Aplicações N8N docker

Templates de aplicações desenvolvidas em N8N

- Local AI with Docker, n8n, Qdrant, and Ollama
- Templates N8N utilizando QDRANT
- Build a Financial Documents Assistant using Qdrant and Mistral.ai
- Links de Aplicações N8N
- Distributed Deployment of Qdrant Cluster with Sharding & Replicas

Local AI with Docker, n8n, Qdrant, and Ollama

Link: https://www.datacamp.com/tutorial/local-ai

Contents

Companies worldwide are increasingly concerned about protecting sensitive information while harnessing the power of AI. This guide presents a comprehensive solution for building secure, local AI applications using a powerful combination of open-source tools.

We will use the Self-hosted AI Starter Kit to quickly set up a local AI environment. This kit will automatically run Ollama, Qdrant, n8n, and Postgres. Additionally, we will learn how to build an AI workflow for a RAG (Retrieval-augmented generation) chatbot using the Harry Potter dataset through the n8n dashboard.

Whether you are a developer, data scientist, or non-technical professional looking to implement secure AI solutions, this tutorial will provide you with the foundation to create powerful, self-hosted AI workflows while maintaining complete control over your sensitive data.

What is Local AI?

Local AI allows you to run artificial intelligence systems and workflows on your own infrastructure rather than cloud services, providing enhanced privacy and cost efficiency.

If you are new to the AI ecosystem, you should first check out our skill track on AI Fundamentals to get up to speed. By completing this series of courses, you will gain actionable knowledge on popular AI topics such as ChatGPT, large language models, generative AI, and more.

Local AI Feature image.

Image by Author

Here is the list of tools that we will use to build and run our local AI applications:

1. Docker: This is your containerization platform that packages all AI components into manageable, isolated environments. It will help us run all the AI tools with a single command.
2. n8n: A workflow automation framework that allows you to build AI workflows using a drag-and-drop interface. It requires no coding knowledge, making it ideal for non-technical individuals.
3. Postgres: This tool stores all data and logs, acting as a memory buffer for the n8n framework.
4. Qdrant: A vector database and search engine that makes AI-generated content searchable and manageable.
5. Ollama: An AI model manager that enables you to run any open-source large language model locally with minimal hardware requirements.

The n8n is our primary framework for building the AI workflow for the RAG Chatbot. We will use Qdrant as the vector store and Ollama as the AI model provider. Together, these components will help us create the RAG system.

Installing Docker

We will download and install the Docker desktop application by going to the official Docker website. It is quite easy to install and get started.

Learn more about Docker by following the Docker for Data Science tutorial or take our Introduction to Docker course.

Windows Docker Desktop

Source: Docker: Accelerated Container Application Development

Windows users need an additional tool to successfully run Docker containers: the Windows Subsystem for Linux (WSL). This allows developers to install a Linux distribution and use Linux applications directly on Windows.

To install WSL on Windows, type the following command in the terminal or PowerShell. Make sure to launch PowerShell as an administrator.

```
$ wsl --install
```

After successfully installing WSL, restart your system. Then, type the following command in PowerShell to check if Docker is working properly.

```
$ docker run hello-world
```

Docker successfully pulled the hello-world image and started the container.

Running the Sample Docker Image

Installing and Running Local AI Applications with Docker Compose

In this guide, we will learn how to use Docker Compose to set up AI services locally. This approach allows you to load Docker images and deploy containers within minutes, providing a simple way to run and manage multiple AI services on your infrastructure.

First, we will clone n8n-io/self-hosted-ai-starter-kit by typing the following command in the terminal.

```
$ git clone https://github.com/n8n-io/self-hosted-ai-starter-kit.git
$ cd self-hosted-ai-starter-kit
```

This code snippet consists of two Bash commands:

1. `git clone https://github.com/n8n-io/self-hosted-ai-starter-kit.git`: This command uses Git to create a local copy (clone) of the repository located at the specified URL. The repository contains the "self-hosted-ai-starter-kit" project files.
2. `cd self-hosted-ai-starter-kit`: This command changes the current directory to the newly cloned "self-hosted-ai-starter-kit" directory, allowing you to work with the project files.

Overall, these commands aim to download a project from GitHub and navigate into its directory to start working on it.

The starter kit is the easiest way to set up the servers and applications needed to build an AI workflow. Then, we will load the Docker images and run the containers.

```
$ docker compose --profile cpu up
```

The code snippet is a command to start Docker containers using Docker Compose. Here's a breakdown:

- `docker compose`: This is the command to use Docker Compose, a tool for defining and running multi-container Docker applications.
- `--profile cpu`: This option specifies a profile named "cpu." Profiles allow you to selectively enable services defined in your `docker-compose.yml` file. Only the services associated with the "cpu" profile will be started.
- `up`: This command starts the containers defined in your `docker-compose.yml` file. It creates and starts the containers in the foreground, showing their logs in your terminal.

