Leveraging Code to Improve In-context Learning for Semantic Parsing

Ben Bogin[1]* **Shivanshu Gupta**[2]* **Peter Clark**[1] **Ashish Sabharwal**[1]

[1]Allen Institute for AI [2]University of California Irvine

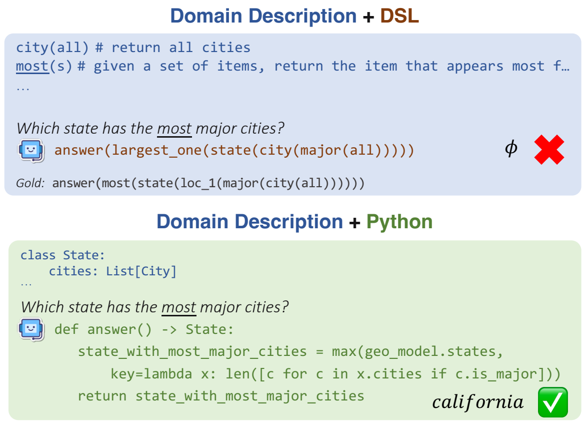
{benb,peterc,ashishs}@allenai.org, shivag5@uci.edu

Abstract

In-context learning (ICL) is an appealing approach for semantic parsing due to its few-shot nature and improved generalization. However, learning to parse to rare domain-specific languages (DSLs) from just a few demonstrations is challenging, limiting the performance of even the most capable LLMs. In this work, we improve the effectiveness of ICL for semantic parsing by (1) using general-purpose programming languages such as Python instead of DSLs, and (2) augmenting prompts with a structured domain description that includes, e.g., the available classes and functions. We show that both these changes significantly improve accuracy across three popular datasets. Combined, they lead to dramatic improvements (e.g. 7.9% to 66.5% on SMCalFlow compositional split), nearly closing the performance gap between easier i.i.d. and harder compositional splits when used with a strong model, and reducing the need for a large number of demonstrations. We find that the resemblance of the target parse language to general-purpose code is a more important factor than the language's popularity in pre-training corpora. Our findings provide an improved methodology for building semantic parsers in the modern context of ICL with LLMs.[1]

1 Introduction

Semantic parsing, the task of translating natural language utterances to unambiguous structured meaning representations (Zelle and Mooney, 1996; Kate et al., 2005) is a core requirement for building task-oriented dialog systems and voice assistants. This task is primarily addressed with two approaches: fine-tuning models on labeled datasets of utterances mapped to domain-specific language (DSL) programs (Xu et al., 2020; Oren et al., 2021; Gupta et al., 2022; Yin et al., 2022) and employing in-context learning (ICL; Brown et al., 2020) to prompt a large language model (LLM) with a few demonstrations.



```
city(all) # return all cities
most(s) # given a set of items, return the item that appears most f…
…
```

Which state has the most major cities?

```
answer(largest_one(state(city(major(all)))))
```

ϕ ✗

Gold: `answer(most(state(loc_1(major(city(all))))))`

```
class State:
    cities: List[City]
…
```

Which state has the most major cities?

```
def answer() -> State:
    state_with_most_major_cities = max(geo_model.states,
        key=lambda x: len([c for c in x.cities if c.is_major]))
    return state_with_most_major_cities
```

california ✅

Figure 1: An example illustrating how moving the problem space from a DSL to a general-purpose programming language such as Python can improve output accuracy. When prompted with a DSL, the model doesn't use the operator `most`, resulting in an incorrect program. When prompted with Python, the model leverages its pre-existing knowledge of coding to produce the correct program and answer.

However, both strategies present significant limitations. Fine-tuning requires substantial pools of labeled data, which can be expensive and time-consuming to obtain. Crucially, fine-tuned models also struggle to compositionally generalize, e.g., to decode programs longer than seen during training or to emit unseen structures (Kim and Linzen, 2020; Keysers et al., 2020; Bogin et al., 2022; Yao and Koller, 2022). While ICL can improve compositional generalization in some cases (Anil et al., 2022; Qiu et al., 2022; Drozdov et al., 2023; Hosseini et al., 2022), learning from a few demonstrations is challenging: LLMs need to not only understand the meaning of the input utterance but also learn how to correctly use a typically rare domain-specific language (DSL), given only few demonstrations. This makes ICL sensitive to demonstration

* Equal contribution

[1]https://github.com/allenai/code-semparse

selection (Zhao et al., 2021), which may not cover all functionalities and subtleties of a DSL.

Given that LLMs show remarkable coding abilities in general-purpose programming languages (PLs; Chen et al. 2021; Xu et al. 2022), in this work, we ask two main questions: (1) How can we leverage these abilities to improve ICL-based semantic parsing? (2) Can LLMs compositionally generalize better with PLs rather than DSLs?

To investigate this, first, we replace DSLs with equivalent code written in *popular programming languages* such as Python or Javascript. This helps better align the output space with pre-training corpora, obviating the need for LLMs to learn new syntax, basic operations, or other coding practices from scratch. For example, consider Figure 1: to select a state that has the *most* major cities, an LLM prompted with DSL needs to use the operator `most`, for which it might not be given an example. In contrast, with a Python prompt, the LLM can leverage its pre-existing knowledge of code to find such a state.

Second, we augment the ICL prompt with a structured description of the output meaning representation, which we refer to as *Domain Description (DD)*. This provides domain-specific information such as types of entities, attributes, and methods (e.g., `State` and its attributes in Figure 1). While such descriptions can also be added to DSLs, we find that domain descriptions for PLs are easier to precisely define with explicit declarations of objects, methods, their signatures, etc. Furthermore, LLMs are more likely to leverage descriptions with PLs rather than DSLs, as using previously defined objects and methods is a common coding practice.

We evaluate our approach on both ChatGPT[2] and Starcoder (Li et al., 2023a), by annotating three complex semantic parsing benchmarks, namely GeoQuery (Zelle and Mooney, 1996), Overnight (Wang et al., 2015), and SMCalFlow (Andreas et al., 2020) with Python programs and DDs, and implementing a Python-executable environment for each of the datasets.

In a *true* few-shot setting, where only a few (e.g., 10) labeled examples are available to use as demonstrations, we find that PL prompts with DDs dramatically improve execution-based accuracy across the board, e.g., 49.7 points absolute improvement (31.0 to 80.7) on the length split of GeoQuery, compared to the standard ICL approach of a DSL-based prompt with no DD. Prompting a model with Python and domain description can often even eliminate the need for many demonstrations: with just a *single* demonstration, accuracy on a compositional split of GeoQuery reaches 80%, compared to 17% for DSL prompting with no DD. In fact, for two datasets, a single PL demonstration with DD outperforms DSL prompts with as many as 25 demonstrations and an equivalent DD. Notably, we find that employing Python with a DD can almost entirely close the compositionality gap, i.e., the performance difference between an i.i.d. split and harder compositional splits. This effect is particularly pronounced for ChatGPT, the stronger model we experiment with.

One might hypothesize that the strong performance of Python is due to its prevalence in the pretraining corpus (Cassano et al., 2023). To investigate this, we evaluate performance of PLs whose popularity differs from that of Python. Surprisingly, we find that prevalence in pre-training corpora does not explain superior: both Scala, a PL much rarer than Python, and Javascript, which is much more prevalent, perform roughly similarly. Further analyses with simplified versions of DSLs indicate that even rare DSLs, as long as they closely resemble general-purpose code, might perform nearly as well as PLs, provided a detailed DD is used.

In conclusion, we demonstrate that using popular PLs instead of DSLs dramatically improves ICL for semantic parsing and that providing a domain description is often more effective than additional demonstrations. Our findings suggest that when LLMs are used for semantic parsing, it is better to either prompt them with PLs or design DSLs to resemble popular PLs. This suggests an improved way of building semantic parsing applications in the modern context of in-context learning with LLMs.

