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# DSPy: Compiling Declarative Language Model Calls into Self-Improving Pipelines

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## Abstract

The ML community is rapidly exploring techniques for prompting language models (LMs), but existing LM pipelines often rely on hard-coded “prompt templates” discovered via trial and error. We introduce DSPy, a programming model that abstracts LM pipelines as imperative computation graphs where LMs are invoked through *declarative* modules. DSPy modules are *parameterized* so they can learn to apply compositions of prompting, finetuning, augmentation, and reasoning techniques. We design a compiler that will optimize any DSPy pipeline to maximize a given metric. We conduct two case studies and show that a few lines of DSPy allow GPT-3.5 and llama2-13b-chat to self-bootstrap pipelines that outperform standard few-shot prompting and pipelines with expert-created demonstrations. DSPy is available at <https://github.com/stanfordnlp/dspy>.

## 1 Introduction

Improvements for language models (LMs) are fueling an exploding space of “prompting” techniques [Wei et al., 2022, Wang et al., 2022b, Lazaridou et al., 2022, Yao et al., 2022], and interest has been growing in building multi-stage *pipelines* and *agents* that decompose complex tasks into more manageable calls to LMs in an effort to improve performance [Qi et al., 2019, Khattab et al., 2021a, Karpas et al., 2022, Dohan et al., 2022, Khot et al., 2022, Pourreza and Rafiei, 2023]. Unfortunately, LMs are known to be sensitive to how they are prompted, so LM calls in existing pipelines and frameworks are generally implemented via hard-coded ‘prompt templates’. These are long strings of instructions and demonstrations, hand crafted via trial and error. This can be brittle and unscalable: a prompt might not generalize to different pipelines or across different LMs, domains, or even inputs.

We propose the **DSPy programming model** (Sec 3),<sup>1</sup> which translates string-based prompting techniques into declarative modules that carry *natural-language typed signatures*. DSPy modules are task-adaptive components—akin to neural network layers—that abstract text transformation, like answering a question or summarizing a paper. We then parameterize each module so that it can *learn* its desired behavior by bootstrapping useful demonstrations within the pipeline. Inspired by PyTorch

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<sup>1</sup>DSPy is pronounced *dee-ess-pie*. It’s the second iteration of our earlier Demonstrate–Search–Predict framework (DSP; Khattab et al. 2022). This paper introduces the key concepts in DSPy. For more extensive and up-to-date documentation of the framework, we refer readers to <https://github.com/stanfordnlp/dspy>.

abstractions [Paszke et al., 2019], DSPy modules can be composed in imperative *define-by-run* computational graphs, by using them in any logical control flow like if statements and loops. We then develop the **DSPy compiler** (Sec 4), which optimizes any DSPy program to improve quality or cost. Given a validation metric and some training inputs, the compiler simulates versions of the program on the inputs and *bootstraps* example traces of each module for self-improvement, using them to construct effective few-shot prompts or finetuning small LMs for steps of the pipeline. Optimization in DSPy is conducted by *teleprompters*:<sup>2</sup> generic optimization strategies that map declarative modules to *high-quality* compositions of prompting, finetuning, reasoning, and augmentation.

We report on two expansive case studies: math word problems (GMS8K; Cobbe et al. 2021) and multi-hop question answering (HotPotQA; Yang et al. 2018) with explorations of chain of thought, multi-chain reflection, multi-hop retrieval, and retrieval-augmented question answering. We find that very short DSPy programs can bootstrap self-improving multi-stage NLP systems using LMs as small as llama2-13b-chat and T5-Large (770M parameters). Without hand-crafted prompts and within tens of minutes of compiling, compositions of DSPy modules can raise the quality of simple programs from 33% to 82% (Sec 5) and from 32% to 46% (Sec 6) for GPT-3.5 and, similarly, from 9% to 47% (Sec 5) and from 22% to 41% (Sec 6) for llama2-13b-chat.

## 2 Related Work

In-context learning methods now routinely invoke tools like retrieval [Chen et al., 2017, Lewis et al., 2020, Guu et al., 2020, Lazaridou et al., 2022, Izacard et al., 2022], APIs [Nakano et al., 2021], and calculators. Toolkits have been developed to facilitate this, including LangChain [Chase, 2022], Semantic Kernel [Microsoft, 2023], LlamaIndex [Liu, 2022].

While these toolkits provide accessible chains, agents, and tools, they express behavior through hand-written prompt templates (Appendix D). In parallel, researchers are exploring discrete optimization and RL to find effective prompts, generally for one LM call [Guo et al., 2023, Pryzant et al., 2023, Huang et al., 2022, Yang et al., 2023]. DSPy aims to generalize this space with a framework for optimizing *arbitrary pipelines* from *high-level declarative signatures*, by bootstrapping *high-quality multi-stage demonstrations*.

## 3 The DSPy Programming Model

We present DSPy, which treats LMs as abstract devices for text generation,<sup>3</sup> and optimizes their usage in arbitrary computational graphs. DSPy programs are expressed in Python: each program takes the task input (e.g., a question to answer or a paper to summarize) and returns the output (e.g., answer or summary) via some steps. DSPy contributes three abstractions for automatic optimization: Signatures abstract the input/output behavior of a module; modules replace hand-prompting techniques and can be composed in pipelines; and teleprompters optimize pipelines to maximize a metric.

### 3.1 Natural Language Signatures can abstract prompting & finetuning

Instead of prompts, DSPy programs use natural language *signatures* to assign work to the LM. This is a short declarative spec that tells DSPy *what* a text transformation needs to do (e.g., “consume questions and return answers”), rather than *how* an LM should be prompted to implement that. More formally, a DSPy signature is a tuple of *input fields* and *output fields* (and an optional *instruction*). A field consists of *field name* and optional metadata. The roles of fields are inferred by DSPy via field names, e.g. DSPy will use in-context learning to interpret question differently from answer and will iteratively refine their usage.

Signatures offer two benefits over prompts: they can be compiled into self-improving and pipeline-adaptive prompts or finetunes. This is primarily done by bootstrapping (Sec 4) useful demonstrating examples for each signature. Additionally, they handle structured formatting and parsing logic to reduce (or, ideally, avoid) brittle string manipulation in user programs. DSPy signatures can be expressed with a shorthand notation like `question -> answer`.

<sup>2</sup>We derive the name *tele*-prompters from the notion of abstracting and automating the task of prompting, in particular, such that it happens *at a distance*, without manual intervention.

<sup>3</sup>We assume access to one or more LMs, which consume a prompt string and return text completions. This may be a promptable LM capable of in-context learning (e.g., GPT-3.5 or Llama2-7b) or a smaller finetuneable LM (e.g., T5-base). An LM may be selected as the default; operations will use it unless configured otherwise.

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```

1 qa = dspy.Predict("question -> answer")
2 qa(question="Where is Guaraní spoken?")
3 # Out: Prediction(answer='Guaraní is spoken mainly in South America.')
```

---

In the shorthand notation, each field’s name indicates the semantic role that the input (or output) field plays in the transformation. DSPy will parse this notation and expand the field names into meaningful instructions for the LM, so that `english_document -> french_translation` would prompt for English to French translation. When needed, DSPy offers more advanced programming interfaces for expressing more explicit constraints on signatures (Appendix C).

### 3.2 Parameterized & templated Modules can abstract prompting techniques

To use a signature, we must declare a *module* with that signature. The core module in DSPy is `Predict` (simplified pseudocode in Appendix F.1). Like layers in PyTorch, the module behaves as a callable function: it takes in arguments corresponding to the signature inputs (e.g., `question`), formats a prompt and includes bootstrapped demonstrations, calls the LM, and parses the outputs. When `Predict` is used in compile mode, it will track input/output traces to assist teleprompters.

DSPy modules translate prompting techniques into modular functions that support any signature, instead of requiring hand-written instructions and/or few-shot examples. DSPy includes a number of modules like `ChainOfThought`, `MultiChainComparison`, and `ReAct`.<sup>4</sup> Modules can be used interchangeably to implement a DSPy signature. Simply changing `Predict` to `ChainOfThought` in the above program leads to a system that thinks step by step before committing to its output field.

These modules themselves are implemented in a few lines of DSPy code. We show a simplified implementation of the built-in `ChainOfThought` in Appendix F.2. Expressed in seven lines (excluding comments), this is a fully-fledged module capable of learning effective few-shot prompting for any LM or task. We contrast that with Appendix E, which copies long reasoning prompts hand-written in recent research and popular libraries.

Uniquely, DSPy *parameterizes* these prompting techniques. To understand this parameterization, observe that any LM call seeking to implement a particular signature needs to specify *parameters* that include: (1) the specific LM to call [Chen et al., 2023], (2) the prompt instructions [Yang et al., 2023] and the string prefix of each signature field and, most importantly, (3) the demonstrations used as few-shot prompts (for frozen LMs) or as training data (for finetuning). We focus primarily on automatically generating and selecting useful demonstrations, and find that bootstrapping good demonstrations gives us a powerful way to teach sophisticated pipelines of LMs new behaviors.

DSPy modules can be composed in arbitrary pipelines in a define-by-run interface. Inspired by PyTorch, one declares the modules needed at initialization, so DSPy tracks them for optimization, and then one expresses arbitrary code that calls the modules in a forward method. DSPy programs may use tools, e.g. retrieval models through a `dspy.Retrieve` module.

As a simple illustration, we offer the following simple but complete retrieval-augmented generation (RAG) system.

---

