Development of a Platform for Scalable Launch of Chatbots Based on RAG Approach

The project aims to develop a scalable platform for deploying chatbots that utilize the Retrieval-Augmented Generation (RAG) approach. The RAG approach combines retrieval of relevant documents with generative models to produce accurate and contextually appropriate responses. The platform will enable efficient scaling to handle multiple chatbots and high user demand ensuring reliability and performance across diverse applications.

1 Introduction

Table 1 shows a comparative analysis of various recent solutions for developing scalable platforms for launching chatbots based on the RAG approach. The table summarizes the strengths and weaknesses of each solution according to the project's quality criteria.

Table 1: Comparative analysis of solutions for scalable RAG-based chatbot platforms

Solution	Strengths	Weaknesses
LangChain framework [1]	Modular components for building RAG pipelines; simplifies integration with various LLMs and vector stores	May have limitations in customization for specific enterprise use cases; relatively new with evolving features
Haystack framework [2]	Open-source and highly customizable; supports various backends for retrieval and generation	Steeper learning curve; requires more setup and configuration
Meta's RAG implementation [3]	State-of-the-art performance; well-researched architecture; open-source code available	Complex implementation; requires significant computational resources; less focus on deployment scalability

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Solution	Strengths	Weaknesses
Microsoft's DeepSpeed Chat [4]	Optimized for training large models efficiently; supports distributed training and inference	Primarily focused on training efficiency; may require adaptation for RAG and deployment; steep learning curve
OpenAI's ChatGPT with Retrieval Plugin [5]	Easy to integrate and deploy; leverages powerful LLM capabilities; supports retrieval augmentation	Dependent on external API; limited customization
Using Kubernetes with ONNX Runtime [6]	Provides robust scaling and orchestration; optimized inference with ONNX; supports containerized deployments	Adds complexity in deployment and management; requires expertise in DevOps and ML model optimization

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