Overall, this command starts the Docker containers associated with the "cpu" profile, allowing you to run a specific subset of your application.

If you have an NVIDIA GPU, try typing the command below to access the acceleration in response generation. Also, set up the NVIDIA GPU for Docker by following the Ollama Docker guide.

```
$ docker compose --profile gpu-nvidia up
```

The code snippet is a command to start Docker containers using Docker Compose with a specific profile. Here's a breakdown:

- `docker compose`: This is the command to use Docker Compose, a tool for defining and running multi-container Docker applications.
- `--profile gpu-nvidia`: This flag specifies a profile named `gpu-nvidia`. Profiles allow you to define different sets of services or configurations in your `docker-compose.yml` file. The `gpu-nvidia` profile likely includes services or configurations optimized for NVIDIA GPU usage.
- `up`: This command starts the services defined in the `docker-compose.yml` file. It builds, (re)creates, starts, and attaches to containers for a service.

Overall, this command aims to start up the Docker containers associated with the `gpu-nvidia` profile, which might be configured to leverage NVIDIA GPUs for tasks like machine learning or other GPU-intensive applications.

It will take a few minutes as it downloads all the Docker images and then runs the Docker containers one by one.

Running the Docker Compose script from the AI starter Kit.

All the Docker services are running. The exited Docker containers were used to download the Llama 3.2 model and import the n8n backup workflow.

Viewing the status of Docker containers.

We can even check the status of running the docker container by typing the following command in the terminal.

```
$ docker compose ps
```

The command `docker compose ps` is used to list the status of containers defined in a Docker Compose setup. When you run this command, it shows you a table of all the containers in your current Docker Compose project, including their names, states (e.g., running, exited), and other relevant details like ports. This is useful for quickly checking which containers are up and running and their current status.

The starter kit included the script for downloading the Llama 3.2 model. However, for a proper RAG Chatbot application, we also need the embedding model. We will go to the Ollama Docker container, click on the “Exec” tab, and type the following command to download the “nomic-embed-text” model.

```
$ ollama pull nomic-embed-text
```

The code snippet is a Bash command that uses the `ollama` tool to pull a specific resource called `nomic-embed-text`.

- `ollama`: This is likely a command-line tool or utility that manages or interacts with resources or models.
- `pull`: This subcommand is used to download or retrieve the specified resource.
- `nomic-embed-text`: This is the name of the resource or model being pulled.

The command aims to download or update the `nomic-embed-text` resource to your local environment using the `ollama` tool.

As we can see, we can interact with a Docker container as if it were a separate virtual machine.

Executing the command in the Docker container.

Open the n8n dashboard URL http://localhost:5678/ in your browser to set up an n8n user account with email and password. Then, click the home button on the main dashboard page and access the Demo workflow.

The demo is a simple LLM workflow that takes the user input and generates the response.

Sample AI workflow on n8n

To run the workflow, click on the Chat button and start typing your question. Within a few seconds, a response will be generated.

Please note that we are using a small language model with GPU acceleration, so the response typically takes only about 2 seconds.

Running the AI workflow on n8n

Create the AI Workflow with a n8n Dashboard

In this project, we will build a RAG (Retrieval-Augmented Generation) chatbot that uses data from the Harry Potter movies to provide context-aware and accurate responses. This project is a no-code solution, meaning all you need to do is search for the necessary workflow components and connect them to create an AI workflow.

n8n is a no-code platform similar to Langchain. Follow the RAG with Llama 3.1 8B, Ollama, and Langchain tutorial to get an overview of how to create a similar AI workflow using Langchain.

1. Adding the chat trigger

Click on the “Add the first step” button in the middle of the dashboard, search for the “Chat Trigger,” and add it.

Adding the Chat trigger to the n8n workflow

Make sure you have enabled “Allow File Uploads”.

activating the allows file uploads option.

2. Adding the Qdrant vector store

You can add another component called “Qdrant Vector Store” by clicking on the plus (+) button on the “Chat Trigger” component and searching for it.

Change the operation mode to “Insert Documents,” change the Qdrant collection to “By ID,” and type the ID as “Harry_Potter.”

Adding the Qdrant Vector Store

When we exit the option, we will see that the chat trigger is connected with our vector store.

connecting the chat trigger with the Qdrant vector store.

