Vectoria: Supercomputer-driven vector database for private LLM retrieval

User Manual, version 1.0

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Summary

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Acronyms and Terminology

AI	Artificial Intelligence	Field of study in computer science that develops and studies intelligent machines.
LLM	Large Language Model	A type of AI model trained on vast amounts of text to perform natural language understanding and generation.
RAG	Retrieval-Augmented Generation	A technique that combines information retrieval and generative AI for producing contextually relevant outputs.
CLI	Command-Line Interface	A text-based interface used to interact with software or operating systems.
FAISS	Facebook AI Similarity Search	A library for fast nearest-neighbor search and vector similarity.
API	Application Programming Interface	A set of rules and tools for building and interacting with software applications.
GPU	Graphics Processing Unit	Specialized hardware designed for accelerating computational tasks, especially in AI and ML.
MMR	Maximal Marginal Relevance	A ranking technique that optimizes information relevance and diversity in retrieved results.
RAGAS	Retrieval-Augmented Generation Assessment	A tool or metric for evaluating the performance of RAG-based systems.
HPC	High-Performance Computing	Computing systems with high-speed processing capabilities used for complex computations.
Embedding	-	A vector representation of data (e.g., text) used for similarity searches and machine learning tasks.
Inference	-	The process of generating predictions or outputs from a trained model.

1. Introduction

Within the framework of the European Project EuroCC2, the national competence center EuroCC Italy developed “Vectoria: Supercomputer-driven vector database for private LLM retrieval”. This project aims to equip small and medium enterprises with a service to streamline access to private, internal documentation through intuitive chatbot-like interactions. This initiative targets the challenges of navigating unstructured and dispersed knowledge stored across diverse organizational repositories, offering an efficient solution for users seeking concise, contextually relevant answers.

By employing state-of-the-art retrieval and generative AI technologies, the system ensures privacy preservation while delivering high-quality responses. This document aims to outline the requirements, core functionalities, and operational guidance for deploying and utilizing the system effectively.

The service is designed to integrate with High Performance Computing (HPC) systems, leveraging the computational power of supercomputers to enhance the speed and precision of a generative model inference. This approach enables scalable, private, and high-performance information retrieval, tailored to meet the needs of users in a data-rich environment.

2. EuroCC: Objectives

EuroCC 2 is a project which works to identify and address the skills gaps in the European High-Performance Computing (HPC) ecosystem and coordinate cooperation across Europe to ensure a consistent skills base. The mission of EuroCC is to improve the technological readiness of Europe. In particular, the role of EuroCC2 is to establish and run a network of more than 30 NCCs across the EuroHPC Participating States. The NCCs act as single points of access in each country between stakeholders and national and EuroHPC systems. They operate on a regional and national level to liaise with local communities, in particular SMEs, map HPC competencies and facilitate access to European HPC resources for users from the private and public sector.

Figure 1: NCCs across Europe

EuroCC2 delivers training, interacts with industry, develops competence mapping and communication materials and activities, and supports the adoption of HPC services in other related fields, such as quantum computing, artificial intelligence (AI), high performance data analytics (HPDA) to expand the HPC user base.

3. Service Description

The “Vectoria: Supercomputer-driven vector database for private LLM retrieval” project introduces a tailored approach to optimize knowledge access within organizations. By focusing on the integration of advanced AI-driven methods, it enables users to interact seamlessly with internal documentation via chatbot-like interfaces. The project emphasizes creating a unified, efficient framework to navigate unstructured data by delivering concise, contextually relevant answers to users while upholding stringent privacy standards.

Key Objectives:

- **Efficient Knowledge Management**: scattered internal documentation is unified into a knowledge source accessible through querying.
- **High Precision and Relevance**: Deliver results that precisely match user queries by using vector-based retrieval techniques.
- **Data Privacy**: Operate entirely within the organization's infrastructure to ensure compliance with internal security protocols.

4. Architectural Diagram

The RAG pipeline consists of several tightly integrated components, each playing a critical role in ensuring the system’s accuracy. Below is a comprehensive breakdown of its architecture and workflow.

