

PDL: A Declarative Prompt Programming Language

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Large language models (LLMs) have taken the world by storm by making many previously difficult uses of AI feasible. LLMs are controlled via highly expressive textual prompts and return textual answers. Unfortunately, this unstructured text as input and output makes LLM-based applications brittle. This motivates the rise of prompting frameworks, which mediate between LLMs and the external world. However, existing prompting frameworks either have a high learning curve or take away control over the exact prompts from the developer. To overcome this dilemma, this paper introduces the Prompt Declaration Language (PDL). PDL is a simple declarative *data-oriented* language that puts prompts at the forefront, based on YAML. PDL works well with many LLM platforms and LLMs. It supports writing interactive applications that call LLMs and tools, and makes it easy to implement common use-cases such as chatbots, RAG, or agents. We hope PDL will make prompt programming simpler, less brittle, and more enjoyable.

1 Introduction

Large language models (LLMs) have made great advances, demonstrating the ability to perform a wide range of useful tasks. As LLMs are controlled via natural-language *prompts*, prompt engineering has emerged as an ad-hoc approach to improve accuracy [31]. Even more capabilities can be unlocked with prompting patterns such as in-context learning [6], chaining multiple LLM calls [7], retrieval-augmented generation (RAG) [18], tool use [28], program-aided language models (PAL) [10], and agents [34]. Unfortunately, while powerful, LLMs remain brittle: they sometimes hallucinate, or even fail to comply with expected syntax and types.

Prompting frameworks [20] make it easier for developers to use LLMs and associated prompting patterns while ameliorating their brittleness. Some, such as LangChain [7] and AutoGen [32], do so via bespoke features for popular patterns such as RAG or agents. Unfortunately, this bespoke nature takes control over basic prompts away from users and forces them to learn many complex framework features. In contrast, low-level prompting frameworks, such as Guidance [23] and LMQL [5], provide more control with syntax and types. Unfortunately, they require users to program in imperative languages such as Python or TypeScript. At the other end of the spectrum, frameworks such as DSPy [15] and Vieira [19] avoid hand-written prompts altogether by automatically generating them. Unfortunately, this takes away even more control from the developer. The problem thus becomes how to make LLM programming less brittle while keeping it simple and keeping the developer in the driver's seat.

To tackle this problem, we turned to tried-and-true programming language design ideas. The principle of *orthogonality* advocates for a small set of simple features that compose in powerful ways [30]. Being orthogonal, or at right angles, here means being irredundant and avoiding exceptional cases as far as possible. For prompting frameworks, orthogonality is a way to avoid bespoke features. Next, developers need to struggle less with brittleness if the language checks *types* and *roles* [12] to enforce structure by construction. One remaining tension is harder to tackle: on the one hand, we want to give developers control over the exact prompts, but on the other hand, we want a simple *declarative* language. To this end, we settled on a *data-oriented language*, which puts prompts at the forefront by intentionally blurring the line between programs (e.g. for chaining and tools) and data (for prompts). This is inspired by the old idea of code as data [21], as well as by seminal work on programming without tiers [8].

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This paper introduces the Prompt Declaration Language (PDL), an orthogonal and typed data-oriented language. Unlike other prompting languages that are embedded in imperative languages, PDL is based on YAML [4]. YAML is a data serialization format that is both human-readable (by promoting a nice and simple syntax for unstructured strings) while also providing structure (by being JSON-compatible). Variables in PDL also hold JSON values and can optionally be typed with JSON Schema [25]. PDL is currently implemented by an interpreter, and the interpreter performs dynamic type checking. One benefit of representing programs as data is that it facilitates program transformations [22], such as for optimization. Rendering programs in a data representation format even facilitates PDL programs that generate PDL programs with LLMs, similar to PAL [10].

PDL programs comprise blocks (YAML objects), where each block appends data to the prompt context. This mental model is a natural fit for prompting techniques such as chatbots or agents: program execution implicitly builds up a conversation or trajectory, without necessitating explicit plumbing. This context then becomes the input to the next LLM call. PDL supports local LLMs, and LLMs hosted by various providers, including but not limited to open-source Granite models [1, 11] on IBM watsonx¹ and on Replicate². PDL provides control constructs for looping and conditionals, as well as functions and file includes for modularity. PDL adopts Jinja2 [26] expressions to template not just prompts but entire programs.

This paper gives a quick overview of PDL by means of an introductory example (Section 2), followed by a tour of the language (Section 3). It describes the tooling for running and editing PDL programs (Section 4) and offers case studies illustrating more uses of PDL (Section 5). Finally, the paper discusses related work (Section 6) and concludes (Section 7). PDL is open-source and available at <https://github.com/IBM/prompt-declaration-language>. Overall, PDL is a simple yet powerful new language for LLM prompt programming.

2 Overview

This section gives an overview of PDL features by means of a chatbot example. A PDL program executes a sequence of *blocks*, each of which generates data that it contributes to the background context. There are different kinds of blocks, capable of generating data in different ways: model calls, reading data from stdin or a file, directly creating various kinds of JSON data, and executing code. In addition, there are a variety of control blocks (if-then-else, for, and repeat) that let PDL users express rich data pipelines and AI applications.

Fig. 1(a) shows the PDL code for a simple chatbot. The **read:** block on Lines 1–4 prints a message asking the user to enter a query, which it reads from stdin. Fig. 1(b) shows an execution trace of the same program. For instance, the user might ask ‘What’s a language salad?’. To avoid duplication, the **contribute:** [context] clause puts the user response into the background context but not the result (printed on stdout).

