LLM SYSTEM DESIGN

Learn to build scalable LLM Application

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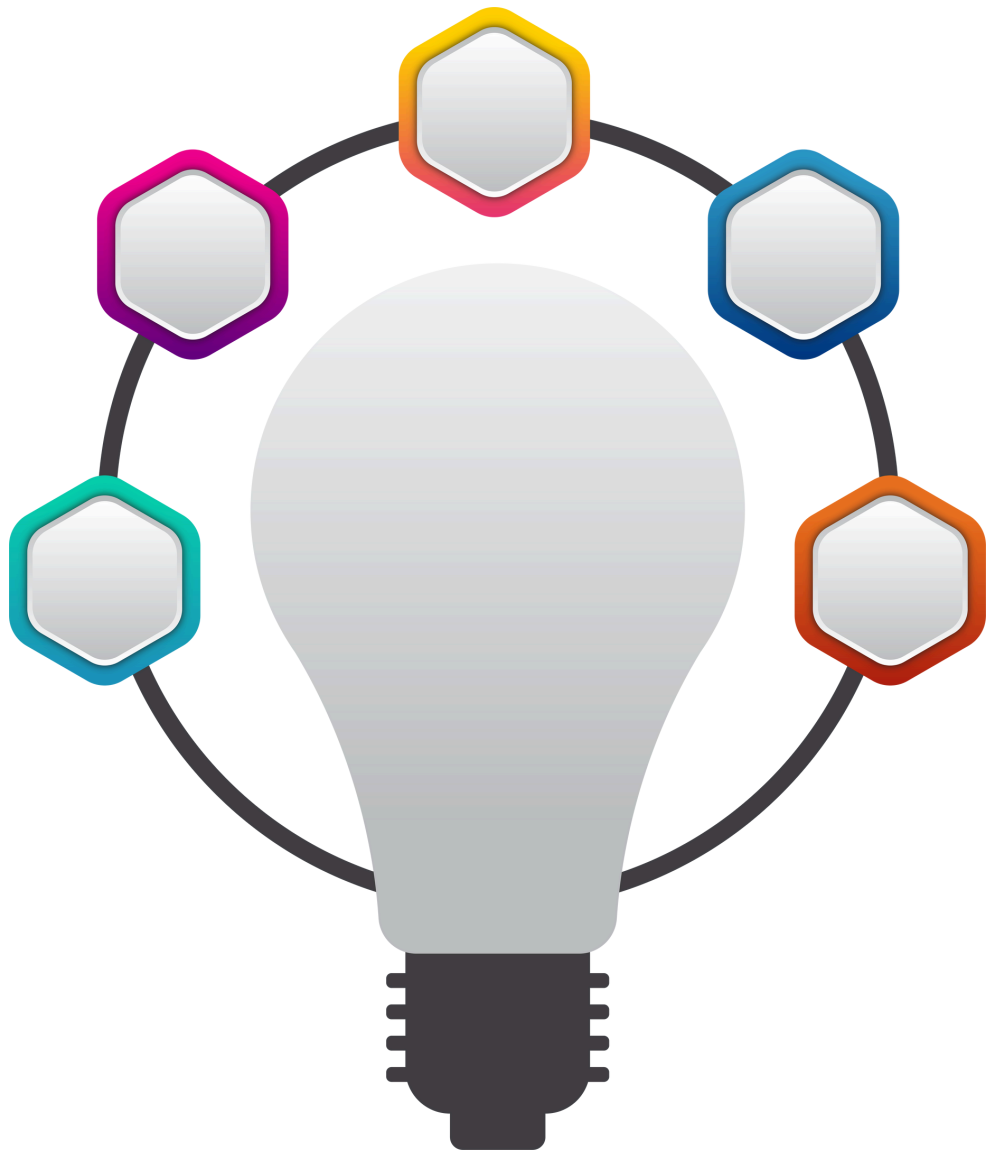
What is LLM System Design?

