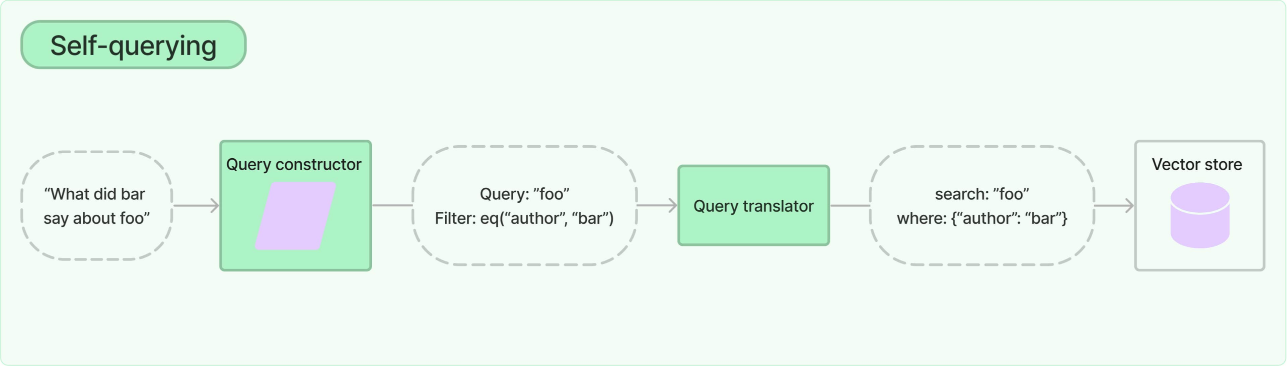
Self-querying

Head to Integrations for documentation on vector stores with built-in support for self-querying.

A self-querying retriever is one that, as the name suggests, has the ability to query itself. Specifically, given any natural language query, the retriever uses a query-constructing LLM chain to write a structured query and then applies that structured query to its underlying VectorStore. This allows the retriever to not only use the user-input query for semantic similarity comparison with the contents of stored documents but to also extract filters from the user query on the metadata of stored documents and to execute those filters.



Get started

For demonstration purposes we’ll use a `Chroma` vector store. We’ve created a small demo set of documents that contain summaries of movies.

Note: The self-query retriever requires you to have `lark` package installed.

```
%pip install --upgrade --quiet  lark chromadb
```

```
from langchain.schema import Document
from langchain_community.vectorstores import Chroma
from langchain_openai import OpenAIEmbeddings

docs = [
    Document(
        page_content="A bunch of scientists bring back dinosaurs and mayhem breaks loose",
        metadata={"year": 1993, "rating": 7.7, "genre": "science fiction"},
    ),
    Document(
        page_content="Leo DiCaprio gets lost in a dream within a dream within a dream
```

```
within a ...",
        metadata={"year": 2010, "director":
"Christopher Nolan", "rating": 8.2},
    ),
    Document(
        page_content="A psychologist /
detective gets lost in a series of dreams
within dreams within dreams and Inception
reused the idea",
        metadata={"year": 2006, "director":
"Satoshi Kon", "rating": 8.6},
    ),
    Document(
        page_content="A bunch of normal-sized
women are supremely wholesome and some men
pine after them",
        metadata={"year": 2019, "director":
"Greta Gerwig", "rating": 8.3},
    ),
    Document(
        page_content="Toys come alive and
have a blast doing so",
        metadata={"year": 1995, "genre":
"animated"},
    ),
    Document(
        page_content="Three men walk into the
Zone, three men walk out of the Zone",
        metadata={
            "year": 1979,
            "director": "Andrei Tarkovsky",
            "genre": "thriller",
            "rating": 9.9,
        },
    ),
]
vectorstore = Chroma.from_documents(docs, OpenAIEmbeddings())
```

Creating our self-querying retriever

Now we can instantiate our retriever. To do this we’ll need to provide some information upfront about the metadata fields that our documents support and a short description of the document contents.

```
from langchain.chains.query_constructor.base import AttributeInfo
from langchain.retrievers.self_query.base import SelfQueryRetriever
from langchain_openai import ChatOpenAI

metadata_field_info = [
    AttributeInfo(
        name="genre",
        description="The genre of the movie. One of ['science fiction', 'comedy', 'drama', 'thriller', 'romance', 'action', 'animated']",
        type="string",
    ),
    AttributeInfo(
        name="year",
        description="The year the movie was released",
        type="integer",
    ),
    AttributeInfo(
        name="director",
        description="The name of the movie director",
        type="string",
    ),
    AttributeInfo(
        name="rating", description="A 1-10 rating for the movie", type="float"
    ),
]
document_content_description = "Brief summary of a movie"
llm = ChatOpenAI(temperature=0)
retriever = SelfQueryRetriever.from_llm(
    llm,
    vectorstore,
    document_content_description,
    metadata_field_info,
)
```