```

1 class RAG(dspy.Module):
2     def __init__(self, num_passages=3):
3         # 'Retrieve' will use the user's default retrieval settings unless overridden.
4         self.retrieve = dspy.Retrieve(k=num_passages)
5         # 'ChainOfThought' with signature that generates answers given retrieval & question.
6         self.generate_answer = dspy.ChainOfThought("context, question -> answer")
7     def forward(self, question):
8         context = self.retrieve(question).passages
9         return self.generate_answer(context=context, question=question)
```

---

To highlight modularity, we use `ChainOfThought` as a drop-in replacement of the basic `Predict`. One can now simply write `RAG()("Where is Guaraní spoken?")` to use it. Notice that, if we use a signature `"context, question -> search_query"`, we get a system that generates search queries rather than answers.

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<sup>4</sup>These modules generalize prompting techniques from the literature, respectively, by Wei et al. [2022], Yoran et al. [2023], and Yao et al. [2022] and, in doing so, generalize the ideas on zero-shot prompting and rationale self-generation from Kojima et al. [2022], Zelikman et al. [2022], Zhang et al. [2022], and Huang et al. [2022] to parameterized modules that can bootstrap arbitrary multi-stage pipelines.

### 3.3 Teleprompters can automate prompting for arbitrary pipelines

We compile a DSPy program by invoking a *teleprompter*: an optimizer that uses a training set and a metric, and returns a new optimized program. Different teleprompters (Sec 4) apply different strategies.

Training sets may be small, and training examples may be *incomplete*, i.e., only *input* values are necessary. We typically assume labels only for (at most) the program’s final output, not intermediate pipeline steps. This is critical for modularity: building a new pipeline in DSPy requires simply *recompiling* the new pipeline’s code, not annotating new pipeline data. Metrics can be simple like exact match (EM), but they can be entire DSPy programs that balance multiple concerns.

```
1 # Small training set with only questions and final answers.
2 qa_trainset = [dspy.Example(question="What is the capital of France?", answer="Paris")]
3 # The teleprompter will bootstrap missing labels: reasoning chains and retrieval contexts.
4 teleprompter = dspy.BootstrapFewShot(metric=dspy.evaluate.answer_exact_match)
5 compiled_rag = teleprompter.compile(RAG(), trainset=qa_trainset)
```

The example above compiles RAG above against a dataset of question–answer pairs with the metric EM to bootstrap few-shot demonstrations. The BootstrapFewShot teleprompter (Sec 4, Appendix G.1) simulates RAG on the training examples, collecting *demonstrations* of each module that collectively lead to valid output (i.e., respecting the signatures and the metric).

## 4 The DSPy Compiler

Compiling relies on a teleprompter, which improves modules via prompting or finetuning. Typical teleprompters go through three stages. For **candidate generation**, the compiler recursively finds all Predict modules (predictors) in a program. For each predictor  $p$ , the teleprompter generates candidate demonstrations (i.e., input–output pairs). For instance, the simple BootstrapFewShot teleprompter (simplified pseudocode in Appendix G.1) will simulate a teacher program (or, if unset, the zero-shot version of the program) on training inputs, possibly multiple times with a high temperature. The program’s metric is used to filter for multi-stage traces that help the pipeline pass the metric, yielding potential labels for all signatures in the program.

For **parameter optimization**, hyperparameter tuning algorithms (e.g., random search or Tree-structured Parzen Estimators as in HyperOpt [Bergstra et al., 2013] and Optuna [Akiba et al., 2019]) can be applied for selecting among candidate demonstrations. We report simplified implementations of BootstrapFewShotWithRandomSearch and BootstrapFewShotWithOptuna in Appendix G.2 and Appendix G.3. Another optimization type is *finetuning* with BootstrapFinetune where demonstrations are used to update the LM’s weights per module. This all is applicable even with no labels for any stages, depending on the metric.

A different type of optimization that the DSPy compiler supports is **higher-order program optimization**, i.e. modifying the control flow of the program. Of the simplest forms of these are ensembles, which bootstrap multiple copies of the program then return a new program that runs them all in parallel and *reduces* their predictions (e.g., using majority voting).

## 5 Case Study: Math Word Problems

We evaluate on the GSM8K dataset with math word problems [Cobbe et al., 2021]. We sample 200 and 300 examples from the official training set as train/dev, respectively. We report extensive comparisons on the dev set, and evaluate promising representatives of each approach on the test set.

**Programs Considered** We consider three simple DSPy programs: a one-step Predict module (vanilla), a two-step ChainOfThought module (CoT), and a multi-stage reflection module.

```
1 vanilla = dspy.Predict("question -> answer") # GSM8K Program 'vanilla'
2 CoT = dspy.ChainOfThought("question -> answer") # GSM8K Program 'CoT'
```

In reflection, five reasoning chains are sampled from the LM (alongside their answers) and they are compared in parallel by a built-in MultiChainComparison module, which generalizes Yoran et al. [2023]. This generates a new answer taking into account the patterns from the five attempts. Critically, the modules used are all generic, none is specific to math problems or particular LM.

Table 1: Results with in-context learning on GSM8K math word problems. Each row represents a separate pipeline: the module in the Program column is compiled against the examples in the Training set. The programs, compilers, and (small) training sets are defined in Section 5.

Program	Compilation	Training	GPT-3.5-turbo-instruct		Llama2-13b-chat	
			Dev	Test	Dev	Test
vanilla	none	n/a	24.0	25.2	7.0	9.4
	fewshot	trainset	33.1	–	4.3	–
	bootstrap	trainset	44.0	–	28.0	–
	bootstrap×2	trainset	64.7	61.7	37.3	36.5
	+ensemble	trainset	62.7	61.9	39.0	34.6
CoT	none	n/a	56.0	–	26.7	–
	fewshot	trainset	65.1	–	27.3	–
	fewshot	+human_CoT	78.6	72.4	34.3	33.7
	bootstrap	trainset	80.3	72.9	43.3	–
	+ensemble	trainset	<b>88.3</b>	81.6	43.7	–
reflection	none	n/a	65.0	–	36.7	–
	fewshot	trainset	71.7	–	36.3	–
	bootstrap	trainset	83.0	76.0	44.3	40.2
	+ensemble	trainset	86.7	–	<b>49.0</b>	<b>46.9</b>

```

1 class ThoughtReflection(dspy.Module):
2     def __init__(self, num_attempts):
3         self.predict = dspy.ChainOfThought("question -> answer", n=num_attempts)
4         self.compare = dspy.MultiChainComparison('question -> answer', M=num_attempts)
5     def forward(self, question):
6         completions = self.predict(question=question).completions
7         return self.compare(question=question, completions=completions)
8
9 reflection = ThoughtReflection(num_attempts=5) # GSM8K Program 'reflection'

```

**Compiling** In our experiments, we evaluate the programs zero-shot (no compiling) as well as a number of strategies for compiling. Our simplest compiler is LabeledFewShot.

```

1 fewshot = dspy.LabeledFewShot(k=8).compile(program, trainset=trainset)

```

This samples  $k=8$  random demonstrations from the trainset for the fields common to the training examples and the signature(s) in the program—in this case, question and answer, but not the reasoning for instance. We average 3–5 runs (depending on the setting) when applying such random sampling. Next, we also consider bootstrapping few-shot examples with random search:

```

1 tp = BootstrapFewShotWithRandomSearch(metric=gsm8k_accuracy)
2 bootstrap = tp.compile(program, trainset=trainset, valset=devset)

```

This generates demonstration chains for examples in the training set and self-improves the program’s modules via random search, treating the selection of demonstrations as a parameter to optimize. Next, if desired, this bootstrapping process can be nested in DSPy. In particular, we can use the optimized bootstrap program itself to further bootstrap another program. This is relevant, for example, whenever the original zero-shot program performs relatively poorly.

