

Al Assistants

From Click-Deploy to Production

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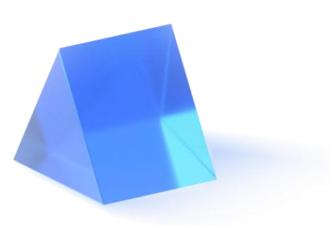
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Deltatre Innovation Lab



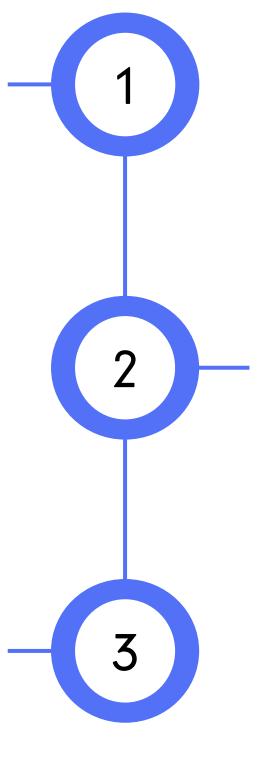
Al Assistants





What are Al Assistants?

Al-driven tools that engage with users via natural language to provide intelligent, adaptive support



Why Al Assistants?



- Domain Expertise
- 24/7 Available
- Consistent and Adaptable
- Boost efficiency
- Scalable



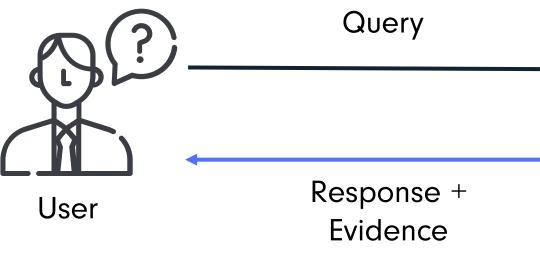
How Assistants Work

Retrieval Augmented Generation (RAG) is a combination of an information system retrieval with LLM skills to create contextually grounded responses

How does RAG work?

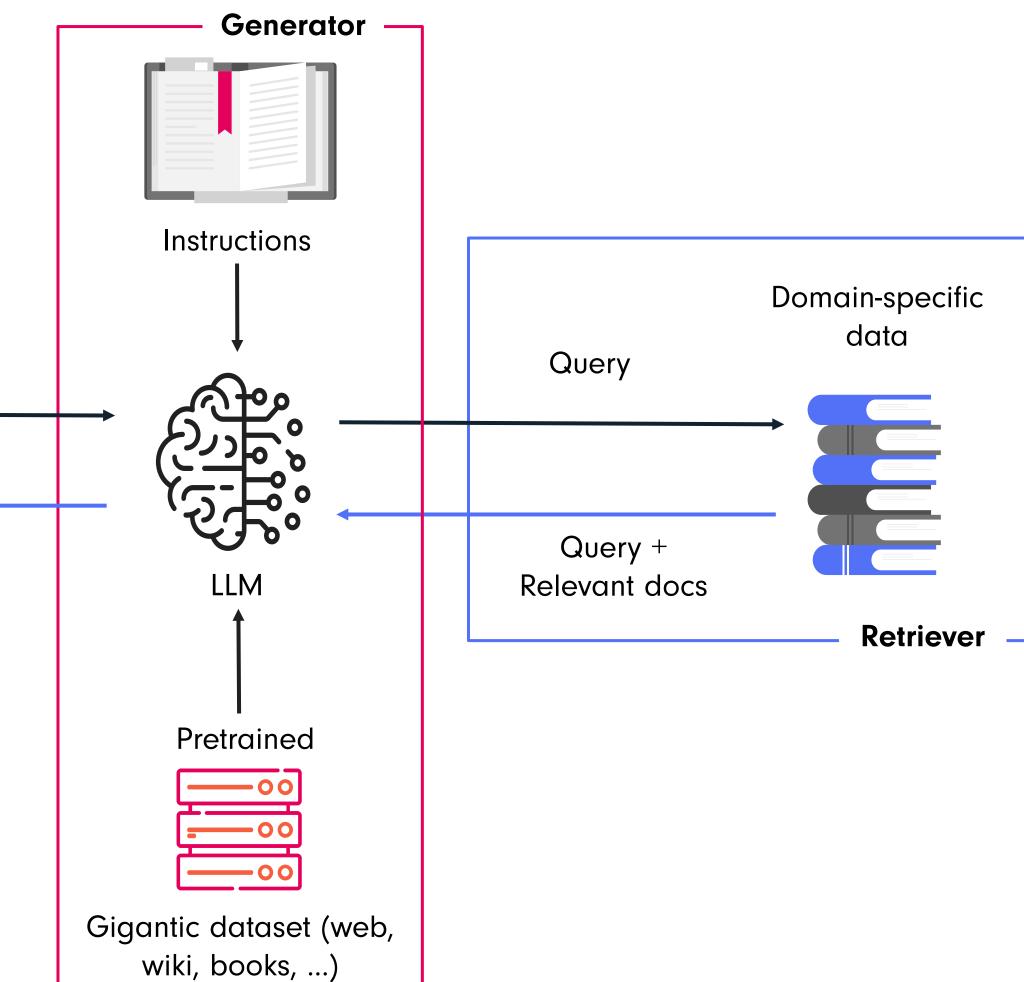
1. Retrieval

The solution queries a vast database to retrieve the most relevant documents to user input.

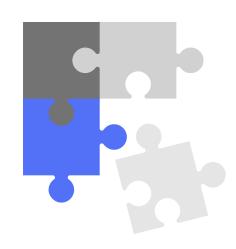


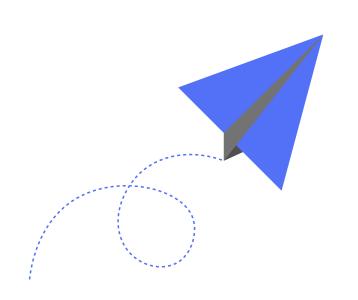
2. Augmentation

This content is served to the generative model to generate accurate, context-aware responses.



Why RAG over Fine-Tuning?



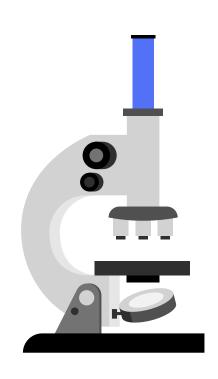


Always Up-to-Date

- Replies are always up-to-date
- Adapts to changes in your data, making it flexible for evolving business needs

Cost-Effective & Scalable

- No need for retraining
- Scales efficiently, adapting to user needs



Trustworthy & Transparent

- Verifiable response
- Tracing answers back to the original content for deep-dive

Exploration Phase

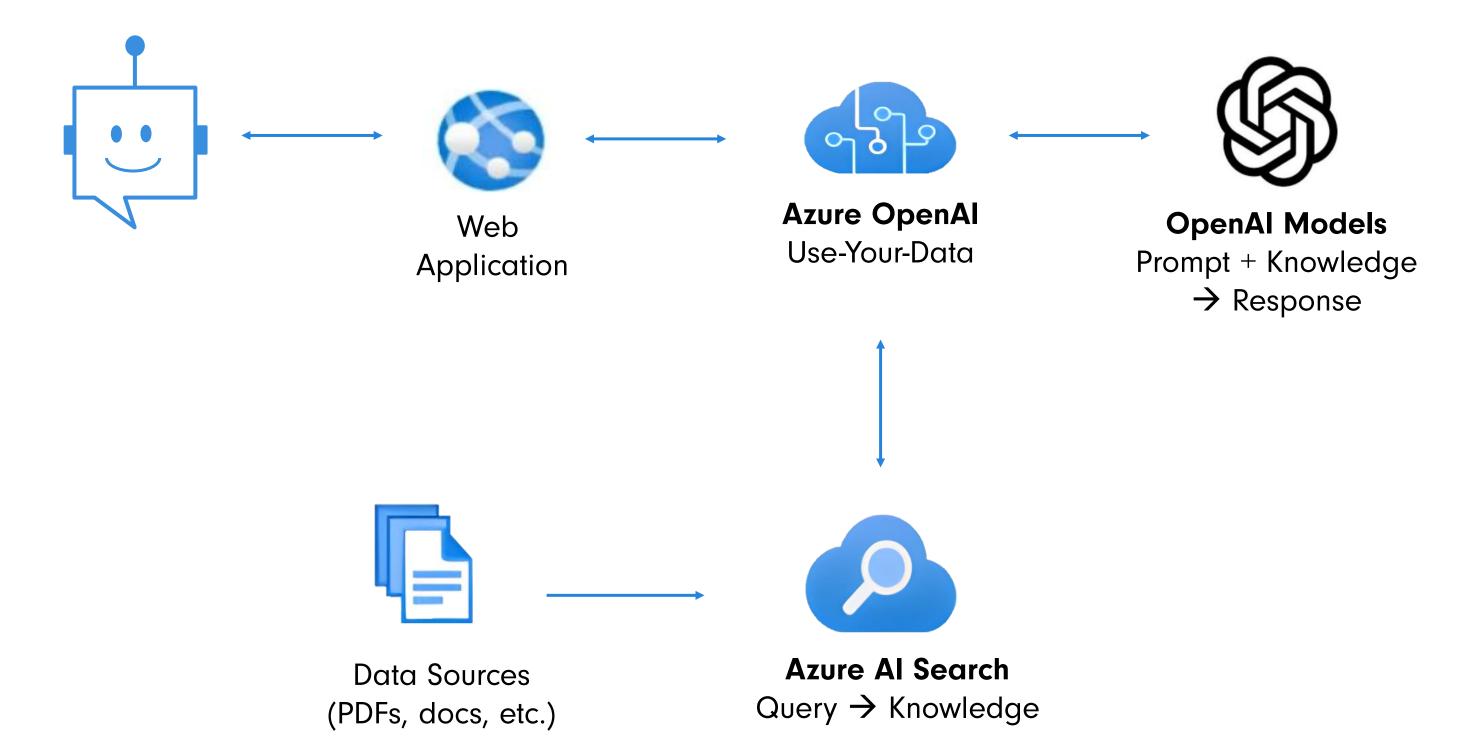


Azure OpenAl Services

Azure OpenAl Service integrates
OpenAl's generative Al models with
Azure's enterprise-grade cloud, offering
secure, scalable access via REST APIs.

