databricks

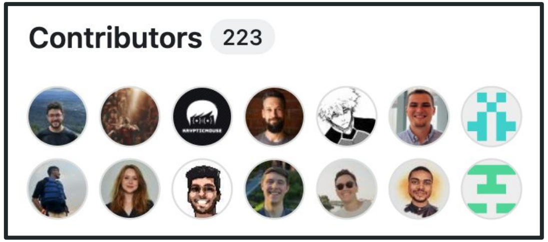
Stanford NLP

Compound AI Systems & DSPy

Omar Khattab

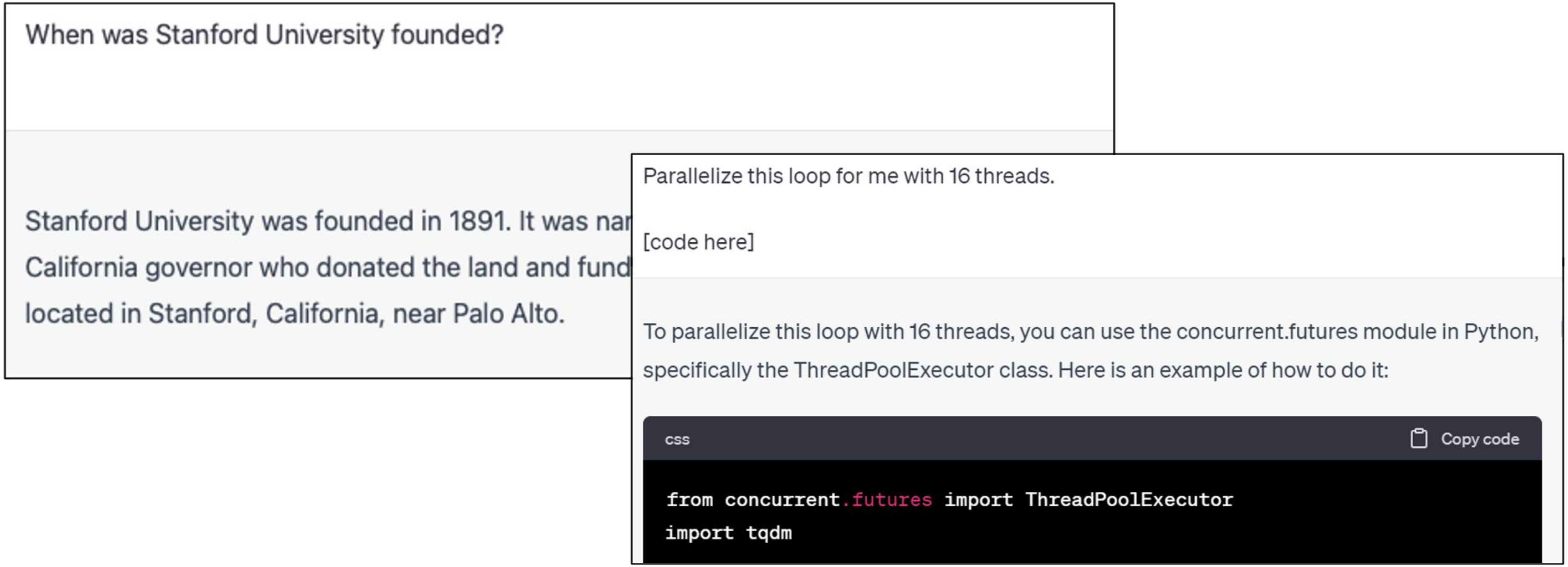
Research Scientist, Databricks

Incoming Assistant Professor, MIT EECS (Fall 2025)



Includes slides adapted from Krista Opsahl-Ong & Michael Ryan

It’s never been easier to prototype impressive AI demos.



Turning monolithic LMs into reliable AI systems remains challenging.

When was Stanford University founded?

Stanford University was founded in 1891. It was nar

California governor who donated the land and fund

located in Stanford, California, near Palo Alto.

Parallelize this loop for me with 16 threads.

[code here]

To parallelize this loop with 16 threads, you can use the concurrent.futures module in Python, specifically the ThreadPoolExecutor class. Here is an example of how to do it:

css Copy code

```
from concurrent.futures import ThreadPoolExecutor
import tqdm
```

The Register

Air Canada must pay damages after chatbot lies to grieving passenger about discount

Airline tried arguing virtual assistant was solely responsible for its own actions

Every AI system will make mistakes.

But the monolithic nature of LMs makes them hard to control, debug, and improve.

To tackle this, AI researchers increasingly build Compound AI Systems,

i.e. modular programs that use LMs as specialized components

Compound AI Systems, *i.e. modular programs that use LMs as specialized components*

Example: Retrieval-Augmented Generation

What compounds protect the digestive system? → ~~Monolithic LM~~ → The stomach is protected by gastric acid and proteases.

⚡ **Transparency:** can debug traces & offer user-facing attribution

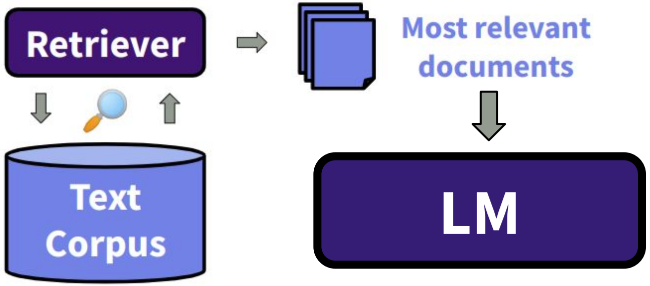
⚡ **Efficiency:** can use smaller LMs, offloading knowledge & control flow

Literature: DrQA (Chen et al., 2017), ORQA (Lee et al., 2019), RAG (Lewis et al., 2020), ColBERT-QA (Khattab et al., 2020)

Compound AI Systems, *i.e. modular programs that use LMs as specialized components*

Example: Retrieval-Augmented Generation

What compounds protect the digestive system?



The stomach is protected by gastric acid and proteases.

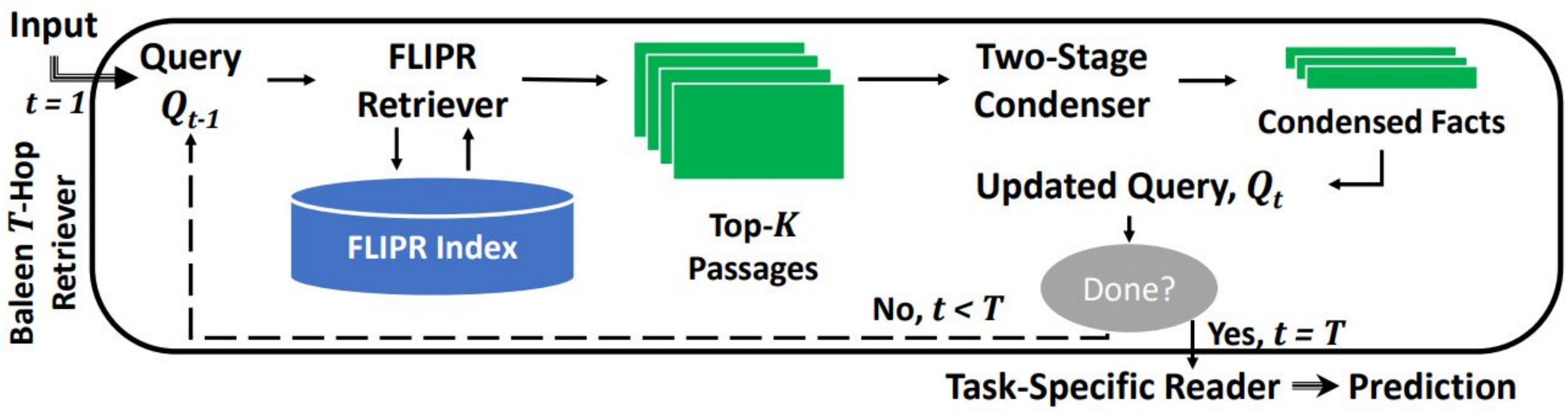
⚡ **Transparency:** can debug traces & offer user-facing attribution

⚡ **Efficiency:** can use smaller LMs, offloading knowledge & control flow

Literature: DrQA (Chen et al., 2017), ORQA (Lee et al., 2019), RAG (Lewis et al., 2020), ColBERT-QA (Khattab et al., 2020)

Compound AI Systems, *i.e. modular programs that use LMs as specialized components*

Example: *Multi-Hop* Retrieval-Augmented Generation



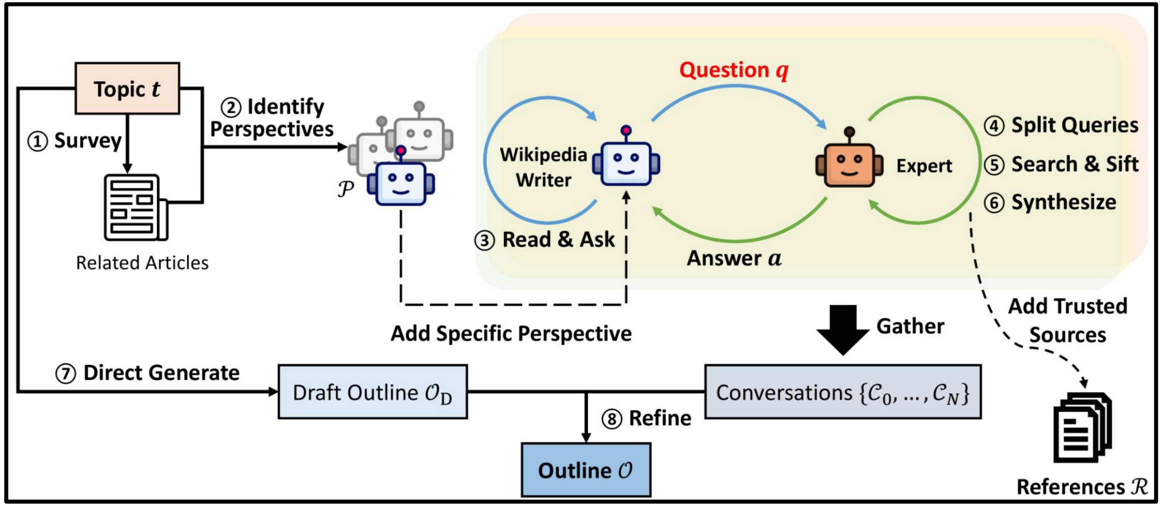
⚡ **Control**: can iteratively improve the system & ground it via tools

Literature: GoldEn (Qi et al., 2019), DecompRC (Min et al., 2019), MDR (Xiong et al., 2020), Baleen (Khattab et al., 2021)

Compound AI Systems, *i.e. modular programs that use LMs as specialized components*

Example: Compositional Report Generation, *i.e. brainstorming an outline, collecting references, etc.*

“The ColBERT retriever”



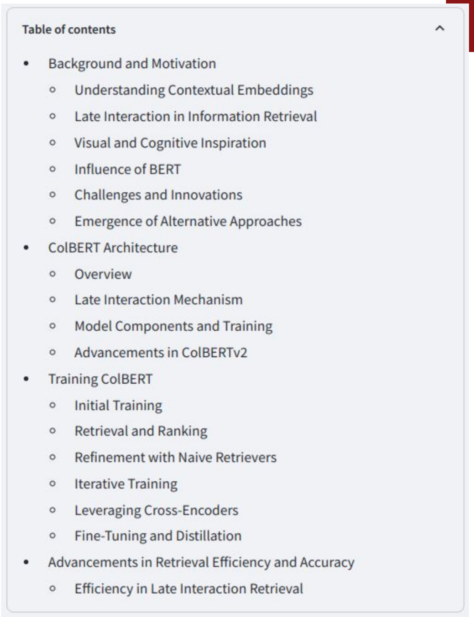
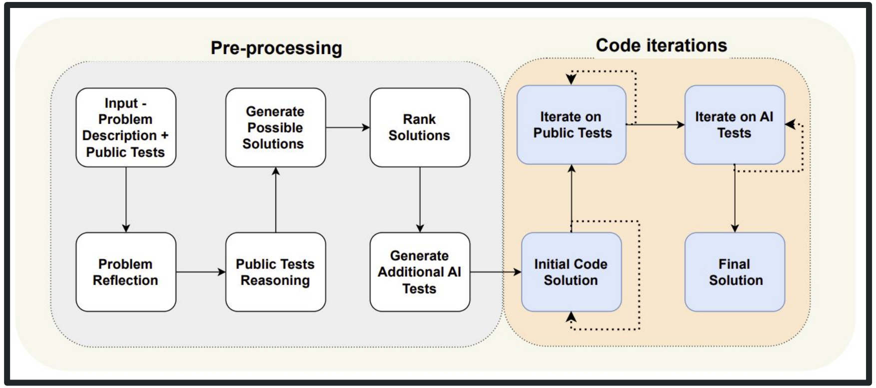


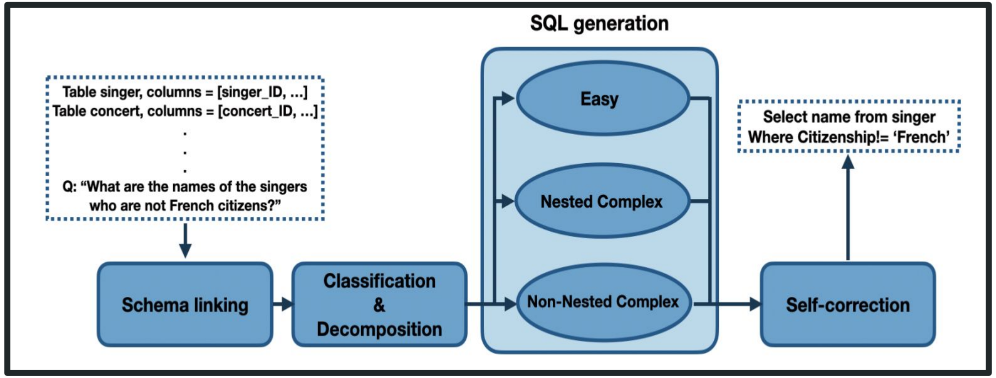
Table of contents

⚡ **Quality**: more reliable composition of better-scoped LM capabilities

STORM: Assisting in Writing Wikipedia-like Articles From Scratch with Large Language Models (Shao et al., 2024)

Compound AI Systems, *i.e. modular programs that use LMs as specialized components*





\+ **Task-agnostic prompting strategies, e.g. Best-of-N, Chain Of Thought, Program of Thought, ReAct, Reflexion, Archon, …**

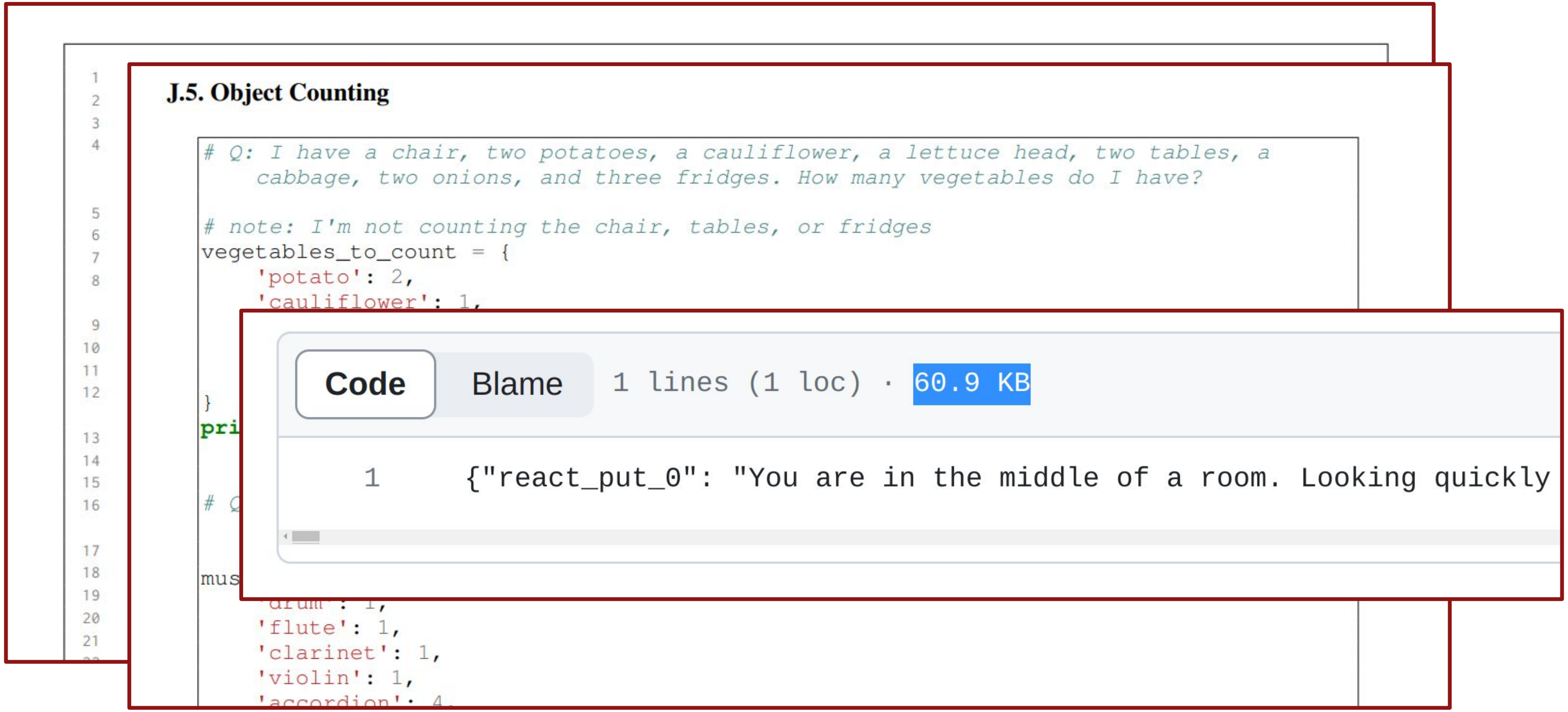
⚡ **Inference-time Scaling**: systematically searching for better outputs

Literature: AlphaCodium (Ridnik, 2024), DIN-SQL (Pourreza & Rafiei, 2023), RARR (Gao et al., 2023), and many others

(Summary) Why Compound AI Systems?