The **repeat:until:** block on Lines 5–16 has one nested **text:** block, which in turn has a sequence of two nested blocks. The **text:** block turns the results of its nested blocks into strings and concatenates them. The **model:** block on Lines 7–9 calls an LLM, using the accumulated context so far as the prompt. In the first loop iteration, that context comprises only two lines ‘What is your query?’ and ‘What’s a language salad?’. The **stop:** [\n\n] model parameter causes the LLM to stop producing tokens after generating two consecutive newline characters. The LLM interpreter prints LLM outputs in green; Fig. 1(b) shows that in this example, the LLM produced ‘A language salad is [...]’. The **read:** block on Lines 10–15 prints a message using YAML’s multi-line string syntax starting with a vertical bar (|). This example illustrates how PDL keeps prompts at the forefront

¹<https://www.ibm.com/watsonx>

²<https://replicate.com/>

<pre> 1 - read: 2 contribute: [context] 3 message: 4 What is your query? 5 - repeat: 6 text: 7 - model: watsonx/ibm/granite-13b-chat-v2 8 parameters: 9 stop: ["\n\n"] 10 - def: question 11 read: 12 contribute: [context] 13 message: 14 15 Enter a query or say "quit" to exit. 16 until: \${question == "quit"} </pre>	<pre> What is your query? What's a language salad? A language salad is a term used to describe a mix of different languages and dialects in a single conver- sation or piece of text. It can be seen as an [...] Enter a query or say "quit" to exit. Say it as a poem! In a world where many tongues are sown, A language salad is born, in joy they're grown. A medley of words, in harmony flow, Swirling colors of speech, in a vibrant show. Enter a query or say "quit" to exit. quit </pre>
(a) Code	(b) Interpreter trace

Fig. 1. Simple Chatbot in PDL

while making them readable and giving the developer precise control. The interpreter trace on the right shows the user entering ‘Say it as a poem!’, which Line 10 on the left uses to define variable `question` and Line 12 appends to the context. The `until` clause on Line 16 specifies a Jinja2 expression ‘`${question == "quit"}`’ as the loop termination condition. PDL embeds Jinja2 templates using ‘`${...}`’ syntax rather than ‘`{{...}}`’ because the latter interacts poorly with YAML, where curly braces are special characters.

In the second loop iteration, the context includes the effect of the first loop iteration. Hence, the second execution of the `model` block sees the output from its first execution and can paraphrase it as a poem, ‘`In a world where many tongues [...]`’ in Fig. 1(b). Finally, in this example, during the second execution of the `read` block the user entered ‘quit’, causing the loop to terminate. Now that we have seen a few common PDL blocks in action (`read`, `repeat`, `text`, and `model`), we can proceed to Section 3, which describes the remaining blocks and language features.

3 Language

PDL is a language embedded into YAML such that every PDL program is a valid YAML document following the PDL schema³. Fig. 2 is a quick reference of PDL, and this section explains it using grammar rules. A program is a block or a list of blocks where blocks are expressions or structured blocks, as expressed by the following grammar rules:

```

pdl   ::= block | [block, ..., block]
block ::= expression | structured_block

```

All grammar rules in this section use YAML’s flow-style syntax (e.g., `[block, ..., block]`). The same PDL code can also be rendered in YAML’s block-style syntax, e.g.:

```

- block
...
- block

```

Each block has a block body, with keywords indicating the block kind (e.g., `model` or `read`). There are 15 kinds of block bodies (optional fields are annotated with a question mark):