2 Related Work

Compositional Generalization. Semantic parsing has been studied extensively in recent years in the context of compositional generalization (CG), where models are evaluated on examples that contain unseen compositions of structures, rather than easier i.i.d. train-test splits (Finegan-Dollak et al., 2018). As recent work has shown, simply scaling the model size or amount of data CG is not sufficient to improve CG (Hosseini et al., 2022; Qiu et al., 2022). Various works have shown how gen-

[2]`https://chat.openai.com/`

Dataset	MR	# chars	Example
GeoQuery	*input*		*How high is the highest point in the largest state?*
	FunQL	49.4	`answer(elevation_1(highest(place(loc_2(largest(state(all)))))))`

	Python	115.4	`largest_state = max(geo_model.states, key=lambda x:  x.size)`
			`return largest_state.high_point.elevation`

Overnight	*input*		*person whose gender is male and whose birthdate is 2004*
	λ-DCS	282.0	`(call SW.listValue (call SW.filter (call SW.filter (call SW.getProperty (call SW.singleton en.person) (string !type)) (string gender) (string =) en.gender.male) (string birthdate) (string =) (date 2004 -1 -1)))`
	λ-DCS (Simp.)	164.1	`(listValue (filter (filter (getProperty en.person !type) gender = en.gender.male) birthdate = 2004))`

	Python	270.0	`people_born_in_2004 = [p for p in api.people if p.birthdate == 2004]`
			`males_born_in_2004 = [p for p in people_born_in_2004 if p.gender == Gender.male]`
			`return males_born_in_2004`

SMCalFlow	*input*		*Make an appointment in Central Park on Friday.*
	Dataflow	372.6	`(Yield :output (CreateCommitEventWrapper :event (CreatePreflightEventWrapper :constraint (Constraint[Event] :location ( ?= # (LocationKeyphrase "Central Park")) :start (Constraint[DateTime] :date ( ?= (NextDOW :dow # (DayOfWeek "FRIDAY"))))))))`
	Dataflow (Simp.)	118.7	`CreateEvent( AND( at_location( Central Park ) , starts_at( NextDOW( FRIDAY ) ) ) )`

	Python	174.4	`api.add_event(Event(subject="Appointment in Central Park",`
			`    starts_at=[DateTimeClause.get_next_dow(day_of_week="Friday")],`
			`    location="Central Park"))`

Table 1: Example input and program for each of our 3 datasets and each meaning representation considered, along with the average number of characters.

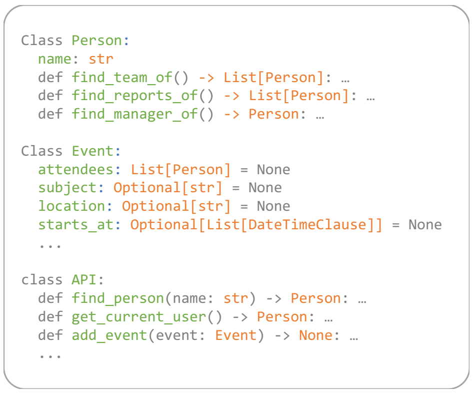
eralization can be improved by selecting a good set of demonstrations (Liu et al., 2021; Ye et al., 2023; An et al., 2023; Li et al., 2023b; Li and Qiu, 2023; Zhang et al., 2022; SU et al., 2023) or covering a diverse set of program structures (Bogin et al., 2022; Levy et al., 2023; Gupta et al., 2023), however all these methods require a large pool of demonstrations or annotation efforts. In contrast, we show that by leveraging pre-existing coding abilities, LLMs do not need as many examples to generalize.

Effect of Meaning Representations. To address specific challenges with DSLs, previous work has proposed to work with simpler meaning representations (MRs) (Herzig et al., 2021; Li et al., 2022; Wu et al., 2023) or synthetic NL utterances (Shin et al., 2021), or prompting models with the grammar of the DSL (Wang et al., 2023). Recently, Jhamtani et al. (2023) used Python to satisfy virtual assistant requests. Differently from that, our work provides an extensive study of semantic parsing in the context of modern LLMs, exploring the advantage of using code and domain descriptions over DSLs, across different datasets and PLs.

Code Prompting. Numerous works have shown that code-pre-trained LLMs can be leveraged to improve various tasks such as arithmetic reasoning, commonsense reasoning, and others with prompts that involve code (Gao et al., 2022; Madaan et al., 2022; Chen et al., 2022; Zhang et al., 2023; Hsieh et al., 2023). In this work, we show for the first time how to effectively use code prompts for semantic parsing, demonstrating that when the output of the task is already programmatic and structured, performance gains can be dramatically high.

3 Setup

Given a natural language request x and an environment e, our task is to "satisfy" the request as follows by executing a program z: If x is an *information-seeking question*, program z should output the correct answer y; if x is an *action request*, z should update the environment e appropriately. For example, an information-seeking question could be *"what is the longest river?"*, where e contains a list of facts about rivers and lengths, and the answer y should be returned based on these facts. An action request could be *"set a meeting with John at 10am"* where e contains a database with a list of all calendar items, and the task is to update e such that the requested meeting event is created. The environment e can be any type of database or system that provides a way to retrieve information or update it using *a formal language program*. Each environment accepts a different for-



```
Class Person:
  name: str
  def find_team_of() -> List[Person]: …
  def find_reports_of() -> List[Person]: …
  def find_manager_of() -> Person: …

Class Event:
  attendees: List[Person] = None
  subject: Optional[str] = None
  location: Optional[str] = None
  starts_at: Optional[List[DateTimeClause]] = None
  ...

class API:
  def find_person(name: str) -> Person: …
  def get_current_user() -> Person: …
  def add_event(event: Event) -> None: …
  ...
```

Figure 2: A partial example of a domain description, which includes information about the names of all objects and operators (in green) and type signatures (in orange).

mal language for z, and has its own specific list of accepted operators (see Table 1 for examples of different formalisms used in this work).

We focus on the **true few-shot setup** where only a small ($\leq$ 10) set of demonstrations is used. Specifically, we assume knowledge of the formalism and operators supported by e, and a set of training examples $\{(x_i, z_i)\}_{i=1}^{k}$ where k is small ($\leq$ 10), and no other data, labeled or otherwise.

4 Domain-Augmented PL Prompts

Semantic parsing has traditionally been explored using DSLs. We posit that using general-purpose PLs could better exploit the potential of modern LLMs, which are pre-trained on a mix of code and natural language. To further align the LLM's output with the code it had encountered during pre-training, we propose to additionally augment the ICL prompt with a structured domain description. Next, we elaborate on both these aspects.

Leveraging Existing Coding Knowledge. While DSLs tailored to specific domains can be valuable to trained domain experts, their rarity can make them challenging for LLMs to learn from just a few demonstrations. In contrast, PLs are prevalent in pre-training corpora; by prompting LLMs to generate PLs rather than DSLs, LLMs can leverage their existing coding knowledge without the need to learn syntax and standard operations for a new language from scratch.

For instance, consider the operator `most` in Figure 1. LLMs with no prior knowledge of the given DSL struggle to correctly apply this operator without sufficient demonstrations. However, with Python, the model can exploit its parametric knowledge to perform this operation by employing the built-in `max` and `len` operators of Python, along with list comprehension. Another example is filtering a sets of items in λ-DCS (Table 1, Overnight). Using a rare DSL, models need to learn how to correctly use the filter operator from just a few demonstrations. However, LLMs have likely already seen a myriad of examples of filtering during pre-training, e.g. in the form of Python's conditional list comprehension.

Domain Descriptions. While the use of PLs allows the model to leverage its parametric knowledge of the language's generic aspects, the LLM is still tasked with understanding domain-specific functionalities from a few in-context demonstrations. This is challenging, often even impossible, in a true few-shot setup, where the few fixed demonstrations may not cover all the functionality necessary to satisfy the test input request. A line of prior work alleviated this issue by selecting the most relevant demonstrations for every test input, but this approach typically requires a large labeled pool of demonstrations.

To address this challenge in a true few-shot setup, we propose an intuitive solution: providing the model with a *Domain Description* (DD) outlining the available operators. Specifically, when using PLs, we prefix the ICL prompt with definitions of the domain classes, methods, attributes, and constants exactly as they are defined in the environment, with the implementations of specific methods concealed for prompt brevity (e.g., replaced with '`...`' in Python).

Figure 2 provides a partial example of a DD for the python environment of SMCalFlow (Andreas et al., 2020), where users can create calendar events with certain people from their organization. Perhaps most importantly, DDs include the names of all available operators (highlighted in green in the figure). Without a list of available operators and relevant demonstrations, models are unlikely to generate a correct program. The type signatures (highlighted in orange in the figure) provide additional important information on how these operators and attributes can be used. The complete DDs are deferred to App. E.

While DDs can also be used with DSLs, there's typically no consistent and formal way to write such descriptions. In contrast, DDs for PLs are not only easier to write, they could be particularly effective as pre-training corpora contain countless examples of how previously defined classes and methods are used later in the code. As we will empirically demonstrate in Section 6, DDs are indeed utilized more effectively with PLs than with DSLs.

Prompt Construction. The prompt that we use is a concatenation of the domain description (such as the example in Figure 2) and demonstrations (such as the inputs and MRs in Table 1) for a given environment. See App. F for the exact format.

5 Experimental Setup

5.1 Datasets and Environments

Datasets. We experiment with 3 semantic parsing datasets, covering both information-seeking questions and action requests. See Table 1 for examples.