1. **Quality:** more reliable composition of better-scoped LM capabilities
2. **Control:** can iteratively improve the system & ground it via tools
3. **Transparency:** can debug trajectories & offer user-facing attribution
4. **Efficiency:** can use smaller LMs, offloading knowledge & control flow
5. **Inference-time Scaling:** can systematically search for better outputs

Unfortunately, LMs are highly sensitive to how they're instructed to solve tasks, so under the hood we often…



Unfortunately, LMs are highly sensitive to how they're instructed to solve tasks, so under the hood we often…

Each "prompt" couples five very different roles:

1. The core *input → output* behavior, a **Signature**.
2. The computation specializing an inference-time strategy to the signature, a **Predictor**.
3. The computation formatting the signature's inputs and parsing its typed outputs, an **Adapter**.
4. The computations defining objectives and constraints on behavior, **Metrics** and **Assertions**.
5. The strings that instruct (or weights that adapt) the LM for desired behavior, an **Optimizer**.

Existing Compound AI Systems are modular in principle, but are too "stringly-typed":
they couple the fundamental <u>system architecture</u> with incidental choices
not portable to new LMs, objectives, or pipelines.

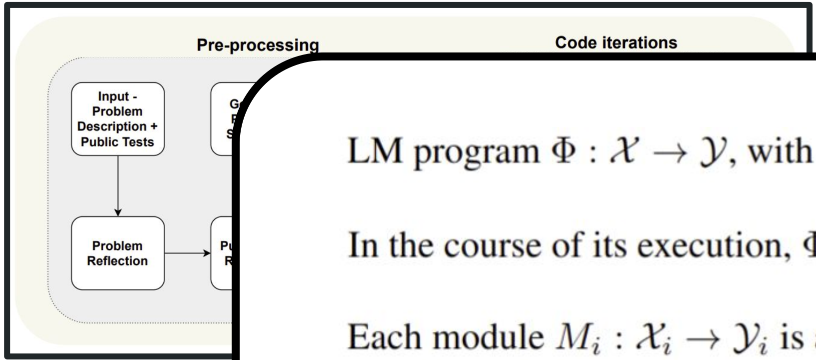
```
'violin': 1,
```

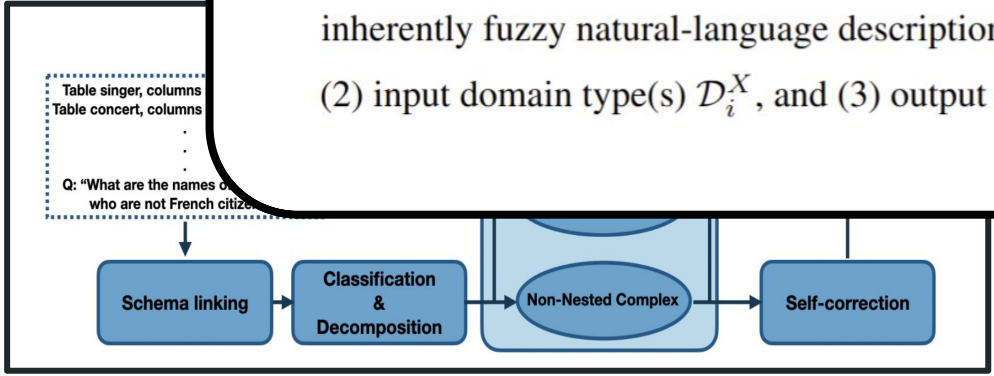
We *know* how to build controllable systems & improve them modularly.

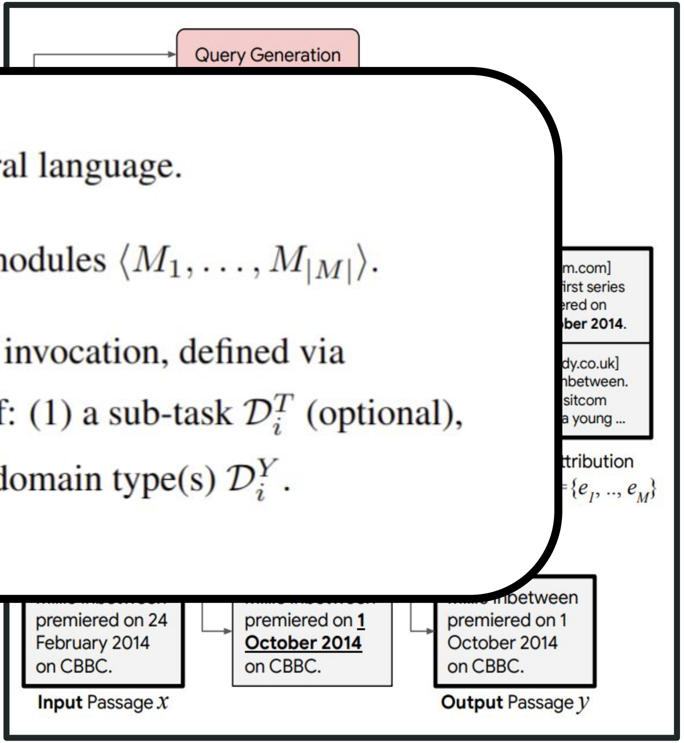
That is called... programming.

What if we could abstract Compound AI Systems as programs with fuzzy natural-language-typed modules that learn their behavior?

DSPy







LM program $\Phi : \mathcal{X} \to \mathcal{Y}$, with $\mathcal{X}$ and $\mathcal{Y}$ in natural language.

In the course of its execution, Φ makes calls to modules $\langle M_1, \ldots, M_{|M|} \rangle$.

Each module $M_i : \mathcal{X}_i \to \mathcal{Y}_i$ is a *declarative* LM invocation, defined via inherently fuzzy natural-language descriptions of: (1) a sub-task $\mathcal{D}_i^T$ (optional), (2) input domain type(s) $\mathcal{D}_i^X$, and (3) output co-domain type(s) $\mathcal{D}_i^Y$.

```python
fact_checking = dspy.ChainOfThought('claims -> verdicts: list[bool]')
fact_checking(claims=["Python was released in 1991.", "Python is a compiled language."])
```

```
Prediction(
    reasoning='The first claim states that "Python was released in 1991," which is true. Python was indeed first released by Guido van Rossum in February 1991. The second claim s
tates that "Python is a compiled language." This is false; Python is primarily an interpr
eted language, although it can be compiled to bytecode, it is not considered a compiled l
anguage in the traditional sense like C or Java.',
    verdicts=[True, False]
)
```

For each module M_i, determine the:

1. String prompt Π_i in which inputs $\mathcal{X}_i$ are plugged in.
2. Weights Θ_i assigned to the LM.

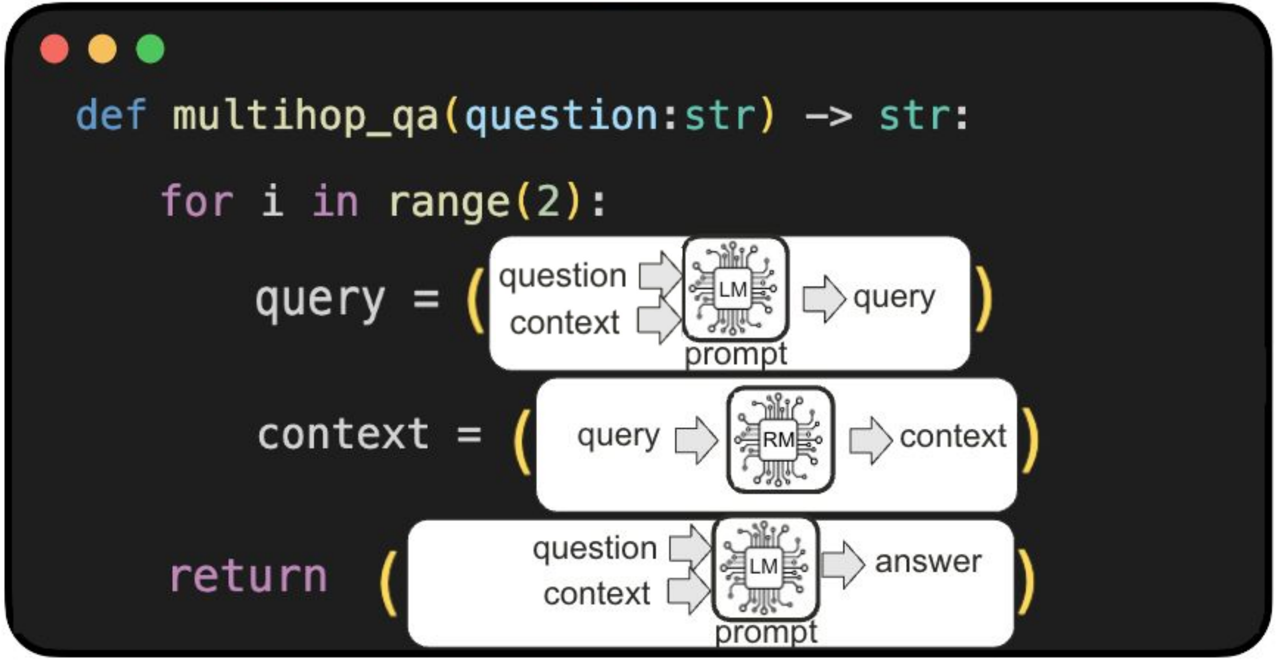
in the optimization problem defined by:

$$\arg\max_{\Theta,\Pi} \frac{1}{|X|} \sum_{(x,m)\in X} \mu(\Phi_{\Theta,\Pi}(x), m)$$

given a small training set $X = \{(x_1, m_1), \ldots, (x_{|X|}, m_{|X|})\}$ and a metric $\mu : \mathcal{Y} \times \mathcal{M} \to \mathbb{R}$ for labels or hints $\mathcal{M}$.

This is hard. We don't have gradients or intermediate labels to optimize each module! How should we go about this?

As an example, let's say we wanted to build this simple pipeline for *multi-hop retrieval-augmented generation*



This can be expressed as the following DSPy program

```python
class MultiHop(dspy.Module):
  def __init__(self):
    self.generate_query  = dspy.ChainOfThought("context, question -> query")
    self.generate_answer = dspy.ChainOfThought("context, question -> answer")

  def forward(self, question):
    context = []
    for hop in range(2):
      query = self.generate_query(context, question).query
      context += dspy.Retrieve(k=3)(query).passages
    answer = self.generate_answer(context, question)

    return answer
```

Anatomy of an LM program in DSPy

```python
class MultiHop(dspy.Module):
  def __init__(self):
    self.generate_query  = dspy.ChainOfThought("context, question -> query")
    self.generate_answer = dspy.ChainOfThought("context, question -> answer")

  def forward(self, question):
    context = []
    for hop in range(2):
      query = self.generate_query(context, question).query
      context += dspy.Retrieve(k=3)(query).passages
    answer = self.generate_answer(context, question)

    return answer
```

Init method defines LM calls

Anatomy of an LM program in DSPy

```python
class MultiHop(dspy.Module):
  def __init__(self):
    self.generate_query  = dspy.ChainOfThought("context, questio
    self.generate_answer = dspy.ChainOfThought("context, question -> answer")

  def forward(self, question):
    context = []
    for hop in range(2):
      query = self.generate_query(context, question).query
      context += dspy.Retrieve(k=3)(query).passages
    answer = self.generate_answer(context, question)

    return answer
```

Forward method defines program logic

Anatomy of an LM program in DSPy

Signature: what to do, not how to prompt!

```python
class MultiHop(dspy.Module):
  def __init__(self):
    self.generate_query  = dspy.ChainOfThought("context, question -> query")
    self.generate_answer = dspy.ChainOfThought("context, question -> answer")

  def forward(self, question):
    context = []
    for hop in range(2):
      query = self.generate_query(context, question).query
      context += dspy.Retrieve(k=3)(query).passages
    answer = self.generate_answer(context, question)

    return answer
```

Anatomy of an LM program in DSPy

Modules define the strategy for expressing a signature

```
class MultiHop(ds
  def __init__(self):
    self.generate_query  = dspy.ChainOfThought("context, question -> query")
    self.generate_answer = dspy.ChainOfThought("context, question -> answer")

  def forward(self, question):
    context = []
    for hop in range(2):
      query = self.generate_query(context, question).query
      context += dspy.Retrieve(k=3)(query).passages
    answer = self.generate_answer(context, question)

    return answer
```

Anatomy of an LM program in DSPy

```python
class MultiHop(dspy.Module):
  def __init__(self):
    self.generate_query  = dspy.ChainOfThought("context, question -> query")
    self.generate_answer = dspy.ChainOfThought("context, question -> answer")

  def forward(self, question):
    context = []
    for hop in range(2):
      query = self.generate_query(context, question).query
      context += dspy.Retrieve(k=3)(query).passages
    answer = self.generate_answer(context, question)

    return answer
```

How can we translate these into high-quality prompts?

First, modules are translated into basic prompts using Adapters and Predictors.

```
self.generate_query = dspy.ChainOfThought("context, question -> query")
```

```
dspy.Adapter(self.generate_query)
```

Predefined *Adapters* are used to translate modules into basic prompts

```
Given the fields “context” and “question”, respond with the field “query”.

Follow the following format:
Context: <context>
Question: <question>
Reasoning: Let’s think step by step to <..>
Query: <query>
```

DSPy's Optimizers can then tune this prompt!

… jointly along with all other prompts in your program

```
Given the fields "context" and "question", respond with the field "query".

Follow the following format:
Context: <context>
Question: <question>
Reasoning: Let's think step by step to <..>
Query: <query>
```

Program Score: 37%

```
optimizer = MIPROv2()
optimized_program = optimizer.compile(program)
```

```
Carefully read the provided `context` and `question`. Your task is to formulate a concise
and relevant `query` that could be used to retrieve information from a search engine to
answer the question most effectively. The `query` should encapsulate...

Follow the following format:
Context: <context>
Question: <question>
Reasoning: Let's think step by step to <..>
Query: <query>

Here are some examples: <...>
```

Program Score: 55%

Instead of tweaking a string prompt...

Solve a question answering task with interleaving Thought, Action, Observation steps. Thought can reason about the current situation, and Action can be three types:

(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.

(2) Lookup[keyword], which returns the next sentence containing keyword in the current passage.

(3) Finish[answer], which returns the answer and finishes the task.

Here are some examples.

Question: What is the elevation range for the area that the eastern sector of the Colorado orogeny extend
Thought 1: I need to search Colorado orogeny, find the area that the eastern sector of the Colorado oroge
elevation range of the area.
Action 1: Search[Colorado orogeny]
Observation 1: The Colorado orogeny was an episode of mountain building (an orogeny) in Colorado and
Thought 2: It does not mention the eastern sector. So I need to look up eastern sector.
Action 2: Lookup[eastern sector]
Observation 2: (Result 1 / 1) The eastern sector extends into the High Plains and is called the Central Pla

[... truncated …]

Scores

33%

with **GPT-3.5**

on a multi-hop QA task

```python
class MultiHop(dspy.Module):
  def __init__(self):
    self.generate_query  = dspy.ChainOfThought("context, question -> query")
    self.generate_answer = dspy.ChainOfThought("context, question -> answer")

  def forward(self, question):
    context = []
    for hop in range(2):
      query = self.generate_query(context, question).query
```

```
Carefully read the provided `context` and `question`. Your task is to formulate a concise and
relevant `search_query` that could be used to retrieve information from a search engine to answer
the question most effectively. The `search_query` should encapsulate...

Context: [1] Twilight is a series of four vampire-themed fantasy romance...
         [2] The Harper Connelly Mysteries is a series of fantasy...
Question: In which year was the first of the vampire-themed fantasy romance novels, for which The
Twilight Saga serves as a spin-off encyclopedic reference book, first published?
Reasoning: Let's determine when that fantasy romance novel was first published.
Search Query: When was the first of the vampire-themed fantasy romance novels published?

Context: [1] The Victorians - Their Story In Pictures is a 2009 British documentary ...
         [2] The Caxtons: A Family Picture is an 1849 Victorian novel by Edward ...
Question: The Victorians is a documentary series written by an author born in what year?
Reasoning: We know that the documentary series is about Victorian art and culture, and it was
written by Jeremy Paxman. We need to find the year in which Jeremy Paxman was born.
Search Query: Jeremy Paxman birth year
```

*** prompt parts adapted & combined for presentation**

Scores

55%

with **GPT-3.5**

on multi-hop QA

39%

with **T5-770M**

50%

with **Llama2-13B**

Multi-Hop Retrieval-Augmented Generation (HotPotQA)

Program	Optimized	GPT 3.5	Llama2-13b-Chat
`dspy.Predict("question -> answer")`	❌	34.3	27.5
`dspy.RAG (with CoT)`	❌	36.4	34.5
	✅	42.3	38.3
`MultiHop`	❌	36.9	34.7
	✅	**54.7**	**50.0**

Compiling `MultiHop` into a small LM (T5-770M) with DSPy's BootstrapFinetune, starting from 200 answers, scores 39%

DSPy Optimizers vary in how they tune the prompts & weights in a program, but at a high level they typically...