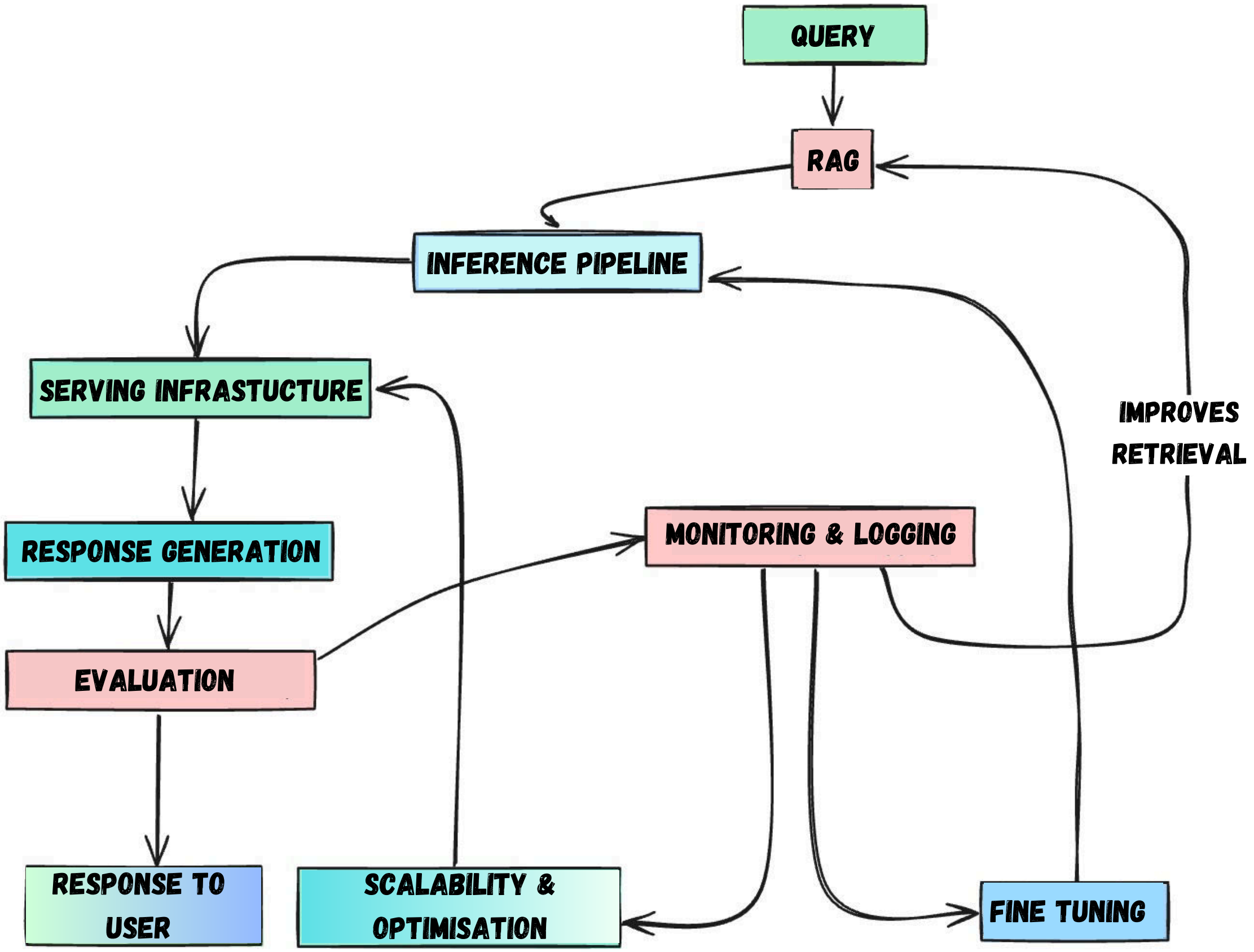
LLM system design is the process of architecting and optimizing large language model applications for efficiency, scalability, and real-world deployment.



1. **Infrastructure planning**: Choosing the right compute resources.
2. **Inference optimization**: Reducing latency and cost using quantization, caching etc.
3. **Prompt Engineering** : Designing & optimizing prompts to guide AI models.
4. **Scalability & deployment**: Deciding b/w cloud, edge, or on-prem solutions.
5. **Cost vs Performance trade-offs**: Balancing accuracy, speed, and affordability.