3. Connecting the embedding model with vector store

Click the plus button under the Qdrant vector store labeled “Embedding.” We will be taken to the model management menu, where we will select embeddings Ollama and change the model to “nomic-embed-text:latest.”

Adding the Embedding Ollama model.

4. Connecting the document loader with vector store

Click the plus button under the Qdrant vector store that says “Document,” and select “Default Data Loader” from the menu. Change the type of the data to “Binary”.

Adding the Default Data loader

Then, add a token splitter with a chunk size of 500 and a chunk overlap of 50 will be added to the document loader.

Adding the token splitter

This is how our workflow should look in the end. This workflow will take the CSV files from the user, convert them into text, then transform the text into embeddings and store them in the vector store.

Data ingestion workflow for vector database.

5. Testing the Qdrant vector store

Click the Chat button at the bottom of the dashboard. Once the chat window opens, click on the file button as shown below.

adding a single file

In this workflow, we will load all the CSV files from the Harry Potter Movies dataset. However, to test our workflow, we will only load a single CSV file called 'spell' based on a user query.

adding a single CSV file

You can go to the Qdrant server using the URL http://localhost:6333/dashboard and check if the file was loaded to the vector store or note.

Qdrant Dashboard

Now, add the rest of the files to the vector store.

adding a multiple file to the vector store

6. Adding the AI agent

We will connect the chat trigger to the vector store, link it to the AI agent, and change the agent type to “Conversation Agent.”

Creating the second workflow.

7. Connecting the chat model with AI agent

Click the “Chat Model” button under AI agent and select the Ollama Chat model from the menu. After that, chant the model name to “Llama3.2:latest”.

Connecting the chat model with AI agent

8. Connecting the vector store tool with AI agent

Click the “Tool” button under the AI agent and select the vector store tool from the menu. Provide the tool name and the description.

Connecting the vector store tool with AI agent.

9. Connecting the Qdrant retriever with the vector store tool

We need to add components to the vector store tool. First, we will incorporate Qdrant as the vector store and set the collection ID to "Harry_Potter." This vector store will access the Harry Potter collection during the similarity search. Additionally, change the operation mode to "Retrieved Documents."

Qdrant Document Retriever

10. Connecting the chat model with the vector store tool

The vector store tool also requires an LLM model. We will connect the Ollama chat model and change the model to the “llama3.2:latest”.

Ollama Chat model

11. Connecting the embedding model with the Qdrant retriever

In the final step, we will supply the retrieval vector store with the embedding model. This allows it to convert the user query into an embedding and then convert the embedding back into text for the LLM to process.

Make sure you provide the correct embedding model for your vector store.

Embedding model

This is how the AI workflow should look like.

Entire AI workflow for RAG Chatbot.

12. Testing the AI workflow

Click the chat button to start asking questions about the Harry Potter universe.

Prompt: “What is the most secret place in Hogwarts?”

Testing the AI workflow 1

Prompt: “What is the most powerful spell?”

Testing the AI workflow 2

Our AI workflow is fast and functioning smoothly. This no-code approach is quite easy to execute. n8n also allows users to share their applications so that anyone can access them using a link, just like a ChatGPT.

Conclusion

n8n is a perfect tool for LLM/AI projects, especially for non-technical individuals. Sometimes, we don’t even have to create the workflow from scratch. All we need to do is search for similar projects on the n8n website, copy the JSON code, and paste it into our n8n dashboard. It’s that simple.

n8n workflow automation templates.

Source: Discover 900+ Automation Workflows from the n8n's Community

In this tutorial, we learned about local AI and how to use the self-hosted AI starter kit to build and deploy various AI services. We then launched the n8n dashboard and created our own AI workflow using Qdrant, embedding models, vector store tools, LLMs, and document loaders. Creating and executing workflows is quite easy with n8n. If you are new to AI tools and want to learn about no-code AI solutions, check out our other resources:

- No-Code LLMs In Practice with Birago Jones & Karthik Dinakar, CEO & CTO at Pienso
- Run LLMs Locally: 7 Simple Methods
- LlaMA-Factory WebUI Beginner's Guide: Fine-Tuning LLMs

Templates N8N utilizando QDRANT

Link: https://n8n.io/workflows/?integrations=Qdrant%20Vector%20Store

Building RAG Chatbot for Movie Recommendations with Qdrant and Open AI

https://n8n.io/workflows/2440-building-rag-chatbot-for-movie-recommendations-with-qdrant-and-open-ai/

Create a recommendation tool without hallucinations based on RAG with the Qdrant Vector database.
This example is based on movie recommendations on the IMDB-top1000 dataset. You can provide your wishes and your "big no's" to the chatbot, for example: "A movie about wizards but not Harry Potter", and get top-3 recommendations. How it works a video with the full design process Upload IMDB-1000 dataset to Qdrant Vector Store, embedding movie descriptions with OpenAI; Set up an AI agent with a chat. This agent will call a workflow tool to get movie recommendations based on a request written in the chat; Create a workflow which calls Qdrant's Recommendation API to retrieve top-3 recommendations of movies based on your positive and negative examples. Set Up Steps You'll need to create a free tier Qdrant Cluster (Qdrant can also be used locally; it's open-sourced) and set up API credentials You'll OpenAI credentials You'll need GitHub credentials & to upload the IMDB Kaggle dataset to your GitHub.

