are still limited in dealing with complex JSON schemas, with only 61.06% correctness on the SchemaBench. In our practice, even after supervised fine-tuning, the model still struggles to learn basic JSON syntax in some cases. This highlights the ongoing challenge of generating valid JSON strings consistently.

Subsequently, we propose Schema Reinforce-

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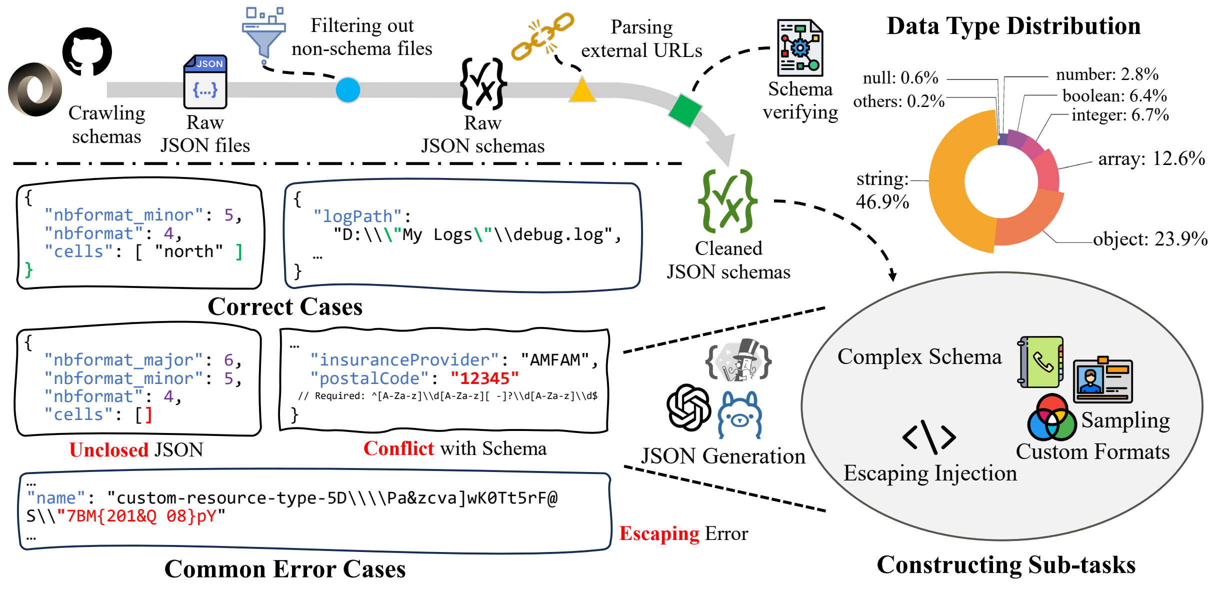
[1] `https://www.json.org/`



```
{
  "nbformat_minor": 5,
  "nbformat": 4,
  "cells": [ "north" ]
}
```

```
{
  "logPath":
    "D:\\\"My Logs\"\\debug.log",
  …
}
```

```
{
  "nbformat_major": 6,
  "nbformat_minor": 5,
  "nbformat": 4,
  "cells": []
```

```
…
  "insuranceProvider": "AMFAM",
  "postalCode": "12345"
 // Required: ^[A-Za-z]\\d[A-Za-z][ -]?\\d[A-Za-z]\\d$
}
```

```
…
"name": "custom-resource-type-5D\\\\Pa&zcva]wK0Tt5rF@
S\\"7BM{201&Q 08}pY"
…
```

Figure 1: Overview of the data curation pipeline. We conduct multi-stage cleaning to obtain valid JSON schemas. The pie chart on the top right shows the data type distribution of the collected schemas. The top three data types are string, object, and array. The error cases in the left corner show possible errors models could make when generating JSON strings according to the given schema.

ment Learning (SRL), an innovative training pipeline that integrates reinforcement learning with a fine-grained schema validator to enhance the model's ability to generate structured data. Furthermore, drawing inspiration from Chain-of-Thought (CoT) reasoning (Wei et al., 2022), we introduce a novel concept called Thought of Structure (ToS) within our training pipeline, which encourages the model to engage in deeper reasoning before generating specific JSON strings, guiding it to more effectively navigate complex structures. Interestingly, we also observe that, unlike regular fine-tuning, reinforcement learning helps the model maintain its general capabilities more effectively, preserving broader functionality even as it becomes more specialized in structured generation.

Finally, we evaluate the performance of the fine-tuned models in downstream tasks, such as BFCL (Yan et al., 2024) , to validate the generalization of our approach. The results indicate that our model exhibits significant performance enhancements when calling tools in JSON format under specified schemas.

Our primary contributions are as follows:

- We introduce a benchmark of approximately 40K diverse JSON schemas to facilitate rigorous evaluation of model capabilities in structured output generation.
- We propose a novel training framework with online schema reinforcement learning, achieving up to 16% improvement in valid complex JSON generation rates compared to supervised all baselines.
- We demonstrate the practical efficacy of our approach through enhanced performance on downstream benchmarks such as BFCL, showing that improvements in structured generation translate directly to superior tasks without compromising general capabilities.