1. Construct an **initial prompt from each module** via an *Adapter*

2. **Generate examples of every module** via rejection sampling

3. Use the examples to **update the program's modules**
   a. Automatic few-shot prompting: `dspy.BootstrapFewShotWithRandomSearch`
   b. Induction of instructions: `dspy.MIPROv2`
   c. Multi-stage fine-tuning: `dspy.BootstrapFinetune`

Optimizing Instructions and Demonstrations for Multi-Stage Language Model Programs

Krista Opsahl-Ong[1*], Michael J Ryan[1*], Josh Purtell[2], David Broman[3], Christopher Potts[1], Matei Zaharia[4], Omar Khattab[1]

[1]Stanford University, [2]Basis, [3]KTH Royal Institute of Technology [4]UC Berkeley

Fine-Tuning and Prompt Optimization: Two Great Steps that Work Better Together

Dilara Soylu Christopher Potts Omar Khattab

Stanford University

That works well in practice…

- May’24: U of Toronto researchers won the MEDIQA competition via DSPy.
- Jun’24: U of Maryland researchers ran a direct case study.

Rank	Team	Error Sentence Detection Accuracy
1	WangLab	83.6%
2	EM_Mixers	64.0%
3	knowlab_AIMed	61.9%
4	hyeonhwang	61.5%
5	Edinburgh Clinical NLP	61.1%
6	IryoNLP	61.0%
7	PromptMind	60.9%
8	MediFact	60.0%
9	IKIM	59.0%
10	HSE NLP	52.0%

Learn Prompting
@learnprompting

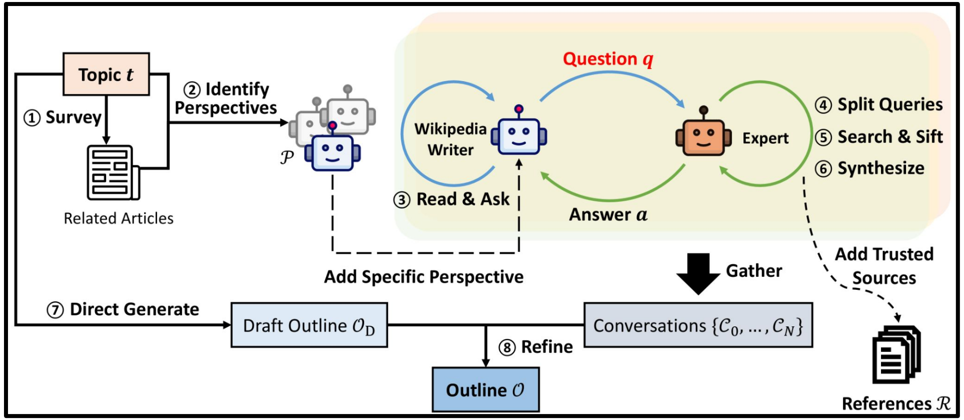
🤖We also put our expert prompt engineer against an AI prompt engineer.

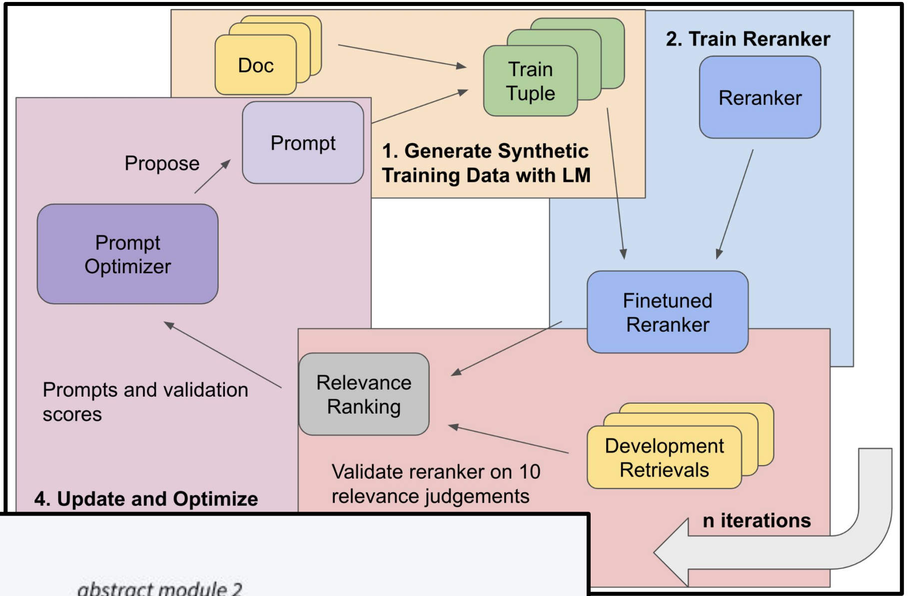
Expert human prompt engineer, @sanderschulhoff faced off against @lateinteraction's DSPy on a labeling task.

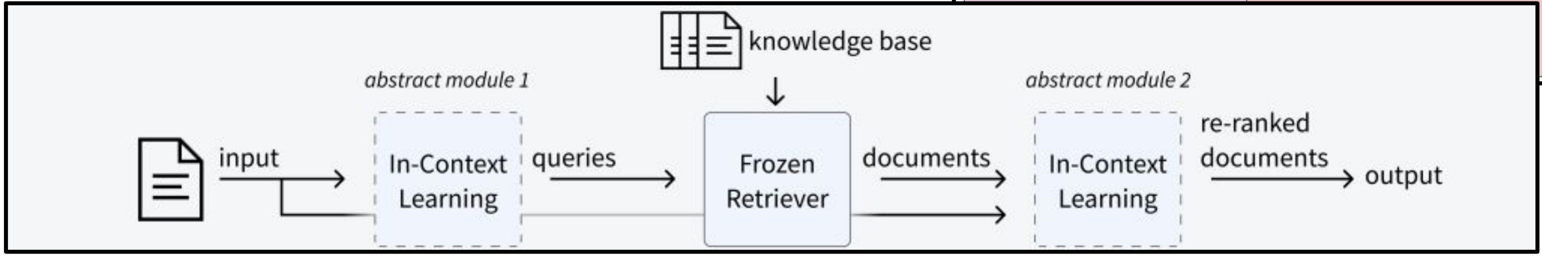
DSPY outperformed our expert Human Prompt Engineer by 50% on our test set and saved over 20 hours!

… and has enabled many SoTA systems

like PATH (Jasper Xia, UWaterloo); IReRa (Karel D'Oosterlink, UGhent), STORM (Yijia Shao, Stanford), EDEN (Siyan Li, Columbia), Efficient Agents (Sayash Kapoor, Princeton), ECG-Chat (Yubao Zhao, Beijing Normal U), …







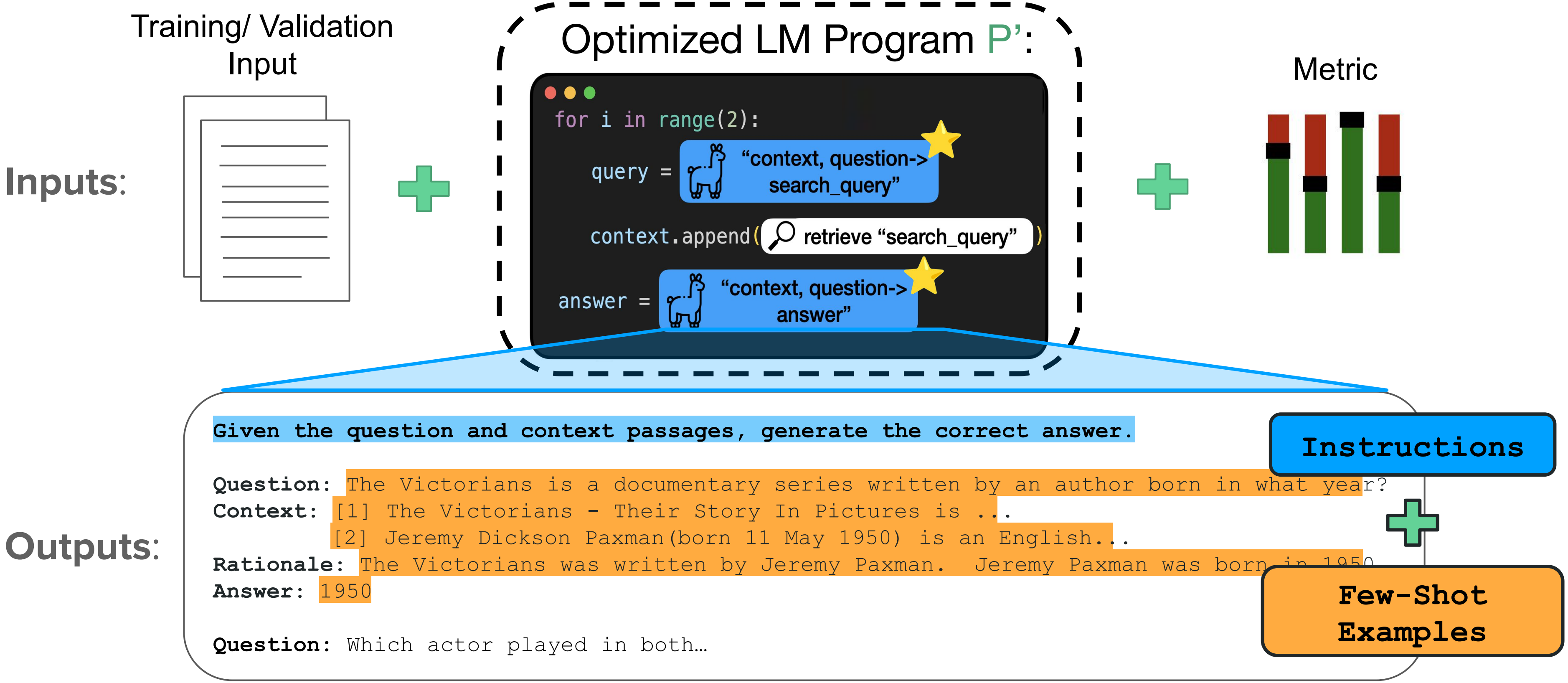
Optimizing Instructions and Demonstrations for Multi-Stage Language Model Programs

Krista Opsahl-Ong[1*], Michael J Ryan[1*], Josh Purtell[2], David Broman[3], Christopher Potts[1], Matei Zaharia[4], Omar Khattab[1]

[1]Stanford University, [2]Basis, [3]KTH Royal Institute of Technology [4]UC Berkeley

Slides adapted from
Krista Opsahl-Ong & Michael Ryan

Problem Setting



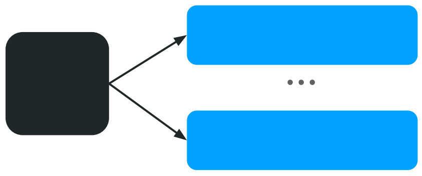
Constraints / Assumptions

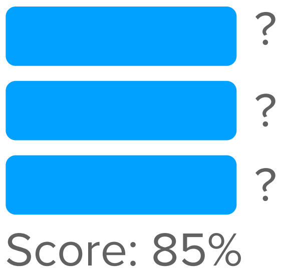
1. **No access to log-probs or model weights**: Developers may want to optimize LM programs for use on API only models.

2. **No intermediate metrics / labels**: We assume no access to manual ground-truth labels for intermediate stages.

3. **Budget-Conscious**: We want to limit the number of input examples we require and the number of program calls we make.

Key Challenges





Prompt Proposal.

Searching over all possible strings is intractable, especially as we add in multiple modules we need to optimize. Instead, we need to propose a *small set* of *high quality* options.

Credit Assignment.

We need efficient ways of inferring how each prompt variable contributes to performance, so that we can find the best set for our program.

Methods

1. Bootstrap Few-shot
2. Extending OPRO
3. MIPRO

Methods

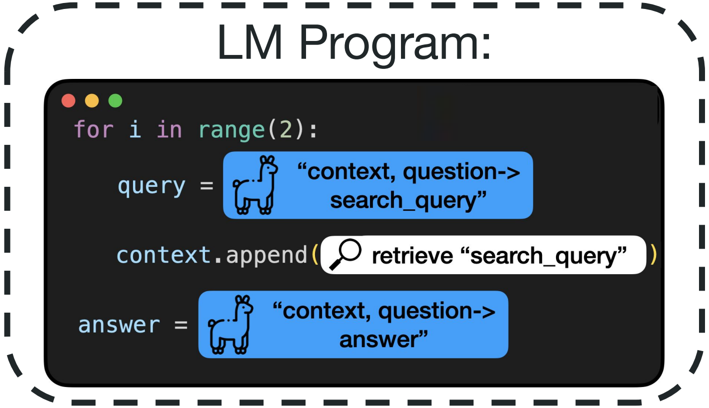
1. Bootstrap Few-shot
2. Extending OPRO
3. MIPRO

💡 *Bootstrap Few-shot examples with simple rejection sampling*

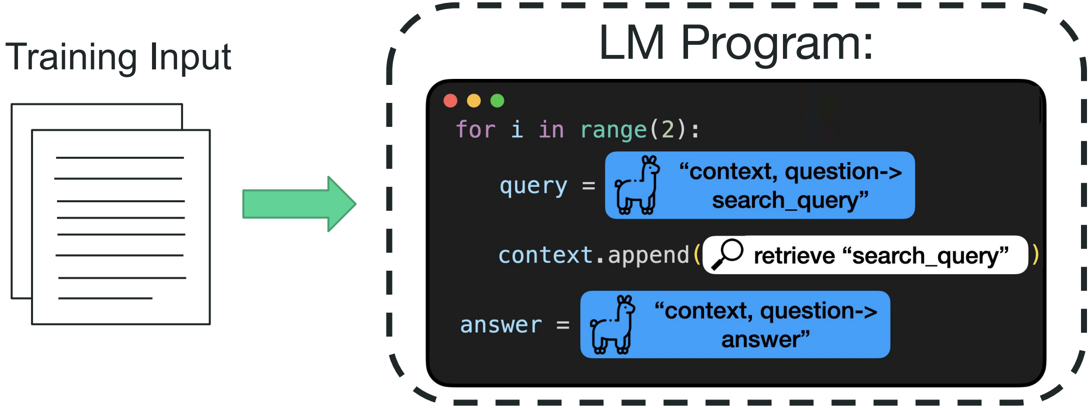
Bootstrap Few-Shot Examples

O. Khattab, A. Singhvi, P. Maheshwari, Z. Zhang, K. Santhanam, S. Vardhamanan, S. Haq, A. Sharma, T. T. Joshi, H. Moazam, H. Miller, M. Zaharia, C. Potts “DSPY: COMPILING DECLARATIVE LANGUAGE MODEL CALLS INTO SELF-IMPROVING PIPELINES”

