Sinergija24

Cooking RAG like a Chef de Cuisine

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Goals

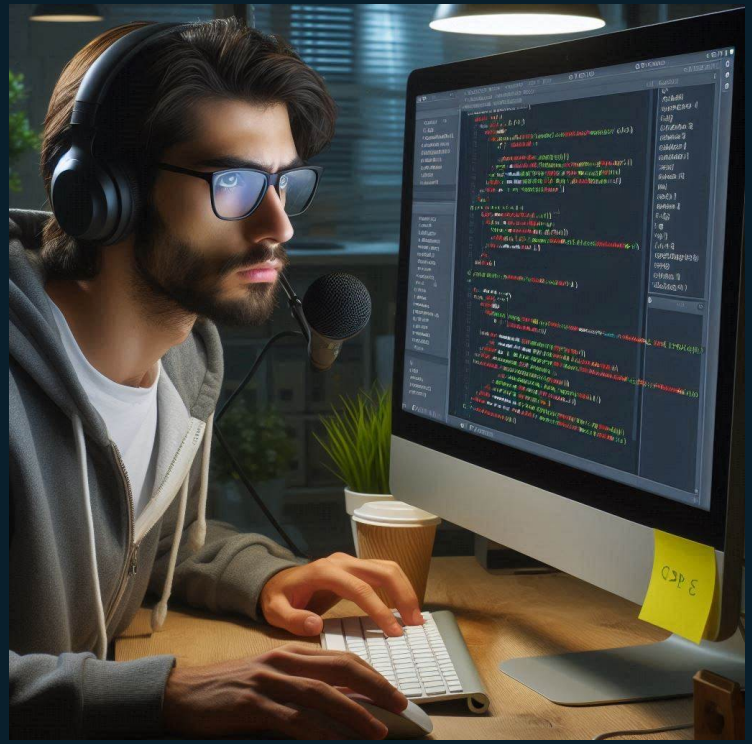
- Help navigate complex Gen AI space
- Help understand Azure 1st Party options
- Learn basic and advanced AI RAG concepts

Agenda

- Why RAG?
- Choosing RAG Components
  - LLMs
  - Retrievers
  - Orchestrators
- Running RAG on Azure
- RAG Evaluation and Security
- Beyond RAG (Agentic RAG, GraphRAG)

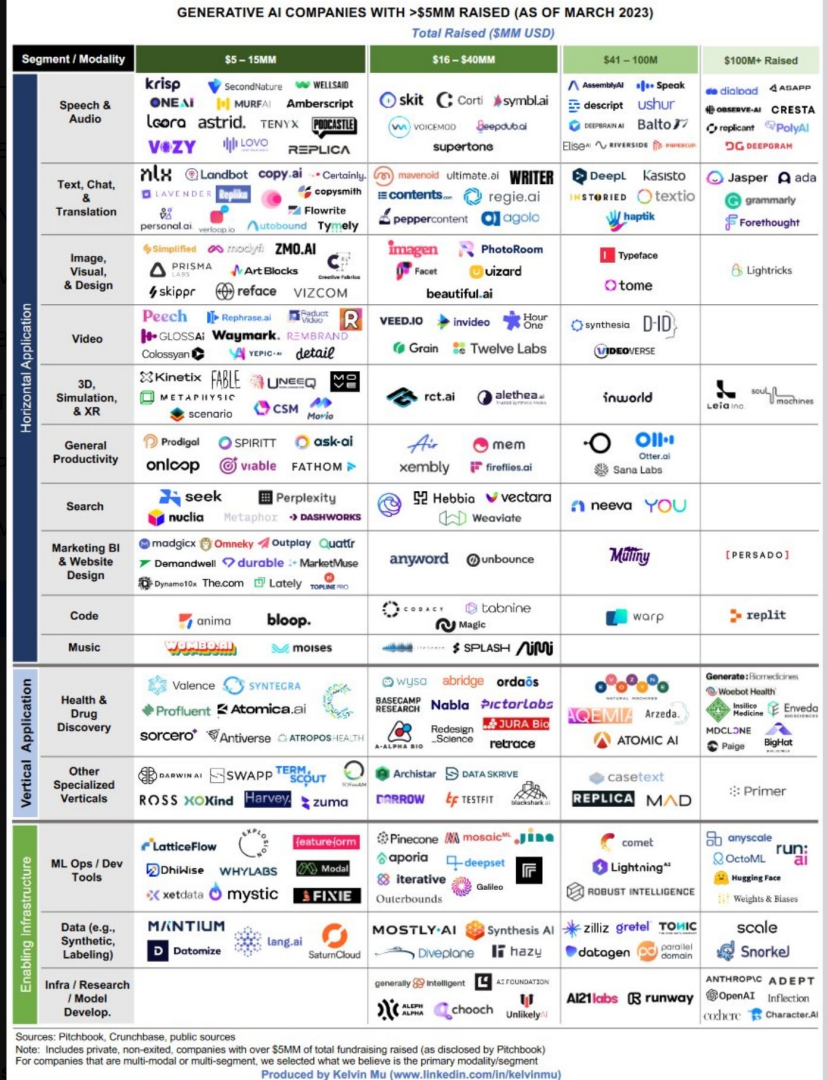
AI Development these days

Classic development

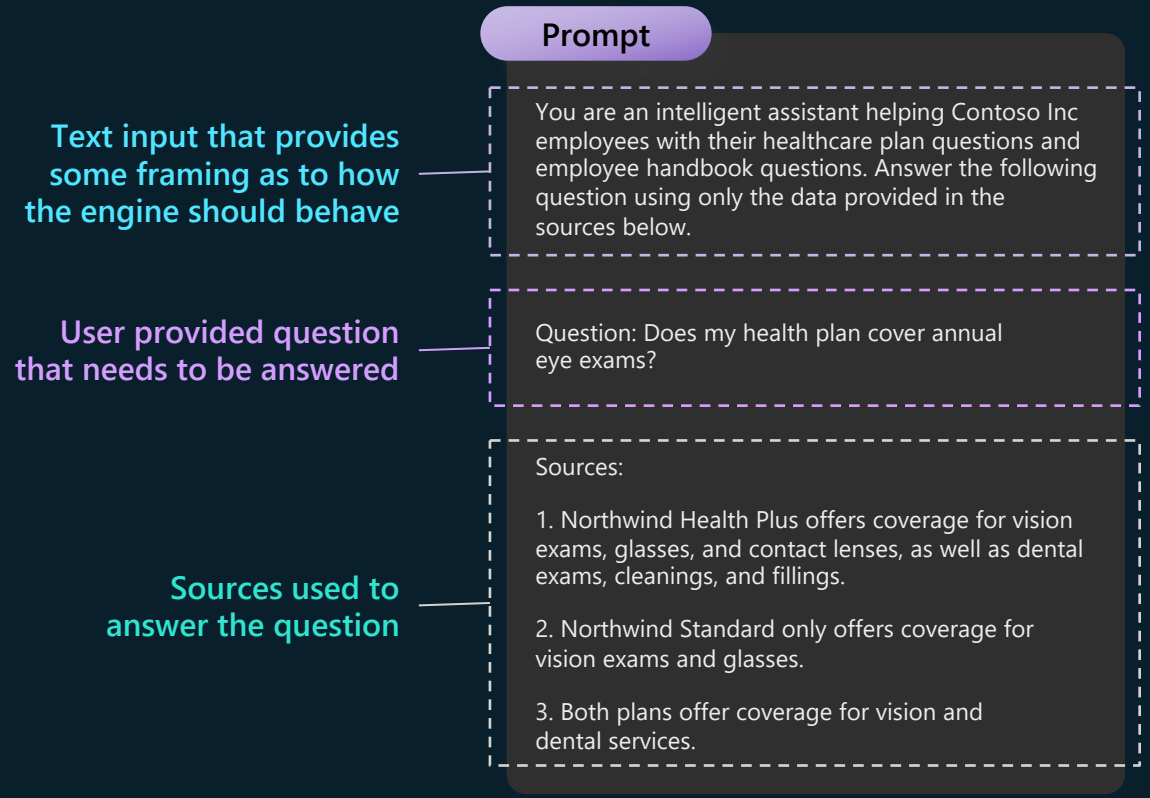


AI Development

Gen AI field - “let the flowers bloom”