```

1 bootstrap2 = tp.compile(program, teacher=bootstrap, trainset=trainset, valset=devset)

```

And lastly, we consider *ensembling* these bootstraps:

```

1 ensemble = Ensemble(reduce_fn=dspy.majority).compile(bootstrap.programs[:7])

```

GSM8K includes human reasoning chains. Above, trainset does not include these reasoning chains. We also evaluate with trainset\_human\_CoT, which extends the examples in trainset with the human reasoning string. These two datasets can be used interchangeably as the value for the trainset parameter above. We note here that compiling generally runs on the order of tens of minutes as even the more expensive settings only require running the program a few thousand times (e.g., 10–20 trials over 150–300 validation examples) and they can occur in parallel.



**Results** As in Table 1, the vanilla program shows that the LMs struggle when they have to predict answers without a reasoning chain. This is pronounced in the zero-shot (none) and fewshot settings. Interestingly, vanilla is helped substantially by compiling with bootstrap and by iterating this into bootstrap $\times 2$ . We find that the prompts bootstrapped (Appendix H) leverage the answer field for reasoning first, as the metric extracts the final numerical value for evaluation.

Next, we consider the CoT program. While expert human reasoning (+human\_CoT) provides a large boost when available, we can match or surpass this using bootstrap, supporting our hypothesis that DSPy can cut the need for hand-crafted prompts. The reflection program, while only a few lines long, is a clear winner, though CoT is quite effective with ensemble. Overall, the bootstrap compilation procedure leads to large gains for every program, across both LMs. Indeed, all programs in this table are expressed by composing two to four DSPy modules and teleprompters, and they reveal overall that—in the new paradigm prescribed by DSPy—composing the right generic *modules*, rather than manipulating string prompts, can improve different LMs from 4–20% accuracy to 49–88% accuracy.

On this task, Zhang et al. [2022] reports 47% (48%) for text-davinci-002 with manual (automatic) CoT, which is close to our results with the small llama2-13b-chat. They reports 59% (63%) with codex via manual (automatic) CoT. The Llama2 authors [Touvron et al., 2023] presents 28.7% for llama2-13b, 42.2% for llama2-34b, and 56.8% for llama2-70b. Our program with the 13b variant of the model is competitive with their 34b-based results even though we don’t use human reasoning chains in our program. Zhao et al. [2023b] reports 80.8% for CoT with gpt-3.5-turbo from April 2023. The GPT-4 authors [OpenAI, 2023] reports 92% for GPT-4 but they note that GPT-4 was pre-trained on a subset of GSM8K’s training set.

## 6 Case Study: Complex Question Answering

We now explore multi-hop question answering with HotPotQA [Yang et al., 2018] in the open-domain “fullwiki” setting. We retrieve with a ColBERTv2 [Santhanam et al., 2021] search index of the official Wikipedia 2017 “abstracts” dump of HotPotQA. The HotPotQA test set is hidden, so we reserve the official dev set for our testing, and sample 1000 examples for that. For training and for reporting development results, we sample 200 and 300 examples from the “hard” subset of the training set, which matches the designation of the official dev and test sets.

**Programs Considered** Our simplest baseline is the vanilla program used in the previous case study on GSM8K (Sec 5); the “question  $\rightarrow$  answer” signature is universal enough that it will work for this task (and many others) when compiled appropriately. Our baseline RAG program is the one given in Section 3 as a simple example of RAG with a dspy.ChainOfThought layer. We also test the following custom program, which simulates the information flow in Baleen [Khattab et al., 2021a] and IRRR [Qi et al., 2020] and has similarities to IRCOT [Trivedi et al., 2022].

```

1 class BasicMultiHop(dspy.Module):
2     def __init__(self, passages_per_hop):
3         self.retrieve = dspy.Retrieve(k=passages_per_hop)
4         self.generate_query = dspy.ChainOfThought("context, question -> search_query")
5         self.generate_answer = dspy.ChainOfThought("context, question -> answer")
6
7     def forward(self, question):
8         context = []
9         for hop in range(2):
10             query = self.generate_query(context=context, question=question).search_query
11             context += self.retrieve(query).passages
12         return self.generate_answer(context=context, question=question)
13
14 multihop = BasicMultiHop(passages_per_hop=3)

```

**Compiling** For compilers, we continue to use the ones that we used for GSM8K (see Sec 5). We also consider two compositions of our teleprompters. For the multihop program, we also consider fine-tuning with T5-Large starting from the earlier bootstrap of that program.

```

1 multihop_t5 = dspy.BootstrapFinetune(metric=answer_exact_match).compile(program,
    teacher=bootstrap, trainset=trainset, target='t5-large')

```

**Results** Table 2 summarizes our results. Compared with the vanilla few-shot prompting, a chain-of-thought and retrieval-augmented generation (CoT\_RAG) program can self-bootstrap in DSPy to

Table 2: Results with in-context learning on HotPotQA multi-hop retrieval question answering. We report answer exact match (Ans) and pair-retrieval accuracy (Psg). For HotPotQA, we use the training set (not dev) for cross-validation. \*The marked result is evaluated on 50% of our test set due to cost.

Program	Compiler	GPT-3.5-turbo-instruct				Llama2-13b-chat			
		Dev		Test		Dev		Test	
		Ans	Psg	Ans	Psg	Ans	Psg	Ans	Psg
vanilla	fewshot	34.3	n/a	31.5	n/a	27.5	n/a	21.8	n/a
CoT_RAG	fewshot	36.4	36.0	29.8	34.4	34.5	36.0	28.0	34.4
	bootstrap	42.3	36.0	–	–	38.3	36.0	32.9	34.4
multihop	fewshot	36.9	38.3	31.2	40.8	34.7	32.0	31.3	30.8
	bootstrap	<b>48.7</b>	<b>47.0</b>	<b>39.6</b>	<b>43.8</b>	<b>42.0</b>	<b>48.3</b>	<b>36.4</b>	<b>43.5</b>
	ensemble	<b>54.7</b>	–	<b>45.6*</b>	–	<b>50.0</b>	–	<b>41.0</b>	–

increase answer EM substantially. However, this relies entirely on the ColBERTv2 retriever to find relevant passages directly from the original questions, limiting its passage recall. Indeed, a simple multihop program performs better, and in general bootstrap again proves to be very effective at raising its quality relative to its fewshot variant for both LMs. Perhaps most importantly, we can make llama2-13b-chat competitive with GPT-3.5 by simply compiling our programs.

To assess DSPy at finetuning, we also evaluated the compiler multihop\_t5 defined above which produces a T5-Large (770M parameter) model. This program scores 39.3% answer EM and 46.0% passage accuracy on the dev set using only 200 labeled inputs and 800 unlabeled questions. For compiling, we use a teacher program consisting of an ensemble (union) of two multihop with llama2-13b-chat. This compiled program with T5-Large would impose orders of magnitude lower costs for inference than GPT-3.5.

Our results may be informally compared against a number of recent papers, though there is significant variation in methodology and test samples across studies. Using CoT prompting, Si et al. [2022] achieve 25.2% EM. With a “recite-and-answer” technique that uses PaLM-62B [Chowdhery et al., 2022], Sun et al. [2022] achieve 26.5% EM. Wang et al. [2022a] achieve 33.8% EM and 44.6% F1 when applying self-consistency for PaLM-540B. Yao et al. [2022] achieve 27.4% EM using ReAct with PaLM-540B and 30.8 with text-davinci-002, with a Wikipedia search API. They push their PaLM results to 35.1% EM by applying an additional CoT step with self-consistency, which resembles our ensemble approach in aggregating multiple answers. Trivedi et al. [2022] report 49% using a pipeline with code-davinci-002 on a sample of 500 questions.

## 7 Conclusion

This paper introduced DSPy, a new programming model for designing AI systems using pipelines of pretrained LMs and other tools. We presented three new concepts introduced in this abstraction (DSPy signatures, modules, and teleprompters), and showed in two very different case studies that it supports rapid development of highly effective systems that use relatively small LMs. We have maintained open-source versions of this framework for close to a year. In this period, we have seen and created a large number of programs that were compiled to high-quality systems by DSPy, spanning tasks from information extraction to low-resource synthetic data generation. In the interest of space and to maintain reasonable scope in this paper, we leave reporting on such tasks under controlled experimental conditions to future work. While in-context learning has proved transformative over the past 2–3 years of LM research, we argue that the true expressive power in this emerging paradigm is in building sophisticated text transformation graphs in which composable modules and optimizers (teleprompters) come together to leverage LMs in more systematic and reliable ways.

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## A Extended Related Work

This work is inspired by the role that Torch [Collobert et al., 2002], Theano [Bergstra et al., 2010, 2011, Al-Rfou et al., 2016], Chainer [Tokui et al., 2015], and others played in the development in deep learning by providing powerful abstractions. A similar transformation is emerging with higher-level pipelines of LMs, and we are seeking to offer a solid conceptual framework and programming abstractions for what we call *foundation model programming*. We draw on differentiable programming [Wang et al., 2018] but applied to LM calls rather than neural networks, and borrow syntactic elements from PyTorch [Paszke et al., 2019].

In-context learning (McCann et al. 2018, Radford et al. 2018, Brown et al. 2020) is a key mechanism for foundation model programming. A growing body of work has revealed that, especially with instruction tuning [Ouyang et al., 2022], we can elicit sophisticated behavior via prompting [Wei et al., 2022, Wang et al., 2022b, Press et al., 2022, Yao et al., 2022, Khot et al., 2022, Madaan et al., 2023]. Similarly, forms of weak supervision that would normally require task-specific [Khattab et al., 2021a,b] or hand-built [Ratner et al., 2016, Hancock et al., 2018] heuristics are now done by LMs [Wang et al., 2022b, Zelikman et al., 2022, Zhang et al., 2022, Shao et al., 2023].

In-context learning methods now routinely invoke tools, leading to LM pipelines that use retrieval models [Chen et al., 2017, Lewis et al., 2020, Guu et al., 2020, Lazaridou et al., 2022, Izacard et al., 2022], multimodal foundation models, and more traditional tools like APIs [Nakano et al., 2021] and calculators. A number of toolkits have been developed to facilitate this, including LangChain [Chase, 2022], Semantic Kernel [Microsoft, 2023], LlamaIndex [Liu, 2022], and many other retrieval and agent libraries. These toolkits provide pre-packaged chains and agents that connect LMs with numerous accessible tools. However, they suffer from the pervasive prompt engineering challenges we address in DSPy: they express task-specific behavior through hand-written prompt templates (for detailed discussion, see Appendix D).

Researchers are starting to apply discrete optimization and RL to find effective prompts, generally for a single logical LM call [Guo et al., 2023, Pryzant et al., 2023, Huang et al., 2022, Yang et al., 2023]. DSPy seeks to generalize this space: it offers a rich framework for optimizing *arbitrary pipelines* from *high-level declarative signatures*, by bootstrapping high-quality *multi-stage demonstrations* with constraints. In this framework, DSPy teleprompters may apply optimization using model selection techniques like cross-validation or, in principle, with sophisticated techniques involving RL and LM feedback [Hu et al., 2023, Zhao et al., 2023a, Shinn et al., 2023] or learned or Bayesian hyperparameter optimization methods [Bergstra et al., 2013, Akiba et al., 2019].

The present paper seeks to motivate DSPy as a programming model and to report new empirical findings from applying the DSPy compiler. This is inspired by formative work by Bergstra et al. [2010, 2013], Paszke et al. [2019], and Wolf et al. [2020], who support their respective programming models with a mix of benchmark numbers and some qualitative measures. For the current paper, we focus on showing that DSPy and its compiler allow us to build outstanding LM systems without hand-crafted prompt strings, but instead from truly modular units, and that this opens up doors for systematically exploring a rich design space at a very high programmatic level of abstraction.

## B Goals of Evaluation

Programming frameworks can be evaluated along many dimensions: computational efficiency, developer efficiency, intuitiveness of the code and concepts, and so forth. In this paper, we focus on perhaps the most pressing issue for current LM pipelines: the role of hand-written, task-specific prompts in achieving performant systems. Our evaluations seek to test the following hypotheses:

- H1** With DSPy, we can replace hand-crafted prompt strings with concise and well-defined modules, without reducing quality or expressive power.
- H2** Parameterizing the modules and treating prompting as an optimization problem makes DSPy better at adapting to different LMs, and it may outperform expert-written prompts.
- H3** The resulting modularity makes it possible to more thoroughly explore complex pipelines that have useful performance characteristics or that fit nuanced metrics.

Our evaluation will explore these hypotheses using diverse task–program pairs. We hope this begins a shift from underspecified questions like “how do different LMs compare on GSM8K” toward “how they compare on GSM8K with program P when compiled with strategy S”, which is a well-defined and reproducible run. Ultimately, our goal is to reduce the role of artful prompt construction in modern AI in favor of the development of new modular, composable programs and optimizers.



## C Advanced Signatures

When more control is desired, one can express signatures as Python classes to provide explicit instructions of the transformation and describe the format or role of each field more directly. For instance, the following signature generates search queries using context and an optional question:

```
1 class GenerateSearchQuery(dspy.Signature):
2     """Write a simple search query that will help answer a complex question."""
3
4     context = dspy.InputField(desc="may contain relevant facts")
5     question = dspy.InputField()
6     query = dspy.OutputField(dtype=dspy.SearchQuery)
```

Using the above, we can specify a complete system for the generation of a synthetic IR dataset where the queries are mediated by a question generated by the LM:

```
1 query_gen = dspy.Predict(GenerateSearchQuery)
2 query_gen(context="Language typology")
3 # Out: Prediction(question='What are the main types of language classification?',
4         query="language classification" OR "language typology" -wikipedia')
```

If questions are available, they can be supplied as shown: `query_gen(context="Language typology", question="What are the primary language families of South America?")`.

As a work in progress feature, users can optionally specify the type of output fields as `bool`, `int`, `float`, `list`, or `dict` instead of the default free-form string type, as in `contexts`, `question` -> `answer_found`: `bool`.

## D Comparison with existing libraries like LangChain and LlamaIndex

LangChain and LlamaIndex are perhaps the most popular library in the general space of prompting LMs. These libraries have a different focus compared to DSPy and they suffer internally from the prompt engineering challenges that DSPy aims to resolve. In particular, whereas the goal of DSPy is to tackle the fundamental challenges of prompt engineering for building new LM computational graphs, LangChain and LlamaIndex generally help application developers who need pre-packaged components and chains, e.g., implementations of popular and reusable pipelines (e.g., particular agents and specific retrieval pipelines) and tools (e.g., connections to various databases and implementations of long- and short-term memory for agents).

These off-the-shelf higher-level abstractions contrast with DSPy’s focus on introducing core composable operators. In particular, DSPy introduces signatures (to abstract prompts), modules (to abstract prompting techniques), and teleprompters to act as optimizers for arbitrary imperative code (DSPy programs) that chain modules together. Its goal is to help researchers and practitioners build new LM pipelines quickly and achieve very high quality through automatic compilation (self-improvement) instead of manual prompt engineering.

In contrast, typical existing research implementations and existing libraries like LangChain and LlamaIndex are implemented using manual prompt engineering, which is the key problem that DSPy tackles. We conducted an informal study to highlight this. In late September 2023, we found that the LangChain codebase contains 50 strings exceeding 1000 characters, which are generally prompts, compared to none at all in DSPy. Indeed, a substantial number of LangChain’s Python files are singularly dedicated to task-related templating and prompt engineering with 12 `prompts.py` files and 42 `prompt.py` files. DSPy, on the other hand, provides a structured framework that automatically bootstraps prompts. The library itself does not contain a single hand-written prompt demonstration for any tasks at the time of writing, despite the very high quality with various LMs.

To review the typical forms of prompt engineering in existing libraries, we consider the following in LangChain. The LangChain Program-Aided Language Model [Gao et al. \[2023a\]](#) chain program uses few-shot learning, leveraging a template that is 3982 characters long with 8 math word problems (Prompt 2) and corresponding outputted programs as learning examples for the language model. LangChain also contains a prompt for SQL query tasks for *each* of the databases like Oracle, GoogleSQL, DuckDB, Crate, and MySQL, with the average length of these prompts at 1058 characters. Other task areas such as QA with sources (Prompt D) and Graph\_QA also have significantly lengthy prompt templates, with averages of 1337 and 722 characters, respectively. While expert-written prompts can be useful, we believe that LM- and task-adaptive prompts bootstrapped automatically

can offer far more power (and are far more modular) than hard-coding a prompt per database provider inside the code base. The next appendix section contains a number of prompts copied from related research papers and existing libraries.

## E Sample large prompts

This section highlights a few popular existing frameworks that structure prompts with extensive prompt engineering templates. The primary objective is to capture how many words and characters are used for such large multi-line prompts defined for tasks or tools and present these example prompts retrieved from open-sourced papers and repositories. The formatting of these example prompts is adapted from [Gao et al. \[2023a\]](#).

Task/Tool Prompt	Source	Words	Characters
Prompt 1: Text-evidence checker	<a href="#">Gao et al. [2023a]</a>	818	4964
Prompt 2: Math word problems (PAL)	LangChain & <a href="#">Gao et al. [2023b]</a>	566	3957
Prompt 3: ReAct	<a href="#">Yao et al. [2022]</a>	593	3889
Prompt 4: Zero-shot ReAct	LangChain	101	600
Prompt 5: QA with sources	LangChain	992	6197
Prompt 6: SQL MyScale querying	LangChain	343	2239
Prompt 7: Relevant docs retrieval	LlamaIndex	129	719
Prompt 8: IRS chatbot	LlamaIndex	389	2258

1 [web] I will check some things you said.  
2  
3 (1) You said: Your nose switches back and forth between nostrils. When you sleep, you switch about every 45 minutes. This  
4 is to prevent a buildup of mucus. It's called the nasal cycle.  
5 I checked: How often do your nostrils switch?  
6 I found this article: Although we don't usually notice it, during the nasal cycle one nostril becomes congested and thus  
7 contributes less to airflow, while the other becomes decongested. On average, the congestion pattern switches about every  
8 2 hours, according to a small 2016 study published in the journal PLOS One.  
9 Your nose's switching time is about every 2 hours, not 45 minutes.  
10 This disagrees with what you said.  
11  
12 (2) You said: The Little House books were written by Laura Ingalls Wilder. The books were published by HarperCollins.  
13 I checked: Who published the Little House books?  
14 I found this article: These are the books that started it all - the stories that captured the hearts and imaginations of  
15 children and young adults worldwide. Written by Laura Ingalls Wilder and published by HarperCollins, these beloved books  
16 remain a favorite to this day.  
17 The Little House books were published by HarperCollins.  
18 This agrees with what you said.  
19  
20 (3) You said: The Stanford Prison Experiment was conducted in the basement of Jordan Hall, Stanford's psychology building.  
21 I checked: Where was Stanford Prison Experiment conducted?  
22 I found this article: Carried out August 15-21, 1971 in the basement of Jordan Hall, the Stanford Prison Experiment set  
23 out to examine the psychological effects of authority and powerlessness in a prison environment.  
24 The Stanford Prison Experiment was conducted in Jordan Hall.  
25 This agrees with what you said.  
26  
27 (4) You said: Social work is a profession that is based in the philosophical tradition of humanism. It is an intellectual  
28 discipline that has its roots in the 1800s.  
29 I checked: When did social work have its roots?  
30 I found this article: The Emergence and Growth of the Social work Profession<br><br> Social work's roots were planted in  
31 the 1880s, when charity organization societies (COS) were created to organize municipal voluntary relief associations and  
32 settlement houses were established.  
33 Social work has its roots in the 1880s, not 1800s.  
34 This disagrees with what you said.  
35  
36 (5) You said: The Havel-Hakimi algorithm is an algorithm for converting the adjacency matrix of a graph into its adjacency  
37 list. It is named after Vaclav Havel and Samih Hakimi.  
38 I checked: What is the Havel-Hakimi algorithm?  
39 I found this article: The Havel-Hakimi algorithm constructs a special solution if a simple graph for the given degree  
40 sequence exists, or proves that one cannot find a positive answer. This construction is based on a recursive algorithm.  
41 The algorithm was published by Havel (1955), and later by Hakimi (1962).  
42 Havel-Hakimi algorithm is for constructing a special solution if a simple graph for the given degree sequence exists, or  
43 proving that one cannot find a positive answer, not converting the adjacency matrix of a graph into its adjacency list.  
44 This disagrees with what you said.  
45  
46 (6) You said: "Time of My Life" is a song by American singer-songwriter Bill Medley from the soundtrack of the 1987 film  
47 Dirty Dancing. The song was produced by Michael Lloyd.  
48 I checked: Who was the producer of "(I've Had) The Time of My Life"?  
49 I found this article: On September 8, 2010, the original demo of this song, along with a remix by producer Michael Lloyd,  
50 was released as digital files in an effort to raise money for the Patrick Swayze Pancreas Cancer Research Foundation at  
51 Stanford University.  
52 "Time of My Life" was produced by Michael Lloyd.  
53 This agrees with what you said.  
54  
55 (7) You said: Kelvin Hopkins was suspended from the Labor Party because he had allegedly sexually harassed and behaved  
56 inappropriately towards a Labour Party activist, Ava Etemadzadeh.  
57 I checked: Why was Kelvin Hopkins suspended from the Labor Party?  
58 I found this article: A former Labour MP has left the party before an inquiry into sexual harassment allegations against  
59 him was able to be concluded, the party has confirmed. Kelvin Hopkins was accused in 2017 of inappropriate physical contact  
60 and was suspended by the Labour party pending an investigation. This agrees with what you said.  
61 Kelvin Hopkins was suspended because he had allegedly sexually harassed and behaved inappropriately towards a Labour Party  
62 activist, Ava Etemadzadeh.  
63 This agrees with what you said.  
64  
65 (8) You said: In the battles of Lexington and Concord, the British side was led by General Thomas Smith.  
66 I checked: Who led the British side in the battle of Lexington and Concord?  
67 I found this article: Interesting Facts about the Battles of Lexington and Concord. The British were led by Lieutenant  
68 Colonel Francis Smith. There were 700 British regulars.  
69 The British side was led by Lieutenant Colonel Francis Smith, not General Thomas Hall.  
70 This disagrees with what you said.  
71  
72 (9) You said: {text}  
73 I checked: {query}  
74 I found this article: {evidence}  
75 -----

Figure 1: Example few-shot prompt using a reasoning chain for agreement model that identifies inconsistencies between text and evidence [Gao et al., 2023a].