- **GeoQuery** (Zelle and Mooney, 1996) contains user utterances querying about geographical facts such as locations of rivers and capital cities. We use the FunQL formalism (Kate and Mooney, 2006), which is functional and variable-free.
- **SMCalFlow** (Andreas et al., 2020) contains user requests to a virtual assistant helping with actions such as setting up calendar events in an organization, using the Dataflow formalism created specifically for the task.
- **Overnight** (Wang et al., 2015) contains user queries about various domains; in this work we use the 'social network' domain, with questions about people employment, education and friends. Overnight uses the λ-DCS formal language (Liang et al., 2011).

DSLs. Unless mentioned otherwise, we experiment with FunQL as the DSL for GeoQuery, Dataflow for SMCalFlow, and λ-DCS for Overnight. We also experiment with a simpler version of λ-DCS for Overnight, where we reversibly remove certain redundant keyword, and Dataflow-Simple (Meron, 2022), a simpler (and less expressive) version of Dataflow, to better understand the effect of the design of DSLs (§6.2).

Dataset Splits. For GeoQuery, we use the splits provided by Shaw et al. (2021), comprising the original i.i.d. split and various compositional generalization splits. For SMCalFlow, we use the i.i.d. and compositional splits proposed by Yin et al. (2021). These compositional splits evaluate predictions for queries that combine two domains: event creation and organizational chart. Specifically, we use the hardest "0-C" split, where the training set contains examples only from each of the domains separately, with no single example that combines both domains. For Overnight, we take the i.i.d. split and one arbitrary compositional split from those published in Bogin et al. (2022).

We used the development sets for each of the datasets only to make sure predicted programs were executed as expected. For Overnight, where such a set was unavailable, we used 50 examples from the training set. All results are reported over the development set where available, except for Tables 2 and 3 which report results over the test sets.

Executable environments. For each dataset, we implement an executable environment for both the DSL formalism and Python, or use an existing one if available. An environment is capable of executing a program z and either outputting an answer y (e.g., the name of a river) or modifying its own state (e.g., creating an event). See App. A for implementation details for each environment.

To implement the Python environments, we first identify the requisite classes, their properties, and their methods based on usage of the original DSL, and then write Python code to create an executable Python environment. Importantly, whenever possible we retain the original names of properties and constants used in the DSLs, ensuring that performance improvements can be attributed to the change of the MR rather than changes in naming.

5.2 Evaluation

Metrics. The executable environments we have for all datasets, for both DSL and Python, allow us to compute *execution-based* accuracy. For GeoQuery and Overnight, we compare answers returned by generated programs to those generated by gold programs. For SMCalFlow, we compare the state (i.e., calendar events) of the environments after executing gold and predicted programs. For DSL experiments, we additionally provide Exact Match metric results in App. B, which are computed by comparing the generated programs to gold-annotated programs.

For SMCalFlow and Overnight, we sample 250 examples from the evaluation set, while for GeoQuery, we use the entire evaluation sets. We run all experiments with three seeds, each with a different sample of demonstrations, and report average accuracy. For each seed, the same set of demonstrations is used across different test instances, formalisms, and prompt variations.

Conversion to Python. To generate demonstrations for Python programs, we convert some or all of the DSL programs of each dataset to Python using semi-automatic methods. Specifically, we manually convert 2-10 examples to Python programs to seed our pool of Python-annotated instances and then iteratively sample demonstrations from the pool and prompt an LLM with the Python DD (§4) to automatically annotate the rest of the examples (we use either OpenAI's gpt-3.5-turbo or gpt-4[2]). Only predictions that are evaluated to be correct, using the same execution-based evaluation described above, are added to the pool (see App. C for further details).

Models. We experiment with OpenAI's ChatGPT (GPT-3.5-turbo) and the open-source StarCoder LLM (Li et al., 2023a). Since GPT's maximum context length is longer, we conduct our experiments with GPT with $k = 10$ demonstrations, and provide main results for StarCoder with $k = 5$ as well. We use a temperature of 0 (greedy decoding) for generation.

Domain Descriptions for DSLs. For a thorough comparison, we also provide DDs for each of the DSLs. These DDs contain similar information to the PL-based DDs (§4). We manually write these DDs based on the existing environments, listing all operators and describing type signatures (see App. E for all DDs).

We note that providing DDs for DSLs is often not as straightforward as for PLs; we design the DSL-based DDs to be as informative as possible, but do not explore different description design choices. This highlights another advantage of using PLs—their DDs can simply comprise extracted definitions of different objects, without the need to describe the language itself.

6 Results

We first compare Python-based prompts with DSL-based prompts and the effect of DDs (§6.1). We then experiment with several other PLs and variations of DSLs to better understand how the design of the output language affects performance (§6.2).

6.1 Python vs DSLs

Baselines and Ablations. We compare multiple variations of DDs. *List of Operators* simply lists all available operators without typing or function signatures (i.e., we keep only green text in Figure 2). *Full DD* contains the entire domain description, while *DD w/o typing* is the same as Full DD, except that it does not contain any type information (i.e., none of the orange text in Figure 2).

Main Results. Tables 2 and 3 present the results for ChatGPT (k=10) and Starcoder (k=5), respectively. We observe that Python programs without a DD outperform not only DSLs without a DD but even surpass DSLs prompted with a full DD across all splits for GPT and on most splits for Starcoder. Python with a full DD performs best in all 8 splits for GPT and on 6 splits for Starcoder. Notably, for GPT-3.5, using Python with Full DD almost entirely eliminates the compositionality gap, i.e., the difference in performance between the i.i.d. split and compositional splits.

Ablating different parts of the DDs (rows named "List of operators" and "DD w/o typing") reveals that in some cases, most of the performance gain is already achieved by adding the list of operators (e.g., GeoQuery i.i.d. split), while in other cases (e.g., GeoQuery length split) providing typing and signatures further improves accuracy.

Prompt Length Trade-off. Figure 3 demonstrates that using Python consistently outperforms DSLs across varying number (k) of demonstrations. For both GeoQuery and SMCalFlow, just a single demonstration with a DD outperforms 25 demonstrations without a DD. However, the impact of DDs depends on the dataset and the domain: in Overnight, where the domain is small, the impact of DDs is limited.

Considering a real-world setup with constrained resources, where one might want to optimize performance given a maximum prompt length, we also investigate accuracy as a function of the *total number of prompt tokens* for three Python DD variations. Results (Figure 5 in App. B.2) show that the optimal point in the trade-off between DD detail and number of demonstrations in the prompt varies per dataset. For Overnight, where the domain is simple, using demonstrations alone might suffice. However, for both GeoQuery and SMCalFlow, having the Full DD is preferred whenever it can fit.

		GeoQuery				SMCalFlow-CS		Overnight	
		i.i.d.	Templ.	TMCD	Len.	i.i.d.	0-C	i.i.d.	Templ.
DSL	No DD	37.6	34.2	43.5	31.0	42.9	7.3	34.0	23.1
	List of operators	48.6	31.8	47.3	38.0	45.9	20.1	38.1	24.0
	Full DD	61.0	41.5	52.5	39.4	40.7	20.7	38.8	23.2
Python	No DD	72.6	54.6	67.1	57.3	58.0	28.0	62.8	69.2
	List of operators	83.5	83.0	81.9	75.3	59.6	46.9	61.7	71.5
	DD w/o typing	82.1	83.1	83.4	75.7	69.1	65.6	62.1	68.5
	Full DD	**84.4**	**84.4**	**84.9**	**80.7**	**69.2**	**66.7**	**64.5**	**72.9**

Table 2: Execution accuracy of GPT-3.5-turbo, comparing Python-based prompts with DSL-based prompts, across different DD variations, when 10 in-context demonstrations are used. Python-based prompts with Full DD consistently outperform DSL-based prompts by substantial amounts. Test sets results.

		GeoQuery				SMCalFlow-CS		Overnight	
		i.i.d.	Templ.	TMCD	Len.	i.i.d.	0-C	i.i.d.	Templ.
DSL	No DD	24.4	19.0	28.0	14.7	23.3	0.7	18.1	7.7
	List of operators	39.8	27.2	36.2	32.3	18.4	0.3	23.2	9.9
	Full DD	46.9	45.2	45.2	38.9	22.7	2.0	22.4	12.0
Python	No DD	56.1	42.2	50.2	32.4	22.8	5.1	51.9	**39.9**
	List of operators	**73.3**	**70.1**	70.7	61.7	22.4	13.2	55.5	38.1
	DD w/o typing	73.0	70.0	69.7	62.3	35.1	25.2	56.1	36.8
	Full DD	73.2	69.7	**75.2**	**68.6**	**43.7**	**33.2**	**56.9**	36.9

Table 3: Execution accuracy of Starcoder, comparing Python-based prompts with DSL-based prompts, across different DD variations, with 5 in-context demonstrations. Similarly to ChatGPT (Table 2), Starcoder used with Python-based prompts with Full DD is consistently better than with DSL-based prompts. Test sets results.

