programmatic LLM & VLM use through DSPy

Igor Zubrycki

Follow along with the notebook provided for this tutorial

https://github.com/AdoHaha/dspy_fun/

Large Language Models are super capable and available

- Text: free form text, code, classification
- Images: image understanding, OCR, …

Ever nicer features:

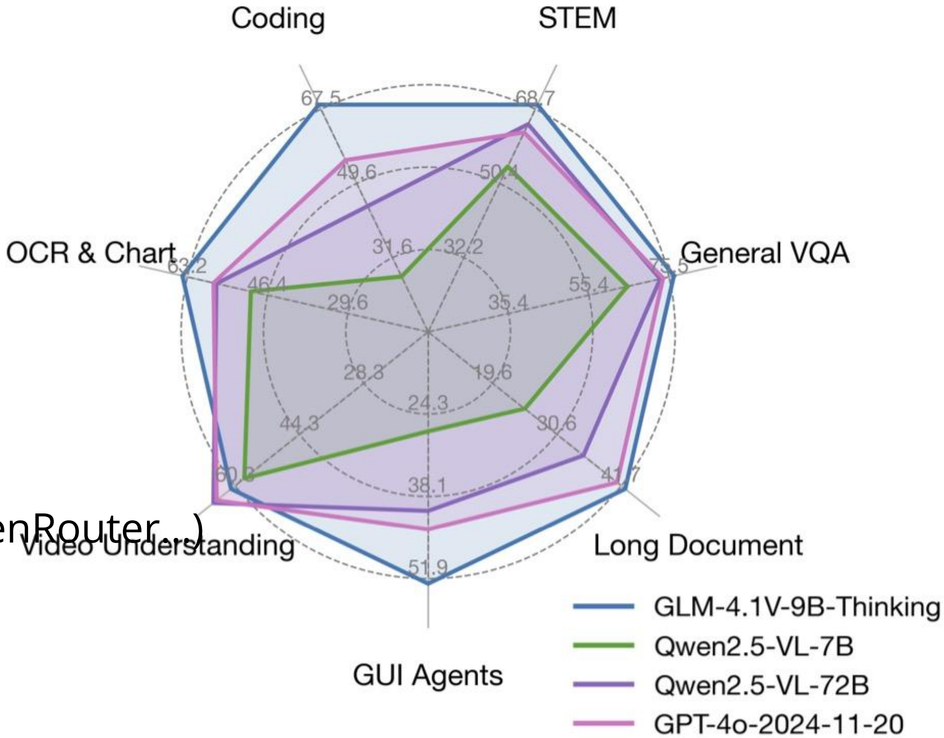
- becoming smart/ specialized
- more and more are open source

Available:

- run locally
- choose from many cloud provides (OpenRouter,..)

Cheap!

- single image call in rage of 0.001 EUR



How to get all those goodies? OPEN AI API

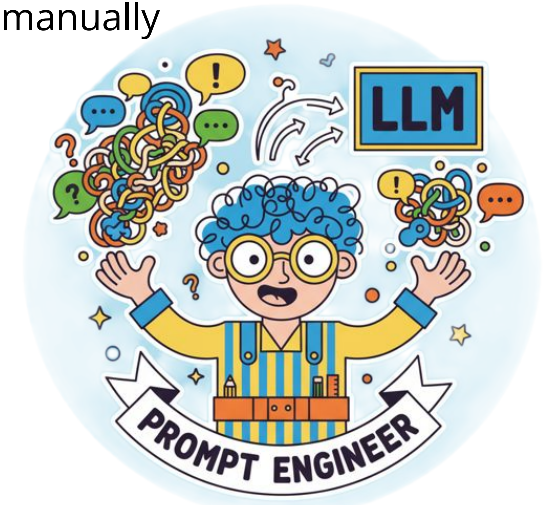
```
from openai import OpenAI

client = OpenAI(
api_key="GEMINI_API_KEY",base_url="https://generativelanguage.googleapis.com/v1beta/openai/")

completion = client.chat.completions.create(

  model="gemini-2.5-flash",

  messages=[

    {"role": "system", "content": "You are a helpful assistant."},

    {"role": "user", "content": "what is 2+2"}

  ])

  print(completion.choices[0].message)
  4
```