Chat with your data enables the Assistant to craft system prompts and integrate the LLM with your data.

Azure Al Search is the RAG retrieval system indexing data with relevance tuning, security, and global reach.



Azure Al Search Retrieval Methods



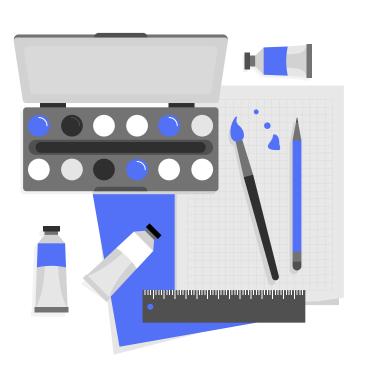


- Vector-embedded space
- Measures similarity between queries and documents
- Identifies conceptually related content



Keyword Search

- Match exact terms
- Traditional search needs
- Combines with Vector Search to form Hybrid Search



Semantic Search

- Understand the query intent ranking results by contextual relevance and meaning.
- Human-like understanding and deeper insights

Azure Al Search Core Components





It's the Assistant's **knowledge base** storing processed content and associated metadata. It is **highly customizable**, allowing the configuration of metadata attributes like titles, paths, and vectors for retrieval, filtering, or sorting



Defines **cognitive skills** for preparing and enriching data, including chunking, embedding, field mapping, and custom enrichments for Al processing.

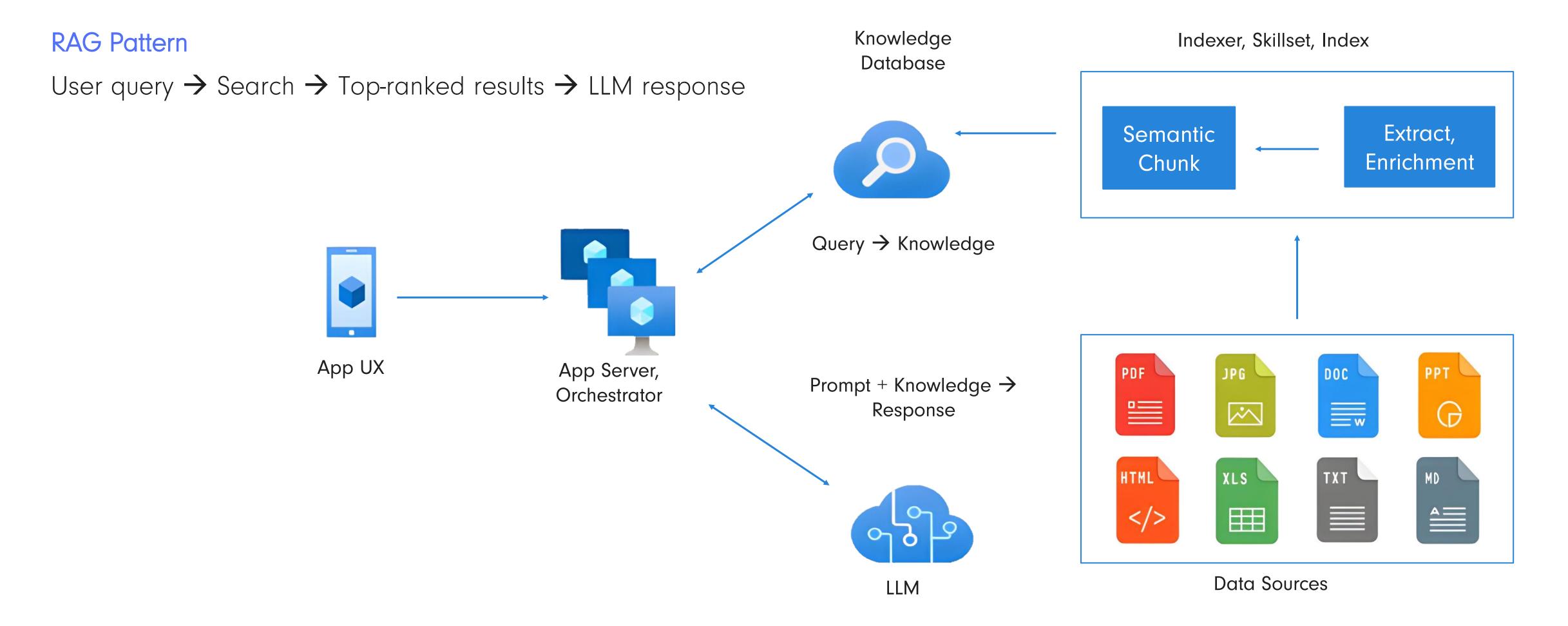


Handles **connecting**, **populating**, and **updating** the index with data from the source based on skillset instructions

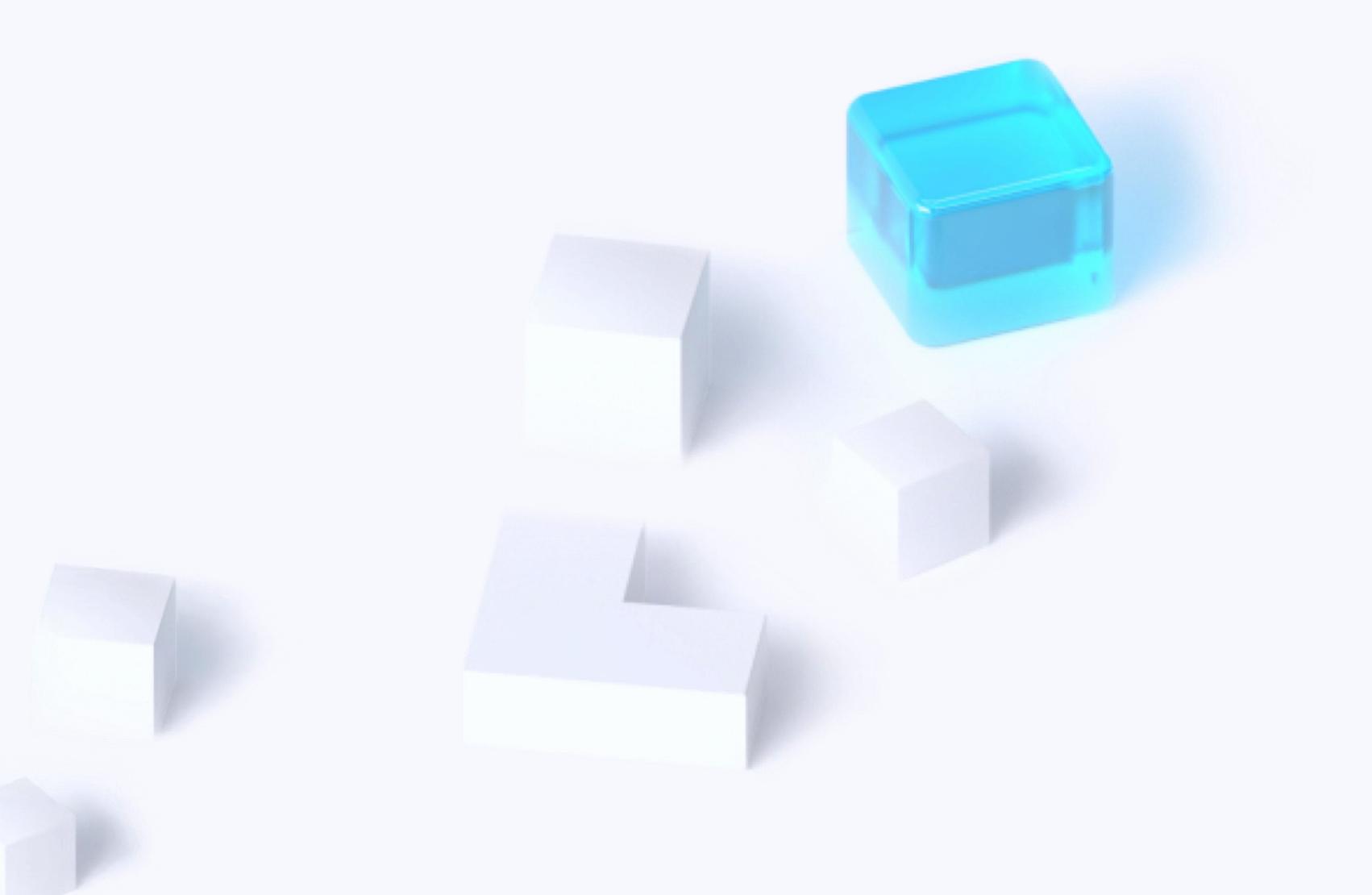


Connects to original data sources, storing raw data before enrichment and indexing.