³<https://ibm.github.io/prompt-declaration-language/dist/pdl-schema.json>

LLM call with current context	Including a PDL file	Optional keywords for any block
<code>model: watsonx/ibm/granite-13b-chat-v2</code> <code>parameters:</code> <code> temperature: 0.1</code>	<code>include: ./helper_defs.pdl</code>	<code>description:</code> documentation text <code>def: x</code> # define variable from block <code>defs:</code> # define multiple variables <code> x: v1</code> <code> y: v2</code> <code>role: user</code> # or system or assistant <code>contribute:</code> [result, context] # or less <code>parser:</code> json # or json1, yaml, regex <code>spec:</code> type # type specification
LLM call with explicit input	Declaring and calling functions	spec Types (shorthand for JSON Schema)
<code>model: watsonx/ibm/granite-13b-chat-v2</code> <code>parameters:</code> <code> temperature: 0.1</code> <code>input:</code> <code> array:</code> <code> - role: user</code> <code> content: Hello,</code>	<code>def: add</code> <code>function:</code> <code> x: int</code> <code> y: int</code> <code>return: \$(x + y)</code> <code>call: add</code> <code>args:</code> <code> x: 2</code> <code> y: 2</code> <code>pdl_context:</code> [] # optional	Basic types str, int, float, bool, null Arrays [int] Objects {x: int, y: int} Enums {enum: [red, green, blue]}
Reading from a file or stdin	Control constructs (all lists use implicit lastOf)	Basic types
<code>read:</code> # optionally, add file name <code>message:</code> Please enter an input. <code>multiline:</code> true # omit to stop at \n	<code>if: \$(x > 0)</code> <code> then:</code> positive <code> else:</code> non-negative <code>for:</code> # outputs 2_0_5 <code> i:</code> [1, 0, 1] <code> j:</code> [2, 3, 5] <code>repeat:</code> \${i * j} <code>join:</code> <code> with:</code> _ # optional <code>repeat:</code> # implicit lastOf, outputs HoHoHo <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> # outputs HiHoHiHoHiHo <code> text:</code> <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> <code> def: x</code> <code> read:</code> <code>until:</code> \${x trim} == "stop"]	Arrays [int] Objects {x: int, y: int} Enums {enum: [red, green, blue]}
Creating data (v1, v2 can be any block)	Control constructs (all lists use implicit lastOf)	Arrays/objects
<code>text:</code> # outputs "v1v2" <code> - v1</code> <code> - v2</code> <code>lastOf:</code> # outputs v2 <code> - v1</code> <code> - v2</code> <code># implicit lastOf, outputs v2</code> <code>- v1</code> <code>- v2</code> <code>array:</code> # outputs [v1, v2] <code> - v1</code> <code> - v2</code> <code>object:</code> # outputs {k1: v1, k2: v2} <code> k1: v1</code> <code> k2: v2</code> <code>data:</code> # outputs {k1: v1, model: v2} <code> k1: v1</code> <code> model: v2</code> # no LLM call	<code>if: \$(x > 0)</code> <code> then:</code> positive <code> else:</code> non-negative <code>for:</code> # outputs 2_0_5 <code> i:</code> [1, 0, 1] <code> j:</code> [2, 3, 5] <code>repeat:</code> \${i * j} <code>join:</code> <code> with:</code> _ # optional <code>repeat:</code> # implicit lastOf, outputs HoHoHo <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> # outputs HiHoHiHoHiHo <code> text:</code> <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> <code> def: x</code> <code> read:</code> <code>until:</code> \${x trim} == "stop"]	Variables x, y[0], z.f Operators +, -, *, /, //, %, **, -, and, or, not, ==, <, >, in
Creating data (v1, v2 can be any block)	Control constructs (all lists use implicit lastOf)	Tests
<code>text:</code> # outputs "v1v2" <code> - v1</code> <code> - v2</code> <code>lastOf:</code> # outputs v2 <code> - v1</code> <code> - v2</code> <code># implicit lastOf, outputs v2</code> <code>- v1</code> <code>- v2</code> <code>array:</code> # outputs [v1, v2] <code> - v1</code> <code> - v2</code> <code>object:</code> # outputs {k1: v1, k2: v2} <code> k1: v1</code> <code> k2: v2</code> <code>data:</code> # outputs {k1: v1, model: v2} <code> k1: v1</code> <code> model: v2</code> # no LLM call	<code>if: \$(x > 0)</code> <code> then:</code> positive <code> else:</code> non-negative <code>for:</code> # outputs 2_0_5 <code> i:</code> [1, 0, 1] <code> j:</code> [2, 3, 5] <code>repeat:</code> \${i * j} <code>join:</code> <code> with:</code> _ # optional <code>repeat:</code> # implicit lastOf, outputs HoHoHo <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> # outputs HiHoHiHoHiHo <code> text:</code> <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> <code> def: x</code> <code> read:</code> <code>until:</code> \${x trim} == "stop"]	Filters x default(0)
Creating data (v1, v2 can be any block)	Control constructs (all lists use implicit lastOf)	Executing code
<code>text:</code> # outputs "v1v2" <code> - v1</code> <code> - v2</code> <code>lastOf:</code> # outputs v2 <code> - v1</code> <code> - v2</code> <code># implicit lastOf, outputs v2</code> <code>- v1</code> <code>- v2</code> <code>array:</code> # outputs [v1, v2] <code> - v1</code> <code> - v2</code> <code>object:</code> # outputs {k1: v1, k2: v2} <code> k1: v1</code> <code> k2: v2</code> <code>data:</code> # outputs {k1: v1, model: v2} <code> k1: v1</code> <code> model: v2</code> # no LLM call	<code>if: \$(x > 0)</code> <code> then:</code> positive <code> else:</code> non-negative <code>for:</code> # outputs 2_0_5 <code> i:</code> [1, 0, 1] <code> j:</code> [2, 3, 5] <code>repeat:</code> \${i * j} <code>join:</code> <code> with:</code> _ # optional <code>repeat:</code> # implicit lastOf, outputs HoHoHo <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> # outputs HiHoHiHoHiHo <code> text:</code> <code> - Hi</code> <code> - Ho</code> <code>num_iterations:</code> 3 <code>repeat:</code> <code> def: x</code> <code> read:</code> <code>until:</code> \${x trim} == "stop"]	<code>lang:</code> python <code>code:</code> <code> result = "Hello, world!"</code>

Fig. 2. PDL Quick Reference

```

block_body ::= model: expression, input: ?pdl, parameters: ?expression
| read: file, message: ?string, message: ?bool
| text: pdl
| lastOf: pdl
| array: pdl
| object: pdl
| data: json
| include: file
| function: args, return: pdl
| call: f, args: args
| if: expression, then: pdl, else: ?pdl
| for: args, repeat: pdl, join: ?join
| repeat: pdl, num_iterations: n, join: ?join
| repeat: pdl, until: expression, join: ?join
| code: pdl, lang: string
    
```

We already saw `model:` and `read:` blocks in the previous section. A `model:` block calls an LLM. The prompt comes from the current context, unless the optional `input:` field is specified, in which case it comes from there. The optional `parameters:` configure the model inferencing behavior. A `read:` block reads input from a file or from stdin if no file name is specified. The optional `message:` is displayed to the user and the optional `multiline:` field determines whether to stop at newline.

There are five kinds of blocks for creating data: `text:`, `lastOf:`, `array:`, `object:`, and `data:`. Fig. 2 illustrates them on simple examples. A plain list of blocks without a keyword behaves like `lastOf:`.

The difference between an **object**: block and a **data**: block is that the PDL interpreter ignores PDL keywords in the latter, treating them like plain JSON fields instead.

For modularity, PDL supports **include**: blocks and functions. An **include**: block opens the PDL program at the given relative path and adds its output at the place where it occurred. Function arguments have the following syntax:

```
args ::= {x: expression, ..., x: expression}
```

Each $x: expression$ maps an argument name to either a type specification (in a **function**: definition) or a value (in a function call:). The **return**: keyword provides the function body, which can have nested blocks; Fig. 2 shows a simple case where it is just a Jinja2 expression. The optional **pdl_context**: keyword can reset the background context for the duration of a call, e.g. to the empty context [].