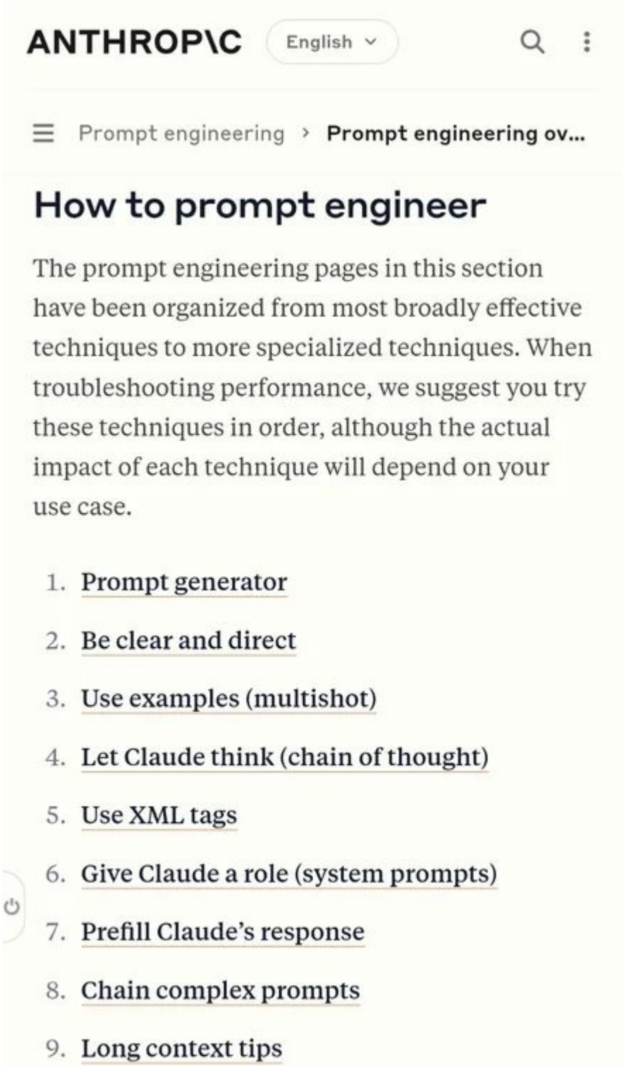
Structured output

```
  response_mime_type="application/json",
        response_schema=genai.types.Schema(
            type = genai.types.Type.OBJECT,
            required = ["sum_of_numbers"],
            properties = {
                "sum_of_numbers": genai.types.Schema(
                    type = genai.types.Type.NUMBER,
                ),}, )
```

Prompts

- how to ensure that you get what you want
    - correct answer
    - correct format
- necessarily context
- difficult, time consuming job if doing this manually




ANTHROP\C English

Prompt engineering › Prompt engineering ov...

How to prompt engineer

The prompt engineering pages in this section have been organized from most broadly effective techniques to more specialized techniques. When troubleshooting performance, we suggest you try these techniques in order, although the actual impact of each technique will depend on your use case.

1. Prompt generator
2. Be clear and direct
3. Use examples (multishot)
4. Let Claude think (chain of thought)
5. Use XML tags
6. Give Claude a role (system prompts)
7. Prefill Claude's response
8. Chain complex prompts
9. Long context tips

We want models to do particular tasks

-> maybe we want to give required knowledge?

-> maybe we want to limit the output or re-verify?

-> obviously we want to connect these models to various inputs, outputs

For that we need to use more complex interactions

There are strategies to use models to get what we want frequently requiring more than a single tool call. **Bonus complexity if we want multimodality**

Zero-shot Prompting	Few-shot Prompting	Chain-of-Thought Prompting
Meta Prompting	Self-Consistency	Generate Knowledge Prompting
Prompt Chaining	Tree of Thoughts	Retrieval Augmented Generation
Automatic Reasoning and Tool-use	Automatic Prompt Engineer	Active-Prompt
Directional Stimulus Prompting	Program-Aided Language Models	ReAct

In the ideal world, we would focus on:

- focus on information flow
- decouple from underlying technology, modularize
- make it understandable, modifiable
- align the models to the system

So essentially we want to **program these things**

Ideally program in **higher level language**, i.e. be able to say what we want

Let's use DSPy

```
import dspy

small_model = dspy.LM("gemini/gemini-2.5-flash-lite", api_key=GEMINI_API_KEY)
dspy.configure(lm=small_model)
sum_of_numbers = dspy.Predict('numbers -> sum_of_numbers')
result = sum_of_numbers(numbers = (12,13,15))

print(result)
Prediction(

    sum_of_numbers='40'

)
```

but we did not specify what numbers are, right?