Key Components of LLM System

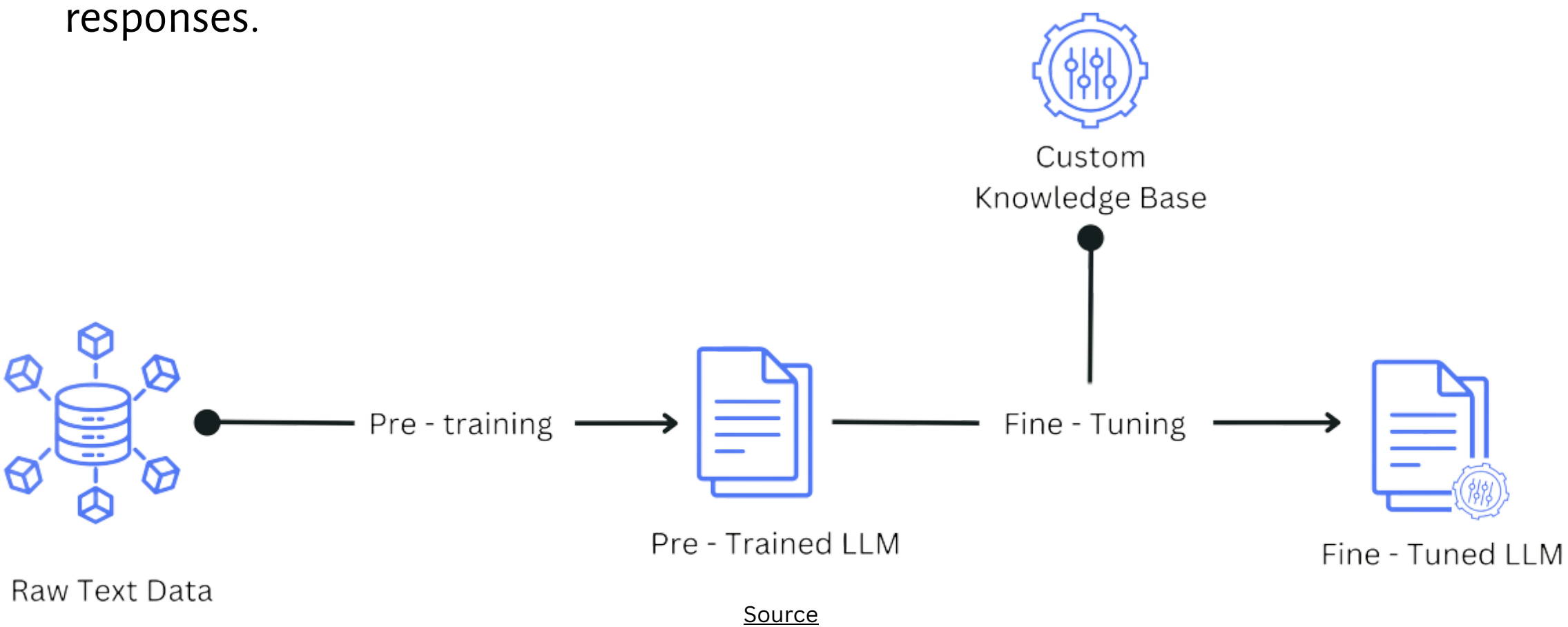
*RAG specific use case



- **User query** – The user inputs a query, which could be text, image, or multimodal data.

- **RAG** (Retrieval-Augmented Generation) – Enhances the query by fetching relevant contextual data from external sources before passing it to the model.

- **Inference pipeline** – Processes the query using the LLM, applying prompt engineering, model execution, and reasoning.
- **Serving infrastructure** – Manages API calls, load balancing, and efficient model deployment.
- **Fine-tuning** – Uses logged data to refine model performance and improve future responses.



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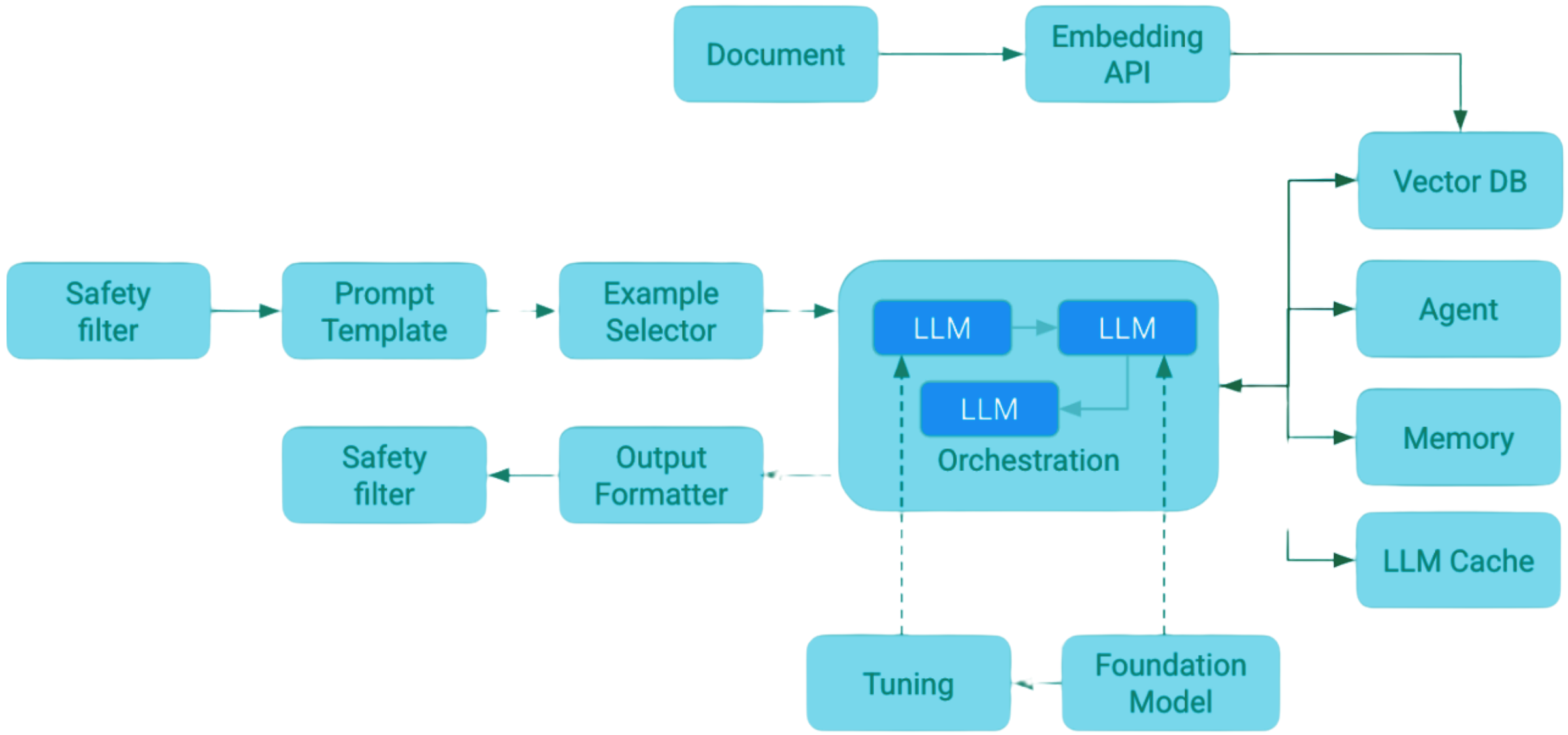
- **Response generation** – Formats the model's output into a structured and coherent response.
- **Evaluation & safety** – Applies filters for bias detection, hallucination reduction, and security checks.
- **Final response to User** – The refined output is sent back to the user.
- **Monitoring & logging** – Tracks system performance, logs errors, and records feedback for improvements.
- **Scalability & Latency optimization** – Ensures low-latency response times and system efficiency.