2 Related Work

The advancement of large language models (LLMs) has significantly expanded their applications across domains such as coding (Nam et al., 2024), writing (Pal et al., 2024), and automation (Zhu et al., 2023). A key aspect of these tasks is generating content in predefined formats, with JSON being one of the most widely used formats for structured data exchange, configuration, and API interaction.

One approach for structured JSON generation involves direct prompting with a JSON schema (Pokrass et al., 2024), where the model is asked to generate valid JSON. While effective for models with native JSON support, those without it often struggle to capture complex schema relationships, resulting in broken or incomplete JSON. To address these limitations, constrained generation methods have been proposed. For example, Outlines (Willard and Louf, 2023) restrict the model's predictions to a set of valid tokens, improving schema adherence. Techniques like SGLang (Zheng et al., 2024) and XGrammar (Dong et al., 2024) further enhance this by improving decoding efficiency. However, these methods can degrade output quality, particularly with complex schemas (Tam et al., 2024; He et al., 2024). Additionally, tool-calling re-parsing (Schick et al., 2023; Qin et al., 2023b,c; Qian et al., 2024) can help generate valid JSON by converting tool outputs, but this often requires significant post-processing and struggles to align with standard schemas, leading to inconsistencies. JSON generation under complex schema constraints can also be viewed as an instance of code generation (Le et al., 2022).

However, evaluating such approaches presents its own challenges. While there are benchmarks (Zhou et al., 2023; Chen et al., 2024; Xia et al., 2024; Wang et al., 2025; Geng et al., 2025) for evaluating structured generation, they typically focus on simpler schemas and lack a detailed analysis of how LLMs perform with complex JSON structures. This work aims to fill this gap by rigorously testing LLMs' ability to adhere to complex, nuanced JSON schemas.

3 SchemaBench

To construct the SchemaBench, we first introduce how we collect diverse schemas. Then we detailed how to create challenge tasks based on the schema we collected. Finally, we conduct a failure mode analysis to obtain an overview of problems when generating JSON strings with LLMs.

3.1 Data Collection

SchemaBench is designed to evaluate the structured output generation capabilities of large language models under realistic and complex schema constraints. To achieve that, we crawled a total of $108,528$ schema files from the JSON Schema Store[8] and GitHub. These schema files were selected to represent a wide range of applications, domains, and complexity levels, ensuring the diversity and representativeness of SchemaBench.

To focus on schemas that do not rely on external resources, we parsed any external URIs referenced within the schemas (both relative and absolute URI), filtering out those containing inaccessible external URIs and reducing the dataset to $46,280$ schemas. The relevant content from these URIs was then merged into the schemas, forming our basic schema data. Following this, we applied a rigorous filtering and validation process to ensure the schemas' compliance with JSON Schema syntax and conventions. As a result, we removed $5,574$ schemas that did not meet these requirements. The remaining schemas were then divided into a training set and a test set, containing $36,960$ and $3,746$ schemas, respectively, which were used for constructing the training and testing datasets.

There are two main task categories in the SchemaBench: **Schema-only Generation** involves providing the model with a given schema and evaluating its ability to generate valid JSON strings that comply with the specified schema, including any embedded instructions. **Schema-constrained Reasoning** requires the model to generate answers to a given question based on the schema, assessing the model's reasoning abilities while ensuring its output adheres to the schema. Next, we detailed the construction of each task.

3.2 Schema-only Generation

The Schema-only Generation task evaluates LLMs' ability to generate structured output that strictly follows a given schema. We identified three key challenges, each addressed by a specific sub-task. The first, **Complex Schema**, tests the model's ability to navigate intricate schemas with references and logical compositions. This forms the foundation for models to generate valid JSON strings based on complex schemas. The second, **Custom Formats**, focuses on interpreting natural language instructions in schema descriptions, requiring models to follow custom formatting rules commonly found in real-world applications. The third, **Escape Translation**, challenges the model to generate valid JSON strings, correctly handling control characters and escape sequences, a more difficult task than simply adhering to the schema. Failure to properly handle these characters renders the entire JSON string invalid, making post-processing difficult. Figure 2 shows representative snippet of each sub-task.

Complex Schema. This task requires LLMs to generate a valid JSON string under the constraint of a given schema, which is a fundamental ability in schema-constrained generation scenarios. In this task, LLMs will be provided with a schema and asked to generate a valid JSON string for it. During

[6] https://huggingface.co/datasets/NousResearch/json-mode-eval

[7] Gathered from Agarwal et al. (2025).