PoC Architecture

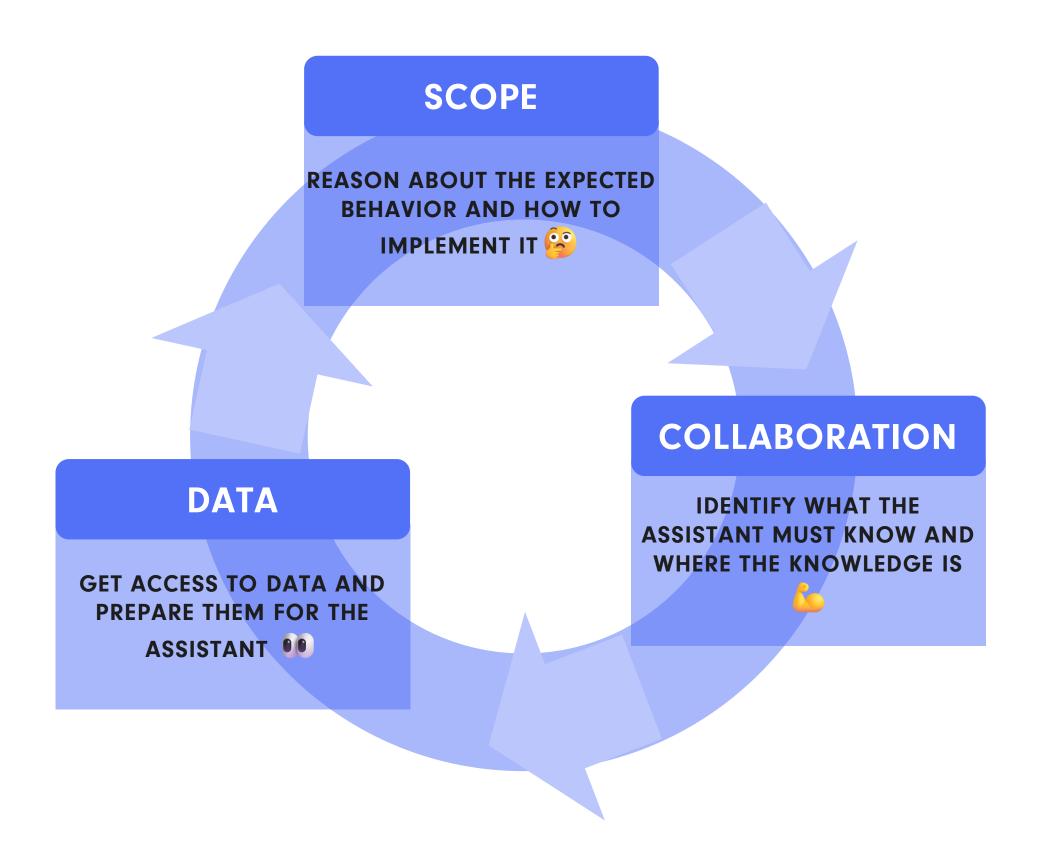


Demo



Identify Relevant Data Sources

An effective Al Assistant strictly depends on high-quality data source identification.



Inputs

- The relevance of data sources depends on the Assistant's scope
- Early collaboration with end users accelerates behavior shaping and offers insights into key information's *location*, format, and accessibility

Knowledge Sources

- Internal Sources: Confluence, GitHub (specs, guidelines), Teams threads, and training materials (video transcriptions, diagrams)
- External Sources: Public content (blogs, websites) and secure third-party partner documentation

Knowledge Mining

To ensure Azure AI Search works effectively, data must be optimized for indexing and retrieval.



Data Preparation

Python pipelines to collect, clean, and manipulate data



PDFs

Format for easy indexing



Diagrams

Use Mermaid syntax for better usability



LLM-Assisted Transformations

Convert informal content (chats, transcripts) into structured, informative documents

CHAT_SUPPORT_TO_DOCs = """

You are a sophisticated processing tool tasked with analyzing and structuring technical support dialogues.

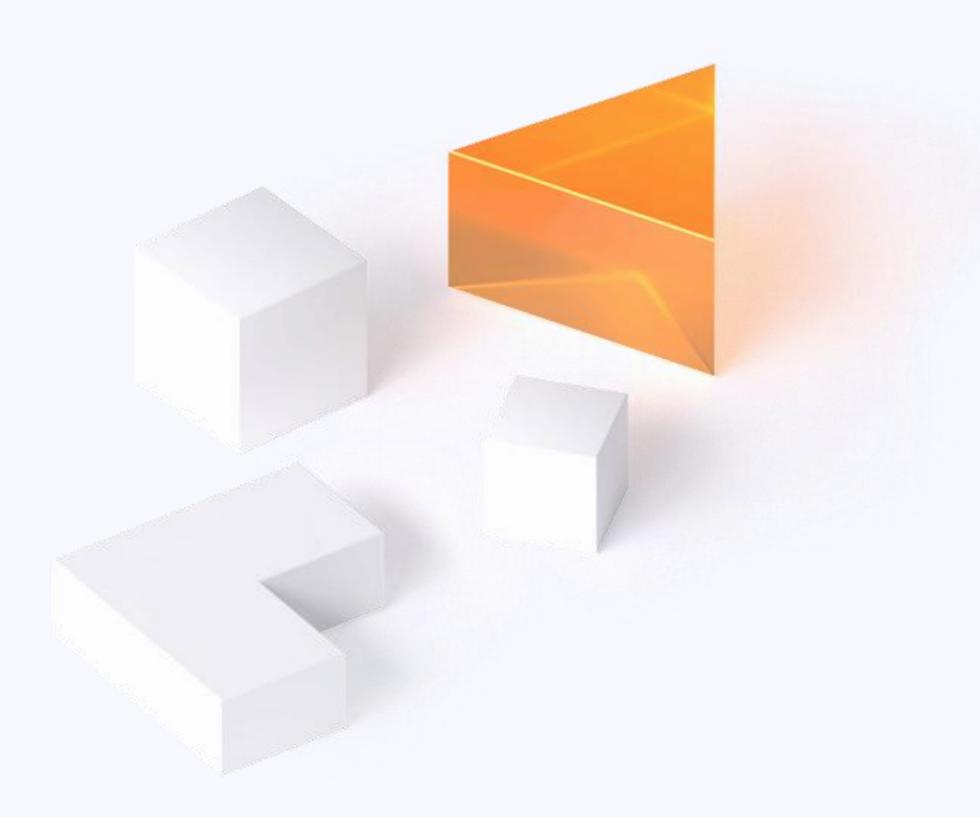
Your main objectives include:

- Identifying the main issue from the dialogue's title.
- Summarizing the core problem from the main text.
- Extracting and listing solutions and steps from the responses.

Operating guidelines:

- Output should be organized in a predefined format, focusing on clarity and relevance.
- Strictly use the data provided in the structured input without adding assumptions.
- Maintain professionalism and ensure privacy by omitting personal details.

Transition to Production



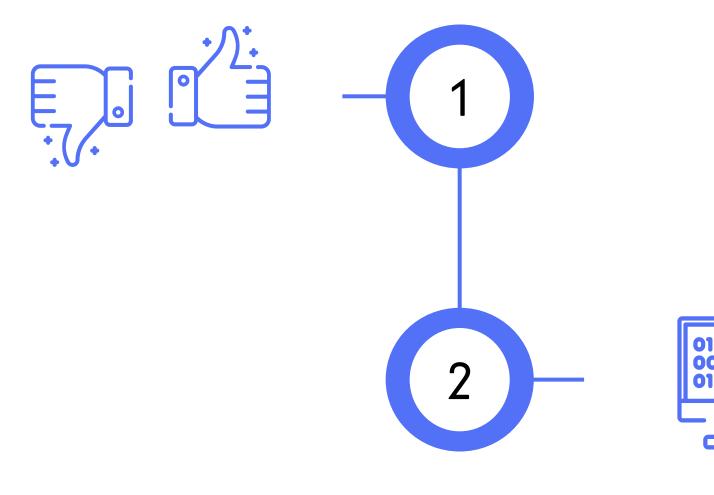
Evaluation & Feedback

Actively using and monitoring the Assistant's impact is the **compass for identifying improvement areas**. **Note**. Guidelines and best practices were provided to users to maximize the Assistant's effectiveness



Human Feedback

- In-Interface Thumbs Up/Down: Evaluation of single messages
- Dedicated Surveys: assessing the Assistant's impact – usage, satisfaction, and time saved.



Automatic Evaluation

Objectively assess user intent understanding and response quality

- Ground truth based
- Only exploiting LLMs

LLM-as-a-Judge







Context Relevance

Check if the response *fits* the query and stays aligned with the **prior messages**

What are popular attractions in Paris?

- ©: The Eiffel Tower and Notre-Dame Cathedral.
- The Eiffel Tower is amazing. Do you like French food?

Answer Relevance

Assess if the Assistant's response is **relevant and exhaustive**.

What is the best time to visit Paris?

- ©: April to June or October for mild weather.
- 😂: Paris is a major European city.

Groundedness

Measurement of **knowledge base usage**, and the answer **faithfulness**.

How many people visit the Eiffel Tower each year?

- ©: About 7 million annually.
- ②: Around 20 million people annually (incorrect data).

Answer Relevance

ANSWER_RELEVANCE_TRULENS = """You are a RELEVANCE grader; providing the relevance of the given RESPONSE to the given PROMPT. Respond only as a number from 0 to 10 where 0 is the least relevant and 10 is the most relevant.

A few additional scoring guidelines:

- Long RESPONSES should score equally well as short RESPONSES.
- Answers that purposely do not answer the question, such as 'I don't know' and model refusals, should also be counted as RELEVANT.
- RESPONSE must be relevant to the entire PROMPT to get a score of 10.
- RELEVANCE score should increase as the RESPONSE provides RELEVANT context to more parts of the PROMPT.
- RESPONSE that is RELEVANT to none of the PROMPT should get a score of 0.
- RESPONSE that is RELEVANT to some of the PROMPT should get a score of 2, 3, or 4.
- RESPONSE that is RELEVANT to most of the PROMPT should get a score between a 5, 6, 7 or 8.
- RESPONSE that is RELEVANT to the entire PROMPT should get a score of 9 or 10.
- RESPONSE that is RELEVANT and answers the entire PROMPT completely should get a score of 10.
- RESPONSE that confidently FALSE should get a score of 0.
- RESPONSE that is only seemingly RELEVANT should get a score of 0.
- Never elaborate.