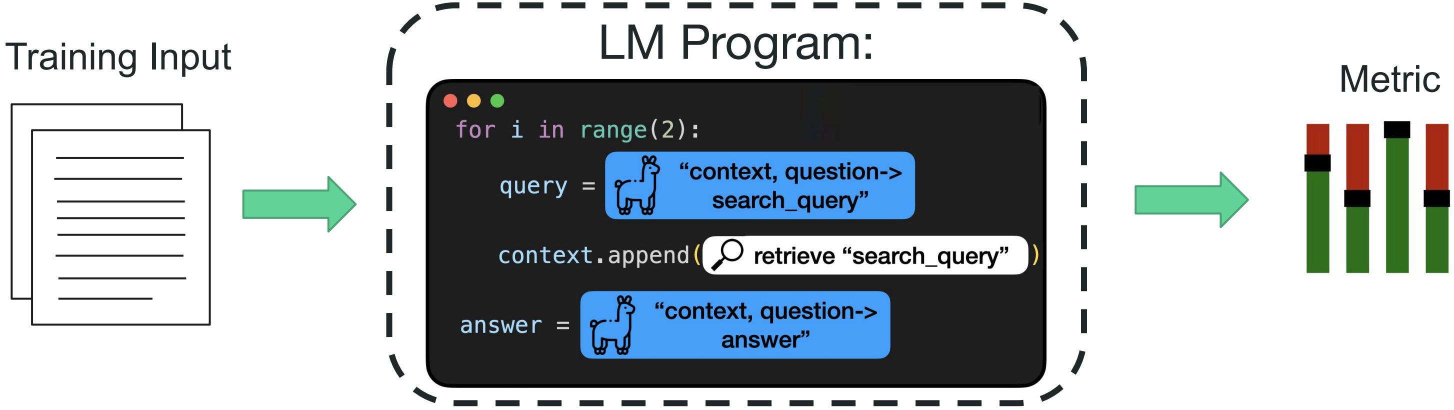
Bootstrap Few-Shot Examples



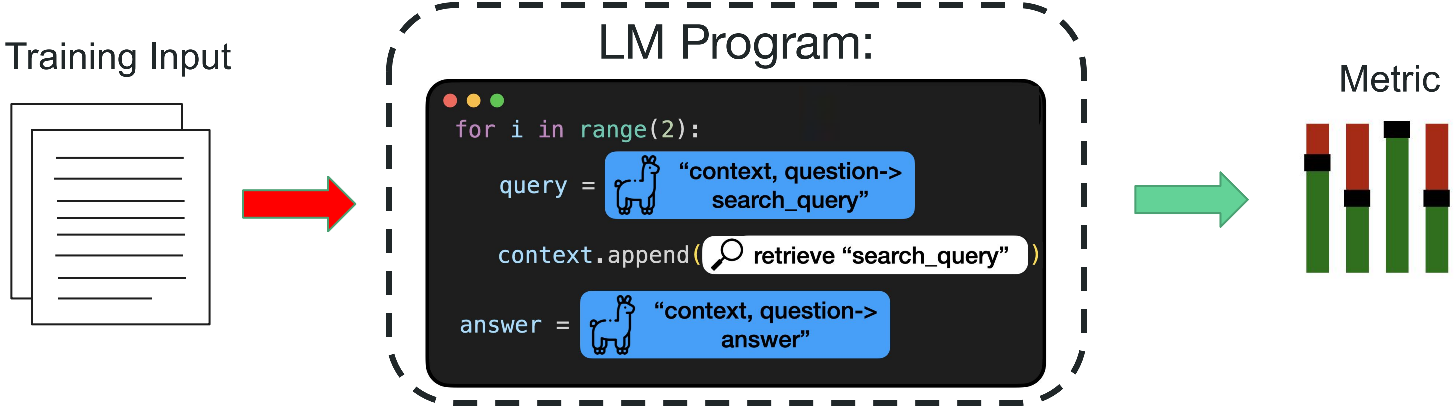
Bootstrap Few-Shot Examples



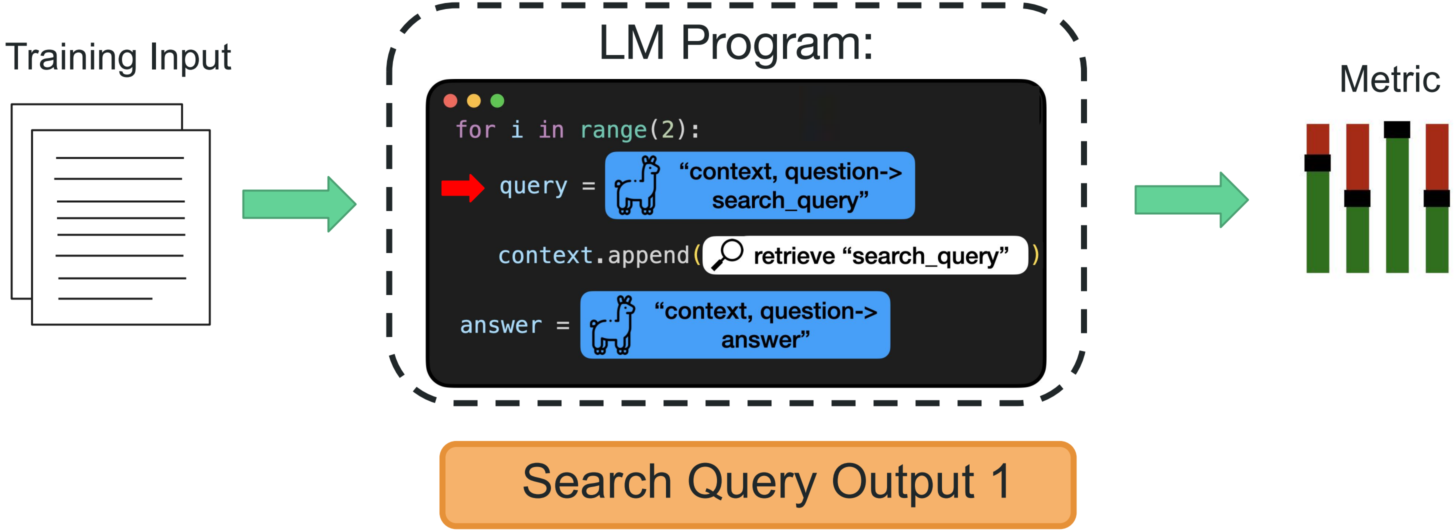
Bootstrap Few-Shot Examples



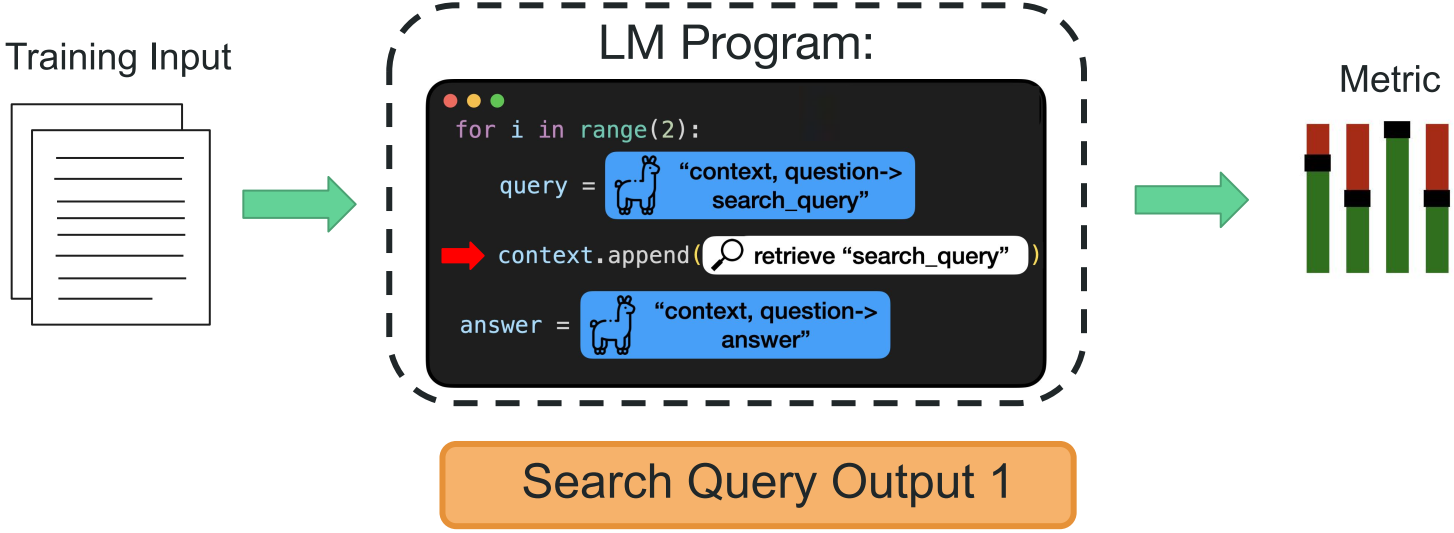
Bootstrap Few-Shot Examples



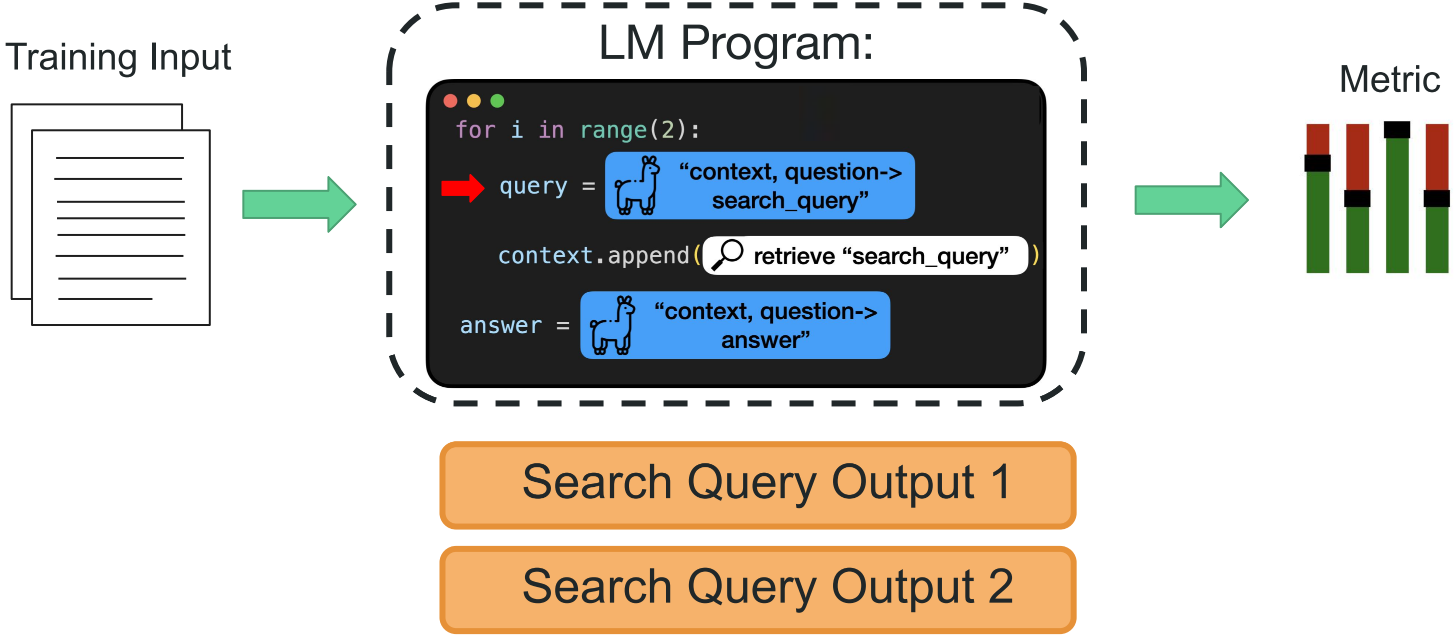
Bootstrap Few-Shot Examples



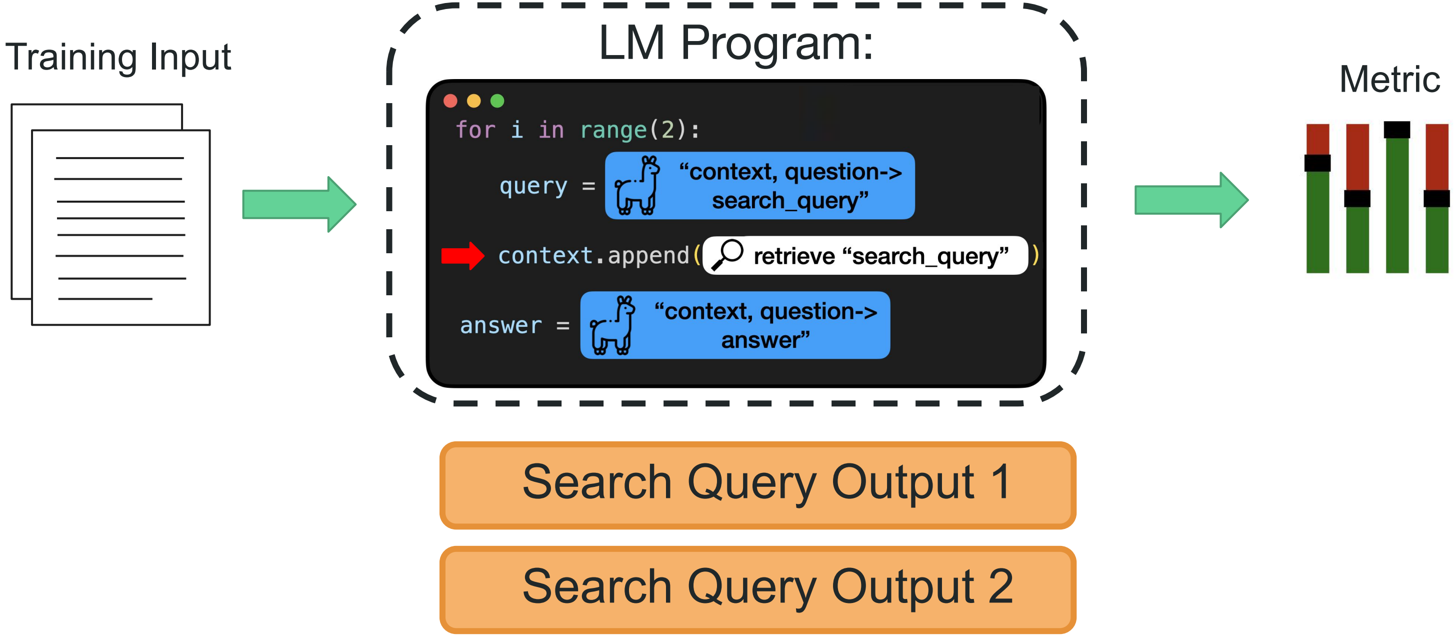
Bootstrap Few-Shot Examples



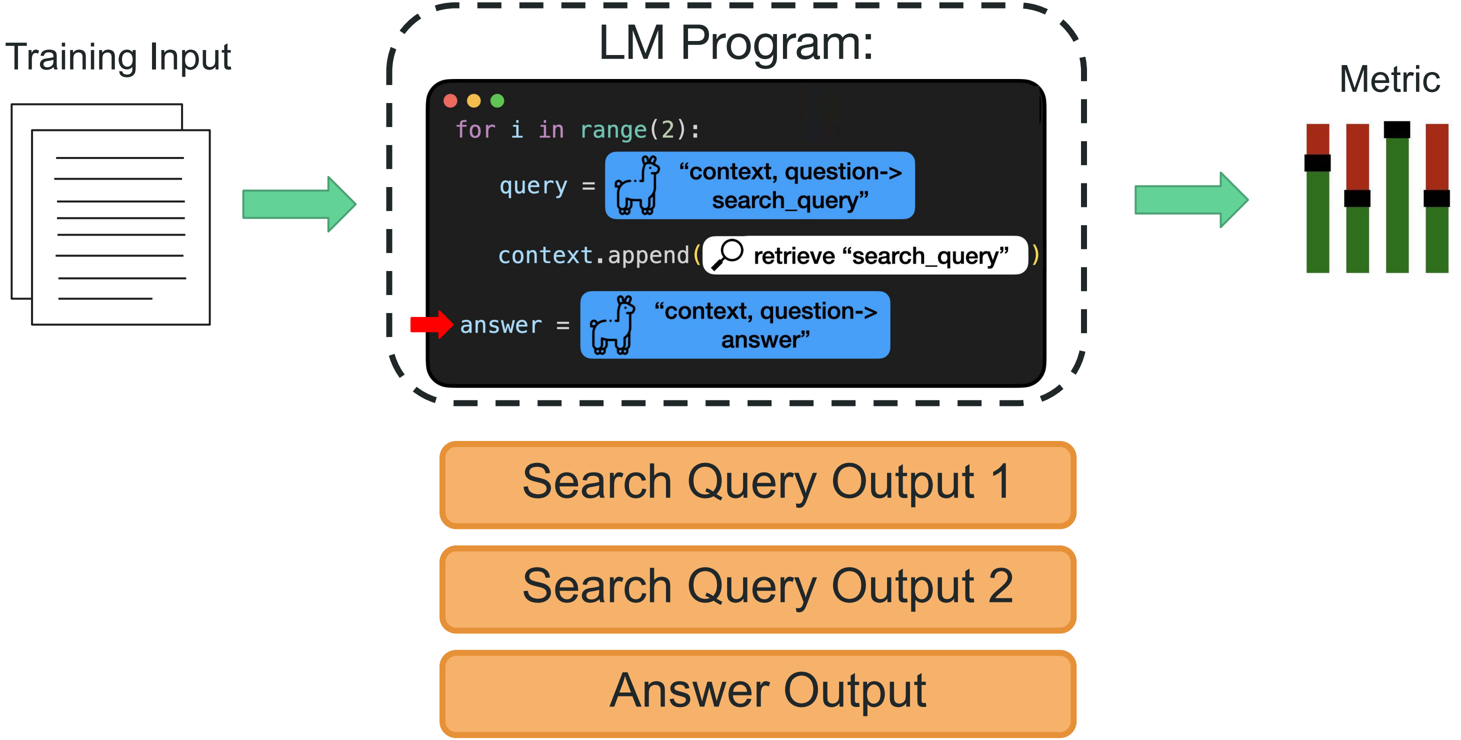
Bootstrap Few-Shot Examples



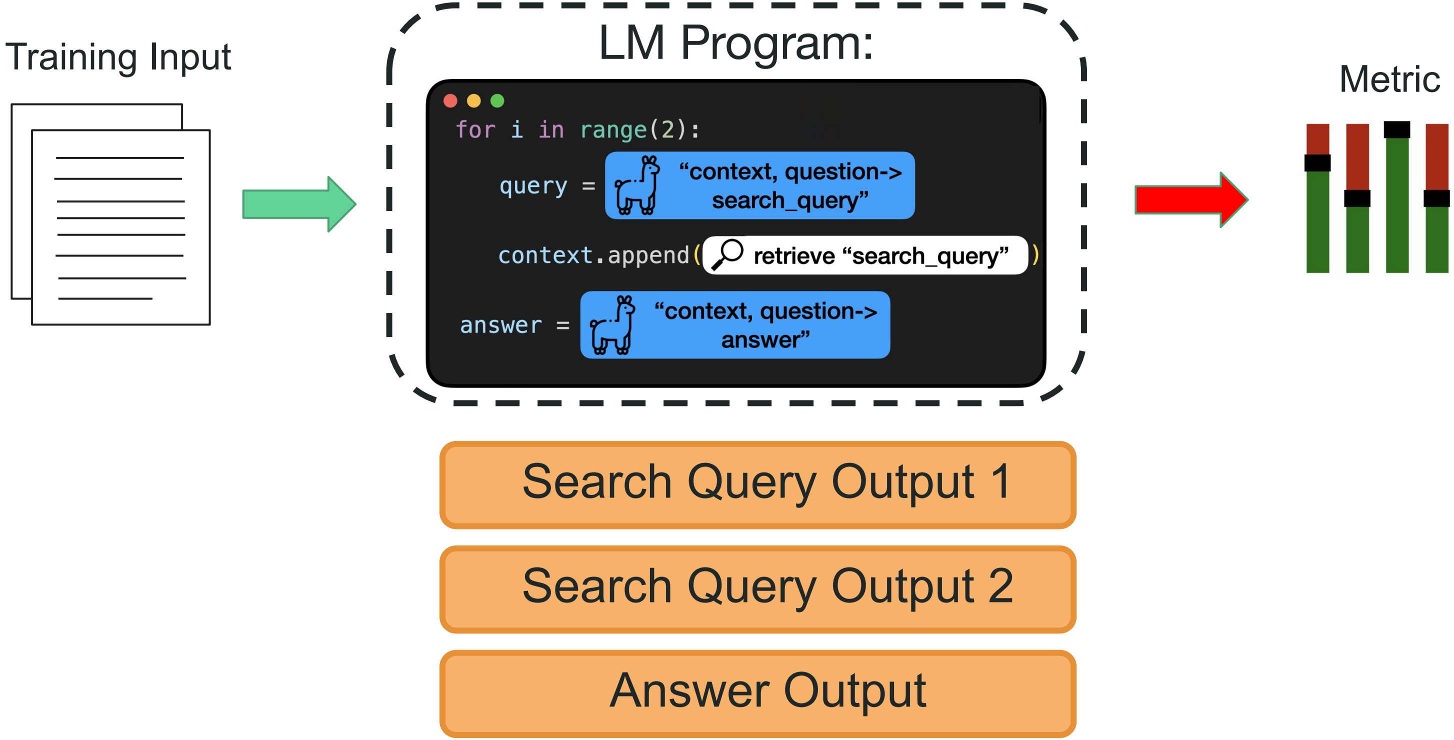
Bootstrap Few-Shot Examples



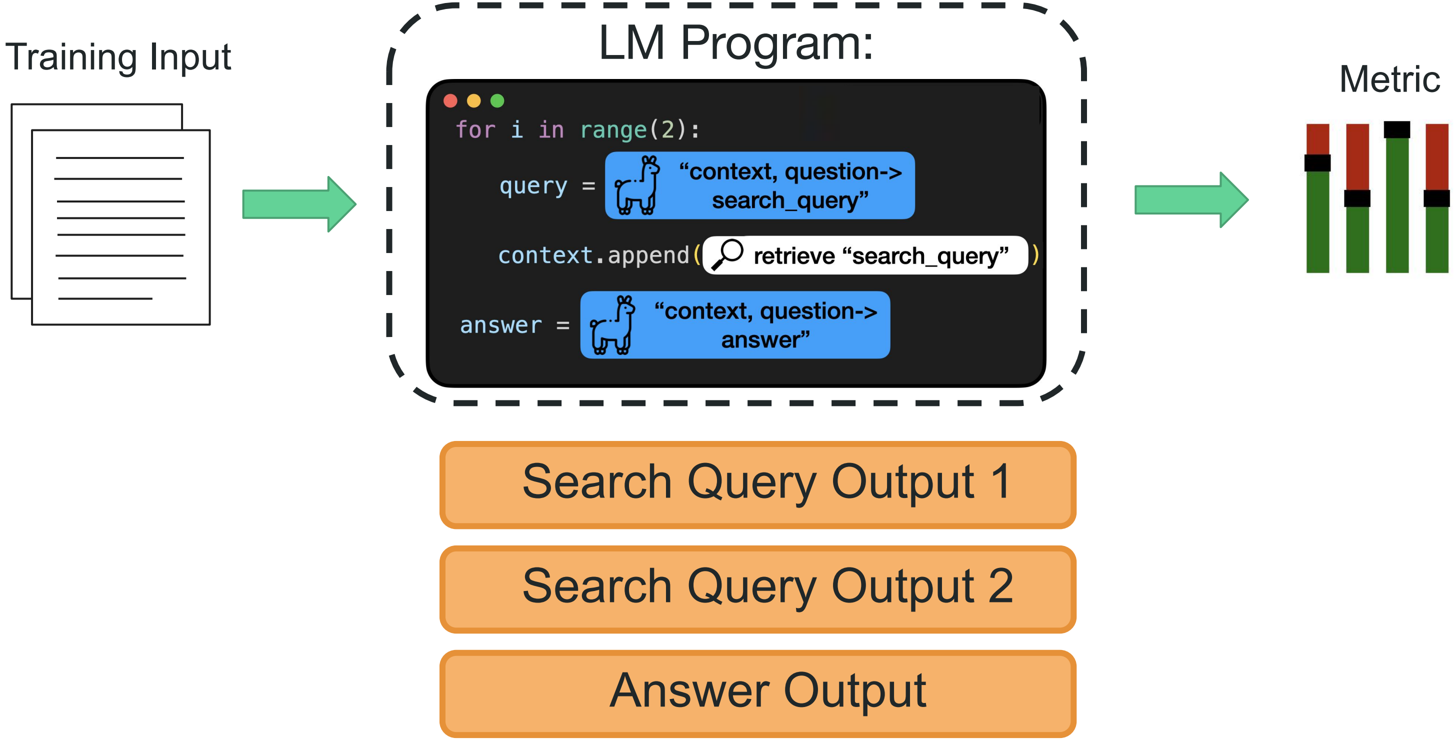
Bootstrap Few-Shot Examples



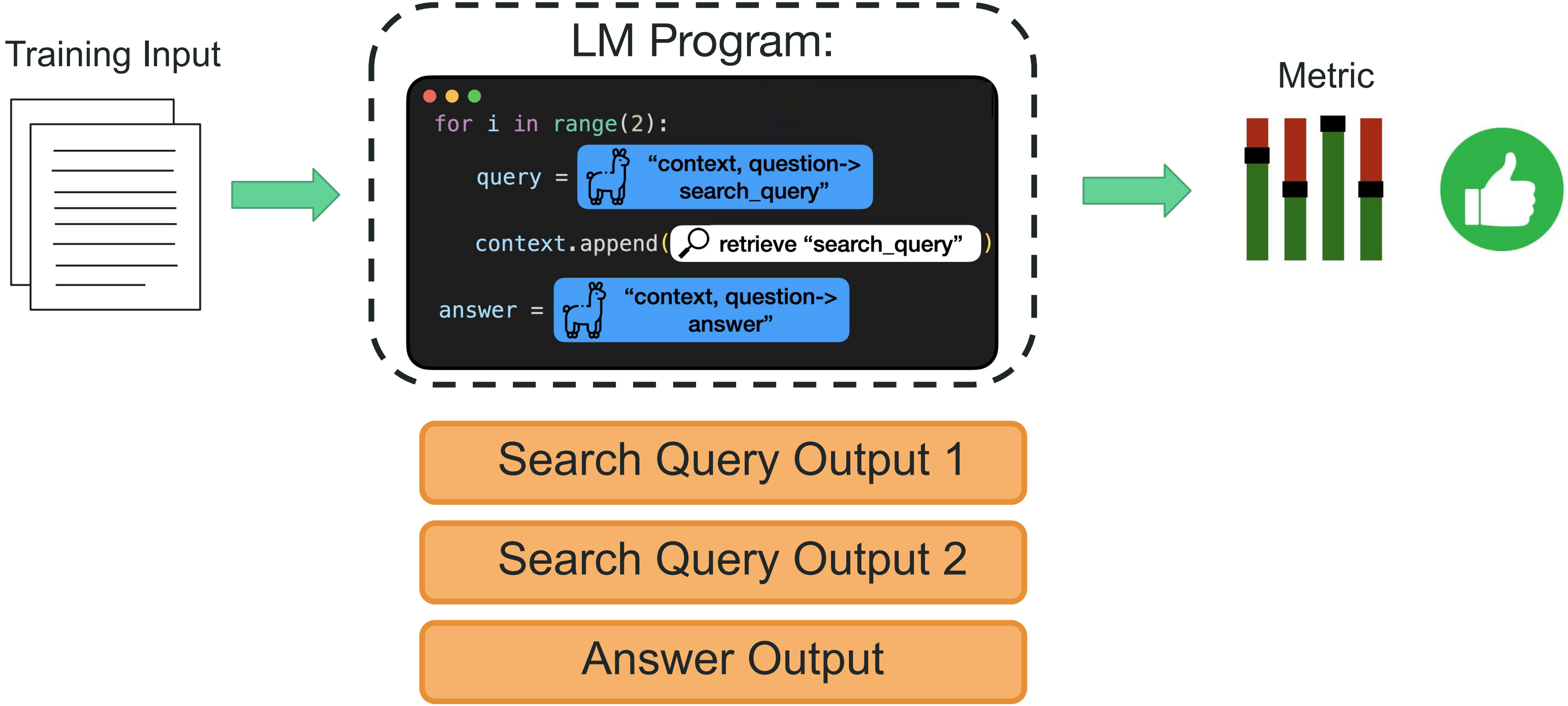
Bootstrap Few-Shot Examples



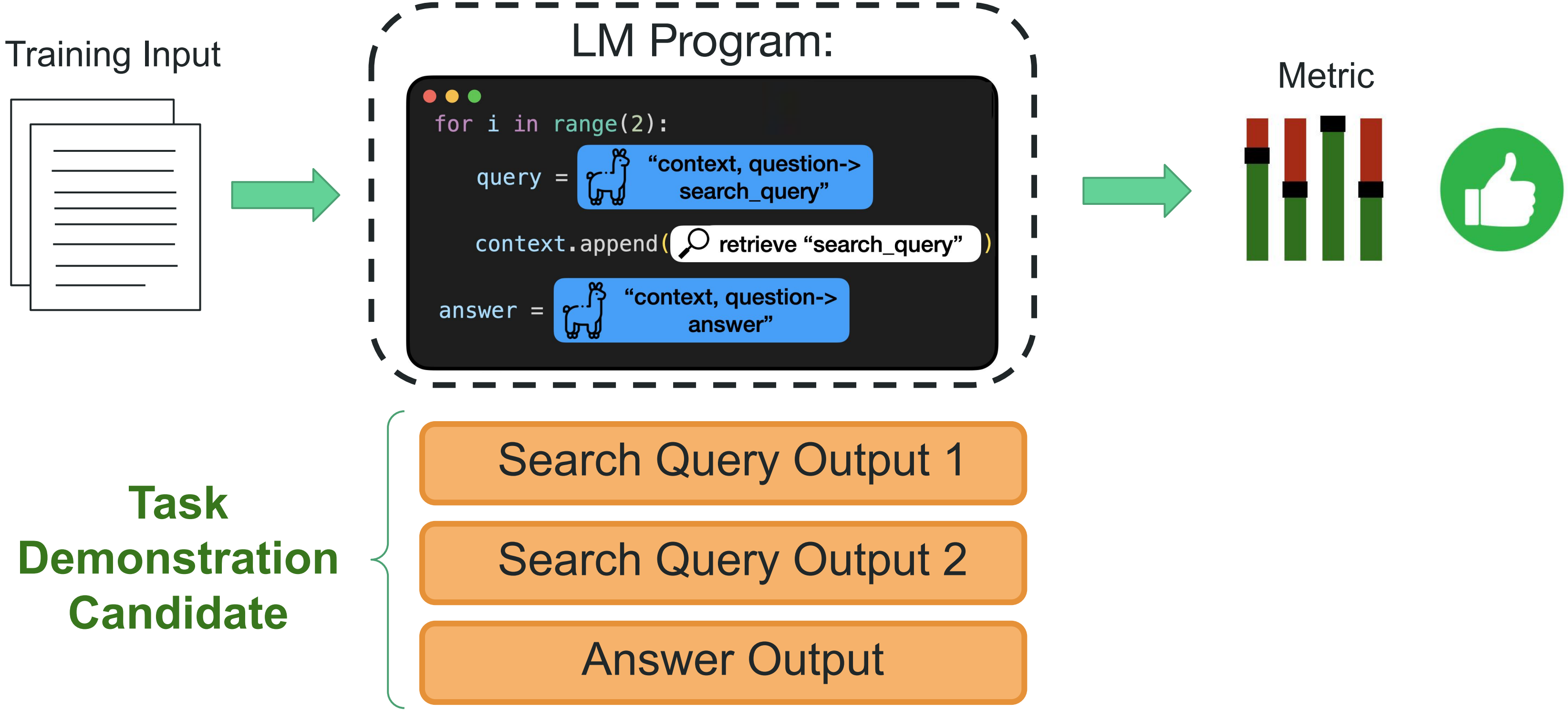
Bootstrap Few-Shot Examples



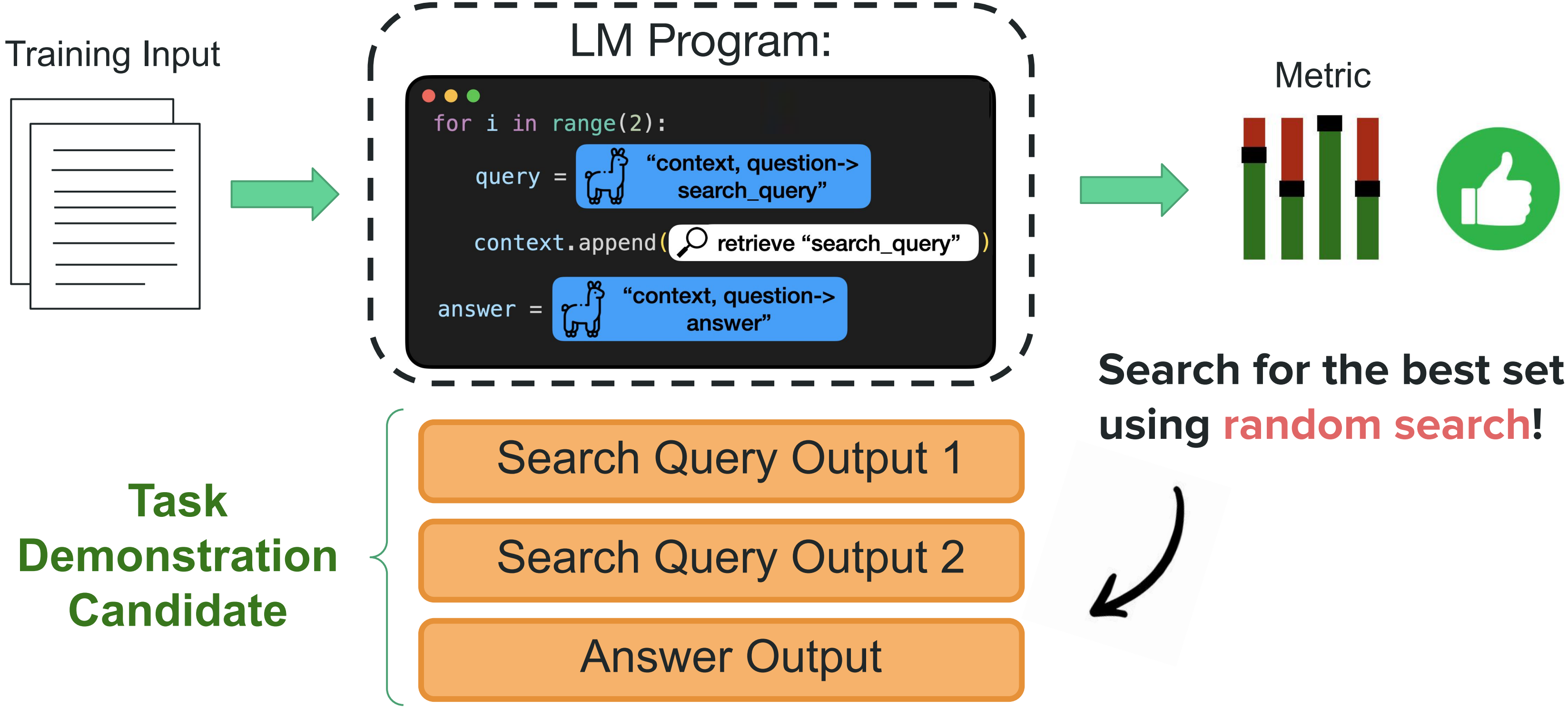
Bootstrap Few-Shot Examples



Bootstrap Few-Shot Examples



Bootstrap Few-Shot (w/ Random Search)



Bootstrap Few-Shot (w/ Random Search)

```
Given the context passages and a question, generate the correct answer.

Context: [1] The Victorians - Their Story In Pictures is ...
         [2] Jeremy Dickson Paxman(born 11 May 1950) is an English...
Question: The Victorians is a documentary series written by an author born in what year?
Rationale: The Victorians was written by Jeremy Paxman.  Jeremy Paxman was born in 1950.
Answer: 1950

...
```

Task Demonstration Candidate

- Search Query Output 1
- Search Query Output 2
- Answer Output

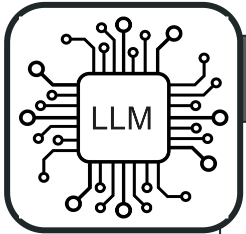
Methods

1. Bootstrap Few-shot
2. Extending OPRO
3. MIPRO

💡 *Extend existing instruction opt. method (OPRO) to multi-stage*

What is OPRO? Optimization through Prompting

"Proposer LM"



Prompt Proposals

"Think step by step"

"Take a deep breath and think step by step"

"Carefully solve the problem"

"Let's do the math"

Evaluate

Propose More Prompts

Given prompts/scores propose more prompts.