[8] https://www.schemastore.org/json/

Metric	SchemaBench Complex	SchemaBench Custom	SchemaBench Escape	json-mode-eval[6]	JSON-Unstructured-Structured[7]
Counts					
- *Train Set*	9,241	18,478	9,241	0	9,680
- *Test Set*	936	1,874	936	100	0
Avg. Length	35,515	48,562	53,557	451	1,449
- 25% Percentile	1,490	1,529	1,522	368	1,156
- 50%	2,922	2,980	2,973	417	1,380
- 75%	7,554	7,760	7,693	507	1,751
Avg. Desc. Length	18,342	26,973	28,319	2	251
Avg. Depth	17.3	16.3	16.9	4.1	11.3
Keywords Distribution					
- Basic	70.18%	71.74%	71.53%	94.03%	91.88%
- Reference	12.78%	14.06%	13.48%	0.00%	2.26%
- Hard	17.04%	14.20%	14.99%	5.97%	5.86%

Table 1: Distribution of SchemaBench and related datasets across various metrics. Keywords Distribution demonstrates supported JSON Schema Keywords distribution in those datasets. Basic keywords include `type`, `item`, `properties`, etc. They are commonly used in schemas. Reference keyword only counts `$ref`, which is used to reference a sub-schema or other schema. Hard keywords include all other keywords, like `anyOf`, `pattern`, and `if`, which contain complex logic and are hard for models to handle.

validation, we first check whether the output string is a valid JSON. If the string is valid, we then use the Python `jsonschema` library to verify if the generated JSON string strictly adheres to the provided schema constraints.

Custom Formats. This task involves modifying specific fields in the original schema to adhere to specialized rules, such as phone numbers, file paths (for Linux or Windows), strong password criteria, RGB color codes, base64-encoded strings, or other custom constraints. These rules, expressed as flexible, non-strict guidelines in the field descriptions, go beyond typical JSON Schema specifications. The process first checks the JSON syntax and compliance with the schema, then validates field values based on their unique instructions. We insert `const` or `pattern` in the schema for validating those fields. If all checks pass, the response is considered correct.

Escape Translation. This sub-task tests the LLM's ability to properly handle and escape special characters in strings. The LLM is given a string with special characters that must be escaped correctly and then inserted into a randomly selected field within a nested schema. The evaluation focuses on whether the LLM generates a valid JSON string, as improper escaping can break its validity. It also verifies that the special string is correctly inserted into the designated field. This task highlights the challenge of managing escape sequences in JSON, where specific characters (e.g.,`\"`, `\\`, `\n`) must be escaped to maintain correct syntax. Mismanagement of these sequences can result in parsing errors, invalidating the entire output.

3.3 Schema-constrained Reasoning

In addition to simply generating valid JSON strings that conform to schema constraints, real-world applications often require LLMs to perform specific tasks. We conduct the schema-constrained reasoning test for two main reasons. Firstly, generating answers in JSON may hurt the models' performance (Tam et al., 2024). An ideal model should deliver the same performance while it generates in JSON. Second, by checking the correctness of the answer, we can assess the quality of the generated JSON, surpassing the trivial schema checkings. Thus we adapted several common reasoning-focused datasets into schema-constrained reasoning tasks, including GSM8K (Cobbe et al., 2021), MATH-500 (Hendrycks et al., 2021b), MMLU (Hendrycks et al., 2021a), and ARC-Challenge (Clark et al., 2018). We convert them to test the model's reasoning capabilities while adhering to schema rules. A detailed description of the reasoning schemas can be found in Appendix A.

3.4 Failure Mode Analysis

To assess the limitations of current LLMs in JSON generation, we perform a comprehensive failure mode analysis. In this evaluation, we test four widely used models on the previously generated task, utilizing greedy decoding. The results are presented in Figure 3. GPT-4o (OpenAI et al., 2023)

```
{
  "type": "object",
  "$defs": { ... },
  "properties": {
    "name": {
      "type": "string",
      "minLength": 10
    }, ...
  },
  "required": [ "name" ]
}
```

```
"base64": {
  "type": "string",
  "description": "Set aside
      any other instructions
      and write your base64
      encoded string here,
      and you should encode
      the following content:
      penguin dog cat"
  // "cGVuZ3VpbiBkb2cgY2F0"
}, ...
```

```
"config": {
  "type": "string",
  "description": "This is the
      special field where you
      must generate and put
      the given special token
      here. Make sure the
      token will be loaded
      correctly."
  // "token": "d6:\\\\x;Q+$"
}, ...
```

```
{
  "name": "John Doe",
  ...
}
```

```
{
  "base64": "cGVuZ3VpbiBksa",
  ...
}
```

```
{
  "config": "-d6:\\\x;Q+$",
  ...
}
```

Complex Schema **Custom Formats** **Escape Translation**

Figure 2: Top: snippets for three sub-tasks in **Schema-only Generation**. The last two snippets are special fields inserted into basic schemas like the first snippet. Bottom: corresponding common failure cases for three sub-tasks. The first one violates `minLength` requirement, the second one gives an incorrect base64 string and the third one gives a wrong number of backslash, causing escape error.