There are three kinds of blocks for control constructs: **if**:, **for**:, and different flavors of **repeat**:. They can have nested blocks or simple expressions, and if they contain a list of blocks, that list implicitly behaves like **lastOf**:. If the **lastOf**: behavior is not intended, a common idiom is to wrap the body of a loop in a **text**: block, or to combine loop iteration results with the **join**: keyword:

```
join ::= as:?(text | array | lastOf), with:? string
```

Each of the 15 kinds of block bodies described above can be orthogonally composed with zero or more optional keywords that work for any block:

```
structured_block ::= { block_body,
                      description:?string,
                      def: ?x,
                      defs: ?defs,
                      role: ?string,
                      contribute: ?contribute,
                      parser: ?parser,
                      spec: ?type }
```

A **description**: is a special comment. A **def**: assigns the result of the block to a variable; we already saw an example for that in Line 10 of Fig. 1. In contrast, **defs**: creates multiple variable definitions, each with its own name x and a value given by a nested PDL program:

```
defs ::= {x: pdl, ..., x: pdl}
```

A **role**: causes the data resulting from a block to be decorated with a role, such as ‘user’, ‘assistant’, or ‘system’. When PDL calls a chat model, it follows common practice of modern chat APIs and passes not a flat string as the prompt, but rather, a sequence of {content:str, role:str} pairs. Then, the model API applies a model-specific chat template, which flattens that sequence by inserting the appropriate control tokens for that model [12]. This gives PDL programs some degree of model-independence. If a block does not have an explicit **role**:, it defaults to ‘assistant’ for model blocks and to ‘user’ for all other blocks. Inner nested blocks have the same role as their outer enclosing block. In future work, we also plan to leverage roles for privilege-based security.

The **contribute**: keyword can specify a (possibly empty) subset of the two destinations ‘result’ or ‘context’. By default, every block contributes to both its own result and the background context for later LLM calls. Line 2 of Fig. 1 showed an example of limiting the contribution of a block to just the context to declutter the output.

The **parser**: keyword makes it possible for a block that would ordinarily just produce a flat string (e.g., an LLM call) to instead produce structured data. The supported parsers are json, yaml, regex, and jsonl. The **spec**: keyword can specify a type. PDL’s types are a subset of JSON Schema [25], with shorthand syntax for simple commonly used types illustrated in Fig. 2. For example, type ‘{questions: [str], answers: [str]}’ is an object with two fields questions and answers, both of which

hold arrays of strings. Section 5 will illustrate how `parser:` and `spec:` can work together. Future work will also leverage these keywords for constrained decoding [29].

An atomic block is an expression:

$$\textit{expression} ::= \textit{bool} \mid \textit{number} \mid \textit{string} \mid \${jinj\!a_expression} \mid \textit{string_expression}$$

Expressions can be basic values, Jinja2 expressions [26], or strings containing Jinja expressions. Jinja2 is a convenient way for specifying prompt templates, where parts of a prompt are hardcoded and others are filled in from expressions. But PDL takes the use of Jinja2 further, by letting developers template not just individual prompts, but entire chains of model calls and other blocks. While we refer the reader to the Jinja2 documentation for an exhaustive list of possible expressions, Fig. 2 briefly lists the most common ones. PDL adopts only Jinja2 expressions, not Jinja2 statements such as `{% if .. %}` or `{% for .. %}`, because those are redundant with PDL’s own `if:` and `for:`.

Last but not least, PDL has a `code:` block that allows it to execute code in a given programming language (at the time of writing, only Python is supported). The next section will describe PDL tooling, including the interpreter, which provides a sandboxing feature to reduce risks associated with executing arbitrary code. To learn more, see the tutorial linked from PDL’s github repository.

4 Tooling

PDL comes with tools for making PDL programs easy to write, run, and understand.

First and foremost, the PDL *interpreter* is an execution engine with a command-line interface, as one would expect from a scripting language. The interpreter supports a streaming mode, where LLM outputs become visible incrementally as they are being produced, for a more interactive chat experience. The interpreter also supports sandboxing, which causes it to launch in a container, recommended when executing LLM-generated actions or code.

The PDL *IDE support* enhances VSCode, making it easier to write PDL code via syntax highlighting, auto-complete, tooltips for PDL keywords, and error checking. These capabilities are, in part, driven by the PDL meta-schema i.e., the JSON schema that defines what constitutes valid PDL.

The `%pdl cell magic` enhances Jupyter Notebooks so developers can write code cells directly in PDL. That way, hosted notebook platforms can serve as a simple playground for interactively exploring prompts. Given multiple PDL code cells in the same notebook, later cells can use variables defined in earlier cells. Furthermore, the background context for later cells is continued from earlier cells; when not desired, developers can override this behavior via `%pdl --reset-context`.

The PDL *live document visualizer* shows the concrete execution trace of a PDL program with colored nested boxes, similar to typical figures in papers or blog posts about LLM prompting. Then, the user can select one of the boxes to display the corresponding PDL code, similar to how spreadsheet cells show data, but the user can select them to inspect the formula that created that data. This live view is a way to let users quickly understand concrete data, and then move from that to understanding the code that produced it.

Finally, PDL has an *SDK* (software development kit), which is a small Python library for calling from Python into PDL. This is useful for extending larger Python applications to use prompt-based programs, such as agents. As discussed in Section 3, a PDL file can contain Python in `code:` blocks. When developing larger applications with PDL, we have found it useful to keep these to a few lines of code, by defining a function in a separate Python file and then calling it from PDL. A good practice is to pass data from PDL to Python and vice versa as JSON objects. Optionally, this can be type-checked using the `spec:` keyword in PDL, and TypedDict or Pydantic on the Python side, as illustrated in the next section in Fig. 3.

```

1 text:
2 - lang: python
3 code: |
4   import rag_mbpp
5   PDL_SESSION.mbpp = rag_mbpp.initialize()
6   result = ""
7 - defs:
8   test_query: >-
9     Write a python function to remove first and
10    last occurrence of a given character from
11    the string.
12 retrieved:
13   lang: python
14   spec: [{query: str, answer: str}]
15   code: |
16     import rag_mbpp
17     result = rag_mbpp.retrieve(
18       PDL_SESSION.mbpp, "${test_query}", 5
19     )
20 text: >
21   Given the text after "Q:", generate a Python
22   function after "A:".
23
24   Here are some examples, complete the last one:
25 - for:
26   few_shot_sample: ${retrieved}
27 repeat: |
28   Q: ${few_shot_sample.query}
29   A: ```${few_shot_sample.answer}```
30 - |-
31   Q: ${test_query}
32   A:
33 - model: watsonx/ibm/granite-3-8b-instruct
34 parameters:
35   stop: ["Q:", "A:"]