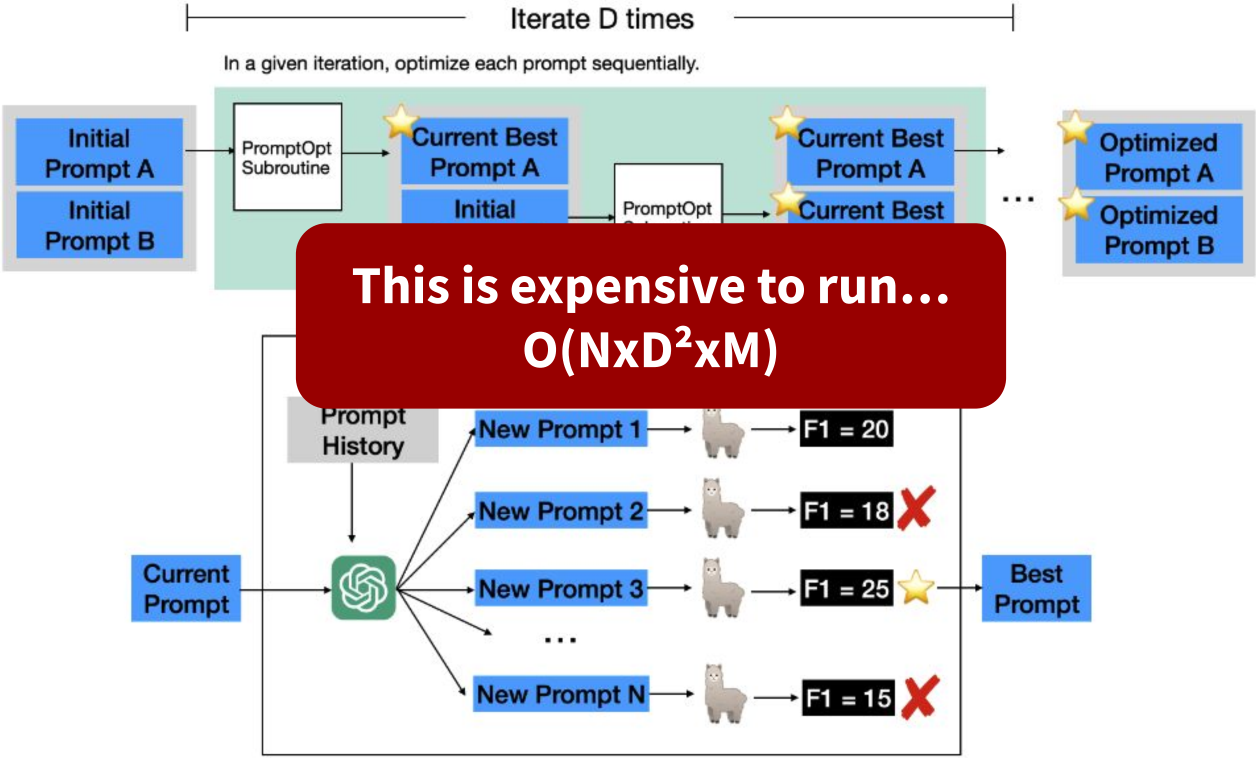
"Think step by step"
Score: 31

"Take a deep breath and think step by step"
Score: 42

C. Yang*, X. Wang, Y. Lu, H. Liu, Q. V. Le, D. Zhou, X. Chen* "Large Language Models as Optimizers"

Initial extension to multi-stage: CA-OPRO

Coordinate-Ascent OPRO



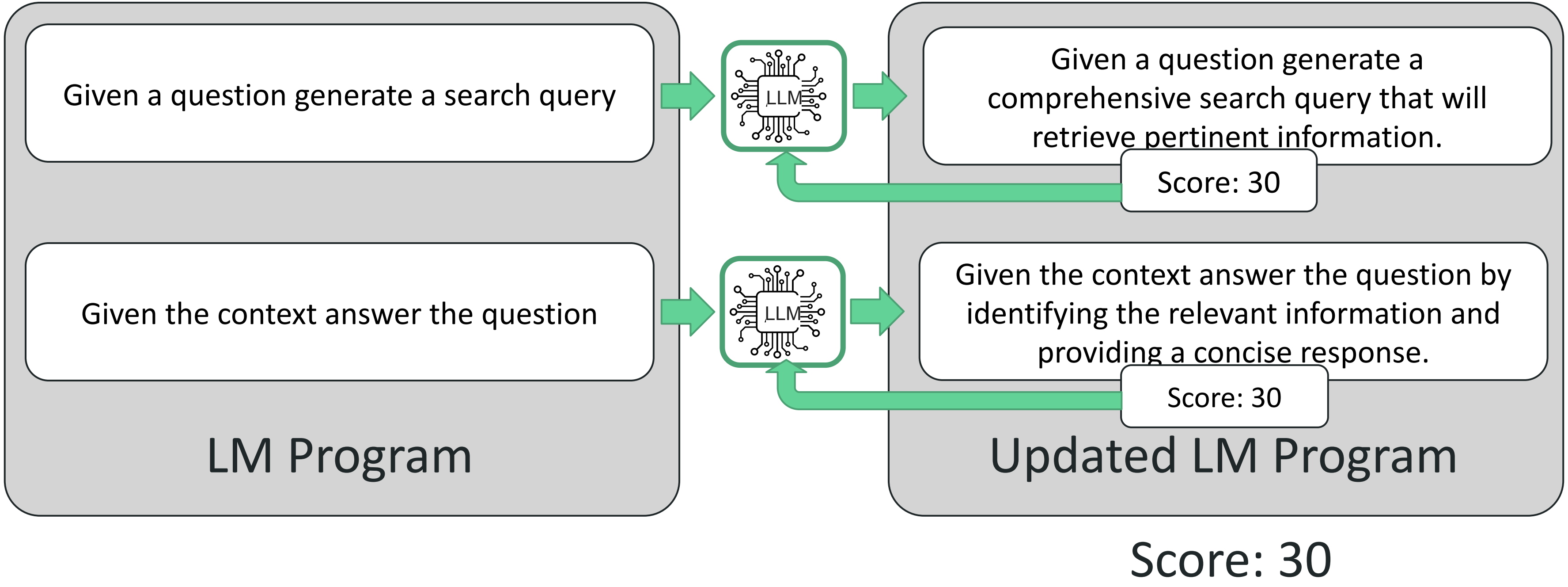
This is expensive to run…
$O(N \times D^2 \times M)$

Module-Level OPRO

Key Idea: Coordinate-Ascent was expensive, maybe we don't need explicit credit assignment? Let's just change both prompts at a time in parallel!

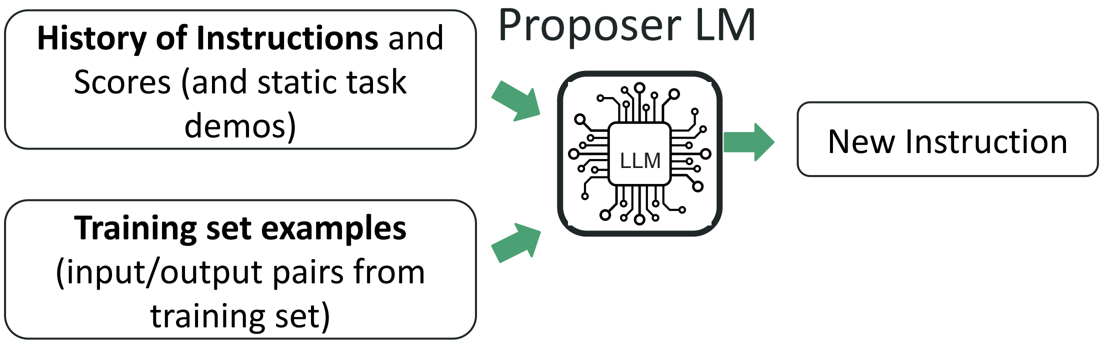
Module-Level OPRO

Key Idea: Coordinate-Ascent was expensive, maybe we don't need explicit credit assignment? Let's just change both prompts at a time in parallel!



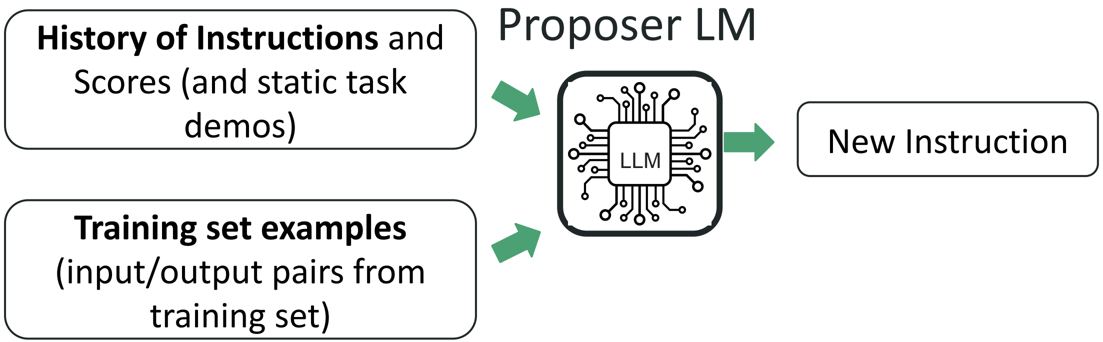
Finally, Grounding!

Hypothesis: Providing our proposer LM with more information relevant to the task can help us propose better instructions.

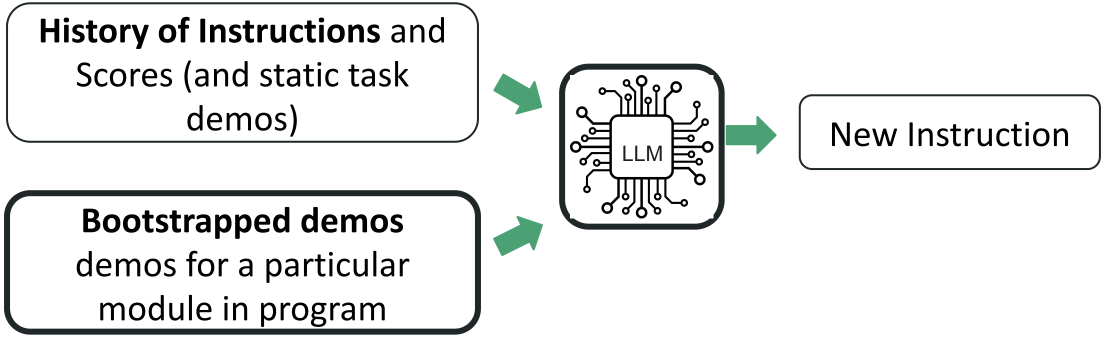


Finally, Grounding!

Key idea: What if we built a multi-stage LM program to bootstrap and synthesize information about the task for use in instruction proposal?



Finally, Grounding!



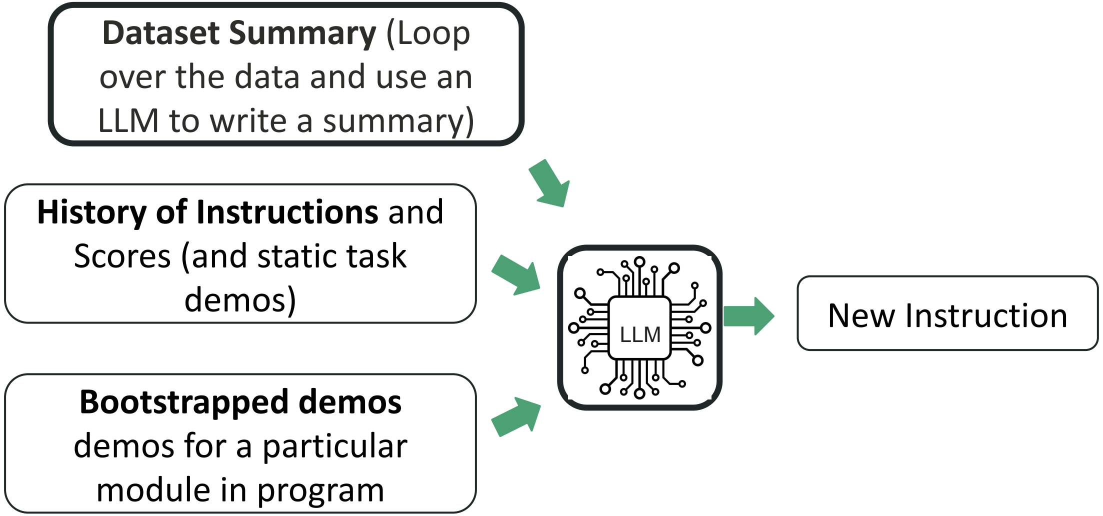
Bootstrapped demo example:

Question: The Victorians - Their Story In Pictures is a documentary series written by an author born in what year?

Reasoning: Let's think step by step in order to find the search query. We need to find the author's birth year. We can search for the author's name along with the phrase "birth year" or "birthday" to get the desired information.

Search Query: "author of The Victorians - Their Story In Pictures birth year" or "author of The Victorians - Their Story In Pictures birthday"

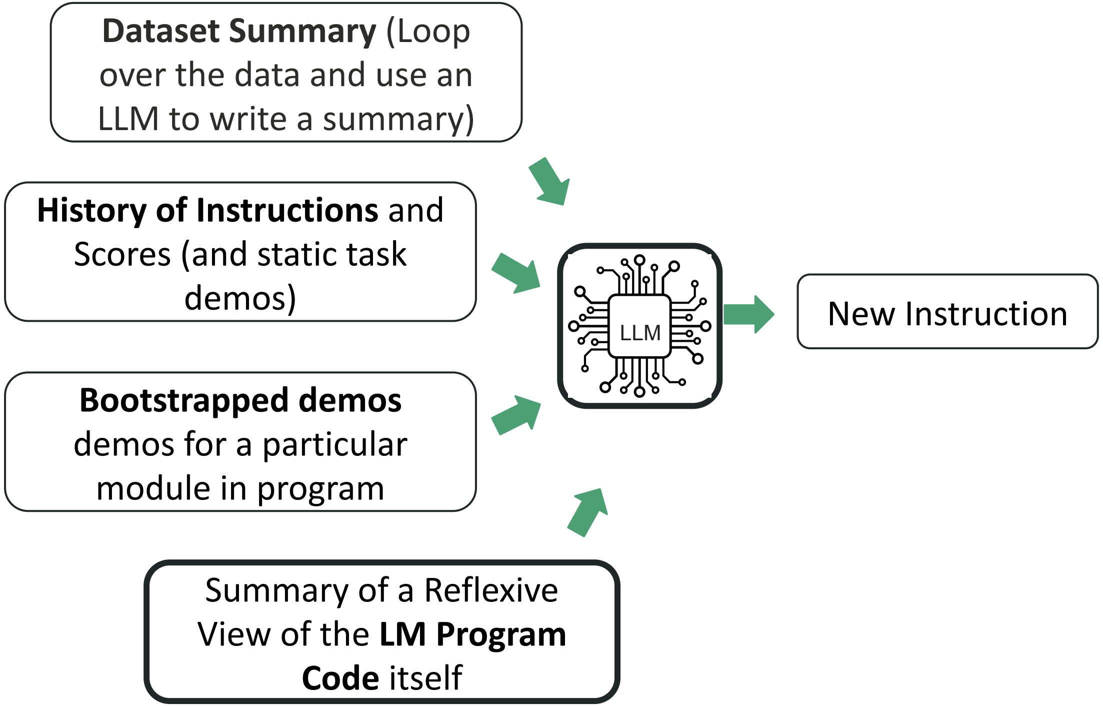
Finally, Grounding!



Dataset summary example:

"The dataset **consists of factual, trivia-style questions** across a wide range of topics, presented in a clear and concise manner. These questions are likely designed for use in trivia games.."

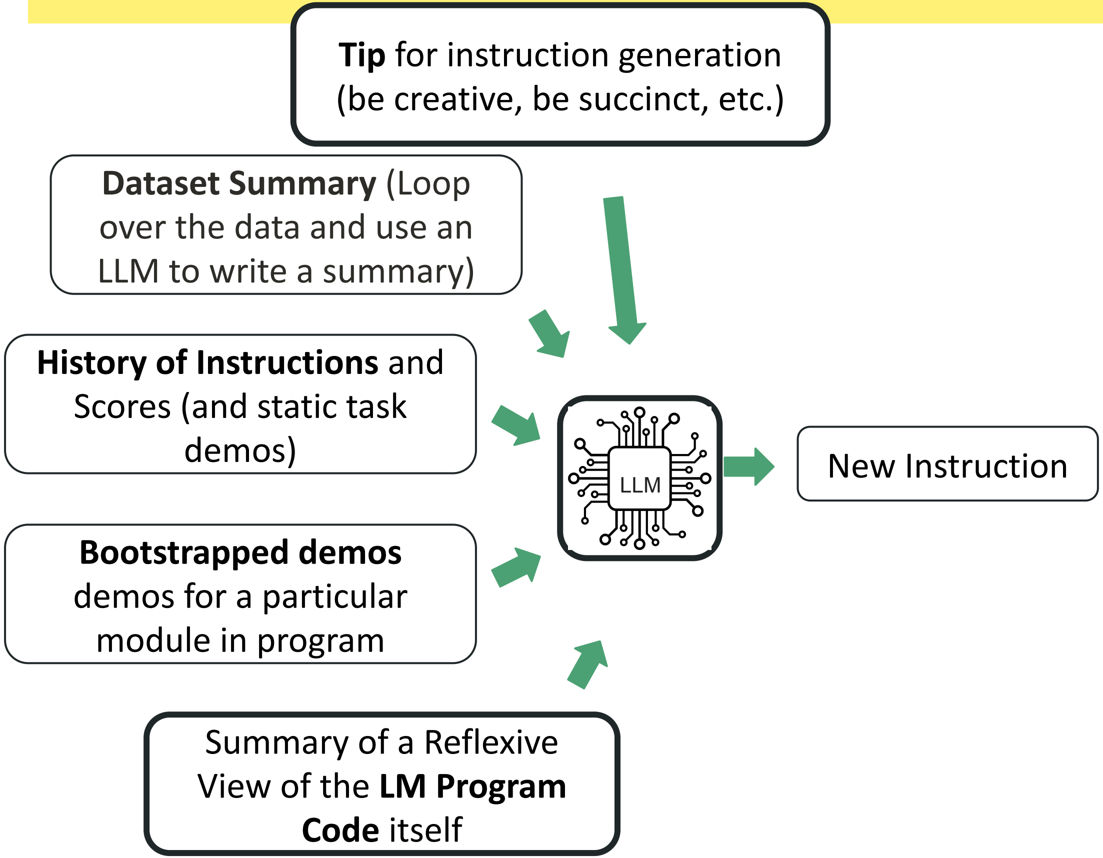
Finally, Grounding!