Testing it out

And now we can actually try using our retriever!

```
# This example only specifies a filter
retriever.invoke("I want to watch a movie rated higher than 8.5")
```

```
[Document(page_content='Three men walk into the Zone, three men walk out of the Zone', metadata={'director': 'Andrei Tarkovsky', 'genre': 'thriller', 'rating': 9.9, 'year': 1979}),
 Document(page_content='A psychologist / detective gets lost in a series of dreams within dreams within dreams and Inception reused the idea', metadata={'director': 'Satoshi Kon', 'rating': 8.6, 'year': 2006})]
```

```
# This example specifies a query and a filter
retriever.invoke("Has Greta Gerwig directed any movies about women")
```

```
[Document(page_content='A bunch of normal-sized women are supremely wholesome and some men pine after them', metadata={'director': 'Greta Gerwig', 'rating': 8.3, 'year': 2019})]
```

```
# This example specifies a composite filter
retriever.invoke("What's a highly rated (above 8.5) science fiction film?")
```

```
[Document(page_content='A psychologist / detective gets lost in a series of dreams within dreams within dreams and Inception reused the idea', metadata={'director': 'Satoshi Kon', 'rating': 8.6, 'year': 2006}),
 Document(page_content='Three men walk into the Zone, three men walk out of the Zone', metadata={'director': 'Andrei Tarkovsky', 'genre': 'thriller', 'rating': 9.9, 'year': 1979})]
```

```
# This example specifies a query and composite filter
retriever.invoke(
    "What's a movie after 1990 but before 2005 that's all about toys, and preferably is animated"
)
```

```
[Document(page_content='Toys come alive and have a blast doing so', metadata={'genre': 'animated', 'year': 1995})]
```

Filter k

We can also use the self query retriever to specify `k`: the number of documents to fetch.

We can do this by passing `enable_limit=True` to the constructor.

```
retriever = SelfQueryRetriever.from_llm(
    llm,
    vectorstore,
    document_content_description,
    metadata_field_info,
    enable_limit=True,
)

# This example only specifies a relevant query
retriever.invoke("What are two movies about dinosaurs")
```

```
[Document(page_content='A bunch of scientists bring back dinosaurs and mayhem breaks loose', metadata={'genre': 'science fiction', 'rating': 7.7, 'year': 1993}),
 Document(page_content='Toys come alive and have a blast doing so', metadata={'genre': 'animated', 'year': 1995})]
```

Constructing from scratch with LCEL

To see what’s going on under the hood, and to have more custom control, we can reconstruct our retriever from scratch.

First, we need to create a query-construction chain. This chain will take a user query and generated a `StructuredQuery` object which captures the filters specified by the user. We provide some helper functions for creating a prompt and output parser. These have a number of tunable params that we’ll ignore here for simplicity.

```
from langchain.chains.query_constructor.base
import (
    StructuredQueryOutputParser,
    get_query_constructor_prompt,
)

prompt = get_query_constructor_prompt(
    document_content_description,
    metadata_field_info,
)
output_parser =
StructuredQueryOutputParser.from_components()
query_constructor = prompt | llm |
output_parser
```

Let’s look at our prompt:

```
print(prompt.format(query="dummy question"))
```

~~~
Your goal is to structure the user's query to
match the request schema provided below.

<< Structured Request Schema >>
When responding use a markdown code snippet
with a JSON object formatted in the following
schema:

```json
{
    "query": string \ text string to compare
to document contents
    "filter": string \ logical condition
statement for filtering documents
}
```


The query string should contain only text
that is expected to match the contents of
documents. Any conditions in the filter
should not be mentioned in the query as well.

A logical condition statement is composed of
one or more comparison and logical operation
statements.
~~~

```
A comparison statement takes the form:
`comp(attr, val)`:
- `comp` (eq | ne | gt | gte | lt | lte |
contain | like | in | nin): comparator
- `attr` (string):  name of attribute to
apply the comparison to
- `val` (string): is the comparison value

A logical operation statement takes the form
`op(statement1, statement2, ...)`:
- `op` (and | or | not): logical operator
- `statement1`, `statement2`, ... (comparison
statements or logical operation statements):
one or more statements to apply the operation
to

Make sure that you only use the comparators
and logical operators listed above and no
others.
Make sure that filters only refer to
attributes that exist in the data source.
Make sure that filters only use the
attributed names with its function names if
there are functions applied on them.
Make sure that filters only use format `YYYY-
MM-DD` when handling date data typed values.
Make sure that filters take into account the
descriptions of attributes and only make
comparisons that are feasible given the type
of data being stored.
```

~~~
Make sure that filters are only used as
needed. If there are no filters that should
be applied return "NO_FILTER" for the filter
value.

<< Example 1. >>
Data Source:
```json
{
    "content": "Lyrics of a song",
    "attributes": {
        "artist": {
            "type": "string",
            "description": "Name of the song
artist"
        },
        "length": {
            "type": "integer",
            "description": "Length of the
song in seconds"
        },
        "genre": {
            "type": "string",
            "description": "The song genre,
one of "pop", "rock" or "rap""
        }
    }
}
```

User Query:
~~~

~~~
What are songs by Taylor Swift or Katy Perry about teenage romance under 3 minutes long in the dance pop genre

Structured Request:
```json
{
    "query": "teenager love",
    "filter": "and(or(eq(\"artist\", \"Taylor Swift\"), eq(\"artist\", \"Katy Perry\")), lt(\"length\", 180), eq(\"genre\", \"pop\"))"
}
~~~

<< Example 2. >>
Data Source:
```json
{
    "content": "Lyrics of a song",
    "attributes": {
        "artist": {
            "type": "string",
            "description": "Name of the song artist"
        },
        "length": {
            "type": "integer",
            "description": "Length of the song in seconds"
        },
```

~~~
        "genre": {
            "type": "string",
            "description": "The song genre,
one of "pop", "rock" or "rap""
        }
    }
}
```

User Query:
What are songs that were not published on
Spotify

Structured Request:
```json
{
    "query": "",
    "filter": "NO_FILTER"
}
```


<< Example 3. >>
Data Source:
```json
{
    "content": "Brief summary of a movie",
    "attributes": {
    "genre": {
        "description": "The genre of the
movie. One of ['science fiction', 'comedy',
~~~

~~~
'drama', 'thriller', 'romance', 'action',
'animated']",
        "type": "string"
    },
    "year": {
        "description": "The year the movie
was released",
        "type": "integer"
    },
    "director": {
        "description": "The name of the movie
director",
        "type": "string"
    },
    "rating": {
        "description": "A 1-10 rating for the
movie",
        "type": "float"
    }
}
}
```


User Query:
dummy question

Structured Request:
~~~

And what our full chain produces:

```
query_constructor.invoke(
    {
        "query": "What are some sci-fi movies from the 90's directed by Luc Besson about taxi drivers"
    }
)
```

```
StructuredQuery(query='taxi driver',
filter=Operation(operator=<Operator.AND:
'and'>, arguments=[Comparison(comparator=
<Comparator.EQ: 'eq'>, attribute='genre',
value='science fiction'), Operation(operator=
<Operator.AND: 'and'>, arguments=
[Comparison(comparator=<Comparator.GTE:
'gte'>, attribute='year', value=1990),
Comparison(comparator=<Comparator.LT: 'lt'>,
attribute='year', value=2000)]),
Comparison(comparator=<Comparator.EQ: 'eq'>,
attribute='director', value='Luc Besson')]),
limit=None)
```

The query constructor is the key element of the self-query retriever. To make a great retrieval system you'll need to make sure your query constructor works well. Often this requires adjusting the prompt, the examples in the prompt, the attribute descriptions, etc. For an example that walks through refining a query constructor on some hotel inventory data, check out this cookbook.

The next key element is the structured query translator. This is the object responsible for translating the generic `StructuredQuery` object into a metadata filter in the syntax of the vector store you’re using. LangChain comes with a number of built-in translators. To see them all head to the Integrations section.

```
from langchain.retrievers.self_query.chroma
import ChromaTranslator

retriever = SelfQueryRetriever(
    query_constructor=query_constructor,
    vectorstore=vectorstore,

structured_query_translator=ChromaTranslator(),
)
```

```
retriever.invoke(
    "What's a movie after 1990 but before
2005 that's all about toys, and preferably is
animated"
)
```

```
[Document(page_content='Toys come alive and
have a blast doing so', metadata={'genre':
'animated', 'year': 1995})]
```