			GeoQuery				SMCalFlow-CS		Overnight	
	% in the Stack		i.i.d.	Templ.	TMCD	Len.	i.i.d.	0-C	i.i.d.	Templ.
DSL		No DD	38.7	32.1	42.7	25.8	42.9	7.5	34.0	23.1
		Full DD	61.9	44.8	56.7	39.1	40.8	22.0	38.8	23.2
Python	6.1%	No DD	71.6	50.9	61.5	51.8	58.1	29.7	62.8	69.2
		Full DD	83.1	80.6	80.9	80.9	**69.3**	69.9	64.5	**72.9**
Javascript	15.5%	No DD	80.0	72.1	75.2	73.6	64.1	46.1	61.6	51.3
		Full DD	81.1	80.0	77.3	73.6	68.1	71.6	61.1	50.1
Scala	0.5%	No DD	82.5	73.3	73.9	68.5	62.3	45.9	69.7	65.1
		Full DD	**83.5**	**83.3**	**82.4**	**82.1**	69.2	**72.4**	**69.9**	61.9
Dataflow-Simple		No DD					50.9	22.7		
		Full DD					59.7	63.9		
λ-DCS Simple		No DD							37.3	27.5
		Full DD							38.0	31.7

Table 4: Execution accuracy for different PLs along with the percentage of their prevelance in the Stack, a popular code corpus, along with two DSL variations. There is no consistent winner among the different PLs, suggesting that the popularity of PLs in pre-training corpora is not a good predictor of performance. Dev sets results.

Effect of Better Demonstrations Selection. Our results so far have demonstrated performance with a *random*, fixed set of demonstrations, in line with our goal of minimizing labeling workload. However, in some scenarios, the budget may allow for access to a larger pool of demonstrations. In the next experiment, we evaluate the performance of PL-based prompts when a large pool of labeled data is available, allowing more sophisticated demonstration selection methods to be applied.

The first selection method optimizes for *operator coverage* (Levy et al., 2023; Gupta et al., 2023) by selecting a fixed set of demonstrations that cover as many of the operators as possible. This is achieved

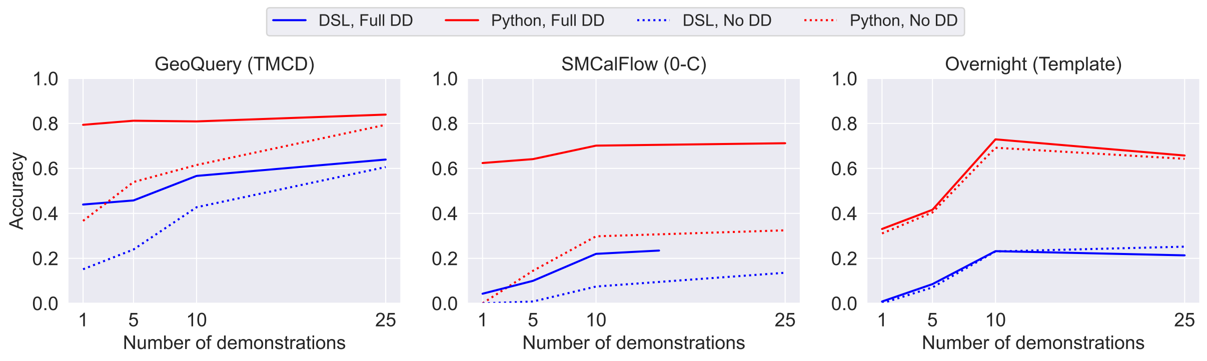


Figure 3: Execution accuracy for varying number of demonstrations. In almost all cases, Python outperforms DSL, both with a domain description and without, across different numbers of demonstrations (prompt for SMCalFlow, DSL, Full DD could not fit more than 15 examples given the model's context length limitation).

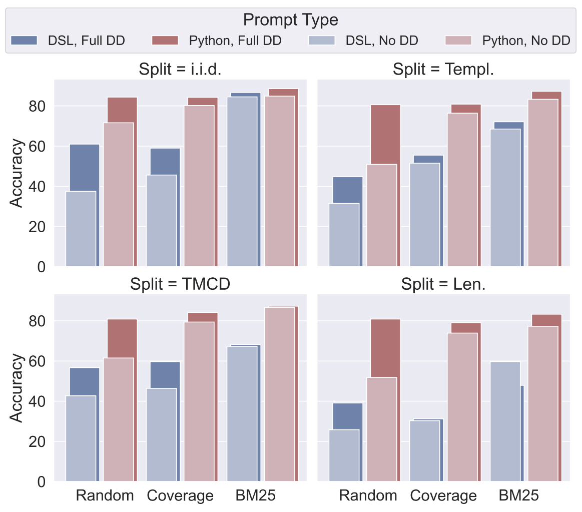


Figure 4: Python-based prompts, both with and without DD, consistently outperform DSL-based prompts even with better demonstrations, for every split of GeoQuery.

by greedily and iteratively selecting demonstrations to cover operators (see App. D for details). This fixed set covers 68% to 81% of the operators with $k = 10$ (coverage varies across splits). Our second selection method is similarity-based retrieval: given a test example utterance, we retrieve the training examples with the most similar utterances using BM25 (Robertson and Zaragoza, 2009).

We present the results for the different demonstration selection methods in Figure 4 for GeoQuery, for which we have annotated the entire training set with Python programs. We observe that for every selection method, both with and without DD, Python-based prompts consistently outperform DSL-based prompts.

Error Analysis. We now analyze the kinds of errors made by the LLM when prompted with Python and a DD. For SMCalFlow and ChatGPT, the development set of the compositional split (of size 250) resulted in 78 errors on one of the seeds; we include common examples of errors in Table 5 and examples of correct predictions in Table 6. 42 (54%) of the errors were because the program failed to execute. The remaining 36 were due to incorrect execution. Closer analysis revealed most of these errors to be due to failure to understand the input utterance or not using the API correctly. A small fraction (11, 14%) of the error instances were found to be unsupported by the original environment or our Python re-implementation. For GeoQuery, on the other hand, among the 18 errors made by ChatGPT on the development set of the TMCD split (of size 100) on one of the seeds, only 8 were attributed to model errors, while 8 were due to discrepancies in the dataset and 2 resulted from environment limitations. The above analysis suggests that while using PLs and DDs greatly improves the performance of LLMs, there is still scope for improvement in more complex domains (like SMCalFlow). Future work can explore how to ensure LLMs remain faithful to the DD and how to design environments to be more amenable to LLMs.

6.2 What Makes a Good MR?

Building on the findings from Section 6.1, showing that Python prompts consistently outperform DSLs, we now investigate the source of these performance gains. Specifically, in this section, we ask:

1. Is the performance gain of a PL linked to its prevalence in pre-training corpora?
2. Can rare DSLs be simplified in a way that enables them to perform as well as PLs?

Input	Predicted Python Program	Error
Put lunch with Jane 's boss in her office down for next Wednesday at noon .	`def answer(): jane = api.find_person("Jane") boss = jane.find_manager_of() api.add_event(Event(subject="Lunch with Jane's Boss", attendees=[jane, boss], starts_at=[DateTimeValues.NextWeek, DateTimeClause.time_by_hm(hour=12, am_or_pm="pm")], location="Jane's Office"))`	Execution error due to incorrect API use: `NextWeek` is not a valid `DateTimeValue`.
i need to have all of jake 's team except jennifer at my staff meeting this friday	`def answer(): jake = api.find_person("Jake") team = jake.find_team_of() team.remove(api.find_person("Jennifer")) api.add_event(Event(subject="Staff Meeting", attendees=team, starts_at=[DateTimeClause.get_next_dow(day_of_week="Friday")]))`	Execution error due to incorrect API use: The right way to exclude people is to use `attendees_to_avoid` argument of the `Event` class.
I am going to be with Abby and her Skip tomorrow	`def answer(): abby = api.find_person("Abby") skip = abby.find_manager_of() api.add_event(Event(attendees=[abby, skip], starts_at=[DateTimeValues.Tomorrow]))`	Incorrect execution as the model did not understand *skip* means manager's manager.
create drinks with boss on Tuesday	`def answer(): boss = api.find_person("boss") api.add_event(Event(subject="Drinks with Boss", starts_at=[DateTimeClause.get_next_dow(day_of_week="Tuesday")], attendees=[boss]))`	Incorrect execution as the model did not use `find_manager_of` to find the manager.

Table 5: Examples of common errors made by GPT-Turbo-3.5 on the compositional 0-C split of SMCalFlow. Majority of errors were due to the LLM failing to understand the input utterance or incorrectly using the API.

