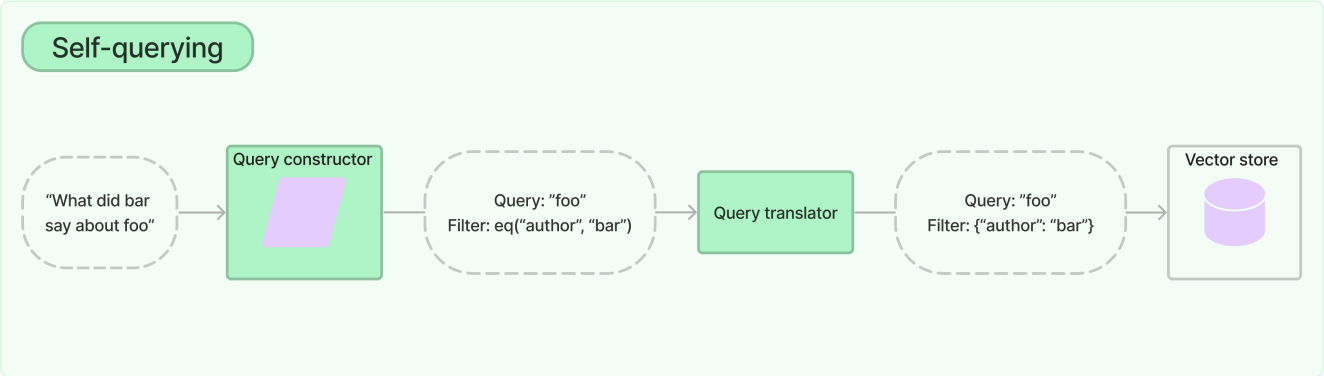
Self-querying

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 it's underlying VectorStore. This allows the retriever to not only use the user-input query for semantic similarity comparison with the contents of stored documented, but to also extract filters from the user query on the metadata of stored documents and to execute those filters.



Get started

We'll use a Pinecone vector store in this example.

First we'll want to create a `Pinecone` VectorStore and seed it with some data. We've created a small demo set of documents that contain summaries of movies.

To use Pinecone, you need to have `pinecone` package installed and you must have an API key and an Environment. Here are the installation instructions.

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

```
# !pip install lark pinecone-client
```

```
import os

import pinecone
```

```
pinecone.init(api_key=os.environ["PINECONE_API_KEY"],
environment=os.environ["PINECONE_ENV"])
```

```
from langchain.schema import Document
from langchain.embeddings.openai import OpenAIEmbeddings
from langchain.vectorstores import Pinecone

embeddings = OpenAIEmbeddings()
# create new index
pinecone.create_index("langchain-self-retriever-demo", dimension=1536)
```

```
docs = [
    Document(page_content="A bunch of scientists bring back dinosaurs
and mayhem breaks loose", metadata={"year": 1993, "rating": 7.7,
"genre": ["action", "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, "rating": 9.9, "director":
"Andrei Tarkovsky", "genre": ["science fiction", "thriller"], "rating":
9.9})
]
vectorstore = Pinecone.from_documents(
    docs, embeddings, index_name="langchain-self-retriever-demo"
)
```

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.llms import OpenAI
from langchain.retrievers.self_query.base import SelfQueryRetriever
from langchain.chains.query_constructor.base import AttributeInfo

metadata_field_info=[
    AttributeInfo(
        name="genre",
        description="The genre of the movie",
        type="string or list[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 = OpenAI(temperature=0)
retriever = SelfQueryRetriever.from_llm(llm, vectorstore,
document_content_description, metadata_field_info, verbose=True)
```

Testing it out

And now we can actually try using our retriever!

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

```
    query='dinosaur' filter=None
```

```
    [Document(page_content='A bunch of scientists bring back dinosaurs
and mayhem breaks loose', metadata={'genre': ['action', 'science
fiction'], 'rating': 7.7, 'year': 1993.0}),
     Document(page_content='Toys come alive and have a blast doing so',
metadata={'genre': 'animated', 'year': 1995.0}),
     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':
2006.0}),
     Document(page_content='Leo DiCaprio gets lost in a dream within a
dream within a dream within a ...', metadata={'director': 'Christopher
Nolan', 'rating': 8.2, 'year': 2010.0})]
```

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

```
    query=' ' filter=Comparison(comparator=<Comparator.GT: 'gt'>,
attribute='rating', value=8.5)


    [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':
2006.0}),
     Document(page_content='Three men walk into the Zone, three men
walk out of the Zone', metadata={'director': 'Andrei Tarkovsky',
'genre': ['science fiction', 'thriller'], 'rating': 9.9, 'year':
1979.0})]
```

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

```
    query='women' filter=Comparison(comparator=<Comparator.EQ: 'eq'>,
attribute='director', value='Greta Gerwig')


    [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': 2019.0})]
```

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

```
    query=' ' filter=Operation(operator=<Operator.AND: 'and'>,
arguments=[Comparison(comparator=<Comparator.EQ: 'eq'>,
attribute='genre', value='science fiction'), Comparison(comparator=
<Comparator.GT: 'gt'>, attribute='rating', value=8.5)])


    [Document(page_content='Three men walk into the Zone, three men
walk out of the Zone', metadata={'director': 'Andrei Tarkovsky',
'genre': ['science fiction', 'thriller'], 'rating': 9.9, 'year':
1979.0})]
```

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

```
    query='toys' filter=Operation(operator=<Operator.AND: 'and'>,
arguments=[Comparison(comparator=<Comparator.GT: 'gt'>,
attribute='year', value=1990.0), Comparison(comparator=<Comparator.LT:
'lt'>, attribute='year', value=2005.0), Comparison(comparator=
<Comparator.EQ: 'eq'>, attribute='genre', value='animated')])


    [Document(page_content='Toys come alive and have a blast doing so',
metadata={'genre': 'animated', 'year': 1995.0})]
```

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,
    verbose=True
)
```

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