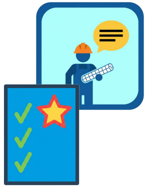
```
numbers_image = dspy.Image.from_file("./numbers.png")
```


```
result_image = sum_of_numbers(numbers = numbers_image)
print(result_image)
Prediction(
    sum_of_numbers='33'
)
```

DSPy - Declarative Self-improving Python

– Set of components to build an AI system

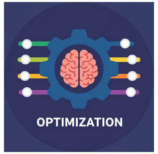
– Define expected behavior from fuzzy, natural language-defined pieces



– (Usually) invisible tools to adapt to a particular model, good defaults

– Specify information flow/ strategies (what happens to output / how to proceed)

– Improving the model behaviour automatically



signature

– we define what should be the input, output, provide instructions and descriptions

– supports typing

```
from typing import Optional
class NumberAdd(dspy.Signature):
"""Please add numbers provided in a various ways together. Numbers can also be symbolic or require computation.
Only if there are no numbers in input, write a sad haiku using the contents of input"""
numbers = dspy.InputField(description="numbers to add")
sum_of_numbers: float = dspy.OutputField(description="resulting sum")

sum_of_numbers(numbers = [“one, 2”])
```

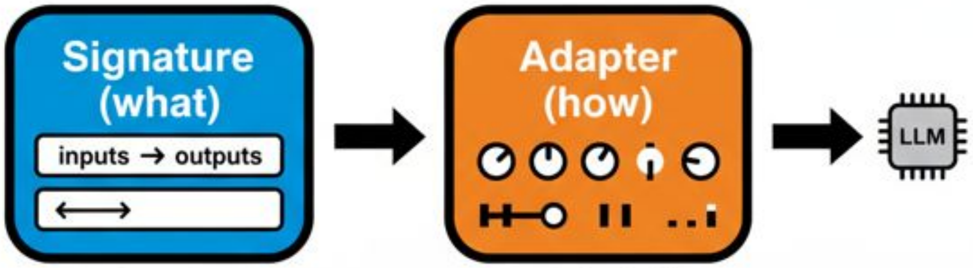
```
Prediction(
    sum_of_numbers=3,
    haiku='Empty bowl waits now,\nNo kibble, just silent air,\nSadness fills the room.'
)
```

Adapter

– Allows using different models (json enabled or not), better or worse at formatting

– Formats input, suggests output and formats the outcoming data (with fallbacks)

JsonAdapters, XML Adapters, chat adapters, two step adapters ...



Adapters: translators for LLMs

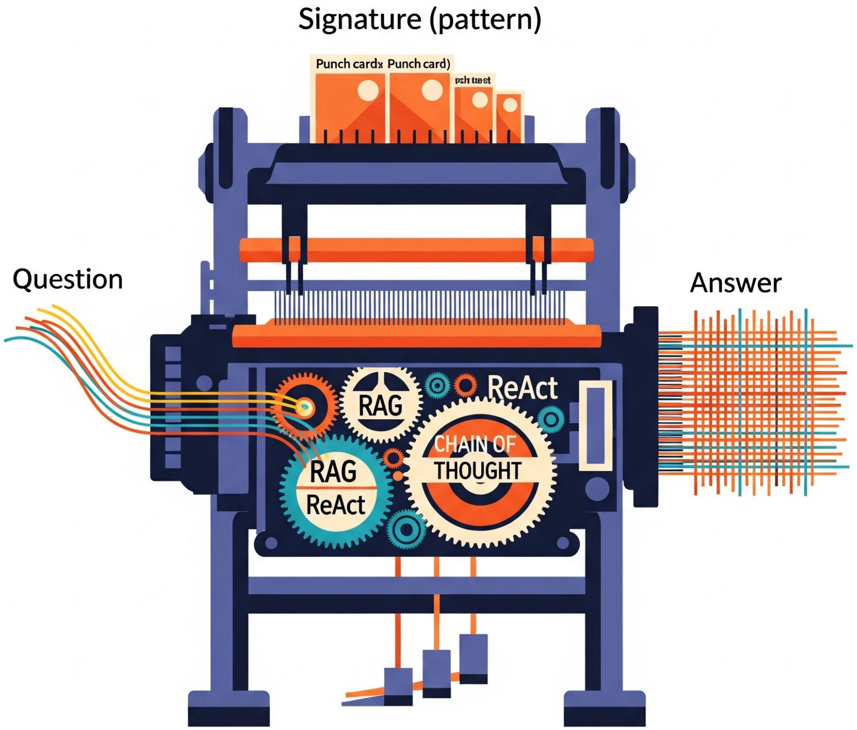
```
sum_of_numbers =
dspy.Predict('numbers
-> sum_of_numbers')
```

```
result_image =
sum_of_numbers(numbers =
numbers_image)
```

```
sum_of_numbers.history[-1]
```