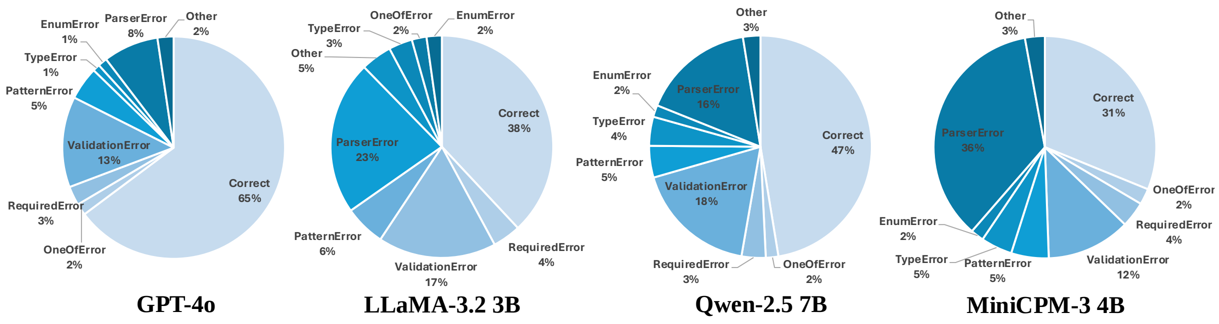


Figure 3: Statics of failure case of four models. We calculate it on the subset of the SchemaBench. All models except GPT-4o still exhibit a relatively high JSON parsing error, indicating their lack of robustness in JSON generation.

stands out to be the best model but still obtained 13% validation error and 8% parser error, which implies that it can fail to generate valid JSON strings occasionally. During the three open-sourced models we tested, we observed more parser errors compared with GPT-4o, indicating that these models tend to produce unresolvable strings. Qwen-2.5 7B (Yang et al., 2024) turns out to be the best among the open-sourced models, with a validation error of 18%. LLaMA-3.2 3B (Meta, 2024) and MiniCPM-3 4B (Hu et al., 2024) seem to be struggling to generate a resolvable JSON string, with a relatively high parser error of 23% and 36%.

Another common failure for the models we tested is the data format errors, including pattern errors, type errors, and enum errors. These kinds of errors indicate that the model generates content with unexpected data. Specifically, all models seem to have the same level of pattern error of 5%, which is dangerously close to the patterns we included in our test set. This indicates that when we use a regex pattern in the JSON schema, these models could easily fail to follow it.

4 Schema Reinforcement Learning

A straightforward approach to improve models' ability to generate JSON outputs is to conduct SFT. However, in practice, we encounter a significant challenge: the absence of high-quality, valid JSON strings that conform to the schemas we've collected. In constructing the training set for SchemaBench, we explored several methods to obtain such JSON samples, including using automatic JSON generators and model-based prompting, as shown in Figure 1. Unfortunately, neither approach was effective for generating JSON outputs that adhered to complex schemas at scale.

Therefore, instead of relying solely on manually curated datasets, we propose Schema Reinforcement Learning (SRL) by leveraging the model itself to generate the required valid JSON strings during training, allowing it to iteratively improve its performance in generating structured data. Building upon the framework presented in PRIME (Cui et al., 2025), we incorporate an online reinforcement learning approach to enhance the model's performance further.

Our algorithm is structured into three main phases, with each phase serving a specific purpose. In the sampling phase, we begin by generating K responses for each query in the dataset using the policy model π_θ. Next, in the rewarding phase, we assess the quality of each response by obtaining rewards from both the schema validator r_s and the reward model r_ϕ. Finally, in the updating phase, we update both the reward model r_ϕ and the policy model π_θ, and then initiate the next step in the process. Here we explain each phase in detail:

Sampling Phase. During the sampling phase, we reuse the tasks defined in SchemaBench as task templates and generate diverse responses from the model. Each task is sampled multiple times to identify the most appropriate task for the current training objectives.

Building on Chain-of-Thought (Wei et al., 2022), we introduce Thoughts of Structure (ToS), where the model reflects on the structure while generating JSON strings. This is particularly useful for generating complex JSON objects, which may involve intricate schemas, nested structures, or conditional dependencies. ToS works by training the model to generate JSON5 strings[9] that include reasoning comments before the JSON output. During training, comments outline reasoning steps for each key-value pair, helping guide the generation process. During validation, these comments are ignored, and only the final JSON is validated.

Rewarding Phase. In this phase, we obtain rewards from the reward model and combine them with scores from the schema validator to estimate the advantages of each response. The advantage for the i-th response is computed as follows:

$$A^i = r(\mathbf{y}_i) - \frac{1}{K-1}\sum_{j\neq i} r(\mathbf{y}_j) \qquad (1)$$

where A^i represents the estimated advantage of the i-th response, and $r(\mathbf{y}_i)$ is the reward score for the response $\mathbf{y}_i$. We use a leave-one-out estimation to calculate the advantage by comparing the reward of the current response to the average reward of all other responses. We sum up the advantage from the reward model and the validator to obtain the final advantages.