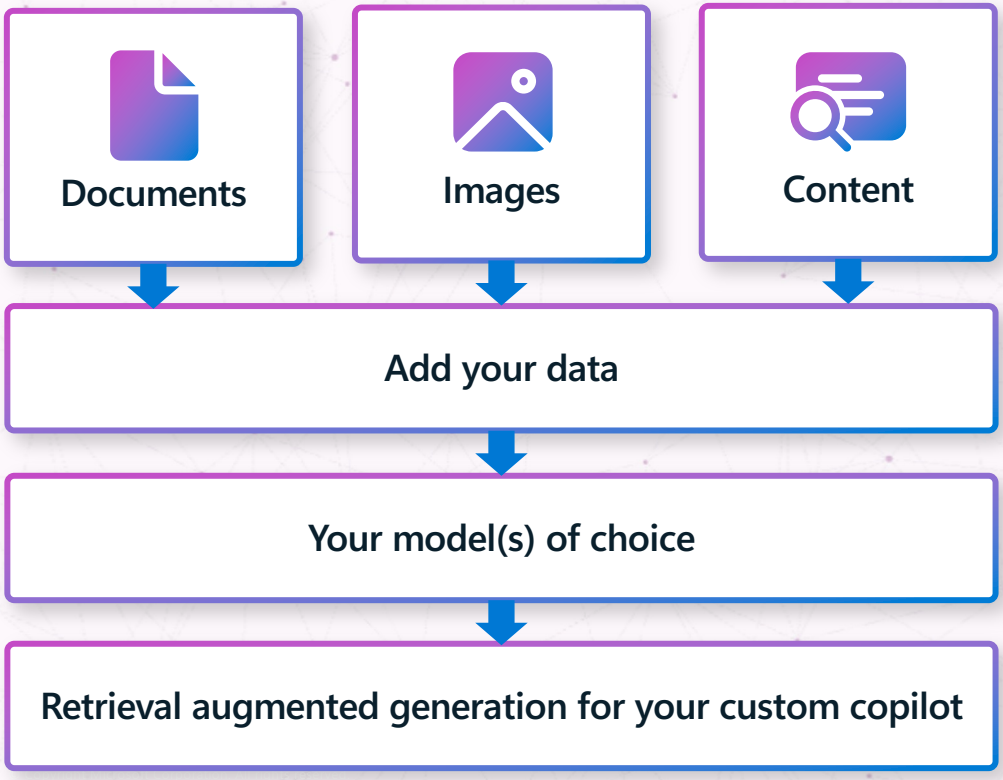
Retrieval augmented generation: bring your data to the prompt



Response

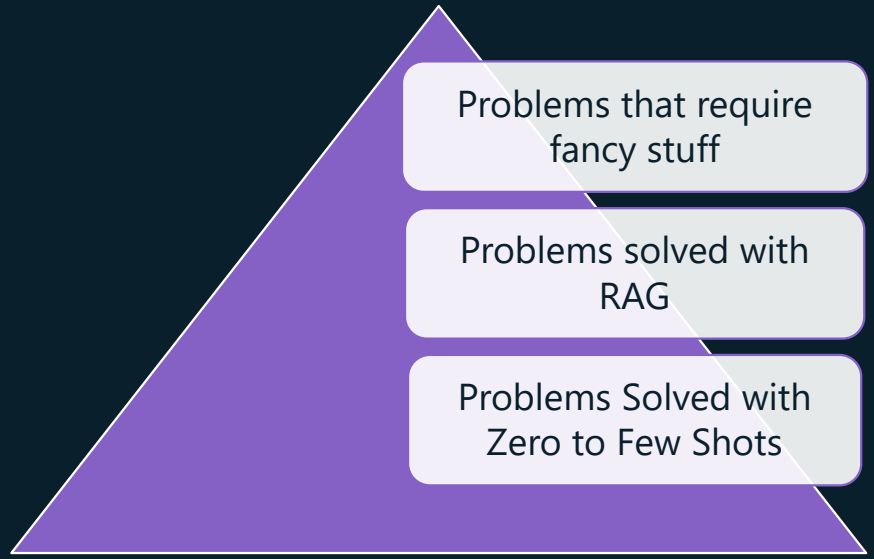
Based on the provided information, it can be determined that both health plans offered by Northwind Health Plus and Northwind Standard provide coverage for vision exams. Therefore, your health plan should cover annual eye exams.

Retrieval Augmented Generation



Why RAG?

- 80% of the customer use cases can be reduced to RAG
- RAG is the easiest way to give model “knowledge” beyond training data
- RAG is solving 2 problems:
  - Models are limited in context size (128k/256k)
  - Given very large context, models are getting confused and struggling to answer



Retrieval Augmented Generation

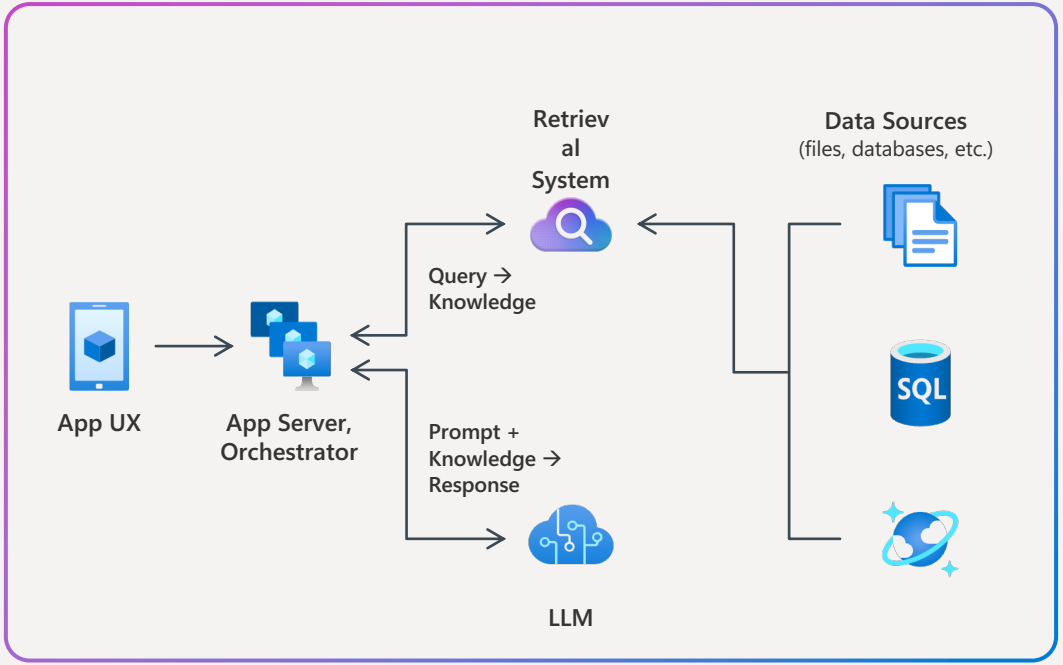
Combine reasoning + knowledge

Key elements

- Externalized knowledge
- Orchestrator drives interaction
- Prompts =
  instructions + context + grounding data

Achieving quality results

- Different workflows for different tasks
- Evaluation & RAI



Naïve RAG vs Advanced RAG

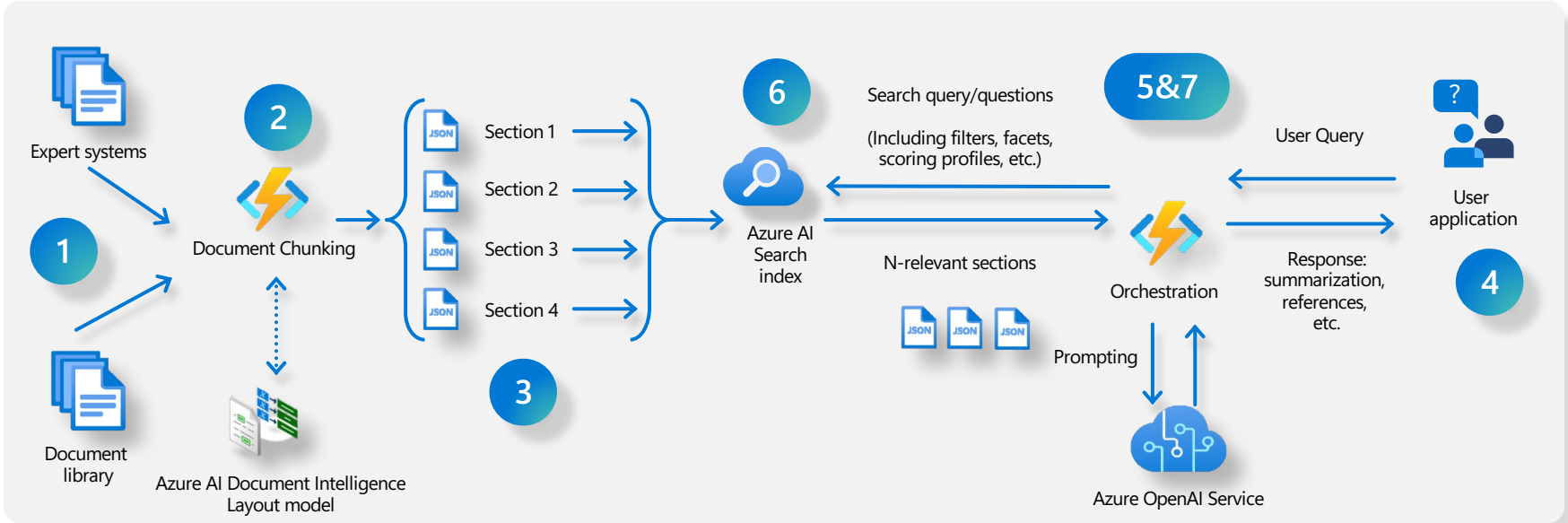
Naïve RAG

- Very little orchestration
- Unsophisticated query rewrites
- Straightforward retrieval
  - Vector
  - Hybrid
- One data source / document type
- One modality
- Simple filtering