Please answer with this template:

TEMPLATE:

Criteria: <Provide the criteria for this evaluation>

Supporting Evidence: <Provide your reasons for scoring based on the listed criteria step by step. Tie it back to the evaluation being completed.>

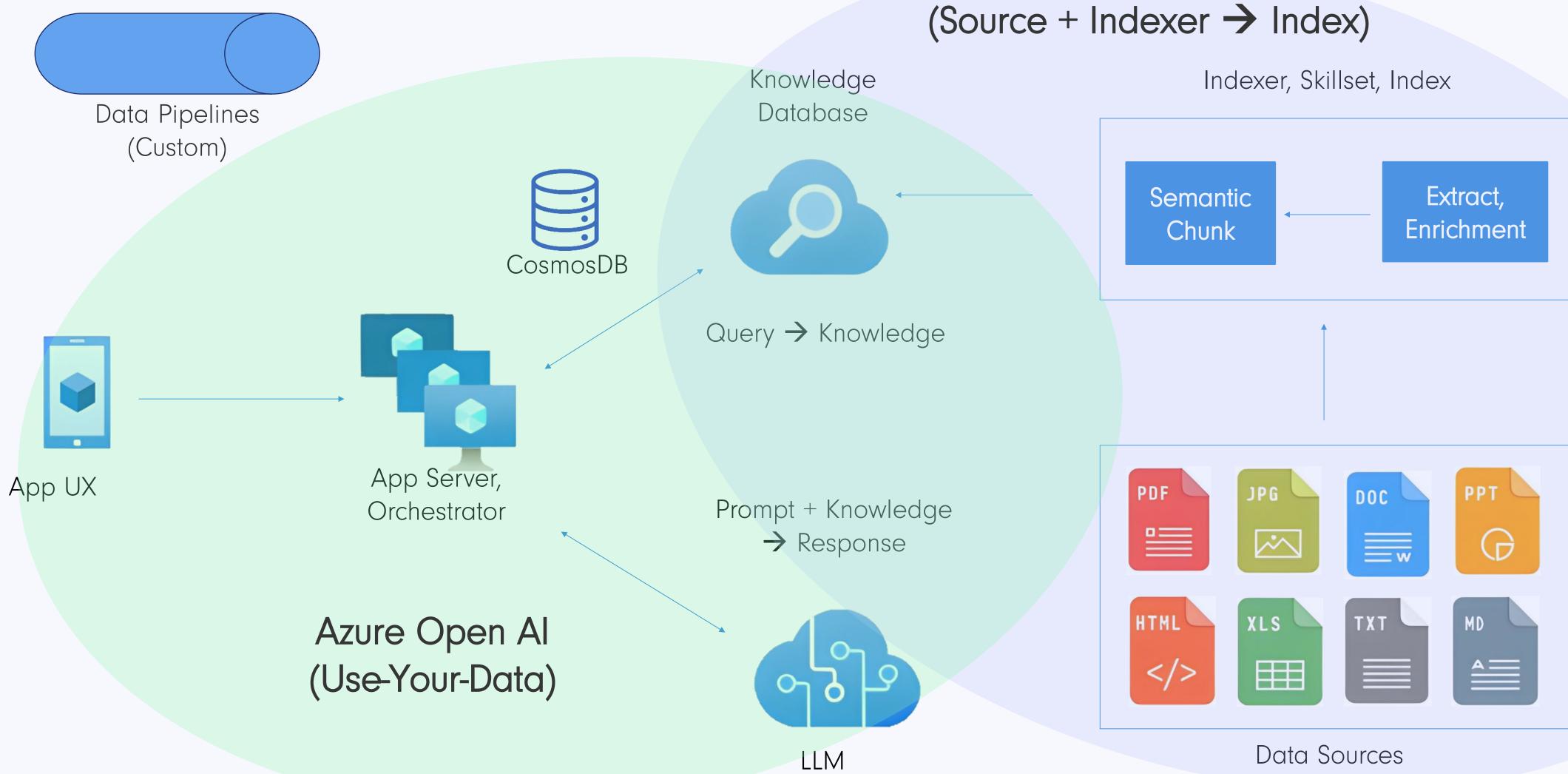
Score: <The score 0-10 based on the given criteria>"""

Recognized Challenges

Front End	Back End	Optimization
Customization Demands	Automating Data Flow	Feedback Loop
Chat History	Security Enhancements	Monitoring and Optimization
Navigable Links and Schema	Scalability	System Integration