3. Does the ability to break down programs into intermediate steps contribute to the improved performance of PLs?

6.2.1 Effect of a PL's Prevalence

To answer the first question, we extend our experiments to include Scala and Javascript. According to the PL distribution provided by the Stack (Kocetkov et al., 2023), a large corpus of GitHub code, Scala is far less common than Python (0.5% vs 6.1%), while Javascript is more popular than Python (15.5%).

Evaluation Procedure for Additional PLs. We evaluate the performance of these additional PLs by prompting LLMs similarly to how we evaluated Python prompts (§6.1). However, to avoid the undue engineering effort of implementing a complete executable environment, as we did for Python, we evaluate generated programs by first automatically converting them to Python, similar to previous work (Cassano et al., 2023). During evaluation, we convert predictions using GPT-4, with a prompt that includes both the Python and the target language's DDs and 15 conversion demonstrations. We test the correctness of converted Python programs by executing them within the Python environment. To obtain a pool of demonstrations in the target language, we use a similar iterative procedure as the one described for Python in §5.

To confirm that the conversion is *faithful* and does not introduce bias, such as fixing incorrect programs or breaking correct ones, we manually analyzed 100 random examples of the converted Python programs, 50 each from Javascript and Scala, finding only 1 instance each of an unfaithful conversion. We provide the complete procedure and prompts in App. C.2.

Results. Table 4 demonstrates that all three PLs outperform DSL-based prompts. However, the performance of the three PLs varies across datasets and splits, with Scala performing best in most splits. This suggests that the prevalence of a PL in pre-training corpora alone does not reliably predict performance in semantic parsing tasks. This finding offers a subtle counterpoint to the results of Cassano et al. (2023), who identified a correlation between the prevalence of a PL in pre-training data and performance on other programming benchmarks.

6.2.2 Simplifying PLs

If the prevalence of a PL in pre-training corpora doesn't correlate with performance, could it be that DSL-based prompts perform worse because DSLs are overly complex, and simplifying them could improve performance (Herzig et al., 2021; Li et al., 2022)?

Dataset	Input	Predicted Python Program
GeoQuery	*Which states border states through which the Mississippi traverses ?*	`def answer() -> List[State]:` `mississippi_river = geo_model.find_river("mississippi")` `bordering_states = set()` `for state in mississippi_river.traverses:` `bordering_states.update(state.next_to)` `return list(bordering_states)`
SMCalFlow	*Schedule a meeting with my team on November 3rd at 11 am as well .*	`def answer():` `team = api.get_current_user().find_team_of()` `api.add_event(Event(subject="Meeting with Team", starts_at=[DateTimeClause.date_by_mdy(month=11, day=3), DateTimeClause.time_by_hm(hour=11, am_or_pm="am")], attendees=team))`
Overnight	*student whose start date is end date of employee alice*	`def answer():` `alice = api.find_person_by_id("en.person.alice")` `students_with_same_start_date = [person for person in api.people if person.education and any(e.start_date == alice_employment.end_date for e in person.education for alice_employment in alice.employment)]` `return students_with_same_start_date`

Table 6: Examples of correct Python predictions made by GPT-Turbo-3.5 on the compositional TMCD split of GeoQuery, 0-C split of SMCalFlow, and Template split of Overnight.

To investigate this, we experiment with simplified versions of SMCalFlow and Overnight's DSLs. Specifically, we use Dataflow-Simple (Meron, 2022), a version of Dataflow tailored for creating events and querying organizational charts, which uses fewer operators and an entirely different syntax, with function calls in the style of popular PLs. While Dataflow-Simple isn't equivalent to Dataflow, it can be used to satisfy all of the requests in SMCalFlow's dataset. For Overnight, we use a simplified version of λ-DCS, where we remove redundant operators in the context of the evaluation setup, reducing its length by 42% on average. Specifically, we remove the `call` operator, typing (`string`, `date`, `number`), redundant parentheses and the namespace `SW`. Examples for both MRs are provided in Table 1.

The results presented in the bottom two sections of Table 4 reveal that the surface-level simplification of λ-DCS provides only a marginal boost to performance. On the other hand, Dataflow-simple surprisingly performs nearly as well as the other PLs. These findings suggest that designing DSLs to resemble PLs could also be effective (when DD is included), even when DSLs are rare in pre-training corpora. However, what unique elements of PLs should be adopted in DSLs to yield comparable performance gains remains an open question.

6.2.3 Effect of Intermediate Steps

A key distinction between the PLs and the DSLs evaluated in this work lies in the fact that PLs allow breaking down the programs into multiple steps and assigning intermediate results to variables. To measure the impact of this aspect, we modify PL programs such that if a program contains more than one line, we compress it into a single line, eliminating intermediate variables, and vice versa. We employ GPT-4 to perform these modifications and use execution-based evaluation to ensure that the program meaning does not change (see App. C.3 for the exact prompt). We note that the only modification made is to the programs of the prompt demonstrations, however models can still output a program of any line length.

	GeoQuery				**SMCalFlow-CS**		**Overnight**	
	i.i.d.	Templ.	TMCD	Len.	i.i.d.	0-C	i.i.d.	Templ.
Single	83.2	**80.9**	**80.3**	79.1	64.8	60.4	62.9	57.6
Multi.	**83.7**	80.6	80.0	**80.3**	**67.7**	**70.0**	**64.5**	**72.9**

Table 7: Accuracy of single-line programs compared with multiple-line programs with intermediate steps.

Results presented in Table 7 suggest that breaking down code into intermediate steps indeed contributes to higher performance in most cases. However, even single line demonstrations still significantly outperform DSL-based prompts.

7 Conclusions

In this work, we have shown that leveraging PLs and DDs does not only improve the effectiveness of in-context learning for semantic parsing, leading to substantial accuracy improvements across various datasets, but also significantly narrows the performance gap between i.i.d. and compositional splits and reduces the need for large demonstration pools. Our findings carry significant implications for the development of semantic parsing applications using modern LLMs.

Acknowledgements

We thank Alexander Koller and Matt Gardner for their helpful comments. This work was sponsored in part by the DARPA MCS program under Contract No. N660011924033 with the United States Office Of Naval Research and in part by the NSF award #IIS-2046873. The views expressed are those of the authors and do not reflect the policy of the funding agencies.

References

Shengnan An, Zeqi Lin, Qiang Fu, Bei Chen, Nanning Zheng, Jian-Guang Lou, and Dongmei Zhang. 2023. How do in-context examples affect compositional generalization? In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 11027–11052, Toronto, Canada. Association for Computational Linguistics.

Jacob Andreas, John Bufe, David Burkett, Charles Chen, Josh Clausman, Jean Crawford, Kate Crim, Jordan DeLoach, Leah Dorner, Jason Eisner, Hao Fang, Alan Guo, David Hall, Kristin Hayes, Kellie Hill, Diana Ho, Wendy Iwaszuk, Smriti Jha, Dan Klein, Jayant Krishnamurthy, Theo Lanman, Percy Liang, Christopher H. Lin, Ilya Lintsbakh, Andy McGovern, Aleksandr Nisnevich, Adam Pauls, Dmitrij Petters, Brent Read, Dan Roth, Subhro Roy, Jesse Rusak, Beth Short, Div Slomin, Ben Snyder, Stephon Striplin, Yu Su, Zachary Tellman, Sam Thomson, Andrei Vorobev, Izabela Witoszko, Jason Wolfe, Abby Wray, Yuchen Zhang, and Alexander Zotov. 2020. Task-oriented dialogue as dataflow synthesis. *Transactions of the Association for Computational Linguistics*, 8:556–571.

Cem Anil, Yuhuai Wu, Anders Johan Andreassen, Aitor Lewkowycz, Vedant Misra, Vinay Venkatesh Ramasesh, Ambrose Slone, Guy Gur-Ari, Ethan Dyer, and Behnam Neyshabur. 2022. Exploring length generalization in large language models. In *Advances in Neural Information Processing Systems*.

Ben Bogin, Shivanshu Gupta, and Jonathan Berant. 2022. Unobserved local structures make compositional generalization hard. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 2731–2747, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Federico Cassano, John Gouwar, Francesca Lucchetti, Claire Schlesinger, Carolyn Jane Anderson, Michael Greenberg, Abhinav Jangda, and Arjun Guha. 2023. Knowledge transfer from high-resource to low-resource programming languages for code llms.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating large language models trained on code.

Wenhu Chen, Xueguang Ma, Xinyi Wang, and William W. Cohen. 2022. Program of thoughts prompting: Disentangling computation from reasoning for numerical reasoning tasks. *ArXiv*, abs/2211.12588.

Andrew Drozdov, Nathanael Schärli, Ekin Akyürek, Nathan Scales, Xinying Song, Xinyun Chen, Olivier Bousquet, and Denny Zhou. 2023. Compositional semantic parsing with large language models. In *The Eleventh International Conference on Learning Representations*.