Scale Deal Flow with a Pitch Deck AI Vision, Chatbot and QDrant Vector Store

https://n8n.io/workflows/2464-scale-deal-flow-with-a-pitch-deck-ai-vision-chatbot-and-qdrant-vector-store/

Are you a popular tech startup accelerator (named after a particular higher order function) overwhelmed with 1000s of pitch decks on a daily basis? Wish you could filter through them quickly using AI but the decks are unparseable through conventional means? Then you're in luck!

This n8n template uses Multimodal LLMs to parse and extract valuable data from even the most overly designed pitch decks in quick fashion. Not only that, it'll also create the foundations of a RAG chatbot at the end so you or your colleagues can drill down into the details if needed. With this template, you'll scale your capacity to find interesting companies you'd otherwise miss!

Build a Financial Documents Assistant using Qdrant and Mistral.ai

https://n8n.io/workflows/2335-build-a-financial-documents-assistant-using-qdrant-and-mistralai/

This n8n workflow demonstrates how to manage your Qdrant vector store when there is a need to keep it in sync with local files. It covers creating, updating and deleting vector store records ensuring our chatbot assistant is never outdated or misleading.

This workflow depends on local files accessed through the local filesystem and so will only work on a self-hosted version of n8n at this time. It is possible to amend this workflow to work on n8n cloud by replacing the local file trigger and read file nodes.

Customer Insights with Qdrant, Python and Information Extractor

This n8n template is one of a 3-part series exploring use-cases for clustering vector embeddings: Survey Insights Customer Insights Community Insights This template

Build a Financial Documents Assistant using Qdrant and Mistral.ai

Link: https://n8n.io/workflows/2335-build-a-financial-documents-assistant-using-qdrant-and-mistralai/

Click to explore

Template description

This n8n workflow demonstrates how to manage your Qdrant vector store when there is a need to keep it in sync with local files. It covers creating, updating and deleting vector store records ensuring our chatbot assistant is never outdated or misleading.

Disclaimer

This workflow depends on local files accessed through the local filesystem and so will only work on a self-hosted version of n8n at this time. It is possible to amend this workflow to work on n8n cloud by replacing the local file trigger and read file nodes.

How it works

- A local directory where bank statements are downloaded to is monitored via a local file trigger. The trigger watches for the file create, file changed and file deleted events.
- When a file is created, its contents are uploaded to the vector store.
- When a file is updated, its previous records are replaced.
- When the file is deleted, the corresponding records are also removed from the vector store.

- A simple Question and Answer Chatbot is setup to answer any questions about the bank statements in the system.

Requirements

- A self-hosted version of n8n. Some of the nodes used in this workflow only work with the local filesystem.
- Qdrant instance to store the records.

Customising the workflow

This workflow can also work with remote data. Try integrating accounting or CRM software to build a managed system for payroll, invoices and more.

Want to go fully local?

A version of this workflow is available which uses Ollama instead. You can download this template here: https://drive.google.com/file/d/189F1fNOiw6naNSlSwnyLVEm_Ho_IFfdM/view?usp=sharing

Links de Aplicações N8N

Popular ways to use Read/Write Files from Disk integration

Distributed Deployment of Qdrant Cluster with Sharding & Replicas

Link: https://medium.com/@vardhanam.daga/distributed-deployment-of-qdrant-cluster-with-sharding-replicas-e7923d483ebc

Segregating your vector data into multiple nodes to enhance resiliency, scalability, and performance.

May 24, 2024

Problem Statement

In this blog, we are going to address the challenges faced by a single node Qdrant setup. And then we are going to demonstrate how we can overcome it by deploying a distributed node setup. By the end of this blog, you will have both a conceptual understanding of distributed networks as well as the technical know-hows of setting it up.