Architecting the LLM Application



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Frontend & User interaction

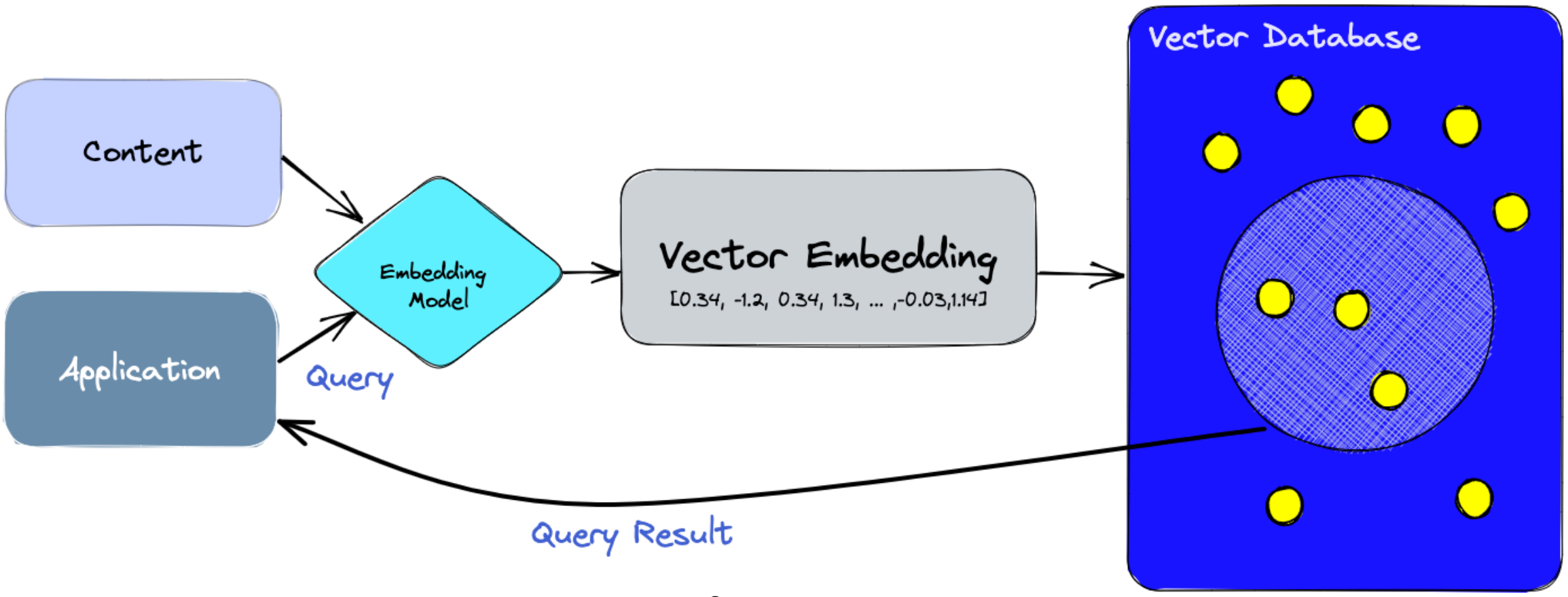
- Interface design – Web, mobile, chatbot, or API-based system?
- User input handling – Text, voice, or multimodal queries?