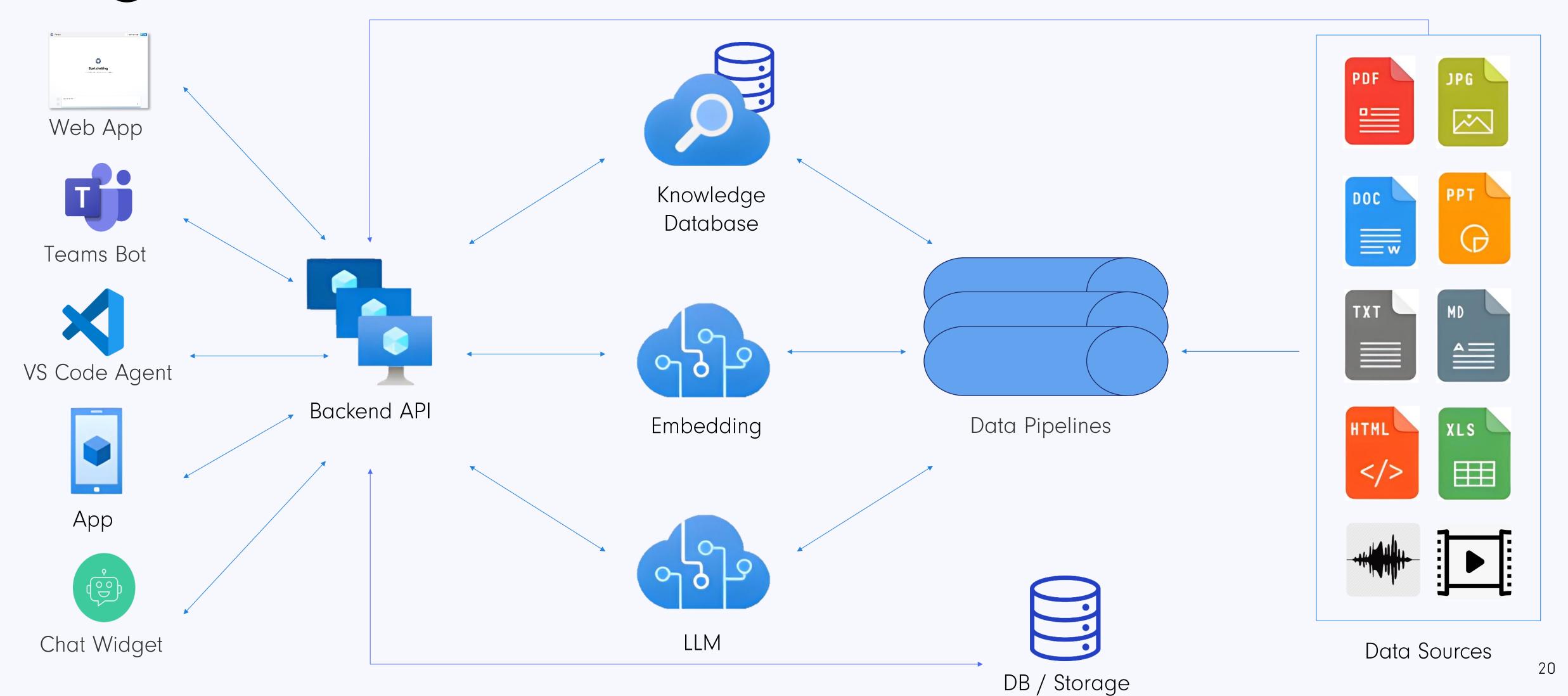


PoC Architecture Recap



Azure Al Search

High-Level Overview



Customization Needs



All-in-1 Assistants



Cloud Agnostic



Extended References



Enhanced Feedback



Enterprise Guidelines



Styling & Localization



Monitoring & Optimization



Security

Production Architecture

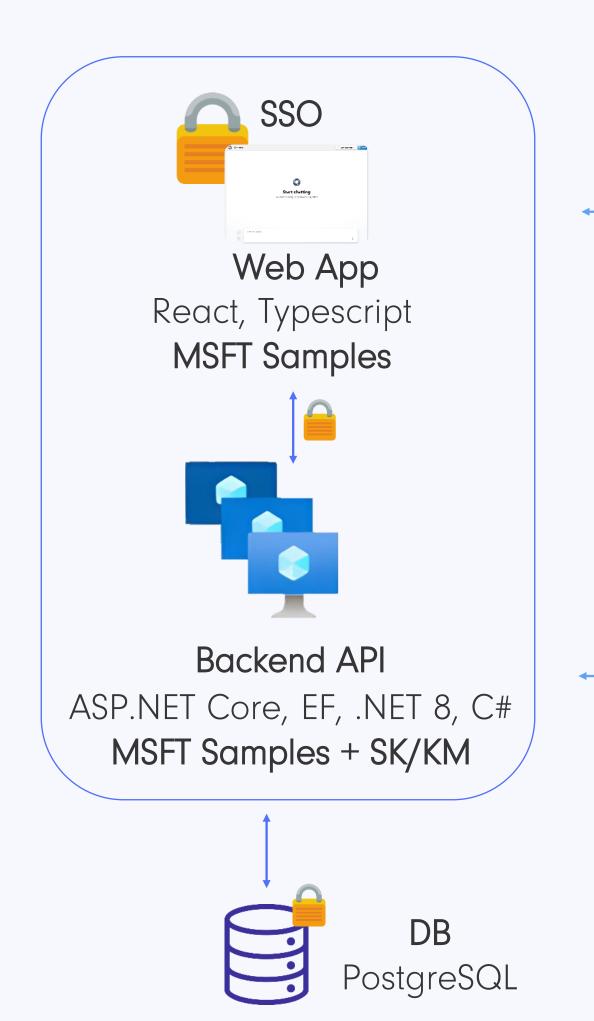


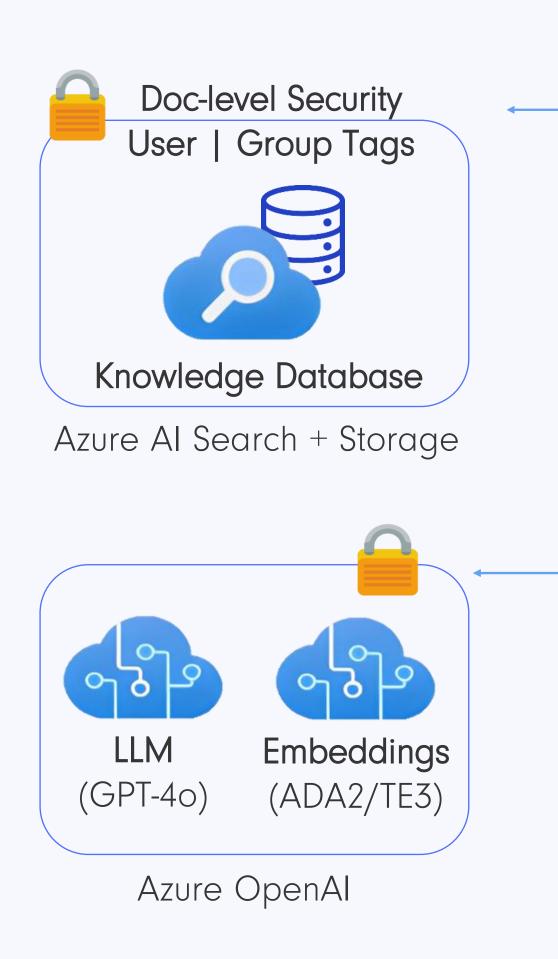


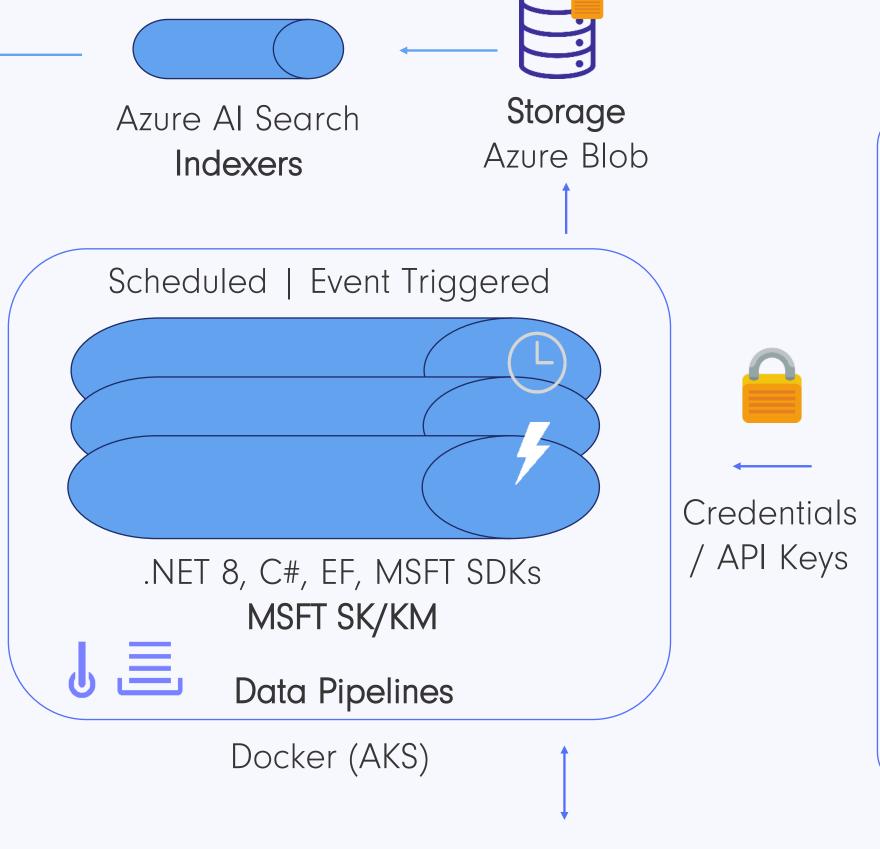


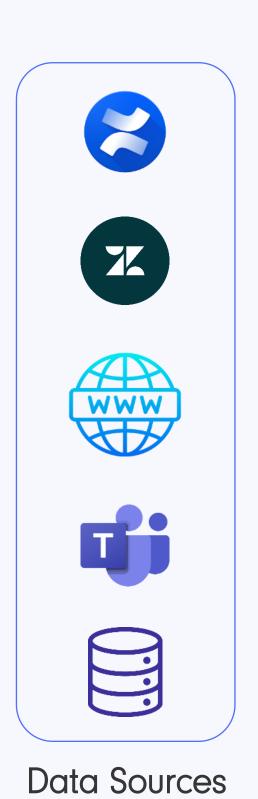
GitHub

Infra
Terraform GitOps

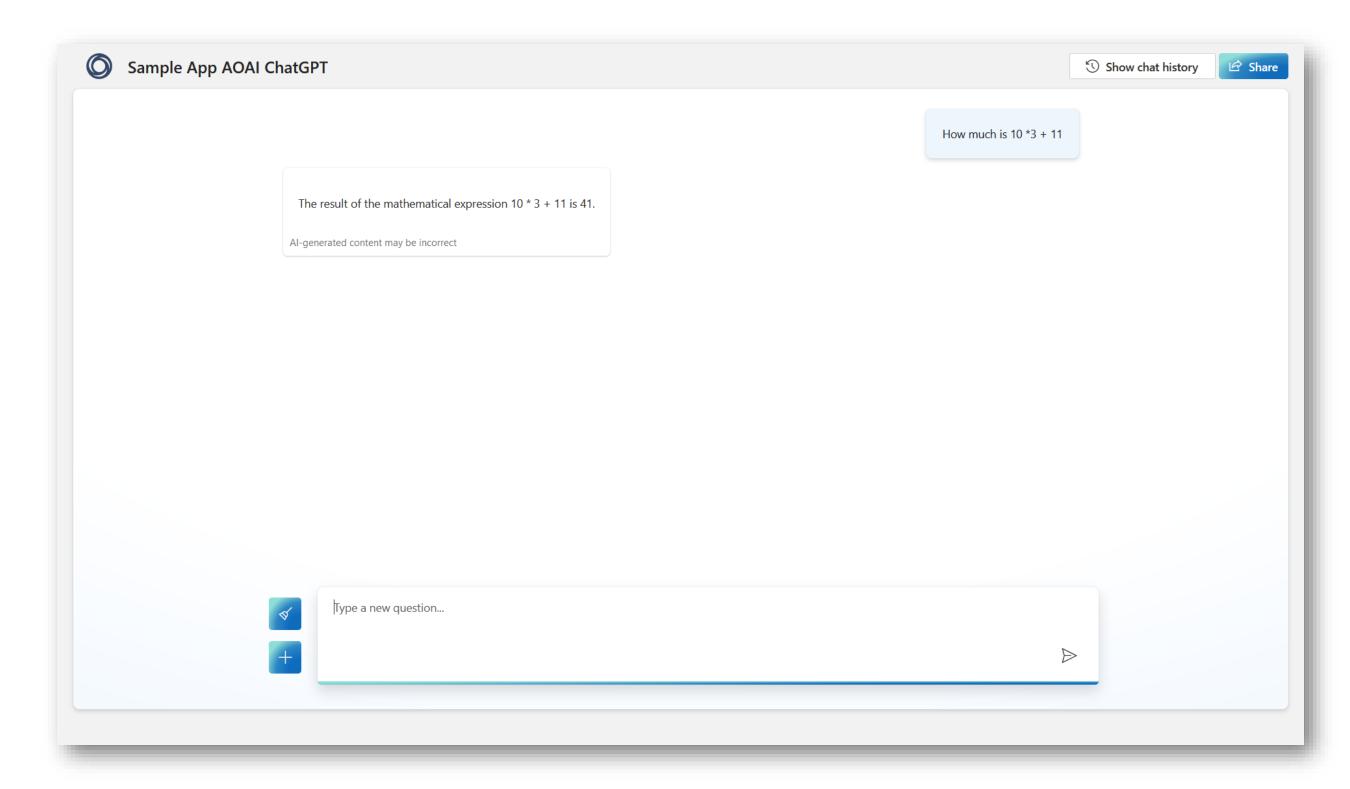


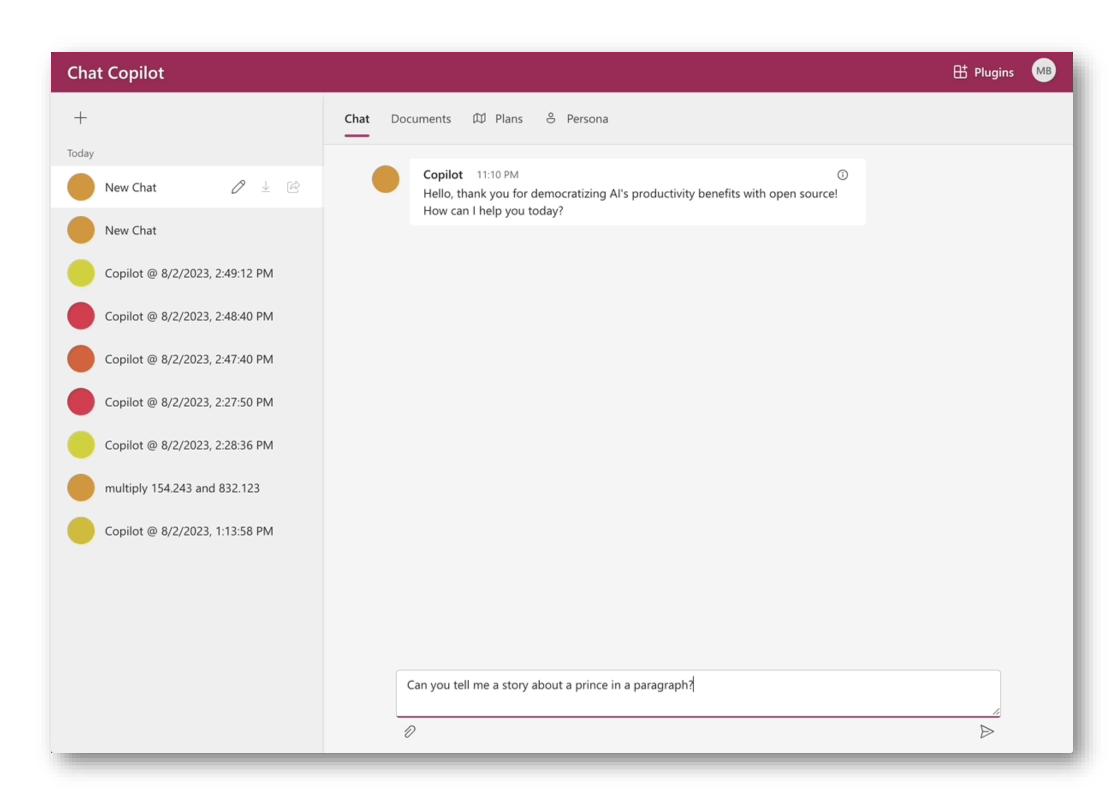






Technologies & Frameworks





https://github.com/microsoft/sample-app-aoai-chatGPT

React, Typescript
Python
Azure OpenAl API (UYD)

https://github.com/microsoft/chat-copilot/

React, Typescript
ASP.NET Core, .NET 8, C#
Semantic Kernel + Kernel Memory

LLMs, Chats, Tools



Semantic Kernel

A lightweight, open-source development kit



Enterprise-ready