Advanced RAG

- Complex orchestration (ReACT, Chain or Tree of Thought)
- Sophisticated query rewrites
  - Rephrasing, decomposition, step back, HyDe
- Complex retrieval / embedding
  - Small-to-big, hierarchical, reference etc.
- Knowledge Graphs
- Agentic RAG

Anatomy of RAG



1. Data ingestion	2. Chunking	3. Indexing	4. User interface	5. Orchestration	6. Data retrieving	7. Orchestration
Different data formats and system of records	What is the best Chunking strategy?	Shall I use vector embeddings data transformation, mappings?	Chatbot for Q&A surfaced to end users	Communication coordination and prompting— Prompt to get retriever query	Shall I use vector, semantic, keyword or hybrid approach?	Communication coordination: create user response based on retrieve data and send to User app

Azure OpenAI on your data

Connect or ingest your data

Ground Azure OpenAI models using your data

Retrieval augmented generation made easy

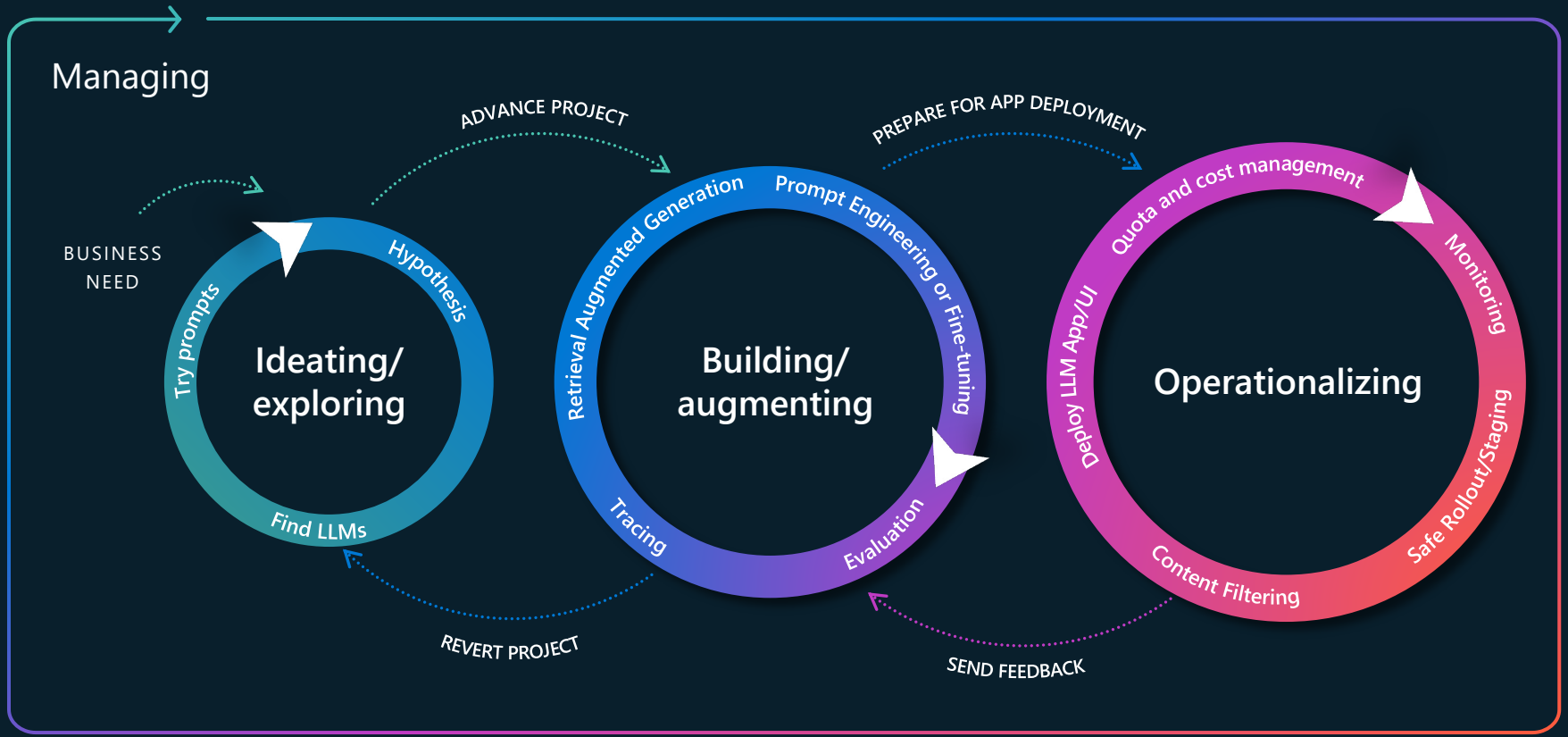
Restrict responses to your data

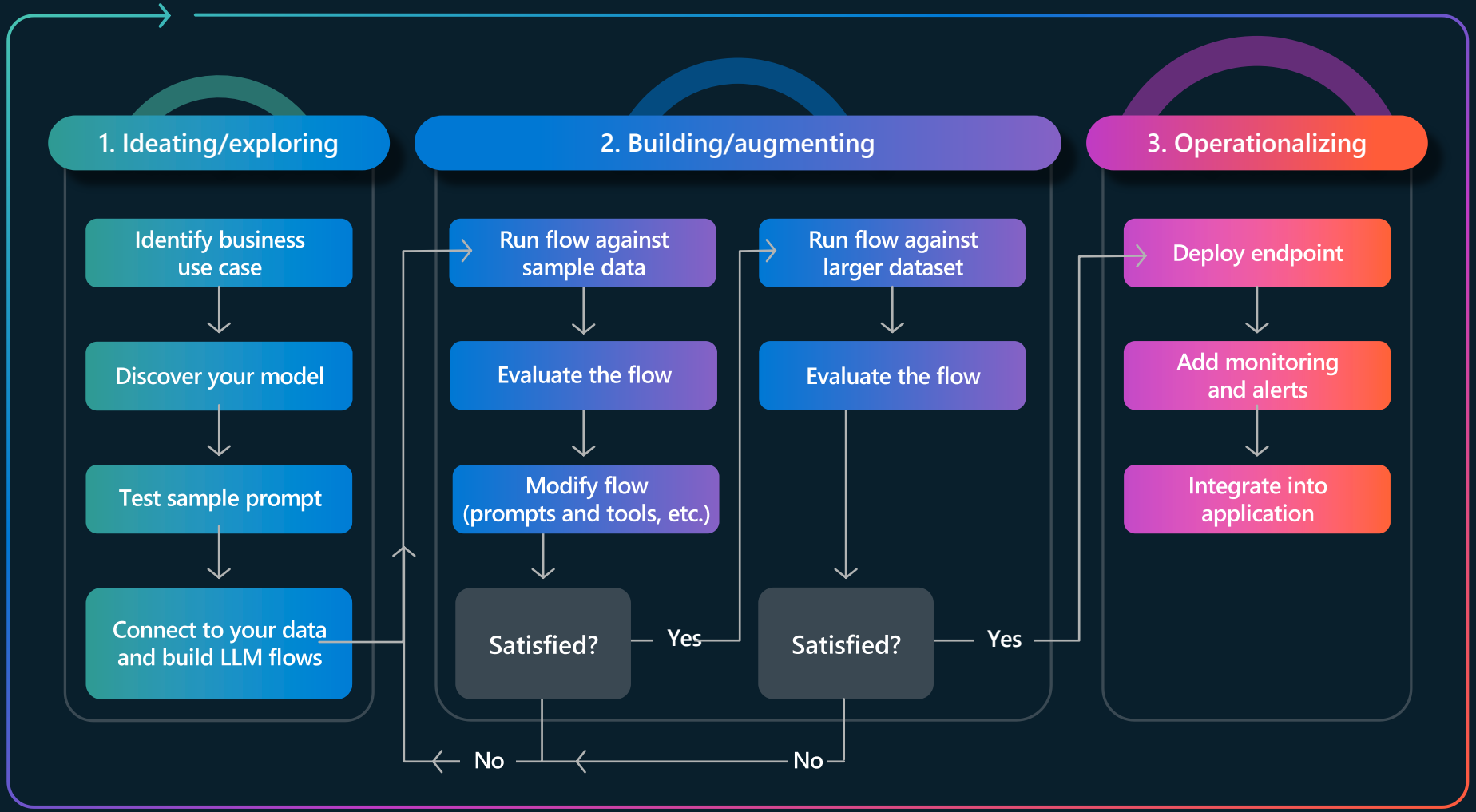
Enterprise grade security including private network, VPN, document level access control, etc.