Catherine Finegan-Dollak, Jonathan K. Kummerfeld, Li Zhang, Karthik Ramanathan, Sesh Sadasivam, Rui Zhang, and Dragomir Radev. 2018. Improving text-to-SQL evaluation methodology. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 351–360, Melbourne, Australia. Association for Computational Linguistics.

Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon, Pengfei Liu, Yiming Yang, Jamie Callan, and Graham Neubig. 2022. Pal: Program-aided language models. *arXiv preprint arXiv:2211.10435*.

Shivanshu Gupta, Matt Gardner, and Sameer Singh. 2023. Coverage-based example selection for in-context learning.

Shivanshu Gupta, Sameer Singh, and Matt Gardner. 2022. Structurally diverse sampling for sample-efficient training and comprehensive evaluation. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 4966–4979, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Jonathan Herzig and Jonathan Berant. 2018. Decoupling structure and lexicon for zero-shot semantic parsing. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1619–1629, Brussels, Belgium. Association for Computational Linguistics.

Jonathan Herzig, Peter Shaw, Ming-Wei Chang, Kelvin Guu, Panupong Pasupat, and Yuan Zhang. 2021. Unlocking compositional generalization in pre-trained models using intermediate representations. *arXiv preprint arXiv:2104.07478*.

Arian Hosseini, Ankit Vani, Dzmitry Bahdanau, Alessandro Sordoni, and Aaron Courville. 2022. On the compositional generalization gap of in-context learning. In *Proceedings of the Fifth BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 272–280, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.

Cheng-Yu Hsieh, Si-An Chen, Chun-Liang Li, Yasuhisa Fujii, Alexander Ratner, Chen-Yu Lee, Ranjay Krishna, and Tomas Pfister. 2023. Tool documentation enables zero-shot tool-usage with large language models.

Harsh Jhamtani, Hao Fang, Patrick Xia, Eran Levy, Jacob Andreas, and Ben Van Durme. 2023. Natural language decomposition and interpretation of complex utterances.

Rohit J. Kate and Raymond J. Mooney. 2006. Using string-kernels for learning semantic parsers. In *Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics*, pages 913–920, Sydney, Australia. Association for Computational Linguistics.

Rohit J. Kate, Yuk Wah Wong, and Raymond J. Mooney. 2005. Learning to transform natural to formal languages. In *AAAI Conference on Artificial Intelligence*.

Daniel Keysers, Nathanael Schärli, Nathan Scales, Hylke Buisman, Daniel Furrer, Sergii Kashubin, Nikola Momchev, Danila Sinopalnikov, Lukasz Stafiniak, Tibor Tihon, Dmitry Tsarkov, Xiao Wang, Marc van Zee, and Olivier Bousquet. 2020. Measuring compositional generalization: A comprehensive method on realistic data. In *International Conference on Learning Representations*.

Najoung Kim and Tal Linzen. 2020. COGS: A compositional generalization challenge based on semantic interpretation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9087–9105, Online. Association for Computational Linguistics.

Denis Kocetkov, Raymond Li, Loubna Ben allal, Jia LI, Chenghao Mou, Yacine Jernite, Margaret Mitchell, Carlos Muñoz Ferrandis, Sean Hughes, Thomas Wolf, Dzmitry Bahdanau, Leandro Von Werra, and Harm de Vries. 2023. The stack: 3 TB of permissively licensed source code. *Transactions on Machine Learning Research*.

Itay Levy, Ben Bogin, and Jonathan Berant. 2023. Diverse demonstrations improve in-context compositional generalization. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1401–1422, Toronto, Canada. Association for Computational Linguistics.

Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, Qian Liu, Evgenii Zheltonozhskii, Terry Yue Zhuo, Thomas Wang, Olivier Dehaene, Mishig Davaadorj, Joel Lamy-Poirier, João Monteiro, Oleh Shliazhko, Nicolas Gontier, Nicholas Meade, Armel Zebaze, Ming-Ho Yee, Logesh Kumar Umapathi, Jian Zhu, Benjamin Lipkin, Muhtasham Oblokulov, Zhiruo Wang, Rudra Murthy, Jason Stillerman, Siva Sankalp Patel, Dmitry Abulkhanov, Marco Zocca, Manan Dey, Zhihan Zhang, Nour Fahmy, Urvashi Bhattacharyya, Wenhao Yu, Swayam Singh, Sasha Luccioni, Paulo Villegas, Maxim Kunakov, Fedor Zhdanov, Manuel Romero, Tony Lee, Nadav Timor, Jennifer Ding, Claire Schlesinger, Hailey Schoelkopf, Jan Ebert, Tri Dao, Mayank Mishra, Alex Gu, Jennifer Robinson, Carolyn Jane Anderson, Brendan Dolan-Gavitt, Danish Contractor, Siva Reddy, Daniel Fried, Dzmitry Bahdanau, Yacine Jernite, Carlos Muñoz Ferrandis, Sean Hughes, Thomas Wolf, Arjun Guha, Leandro von Werra, and Harm de Vries. 2023a. Starcoder: may the source be with you!

Xiaonan Li, Kai Lv, Hang Yan, Tianyang Lin, Wei Zhu, Yuan Ni, Guotong Xie, Xiaoling Wang, and Xipeng Qiu. 2023b. Unified demonstration retriever for in-context learning. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 4644–4668, Toronto, Canada. Association for Computational Linguistics.

Xiaonan Li and Xipeng Qiu. 2023. Finding supporting examples for in-context learning.

Zhenwen Li, Jiaqi Guo, Qian Liu, Jian-Guang Lou, and Tao Xie. 2022. Exploring the secrets behind the learning difficulty of meaning representations for semantic parsing. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 3616–3625, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Percy Liang, Michael Jordan, and Dan Klein. 2011. Learning dependency-based compositional semantics. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 590–599, Portland, Oregon, USA. Association for Computational Linguistics.

Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. 2021. What makes good in-context examples for gpt-3? In *Workshop on Knowledge Extraction and Integration for Deep Learning Architectures; Deep Learning Inside Out*.

Aman Madaan, Shuyan Zhou, Uri Alon, Yiming Yang, and Graham Neubig. 2022. Language models of code are few-shot commonsense learners. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 1384–1403, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

J. Meron. 2022. Simplifying semantic annotations of smcalflow. In *Proceedings of the 18th Joint ACL - ISO Workshop on Interoperable Semantic Annotation within LREC2022*, pages 81–85, Marseille, France. European Language Resources Association.

Inbar Oren, Jonathan Herzig, and Jonathan Berant. 2021. Finding needles in a haystack: Sampling structurally-diverse training sets from synthetic data for compositional generalization. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 10793–10809, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Linlu Qiu, Peter Shaw, Panupong Pasupat, Tianze Shi, Jonathan Herzig, Emily Pitler, Fei Sha, and Kristina Toutanova. 2022. Evaluating the impact of model scale for compositional generalization in semantic parsing. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9157–9179, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Stephen Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends® in Information Retrieval*, 3(4):333–389.

Peter Shaw, Ming-Wei Chang, Panupong Pasupat, and Kristina Toutanova. 2021. Compositional generalization and natural language variation: Can a semantic parsing approach handle both? In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 922–938, Online. Association for Computational Linguistics.

Richard Shin, Christopher Lin, Sam Thomson, Charles Chen, Subhro Roy, Emmanouil Antonios Platanios, Adam Pauls, Dan Klein, Jason Eisner, and Benjamin Van Durme. 2021. Constrained language models yield few-shot semantic parsers. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7699–7715, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Hongjin SU, Jungo Kasai, Chen Henry Wu, Weijia Shi, Tianlu Wang, Jiayi Xin, Rui Zhang, Mari Ostendorf, Luke Zettlemoyer, Noah A. Smith, and Tao Yu. 2023. Selective annotation makes language models better few-shot learners. In *The Eleventh International Conference on Learning Representations*.

Bailin Wang, Zi Wang, Xuezhi Wang, Yuan Cao, Rif A. Saurous, and Yoon Kim. 2023. Grammar prompting for domain-specific language generation with large language models.

Yushi Wang, Jonathan Berant, and Percy Liang. 2015. Building a semantic parser overnight. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1332–1342, Beijing, China. Association for Computational Linguistics.

Zhengxuan Wu, Christopher D. Manning, and Christopher Potts. 2023. ReCOGS: How incidental details of a logical form overshadow an evaluation of semantic interpretation. Ms., Stanford University.

Frank F. Xu, Uri Alon, Graham Neubig, and Vincent Josua Hellendoorn. 2022. A systematic evaluation of large language models of code. In *Proceedings of the 6th ACM SIGPLAN International Symposium on Machine Programming*, MAPS 2022, page 1–10, New York, NY, USA. Association for Computing Machinery.

