Pipeline Inspection, Visualization, and Interoperability in PyTerrier

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Abstract. PyTerrier provides a declarative framework for building and experimenting with Information Retrieval (IR) pipelines. In this demonstration, we highlight several recent pipeline operations that improve their ability to be programmatically inspected, visualized, and integrated with other tools (via the Model Context Protocol, MCP). These capabilities aim to make it easier for researchers, students, and AI agents to understand and use a wide array of IR pipelines.

1 Introduction

PyTerrier [10] provides an interface between state-of-the-art retrieval components, including highly-efficient inverted indexes [8], generative re-rankers [3], and retrieval-augmented generation methods [9]. Users can combine these components into pipelines (Sect. 2) through a declarative Python syntax. For example, Fig. 1(a) shows a sophisticated pipeline that performs a variety of operations, including lexical retrieval, query reformulation, result fusion, neural re-ranking, and answer generation.

This demonstration presents three recent enhancements to PyTerrier pipelines designed to make them easier to understand and interact with. First, we introduce a core *inspection* mechanism (Sect. 3), which provides programmatic access to information about pipelines, including input/output specifications, constituent components, and other settings. Building on this foundation, we provide interactive pipeline visualizations that we call *schematics* (Sect. 4, Fig. 1(b)). Schematics are automatically rendered for pipelines in Python notebooks to help users understand the pipelines they construct. They are also integrated into the documentation to serve illustrative examples and can be rendered *ad hoc* for other purposes. Finally, we enable users to expose PyTerrier pipelines as tools via a Model Context Protocol (MCP) server [1], allowing other systems to interact with them through MCP's unified API (Sect. 5). For instance, the MCP feature enables pipelines to be easily integrated as components of agentic systems for research and deployment, or used as tools through systems such as Copilot[1] or Cursor[2].

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[1] https://github.com/features/copilot.
[2] https://cursor.com/.

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```
index = pt.Artifact.from_hf('pyterrier/msmarco-passage.terrier')
pipeline = pta.RRFusion(
    index.bm25(),
    SequentialDependence() >> index.bm25(),
) >> index.text_loader() >> MonoT5() >> T5FiD('terrierteam/t5fid_base_nq')
```

(a) Python code to declare the pipeline (imports omitted for brevity).

(b) Generated schematic for the pipeline defined in (a).

Fig. 1. Example PyTerrier pipeline that performs retrieval, fusion, re-ranking, and answer generation stages. The pipeline is shown both as (a) declarative Python code and (b) the corresponding generated schematic.

2   Background: PyTerrier Pipelines

The core components of pipelines in PyTerrier are called transformers. A transformer provides a function that modifies the current *state* of one or more search requests. For example, a BM25 transformer accepts search queries and returns the search results from an index. The state is represented as a relation (i.e., a data table such as a Pandas DataFrame or a list of Python dictionaries). PyTerrier's data model defines a variety of typical column definitions that represent different stages of an engine's processing as shown in Table 1. These configurations can be extended with additional information as needed by transformers (e.g., a document's text or a query's vector). PyTerrier hosts components for a wide variety of IR pipeline operations, including lexical retrieval, dense retrieval, learned sparse retrieval, query reformulation, and answer generation.

Table 1. PyTerrier data model columns for typical stages of a search engine.

Name	Abbr.	Columns
Query Frame	Q	`qid` (PK, query identifier), `query`
Document Frame	D	`docno` (PK, document identifier), `text`
Result Frame	R	`qid` (PK), `docno` (PK), `score`, `rank`
Answer Frame	A	`qid` (PK), `qanswer`

PyTerrier's data model enables transformers to be combined together into larger pipelines. In a typical sequential pipeline (represented as `A >> B`), the output of one transformer (`A`) can be fed as input to the next transformer (`B`). Other types of pipelines include linear score combination (e.g., `A + B`) and reciprocal rank fusion [2] (e.g., `RRFusion(A, B)`). In all cases, it is important that the pipelines are combined in a way where the input/output specifications are compatible with one another. For instance, if a pipeline is constructed that does

not provide the text of a document to a neural re-ranking method that relies on it, the pipeline will raise an error when executed. This demonstration highlights new features that overcome shortcomings of these pipelines, namely the ability to programmatically inspect and validate the inputs/outputs of transformers, the ability to visualize them, and the ability to use them as tools for an LLM.

3   Inspecting Pipelines

PyTerrier transformers can be defined with as little as a function that maps one relation to another. This flexility makes implementing transformers simple and allows arbitrary pipelines to be constructed, but can result in incompatible pipelines. Without knowing the input and output specifications of individual transformers, it can be challenging to know whether a pipeline is compatible. Previously the only way to check these would be to check the documentation or run an example through and check the outputs (or interpret the resulting error).

To overcome this inconvenience, we introduce a new `pt.inspect` module that allows for the programmatic inspection of transformers and pipelines. The module provides functions that return which columns are required as inputs (e.g., a BM25 retriever expects `qid` and `query`, while a FAISS [4] dense retriever expects `qid` and `query_vec`) and which columns are returned for the provided inputs (e.g., BM25 returns `qid`, `query`, `docno`, `rank`, and `score`). Other functions in the module provide additional information about transformers, such as its attributes and any other transformers that it invokes (subtransformers). In most cases, `pt.inspect` identifies these automatically[3] by leveraging best practices in transformer implementation (e.g., performing input validation). To provide additional clarity on the implementation, a notebook is included in PyTerrier that demonstrates the inspection functionality.[4]

Transformer inspection has a number of applications. It enables pipeline *validation* to ensure that a pipeline is fully compatible (which is now applied automatically before experiments are conducted). Inspection also helps in visualization and interoperability, which are covered in the following two sections.

4   Visualizing Pipelines with Schematics

As shown in Fig. 1(a), pipeline definitions can get complex, especially when they involve multiple components and stages. Therefore, we added a new pipeline visualization feature that renders pipelines as interactive HTML snippets. We call these visitations schematics. Schematics render the pipeline as a sequence of transformers and the data between then, allowing users to better understand the transformers in a pipeline and how data flows between them. Hovering over elements provide additional information, like specific information about columns

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[3] The details are too intricate to describe here, but are covered in the documentation.
[4] https://github.com/terrier-org/pyterrier/blob/master/examples/notebooks/inspect-demo.ipynb.

or transformer settings. Schematics leverage the inspection features covered in Sect. 3. A non-interactive screenshot of a schematic is shown in Fig. 1(b).

Although schematics can be displayed anywhere that can render HTML, we have applied them in a couple of convenient places. First, they are automatically rendered in Python notebooks when the output of a cell is a pipeline, aiding in the construction of pipelines in interactive sessions. We also render them in several places throughout PyTerrier's documentation to better demonstrate core concepts of the platform. PyTerrier contains an interactive notebook containing schematics for a range of pipelines.[5]