Flexible, secure, modular, and observable



Orchestration & Plans

Combines Al models, embeddings, prompts with APIs & tools to perform actions & business automation



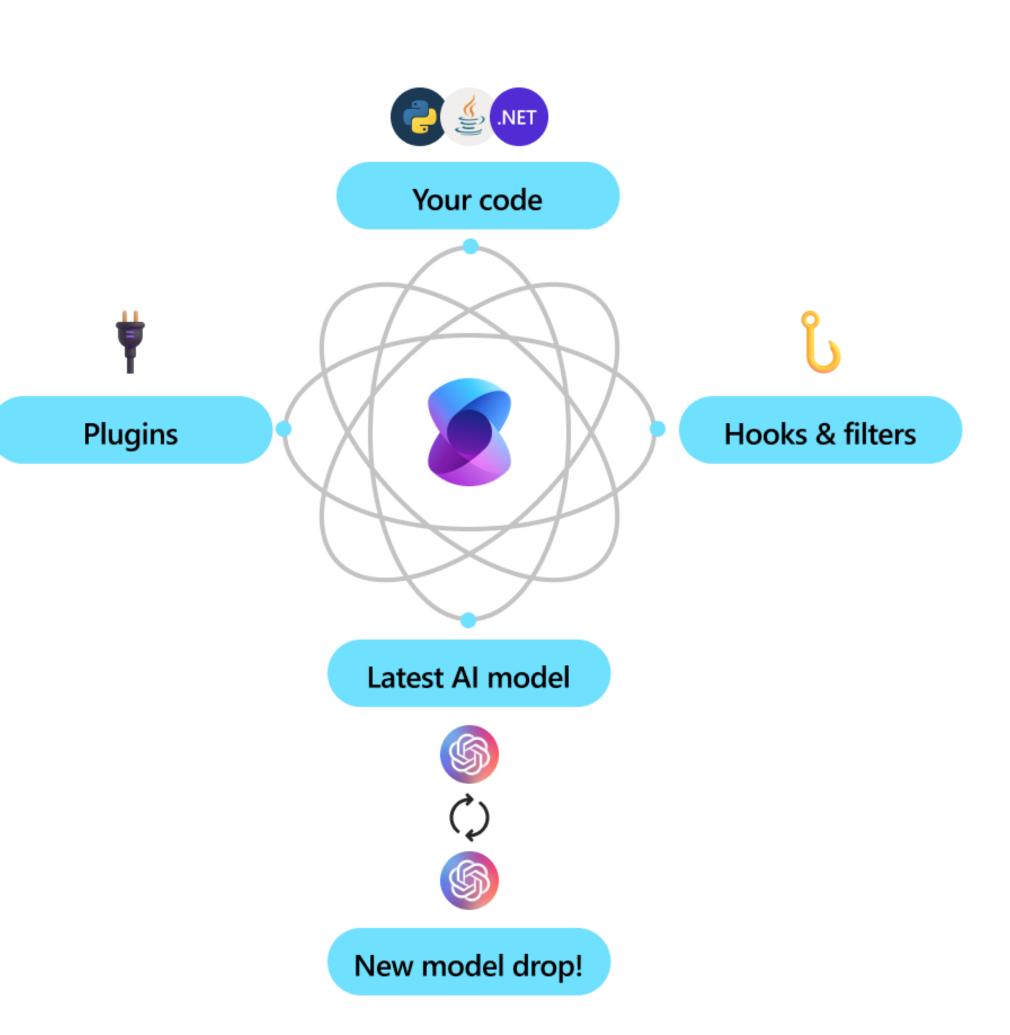
Modular and Extensible

Many out-of-the-box connectors
Support for integrating *existing* code as **plugin**



Cross-Platform

.NET, Python, and Java



Memory, Data, Workflows



Kernel Memory

A multi-modal, open-source Al Service for efficient datasets indexing



Data Pipelines & Workflow Orchestration

Supports Data Retrieval, Custom Pipelines, and Semantic Memory processing



RAG Support

Advanced querying via embeddings and LLMs, over multiple knowledge bases



Built-in Data Formats & Transformations + Custom

Supports various data types, including PDFs, documents, web pages, and images



Out-of-the-Box Connectors + Custom

Support a wide range of data stores (Vector DBs, RDBMS, File System, etc.)
Integrates with external tools like Azure OpenAl, ChatGPT and Microsoft Copilot