```

(a) PDL code

```

1 from typing import TypedDict
2 import datasets
3 from sklearn.feature_extraction.text \
4   import TfidfVectorizer
5
6 def initialize():
7   train_in = datasets.load_dataset(
8     "mbpp", "sanitized", split="train"
9   )
10  corpus = [row["prompt"] for row in train_in]
11  tfidf = TfidfVectorizer().fit(corpus)
12  def embed(text):
13    sparse_result = tfidf.transform(
14      raw_documents=[text]
15    )
16    return sparse_result.toarray().flatten()
17  train_em = train_in.map(
18    lambda row: {"em": embed(row["prompt"])})
19  )
20  vec_db = train_em.add_faiss_index("em")
21  return vec_db, embed
22
23  QA = TypedDict("QA", {"query":str,"answer":str})
24  def retrieve(mbpp, query, n: int) -> list[QA]:
25    vec_db, embed = mbpp
26    key = embed(query)
27    nearest = vec_db.get_nearest_examples(
28      "em", key, n
29    )
30    queries = nearest.examples["prompt"]
31    answers = nearest.examples["code"]
32    return [
33      {"query": q, "answer": a}
34      for q, a in zip(queries, answers)
35    ]

```

(b) Python code

Fig. 3. RAG example in PDL

5 Case Studies

We already saw a simple PDL chatbot example in Section 2. This section illustrates slightly more advanced use-cases for PDL: RAG, agents, and generating PDL from PDL.

5.1 Retrieval-Augmented Generation

Retrieval-augmented generation, or *RAG*, works by first retrieving relevant context, then adding that to the prompt for a model to generate an answer [18]. Fig. 3(a) shows a PDL program that uses RAG to retrieve few-shot samples for a code-generation task. The `code` block in Lines 2–6 uses Python to initialize a vector database for the training split of the MBPP dataset of “mostly basic Python programs” [2]. It uses a Python function defined in Fig. 3(b), together with a `PDL_SESSION` special variable that enables it to carry state to a later code block. Lines 8–11 of Fig. 3(a) initialize variable `test_query` with a natural-language request for Python code to be generated. Lines 12–19 initialize variable `retrieved` with the five most similar samples from the training data.

```

1 text:
2 - read: react_few_shot_samples.txt
3 - |
4
5 When was the discoverer of the Hudson River born?
6 - repeat:
7   text:
8   - def: thought
9     model: watsonx/ibm/granite-34b-code-instruct
10    parameters:
11      stop: ["Act:"]
12      include_stop_sequence: true
13   - def: action
14     model: watsonx/ibm/granite-34b-code-instruct
15     parameters:
16       stop: ["\n"]
17     parser: json
18     spec: {name: str, arguments: {topic: str}}
19   - def: observation
20     if: ${ action.name == "Search" }
21     then:
22       text:
23       - "Obs: "
24       - lang: python
25       code: |
26         import wikipedia
27         query = "${ action.arguments.topic }"
28         result = wikipedia.summary(query)
29   until: ${ action.name != "Search" }

```

(a) Code

```

What is the elevation range for the area that the
eastern sector of the Colorado orogeny extends
into?
Tho: I need to search Colorado orogeny, find the
area that the eastern sector of the Colorado [...]
Act: {"name": "Search", "arguments": {"topic":
"Colorado orogeny"}}
Obs: The Colorado orogeny was an episode [...]
[...]

```

```

When was the discoverer of the Hudson River
born?
Tho: I need to search the discoverer of the Hud-
son River, find when he was born.
Act: {"name": "Search", "arguments": {"topic": "dis-
coverer of the Hudson River"}}
Obs: The Hudson River is a 315-mile [...]
Tho: The discoverer of the Hudson River is Henry
Hudson. I need to search Henry Hudson, find
when he was born.
Act: {"name": "Search", "arguments": {"topic":
"Henry Hudson"}}
Obs: Henry Hudson (c. 1565 – disappeared [...]
Tho: Henry Hudson was born in 1565. Act:
{"name": "Finish", "arguments": {"topic": "1565"}}

```

(b) Interpreter trace

Fig. 4. ReAct agent in PDL

Lines 20–24 add an instruction to the context, Lines 25–29 add the few-shot samples to the context, and Lines 30–32 add the test query to the context. The `for` loop on Line 25 is an idiomatic way to use PDL for generating data, in this case, for in-context learning. Finally, Lines 33–35 call a Granite 3 model [11] with the accumulated context, causing it to generate the Python function requested by the test query. While this is a simple example, we have also used PDL with Codellm-Devkit [16], which performs static analysis on source code from various programming languages to retrieve other relevant context when prompting LLMs for coding tasks.

5.2 ReAct Agent

An LLM-based *agent* lets an LLM select and configure *actions*, executes those actions in an *environment*, and feeds the outputs from the actions back to the LLM as *observations*. There are different patterns for such agents, such as ReAct [34] and ReWOO [33]. An action is an LLM-based *tool call* [28], and an agent chains together multiple tool calls in a dynamic LLM-directed sequence. The ambition is to make AI-based applications less prescriptive and more goal-driven. Moreover, when something goes wrong with an action, agents can use the observation as feedback to recover.

