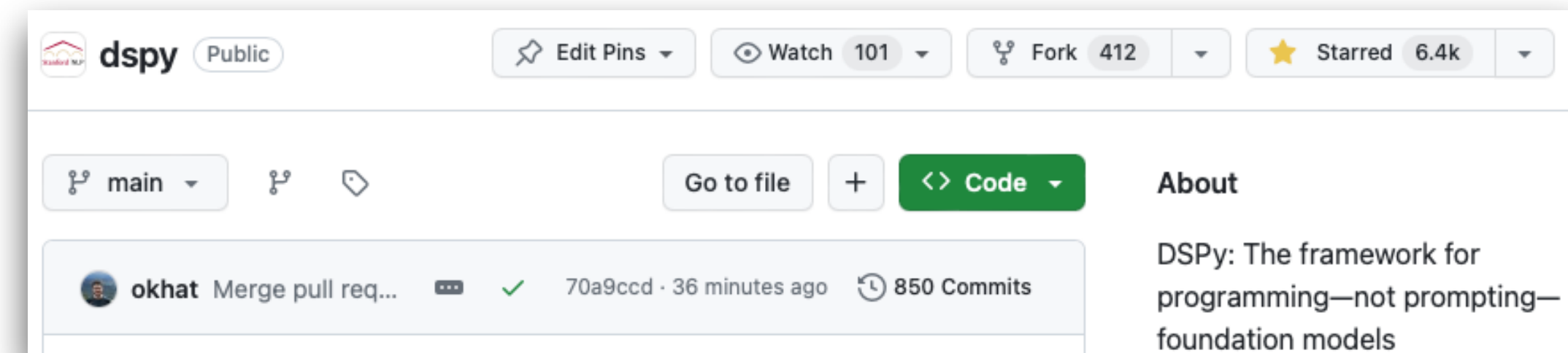


DSPy overview

**Programming—not prompting
—Foundation Models**

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DSPY: COMPILING DECLARATIVE LANGUAGE MODEL CALLS INTO SELF-IMPROVING PIPELINES

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Agenda

Motivation

DSPy overview

Resources

Motivation

LM usage

- Zero-shot: ask a question and LM answers.
- Few-shot: ask a question and provide examples, then LM answers. This is also called in-context learning.
- Retrieval-augmented generation (RAG): retrieve relevant contexts first, then use the contexts as part of the query.

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
1 Translate English to French: ← task description
2 cheese => ..... ← prompt
```

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
1 Translate English to French: ← task description
2 sea otter => loutre de mer ← example
3 cheese => ..... ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1 Translate English to French: ← task description
2 sea otter => loutre de mer ← examples
3 peppermint => menthe poivrée ←
4 plush girafe => girafe peluche ←
5 cheese => ..... ← prompt
```

Development with LLMs

- Test prompts using the playground.
 - Put together prompts and use the API to generate text.
 - As the prompt and parsing get more complicated, use LLM orchestration software, such as Langchain or llamaindex.
 - These tools allow you to perform advanced operations and chain operations, but they also hide details, so they are hard to debug.
 - When the models are updated, you need to update your prompt.
- Links: [Langchain](#), [llamaindex](#)

Why DSPy?

- DSPy introduces a small set of much more powerful and *general-purpose modules* that can learn to prompt your LM within your pipeline on your data.
- When you *change your data*, make tweaks to your program's control flow, or change your target LM, DSPy compiler can map your program into a new set of prompts that are optimized specifically for this pipeline.
- In short, DSPy is for when you need a *lightweight* but automatically-optimizing programming model — not a library of predefined prompts and integrations.

Overview

LM usage

- LM can be defined and used.
- Multiple LMs can be set.
 - OpenAI APIs.
 - OSS LMs using APIs from together, Anyscale.
 - OSS LMs from locally hosted server.
 - OSS LMs running on a local machine.

```
# OpenAI
model_name = "gpt-3.5-turbo"
lm = dsp.py.OpenAI(model=model_name)

# Azure OpenAI
model_arg = {"engine": model_name, "deployment_id": model_name,
             "api_version": openai.api_version,
             "api_base": openai.api_base,
            }
provider_name = "azure"
lm = dsp.py.OpenAI(model=model_name,
                  api_key=openai.api_key,
                  api_provider=provider_name,
                  **model_arg)

# Together.ai
model="mistralai/Mistral-7B-v0.1"
lm = dsp.py.Together(model=model)

# local model using Ollama
lm = dsp.py.OllamaLocal(model='mistral')

# OR use recent Ollama's OpenAI API support
lm = dsp.py.OpenAI(api_base='http://localhost:11434/v1/',
                  api_key='anything',
                  model='mistral:7b-instruct-v0.2-q6_K',
                  stop='\n\n',
                  model_type='chat')
```