Key Features of a Distributed Deployment Setup in Qdrant

To understand what distributed deployment is, it is important to first understand the following features:

Single Node Qdrant

A single node Qdrant setup uses one server to store and manage all the data and processes. It is less expensive and simpler to set up, but has notable drawbacks. If the server goes down for any reason, such as maintenance or a breakdown, the entire Qdrant service will become unavailable. Furthermore, the performance of the service is limited to what a single server can handle.

Qdrant Cluster

A Qdrant Cluster is a more advanced setup that involves multiple servers, known as nodes, working together. This arrangement distributes the data and workload among several servers, which offers multiple benefits over a single node setup. It’s more resilient because if one server has an issue, the others can keep the service running. It also allows for scalability, meaning more servers can be added as needed to handle more data or more user requests, thus enhancing overall performance.

Cluster Communication

In a cluster, the servers communicate using the Raft consensus protocol. This protocol helps keep the servers synchronized, ensuring that they all agree upon any changes or updates before they are made. This coordination is crucial for maintaining data accuracy and consistency across the cluster.

For operations on individual points though, Qdrant prioritizes speed and availability over strict adherence to this protocol, which allows for faster processing without the complexity of coordinating every detail across all servers.

Sharding

Sharding is a technique to break down a database into different segments. In Qdrant, a collection can be divided into multiple shards, each representing a self-contained store of points.

This distribution allows for parallel processing of search requests, leading to significant performance improvements. Qdrant supports both automatic sharding, where points are distributed based on a consistent hashing algorithm, and user-defined sharding, offering more control over data placement for specific use cases.

Importance of Distributed Development

Distributed development, which involves spreading out data and processing across multiple locations or servers, is essential for creating systems that are reliable and can scale according to demand. In the context of Qdrant, this approach offers several key advantages:

- **Resilience:** By distributing operations across multiple servers, the system can still function even if one server fails.

- **Scalability:** It’s easier to handle more data and more users by adding more servers to the system.

- **Performance:** Distributing the workload helps speed up data processing and retrieval by allowing multiple operations to run in parallel across different servers.

How to Launch a Multi-Node Cluster on Qdrant

We’ll use Docker Compose to launch a 4-node Qdrant Cluster setup. First create a file called docker-compose.yml and paste the following in it:

```
services:
  qdrant_node1:
    image: qdrant/qdrant:v1.9.1
    container_name: qdrant_node1
    volumes:
      - ./data/node1:/qdrant/storage
    ports:
      - "6333:6333"
    environment:
      QDRANT__CLUSTER__ENABLED: "true"
    command: "./qdrant --uri http://qdrant_node1:6335"


  qdrant_node2:
    image: qdrant/qdrant:v1.9.1
    container_name: qdrant_node2
    volumes:
      - ./data/node2:/qdrant/storage
    depends_on:
      - qdrant_node1
    environment:
      QDRANT__CLUSTER__ENABLED: "true"
    command: "./qdrant --bootstrap http://qdrant_node1:6335 --uri http://qdrant_node2:6335"


  qdrant_node3:
    image: qdrant/qdrant:v1.9.1
    container_name: qdrant_node3
    volumes:
      - ./data/node3:/qdrant/storage
    depends_on:
      - qdrant_node1
    environment:
      QDRANT__CLUSTER__ENABLED: "true"
    command: "./qdrant --bootstrap http://qdrant_node1:6335 --uri http://qdrant_node3:6335"


  qdrant_node4:
    image: qdrant/qdrant:v1.9.1
    container_name: qdrant_node4
    volumes:
      - ./data/node4:/qdrant/storage
    depends_on:
      - qdrant_node1
    environment:
      QDRANT__CLUSTER__ENABLED: "true"
    command: "./qdrant --bootstrap http://qdrant_node1:6335 --uri http://qdrant_node4:6335"
```

The Docker Compose file defines four services, each corresponding to a Qdrant node in the cluster. Here’s what each section generally specifies:

Common elements for all nodes:

- image: Specifies the Docker image to use for the container. All nodes use qdrant/qdrant:v1.9.1.
- container_name: Assigns a unique name to each container running a Qdrant node.
- volumes: Maps a local directory (./data/nodeX) to a directory inside the container (/qdrant/storage). This setup is used for data persistence across container restarts.
- environment: Sets environment variables inside the container. QDRANT__CLUSTER__ENABLED: “true” enables cluster mode in each Qdrant node.

Specifics for individual nodes:

- qdrant_node1
- ports: Maps port 6333 on the host to port 6333 on the container, used for API access to the Qdrant service.