{
  "prompt": null,
  "messages": [{
    "role": "system",
    "content": "Your input fields are:\n1. `numbers` (str)\nYour output fields are:\n1. `sum_of_numbers` (str)\n\n[[## numbers ##]]\n{numbers}\n\n[[## sum_of_numbers ##]]\n{sum_of_numbers}\n\n[[## completed ##]]\n\nObjective: Given `numbers`, produce `sum_of_numbers`."
   }, {
    "role": "user",
    "content": [
     {"type": "text", "text": "[[## numbers ##]]\n"},
     {"type": "image_url", "image_url": {"url": "https://raw.githubusercontent.com/AdoHaha/dspy_fun/refs/heads/main/example_files/image_numbers.png"}},
     {"type": "text", "text": "\n\nRespond with the output fields, starting with `[[ ## sum_of_numbers ## ]]`, then end with `[[ ## completed ## ]]`."}
    ]}]}

Modules: use a strategy to be able to realise the signature



Patterns of use are available, advanced multistep prompting

Predict: take defined input, get defined output

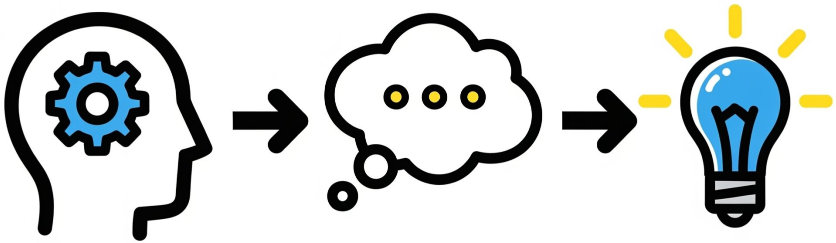
Chain of Thought: improve output through thinking

ReAct: use a set of tools

Retreive (RAG): search for information based on prompt to build context (RAG)

...

Chain of Thought



```
sum_of_numbers_haiku = dspy.ChainOfThought(NumberAdd)
```

```
sum_of_numbers_haiku(numbers = "dragon,siete, enterprise")
```

Prediction(
    reasoning='The input contains words that do not represent numerical values. "dragon", "siete" **(Spanish for seven)**, and "enterprise" are not directly convertible to numbers. Therefore, no numerical sum can be calculated.',
    sum_of_numbers=0.0,
    haiku='Words float like lost dreams,\nNumbers hide, a silent plea,\nSum remains unseen.'
)

Still not super smart ;-(lets use a more costly model:

```
with dspy.context(lm = dspy.LM("gemini/gemini-2.5-flash",api_key=GEMINI_API_KEY)):
    sum_of_numbers_haiku = dspy.ChainOfThought(NumberAdd)
    print(sum_of_numbers_haiku(numbers ="dragon,siete, enterprise"))

Prediction(
    reasoning='I identified "siete" as the Spanish word for seven. "Dragon" and "enterprise" were not recognized as numerical values or symbolic representations of numbers. Therefore, the only number to sum is 7.',
    sum_of_numbers=7.0,
    haiku=None
)
big_cost = larger_lm.history[-1]["cost"]
small_cost = small_model.history[-1]["cost"]

print(f"Big cost: {big_cost}")
print(f"Small cost: {small_cost}")
print(f"Smaller model is {big_cost/small_cost} times cheaper")
Big cost: 0.0007455000000000001
Small cost: 7.19e-05
Smaller model is 10.368567454798333 times cheaper
```

Own modules

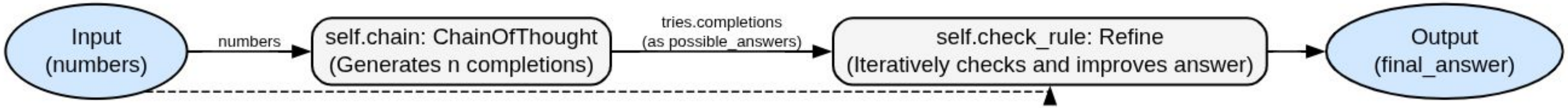
– create sophisticated interactions with users, tools