```

1  Q: Olivia has $23. She bought five bagels for $3 each. How much money does she have left?
2
3  # solution in Python:
4
5
6  def solution():
7      """Olivia has $23. She bought five bagels for $3 each. How much money does she have left?"""
8      money_initial = 23
9      bagels = 5
10     bagel_cost = 3
11     money_spent = bagels * bagel_cost
12     money_left = money_initial - money_spent
13     result = money_left
14     return result
15
16
17
18
19
20 Q: Michael had 58 golf balls. On tuesday, he lost 23 golf balls. On wednesday, he lost 2 more. How many golf balls did he
    have at the end of wednesday?
21
22 # solution in Python:
23
24
25 def solution():
26     """Michael had 58 golf balls. On tuesday, he lost 23 golf balls. On wednesday, he lost 2 more. How many golf balls
    did he have at the end of wednesday?"""
27     golf_balls_initial = 58
28     golf_balls_lost_tuesday = 23
29     golf_balls_lost_wednesday = 2
30     golf_balls_left = golf_balls_initial - golf_balls_lost_tuesday - golf_balls_lost_wednesday
31     result = golf_balls_left
32     return result
33
34
35
36
37
38 Q: There were nine computers in the server room. Five more computers were installed each day, from monday to thursday. How
    many computers are now in the server room?
39
40 # solution in Python:
41
42
43 def solution():
44     """There were nine computers in the server room. Five more computers were installed each day, from monday to thursday.
    How many computers are now in the server room?"""
45     computers_initial = 9
46     computers_per_day = 5
47     num_days = 4
48     computers_added = computers_per_day * num_days
49     computers_total = computers_initial + computers_added
50     result = computers_total
51     return result
52
53
54
55
56
57 Q: Shawn has five toys. For Christmas, he got two toys each from his mom and dad. How many toys does he have now?
58
59 # solution in Python:
60
61
62 def solution():
63     """Shawn has five toys. For Christmas, he got two toys each from his mom and dad. How many toys does he have now?"""
64     toys_initial = 5
65     mom_toys = 2
66     dad_toys = 2
67     total_received = mom_toys + dad_toys
68     total_toys = toys_initial + total_received
69     result = total_toys
70     return result
71
72
73
74
75
76 Q: Jason had 20 lollipops. He gave Denny some lollipops. Now Jason has 12 lollipops. How many lollipops did Jason give to
    Denny?
77
78 # solution in Python:
79
80
81

```

```

1
2
3
4 def solution():
5     """Jason had 20 lollipops. He gave Denny some lollipops. Now Jason has 12 lollipops. How many lollipops did Jason give
6     to Denny?"""
7     jason_lollipops_initial = 20
8     jason_lollipops_after = 12
9     denny_lollipops = jason_lollipops_initial - jason_lollipops_after
10    result = denny_lollipops
11    return result
12
13
14
15
16 Q: Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?
17
18 # solution in Python:
19
20 def solution():
21     """Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?"""
22     leah_chocolates = 32
23     sister_chocolates = 42
24     total_chocolates = leah_chocolates + sister_chocolates
25     chocolates_eaten = 35
26     chocolates_left = total_chocolates - chocolates_eaten
27     result = chocolates_left
28     return result
29
30
31
32
33
34 Q: If there are 3 cars in the parking lot and 2 more cars arrive, how many cars are in the parking lot?
35
36 # solution in Python:
37
38
39 def solution():
40     """If there are 3 cars in the parking lot and 2 more cars arrive, how many cars are in the parking lot?"""
41     cars_initial = 3
42     cars_arrived = 2
43     total_cars = cars_initial + cars_arrived
44     result = total_cars
45     return result
46
47
48
49
50
51 Q: There are 15 trees in the grove. Grove workers will plant trees in the grove today. After they are done, there will be
52 21 trees. How many trees did the grove workers plant today?
53
54 # solution in Python:
55
56 def solution():
57     """There are 15 trees in the grove. Grove workers will plant trees in the grove today. After they are done, there will
58     be 21 trees. How many trees did the grove workers plant today?"""
59     trees_initial = 15
60     trees_after = 21
61     trees_added = trees_after - trees_initial
62     result = trees_added
63     return result
64
65
66
67
68 Q: {question}
69
70 # solution in Python:

```

Figure 2: PAL example few-shot prompt for solving math questions by generating code.