- command: Specifies the command to run inside the container. For qdrant_node1, it initializes with its own URI for cluster communication (http://qdrant_node1:6335).
- qdrant_node2, qdrant_node3, qdrant_node4
- depends_on: Ensures that these nodes start only after qdrant_node1 has started. This dependency is crucial because the subsequent nodes need to connect to the first node for cluster setup.
- command: For these nodes, the command includes both a — bootstrap option pointing to qdrant_node1 (to join the cluster) and a — uri with their own unique URI. This setup is necessary for proper communication within the cluster.

To launch the cluster, run the following command:

```
docker-compose up
```

Now you can access the cluster via the Qdrant client:

```
from qdrant_client import QdrantClient

# Initialize the Qdrant client
client = QdrantClient(host="localhost", port=6333)
```

Next, let’s define the collection and the shard_key.

```
collection_name = "sharding_collection"
key = "tempKey"


# Deleting an existing collection if it exists
response = client.delete_collection(collection_name=f"{collection_name}")


# Creating a new collection with specific configuration
response = client.create_collection(
    collection_name=f"{collection_name}",
    shard_number=6,
    sharding_method=models.ShardingMethod.CUSTOM,
    vectors_config=models.VectorParams(size=768, distance=models.Distance.COSINE),
    replication_factor= 2,
)


# Creating a shard key for the collection
response = client.create_shard_key(f"{collection_name}", f"{key}")
```

Shard Number implies the number of shards per Shard Key. Replication factor implies the number of times the shards are replicated evenly across all the nodes.

In this case, since we have defined only 1 Shard Key, the total number of Physical Shards would be 1*6*2 = 12.

Now let’s input some random vectors into our cluster using the shard key.

```
# Counter for generating unique point IDs
point_counter = 0


# Function to generate a random vector of 768 dimensions with up to 15 decimal points
def generate_random_vector():
    return [round(random.uniform(0, 1), 15) for _ in range(768)]


# Run the loop 1000 times
for _ in range(1000):
    random_vector = generate_random_vector()
    point_counter += 1
    response = client.upsert(
        collection_name=f"{collection_name}",
        points=[
            models.PointStruct(
                id=point_counter,
                vector=random_vector,
            ),
        ],
        shard_key_selector=f"{key}",
    )
```

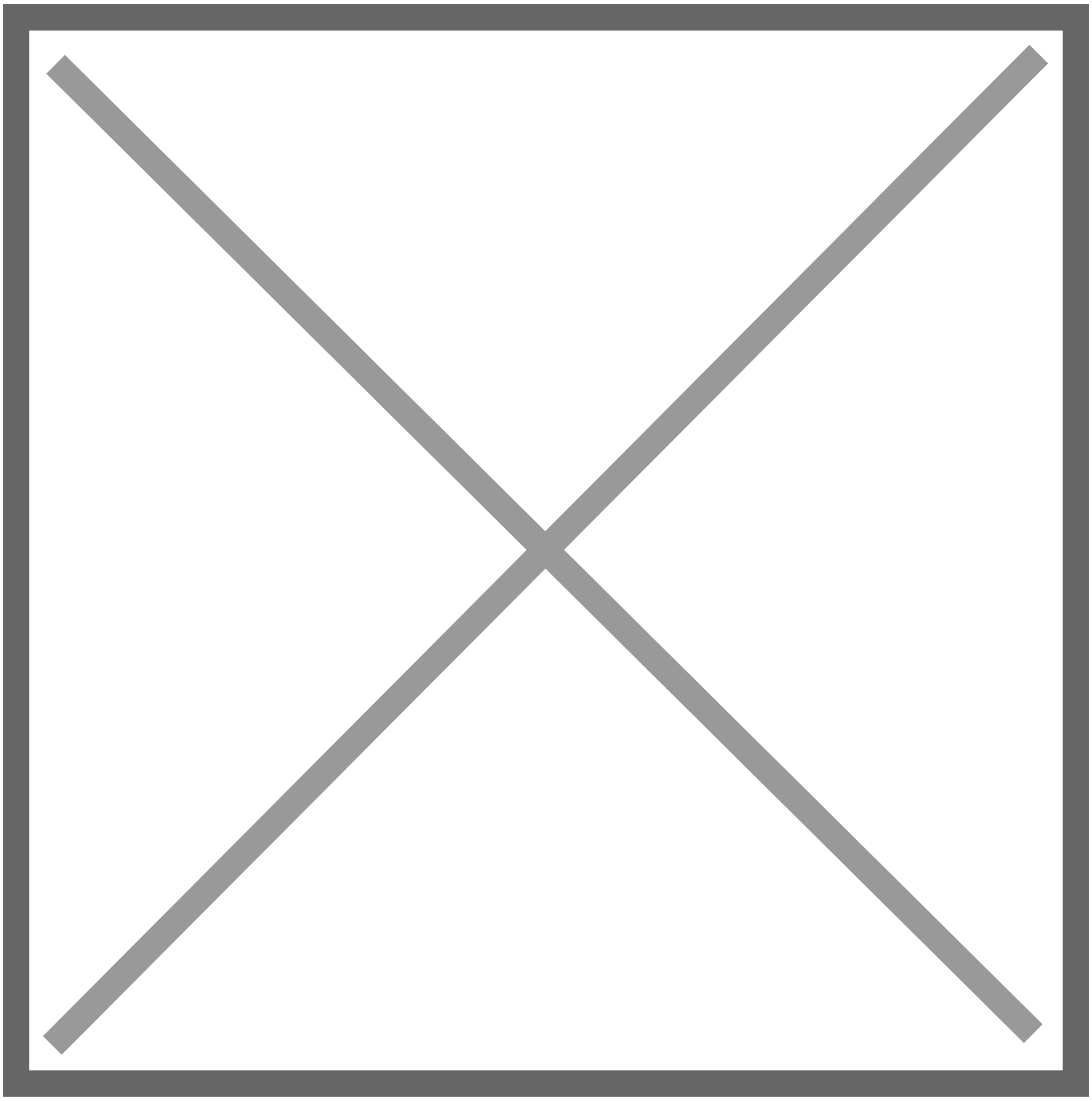
What Happens When We Turn Off a Node?