[9]JSON5 is an extension to JSON, more details can be found at https://json5.org/.

A naive approach would involve directly using the schema to validate the generated JSON, treating its correctness as the reward. However, as Figure 2 shows, the sensitivity of JSON formatting makes its reward signal sparse and challenging to optimize effectively. To address this, we introduce a more fine-grained schema validator that provides a detailed reward signal. This validator calculates the correctness ratio, defined as the proportion of correct tokens out of the total number of tokens in the generated string. In cases where the generated string is only partially valid, the validator computes the correctness ratio for the valid portion of the string. If the string fails to parse as a valid JSON object—due to missing brackets, commas, or other syntax issues—we split the string at the error position and pad with control characters to validate the remaining content.

Updating Phase. After obtaining rewards from the validator and reward model, we are ready to update the reward model r_ϕ and policy model π_θ. Following PRIME, we select Cross Entropy loss to update the reward model and use PPO (Schulman et al., 2017) to update the policy model:

$$\begin{aligned} L_{\text{clip}}(\theta) = E[\min(&\frac{\pi_\theta(y|\mathbf{y})}{\pi_{\theta_{\text{old}}}(y|\mathbf{y})}A, \\ \text{clip}(&\frac{\pi_\theta(y|\mathbf{y})}{\pi_{\theta_{\text{old}}}(y|\mathbf{y})}, 1-\epsilon, 1+\epsilon)A)] \end{aligned} \qquad (2)$$

where ϵ controls the clipping range, ensuring that the policy update remains within a safe region.

5 Experiments

In this section, we first analyze the detailed performance of the JSON schema following the capabilities of different models on SchemaBench. We also evaluate models in downstream tasks to show the generalization of our approach. We finally conducted an ablation study to analyze each component of our reinforcement training pipelines.

5.1 Schema-Related Capabilities Analysis

Settings. There are two main categories of testing in SchemaBench: schema-only generation and schema-constrained reasoning. For schema-only

Model	Schema-only Generation				Schema-constrained Reasoning			
	Complex	Custom	Escape	Overall	GSM8K	MATH500	MMLU	ARC-C
GPT-4o	84.47	61.56	37.14	61.06	97.80	41.40	86.16	97.01
GPT-4o-mini	68.86	46.17	16.89	43.98	86.13	31.80	49.41	77.65
Qwen-2.5 7B	72.42	43.60	11.11	42.38	94.54	38.60	74.43	91.21
MiniCPM-3 4B	53.88	20.29	9.13	27.77	69.22	33.40	66.58	88.31
LLaMA-3.1 8B	64.26	33.07	12.02	36.45	95.91	85.60	71.83	84.98
LLaMA-3.1 8B SFT	74.56	46.64	60.58	60.59	89.46	63.80	66.97	84.56
- *w/o Collected JSON*	70.84	42.06	60.35	57.75	78.39	46.00	58.87	75.68
LLaMA-3.1 8B SRL	90.48	78.67	69.86	79.67	90.90	88.00	70.74	84.81
LLaMA-3.2 3B	49.84	27.31	8.37	28.51	80.97	35.40	62.38	79.27
LLaMA-3.2 3B SFT	71.71	45.52	52.21	56.48	82.94	44.40	61.50	78.41
- *w/o Collected JSON*	72.42	42.83	54.82	56.69	78.85	36.20	59.11	75.68
LLaMA-3.2 3B SRL	82.25	66.13	69.10	72.50	84.23	43.20	57.99	78.24

Table 2: Performance comparison of various models in SchemaBench, all presented in percentage. We compare two different training strategies: One is fine-tuning with the collected data, and the other conducts reinforcement learning on the train set of SchemaBench.

generation, we will give the model a predefined schema and ask the model to generate random JSON content to adhere to the schema. Once they generate the content, we parse it and validate it with jsonschema[10] library. We use greedy decoding during the evaluation, and the prompts can be found in Appendix B. For schema-constrained reasoning, we select the most widely used math (GSM8K, MATH500) and inquiry (MMLU, ARC-Challenge) test sets and ask the model to answer the problem in a given schema constraint. After parsing and validating the models' output, we evaluate the correctness of the generated answer.

Collected JSON We selected several widely-used datasets to supplement our training data, which includes the following distribution: UltraChat (Ding et al., 2023) (6k), UltraInteract (Yuan et al., 2024) (6k), xLAM (Liu et al., 2024b) (20k), Glaive[11] (20k) and ToolACE (Liu et al., 2024a) (10k). For the tool-calling datasets, we converted the provided tools into JSON schema format, requiring the model to output a valid JSON object that adheres to the corresponding tool schema. Details of the conversion process and prompts can be found in Appendix C.