– usually composed of submodules

– form a foundations for expressing information flow for context building

– many goodies build-in: ease of logging, asynchronous operations

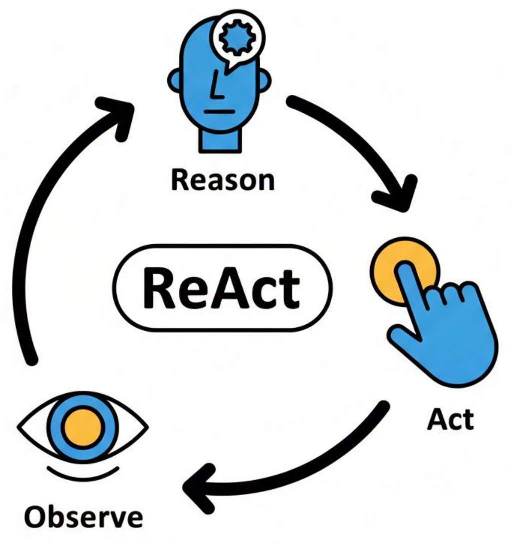
```
class BestNumber (dspy.Module):
 """module returns sum of numbers through generating multiple answers, analyzing
them and
 finally verifying the best answer"""
 def __init__(self, n):
   self.n = n
   # will generate n answers
   self.chain = dspy.ChainOfThought(NumberAdd, n=n)
   signature_possible = NumberAdd.append( "possible_answers" ,
                 dspy.InputField(
                     desc= "choice of possible answers, with reasoning" ,
                 ))
   best_answer = dspy.ChainOfThought(signature_possible)

   self.check_rule = dspy.Refine(best_answer, N= 3, reward_fn= self.check_result,
threshold= 1.0)

 def check_result (self, args, result):
   """when number is not zero, haiku should not be generated"""
   rule_exclusive_or = (result.sum_of_numbers != 0) ^ (result.haiku is not None)
   return rule_exclusive_or

 def forward(self, numbers):
   tries = self.chain(numbers=numbers)

   final_answer = self.check_rule(possible_answers = tries.completions,
numbers=numbers)

   return final_answer


bestnumber = BestNumber(n= 4)

print(bestnumber(numbers = "dragon,siete,enterprise" ))
```



ReAct: Reasoning and Acting

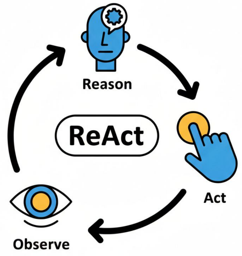
- Plans steps and uses tools

```python
import sympy

def symbolic_expression_sympy(expression: str,
*Args) -> float:
 """
 Takes a symbolic math expression (written as a
string) and returns a result as a float,
evaluated to 5 significant numbers, using
sympy.
 For example
symbolic_expression_sympy("2*log(E)") would
result in 2.0000
 """
 expr = sympy.sympify(expression)
 return expr.evalf(5)
```




```python
sum_of_numbers_smarter =
dspy.ReAct('numbers ->
sum_of_numbers',
tools=[symbolic_expression_sympy
])
```

ReAct: Reasoning and Acting

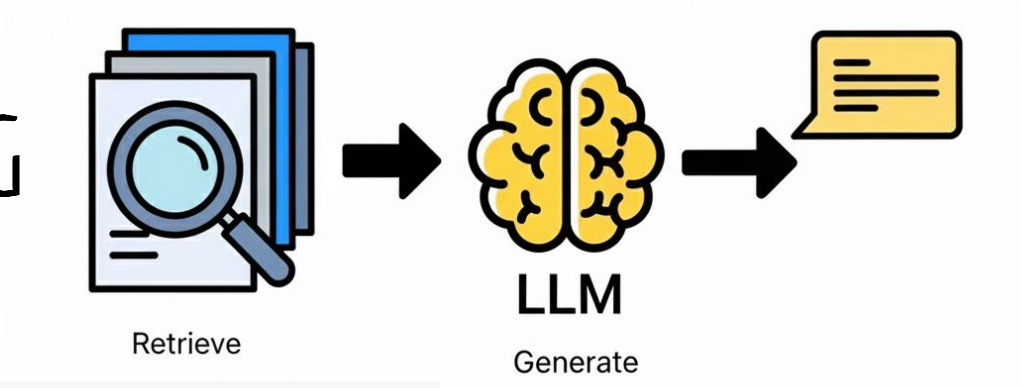



```
sum_of_numbers_smarter(numbers=[ "2*sin(10)","pi"])
```

Prediction(
    trajectory={'thought_0': 'The user wants to calculate the sum of the given numbers. The numbers are provided as strings, some of which are mathematical expressions. I need to evaluate these expressions first and then sum them up. The `symbolic_expression_sympy` tool can be used to evaluate the expressions. I will start by evaluating the first expression "2*sin(10)".', 'tool_name_0': 'symbolic_expression_sympy', 'tool_args_0': {'expression': '2*sin(10)'}, 'observation_0': -1.0880, ...
 'thought_3': 'The sum of the numbers has been calculated. I can now finish the task.', 'tool_name_3': 'finish', 'tool_args_3': {}, 'observation_3': 'Completed.'},
    reasoning='The user wants to sum the numbers provided in the `numbers` field.\nThe numbers are:\n1. "2*sin(10)"\n2. "pi"\n\nI will use the `symbolic_expression_sympy` tool to evaluate each expression and then sum the results.\n\nStep 1: Evaluate "2*sin(10)".\n`symbolic_expression_sympy("2*sin(10)")` returns -1.0880.\n\nStep 2: Evaluate "pi".\n`symbolic_expression_sympy("pi")` returns 3.1416.\n\nStep 3: Sum the results from Step 1 and Step 2.\n`symbolic_expression_sympy("-1.0880 + 3.1416")` returns 2.0536.\n\nTherefore, the sum of the numbers is 2.0536.',
    sum_of_numbers='2.0536')

)

Retreive strategy: RAG



Retreival-augmented generation is a common strategy to deliver context.