Program Summary example:

"The program code appears to be **designed to answer complex questions by retrieving and processing information from multiple sources** or passages. In this case, the program is set up for two hops, … The **module `self.generate_query` in this program is responsible for generating a search query** based on the context and question provided."

Finally, Grounding!



Tip example:

"Don't be afraid to be creative when generating the new instruction"

"Keep the instruction clear and concise."

"Make sure your instruction is very informative and descriptive."

Methods

1. Bootstrap Few-shot
2. Extending OPRO
3. MIPRO

💡 *Co-optimize instructions & few-shot examples efficiently*

MIPRO works in 3 steps:

Multi-prompt Instruction PRoposal Optimizer

Prompt Proposal

1. Bootstrap Task Demonstrations

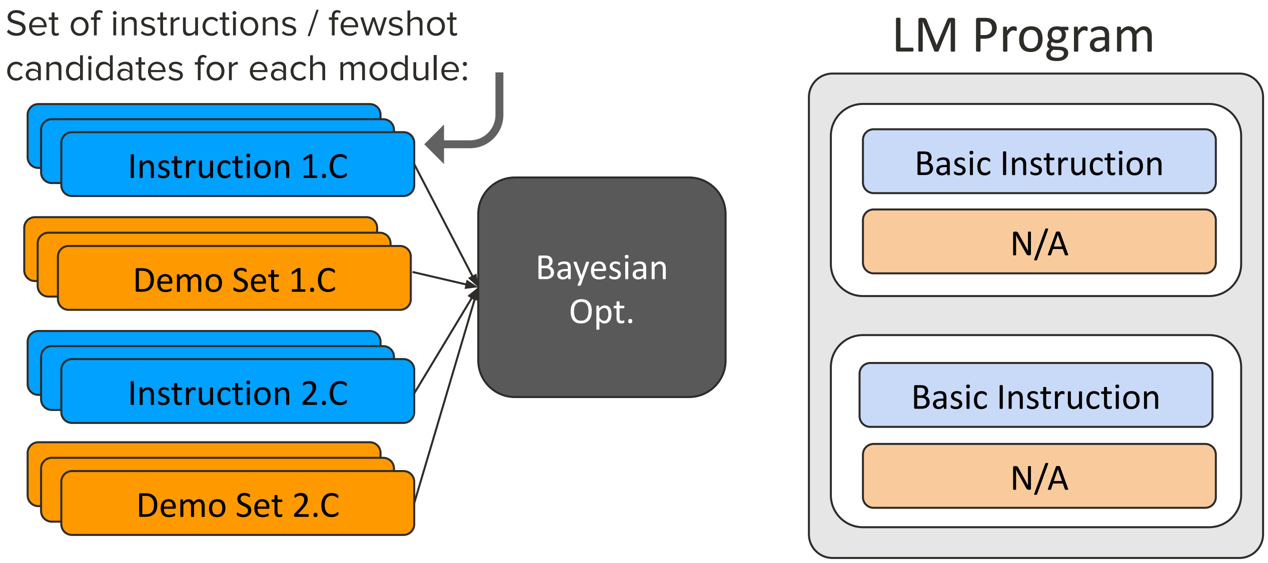
2. Propose Instruction Candidates using an LM Program