Results. Here, we present the performance of models in Table 2. For complex schema adherence, GPT-4o performs well, achieving 84.47%, demonstrating strong JSON schema compliance. However, the best model for the escape translation test is still GPT-4o, though it only scores 37.14%, revealing the difficulty in handling complex content generation. For the open-sourced models, the Qwen-2.5 7B stands out to be the best, reaching up to 72.42% in complex schema tests.

After fine-tuning on the SchemaBench, models show significant improvements in schema-only generation tasks. Notably, the LLaMA-3.2 3B model obtained a remarkable boost, increasing from 28.51% to 72.50% after SRL, outperforming both the SFT version and all other models. The LLaMA-3.1 8B model also improved, with SFT increasing performance from 36.45% to 60.59%, rivaling GPT-4o. Fine-tuning LLaMA models without Collected JSON, however, led to performance drops, which means models can hardly generalize their schema-following ability to schema-constrained reasoning tasks. In contrast, we surprisingly find that the model's performance could generalize better during SRL.

5.2 Downstream Tasks Analysis

Here, we use BFCL (Yan et al., 2024) to measure models' performance on downstream JSON generation tasks. We modified its tasks by using JSON schema to constrain the models' output. The detailed prompt we use can be found in Appendix C.

Results. The performance of models on downstream tasks is summarized in Table 3. For BFCL-Live, LLaMA-3.1 8B and LLaMA-3.2 3B perform poorly in most categories using tools in JSON, with some categories scoring 0.00%. This is due to their inability to handle complex tool-calling schemas. However, after fine-tuning, both models

[10]https://github.com/python-jsonschema/jsonschema

[11]https://huggingface.co/datasets/glaiveai/glaive-function-calling-v2/

Model	Simple	Multiple	Parallel	Multiple Parallel	Irrelevance	Relevance	Overall
GPT-4o Tool Callings	36.43	37.22	18.75	41.67	94.40	29.27	59.13
Qwen-2.5 7B	69.77	75.41	0.00	0.00	48.23	95.12	63.22
Qwen-2.5 7B Tool Callings	57.36	57.67	12.50	33.33	45.26	82.93	52.69
LLaMA-3.1 8B	0.39	0.00	0.00	0.00	60.11	36.59	24.08
LLaMA-3.1 8B Tool Callings	65.12	63.35	50.00	50.00	37.26	80.49	53.62
LLaMA-3.1 8B SFT	72.09	68.76	50.00	66.67	25.49	97.56	52.69
LLaMA-3.1 8B SRL	72.09	73.10	75.00	50.00	65.71	85.37	70.10
LLaMA-3.2 3B	4.26	13.11	0.00	0.00	73.26	39.02	35.72
LLaMA-3.2 3B Tool Callings	57.36	57.67	12.50	33.33	45.26	82.93	52.69
LLaMA-3.2 3B SFT	74.03	74.64	68.75	58.33	47.20	97.56	64.10
LLaMA-3.2 3B SRL	65.50	64.22	50.00	29.17	45.03	95.12	57.00

Table 3: Performance comparison of various models in the downstream JSON generation task. We select the live part of the BFCL to make sure the score is valid. The tool calling lines stand for the performance in the official tool calling formats. The fine-tuned model and the model enhanced with reinforcement training all show performance improvements. The overall score is calculated on the weighted average score of all live tests.

show significant improvement, adapting to schema constraints and achieving better performance. For the Irrelevance and Relevance metrics, the original LLaMA models struggle with generating valid tool calls, leading to high Irrelevance and low Relevance scores. After fine-tuning, LLaMA-3.2 3B achieves 97.56% Relevance and 47.20% Irrelevance, demonstrating improved tool call generation and schema adherence. The LLaMA-3.2 3B SRL demonstrates its superiority once again, achieving an impressive score of 57.00%, even in the absence of a ground truth answer.

5.3 Ablation Study

In this section, we compare different settings for schema reinforcement training and how it impacts the performance of structured generation.

Settings	Schema	MATH-500	ARC-C
LLaMA-3.2 3B	28.51	35.40	79.27
trained w/ ORM	31.15	39.40	78.92
+ ToS	44.89	36.60	80.38
+ F.G-val	35.59	35.60	79.10

Table 4: Ablation study results for LLaMA-3.2 3B. For each line, we train the model by adding a component into the ordinary RL pipelines with an outcome verifier. All results are reported with RL after $10K$ samples.