```

1  Solve a question answering task with interleaving Thought, Action, Observation steps. Thought can reason about the current
  situation, and Action can be three types:
2  (1) Search[entity], which searches the exact entity on Wikipedia and returns the first paragraph if it exists. If not, it
  will return some similar entities to search.
3  (2) Lookup[keyword], which returns the next sentence containing keyword in the current passage.
4  (3) Finish[answer], which returns the answer and finishes the task.
5  Here are some examples.
6  Question: What is the elevation range for the area that the eastern sector of the Colorado orogeny extends into?
7  Action 1: Search[Colorado orogeny]
8  Observation 1: The Colorado orogeny was an episode of mountain building (an orogeny) in Colorado and surrounding areas.
9  Action 2: Lookup[eastern sector]
10 Observation 2: (Result 1 / 1) The eastern sector extends into the High Plains and is called the Central Plains orogeny.
11 Action 3: Search[High Plains]
12 Observation 3: High Plains refers to one of two distinct land regions:
13 Action 4: Search[High Plains (United States)]
14 Observation 4: The High Plains are a subregion of the Great Plains. From east to west, the High Plains rise in elevation
  from around 1,800 to 7,000 ft (550 to 2,130 m).[3]
15 Action 5: Finish[1,800 to 7,000 ft]
16 Question: Musician and satirist Allie Goertz wrote a song about the "The Simpsons" character Milhouse, who Matt Groening
  named after who?
17 Action 1: Search[Milhouse]
18 Observation 1: Milhouse Mussolini Van Houten is a recurring character in the Fox animated television series The Simpsons
  voiced by Pamela Hayden and created by Matt Groening.
19 Action 2: Lookup[named after]
20 Observation 2: (Result 1 / 1) Milhouse was named after U.S. president Richard Nixon, whose middle name was Milhous.
21 Action 3: Finish[Richard Nixon]
22 Question: Which documentary is about Finnish rock groups, Adam Clayton Powell or The Saimaa Gesture?
23 Action 1: Search[Adam Clayton Powell]
24 Observation 1: Could not find [Adam Clayton Powell]. Similar: ['Adam Clayton Powell III', 'Seventh Avenue (Manhattan)',
  'Adam Clayton Powell Jr. State Office Building', 'Isabel Washington Powell', 'Adam Powell', 'Adam Clayton Powell (film)',
  'Giancarlo Esposito'].
25 Action 2: Search[Adam Clayton Powell (film)]
26 Observation 2: Adam Clayton Powell is a 1989 American documentary film directed by Richard Kilberg. The film is about the
  rise and fall of influential African-American politician Adam Clayton Powell Jr.[3][4] It was later aired as part of the
  PBS series The American Experience.
27 Action 3: Finish[The Saimaa Gesture]
28 Question: What profession does Nicholas Ray and Elia Kazan have in common?
29 Action 1: Search[Nicholas Ray]
30 Observation 1: Nicholas Ray (born Raymond Nicholas Kienzle Jr., August 7, 1911 – June 16, 1979) was an American film
  director, screenwriter, and actor best known for the 1955 film Rebel Without a Cause.
31 Action 2: Search[Elia Kazan]
32 Observation 2: Elia Kazan was an American film and theatre director, producer, screenwriter and actor.
33 Action 3: Finish[director, screenwriter, actor]
34 Question: Which magazine was started first Arthur's Magazine or First for Women?
35 Action 1: Search[Arthur's Magazine]
36 Observation 1: Arthur's Magazine (1844-1846) was an American literary periodical published in Philadelphia in the 19th
  century.
37 Action 2: Search[First for Women]
38 Observation 2: First for Women is a woman's magazine published by Bauer Media Group in the USA.[1] The magazine was started
  in 1989.
39 Action 3: Finish[Arthur's Magazine]
40 Question: Were Pavel Urysohn and Leonid Levin known for the same type of work?
41 Action 1: Search[Pavel Urysohn]
42 Observation 1: Pavel Samuilovich Urysohn (February 3, 1898 – August 17, 1924) was a Soviet mathematician who is best known
  for his contributions in dimension theory.
43 Action 2: Search[Leonid Levin]
44 Observation 2: Leonid Anatolievich Levin is a Soviet-American mathematician and computer scientist.
45 Action 3: Finish[yes]

```

Figure 3: ReAct example prompt for interleaving Thought, Action, Observation steps.

```
1 Answer the following questions as best you can. You have access to the following tools:
2 Search: useful for when you need to answer questions about the world
3 Use the following format:
4 Question: the input question you must answer
5 Thought: you should always think about what to do
6 Action: the action to take, should be one of [Search]
7 Action Input: the input to the action
8 Observation: the result of the action
9 ... (this Thought/Action/Action Input/Observation can repeat N times)
10 Thought: I now know the final answer
11 Final Answer: the final answer to the original input question
12 Begin!
13 Question: {question}
14 Thought:
```

Figure 4: Langchain ReAct example prompt for interleaving Thought, Action, Observation steps.

1 Given the following extracted parts of a long document and a question, create a final answer with references ("SOURCES").  
2 If you don't know the answer, just say that you don't know. Don't try to make up an answer.  
3 ALWAYS return a "SOURCES" part in your answer.  
4  
5 QUESTION: Which state/country's law governs the interpretation of the contract?  
6 =====  
7 Content: This Agreement is governed by English law and the parties submit to the exclusive jurisdiction of the English  
8 courts in relation to any dispute (contractual or non-contractual) concerning this Agreement save that either party may  
9 apply to any court for an injunction or other relief to protect its Intellectual Property Rights.  
10 Source: 28-pl  
11 Content: No Waiver. Failure or delay in exercising any right or remedy under this Agreement shall not constitute a waiver  
12 of such (or any other) right or remedy.  
13 11.7 Severability. The invalidity, illegality or unenforceability of any term (or part of a term) of this Agreement shall  
14 not affect the continuation in force of the remainder of the term (if any) and this Agreement.  
15 11.8 No Agency. Except as expressly stated otherwise, nothing in this Agreement shall create an agency, partnership or  
16 joint venture of any kind between the parties.  
17 11.9 No Third-Party Beneficiaries.  
18 Source: 30-pl  
19 Content: (b) if Google believes, in good faith, that the Distributor has violated or caused Google to violate any  
20 Anti-Bribery Laws (as defined in Clause 8.5) or that such a violation is reasonably likely to occur,  
21 Source: 4-pl  
22 =====  
23 FINAL ANSWER: This Agreement is governed by English law.  
24 SOURCES: 28-pl  
25  
26 QUESTION: What did the president say about Michael Jackson?  
27 =====  
28 Content: Madam Speaker, Madam Vice President, our First Lady and Second Gentleman. Members of Congress and the Cabinet.  
29 Justices of the Supreme Court. My fellow Americans.  
30 Last year COVID-19 kept us apart. This year we are finally together again.  
31 Tonight, we meet as Democrats Republicans and Independents. But most importantly as Americans.  
32 With a duty to one another to the American people to the Constitution.  
33 And with an unwavering resolve that freedom will always triumph over tyranny.  
34 Six days ago, Russia's Vladimir Putin sought to shake the foundations of the free world thinking he could make it bend to  
35 his menacing ways. But he badly miscalculated.  
36 He thought he could roll into Ukraine and the world would roll over. Instead he met a wall of strength he never imagined.  
37 He met the Ukrainian people.  
38 From President Zelenskyy to every Ukrainian, their fearlessness, their courage, their determination, inspires the world.  
39 Groups of citizens blocking tanks with their bodies. Everyone from students to retirees teachers turned soldiers defending  
40 their homeland.  
41 Source: 0-pl  
42 Content: And we won't stop.  
43 We have lost so much to COVID-19. Time with one another. And worst of all, so much loss of life.  
44 Let's use this moment to reset. Let's stop looking at COVID-19 as a partisan dividing line and see it for what it is: A  
45 God-awful disease.  
46 Let's stop seeing each other as enemies, and start seeing each other for who we really are: Fellow Americans.  
47 We can't change how divided we've been. But we can change how we move forward-on COVID-19 and other issues we must face  
48 together.  
49 I recently visited the New York City Police Department days after the funerals of Officer Wilbert Mora and his partner,  
50 Officer Jason Rivera.  
51 They were responding to a 9-1-1 call when a man shot and killed them with a stolen gun.  
52 Officer Mora was 27 years old.  
53 Officer Rivera was 22.  
54 Both Dominican Americans who'd grown up on the same streets they later chose to patrol as police officers.  
55 I spoke with their families and told them that we are forever in debt for their sacrifice, and we will carry on their  
56 mission to restore the trust and safety every community deserves.  
57 Source: 24-pl  
58 Content: And a proud Ukrainian people, who have known 30 years of independence, have repeatedly shown that they will not  
59 tolerate anyone who tries to take their country backwards.  
60 To all Americans, I will be honest with you, as I've always promised. A Russian dictator, invading a foreign country, has  
61 costs around the world.  
62 And I'm taking robust action to make sure the pain of our sanctions is targeted at Russia's economy. And I will use every  
63 tool at our disposal to protect American businesses and consumers.  
64 Tonight, I can announce that the United States has worked with 30 other countries to release 60 Million barrels of oil  
65 from reserves around the world.  
66 America will lead that effort, releasing 30 Million barrels from our own Strategic Petroleum Reserve. And we stand ready  
67 to do more if necessary, unified with our allies.  
68 These steps will help blunt gas prices here at home. And I know the news about what's happening can seem alarming.  
69 But I want you to know that we are going to be okay.  
70 Source: 5-pl  
71 Content: More support for patients and families.  
72 To get there, I call on Congress to fund ARPA-H, the Advanced Research Projects Agency for Health.  
73 It's based on DARPA-the Defense Department project that led to the Internet, GPS, and so much more.  
74 ARPA-H will have a singular purpose-to drive breakthroughs in cancer, Alzheimer's, diabetes, and more.