Backend & API layer

- API gateway: Manage requests efficiently (e.g., FastAPI, Flask, GraphQL).
- Orchestration: Route queries b/w LLMs, fallback mechanisms, error handling(LangChain, Ray Serve)
- Logging & monitoring: Track model performance, API usage, and failures(Prometheus + Grafana, OpenTelemetry)

Model selection & processing

- Choosing the right LLM – Open-source vs proprietary, fine-tuned vs general-purpose.
- Inference optimization – Quantization, distillation, RAG, caching to reduce costs.
- Context management – Use embeddings and history tracking for better responses.



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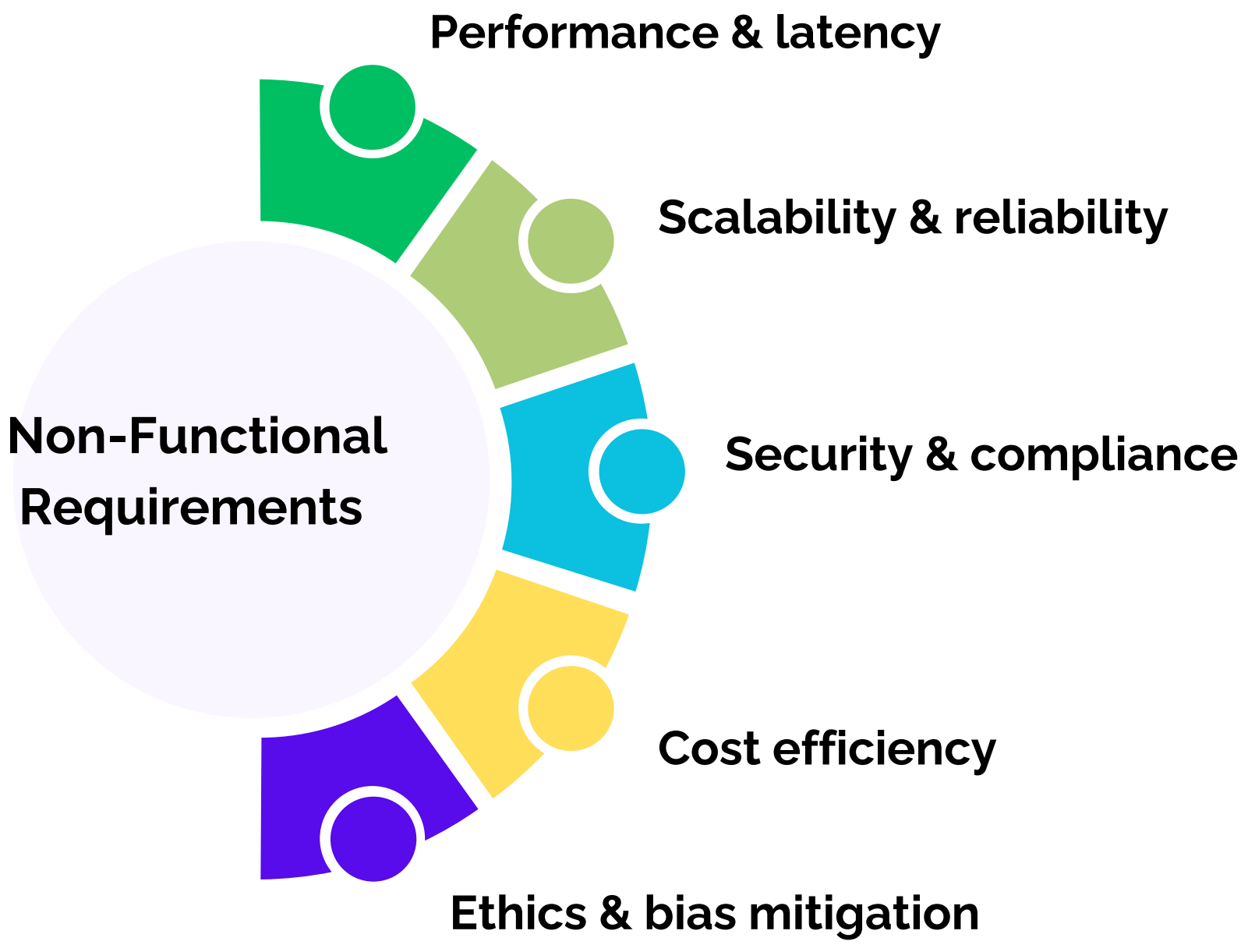
Data storage & retrieval

- Vector database (for RAG) – FAISS, ChromaDB, Weaviate for context retrieval.
- Traditional databases – Store user queries, responses, and metadata (MySQL, MongoDB)
- File storage – Cloud storage for documents, images, and structured datasets.