Silei Xu, Sina Semnani, Giovanni Campagna, and Monica Lam. 2020. AutoQA: From databases to QA semantic parsers with only synthetic training data. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 422–434, Online. Association for Computational Linguistics.

Yuekun Yao and Alexander Koller. 2022. Structural generalization is hard for sequence-to-sequence models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5048–5062, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Jiacheng Ye, Zhiyong Wu, Jiangtao Feng, Tao Yu, and Lingpeng Kong. 2023. Compositional exemplars for in-context learning.

Pengcheng Yin, Hao Fang, Graham Neubig, Adam Pauls, Emmanouil Antonios Platanios, Yu Su, Sam Thomson, and Jacob Andreas. 2021. Compositional generalization for neural semantic parsing via span-level supervised attention. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2810–2823, Online. Association for Computational Linguistics.

Pengcheng Yin, John Wieting, Avirup Sil, and Graham Neubig. 2022. On the ingredients of an effective zero-shot semantic parser. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1455–1474, Dublin, Ireland. Association for Computational Linguistics.

John M. Zelle and Raymond J. Mooney. 1996. Learning to parse database queries using inductive logic programming. In *AAAI/IAAI, Vol. 2*.

Li Zhang, Liam Dugan, Hainiu Xu, and Chris Callison-burch. 2023. Exploring the curious case of code prompts. In *Proceedings of the 1st Workshop on Natural Language Reasoning and Structured Explanations (NLRSE)*, pages 9–17, Toronto, Canada. Association for Computational Linguistics.

Yiming Zhang, Shi Feng, and Chenhao Tan. 2022. Active example selection for in-context learning. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9134–9148, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. 2021. Calibrate before use: Improving few-shot performance of language models. In *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 12697–12706. PMLR.

A Executable Environments

We describe the executable environments we use separately for each dataset and formalism.

A.1 Geoquery

FunQL To execute the FunQL queries, we use the GeoQuery[3] system, a prolog-based implementation that we execute using SWI-Prolog[4].

Python We manually write a Python environment that is functionally equivalent to the GeoQuery system. The environment includes two components: a class for parsing and loading the Geobase database and an API for executing queries against this database. We show the API in Figures 10 and 11.

Evaluation Running the FunQL queries with the GeoQuery system as well as the Python programs based on our API results in either a numeric result of a set of entities. We evaluate these by comparing them against the gold denotation obtained by executing the gold FunQL program for each query.

A.2 SMCalFlow

Dataflow and Dataflow-Simple We use the software provided by Meron (2022)[5] to execute Dataflow-Simple. Dataflow programs are executed by 'simplifying' them, i.e. converting them to Dataflow-Simple, using the code provided in that package. The environment holds a database with people, the relationship between them in the organization, and a list of events.

Python We run Python programs by automatically converting them to Dataflow-Simple in a determinstic method, then executing them as mentioned above. Conversion is done by implementing each of the python classes and operators with a method that returns an AST that represents a relevant Dataflow-Simple sub-tree. For example, the Python method `find_manager_of('person')` returns the corresponding AST of Dataflow-Simple's method, `FindManager('person')`.

Evaluation All of the test instances in the splits we work with are requests to create events. Thus, to evaluate programs, we compare if the events created after running a generated program is exactly the same as the event create after running the gold Dataflow program. Since programs are executed using a database, which is used, for example, to find people by their names, we populate the database with a short list of people with random names. During evaluation, we extract names of people from both generated and gold programs, and arbitrarily map and replace each name in the programs to one of the people in the database. We do this for both generated and gold programs, while making sure that mapping is consistent in both of them during an evaluation for a single example.

We ignore the generated subject of the meeting, as we found that there are many inconsistencies in the way subjects were annotated: underspecified requests such as *Set up a meeting with John* are often be annotated inconsistently, having either no subject, the subject "meeting", or something else.

A.3 Overnight

λ-DCS and λ-DCS-Simple To execute λ-DCS programs, we use Sempre.[6] Specifically, we use the executable Java program provided by Herzig and Berant (2018).[7]

Python To create the Python environment, we first use Sempre to output all entities in the 'social-network' domain. We implement the python environment to be executed over these loaded entities.

Evaluation Running the programs returns a list of entities. For all formalisms, we consider accuracy to be correct iff the list of entities is exactly the same as the list of entities returned by running the gold λ-DCS program.

B Additional Results

B.1 Exact Match Accuracy

We provide results for all DSL experiments with exact match as the metric for reference in Table 8. Note that for Geoquery, while Full DD leads to significant improvements in execution accuracy (Table 2), when measuring exact match we see less of an improvement (e.g. 37.6 to 61.0 vs 20.7 to 27.6 in the i.i.d. split). We find that this is due to correct but

[3]https://www.cs.utexas.edu/users/ml/nldata/geoquery.html
[4]https://www.swi-prolog.org/
[5]https://github.com/telepathylabsai/OpenDF
[6]https://github.com/percyliang/sempre
[7]https://github.com/jonathanherzig/zero-shot-semantic-parsing/blob/master/evaluator/evaluator.jar

different usage of the DSL, e.g. the model generates `answer(count(traverse_2(stateid('colorado'))))`, which is different from the gold program `answer(count(river(loc_2(stateid('colorado'))))).`

B.2 Accuracy vs # of Tokens

We present execution-based accuracy against the number of prompt tokens in Figure 5 for three Python DD variations.

C Program Annotations

C.1 Python

We use the prompt in Figure 6 with Python DD to generate Python programs.

C.2 Scala and Javascript

We use the prompt in Figure 6 with the Scala or Javascript DD to generate programs for the corresponding language. To further convert to Python for execution-based evaluation, we use the prompt in Figure 7. Tables 9 and 10 contain example conversions from Javascript and Scala respectively to Python for GeoQuery.

C.3 Single/Multi Line Conversion

As described in §6.2.3, we convert single-line programs to multiple lines programs with intermediate steps and vice-versa, using GPT-4. We make sure conversions are correct by validating the execution-based accuracy of converted programs; if programs are invalid, we regenerate programs with a a temperature of 0.4 until a correct solution is found. We use GPT-4 with the prompts provided in Fig. 8 and Fig. 9.

The following is an example for a conversion of a multi-line program given the utterance *"Which states have points higher than the highest point in Colorado?"*. The original annotation:

```
def answer():
    colorado_state = geo_model.find_state("colorado")
    highest_point_in_colorado = colorado_state.high_point.elevation
    states_with_higher_points = [s for s in geo_model.states if s.high_point.elevation > highest_point_in_colorado]
    return states_with_higher_points
```

The converted annotation:

```
def answer():
    return [s for s in geo_model.states if s.high_point.elevation > geo_model.find_state("colorado").high_point.elevation]
```

D Demonstration Selection Methods

We experiment with two demonstration selection methods.

Operator Coverage This method selects a single fixed set of demonstrations with maximal coverage of operators that are used for every test input. For this, we use a slightly modified version of the greedy set coverage algorithm of Gupta et al. (2023), shown in Algorithm 1. Here, the set of structures $\mathcal{S}$ is the set of all unigram operators in given formalism, and the measure of set-coverage is defined as $\texttt{setcov}(\mathcal{S}, Z) = \sum_{s\in\mathcal{S}} \max_{z\in Z} \mathbb{1}[s \in S_z]$ where S_z is the set of operators in the candidate demonstration z.

BM25 We use BM25 to retrieve the most similar instances and use as demonstrations for each test input. We use the `rank_bm25`[8] package's implementation of the Okapi variant of BM25.

Algorithm 1 Greedy Optimization of Set Coverage

```
Require: Instance pool $\mathcal{T}$; Set of structures $\mathcal{S}$; desired
    number of demonstrations $k$; coverage scoring function
    setcov
 1: $Z \leftarrow \emptyset$                                  ▷ Selected Demonstrations
 2: $Z_{curr} \leftarrow \emptyset$                            ▷ Current Set Cover
 3: curr_cov $\leftarrow -\inf$
 4: while $|Z| < k$ do
 5:     $z^*$, next_cov $= \arg\max_{z\in\mathcal{T}-Z}$ setcov $(\mathcal{S}, Z_{curr} \cup z)$
 6:     if next_cov $>$ curr_cov then                  ▷ Pick $z^*$
 7:         curr_cov $\leftarrow$ next_cov
 8:         $Z \leftarrow Z \cup z^*$
 9:         $Z_{curr} \leftarrow Z_{curr} \cup z^*$
10:     else                                          ▷ Or start new cover
11:         $Z_{curr} \leftarrow \emptyset$,  curr_cov $\leftarrow -\inf$
12:     end if
13: end while
14: return $Z$
```

E Domain Descriptions

We provide the domain descriptions that we use for each environment in the following figures:

- Geoquery: Python (10, 11), FunQL (12), Javascript (13, 14), Scala (15).
- SMCalFlow: Python (16), Dataflow (17, 18), Dataflow-Simple (19, 20), Javascript (21, 22), Scala (23).
- Overnight: Python (24) λ-DCS (25, 26), λ-DCS Simple (27), Javascript (28), Scala (29).