Easy deployment as a copilot

Demo – Azure OpenAI “On your data”

GenAI Lifecycle in the real world




1. Ideating/exploring
Identify business use case
Discover your model
Test sample prompt
Connect to your data and build LLM flows
2. Building/augmenting
Run flow against sample data
Evaluate the flow
Modify flow (prompts and tools, etc.)
Satisfied?
Yes
No
Run flow against larger dataset
Evaluate the flow
Satisfied?
Yes
No
3. Operationalizing
Deploy endpoint
Add monitoring and alerts
Integrate into application

What can go wrong with Naïve RAG

- At node in the above 2 diagrams, things can go wrong

Low precision/Recall	Right data / wrong answer
Hallucinations / Irrelevant answers	Wrong data / Confident (wrong) answer
Outdated data / no data recency sorting	Fail to report information is missing

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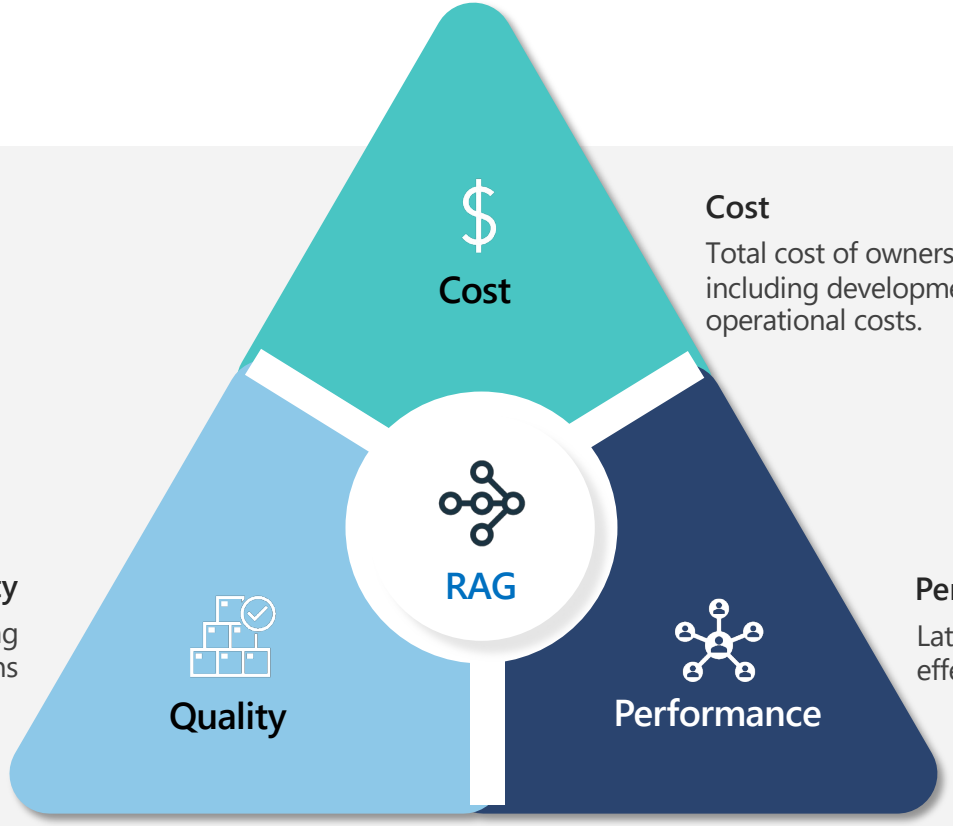
Optimization

is a Long Journey



Cost

Total cost of ownership including development and operational costs.

Quality

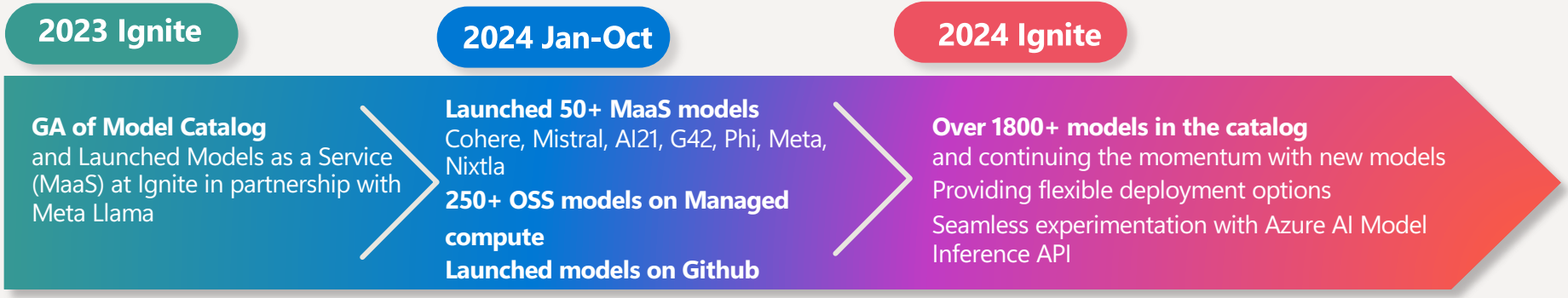
Meeting or exceeding customer expectations

Performance

Latency, efficiency and effectiveness

Step 1: prompt engineering

A year of rapid growth and innovation



Azure AI Model Catalog continues to evolve, providing a diverse range of AI models and unparalleled flexibility for enterprise use cases

Find the best model for every use case.

Avoid model lock-in:

- Flexible model selection
- Curated for enterprise
- Explore, Compare and Swap models quickly

Azure AI Model Catalog

LLMs and SLMs

Flagship LLMs
- GPT-4
- Mistral Large
- Llama3 70b
- Llama 405B
- Command R, R+

Small Language Models
- Phi3
- Mistral OSS models
- Llama3 8b
- Ministral

Modalities, tasks and tools

Multi-modal
- GPT-4o, Phi3-vision

Image generation
- Dalle3, Stability AI

Embedding models
- Ada, Cohere

- Function calling & JSON support

Regional and domain specific

- Core42 JAIS Arabic language LLM
- Mistral Large is focused on European languages
- Nixtla TimeGEN-1 - Timeseries forecasting

Open and propriety

Premium models first on Azure: OpenAI, Mistral Large, Cohere Command R+

100s of Open models from HuggingFace

Open models from Meta, Databricks and Snowflake, Nvidia

Microsoft Phi · Azure OpenAI · Mistral AI · Meta AI · Databricks · Cohere · Hugging Face · NVIDIA · Deci AI · Nixtla · G42 · Snowflake

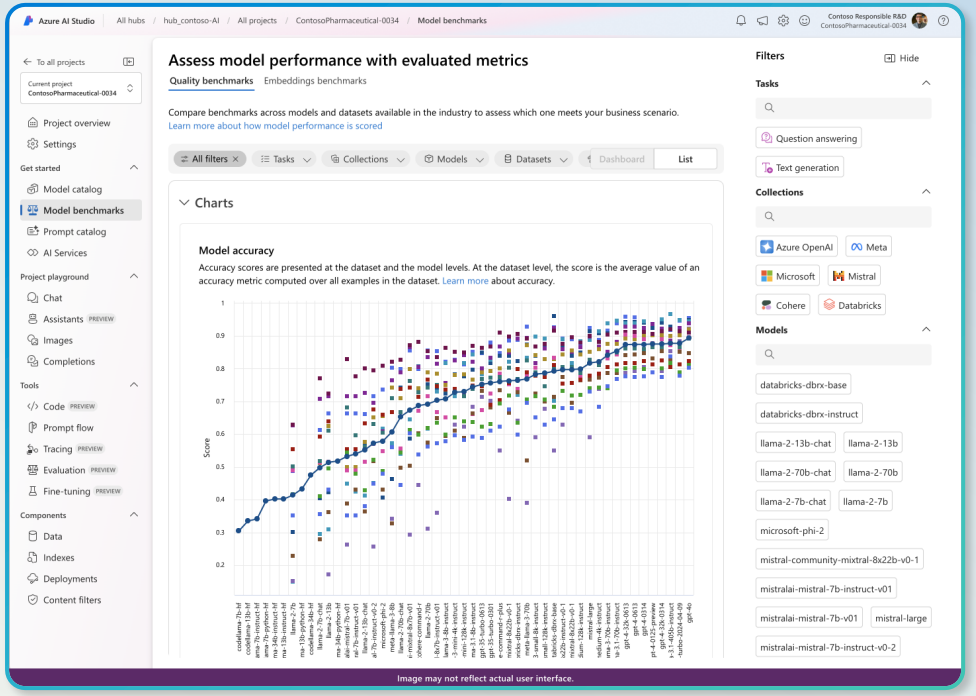
Model benchmarking

Model Benchmarking enables you to review and compare the performance of various AI models, simplifying the selection process and allowing users to make confident choices with their modeling needs.