Deployment & scaling

- Cloud vs edge vs On-Prem – Choose based on cost, security, and latency needs.
- Load balancing & autoscaling – Handle high traffic with distributed inference(NGINX, AWS Auto Scaling)
- Containerization (Docker, Kubernetes) – Ensure portability and efficient scaling.

Considering Non-Functional Req.

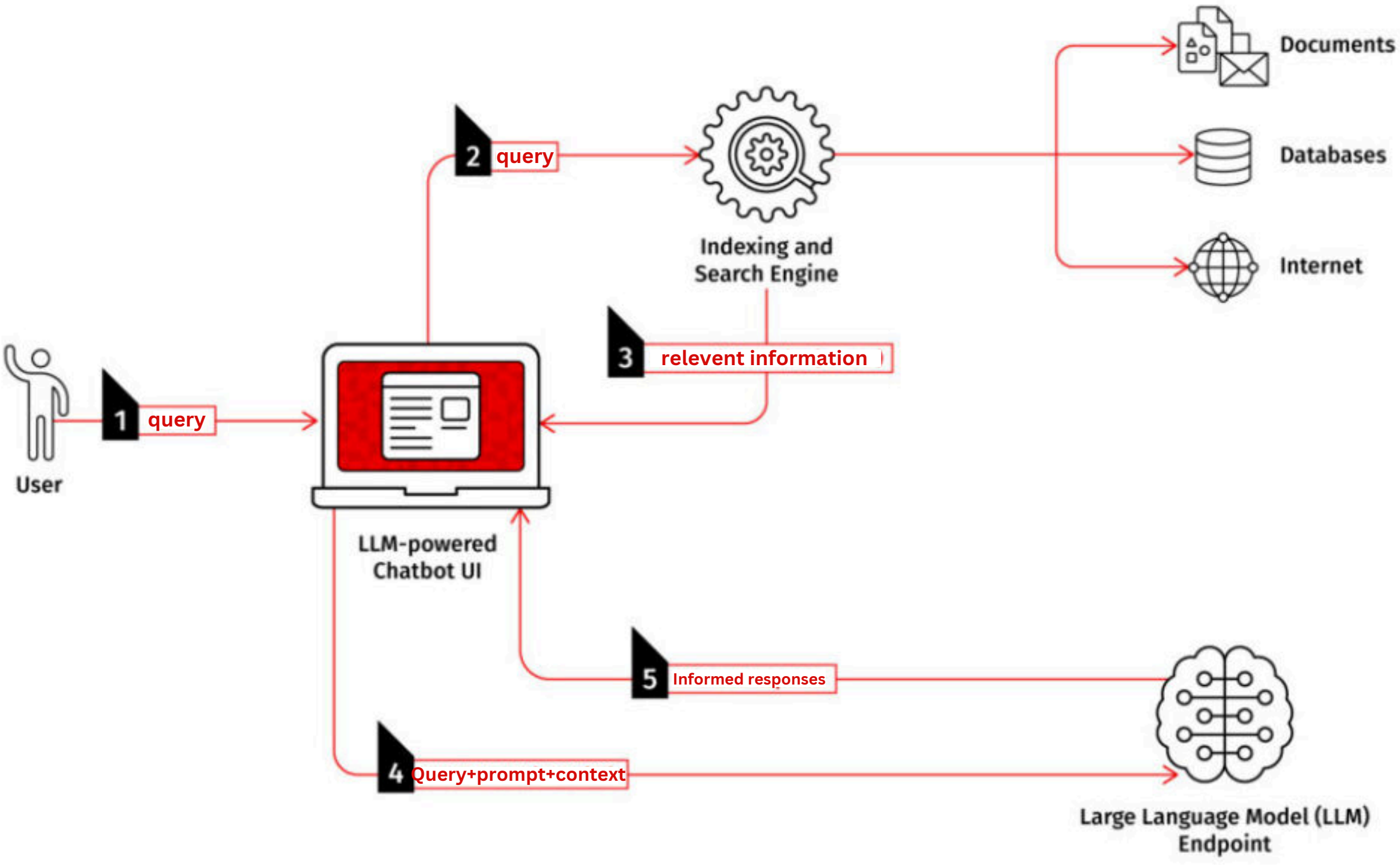


- **Performance & latency** – Optimize inference speed with quantization, caching, and batch processing to reduce delays.
- **Scalability & reliability** – Use horizontal scaling (adding more servers) and vertical scaling (upgrading resources) to handle demand.
- **Security & compliance** – Encrypt user data, restrict access, follow GDPR, HIPAA for compliance. Use authentication (OAuth, API keys) and rate limiting to prevent abuse.
- **Cost efficiency** – Reduce expenses with lightweight models, dynamic scaling, and serverless computing. Continuously monitor API usage and optimize deployments.
- **Ethics & bias mitigation** – Regularly audit model outputs to detect biases and improve fairness. Implement human-in-the-loop mechanisms for accountability.