Fig. 4 shows a PDL example of a simple ReAct agent. The core of ReAct is a think-act-observe loop, which manifests in the code as variable definitions for *thought* (Line 8), *action* (Line 13), and *observation* (Line 19). The *thought* is model-generated natural language e.g., ‘*I need to search the discoverer of the Hudson River, find when he was born*’ in the interpreter trace in Fig. 4(b). The

`action` is model-generated JSON to match the tool-use training data of Granite models [1]. Lines 17 and 18 on the left ensure that the LLM output is parsed as JSON and conforms to a `{name, arguments}` schema, and the interpreter trace on the right shows that the model indeed generates such an object. That makes it possible to access fields of the object with Jinja2, such as `$(action.arguments.topic)` on Line 27. The `observation` is generated by the environment, in this case, Python code calling Wikipedia. As discussed in Section 4, for cases like this that involve running code (partially) generated by an LLM, we recommended PDL’s sandboxing feature.

The interpreter trace in Fig. 4(b) shows that this execution had two iterations of the agentic loop. While this is a simple example, we have also used PDL to implement a code editing agent that we used as part of a submission⁴ to the SWE-bench Lite leaderboard [14]. This submission was the first to resolve 23.7% of instances with only open-source models, which is higher than any previous results with open-source models, and in the same ball-park as frontier models.

5.3 Generating PDL from PDL with LLMs

The previous sections showed examples of how a human developer can use PDL to encode different prompting patterns. This section turns to LLMs and shows how they can also be used to generate PDL. This meta PDL generation is helpful when LLMs need to create a plan for solving a problem, for example as part of an agentic workflow. Traditionally, such plans are just text or JSON or Python code. With PDL, these plans can be a composition of model and code calls that are fully executable. This section explores using PDL meta generation for the GSMHard dataset⁵.

GSMHard is a harder version of GSM8k, which consists of grade-school math problems that require simple arithmetic or symbolic reasoning. GSMHard contains an input which is a math problem statement, together with an output which is Python code that solves the problem. We implemented the PAL [10] approach but instead of generating Python code, we ask an LLM to generate PDL. The textual chain-of-thought is represented as PDL text blocks, and arithmetic is done using PDL code blocks.

Fig. 5 shows a PDL program that generates PDL code and executes it all in the same program. The `demos` variable holds few-shot samples designed to teach a model how to generate PDL code. On Line 32, a model call block uses these samples, together with a `question` , which is a free variable, as input. The result is a PDL program to solve the question. Line 38 extracts the PDL program and executes it in Python. This program is applied to the GSMHard dataset, where `question` is filled with input questions.

This experiment resulted in the discovery that 10% of the GSMHard dataset is actually incorrect in the sense that the ground truth is inconsistent with the question that was asked. Fig. 6 shows an example of such an inconsistency. Using PDL helped in this discovery because the generated PDL code is human-readable, so we were able to easily check data points that did not match the ground truth and found that the ground truth is incorrect in some cases. We used an LLM to cover the entire dataset and systematically pick examples that seemed inconsistent. We then manually filtered the result to remove false positives and identified 10% of data points that present this problem.

6 Related Work

A recent survey defines a *prompting framework* as a layer that manages, simplifies and facilitates the interaction between LLMs and users, tools, or other models [20]. The survey highlights that a major pitfall of prompting frameworks is increasingly steep learning curves.

⁴https://github.com/swe-bench/experiments/tree/main/evaluation/lite/20241016_IBM-SWE-1.0

⁵<https://huggingface.co/datasets/reasoning-machines/gsm-hard>

```

1  defs:
2    demos:
3      data:
4        text:
5          |
6          ...
7
8      Question: Roger has 5 tennis balls.
9      He buys 2 more cans of tennis balls.
10     Each can has 3 tennis balls.
11     How many tennis balls does he have now?
12
13     Answer:
14     ```
15     text:
16     - "Roger started with\n"
17     - def: tennis_balls
18       data: 5
19     - "\ntennis ball.\n"
20     - "2 cans of 3 tennis balls each is\n"
21     - lang: python
22       def: bought_balls
23         code: result = 2 * 3
24     - "\ntennis balls.\n"
25     - "The result is: \n"
26     - lang: python
27       def: RESULT
28         code: result = ${ tennis_balls } + ${ bought_balls }
29     ...
30     raw: true
31   text:
32   - model: watsonx/meta-llama/llama-3-70b-instruct
33     def: PDL
34     input:
35       text:
36         - ${ demos.text }
37         - "Question: ${ question }"
38     - lang: python
39       code: |
40         from pdl.pdl import exec_str
41         s = """"${ PDL }""""
42         pdl = s.split("```")[1]
43         result = exec_str(pdl)
44     def: RESULT

```

Fig. 5. PDL meta generation

James decides to run 1793815 sprints
1793815 times a week.
He runs 60 meters each sprint.
How many total meters does he run a week?

```

def solution():
    sprints_per_day = 1793815
    days_per_week = 3
    meters_per_sprint = 60
    total_sprints = sprints_per_day * days_per_week
    total_meters = total_sprints * meters_per_sprint
    result = total_meters
    return result

```

Fig. 6. GSMHard sample problematic data point

Perhaps the most popular prompting framework today is LangChain [7], whose extensive features make it both powerful and complex. Avoiding this complexity is the main motivation for MiniChain [27], which offers fewer, simpler features that can be composed for advanced use-cases. However, both LangChain and MiniChain are Python frameworks, making them less declarative, since developers must write imperative code. PDL has a similar motivation to MiniChain, but goes a step further, by adopting YAML instead of Python as its foundation.

Like other prompting frameworks, PDL aims to make LLMs less brittle. Guidance [23] is a Python-based framework that provides more structure but is more low-level than LangChain. Similarly, LMQL [5] is a domain-specific language embedded in Python that leverages types and constrained decoding. PDL takes some inspiration from the latter in how it intersperses prompts and programs, but unlike LMQL, relies less on imperative Python code. Crouse et al. use finite state machines to formally specify the internals of various agentic loops [9]; while fascinating, this work does not introduce a full-fledged prompting language.