System Overview

The architecture comprises the following core modules:

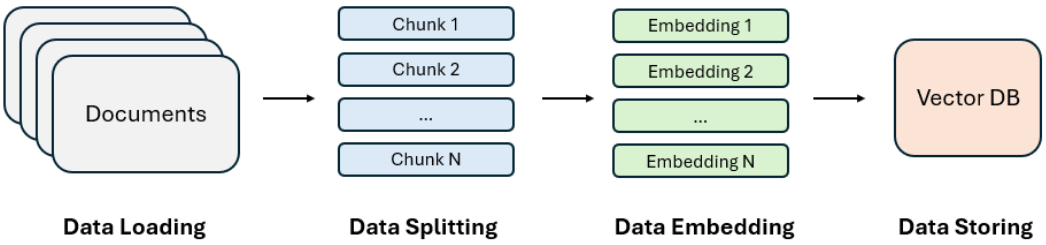
1. **Configuration**: The system can be easily customized through a yaml-based configuration file.
2. **Document Preprocessor**: Handles ingestion, cleaning, and splitting of internal documents into smaller portions of text (*chunks*) and transforming these chunks into embeddings.
3. **Vector Database**: Stores vector embeddings of the document chunks for efficient similarity searches.
4. **Retriever**: Locates relevant chunks from the vector database based on user queries.
5. **Post-retrieval strategies**: Includes re-ranker and full paragraph retriever.
6. **Generative Model**: Synthesizes human-like answers using a pre-trained large language model (e.g., GPT).

Tasks

The RAG pipeline provides two primary operational tasks:

- **Build vector database**: Responsible for preparing and indexing the documents to create a vector database.
- **Inference**: Handles user queries by retrieving and generating context-aware responses.

4.1.1 Build vector db



This task focuses on the ingestion and indexing of internal documents. It transforms a set of documents into a searchable structure, ensuring that subsequent retrieval operations are both fast and accurate. In technical language (and inside the codebase) this operation is also referred as “Build Index”.

Workflow:

Figure 2: Build vector db workflow

Prerequisites: as version 1.0, supported formats include PDF and DOCX.

1. **Data Preprocessing (Loading and Splitting)**: Clean the text to remove irrelevant elements like boilerplate text, extra whitespace, or special characters. Split documents into chunks of manageable size (e.g., 512 characters) to optimize retrieval granularity. Parameters for cleaning and splitting can be configured using a single configuration file.
2. **Data Embedding**: Generate vector embeddings for each chunk using pre-trained models (e.g., bge-m3). Each embedding is a n-dimensional vector which captures the semantic meaning of the chunk.
3. **Data Storing**: Store the embeddings in a vector database (e.g., FAISS vector database) dumped on disk. Attach metadata (e.g., source file, paragraph number) for efficient filtering and explainability.

4.1.2 Inference

The inference task enables the chatbot to provide accurate answers by combining retrieval and generation. It works exploiting the indexed data to ensure high-quality responses.

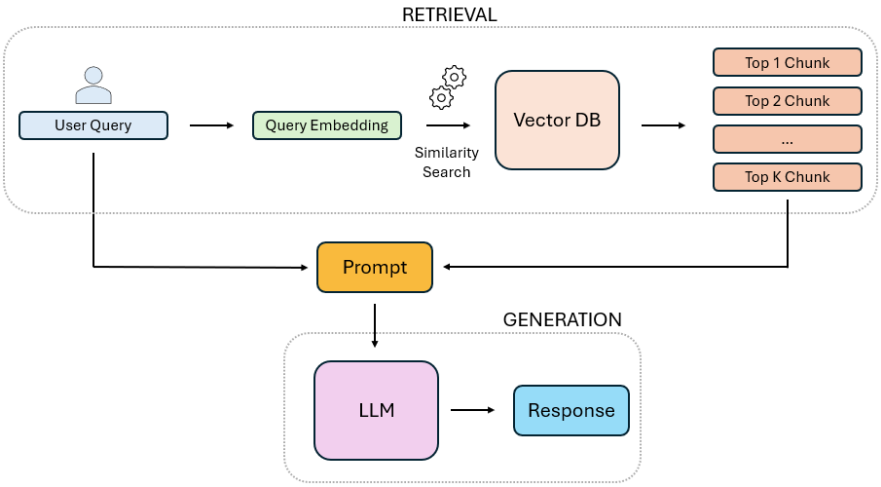


Figure 3: Inference workflow

Workflow:

1. **Query Reception**: User submits a question via a CLI or file
2. **Query Embedding**: Convert the user query into a vector embedding using the same pre-trained model used during indexing.
3. **Vector Search**: Search the vector database for the most semantically similar chunks to the query. Retrieve the top-k chunks (e.g., top 5 most relevant) using a similarity metric (e.g., cosine similarity).
4. **Post-Retrieval strategies**: Perform re-ranking or full paragraph retrieving, if necessary.
5. **Prompt Construction**: Combine the *retrieved chunks* with the *question* and the *instructions* to form a context window for the generative model.
6. **Answer Generation**: Pass the query and context to a generative AI model (e.g., llama3.1) to generate a natural language response tailored to answer the user's query.