[8] https://github.com/dorianbrown/rank_bm25

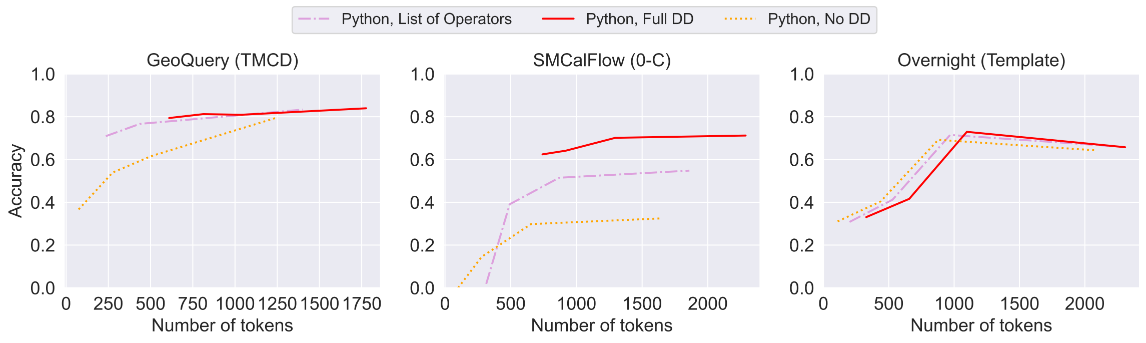


Figure 5: Execution accuracy for varying number of demonstrations, presenting the same data as Figure 3 but visualizes it against the number of prompt tokens. The effect of DDs greatly varies between the datasets. For both GeoQuery and SMCalFlow, having the Full DD is preferred whenever it can fit.

Figure 6: The prompt template we use. [DD] is replaced with the domain description for the environment being used, [query-i] and [solution-i] are replaced with utterance/output demonstrations, and [query-test] is replaced with the test utterance. Lines 1-3 are only included in experiments that contain DD.

Figure 7: The prompt template we use to convert non-Python programs (Javascript in this case) to Python for evaluation. [Python DD] and [Javascript DD] are replaced with the corresponding domain descriptions, [javascript-code-i] and [python-code-i] with demonstrations of javascript to python conversion, and [query-javascript-code] is replaced with test Javascript code to be converted.

Figure 8: Prompt used to convert single-line programs to multiple-line programs.

Figure 9: Prompt used to convert multiple-line programs to single-line programs.

Figure 10: Domain description for Geoquery, using Python. Continued in Fig. 11.

Figure 11: Domain description for Geoquery, using Python. Continued from Fig. 10.

Figure 12: Domain description for Geoquery, using FunQL.

Figure 13: Domain description for Geoquery, using Javascript. Continued in Fig. 14.

Figure 14: Domain description for Geoquery, using Javascript. Continued from Fig. 13.

Figure 15: Domain description for Geoquery, using Scala.

Figure 16: Domain description for SMCalFlow, using Python.

Figure 17: Domain description for SMCalFlow, using DataFlow. Continued in Fig. 18.

Figure 18: Domain description for SMCalFlow, using DataFlow. Continued from Fig. 17.

Figure 19: Domain description for SMCalFlow, using DataFlow Simple. Continued in Fig. 20.

Figure 20: Domain description for SMCalFlow, using DataFlow Simple. Continued from Fig. 19.

		GeoQuery				SMCalFlow-CS		Overnight	
		i.i.d.	Templ.	TMCD	Len.	i.i.d.	0-C	i.i.d.	Templ.
DSL	No DD	20.7	16.5	26.1	14.8	16.7	3.1	26.4	0.3
	List of operators	28.7	13.5	29.4	18.3	17.3	4.3	29.2	0.5
	Full DD	27.6	17.8	31.0	16.1	15.7	4.5	27.3	0.3

Table 8: Exact match accuracy of GPT-3.5-turbo for DSL-based prompts. Test set results.

Input	Directly Annotated Python Program	Javascript Program	Converted Python Program
In which state does the highest point in USA exist ?	`def answer() -> State:` `highest_point = max(geo_model.places, key=lambda x: x.elevation)` `return highest_point.state`	`function answer() {` `let highest_point_state = geo_model.states.reduce((maxState, currentState) => {` `return currentState.high_point > maxState.high_point ? currentState : maxState;` `});` `return highest_point_state.name;` `}`	`def answer() -> str:` `highest_point_state = max(geo_model.states, key=lambda x: x.high_point.elevation)` `return highest_point_state.name`
What rivers flow through the largest state ?	`def answer() -> List[River]:` `largest_state = max(geo_model.states, key=lambda x: x.size)` `return largest_state.rivers`	`function answer() {` `let largest_state = geo_model.states.reduce((maxState, currentState) => {` `return currentState.area > maxState.area ? currentState : maxState;` `});` `return largest_state.rivers;` `}`	`def answer() -> List[River]:` `largest_state = max(geo_model.states, key=lambda x: x.area)` `return largest_state.rivers`
What is the highest point in the state with the capital Des Moines ?	`def answer() -> Place:` `state = [s for s in geo_model.states if s.capital and s.capital.name == "des moines"][0]` `return state.high_point`	`function answer() {` `let des_moines_state = geo_model.find_city("des moines").state;` `return des_moines_state.high_point;` `}`	`def answer() -> Place:` `des_moines_state = geo_model.find_city("des moines").state` `return des_moines_state.high_point`

Table 9: Example conversions of predicted Javascript programs for GeoQuery to Python along with original (direct) Python annotation. Converted programs can differ from the directly annotated Python programs as the conversions were performed without the original query and hence tended to be faithful to given Javascript programs.

F Prompt Construction

We provide the prompt template that we use in Fig. 6.

Input	Directly Annotated Python Program	Scala Program	Converted Python Program
Which rivers run through states bordering New Mexico ?	`def answer() -> List[River]:` `new_mexico_state = geo_model.find_state("new mexico")` `bordering_states = new_mexico_state.next_to` `rivers = []` `for state in bordering_states:` `rivers.extend(state.rivers)` `return rivers` `}`	`def answer(): Option[List[River]] = {` `val newMexicoState = geoModel.findState("new mexico")` `val borderingStates = newMexicoState.map(_.nextTo)` `val rivers = borderingStates.map(_.flatMap(_.rivers))` `rivers` `}`	`def answer() -> List[River]:` `new_mexico_state = geo_model.find_state("new mexico")` `bordering_states = new_mexico_state.next_to` `rivers = [r for state in bordering_states for r in state.rivers]` `return rivers`
What is the most populated state bordering Oklahoma ?	`def answer() -> State:` `oklahoma_state = geo_model.find_state("oklahoma")` `return max(oklahoma_state.next_to, key=lambda x: x.population)`	`def answer(): Option[State] = {` `val oklahomaState = geoModel.findState("oklahoma")` `val borderingStates = oklahomaState.map(_.nextTo)` `borderingStates.flatMap(_.maxByOption(_.population))` `}`	`def answer() -> State:` `oklahoma_state = geo_model.find_state("oklahoma")` `bordering_states = oklahoma_state.next_to` `return max(bordering_states, key=lambda x: x.population)`
Which river goes through the most states ?	`def answer() -> River:` `return max(geo_model.rivers, key=lambda x: len(x.traverses))`	`def answer() -> def answer(): Option[River] = {` `val riverWithMostStates = geoModel.rivers.maxBy(_.traverses.length)` `riverWithMostStates` `}`	`def answer() -> River:` `return max(geo_model.rivers, key=lambda x: len(x.traverses))`

Table 10: Example conversions of predicted Scala programs for GeoQuery to Python along with original (direct) Python annotation. Converted programs can differ from the directly annotated Python programs as the conversions were performed without the original query and hence tended to be faithful to given Scala programs.

Figure 21: Domain description for SMCalFlow, using Javascript. Continued in Fig. 22.

Figure 22: Domain description for SMCalFlow, using Javascript. Continued from Fig. 21.

Figure 23: Domain description for SMCalFlow, using Scala.

Figure 24: Domain description for Overnight, using Python.

Figure 25: Domain description for Overnight, using λ-DCS. Continued in Fig. 26.

Figure 26: Domain description for Overnight, using λ-DCS. Continued from Fig. 25.

Figure 27: Domain description for Overnight, using λ-DCS Simple..

Figure 28: Domain description for Overnight, using Javascript. Continued from Fig. 21.

Figure 29: Domain description for Overnight, using Scala.