One advantage of domain-specific languages is that they enable program transformation, e.g., for optimization [22]. The DSPy prompting framework [15] has the tag-line “programming, not prompting”: it finds prompts automatically so developers need not write them by hand. Similarly, Vieira [19] extends Prolog with LLMs as probabilistic relations, for which it automatically derives prompts. Both DSPy and Vieira are very high-level, but unlike PDL, both take away control from the developer over exact prompts. One language that lets users gradually adjust this tradeoff between automation and control for AI pipelines is Lale [3]; however, Lale does not focus on LLM prompting in particular. Whereas DSPy, Vieira, and Lale optimize for predictive performance, another objective to optimize for is computational performance. SGLang [35] does that by scheduling to better leverage prefix caching (to get more cache hits in a KV cache [17]). Future work will explore whether PDL’s declarative nature can enable similar computational performance optimizations.

Recently, a new crop of prompting framework has emerged that focuses on LLM-based agents. AutoGen [32] is a multi-agent framework where everything consists of agents and conversations. Other multi-agent frameworks include CrewAI [24] and GPTSwarm [36]. These frameworks prioritize support for agents over support for other LLM-based use-cases. While PDL supports agents as well, it aims for a more balanced stance, where agents are just one of many prompting techniques.

7 Conclusion

PDL is a declarative data-oriented language: a program consists of YAML blocks, where each block either is a literal piece of data or produces data. The mental model is that executing a block appends its data to the background context, and subsequent LLM calls use that context as their prompt. This paper introduces the language via example programs and a tour of the grammar and tooling. The declarative nature of the language also makes it amenable to automatic optimizations for speed, accuracy, and security, which will be forthcoming in future work. PDL is ready to use and open-source at <https://github.com/IBM/prompt-declaration-language>.

References

- [1] Ibrahim Abdelaziz, Kinjal Basu, Mayank Agarwal, Sadhana Kumaravel, Matthew Stallone, Rameswar Panda, Yara Rizk, GP Bhargav, Maxwell Crouse, Chulaka Gunasekara, Shajith Iqbal, Sachin Joshi, Hima Karanam, Vineet Kumar, Asim Munawar, Sumit Neelam, Dinesh Raghu, Udit Sharma, Adriana Meza Soria, Dheeraj Sreedhar, Praveen Venkateswaran, Merve Unuvar, David Cox, Salim Roukos, Luis Lastras, and Pavan Kapanipathi. 2024. Granite-Function Calling Model: Introducing Function Calling Abilities via Multi-task Learning of Granular Tasks. <https://arxiv.org/abs/2407.00121>
- [2] Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, and Charles Sutton. 2021. Program Synthesis with Large Language Models. <https://arxiv.org/abs/2108.07732>
- [3] Guillaume Baudart, Martin Hirzel, Kiran Kate, Parikshit Ram, Avraham Shinnar, and Jason Tsay. 2021. Pipeline Combinators for Gradual AutoML. In *Advances in Neural Information Processing Systems (NeurIPS)*. 19705–19718. <https://proceedings.neurips.cc/paper/2021/file/a3b36cb25e2e0b93b5f334ffb4e4064e-Paper.pdf>
- [4] Oren Ben-Kiki, Clark Evans, and Brian Ingerson. 2004. YAML Ain’t Markup Language. <http://yaml.org/spec/history/2004-12-28/2004-12-28.pdf>
- [5] Luca Beurer-Kellner, Marc Fischer, and Martin Vechev. 2023. Prompting Is Programming: A Query Language for Large Language Models. In *Conference on Programming Language Design and Implementation (PLDI)*. 1946–1969. <https://doi.org/10.1145/3591300>