Case Study: Building a Scalable LLM-Based Customer Support Chatbot

Background

A leading e-commerce company wanted to deploy an AI-powered chatbot to handle customer queries, reduce support costs, and improve response times.



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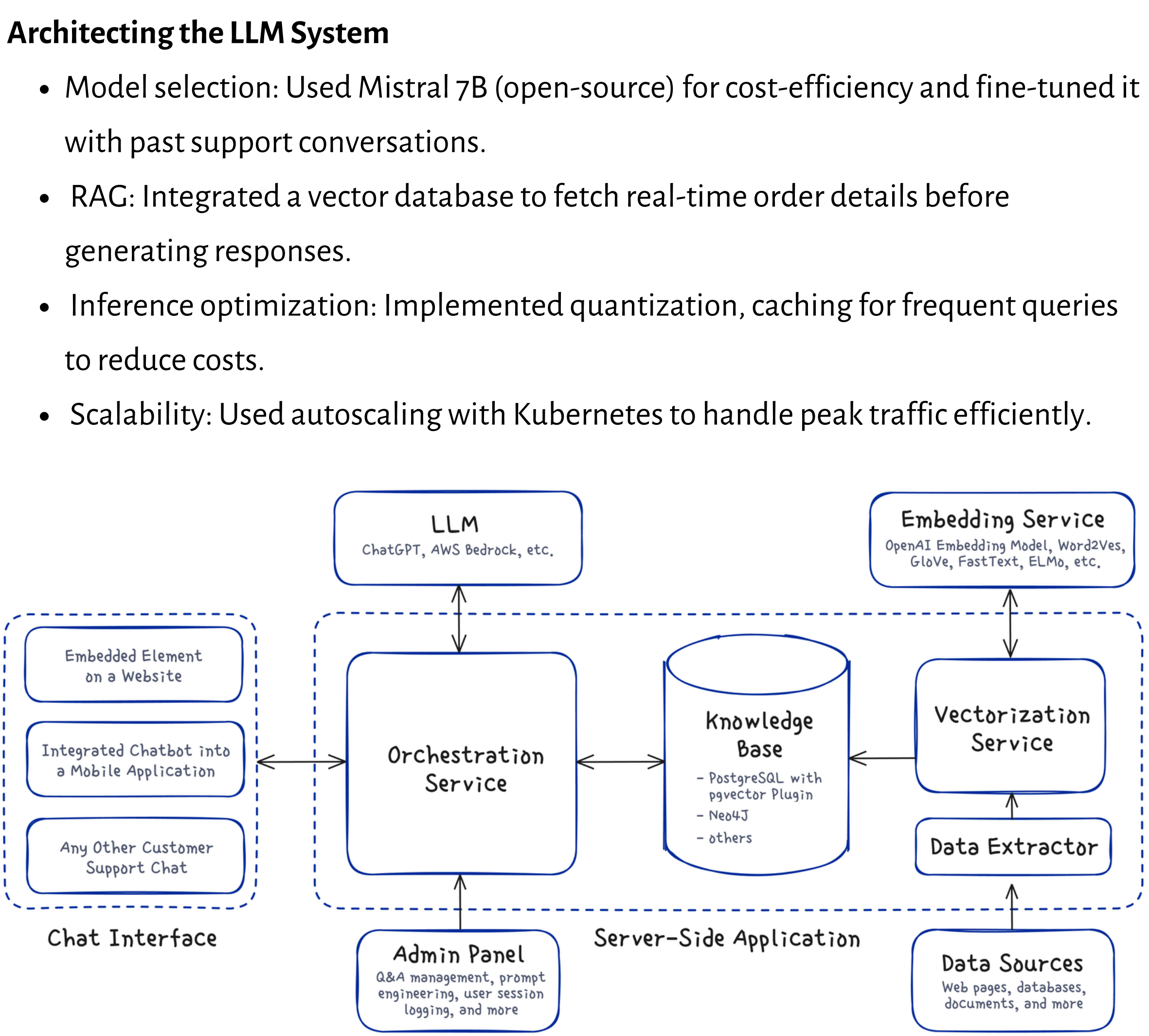
Challenges

- **High query volume**: The chatbot needed to handle thousands of simultaneous users.
- **Personalization**: It had to provide relevant responses based on order history.
- **Cost optimization**: Running a large LLM continuously was expensive.
- **Latency**: Customers expected instant responses without long processing times.