- Gain quality metrics for Azure OpenAI Service, Llama 2 family, Code Llama, and Mistral models
- Access pre-built metrics and benchmark comparison models within the same build, train, deploy environment
- Compute accuracy scores at both the task (dataset) and model levels by utilizing public datasets, yielding a model score for each dataset
- Compare scores of multiple models across datasets and tasks
- Benchmark results originate from public datasets; Azure AI evaluation pipelines download data from original sources, extract prompts from each row, generate model responses, and then compute relevant accuracy metrics

OSS version:Chatbot Arena

API and model choice



Enable the comparison of models based on accuracy and empower users to make data-driven decisions, ensuring their AI solutions are optimized for the best performance.

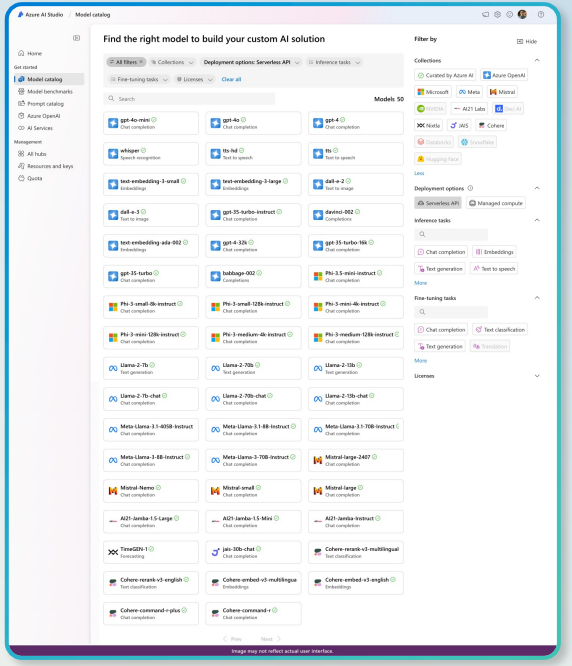
Models as a Service (MaaS)

Offering within the model catalog

Models as a Service (MaaS) lets you fine-tune models without provisioning compute, making it easier for generative AI developers to build custom copilots.

- Ready-to-use APIs with pay-as-you-go billing based on tokens
- Customize models with your own data without the need to set up and manage GPU infrastructure
- Easily integrate the latest AI models as an API endpoint to applications
- Integrate with preferred orchestration tools like prompt flow, Semantic Kernel, or LangChain
- Achieve serverless fine-tuning without provisioning GPUs
- Fine-tune Llama 2 with your own data to enhance the model's ability to generate more precises predictions

API and model choice



MaaS provides simplified management with ready-to-use GPU provisioning, lowering costs and reducing barriers to adoption by eliminating complexity.

Walkthrough – Azure AI foundry Model Catalogue

LiteLLM.ai

https://docs.litellm.ai/docs/

LiteLLM - Getting Started

LiteLLM - Getting Started

https://github.com/BerriAI/litellm

Call 100+ LLMs using the OpenAI Input/Output Format

- Translate inputs to provider's `completion`, `embedding`, and `image_generation` endpoints
- Consistent output, text responses will always be available at `['choices'][0]['message']['content']`
- Retry/fallback logic across multiple deployments (e.g. Azure/OpenAI) - Router
- Track spend & set budgets per project LiteLLM Proxy Server

How to use LiteLLM

You can use litellm through either:

1. LiteLLM Proxy Server - Server (LLM Gateway) to call 100+ LLMs, load balance, cost tracking across projects
2. LiteLLM python SDK - Python Client to call 100+ LLMs, load balance, cost tracking

When to use LiteLLM Proxy Server (LLM Gateway)

> **TIP**
>
> Use LiteLLM Proxy Server if you want a **central service (LLM Gateway) to access multiple LLMs**
>
> Typically used by Gen AI Enablement / ML PLatform Teams

- LiteLLM Proxy gives you a unified interface to access multiple LLMs (100+ LLMs)
- Track LLM Usage and setup guardrails
- Customize Logging, Guardrails, Caching per project

When to use LiteLLM Python SDK

> **TIP**
>
> Use LiteLLM Python SDK if you want to use LiteLLM in your **python code**
>
> Typically used by developers building llm projects

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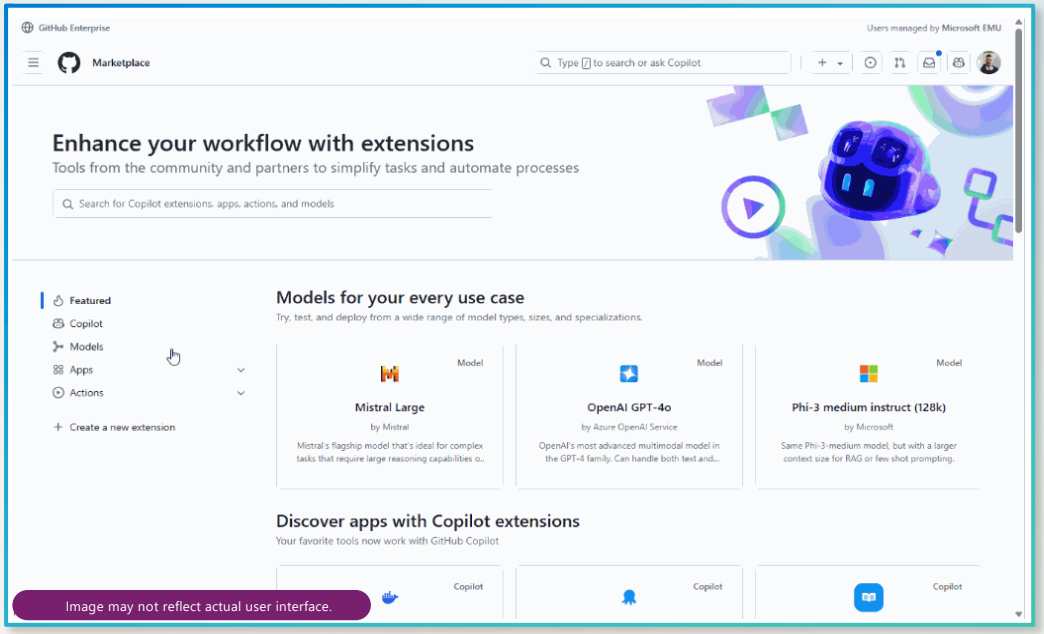
GPT model impact on TCO

Model	Context	Cost per 1,000 tokens		Cost Comparision (1M tokens)		
		Input	Output	Input (20%)	Output (80%)	Total
GPT-4o-2024-08-06 Global Deployment	128K	$0.003	$0.010	$0.50	$8.00	$8.50
GPT-4o Global Deployment	128K	$0.005	$0.015	$1.00	$12.00	$13.00
GPT-4o-mini Global Deployment	128K	$0.00015	$0.0006	$0.03	$0.48	$0.51
GPT-4	32K	$0.03	$0.06	$6.00	$48.00	$54.00
GPT-4	8K	$0.06	$0.12	$12.00	$96.00	$108.00
GPT-3.5-Turbo-0125	16K	$0.0005	$0.0015	$0.10	$1.20	$1.30
GPT-3.5-Turbo-Instruct	4K	$0.0015	$0.002	$0.30	$1.60	$1.90
GPT-3.5-Turbo-0613	16K	$0.003	$0.004	$0.60	$3.20	$3.80
GPT-3.5-Turbo-1106	16K	$0.001	$0.002	$0.20	$1.60	$1.80