5. Self-Deployment Guide

The following provides a detailed description of how to use the script provided to deploy the service.

5.1 Prerequisites

The following prerequisites must be met before continuing:

- System requirements:
  - Minimum: **Embedder** (bge-m3) **+ LLM** (Llama-3.1-8B-Instruct)
    - **VRAM:** ~36GB
  - Recommended: **Embedder** (bge-m3) **+ LLM** (Llama-3.1-70B-Instruct)
    - **VRAM:** ~252GB
- The user setting up the service must have a Linux terminal with Python 3.8 or later.
- If installing on a remote host, SSH access is required.
- For some LLMs, you will also need to register your SSH key to access the download. Consult the documentation of your LLM of choice for instructions.
- `git-lfs` is required to download some larger LLMs. Make sure it is installed and available on the install destination.

5.2 Step-by-step Installation & Deploy

To install Vectoria follow the steps described below.

1. Clone the repository containing the Ansible codebase:

```
git clone https://github.com/Eurocc-Italy/Vectoria.git
```

2. Create and activate a Python virtual environment:

```
python3 -m venv virtualenv
source virtualenv/bin/activate
```

3. Move to the Vectoria ansible folder and install the necessary requirements:

```
cd vectoria/ansible
pip install -r requirements.txt
```

4. In the `inventory/hosts` file, edit the `ansible_host` and `ansible_user` variables with the hostname (or IP address) and the username of the install destination to be used, respectively.

5. If installing locally, edit the `deploy.yml` file, changing the following `hosts` variable from `hpc` to `localhost`.

6. Edit the `inventory/vars/config.yml` file as necessary. Comments explaining what each variable pertains to are provided in the file itself. Some reasonable defaults are provided. For the inference engine of choice, we recommend the following models based on the scenario:
   - Consumer PC (~8GB vRAM): `Llama-3.2-1B-Instruct`
   - High-end workstation (~32 GB vRAM): `Llama-3.1-8B-Instruct`
   - HPC cluster (~256 GB vRAM): `Llama-3.1-70B-Instruct`

7. Run the Ansible playbook:

```
ansible-playbook -i inventory deploy.yml
```

8. Alternatively, it is also possible to install only the Vectoria library locally via pip (editable install mode is required), and configure each setting manually:

```
pip install -e vectoria
```

5.3 USAGE

In this section examples are provided in order to launch tasks.

1. **Build Index:**

```
 python vectoria \
# Launch vectoria command
  --config 'etc/default/default_config.yaml' \
# [Required: TRUE] Specify config file PATH
  build_index \
# [Required: TRUE] Specify task to be executed
  --input-docs-dir 'test/data' \
# [Required: TRUE] Specify dir containing input files to be indexed
  --output-dir 'test/index' \
# [Required: TRUE] Specify dir that will contain the new index
  --output-suffix '_my_test_index'
# [Required: FALSE] Specify suffix to add to the output file name to customize the index
```

2. **Inference:**

```
python vectoria \
# Launch vectoria command
  --config 'etc/default/default_config.yaml' \
# [Required: TRUE] Specify config file PATH
  inference \
# [Required: TRUE] Specify task to be executed
  --index-path 'test/data/index/my_new_test_index' \
# [Required: TRUE] Specify pickle file PATH to an already existing index
  --test-set-path 'test/data/results/my_questions.json' \
# [Required: FALSE] Specify questions file PATH
  --questions 'Who is the CEO?' 'Who is the VP?' \
# [Required: FALSE] Specify questions directly via CLI
  --output-dir 'test/data/results'
# [Required: TRUE] Specify dir that will contain a file with the answers
```

N.B.: `--test-set-path` and `--questions` are both not formally *strictly* required, since vectoria is able to handle a dual mode. Using `--questions` argument will override questions from `--test-set-path` and will provide answers only through CLI, avoiding any dump on file. IMPORTANT: at least one MUST be provided.

5.3.1 Task Configuration

This section explains a configuration file example. It contains every parameter that can be customized to adapt the behavior of the system to the desired one, covering several components in detail.