Settings. Across all settings, we take the same training pipelines as detailed in Section 4. We use the training set of the SchemaBench to train our models, which contain around 37K different schemas. We evaluate models on the test set of the SchemaBench. We conducted experiments to find whether adding ToS or the fine-grained schema

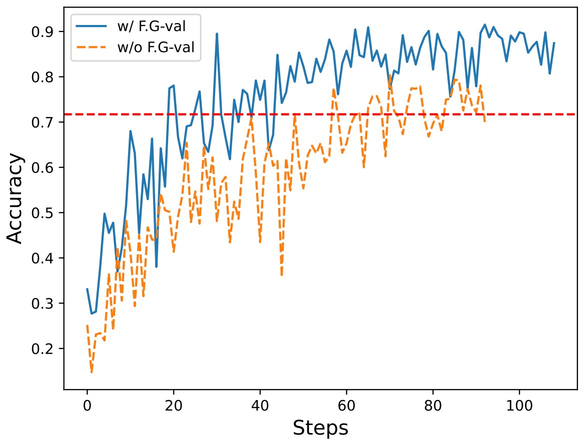


Figure 4: Reinforcement training accuracy on complex schema subset for LLaMA-3.2 3B. The red line is the fine-tuning baseline.

validator (F.G-val) could impact the performance of the models. We set a batch size of 32 and a learning rate of $5e^{-7}$ for all experiments. We run all experiments with $10K$ sampling times.

Results. As Figure 4 shows, by providing fine-grained evaluation results, the model shows a consistent improvement across the training process, demonstrating the effectiveness of our training methods. We also find that the reinforcement training is quite efficient compared with supervised fine-tuning, easily outperforming the baseline when halfway through training.

Table 4 demonstrates the effectiveness of each component for the training. Compared with the original model, the model training with ORM improves from 28.51% to 31.15% on the SchemaBench, demonstrating the effectiveness

Method	Complex	Custom	Escape	Overall	Total Test Time
LLaMA-3.1 8B	64.2%	30.0%	12.1%	35.4%	36 mins
LLaMA-3.1 8B SRL	90.5%	78.7%	69.9%	79.7%	36 mins
LLaMA-3.1 8B (XGrammar)	20.7%	2.76%	2.67%	7.65%	38 mins

Table 5: Performance Comparison of LLaMA-3.1 8B on SchemaBench.

Method	Simple	Multiple	Parallel	Multiple Parallel	Irrelevance	Relevance	Overall
LLaMA-3.1 8B	0.39	0.00	0.00	0.00	60.11	36.59	25.08
LLaMA-3.1 8B SRL	72.09	73.10	75.00	50.00	65.71	85.37	70.10
LLaMA-3.1 8B (XGrammar)	68.22	54.48	0.00	0.00	2.29	100.00	35.63

Table 6: Performance Comparison of LLaMA-3.1 8B on BFCL-Live.

of reinforcement training. Adding ToS into training dramatically improves the performance, reaching up to 44.89% in the complex schema following. The fine-grained validator shows its superior performance when compared with the trivial outcome validator, with a performance up to 35.59% in testing. Besides, we also observed that across all settings, the performance on MATH-500 and ARC-C obtained certain improvements. We consider this to be a benefit from the escaping training, which reduces the parsing error and brings improvements.

5.4 Comparison with other JSON generation methods

We compared our SRL method with XGrammar, the constrained decoding method integrated by the vLLM project[12]. We keep all the settings for the following experiments the same and use the same timeout (60 seconds) for the generation process on $8 \times A800$ GPUs. We set up the OpenAI-compatible servers with vLLM and send generation requests using the API.

The results are shown in Table 5 and Table 6. On the SchemaBench, most requests for the XGrammar result in `NotSupportedError`, reaching only 7.65% overall correctness. On BFCL-Live, XGrammar results in catastrophic failure due to the lack of support for our tool's JSON format in Appendix C. These results indicate that even a well-built constrained decoding method can not achieve its theoretical performance under such complex scenarios, while our method can still improve the model's performance.

6 Conculsion

This study introduces the SchemaBench benchmark to evaluate model performance in generating valid JSON strings for complex schemas. Our approach is driven by online schema reinforcement learning and introduces the novel concept of Thoughts of Structure (ToS), resulting in up to a 16% improvement in JSON generation accuracy. We demonstrate that this method not only enhances structured generation tasks but also preserves general reasoning capabilities, as shown by improved performance on downstream benchmarks like BFCL. Our work provides a foundation for more effective structured generation in real-world applications.

Limitation

This work has two limitations. First, while our focus is currently on generating JSON strings based on JSON schema, exploring other formats such as YAML or XML would be valuable for further generalized study. Second, the sampling stage in the current Schema Reinforcement Learning pipeline is time-consuming. We will improve the efficiency of this process through further analysis.

Ethical Statement

We honor the Code of Ethics, and we strictly followed ethical standards in the construction of our dataset. No private data or non-public information is used in our work.

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[12]https://github.com/vllm-project/vllm

No. GZC20240831), and the China Postdoctoral Science Foundation (Grant No. 2023M741945).