Discover in GitHub Models

https://github.com/marketplace/models

Empowering GitHub Developers to Build with AI

- Get access to a curated list of our top AI models, without leaving GitHub
- Mix, match, and experiment with models in the GitHub playground for free*
- Unlock the full capabilities of the latest models with Azure

*Usage limits apply

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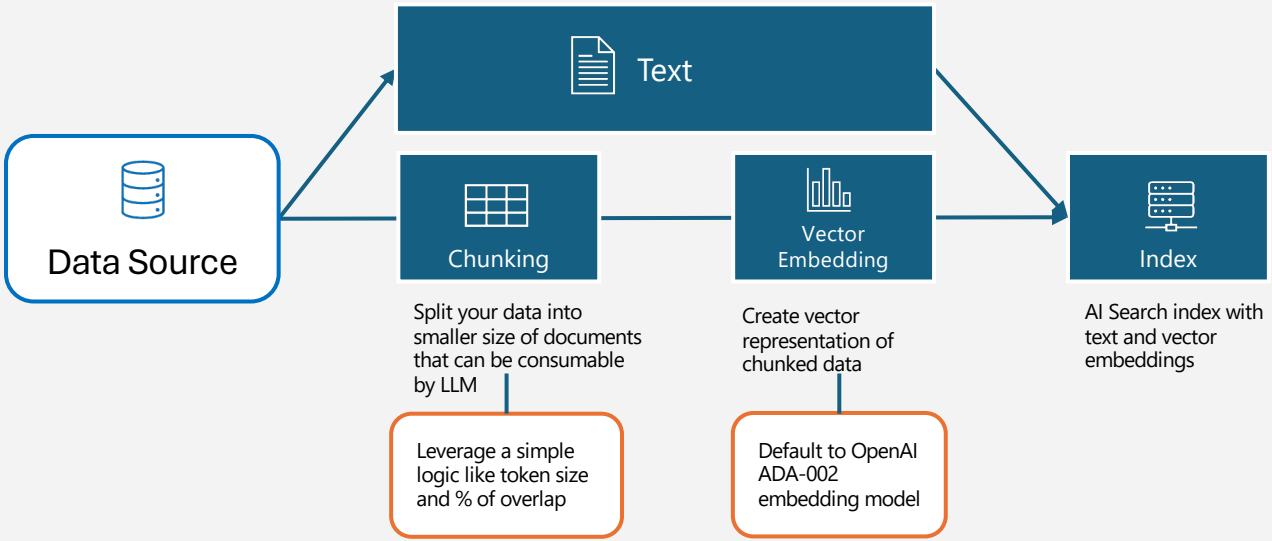
Data Ingestion

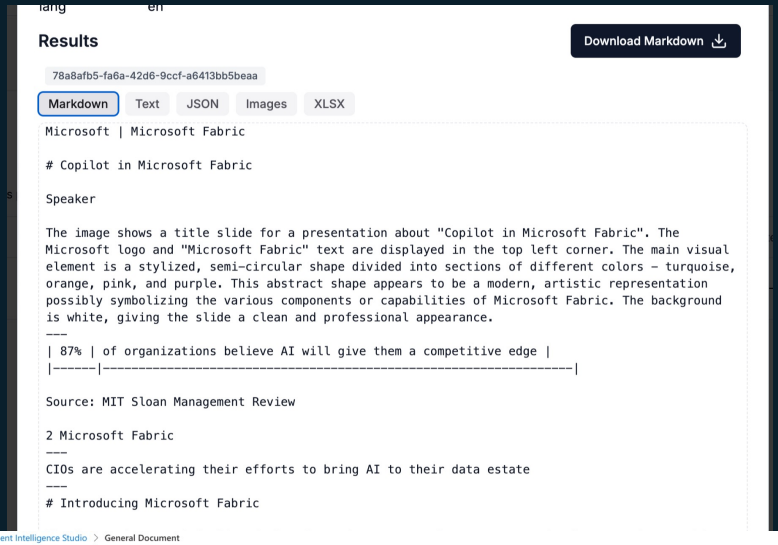
Prepare your data for chat experience

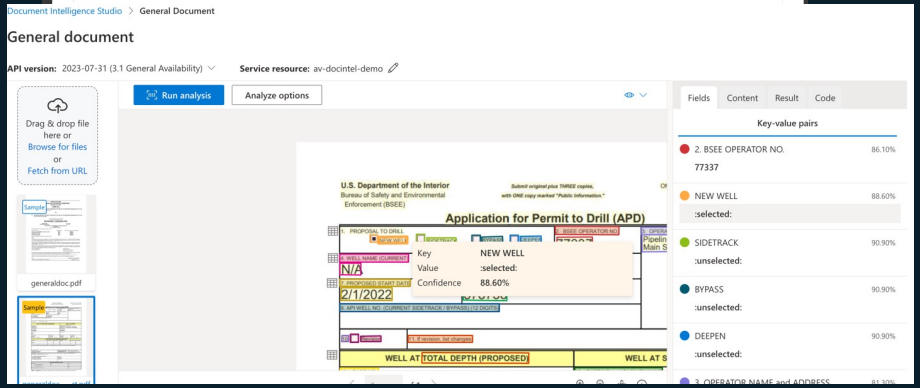


- Index text representation of your data / documents
- Basic index schema, expecting vector representatives to be enough for high accuracy retrieval.

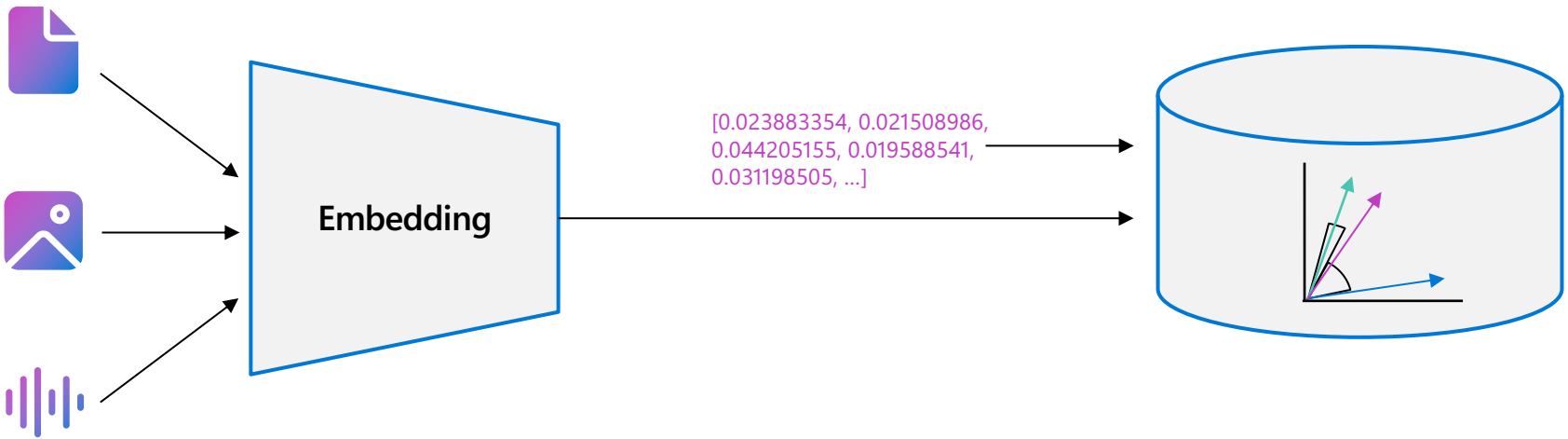
Document parsing

- Azure Document Intelligence
- LLamaParse
- Document loaders
  - Python / langchain / llamaindex etc
- Azure AI services for multi-modal
- Azure Content Understanding