If we have configured our setup to be a 3+ node cluster with a replication factor of at least 2, then even if we stop one node, it’s not going to affect any operations going on in the cluster.

Let’s test that out.

First get ids of the containers using:

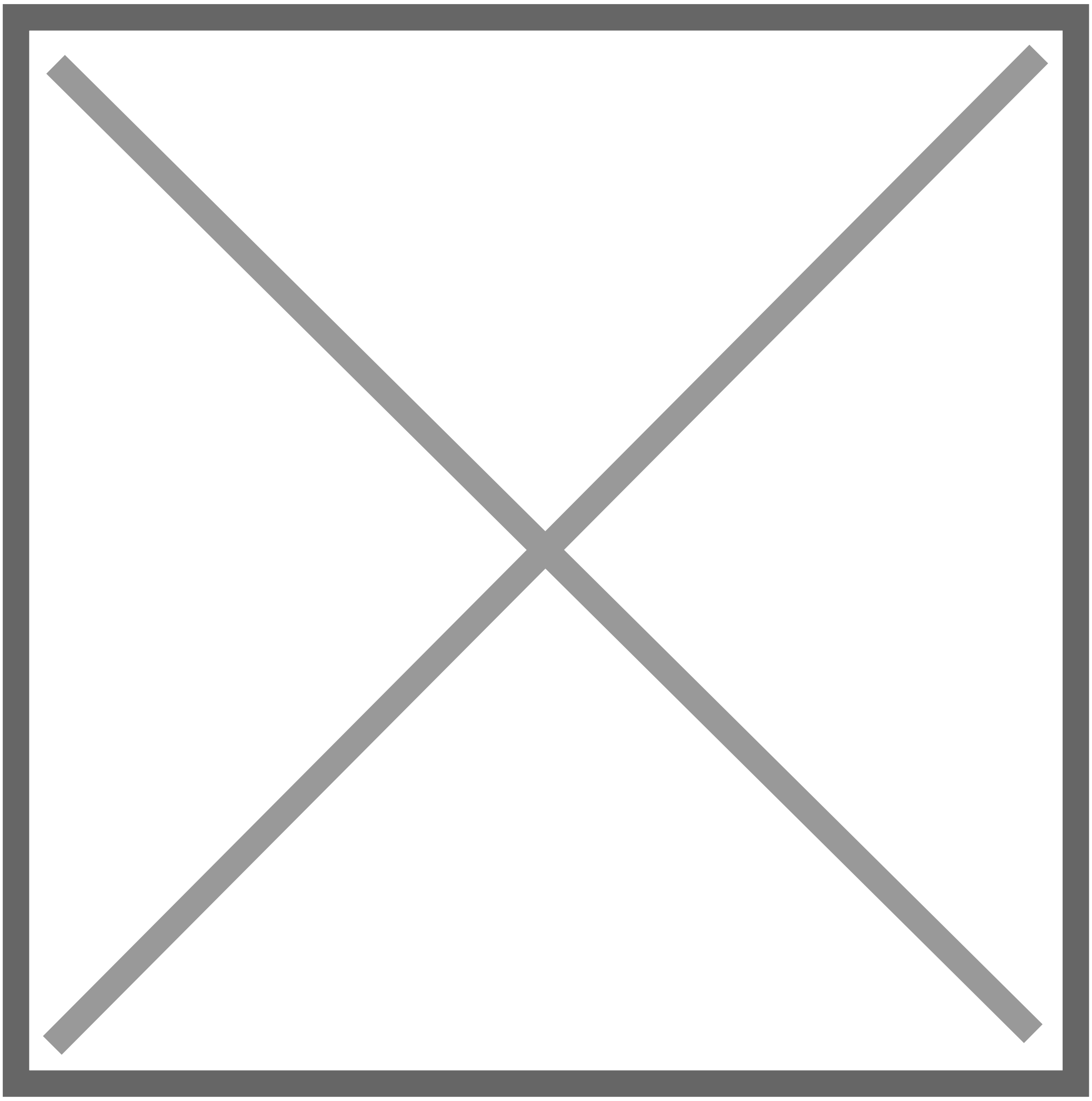
```
docker ps
```



Now let’s stop qdrant_node3.

```
docker stop 0b7fac4c224a
```

Next, let’s investigate our collection.



Even though we switched off a node, we can still access all the points we’ve inserted into our collection!

Data Distribution between Shards

To see how the data is distributed amongst the shards, we need to make a GET request in the following manner.

```
curl localhost:6333/collections/sharding_collection/cluster
```

{“result”:{“peer_id”:2024384091823610,”shard_count”:6,”local_shards”:[{“shard_id”:2,”shard_key”:”tempKey”,”points_count”:135,”state”:”Active”},{“shard_id”:4,”shard_key”:”tempKey”,”points_count”:178,”state”:”Active”},{“shard_id”:6,”shard_key”:”tempKey”,”points_count”:155,”state”:”Active”}],”remote_shards”:[{“shard_id”:1,”shard_key”:”tempKey”,”peer_id”:8555640407930483,”state”:”Active”},{“shard_id”:1,”shard_key”:”tempKey”,”peer_id”:3252676105267795,”state”:”Active”},{“shard_id”:2,”shard_key”:”tempKey”,”peer_id”:3088601394550397,”state”:”Active”},{“shard_id”:3,”shard_key”:”tempKey”,”peer_id”:8555640407930483,”state”:”Active”},{“shard_id”:3,”shard_key”:”tempKey”,”peer_id”:3252676105267795,”state”:”Active”},{“shard_id”:4,”shard_key”:”tempKey”,”peer_id”:3088601394550397,”state”:”Active”},{“shard_id”:5,”shard_key”:”tempKey”,”peer_id”:3252676105267795,”state”:”Active”},{“shard_id”:5,”shard_key”:”tempKey”,”peer_id”:8555640407930483,”state”:”Active”},{“shard_id”:6,”shard_key”:”tempKey”,”peer_id”:3088601394550397,”state”:”Active”}],”shard_transfers”:[]},”status”:”ok”,”time”:0.000067336}