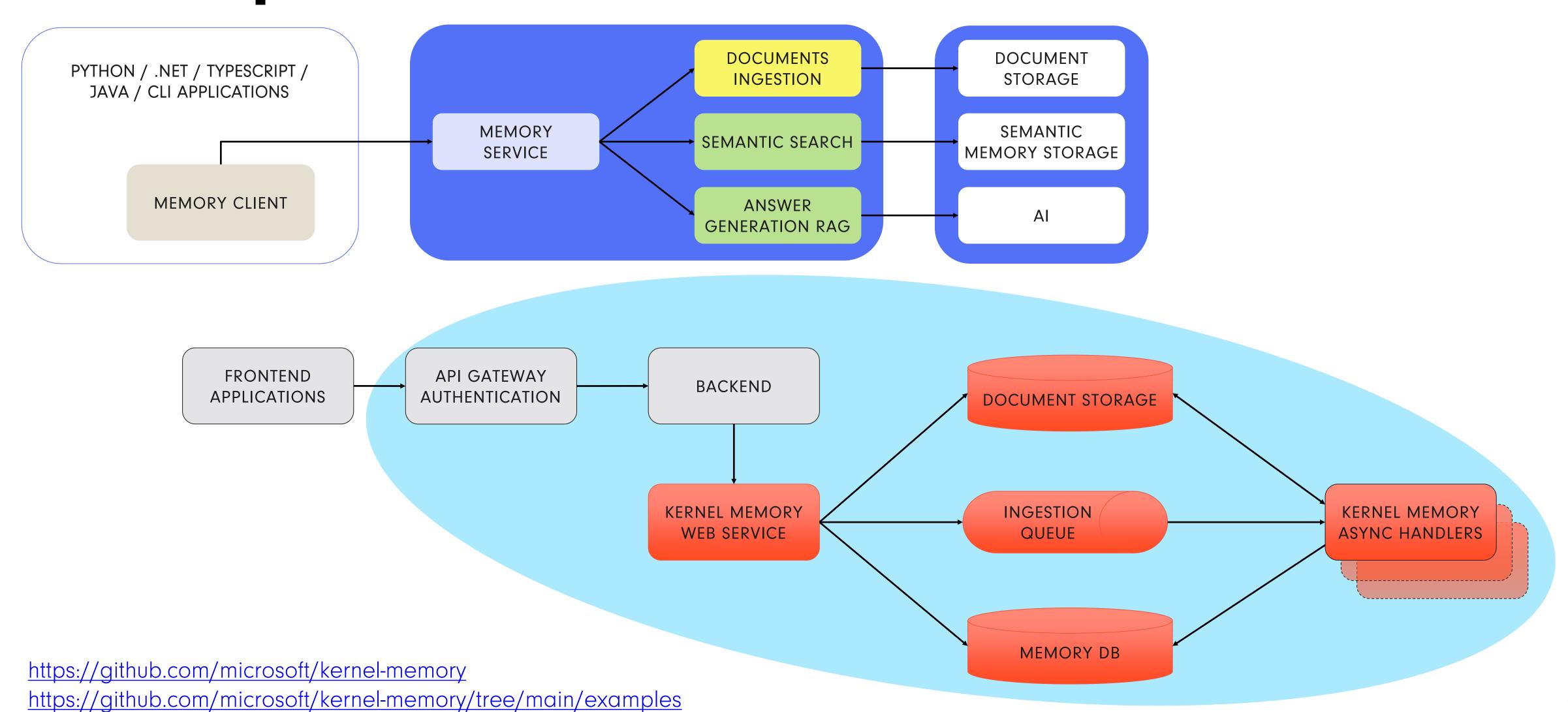


Enterprise-proof

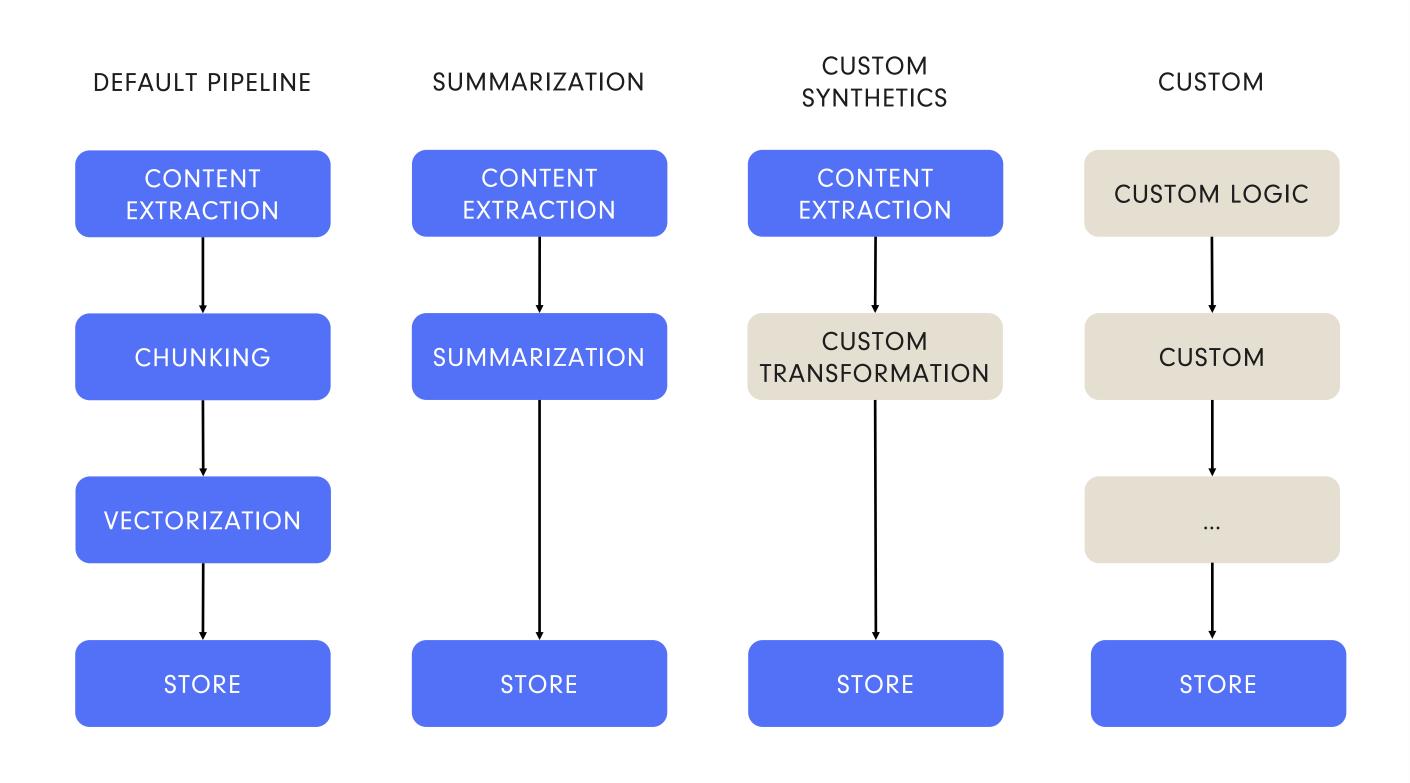
Flexible, modular, observable, and secure



Data Pipelines

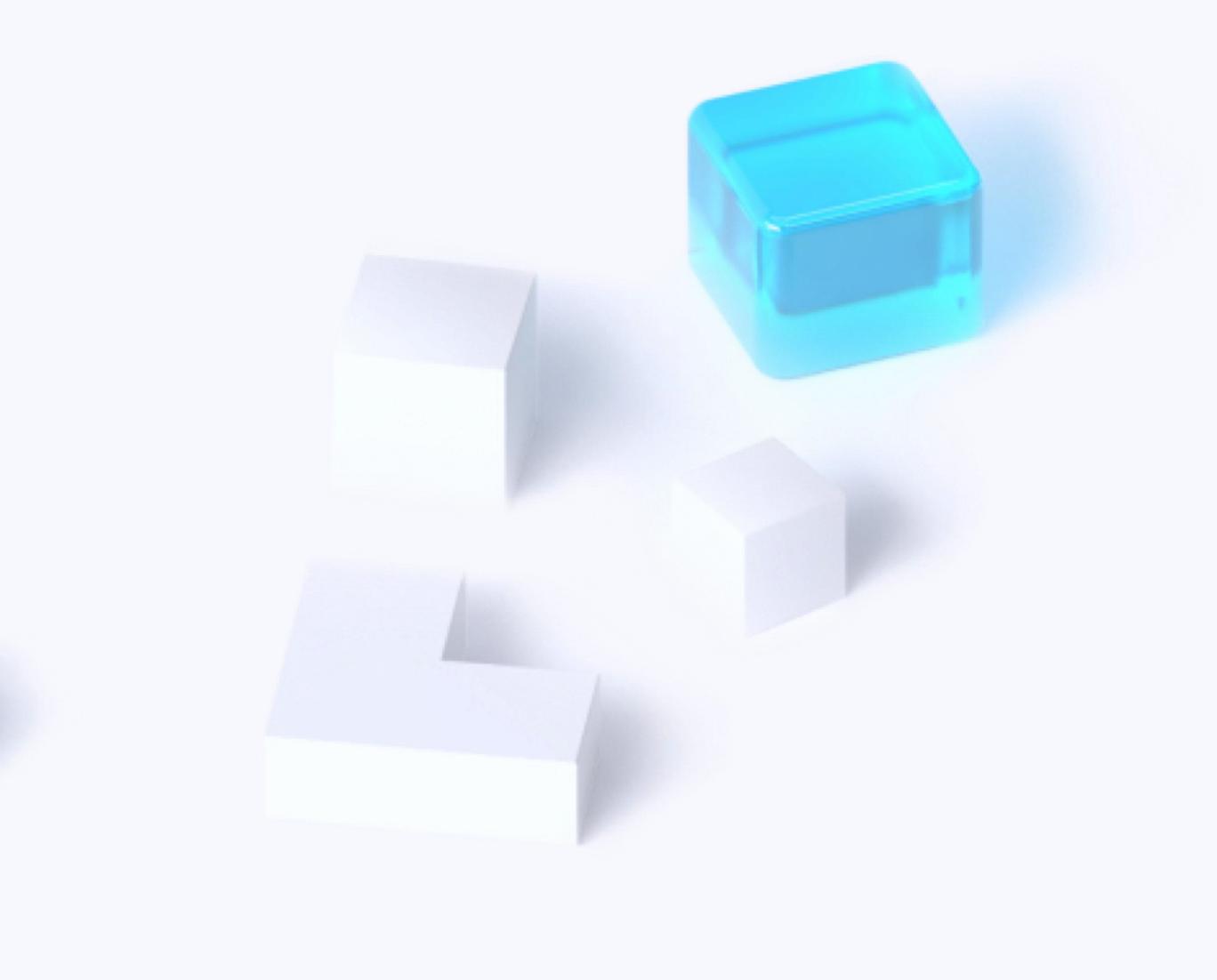


Data Pipelines



```
memory.Orchestrator.AddHandler<TextExtractionHandler>("extract_text");
memory.Orchestrator.AddHandler<TextPartitioningHandler>("split_text_in_partitions");
memory.Orchestrator.AddHandler<GenerateEmbeddingsHandler>("generate_embeddings");
memory.Orchestrator.AddHandler<SummarizationHandler>("summarize");
memory.Orchestrator.AddHandler<SaveRecordsHandler>("save_memory_records");
* Import files using custom handlers
 // Use the custom handlers with the memory object
await memory.ImportDocumentAsync(
   new Document("inProcessTest")
       .AddFile("file1-Wikipedia-Carbon.txt")
       .AddFile("file2-Wikipedia-Moon.txt")
       .AddFile("file3-lorem-ipsum.docx")
       .AddFile("file4-KM-Readme.pdf")
       .AddFile("file5-NASA-news.pdf")
       .AddTag("testName", "example3"),
   index: "user-id-1",
   steps:
       "extract_text",
       "split_text_in_partitions",
       "generate_embeddings",
       "save_memory_records"
   ]);
```

Demo



Lessons Learned (Part 1)



Data is King

High-quality, well-prepared data is essential for success and contextually relevant responses.