Credit Assignment

3. Jointly tune with a Bayesian hyperparameter optimizer

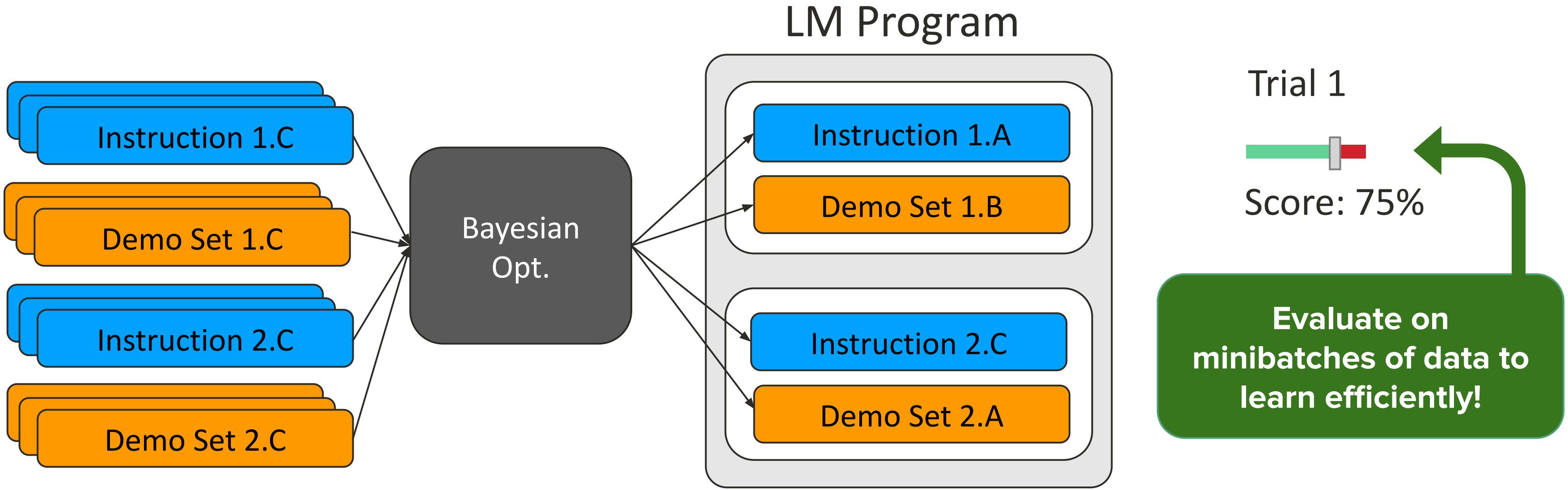
Step 3: Optimize with Bayesian Learning

Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



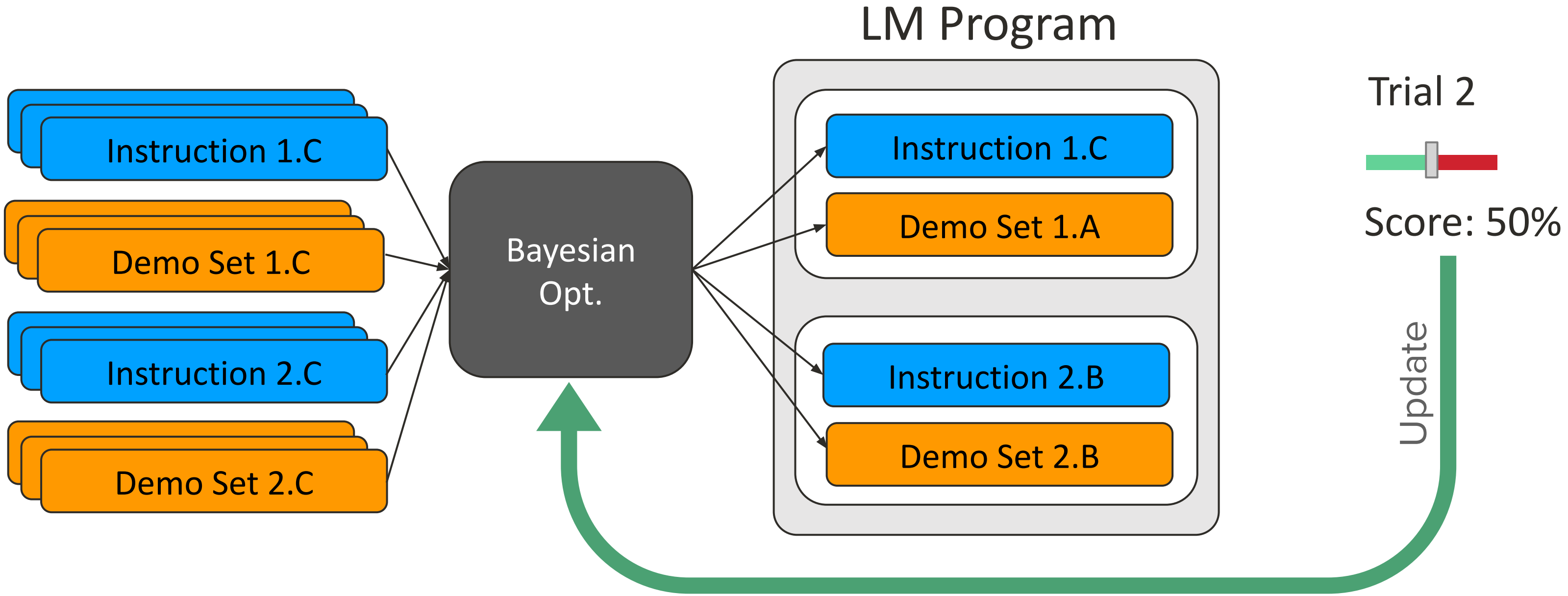
Step 3: Optimize with Bayesian Learning

Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



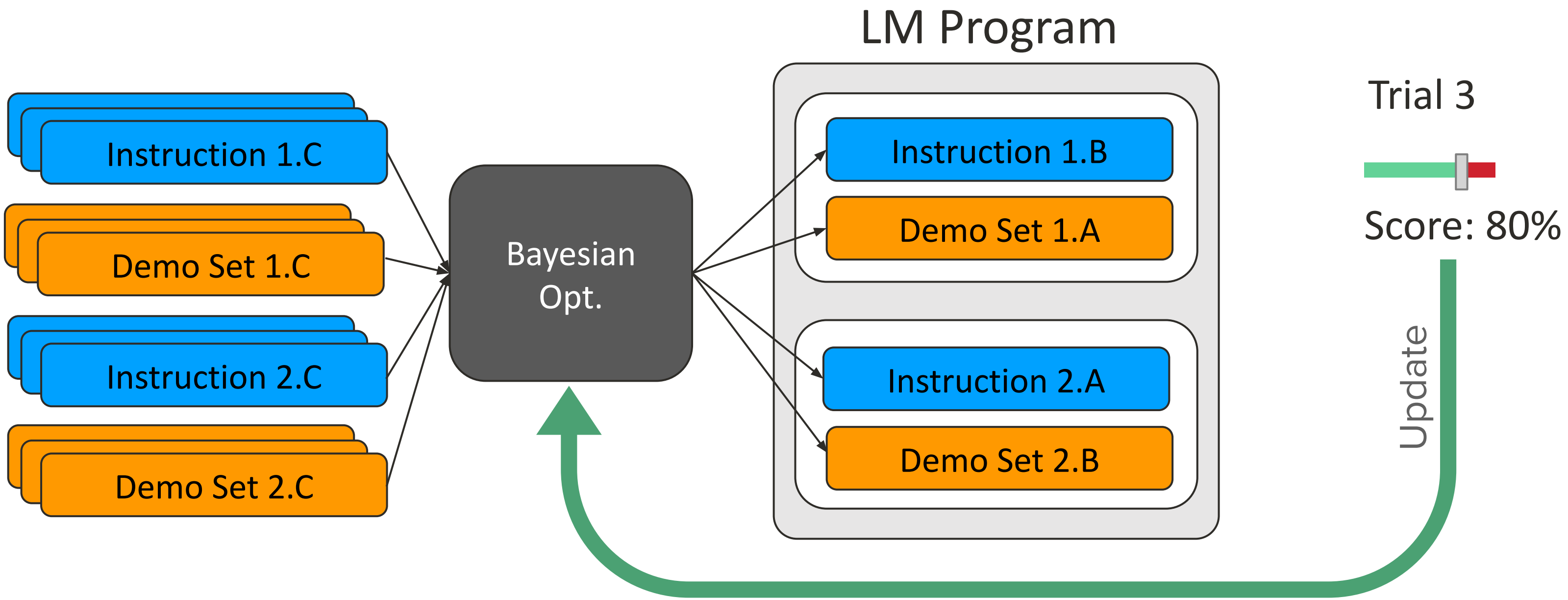
Step 3: Optimize with Bayesian Learning

Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



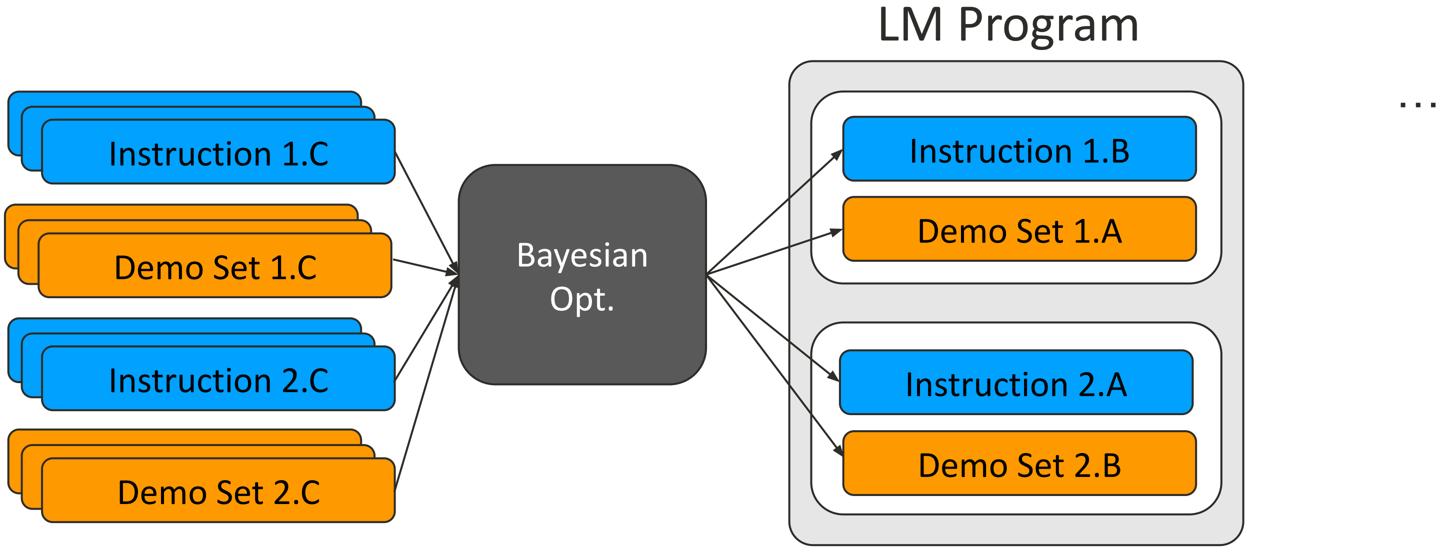
Step 3: Optimize with Bayesian Learning

Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



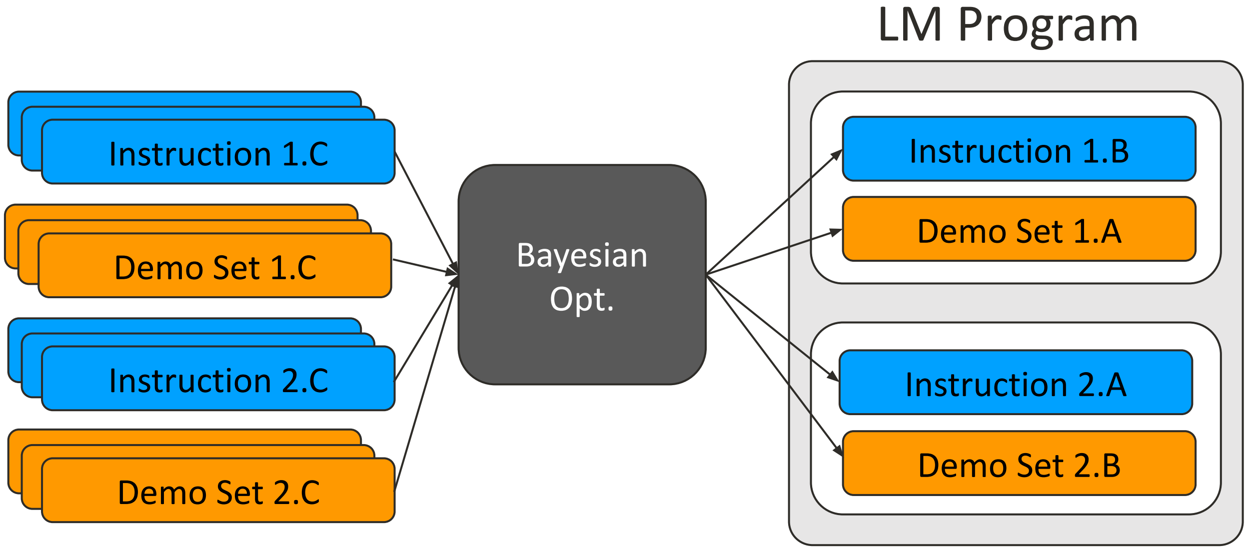
Step 3: Optimize with Bayesian Learning

Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



Step 3: Optimize with Bayesian Learning

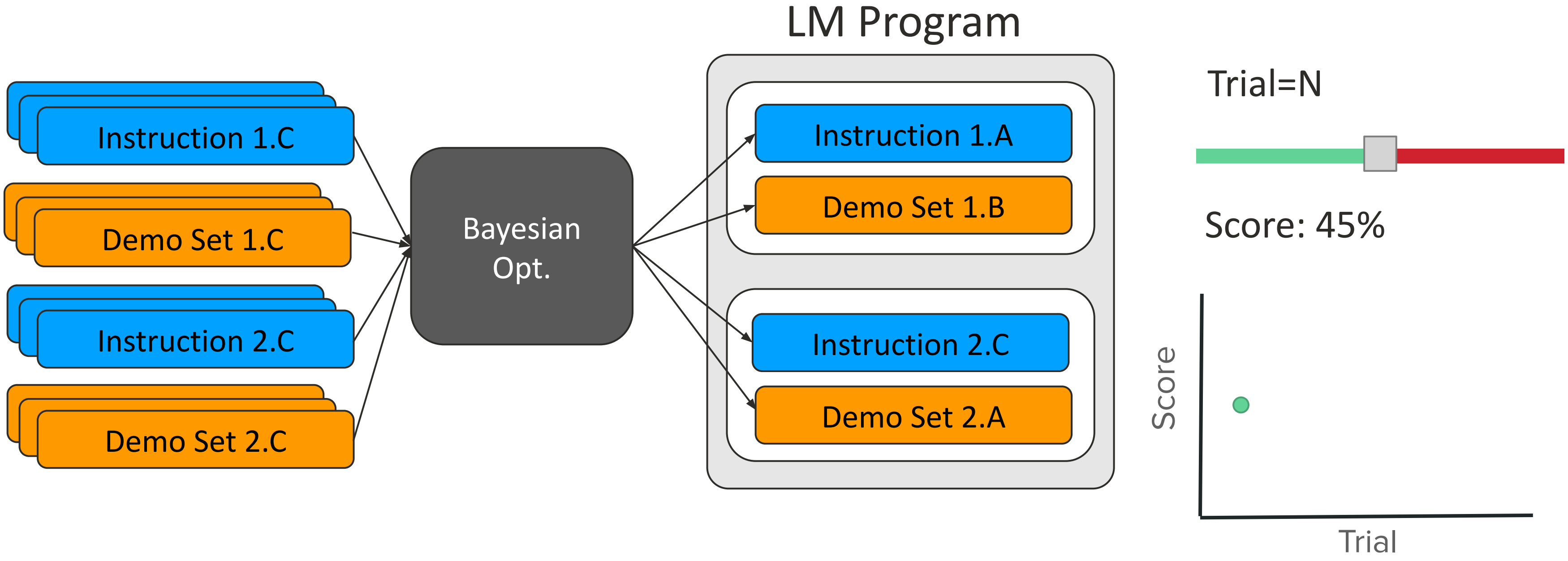
Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



Every N trials, evaluate on our full val set!

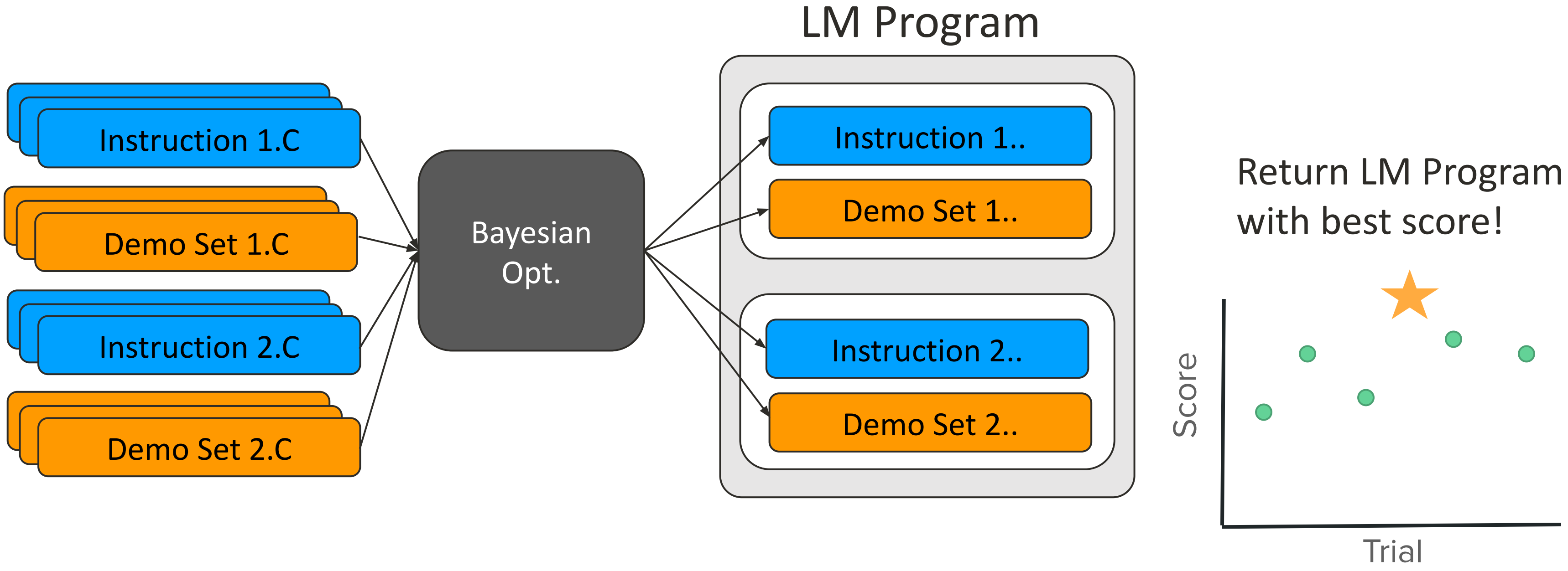
Step 3: Optimize with Bayesian Learning

Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



Step 3: Optimize with Bayesian Learning

Key Idea: MIPRO uses a Bayesian Surrogate Model for Credit Assignment



Experiments & Results

So how do these optimization methods compare?

Enter LangProBe, the Language Model Program Benchmark

Benchmark	Task Type	Program	Modules	LM Calls	Metric
HotPotQA	Multi-Hop QA	Multi-Hop Retrieval	2	3	Exact Match
HotPotQA Conditional	Multi-Hop QA	Multi-Hop Retrieval	2	3	Custom
Iris	Classification	Chain of Thought	1	1	Accuracy
Heart Disease	Classification	Answer Ensemble	2	4	Accuracy
ScoNe	Natural Language Inference	Chain of Thought	1	1	Exact Match
HoVer	Multi-Hop Claim Verify	Multi-Hop Retrieval	4	4	Recall@21

So how do these optimization methods compare?

Enter LangProBe, the Language Model Program Benchmark

Benchmark	Task Type	Program	Modules	LM Calls	Metric
HotPotQA	Multi-Hop QA	Multi-Hop Retrieval	2	3	Exact Match
HotPotQA Conditional	Multi-Hop QA	Multi-Hop Retrieval	2	3	Custom
Iris	Classification	Chain of Thought	1	1	Accuracy
Heart Disease	Classification	Answer Ensemble	2	4	Accuracy
ScoNe	Natural Language Inference	Chain of Thought	1	1	Exact Match
HoVer	Multi-Hop Claim Verify	Multi-Hop Retrieval	4	4	Recall@21

Hypothesis: Instructions become more important in tasks with multiple conditional rules, which cannot be fully expressed with a set # of few-shot ex.

Optimizer	ScoNe	HotPotQA	HoVer	HotPotQA Cond.	Iris	Heart Disease
Instructions only (0-shot)						
N/A	69.1	36.1	25.3	6	32	26.8
Module-Level OPRO −G	76.1	36.0	25.7	–	–	–
Module-Level OPRO	73.5	39.0	32.5	–	–	–
0-Shot MIPRO	71.5	36.8	33.1	14.6	56.7	25.8

Optimizing instructions can deliver gains over baseline signatures.

*Results averaged across 5 runs. Bold values represent the highest average scores compared to the second- highest, with significance supported by Wilcoxon signed-rank tests (p < .05).

Optimizer	ScoNe	HotPotQA	HoVer	HotPotQA Cond.	Iris	Heart Disease
Instructions only (0-shot)						
N/A	69.1	36.1	25.3	6	32	26.8
Module-Level OPRO −G	76.1	36.0	25.7	–	–	–
Module-Level OPRO	73.5	39.0	32.5	–	–	–
0-Shot MIPRO	71.5	36.8	33.1	14.6	56.7	25.8

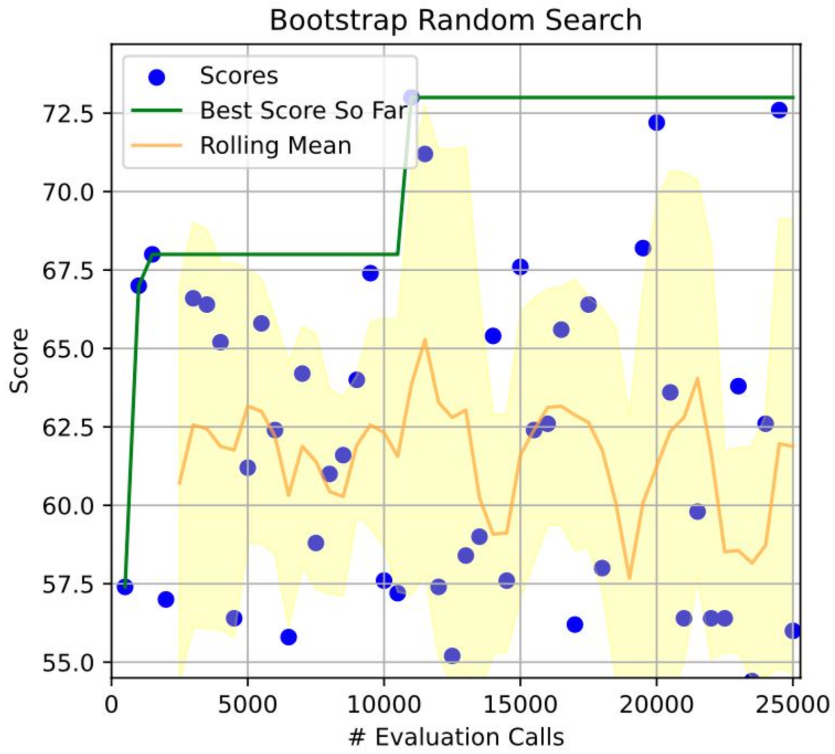
However, there's no obvious best approach to instruction proposal yet.

*Results averaged across 5 runs. Bold values represent the highest average scores compared to the second- highest, with significance supported by Wilcoxon signed-rank tests (p < .05).

Optimizer	ScoNe	HotPotQA	HoVer	HotPotQA Cond.	Iris	Heart Disease
Instructions only (0-shot)						
N/A	69.1	36.1	25.3	6	32	26.8
Module-Level OPRO −G	76.1	36.0	25.7	–	–	–
Module-Level OPRO	73.5	39.0	32.5	–	–	–
0-Shot MIPRO	71.5	36.8	33.1	14.6	56.7	25.8
Demonstrations only (Few-shot)						
Bootstrap RS	75.4	**45.8**	37.2	10.4	58.7	**79.2**
Bayesian Bootstrap	77.4	**46.2**	37.6	–	–	–

Optimizing bootstrapped demonstrations is key!

*Results averaged across 5 runs. Bold values represent the highest average scores compared to the second- highest, with significance supported by Wilcoxon signed-rank tests (p < .05).



The bootstrapped demonstrations we choose matters a lot!
Understanding why is an area for future research.

Optimizer	ScoNe	HotPotQA	HoVer	HotPotQA Cond.	Iris	Heart Disease
Instructions only (0-shot)						
N/A	69.1	36.1	25.3	6	32	26.8
Module-Level OPRO −G	76.1	36.0	25.7	–	–	–
Module-Level OPRO	73.5	39.0	32.5	–	–	–
0-Shot MIPRO	71.5	36.8	33.1	14.6	56.7	25.8
Demonstrations only (Few-shot)						
Bootstrap RS	75.4	**45.8**	37.2	10.4	58.7	**79.2**
Bayesian Bootstrap	77.4	**46.2**	37.6	–	–	–
Both (Few-shot)						
MIPRO	**79.4**	**46.4**	**39.0**	**23.3**	**68.7**	74.2

Optimizing both instructions and demonstrations via MIPRO is a often the most effective approach!

Optimizer	ScoNe	HotPotQA	HoVer	HotPotQA Cond.	Iris	Heart Disease
Instructions only (0-shot)						
N/A	69.1	36.1	25.3	6	32	26.8
Module-Level OPRO −G	76.1	36.0	25.7	–	–	–
Module-Level OPRO	73.5	39.0	32.5	–	–	–
0-Shot MIPRO	71.5	36.8	33.1	14.6	56.7	25.8
Demonstrations only (Few-shot)						
Bootstrap RS	75.4	**45.8**	37.2	10.4	58.7	**79.2**
Bayesian Bootstrap	77.4	**46.2**	37.6	–	–	–
Both (Few-shot)						
MIPRO	**79.4**	**46.4**	**39.0**	**23.3**	**68.7**	74.2

The impact of optimizing instructions (rather than demonstrations) is more visible in tasks that have many isolated conditional rules.

Summary & Lessons

Key Lessons I: Natural Language Progamming

1. Programs can often be more accurate, controllable, transparent, and even efficient than models.

2. You just need declarative programs, not implementation details. High-level optimizers can bootstrap prompts — or weights, or whatever the next paradigm deals with.

DSPy makes it possible to *program* LMs

~~Hand-written prompts~~ ⇒ Signatures

~~Prompting techniques and prompt chains~~ ⇒ Modules

```
qa = dspy.Predict("question -> answer")
mt = dspy.ChainOfThought("english_document -> french_translation")
rc = dspy.ProgramOfThought("contexts, question -> answer_found: bool")
```

~~Manual prompt engineering~~ ⇒ Optimized programs

```
Optimizer(metric).compile(program, dataset)
```

and is being widely used in production & OSS -- dspy.ai

at JetBlue, Databricks, Walmart, VMware, Replit, Haize Labs, Normal Computing, Sephora, Moody's…

Haize Labs Blog

Website

Home » Posts

Red-Teaming Language Models with DSPy

April 9, 2024

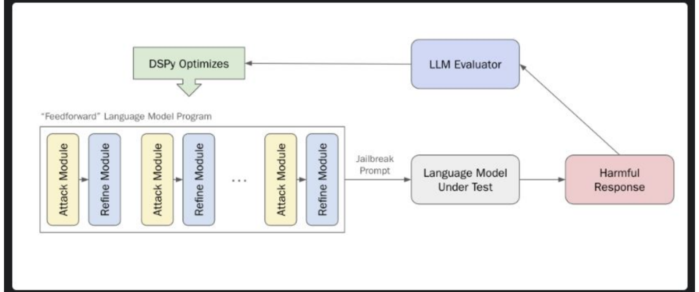


Figure 1: Overview of DSPy for red-teaming. The DSPy MIPRO optimizer, guided by a LLM as a judge, compiles our language program into an effective red-teamer against Vicuna.

Architecture	ASR
None (Raw Input)	10%
Architecture (5 Layer)	26%
Architecture (5 Layer) + Optimization	44%

and is being widely used in production & OSS -- dspy.ai

at JetBlue, Databricks, Walmart, VMware, Replit, Haize Labs, Normal Computing, Sephora, Moody's…

replit

The End of Prompting, The Beginning of Compound Systems

As more and more companies leverage LLMs, the limitations of a generic chatbot interface are increasingly clear. These off-the-shelf platforms are highly dependent on parameters that are outside the control of both end-users and administrators. By constructing compound systems that leverage a combination of LLM calls and traditional software development, companies can easily adapt and optimize these solutions to fit their use case. DSPy is enabling this paradigm shift toward modular, trustworthy LLM systems that can optimize themselves against any metric. With the power of Databricks and DSPy, JetBlue is able to deploy better LLM solutions at scale and push the boundaries of what is possible.

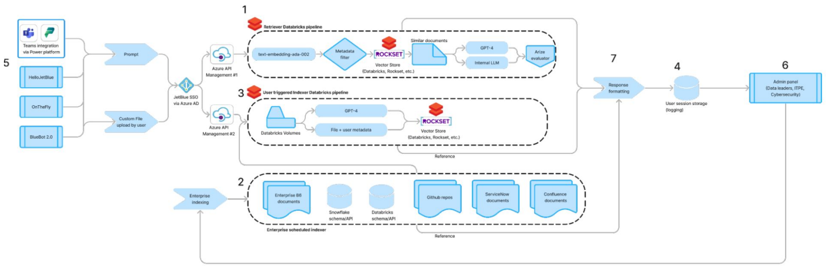


Figure 7: Using Databricks' solutions, JetBlue's complete chatbot architecture makes use of custom document uploads with different user groups

Haize Labs Blog

Website

DSPy

Fork 1.2k

Starred 16.1k

downloads/month 160k

Contributors 206

Key Lessons II: Natural Language Optimization

1. In isolation, on many tasks nothing beats bootstrapping good demonstrations. **Show don’t tell!**

2. Generating good instructions on top of these is possible, and is especially important for tasks with **conditional rules**!

3. But you will need **effective grounding**, and explicit forms of **credit assignment**.

Can open research again lead AI progress?

DSPy (dspy.ai) aims to show that this lies in <u>modularity</u>.

❌ Not ever-larger, opaque LMs in isolation.

❌ Not ad-hoc tricks for prompting or synthetic data.

But well-scoped programs, better inference-time strategies, and new ways to optimize how LMs are used to solve tasks.