PARAMETERS	TYPE	VALUES (default in bold)	DESCRIPTION
vectoria_logs_dir:	str	vectoria_logs	PATH where log files will be dumped
log_level:	str	[**DEBUG** | INFO | CRITICAL]	Sets general log level
langchain_tracking:	str	[**true** | false]	Enables LangChain tracking backend
system_prompts_lang:	str	[**eng** | it]	Language for system prompts, e.g., English or Italian
data_ingestion:			
multiprocessing:	str	[**true** | false]	Enables/disables parallel processing for ingestion tasks
extraction:			
format:	str	[**docx** | pdf]	Specifies input document format
dump_doc_structure_on_file:	str	[**true** | false]	Saves document structure to file if true
regexes_for_metadata_extraction:			List of regex patterns for metadata extraction
- name:	str	DOC_ID	Name of the metadata field
pattern:	str	'^Document Title'	Regex pattern to match the field
regexes_for_replacement:			List of regex rules for text preprocessing
- name:	str	remove_multiple_spaces	Rule name
pattern:	str	'[\t]{2,}'	Regex to find multiple spaces/tabs
replace_with:		' '	Replacement value
- name:	str	remove_bullets	Rule name
pattern:	str	'^\s*[\u2022\u25AA\u27A2]\s*'	Regex to match bullets
replace_with:		''	Replace bullets with empty string
- name:	str	remove_ligature_st	Rule name
pattern:	str	'st'	Regex to match 'st'
replace_with:	str	'st'	Replace 'st' with 'st'
chunking:			
chunk_size:	int	[256 | **512** | 1024]	Size of each chunk for processing
chunk_overlap:	int	[128 | **256** | 512]	Overlap between consecutive chunks
separators:	List[str]	["\n\n", "\n", " ", ""]	List of separators for chunking
is_separator_regex:	List[str]	[false, false, false, false]	Whether separators are regex patterns
dump_chunks_on_file:	str	[**true** | false]	Save chunked output to file if true

vector_store:			
name:	str	faiss	Vector store backend (e.g., FAISS)
model_name:	str	BAAI/bge-m3	Model used for generating embeddings
device:	str	[cuda | cpu]	Device for vector store operations
normalize_embeddings:	str	false	Normalizes embeddings if true
retriever:			
enabled:	str	[true | false]	Enables/disables the retriever
top_k:	int	5	Number of top results to retrieve
search_type:	str	'mmr'	Search type (e.g., Maximal Marginal Relevance)
fetch_k:	int	5	Number of documents to fetch before filtering
lambda_mult:	float	0.5	Lambda parameter for MMR search
reranker:			
enabled:	str	[true | false]	Enables/disables reranking
reranked_top_k:	int	3	Number of reranked results to return
inference_engine:			Inference engine configuration for reranking
name:	str	[huggingface | ollama | openai | vllm]	Name of inference engine backend
url:	str	null	URL for the inference API endpoint (e.g. http://localhost:8898/v1)
api_key:	str	null	API key for the inference engine
model_name:	str	BAAI/bge-reranker-v2-gemma	Model name for reranking
device:	str	[cuda | cpu]	Device for inference engine
load_in_4bit:	str	[true | false]	Enables 4-bit model loading for optimization
load_in_8bit:	str	[true | false]	Enables 8-bit model loading for optimization
max_new_tokens:	int	150	Maximum tokens generated in output
trust_remote_code:	str	[true | false]	Trust code from remote repositories if true
device_map:	str	[auto | null]	Device mapping for distributed inference
temperature:	float	0.1	Sampling temperature for generation
full_paragraphs_retriever:			
enabled:	str	[true | false]	Enables/disables retrieval of full paragraphs
inference_engine:			General inference engine configuration

name:	str	[huggingface | ollama | openai | vllm]	Name of the inference engine
url:	str	null	URL for the inference engine API
api_key:	str	null	API key for the inference engine
model_name:	str	meta-llama/Meta-Llama-3.1-8B-Instruct	Model name for inference
device:	str	[cuda | cpu]	Device for inference
load_in_8bit:	str	[true | false]	Enables 8-bit model loading for optimization
max_new_tokens:	int	150	Maximum tokens generated in output
trust_remote_code:	str	[true | false]	Trust code from remote repositories if true
device_map:	str	[auto | null]	Automatic device mapping for distributed inference
temperature:	float	0.1	Sampling temperature for generation
evaluation:			Evaluation configuration
tool:	str	ragas	Evaluation tool name
inference_engine:			Inference engine for evaluation
name:	str	vllm	Name of the inference engine backend
model_name:	str	hugging-quants/Meta-Llama-3.1-8B-Instruct-AWQ-INT4	Model for evaluation
url:	str	null	API endpoint for inference engine
api_key:		null	API key for the inference engine
embeddings_engine:			Embedding engine for evaluation
name:	str	vllm	Name of the embedding engine
model_name:	str	BAAI/bge-multilingual-gemma2	Model for embedding generation
url:	str	null	API endpoint for embeddings engine
api_key:	str	null	API key for the embeddings engine

Application information and contributions

The application and this manual are released under the MIT open source license.

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This manual, *version 1.0*, refers to tag *v1.0* of repos:

https://github.com/Eurocc-Italy/Vectoria

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