Retretival can use tools such as reverse index search (akin to old school search engines with keywords) or embedding based search.

DSPy can be easly connected to external vector databases (like chromadb),
it plays nicely also with helper tools such as the ones in langchain (for reading standard fileformats, connecting to databases)

The build-in dspy.Embeddings tool uses FAISS internally

Retreive: Building context

```
!git clone http://github.com/python/peps.git

import os

documents = []
for filename in os.listdir('./peps/peps'):
    if filename.endswith('.rst'):
        filepath = os.path.join('./peps/peps', filename)
        with open(filepath, 'r', encoding='utf-8', errors='ignore') as f:
            documents.append(f.read())

print(f"Loaded {len(documents)} documents.")
```

```
#Making inverse index
from inverted_index.inverted_index import InvertedIndex

ii = InvertedIndex()

ii.index(documents)
```

OR

Making mini embeddings database

```
embedder = dspy.Embedder("gemini/embedding-001", dimensions = 768,  api_key = GEMINI_API_KEY, batch_size = 20)
embeddings_peps = dspy.Embeddings(embedder = embedder, corpus = documents, k = 5)
```

Reverse Index based RAG

```
class PEPSearch(dspy.Module):
 def __init__(self):
   self.respond =
dspy.ChainOfThought('context_based_on_search,
python_question ->
easy_to_understand_response_based_on_PEP')
   self.reverseindexquery =
dspy.ChainOfThought('python_question ->
query_to_reverse_index')
 def forward(self, question):
   query = self.reverseindexquery(python_question =
question)
   #print(query)
   search_responses
="\n\n".join(ii.search(query.query_to_reverse_index)[0:
10])
   response = self.respond(context_based_on_search =
search_responses, python_question = question)
   return
response.easy_to_understand_response_based_on_PEP
```

```
pep_trivia = PEPSearch()

pep_trivia(question = "what is PEP 761 about?")
```

```
PEP 761 is about **deprecating and eventually
removing PGP signatures for CPython artifacts …
```

Embedding search based RAG

```
class PEPEmbeddingRetreival(dspy.Module):
 def __init__(self):
   self.respond =
dspy.ChainOfThought('context_based_on_search,
python_question ->
easy_to_understand_response_based_on_PEP')
   self.reverseindexquery =
dspy.ChainOfThought('python_question ->
query_to_embbeding_based_search')
 def forward(self, question):
   query = self.reverseindexquery(python_question =
question)
   #print(query)
   search_responses
=embeddings_peps(query.query_to_embbeding_based_search)
   response = self.respond(context_based_on_search =
search_responses, python_question = question)
   return
response.easy_to_understand_response_based_on_PEP
```

```
pep_trivia_embeddings =
PEPEmbeddingRetreival()
pep_trivia_embeddings(question ="any
news about python 3.14?")
```

Yes, there is information about the Python 3.14 release schedule.