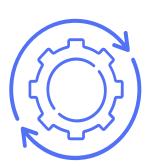
Cross-Functional Collaboration

The key for ensuring all needs are met is the collaboration between Al teams, developers, and end-users



Master Retrieval Techniques

Efficient indexing, data enrichment, and retrieval methods ensure fast, relevant results.



Iterative Approach

Continuously test, refine, and optimize. Constant feedback loops are vital for improving accuracy and performance over time.

Lessons Learned (Part 2)



LLM-as-a-Judge

Use both human feedback and automated evaluation to measure the overall Assistant's impact.



Continuous Improvement

RAG-based solutions evolve rapidly. Stay updated with new methods and technologies.



Scalability and Flexibility

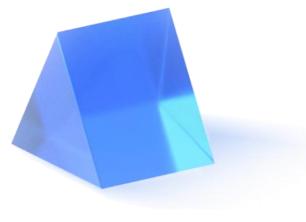
Ensure the Assistant remains scalable and adaptable to growing data and user demands.



Security & Access Management

Implement robust security measures and ensure compliance to protect sensitive information.

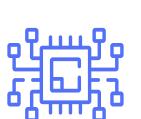
What's Next





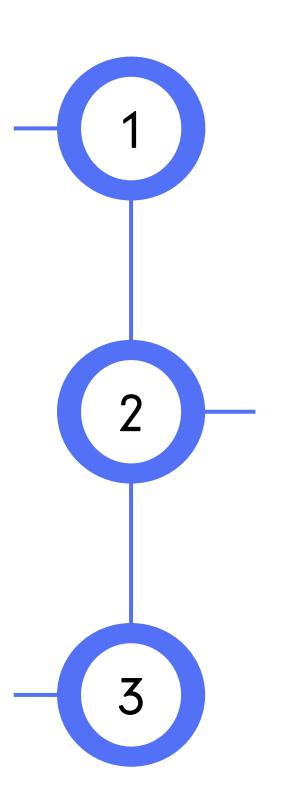
Evaluation and CI Empowerment

- Synthetic Ground Truth to strengthening LLM-as-a-Judge evaluation
- Advanced Monitoring Tools in production like
 Azure Prompt Flow, Nebuly, or LangSmith



Architectural Enhancements & Solutions

- Semantic Cache to improve efficiency by reusing cached context.
- New Frameworks: Evolving architectural solutions in the RAG landscape



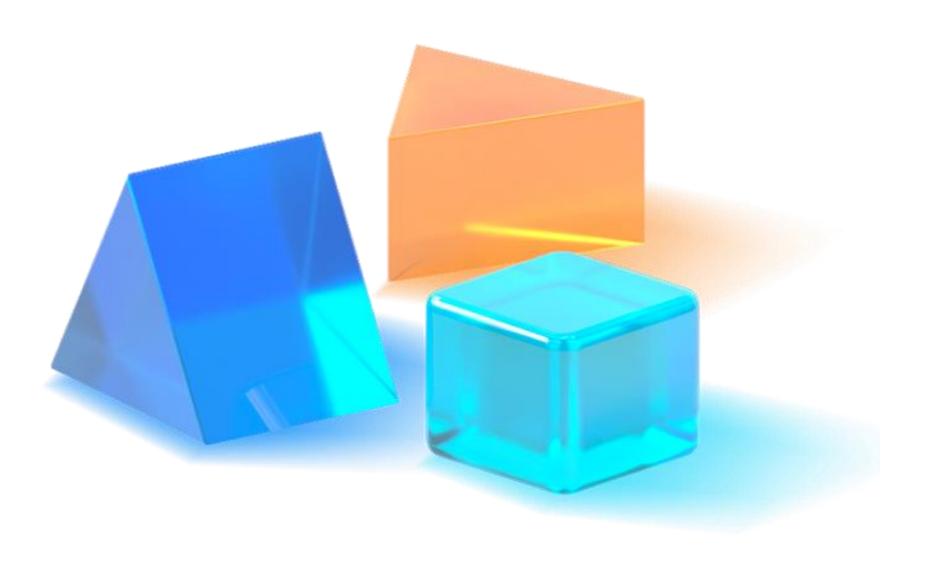
New Approaches



- Al Agents: autonomous systems that combine the adaptability of LLMs with the precision of traditional programming to make decisions and take actions toward specific goals
- Advanced Retrieval and data connections
 to improve understanding, reduce
 hallucinations, and improve
 contextualization



Questions?



Additional References

https://learn.microsoft.com/en-us/azure/ai-services/openai/overview

https://learn.microsoft.com/en-us/azure/search/

https://learn.microsoft.com/en-us/azure/ai-services/openai/use-your-data-quickstart

https://www.trulens.org/

https://github.com/microsoft/chat-copilot/

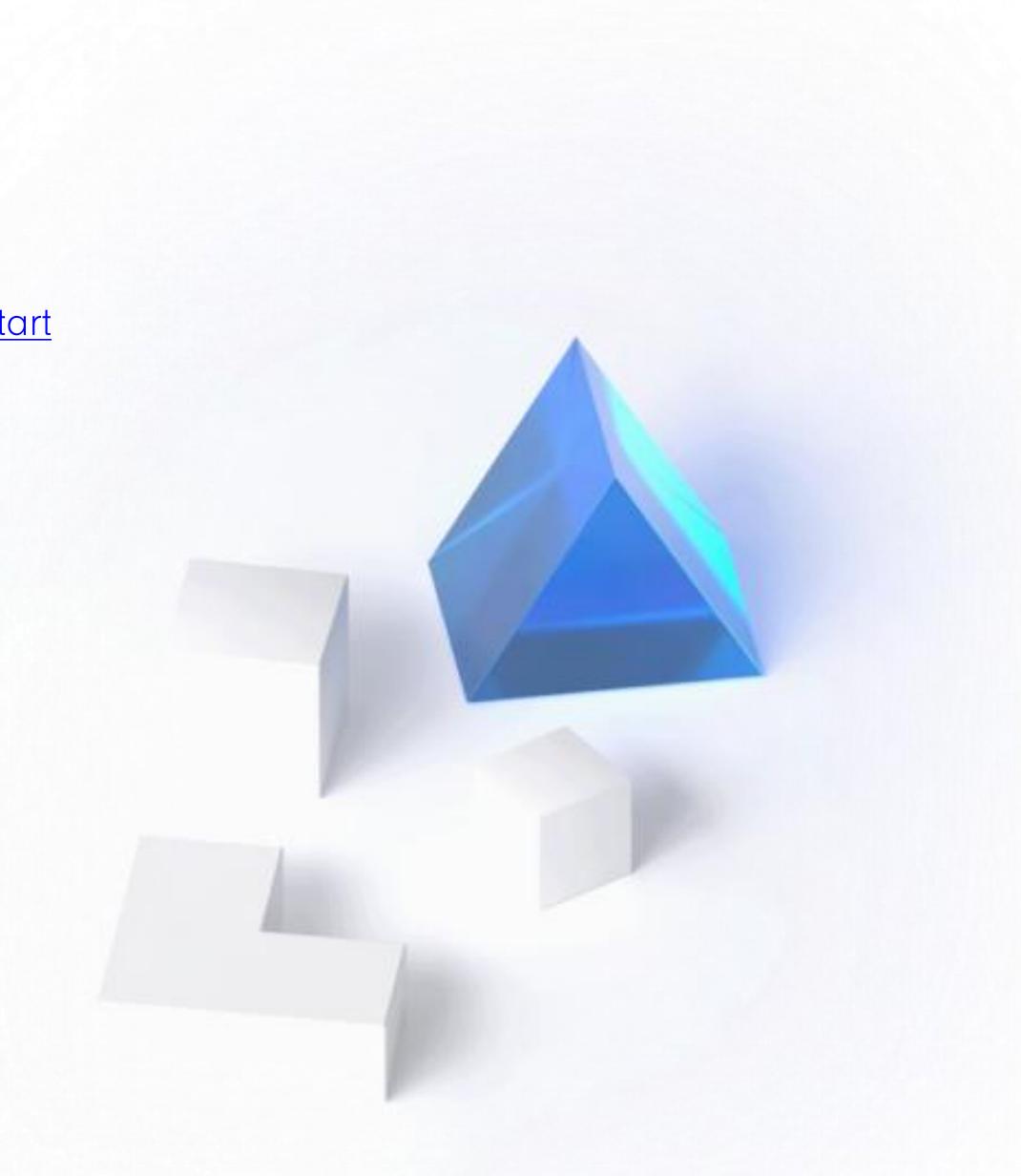
https://github.com/microsoft/sample-app-aoai-chatGPT

https://learn.microsoft.com/en-us/semantic-kernel/overview/

https://github.com/microsoft/kernel-memory

https://github.com/microsoft/kernel-memory/tree/main/examples

https://github.com/Andrew-Jang/RAGHub



About Us



Ing. Morgana LALLI
R&D Data Scientist @ deltatre

Deltatre Innovation Lab

- Biomedical Engineering, focused on sports data analysis.
- Al, Machine Learning, and Deep Learning on multimedia content
- Skilled in exploratory data analysis techniques, handling diverse and complex data types.
- Currently working on RAG-based solutions to advance NLP capabilities
- LinkedIn: https://www.linkedin.com/in/morgana-lalli-b5ab0a172/

About Us



Microsoft Microsoft

Programming in C# Programming in HTML5 CERTIFIED

Solutions Developer

Windows Store Apps Using C#







Ing. Gianni **ROSA GALLINA**

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Deltatre Innovation Lab

- AI, Machine Learning, Deep Learning on multimedia content
- Virtual/Augmented/Mixed Reality
- Immersive video streaming & 3D graphics for sport events
- Cloud solutions, web backends, serverless, video workflows
- Mobile apps dev (Windows / Android / .NET MAUI / Avalonia)
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