To know the node by their peer_id, we’ll run:

```
curl http://localhost:6333/cluster
```

{“result”:{“status”:”enabled”,”peer_id”:2024384091823610,”peers”:{“3252676105267795”:{“uri”:”http://qdrant_node2:6335/"},"8555640407930483":{"uri":"http://qdrant_node3:6335/"},"2024384091823610":{"uri":"http://qdrant_node1:6335/"},"3088601394550397":{"uri":"http://qdrant_node4:6335/"}},"raft_info":{"term":10,"commit":40,"pending_operations":0,"leader":2024384091823610,"role":"Leader","is_voter":true},"consensus_thread_status":{"consensus_thread_status":"working","last_update":"2024-05-22T13:26:49.305470782Z"},"message_send_failures":{}},"status":"ok","time":0.000058492}

Analyzing the above results, and putting them in a clear format, we get:

- Node1 (current peer) has shards 2, 4, and 6.
- Node 3 has shards 1, 3, and 5.
- Node 2 has shards 1, 3, and 5.
- Node 4 has shards 2, 4, and 6.

By looking at the above distribution we see that each shard is available on 2 different nodes, and therefore even if one of the nodes fails, the cluster will continue to function.

Final Words

Multi-node clusters, sharding, and replicas are essential features for production environments. Multi-node clusters distribute the workload and enhance system resilience against individual node failures. Sharding divides data across multiple nodes, facilitating parallel processing that boosts performance and scalability. Replication ensures data availability, even if some nodes fail. Together, these techniques can create a robust and fault-tolerant system capable of reliably handling production-level demands.

References

https://qdrant.tech/documentation/guides/distributed_deployment/

https://github.com/Mohitkr95/qdrant-multi-node-cluster/tree/main