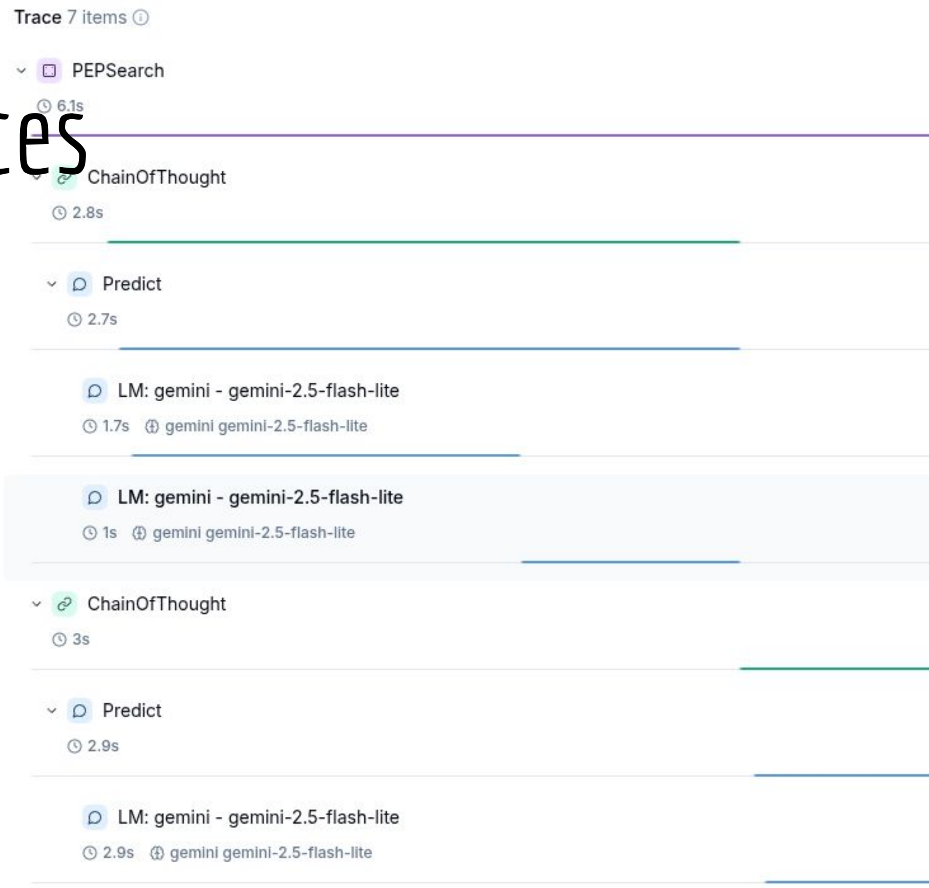
The development for Python 3.14 began on Wednesday, May 8, 2024. The release schedule is based on a 17-month development period, leading to a 12-month release cadence between feature versions, as defined by PEP 602.

Here are some key expected dates:

*   **3.14.0 alpha 1:** Tuesday, October 15, 2024

Logging and analyzing traces

```
import opik
from opik.integrations.dspy.callback import
OpikCallback

opik.configure(use_local=False)
small_model =
dspy.LM("gemini/gemini-2.5-flash-lite",
api_key=GEMINI_API_KEY, max_tokens=20000,
cache=False)
opik_callback =
OpikCallback(project_name="inverse_index_search
")
dspy.configure(lm=small_model, callbacks =
[opik_callback])
```



LM: gemini - gemini-2.5-flash-lite

1s gemini gemini-2.5-flash-lite

+

Input/Output Feedback scores Metadata

Input

Pretty ✨

[[## python_question ##]]
what is PEP 761 about?

Respond with a JSON object in the following order of fields: `reasoning`, then `query_to_reverse_index`.

Output

Pretty ✨

{
"reasoning": "The user is asking for information about a specific Python Enhancement Proposal (PEP). To answer
documentation or discussions related to it.",
"query_to_reverse_index": "PEP 761 python"
}

DSPY optimization

DSPy key idea is that we first create the information flow system from components, focus on the context engineering while later align the models behaviours through compilation

For that we need to have in place:

- some datasets with expected outcomes
- a metric (or metrics) that we will use to optimize. This metric can be a judge model with set of instructions (we can optimize even the judge)
- choice of optimizers (teleprompters). Those vary on requirements (number of examples, type of metrics, helper functions) and scope of optimization: they can provide important examples (demos), optimize prompts or collaborate when finetuneing the model itself

Datasets & Metrics

```
sum_of_numbers_smarter = dspy.ReAct(
    dspy.Signature('numbers ->
sum_of_numbers:float',
                      "Take only numbers (expressed in
various ways) from numbers and output their sum"),

tools=[symbolic_expression_sympy],
                                              )
```

Datasets are built from Examples

```
sum example = dspy.Example(numbers = [ 1,2,3],
sum_of_numbers =  6)

all_examples = [...]
trainset,devset,testset = all_examples[ …
```

Metrics – can be any function that returns a float

```
def metric(example, pred, trace=None):
    gold = example.sum_of_numbers
    pred = pred.sum_of_numbers
    return abs(gold - pred)<0.0001 #lets give
some margin of error
```

```
evaluate = dspy.Evaluate(devset=devset, metric=metric,
num_threads=4, display_progress=True,
                          display_table=0,
max_errors=999)
evaluate(sum_of_numbers_smarter)
Average Metric: 13.00 / 15 (86.7%): 100%|██████████|
15/15 [00:34<00:00,  2.33s/it]2025/08/28 05:37:19 INFO
dspy.evaluate.evaluate: Average Metric: 13 / 15 (86.7%)

EvaluationResult(score=86.67, results=<list of 15
results>)
```

DSPy optimizers ZOO

– selecting / finding or creating examples to pass in the prompt (FewShot approach)

– using best examples for a given prompt (`KNNFewShot)`

– optimizing instructions for each step (COPRO, MIPROv2 ...)