LM example

- Simple text request
- Request text with configurations
 - temperature: high temp. generates creative output
 - n: number of calls
- `inspect_history`: useful to check the text request and output
 - n: number of history
 - white text: prompt sent to LM
 - green text: text generated by LM

```
lm("Which award did Gary Zukav's first book receive?")
✓ 0.8s Python
```

```
['Gary Zukav\'s first book, "The Dancing Wu Li Masters: An Overview of the N
```

```
lm("Which U.S. states border no U.S. states?", temperature=0.9, n=4)
✓ 1.3s Python
```

```
['There are two U.S. states that do not share borders with any other U.S. st
"There are two U.S. states that do not border any other U.S. states:\n\n1.
'There are two U.S. states that do not border any other U.S. states:\n\n1.
'There are two U.S. states that do not border any other U.S. states. They a
```

```
lm.inspect_history(n=1)
✓ 0.0s Python
```

```
Which U.S. states border no U.S. states? There are two U.S. states that do n
1. Alaska: Located in the northwest extremity of the North American continen
2. Hawaii: Located in the central Pacific Ocean, Hawaii consists of a group
```

Signature Basics

- Declarative statements that *what* we want to the model to do.
- “question -> answer” signature and `dspy.Predict` turns this into a QA system

```
basic_predictor = dspy.Predict("question -> answer")
```

✓ 0.0s

```
basic_predictor(question="Which award did Gary Zukav's first book receive?")
```

✓ 0.0s

```
Prediction(  
  answer='Question: Which award did Gary Zukav\'s first book receive?\nAnswer: Gary Zukav' )
```

```
lm.inspect_history(n=1)
```

✓ 0.0s

Given the fields `question`, produce the fields `answer`.

Follow the following format.

Question: \${question}

Answer: \${answer}

Question: Which award did Gary Zukav's first book receive?

Answer: Question: Which award did Gary Zukav's first book receive?

Answer: Gary Zukav's first book, "The Dancing Wu Li Masters," received the American Book

Signature example

- Sentiment analysis: “**sentence -> sentiment**”
- In-line signature examples:
 - Summarization: “**document -> summary**”
 - Retrieval-Augmented Question Answering: “**context, question -> answer**”
 - Multiple-Choice Question Answering with Reasoning: “**question, choices -> reasoning, selection**”

Example from <https://dspy-docs.vercel.app/docs/building-blocks/signatures> ,

```
sentence = "it's a charming and often affecting journey."  
  
classify = dspy.Predict('sentence -> sentiment')  
classify(sentence=sentence).sentiment
```

✓ 0.6s

'Sentiment: positive'

```
lm.inspect_history(n=1)
```

✓ 0.0s

Given the fields `sentence`, produce the fields `sentiment`.

Follow the following format.

Sentence: \${sentence}
Sentiment: \${sentiment}

Sentence: it's a charming and often affecting journey.
Sentiment: **Sentiment: positive**

Signature

Use **dspy.Signature** class

- We can add more descriptions and tweak the initial instruction using dspy.Signature class
- Added description of the task using
`__doc__ = """Answer questions with short factoid answers."""`
- Specify output to be "often between 1 and 5 words"
- Notice that the answer is 1-5 words as specified in signature, this was different when we did not specify outputField signature (see previous slide)

```
class BasicQASignature(dspy.Signature):  
    __doc__ = """Answer questions with short factoid answers."""  
  
    question = dspy.InputField()  
    answer = dspy.OutputField(desc="often between 1 and 5 words")  
  
sig_predictor = dspy.Predict(BasicQASignature)  
  
sig_predictor(question="Which U.S. states border no U.S. states?")
```

✓ 0.6s

```
Prediction(  
    answer='Alaska, Hawaii'  
)
```

Answer questions with short factoid answers.

Follow the following format.

Question: \${question}

Answer: often between 1 and 5 words

Question: Which U.S. states border no U.S. states?

Answer: Alaska, Hawaii

Review PyTorch

- Since DSPy adapts design patterns from PyTorch, let's review the PyTorch pattern using a simple example
- `__init__()`: defines the nodes of the computational graph
- `forward()`: executes the graphs, i.e. forward pass

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

Modules

- The DSPy module follows the pytorch design pattern. This allows DSPy to compose multiple tasks.
- Notice that the answer is 1-5 words, as specified in the signature. This was different when we did not specify the outputField signature (see previous slide).

```
class BasicQA(dspy.Module):  
    def __init__(self):  
        super().__init__()  
        self.generate_answer = dspy.Predict(BasicQASignature)  
  
    def forward(self, question):  
        return self.generate_answer(question=question)  
  
basic_qa_model = BasicQA()  
  
basic_qa_model(question="Which award did Gary Zukav's first book receive?")
```

✓ 0.6s

```
Prediction(  
    answer='Oprah'  
)
```

Answer questions with short factoid answers.

Follow the following format.

Question: \${question}

Answer: often between 1 and 5 words

Question: Which award did Gary Zukav's first book receive?

Answer: Oprah

Modules

Built-in modules

- **dspy.Predict**: Basic predictor. Does not modify the signature. Handles the key forms of learning (i.e., storing the instructions and demonstrations and updates to the LM).
- **dspy.ChainOfThought**: Teaches the LM to think step-by-step before committing to the signature's response.
- **dspy.ProgramOfThought**: Teaches the LM to output code, whose execution results will dictate the response.
- **dspy.ReAct**: An agent that can use tools to implement the given signature.
- **dspy.MultiChainComparison**: Can compare multiple outputs from ChainOfThought to produce a final prediction.
- **dspy.majority**: Can do basic voting to return the most popular response from a set of predictions.