```python
# Register an MCP server as an external tool
tools = [{"type": "mcp","server_label": "PYTERRIER_MCP",
        "server_description": "A server exposing information retrieval pipelines.",
        "server_url": mcp_url, "require_approval": "never"}]

# Invoke the LLM with the MCP tool registered
response = OpenAI().responses.create(model="gpt-4o",
tools=tools,input=[{"role": "user", "content": user_input}])

# The LLM output may include structured tool calls (e.g., McpCall)
# indicating which tool was invoked and its corresponding output.
print(response.output)
```

(1) defines the mcp server so that it can connect and find all available tools

(2) During the call the LLM will call the MCP tool to get the outputs

MCP

Fig. 2. Example usage of the MCP server through the OpenAI API.

5   Pipeline Interoperation with MCP

Another limitation of PyTerrier pipelines is the need for a Python runtime to execute them. Increasingly, external "tools" are invoked directly by Large Language Models (LLMs) [14]. The open-source Model Context Protocol (MCP) [1] is a popular protocol that standardizes LLM access to these tools by exposing them via HTTP endpoints. Despite MCP's original design for LLMs, its scope is much broader and has been referred to as a "universal plugin ecosystem" because it allows for simplified interoperation between virtually any Internet-connected system [15]. This quality makes MCP a natural choice to improve PyTerrier's interoperability with systems outside of Python.

To this end, we built a new package that exposes PyTerrier pipelines via MCP, thereby allowing a growing ecosystem of MCP-compatible tools to use them. The MCP server exposes HTTP endpoints for PyTerrier pipelines along with their associated metadata, such as natural-language descriptions and input/output specifications (using the new inspection functionality described in Sect. 3). The code for the MCP server is publicly available[6].

The MCP server is useful in a variety of settings. First, it can be used programmatically by researchers or practitioners as components in agentic systems.

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[5] https://github.com/terrier-org/pyterrier/blob/master/examples/notebooks/schematics-demo.ipynb.

[6] https://github.com/terrierteam/pyterrier-server.

For instance, one can enable pipeline access for LLMs using the OpenAI[7] package, as shown in Fig. 2. Alternatively, MCP-exposed PyTerrier pipelines can be leveraged by users directly through systems like the Copilot extension in Visual Studio Code. This allows users to leverage PyTerrier pipelines in their day-to-day activities.

To demonstrate the flexibility of the MCP server across different retrieval and reasoning paradigms, we showcase its use with three representative pipelines: (i) a traditional BM25 [13] retrieval pipeline implemented using PISA [8,12]; (ii) a retrieval-augmented generation (RAG) system employing a lightweight Fusion-in-Decoder model for direct question answering [6,7,9]; and (iii) a Doc2Query-based model designed to support question decomposition [5,11]. Given these pipelines, we provide a demo video[8] illustrating the programmatic implementation via a web-based interface, as well as a demonstration of day-to-day usage through Copilot (Fig. 3).

Fig. 3. A PyTerrier MCP server interaction example through Copilot.

7 https://platform.openai.com/docs/overview.
8 https://github.com/terrierteam/pyterrier-server/blob/main/videos/demo.gif.

6   Conclusions

This demonstration covers new features in PyTerrier that improve the inspection, visualization, and interoperability of pipelines. ECIR attendees will be able to interact with each of these features through notebooks and a web interface in the demonstration.

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