```

1 A unity agenda for the nation.
2 We can do this.
3 My fellow Americans—tonight , we have gathered in a sacred space—the citadel of our democracy.
4 In this Capitol, generation after generation, Americans have debated great questions amid great strife, and have done
  great things.
5 We have fought for freedom, expanded liberty, defeated totalitarianism and terror.
6 And built the strongest, freest, and most prosperous nation the world has ever known.
7 Now is the hour.
8 Our moment of responsibility.
9 Our test of resolve and conscience, of history itself.
10 It is in this moment that our character is formed. Our purpose is found. Our future is forged.
11 Well I know this nation.
12 Source: 34-pl
13 =====
14 FINAL ANSWER: The president did not mention Michael Jackson.
15 SOURCES:
16
17 QUESTION: {question}
18 =====
19 {summaries}
20 =====
21 FINAL ANSWER:

```

Figure 5: Langchain example prompt for QA with sources.

```

1 You are a MyScale expert. Given an input question, first create a syntactically correct MyScale query to run, then look
  at the results of the query and return the answer to the input question.
2 MyScale queries has a vector distance function called DISTANCE(column, array) to compute relevance to the user's question
  and sort the feature array column by the relevance.
3 When the query is asking for {top_k} closest row, you have to use this distance function to calculate distance to entity's
  array on vector column and order by the distance to retrieve relevant rows.
4 *NOTICE*: DISTANCE(column, array) only accept an array column as its first argument and a NeuralArray(entity) as its second
  argument. You also need a user defined function called NeuralArray(entity) to retrieve the entity's array.
5 Unless the user specifies in the question a specific number of examples to obtain, query for at most {top_k} results using
  the LIMIT clause as per MyScale. You should only order according to the distance function.
6 Never query for all columns from a table. You must query only the columns that are needed to answer the question. Wrap
  each column name in double quotes (") to denote them as delimited identifiers.
7 Pay attention to use only the column names you can see in the tables below. Be careful to not query for columns that do
  not exist. Also, pay attention to which column is in which table.
8 Pay attention to use today() function to get the current date, if the question involves "today". ORDER BY clause should
  always be after WHERE clause. DO NOT add semicolon to the end of SQL. Pay attention to the comment in table schema.
9
10 Use the following format:
11 ===== table info =====
12 {table_info}
13 Question: {input}
14 SQLQuery:
15
16 Here are some examples:
17 ===== table info =====
18 CREATE TABLE "ChatPaper" (
19   abstract String,
20   id String,
21   vector Array(Float32),
22 ) ENGINE = ReplicatedReplacingMergeTree()
23 ORDER BY id
24 PRIMARY KEY id
25 Question: What is Feature Pyramid Network?
26 SQLQuery: SELECT ChatPaper.title, ChatPaper.id, ChatPaper.authors FROM ChatPaper ORDER BY DISTANCE(vector,
  NeuralArray(PaperRank contribution)) LIMIT {top_k}
27
28 Let's begin:
29 ===== table info =====
30 {table_info}
31 Question: {input}
32 SQLQuery:

```

Figure 6: Langchain example prompt for SQL querying using MyScale.

```

1  A list of documents is shown below. Each document has a number next to it along with a summary of the document. A question
   is also provided.
2  Respond with the numbers of the documents you should consult to answer the question, in order of relevance, as well as the
   relevance score.
3  The relevance score is a number from 1-10 based on how relevant you think the document is to the question.
4  Do not include any documents that are not relevant to the question.
5
6  Example format:
7  Document 1:
8  <summary of document 1>
9
10 Document 2:
11 <summary of document 2>
12
13 ...
14
15 Document 10:
16 <summary of document 10>
17
18 Question: <question>
19 Answer:
20 Doc: 9, Relevance: 7
21 Doc: 3, Relevance: 4
22 Doc: 7, Relevance: 3
23
24 Let's try this now:
25 {context_str}
26 Question: {query_str}
27 Answer:

```

Figure 7: LlamaIndex example prompt for returning relevant documents and corresponding summaries.

```

1  You are an IRS chatbot whose primary goal is to help users with filing their tax returns for the 2022 year.
2  Provide concise replies that are polite and professional.
3  Answer questions truthfully based on official government information, with consideration to context provided below on
   changes for 2022 that can affect tax refund.
4  Do not answer questions that are not related to United States tax procedures and respond with "I can only help with any
   tax-related questions you may have.".
5  If you do not know the answer to a question, respond by saying "I do not know the answer to your question. You may be able
   to find your answer at www.irs.gov/faqs"
6
7  Changes for 2022 that can affect tax refund:
8  Changes in the number of dependents, employment or self-employment income and divorce, among other factors, may affect
   your tax-filing status and refund. No additional stimulus payments. Unlike 2020 and 2021, there were no new stimulus
   payments for 2022 so taxpayers should not expect to get an additional payment.
9  Some tax credits return to 2019 levels. This means that taxpayers will likely receive a significantly smaller refund
   compared with the previous tax year. Changes include amounts for the Child Tax Credit (CTC), the Earned Income Tax Credit
   (EITC) and the Child and Dependent Care Credit will revert to pre-COVID levels.
10 For 2022, the CTC is worth $2,000 for each qualifying child. A child must be under age 17 at the end of 2022 to be a
   qualifying child. For the EITC, eligible taxpayers with no children will get $560 for the 2022 tax year. The Child and
   Dependent Care Credit returns to a maximum of $2,100 in 2022.
11 No above-the-line charitable deductions. During COVID, taxpayers were able to take up to a $600 charitable donation tax
   deduction on their tax returns. However, for tax year 2022, taxpayers who don't itemize and who take the standard deduction,
   won't be able to deduct their charitable contributions.
12 More people may be eligible for the Premium Tax Credit. For tax year 2022, taxpayers may qualify for temporarily expanded
   eligibility for the premium tax credit.
13 Eligibility rules changed to claim a tax credit for clean vehicles. Review the changes under the Inflation Reduction Act
   of 2022 to qualify for a Clean Vehicle Credit.

```

Figure 8: LlamaIndex example prompt for IRS chatbot guidelines.



## F Modules

### F.1 Predict

```
1 class Predict(dspy.Module):
2     def __init__(self, signature, **config):
3         self.signature = dspy.Signature(signature)
4         self.config = config
5
6         # Module Parameters.
7         self.lm = dspy.ParameterLM(None) # use the default LM
8         self.demonstrations = dspy.ParameterDemonstrations([])
9
10    def forward(self, **kwargs):
11        lm = get_the_right_lm(self.lm, kwargs)
12        signature = get_the_right_signature(self.signature, kwargs)
13        demonstrations = get_the_right_demonstrations(self.demonstrations, kwargs)
14
15        prompt = signature(demos=self.demos, **kwargs)
16        completions = lm.generate(prompt, **self.config)
17        prediction = Prediction.from_completions(completions, signature=signature)
18
19        if dsp.settings.compiling is not None:
20            trace = dict(predictor=self, inputs=kwargs, outputs=prediction)
21            dspy.settings.traces.append(trace)
22
23    return prediction
```

### F.2 Chain of Thought

```
1 class ChainOfThought(dspy.Module):
2     def __init__(self, signature):
3
4         # Modify signature from '*inputs -> *outputs' to '*inputs -> rationale, *outputs'.
5         rationale_field = dspy.OutputField(prefix="Reasoning: Let's think step by step.")
6         signature = dspy.Signature(signature).prepend_output_field(rationale_field)
7
8         # Declare a sub-module with the modified signature.
9         self.predict = dspy.Predict(self.signature)
10
11    def forward(self, **kwargs):
12        # Just forward the inputs to the sub-module.
13        return self.predict(**kwargs)
```

## G Teleprompters

### G.1 BootstrapFewShot

```
1 class SimplifiedBootstrapFewShot(Teleprompter):
2     def __init__(self, metric=None):
3         self.metric = metric
4
5     def compile(self, student, trainset, teacher=None):
6         teacher = teacher if teacher is not None else student
7         compiled_program = student.deepcopy()
8
9         # Step 1. Prepare mappings between student and teacher Predict modules.
10        # Note: other modules will rely on Predict internally.
11        assert student_and_teacher_have_compatible_predict_modules(student, teacher)
12        name2predictor, predictor2name = map_predictors_recursively(student, teacher)
13
14        # Step 2. Bootstrap traces for each Predict module.
15        # We'll loop over the training set. We'll try each example once for simplicity.
16        for example in trainset:
17            if we_found_enough_bootstrapped_demos(): break
18
19            # turn on compiling mode which will allow us to keep track of the traces
20            with dspy.setting.context(compiling=True):
21                # run the teacher program on the example, and get its final prediction
22                # note that compiling=True may affect the internal behavior here
23                prediction = teacher(**example.inputs())
24
25                # get the trace of the all internal Predict calls from teacher program
26                predicted_traces = dspy.settings.trace
27
28                # if the prediction is valid, add the example to the traces
29                if self.metric(example, prediction, predicted_traces):
30                    for predictor, inputs, outputs in predicted_traces:
31                        d = dspy.Example(automated=True, **inputs, **outputs)
32                        predictor_name = self.predictor2name[id(predictor)]
33                        compiled_program[predictor_name].demonstrations.append(d)
34
35        return compiled_program
```

### G.2 BootstrapFewShotWithRandomSearch