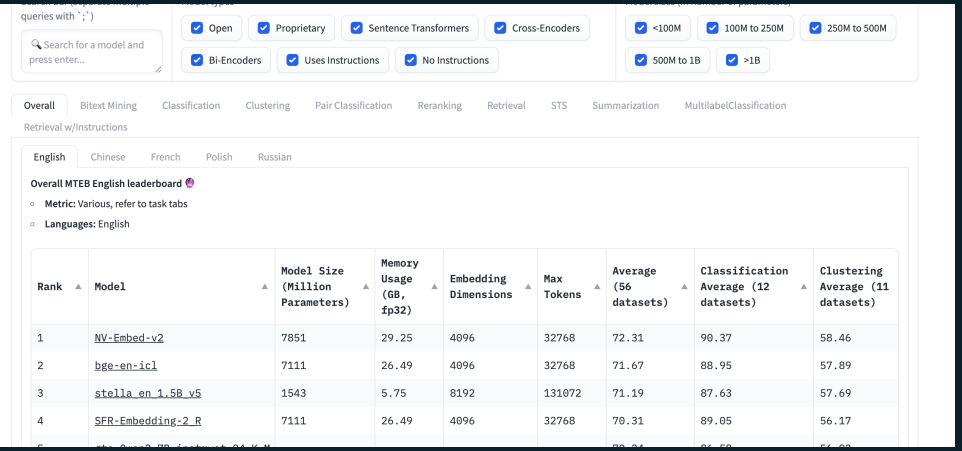


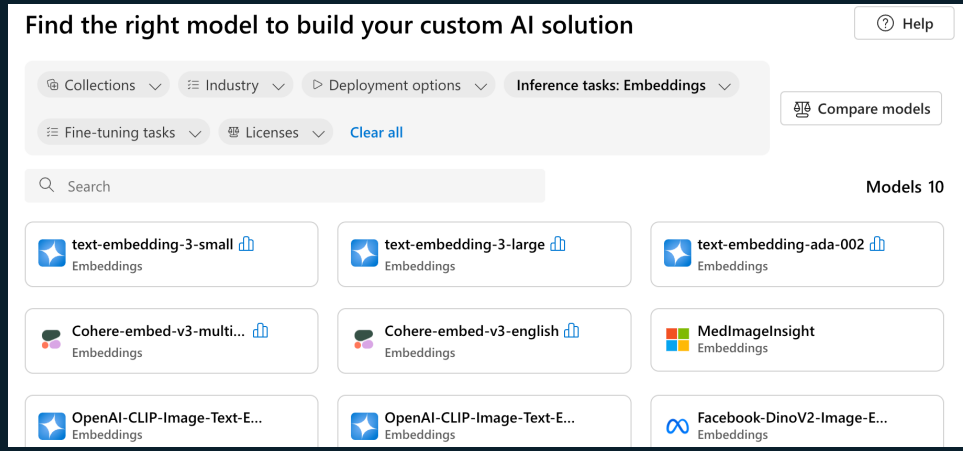
How embeddings work



Find the most relevant information in large datasets using hybrid search with keywords, vectors, and semantic ranker

LLMs for embeddings





https://huggingface.co/spaces/mteb/leaderboard

Integrated Vectorization

End-to-end data ingestion, chunking, vectorization, and advanced retrieval

Chunking

- Built-in Chunking skill (updates to split skill) and updates to index to manage Chunks vs. full documents
- Configure Chunking parameters (e.g., **pages,** overlap window, etc.)
- Automated via Indexer orchestration

Vectorization

- Bring-your-own Azure OpenAI endpoint
- Bring-your-own Azure AI Studio model catalog embedding model (Preview)
- Use AI Vision multimodal embeddings model deployed in AI multi-service account (Preview)
- Support for other embedding model REST endpoints
- Query Vectorization capability

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Your document Chunking strategy matters

Chunking solves context length problems and improves retrieval accuracy

1. Fixed Sizes
2. Overlapped chunking
3. Semantic
4. Percentile
5. Interquartile chunking
6. ...

Retrieval Configuration	Single vector per document *[Recall@50]*	Chunked documents *[Recall@50]*
Queries whose answer is in long documents	28.2	**45.7**
Queries whose answer is deep into a document	28.7	**51.4**

Chunk boundary strategy	Recall@50
512 tokens, break at token boundary	40.9
512 tokens, preserve sentence boundaries	42.4
512 tokens with 10% overlapping chunks	43.1
512 tokens with 25% overlapping chunks	**43.9**

Retrieval Configuration	Recall@50
512 input tokens per vector	**42.4**
1024 input tokens per vector	37.5
4096 input tokens per vector	36.4
8191 input tokens per vector	34.9

Advanced Chunking strategies

Chunking methods

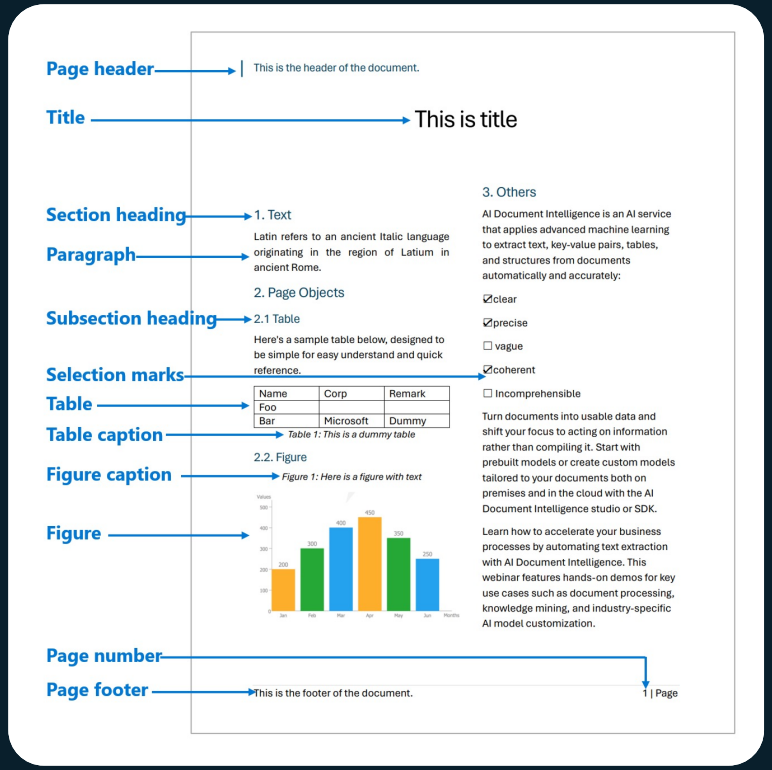
Fixed-size Chunking	Simple and common, maintaining a balance between overlap and semantic context	→ AI Search Built-in Split Skill
Specialized Chunking	For structured content like Markdown and LaTeX	→ AI Search Custom Skill
“Content-aware” Chunking	Content splitting using NLP libraries such as AI Document Intelligence Layout API	
Recursive Chunking	Divides text into smaller Chunks in a hierarchical manner	

Determining the best Chunk size

- Preprocessing data for quality
- Selecting a range of potential Chunk sizes considering content nature and embedding model capabilities
- Evaluating performance of each Chunk size

🔗 Tech blog with suggested Chunking sizes depending on scenario

Indexing-Side Improvements: Structure-Aware Chunking

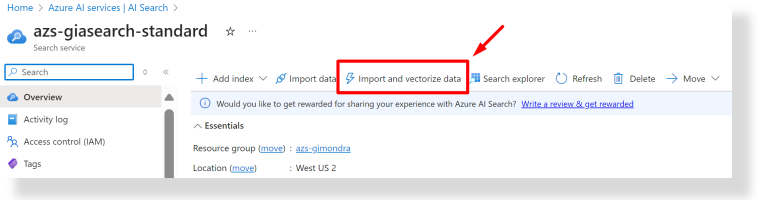


→ Azure AI Search now supports both fixed and content aware chunking

- Powered by Azure AI Document Intelligence
- Headings help understand content hierarchy
- Handles tables, lists, figures, etc.

→ new markdown parsing mode for fast and simple heading handling

Indexing (Pull indexers)



Indexer (pull model)

- Crawler that extracts data from cloud data sources and populates a search index
- Drive skillset execution (AI enrichment)
- Can be run on demand or on a recurring data refresh schedule (incremental indexing)

Best practices

- Understand indexing limits
- Run on a schedule and continuously to correct errors
- Identify data source needs (multiple data sources going to a single index, data source support, limits and configuration
- Configure data source document deletion policy if needed
- Recognize data types for proper parsing (JSON, JSON lines, CSV, etc.)
- If handling PDFs or images with embedded text, consider AI enrichment with OCR or Azure AI Document Intelligence
- Configure batch size based on workload
- Consider integrated Vectorization if using vector search
- Identify AI enrichment needs, such as language translation or recognition, key phrase extraction, etc.
- Test with various data types/sizes to understand indexing time and optimize the process
- Identify type of authentication being used (Managed identity is recommended)
- Recognize if private endpoints will be used for secure connections and configure shared private links appropriately

🔗 Indexing example with Integrated Vectorization

Indexing (Push method)

- Push method uses APIs to upload documents into a search index
- No restrictions on data source type or frequency of execution
- Connectivity and the secure retrieval of documents under your control

Key benefits

Versatility: JSON documents from any source can be uploaded. You can use AI Document Intelligence for data parsing or your preferred parsing library
Flexibility: No restrictions on frequency of data push (no specific schedule, just API restrictions apply)
Control: Retrieval of documents under your own control