Optimizer Teleprompter

- Teleprompter can run the DSPy programs. It updates prompts and/or LM weights based on optimization methods.
- To use teleprompters, we need
 - A metric that evaluates output
 - A few training examples
- **LabeledFewShot** teleprompter add three demonstrations, which will be sampled from the training examples
- With 3 examples provided, notice that the answer is more akin to the question asked compared to the output from the previous slide

```
from dsp.py.teleprompt import LabeledFewShot
fewshot_teleprompter = LabeledFewShot(k=3)
basic_fewshot_qa_model = fewshot_teleprompter.compile(basic_qa_model,
                                                       trainset=squad_train)

basic_fewshot_qa_model(
    question="Which award did Gary Zukav's first book receive?")
```

Answer questions with short factoid answers.

Follow the following format.

Question: \${question}

Answer: often between 1 and 5 words

Question: What group did Paul VI address in New York in 1965?

Answer: United Nations

Question: What did Sander's study show in terms of black law students rankings?

Answer: half of all black law students rank near the bottom of their class after

Question: What problems does linguistic anthropology bring linguistic methods to

Answer: anthropological

Question: Which award did Gary Zukav's first book receive?

Answer: Oprah's Book Club

Available teleprompters (optimizers)

- Automatic Few-Shot Learning
 - **LabeledFewShot**: Simply constructs few-shot examples.
 - **BootstrapFewShot**: Uses your program to self-generate complete demonstrations for every stage of your program. Will simply use the generated demonstrations (if they pass the metric) without any further optimization.
 - **BootstrapFewShotWithRandomSearch**: Applies BootstrapFewShot several times with random search over generated demonstrations, and selects the best program.
- Automatic Instruction Optimization
 - **SignatureOptimizer**: Generates and refines new instructions for each step, and optimizes them with coordinate ascent.
 - **BayesianSignatureOptimizer**: Generates instructions and few-shot examples in each step. The instruction generation is data-aware and demonstration-aware. Uses Bayesian Optimization to effectively search over the space of generation instructions/ demonstrations across your modules.

Evaluation

- Use automatic metrics to evaluate the generated text.
- Built-in exact matches can be useful
- LM can be used as judge for the evaluator

Retrieval

- DSPy supports multiple retriever backend, which can be used in RAG (retrieval augmented generation) pattern.
- Here are the supported retrievers
 - ColBERT
 - ChromaDB
 - Pinecone
 - Qdrant
 - Weaviate
 - [you.com](#)

RAG

- RAG: retrieve context based on the query and use it as part of the prompt
- We can update our signature with context, which is retrieved
- We use Colbert as a retriever in this example

```
class ContextQASignature(dspy.Signature):  
    __doc__ = """Answer questions with short factoid answers."""  
  
    context = dspy.InputField(desc="may contain relevant facts")  
    question = dspy.InputField()  
    answer = dspy.OutputField(desc="often between 1 and 5 words")
```

```
class RAG(dspy.Module):  
    def __init__(self, num_passages=1):  
        super().__init__()  
        self.retrieve = dspy.Retrieve(k=num_passages)  
        self.generate_answer = dspy.Predict(ContextQASignature)  
  
    def forward(self, question):  
        context = self.retrieve(question).passages  
        prediction = self.generate_answer(context=context, question=question)  
        return dspy.Prediction(context=context, answer=prediction.answer)
```

RAG

- With 3 retrieved contexts, LM was able to answer correctly this time. Note the the answer in the previous slide is different

```
rag_model = RAG(num_passages=3)
```

✓ 0.0s

```
rag_model(question="Which award did Gary Zukav's first book receive?")
```

✓ 0.0s

```
Prediction(  
  context=['Gary Zukav | Gary Zukav Gary Zukav (born October 17, 1942) i  
  answer='U.S. National Book Award'  
)
```

Answer questions with short factoid answers.

Follow the following format.

Context: may contain relevant facts

Question: \${question}

Answer: often between 1 and 5 words

Context:

[1] «Gary Zukav | Gary Zukav Gary Zukav (born O

[2] «The Dancing Wu Li Masters | The Dancing Wu

[3] «Markus Zusak | a runner-up for the Printz

Question: Which award did Gary Zukav's first bo

Answer: **U.S. National Book Award**

Resources

- [Multi-hop search example](<https://github.com/stanfordnlp/dspy/blob/main/intro.ipynb>)
- [Why Im excited for DSPy](<https://substack.stephen.so/p/why-im-excited-about-dspy>)
- [DSPy doc](<https://dspy-docs.vercel.app>)
- [Getting Started with RAG in DSPy!](<https://www.youtube.com/watch?v=CEuUG4Umfxs>)
- [DSPy discord](<https://discord.com/invite/HZwtqNzKCu>)