```
1 class SimplifiedBootstrapFewShotWithRandomSearch(Teleprompter):
2     def __init__(self, metric = None, trials=16):
3         self.metric = metric
4         self.trials = trials
5
6     def compile(self, student, *, teacher=None, trainset, valset=None):
7         # we can do forms of cross-validation if valset is unset.
8         valset = trainset if valset is None else valset
9
10        candidates = []
11        for seed in range(self.trials):
12            # Create a new basic bootstrap few-shot program.
13            shuffled_trainset = shuffle(trainset, seed=seed)
14            tp = BootstrapFewShot(metric=metric, max_bootstrap_demos=random_size())
15            candidate_program = tp.compile(student, shuffled_trainset, teacher)
16
17            # Step 2: Evaluate the generated candidate program.
18            score = evaluate_program(candidate_program, self.metric, valset)
19            candidates.append((score, candidate_program))
20
21        # return the best candidate program.
22        return max(candidates, key=lambda x: x[0])[1]
```

### G.3 BootstrapFewShotWithOptuna

```
1 class SimplifiedBootstrapFewShotWithOptuna(Teleprompter):
2     def __init__(self, metric, trials=16):
3         self.metric = metric
4         self.trials = trials
5
6     def objective(self, trial):
7         pool = self.pool
8
9         # Step 1: Create copy of student program.
10        candidate_program = self.student.reset_copy()
11
12        # Step 2: Based on trial, select demos for each predictor in program.
13        # Note. For simplicity, we can just select a single demo for each predictor.
14        # But we can easily tune the number of demonstrations to select here.
15        for (name, predictor1), (_, predictor2) in \
16            zip(pool.named_predictors(), candidate_program.named_predictors()):
17            all_demos = predictor1.demos
18            demo_index = trial.suggest_int(f"demo_index_for_{name}", 0, len(all_demos) - 1)
19            predictor2.demos = [all_demos[demo_index]]
20
21        # Step 3: Evaluate the modified candidate program.
22        score = evaluate_program(candidate_program, self.metric, self.valset)
23
24        # Step 4: Store the candidate for Optuna to select highest-scoring program.
25        trial.set_user_attr("program", candidate_program)
26        return score
27
28    def compile(self, student, trainset, teacher=None, valset=None):
29        self.trainset = trainset
30        self.valset = trainset if valset is None else valset
31
32        self.student = student.deepcopy()
33        self.teacher = teacher.deepcopy() if teacher else student.deepcopy()
34
35        # Leverage BootstrapFewshot to create a large number of potential demonstrations.
36        tp = BootstrapFewShot()
37        self.pool = tp.compile(self.student, self.teacher, self.trainset, self.metric)
38
39        # Use Optuna to find the best program by optimizing the objective function.
40        best_program = optimize_with_optuna(self.objective)
41
42        print('Best score:', best_program.score)
43        print('Best program:', best_program)
44        return best_program
```

## H Examples of the prompts automatically generated by DSPy

For GSM8K, we include the prompt bootstrapped by DSPy for GSM8K llama2-13b-chat for the vanilla program compiled with `bootstrap×2` in Figure 9.

We also include a CoT prompt for GSM8K and a `generate_query` prompt from the multihop program for HotPotQA. All of these, particularly their demonstrations' labels and their selection, are generated by DSPy automatically using llama2-13b-chat.

```

1  Given the fields 'question', produce the fields 'answer'.
2
3  -
4
5  Follow the following format.
6
7  Question: ${question}
8  Answer: ${answer}
9
10 -
11
12 Question: Jimmy and Irene go shopping for clothes on a Tuesday, where senior citizens get a 10% discount on their purchases.
    Jimmy picks out 3 shorts from the $15 rack. Irene grabs 5 shirts from the $17 rack. How much money do they give to the
    cashier?
13 Answer: Jimmy picks out 3 shorts at $15 each = $45. Irene grabs 5 shirts at $17 each = $85. Total cost = $45 + $85 = $130.
    Since senior citizens get a 10% discount, they will pay 10% of $130 = $13. So, they will give the cashier $130 - $13 =
    $117. -
14
15 -
16
17 Question:

```

Figure 9: Copy of the prompt automatically generated by DSPy for GSM8K Llama2-13b-chat vanilla program compiled with bootstrap $\times 2$ .

```

1  Given the fields 'question', produce the fields 'answer'.
2
3  -
4
5  Follow the following format.
6
7  Question: ${question}
8  Reasoning: Let's think step by step in order to $produce the answer. We ...
9  Answer: ${answer}
10
11 -
12
13 Question: Mark is baking bread. He has to let it rise for 120 minutes twice. He also needs to spend 10 minutes kneading
    it and 30 minutes baking it. How many minutes does it take Mark to finish making the bread?
14 Reasoning: Let's think step by step in order to find out how many minutes it takes Mark to finish making the bread. We know
    that he needs to let it rise for 120 minutes twice, so that's 240 minutes. Then, he needs to spend 10 minutes kneading it
    and 30 minutes baking it. So, in total, it will take Mark  $240 + 10 + 30 = 280$  minutes to finish making the bread.
15 Answer: 280 -
16
17 -
18
19 Question: Ben has $2000 for his business operations costs. He orders goods from his supplier and writes them a cheque for
    $600. His debtor pays him $800 from the purchases they had made on credit. Mr. Ben then decides to do equipment maintenance
    and spends $1200 on the whole operation. How much money is Mr. Ben remaining with?
20 Reasoning: Let's think step by step in order to find out how much money Mr. Ben is remaining with. We know that he had
    $2000 to begin with, and he spent $600 on goods from his supplier, so he has  $2000 - 600 = 1400$  left. Then, his debtor
    paid him $800, so he has  $1400 + 800 = 2200$ . Finally, he spent $1200 on equipment maintenance, so he has  $2200 - 1200 = 1000$  left.
21 Answer: $1000 -
22
23 -
24
25 ... several other demonstrations here ...
26
27 -
28
29 Question:

```

Figure 10: Shortened copy of the prompt automatically generated by DSPy for GSM8K Llama2-13b-chat CoT program compiled with bootstrap.

```

1  Given the fields 'context', 'question', produce the fields 'search_query'.
2
3  -
4
5  Follow the following format.
6
7  Context: ${context}
8  Question: ${question}
9  Reasoning: Let's think step by step in order to ${produce the search_query}. We ...
10 Search Query: ${search_query}
11
12 -
13
14 Context:
15 [1] Twilight (novel series) | Twilight is a series of four vampire-themed fantasy romance novels by American author
16   Stephenie Meyer. ...
17 [2] Harper Connelly Mysteries | The Harper Connelly Mysteries is a series of fantasy mystery novels written by Charlaine
18   Harris, and first published in 2005. ...
19 [3] The Dark Heroine | The Dark Heroine is a series of vampire-themed fantasy romance novels written by English author
20   Abigail Gibbs, published by HarperCollins in 2012. ...
21
22 Question: In which year was the first of the vampire-themed fantasy romance novels for which The Twilight Saga: The
23   Official Illustrated Guide serves as a spin-off encyclopedic reference book first published?
24
25 Reasoning: Let's think step by step in order to determine the year the first of the vampire-themed fantasy romance novels
26   was first published. ...
27
28 Search Query: When was the first of the vampire-themed fantasy romance novels published?
29
30 -
31
32 Context:
33 [1] The Victorians | The Victorians - Their Story In Pictures is a 2009 British documentary series which focuses on
34   Victorian art and culture. ...
35 [2] The Caxtons | The Caxtons: A Family Picture is an 1849 Victorian novel by Edward Bulwer-Lytton that was popular in its
36   time.
37 [3] Victorian (comics) | The Victorian is a 25-issue comic book series published by Penny-Farthing Press and starting in
38   1999. ...
39
40 Question: The Victorians - Their Story In Pictures is a documentary series written by an author born in what year?
41
42 Reasoning: Let's think step by step in order to produce the search query. We know that the documentary series is about
43   Victorian art and culture, and it was written and presented by Jeremy Paxman. Therefore, we need to find the year in which
44   Jeremy Paxman was born.
45
46 Search Query: Jeremy Paxman birth year
47
48 -
49
50 Context:

```

Figure 11: Shortened copy of the prompt automatically generated by DSPy for HotPotQA Llama2-13b-chat multi-hop program (generating second hop query) compiled with bootstrap.