Architecting the LLM System

- Model selection: Used Mistral 7B (open-source) for cost-efficiency and fine-tuned it with past support conversations.
- RAG: Integrated a vector database to fetch real-time order details before generating responses.
- Inference optimization: Implemented quantization, caching for frequent queries to reduce costs.
- Scalability: Used autoscaling with Kubernetes to handle peak traffic efficiently.



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Results

- Reduction in support costs by automating common queries.
- Response time improved by ensuring faster resolution.
- Lower operational costs due to optimized model inference.
- Higher customer satisfaction, with increase in CSAT(Customer Satisfaction) scores.

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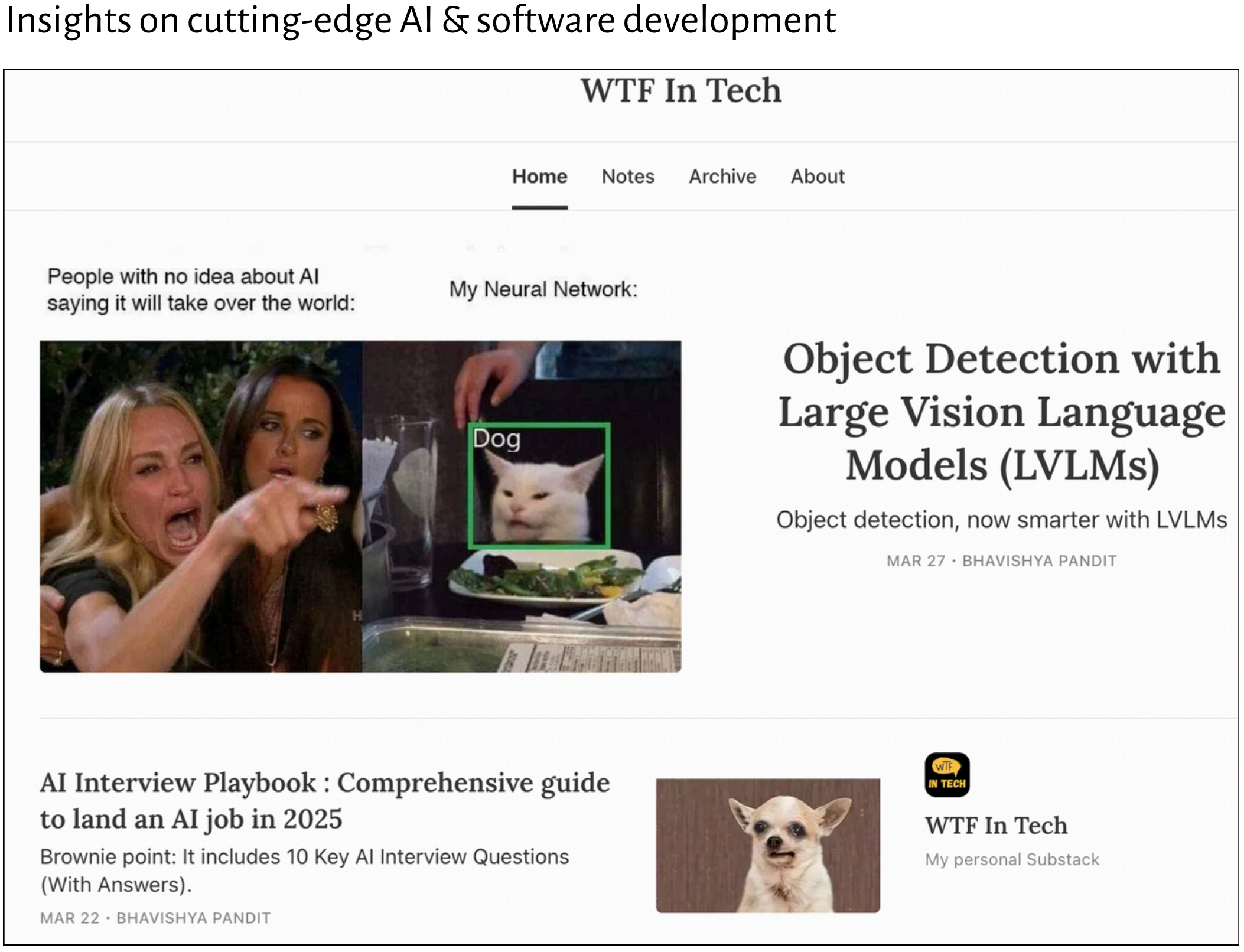

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