– passing the trajectory to a separate language model that proposes prompts, using evolutionary process to select best to refine further (GEPA) can be also used with VLMs (to optimize prompt) New in DSPy 3!

– optimizing prompts and finetuneing models (BootstrapFinetune)

Optimization

Optimizer requirements vary (number of examples, additional functions, models)

but in general the step is that we put the module

into optimizer, a trainset, (valset)

than program optimizes / compiles to figure out best use of the pipeline

```
simba = dspy.SIMBA(metric=metric, max_steps=12,
max_demos=10)
optimized_agent =
simba.compile(sum_of_numbers_smarter,
trainset=trainset, seed=6793115)
simba.save(“optimized_simba.json”)
```

The compiled model can be saved (with or without data)

It has added fields “demos” to the underlying modules

Bonus: GEPA

– Approach where a strong model is used to reflect on the answers and guide the optimization process

– More spots to add feedback

```
def metric_with_feedback (example,prediction,trace=None,
pred_name=None, pred_trace = None):
 correct_answer = float(example.sum_of_numbers)
 try:
   llm_answer = float(prediction.sum_of_numbers)
 except:
   llm_answer = "it was not a number"
 score = float(metric(example,prediction))
 feedback_text = ""
 if score==1:
   feedback_text = f"Your answer is correct
{correct_answer}"
 else:
   print(example)
   feedback_text = f"Your answer: {llm_answer} is not
correct, it should be {correct_answer}"
   print(feedback_text)
 return dspy.Prediction(score = score, feedback =
feedback_text)
```

```
gepa_optimizer = optimizer = dspy.GEPA(
   metric=metric_with_feedback,
   auto="light",
   num_threads=32,
   track_stats=True,
   reflection_minibatch_size=3,

reflection_lm=dspy.LM(model="gemini/gemini-2.5-
flash", temperature=1.0, max_tokens=32000,
api_key=GEMINI_API_KEY)
)
gepa_optimized_program = optimizer.compile(
   sum_of_numbers_smarter,
   trainset=trainset,
   valset=devset,
)
```

Prompt created automatically

2025/08/28 06:16:25 INFO dspy.teleprompt.gepa.gepa: Iteration 16: Proposed new text for extract.predict: The task is to calculate the sum of numbers provided in the `numbers` field. The output `sum_of_numbers` must always be a single floating-point number.

General Strategy and Important Rules:

*   Always identify and process only the valid numeric and mathematical components of the input.

...

N() Function from SymPy is used for numerical approximation, and it is essential for correctly evaluating functions like `arctan`, `sin`, `cos`, etc., and for general numerical results.

*   **Error Handling and Default Value**:

    *   If the `symbolic_expression_sympy` tool returns an error, or if its output (even after being wrapped with `N()`) cannot be interpreted as a numeric float (e.g., for non-mathematical strings like "foo", or malformed expressions that cannot be numerically resolved), the `sum_of_numbers` for that input is explicitly `0.0`.

    ...

The `numbers` field can be provided in two main formats:

1. **A list of items**: The list can contain integers, floats, or strings.

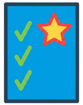
    *   **Processing a list**:

To wrap up DSPy

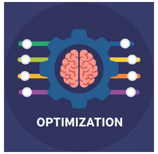
DSPy gives you a set of easy to use elements to compose into a AI system

Engineer’s focus on actual task, using LLM as a natural language specifications

AI Engineers figure out information flow



Good results from start (due to (AI) understandable structure, formatting rules and checks)



Model behaviours can be automatically optimized/ aligned to the task

Programmatic LLM & VLM use through DSPy

Igor Zubrycki @IgorZub

Measure your program

- prepare examples (input output pairs)
- use some metric (example output == model output, use a judge)
-

“Large Langue Models are becoming extremely cheap/capable/ open source/ evolving

Behind is still essentially a stateless machine that accepts text/ images converted to tokens and outputs usually text / images

Magic is in packing essential context and creating a process to use output

```python
code_snippet = """
from collections import deque

class Queue[T]:
    def __init__(self) -> None:
        self.elements: deque[T] = deque()

    def push(self, element: T) -> None:
        self.elements.append(element)

    def pop(self) -> T:
        return self.elements.popleft()
"""
language_guesser(code_example=code_snippet)
```

```
2025/08/10 21:05:33 WARNING dspy.predict.predict: Not all input fields were provided to module. Present: ['code_example']. Missing: ['hint'].



Prediction(

    programming_language_name='Python',

    programming_language_version='3.12'

)
```