- [6] 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. <https://arxiv.org/abs/2005.14165>
- [7] Harrison Chase et al. 2022. LangChain. <https://github.com/langchain-ai/langchain>
- [8] Ezra Cooper, Sam Lindley, Philip Wadler, and Jeremy Yallop. 2006. Links: Web Programming Without Tiers. In *Symposium on Formal Methods for Components and Objects (FMCO)*. 266–296. https://doi.org/10.1007/978-3-540-74792-5_12
- [9] Maxwell Crouse, Ibrahim Abdelaziz, Ramon Astudillo, Kinjal Basu, Soham Dan, Sadhana Kumaravel, Achille Fokoue, Pavan Kapanipathi, Salim Roukos, and Luis Lastras. 2024. Formally Specifying the High-Level Behavior of LLM-Based Agents. <https://arxiv.org/abs/2310.08535>
- [10] Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon, Pengfei Liu, Yiming Yang, Jamie Callan, and Graham Neubig. 2023. PAL: Program-aided Language Models. In *International Conference on Machine Learning (ICML)*. 10764–10799. <https://proceedings.mlr.press/v202/gao23f.html>
- [11] Granite Team, IBM. 2024. Granite 3.0 Language Models. <https://github.com/ibm-granite/granite-3.0-language-models/blob/main/paper.pdf>
- [12] Hugging Face. 2023. Chat Templates. https://huggingface.co/docs/transformers/en/chat_templating
- [13] IBM. 2023. watsonx. <https://www.ibm.com/watsonx>
- [14] Carlos E. Jimenez, John Yang, Alexander Wettig, Shunyu Yao, Kexin Pei, Ofir Press, and Karthik Narasimhan. 2024. SWE-bench: Can Language Models Resolve Real-World GitHub Issues?. In *International Conference on Learning Representations (ICLR)*. <https://openreview.net/forum?id=VTF8yNQm66>
- [15] Omar Khattab, Arnab Singhvi, Paridhi Maheshwari, Zhiyuan Zhang, Keshav Santhanam, Sri Vardhamanan, Saiful Haq, Ashutosh Sharma, Thomas T. Joshi, Hanna Moazam, Heather Miller, Matei Zaharia, and Christopher Potts. 2023. DSPy: Compiling Declarative Language Model Calls into Self-Improving Pipelines. <https://arxiv.org/abs/2310.03714>
- [16] Rahul Krishna, Rangeet Pan, Raju Pavuluri, Srikanth Tamilselvam, Maja Vukovic, and Saurabh Sinha. 2024. Codellm-Devkit: A Framework for Contextualizing Code LLMs with Program Analysis Insights. <https://arxiv.org/abs/2410.13007>
- [17] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph Gonzalez, Hao Zhang, and Ion Stoica. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention. In *Symposium on Operating Systems Principles (SOSP)*. 611–626. <https://doi.org/10.1145/3600006.3613165>
- [18] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. In *Conference on Neural Information Processing Systems (NeurIPS)*. 9459–9474. <https://proceedings.neurips.cc/paper/2020/hash/6b493230205f780e1bc26945df7481e5-Abstract.html>
- [19] Ziyang Li, Jiani Huang, Jason Liu, Felix Zhu, Eric Zhao, William Dodds, Neelay Velingker, Rajeev Alur, and Mayur Naik. 2024. Relational Programming with Foundation Models. In *Conference on Artificial Intelligence (AAAI)*. 10635–10644. <https://doi.org/10.1609/aaai.v38i9.28934>
- [20] Xiaoxia Liu, Jingyi Wang, Jun Sun, Xiaohan Yuan, Guoliang Dong, Peng Di, Wenhai Wang, and Dongxia Wang. 2023. Prompting Frameworks for Large Language Models: A Survey. <https://arxiv.org/abs/2311.12785>
- [21] John McCarthy. 1960. Recursive functions of symbolic expressions and their computation by machine, Part I. *Communications of the ACM (CACM)* 3, 4 (April 1960), 184–195. <https://doi.org/10.1145/367177.367199>
- [22] Marjan Mernik, Jan Heering, and Anthony M. Sloane. 2005. When and how to develop domain-specific languages. *ACM Computing Surveys (CSUR)* 37, 4 (2005), 316–344. <https://doi.org/10.1145/1118890.1118892>
- [23] Microsoft. 2023. {guidance}: A guidance language for controlling large language models. <https://github.com/langchain-ai/langchain>
- [24] João Moura. 2023. CrewAI: Framework for orchestrating role-playing, autonomous AI agents. <https://github.com/crewAIInc/crewAI>
- [25] Felipe Pezoa, Juan L. Reutter, Fernando Suarez, Martín Ugarte, and Domagoj Vrgoč. 2016. Foundations of JSON Schema. In *International Conference on World Wide Web (WWW)*. 263–273. <https://doi.org/10.1145/2872427.2883029>
- [26] Armin Ronacher. 2008. Jinja2 Documentation Release 2.0. <http://mitsuhiko.pocoo.org/jinja2docs/Jinja2.pdf>
- [27] Alexander Rush. 2023. MiniChain: A Small Library for Coding with Large Language Models. In *Conference on Empirical Methods in Natural Language Processing: System Demonstrations (EMNLP-Demo)*. 311–317. <https://aclanthology.org/2023.emnlp-demo.27/>
- [28] Timo Schick, Jane Dwivedi-Yu, Roberto Dessi, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. 2023. Toolformer: Language Models Can Teach Themselves to Use Tools. In *Advances in Neural Information Processing Systems (NeurIPS)*. https://proceedings.neurips.cc/paper_files/paper/2023/hash/d842425e4bf79ba039352da0f658a906-Abstract-Conference.html

- [29] Torsten Scholak, Nathan Schucher, and Dzmitry Bahdanau. 2021. PICARD: Parsing Incrementally for Constrained Auto-Regressive Decoding from Language Models. In *Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 9895–9901. <https://doi.org/10.18653/v1/2021.emnlp-main.779>
- [30] A. van Wijngaarden, B.J. Mailloux, J.E.L. Peck, C.H.A. Koster, M. Sintzoff, C.H. Lindsey, L.G.T. Meertens, and R.G. Fisker. 1977. Revised Report on the Algorithmic Language ALGOL 68. *ACM SIGPLAN Notices* 12, 5 (May 1977), 1–70. <https://doi.org/10.1145/954652.1781176>
- [31] Jules White, Quchen Fu, Sam Hays, Michael Sandborn, Carlos Olea, Henry Gilbert, Ashraf Elnashar, Jesse Spencer-Smith, and Douglas C. Schmidt. 2023. A Prompt Pattern Catalog to Enhance Prompt Engineering with ChatGPT. <https://arxiv.org/abs/2302.11382>
- [32] Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun Zhang, Jiale Liu, Ahmed Hassan Awadallah, Ryen W White, Doug Burger, and Chi Wang. 2023. AutoGen: Enabling Next-Gen LLM Applications via Multi-Agent Conversation. <https://arxiv.org/abs/2308.08155>
- [33] Bin Feng Xu, Zhiyuan Peng, Bowen Lei, Subhabrata Mukherjee, and Dongkuan Xu. 2023. Decoupling Reasoning from Observations for Efficient Augmented Language Models. <https://openreview.net/forum?id=CpgoO6j6W1>
- [34] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik R Narasimhan, and Yuan Cao. 2023. ReAct: Synergizing Reasoning and Acting in Language Models. In *International Conference on Learning Representations (ICLR)*. https://openreview.net/forum?id=WE_vluYUL-X
- [35] Lianmin Zheng, Liangsheng Yin, Zhiqiang Xie, Jeff Huang, Chuyue Sun, Cody Hao Yu, Shiyi Cao, Christos Kozyrakis, Ion Stoica, Joseph E. Gonzalez, Clark Barrett, and Ying Sheng. 2023. Efficiently Programming Large Language Models using SGLang. <https://arxiv.org/abs/2312.07104>
- [36] Mingchen Zhuge, Wenyi Wang, Louis Kirsch, Francesco Faccio, Dmitrii Khizbullin, and Jürgen Schmidhuber. 2024. GPTSwarm: Language Agents as Optimizable Graphs. In *International Conference on Machine Learning (ICML)*. <https://openreview.net/forum?id=uTC9AFXlhg>