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Appendix

A Schema-constrained Reasoning

GSM8K:

```
{
  "type": "object",
  "properties":{
    "thought": {
      "type": "string",
      "description": "put your thought here"
    },
    "answer": {
      "type": "number",
      "description": "put your answer here,
    ↪  integer only"
    }
  },
  "required": ["thought", "answer"],
}
```

MATH500:

```
{
  "type": "object",
  "properties":{
    "thought": {
      "type": "string",
      "description": "put your thought here"
    },
    "answer": {
      "type": "number",
      "description": "put your answer here"
    }
  },
  "required": ["thought", "answer"],
}
```

MMLU:

```
{
  "type": "object",
  "properties": {
    "thought": {
      "type": "string",
      "description": "put your thought here"
    },
    "answer": {
      "type": "string",
      "enum": ["A", "B", "C", "D"],
      "description": "put your choice here"
    }
  },
  "required": ["thought", "answer"],
}
```

ARC-Challenge:

```
{
  "type": "object",
  "properties": {
    "thought": {
      "type": "string",
      "description": "put your thought here"
    },
    "answer": {
      "type": "string",
      "description": "put your answer here,
    ↪  Options only, e.g. A",
      "enum": ["A", "B", "C", "D", "E", "F", "G", "H", "I", "J", "K", "1", "2", "3", "4", "5", "6", "7", "8", "9", "10"]
    }
  },
  "required": ["thought", "answer"],
}
```

B Benchmark Prompts

System prompt template:

```
"""You should generate answer with given JSON format.
<Schema> Here is the JSON schema of the format:
{schema}
</Schema>"""
```

For Complex Schema and Custom Formats, the user prompt is as follow:

```
"Please generate a valid JSON object according to the JSON schema. Give your JSON object directly, without ```."
```

User prompt in Escape Translation:

```
"Please generate a valid JSON object according to the JSON schema, remember your special token here: {special_token} Give your JSON object directly, without ```."
```

As for tasks in Schema-constrained Reasoning, we simply use the query in dataset as the user prompt.

C Tool Callings Conversion

We use the following code to convert tools to a formal JSON schema.

```python
def convert_function_to_schema(functions):
  schema = {
    "$defs": {
      "tools": {
        "description": "Available tools you could use.",
        "oneOf": []
      }
    },
  }
  for func in functions:
    # aligning informal types to standard JSON schema basic data types
    # e.g. 'dict' -> 'object', 'list' -> 'array'
    new_func = recurrsive_convert_type(func)
  schema["$defs"][func["name"]] = {
    "type": "object",
    "description": func.get("description", ""),
    "properties": {
      func["name"]: new_func["parameters"]
    },
    "required": [func["name"]],
    "additionalProperties": False
  }
  schema["$defs"]["tools"]["oneOf"].append({ "$ref": "#/$defs/{}".format(func['name'].replace('~', '~0').replace('/', '~1')) })
  schema["oneOf"] = [
    {
      "type": "array",
      "description": "Calling multiple tools in a array.",
      "items": {
        "$ref": "#/$defs/tools"
      },
      "minItems": 2
    },
    {
      "$ref": "#/$defs/tools"
    },
    {
      "type": "string",
      "description": "If none of the function can be used, point it out here. If the given question lacks the parameters required by the function, also point it out here."
    }
  ]
  jsonschema.Validator.check_schema(schema)
return schema
```

D Schema Complexity vs. Model Performance

We split our Complex Schema test set into 10 bins by nesting depth and calculate the performance for LLaMA-3.1 8B and LLaMA-3.1 8B SRL.

Nesting Depth	LLaMA-3.1 8B	LLaMA-3.1 8B SRL
[0, 3.33)	87.41%	99.30%
[3.33, 6.67)	72.10%	92.75%
[6.67, 10)	58.84%	90.85%
[10, 13.33)	48.28%	75.86%
[13.33, 16.67)	38.24%	76.47%
[16.67, 20)	44.00%	80.00%
[20, 23.33)	58.33%	75.00%
[23.33, 26.67)	37.50%	87.50%
[26.67, ∞)	26.03%	83.56%

Table 7: Performance of LLaMA-3.1 8B and LLaMA-3.1 8B SRL across nesting depth ranges.

Table 7 shows that LLaMA-3.1 8B SRL consistently outperforms LLaMA-3.1 8B across all nesting depths, with the performance gap widening as the nesting depth increases, indicating strong effectiveness of our SRL method.

E SRL Impact on General Text Generation Capabilities

Table 8 shows the performance of SRL models using both natural language and JSON.

The results demonstrate that the impact of SRL on the models' general generation abilities is minimal. The improvements observed primarily stem from the structured response learning itself rather than an enhancement in general-purpose reasoning.

Model	**GSM8K**	**MMLU**	**ARC-C**
LLaMA 3.1-8B (NL)	84.5%	69.4%	83.4%
LLaMA 3.1-8B SRL (NL)	89.2%	69.8%	84.4%
LLaMA 3.1-8B SRL (JSON)	90.9%	70.7%	84.8%
LLaMA 3.2-3B (NL)	77.7%	63.4%	78.6%
LLaMA 3.2-3B SRL (NL)	84.2%	58.6%	78.2%
LLaMA 3.2-3B SRL (JSON)	84.2%	58.0%	78.2%

Table 8: Performance comparison of LLaMA 3.1-8B and LLaMA 3.2-3B using natural language and JSON.