Pushing data to Azure AI Search index

- APIs for single or multiple documents upload
- Follow best practices for indexing large documents

Indexing actions

Upload: Insert new documents or update existing ones
Merge: Updates existing document, replacing values
Merge or upload: Behaves like merge for existing documents and like upload for new ones
Delete: Removes entire document from index

🔗 Push method sample for RAG

Demo: Push indexing from Doc Intel

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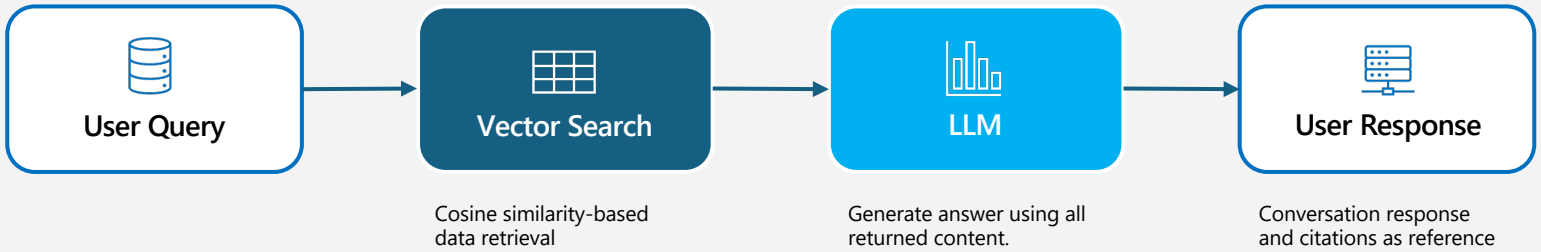
RAG – Data retrieval

Respond user query in conversational chat experience



- Relying on “vector search” for all queries
- Quick and simple “Hello World” implementation

Retrieval strategies

Keyword search

- **For exact, plain text matches**
- "Vocabulary gap" in Q&A systems like Copilot

Vector search

- **For conceptual similarity, or underlying meaning**
- Weak performance on exact matches (like a product ID or code)

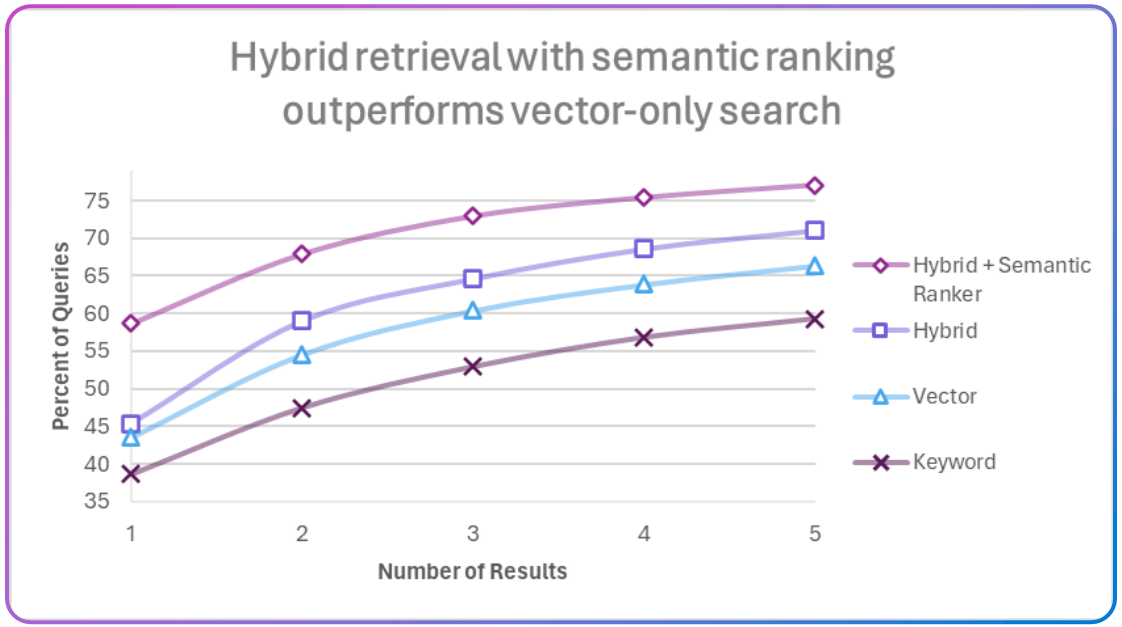
Hybrid search

- **Best of both vectors and keyword**
- Brings more accurate responses across various scenarios

Search re-ranking

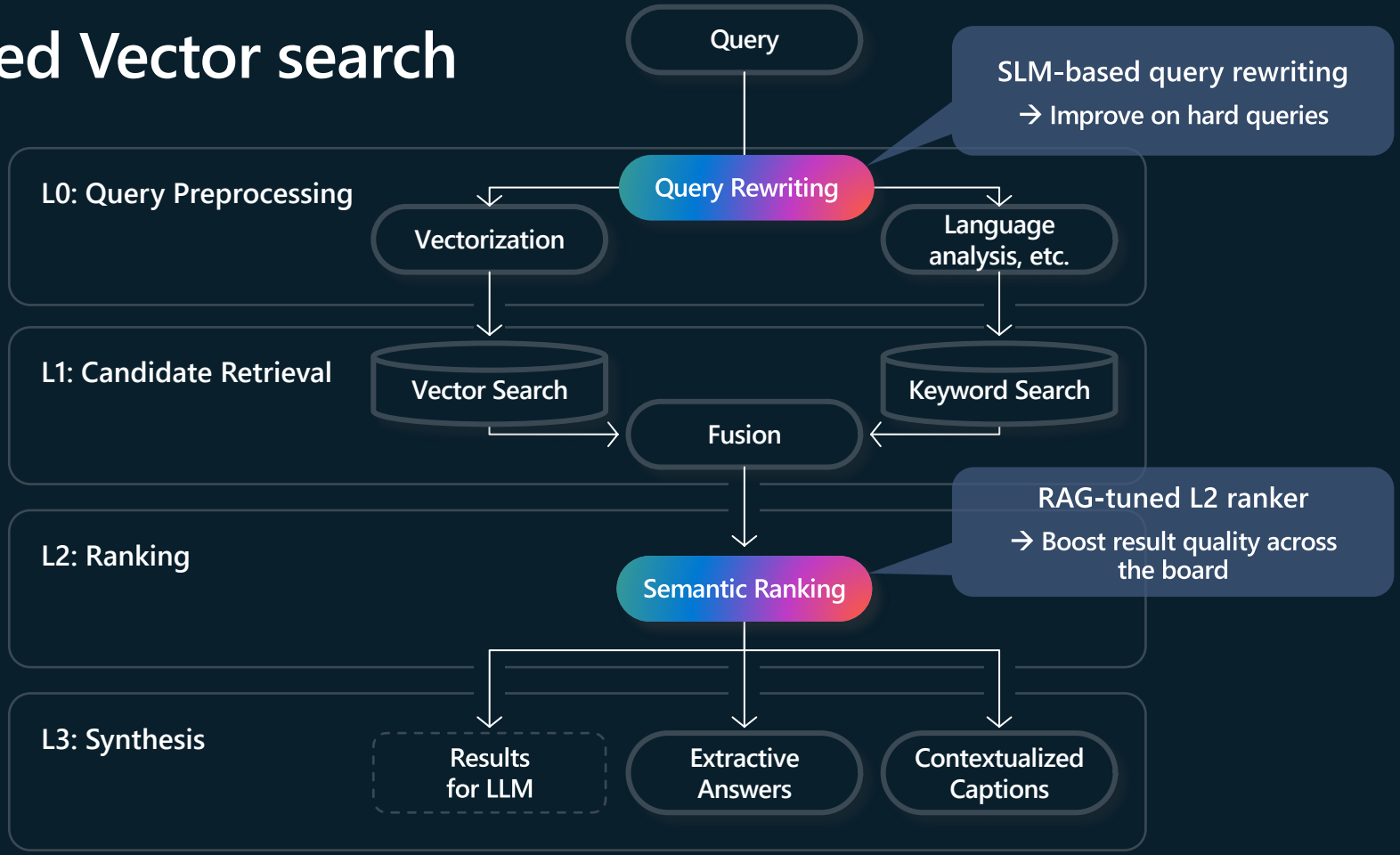
- **Scores and ranks all retrieved documents by relevance**
- Reranking runs after performing search strategy (can't retrieve information)

Retrieve using semantic similarity and hybrid search



Find the most relevant information in large datasets using hybrid search with keywords, vectors, and semantic ranker

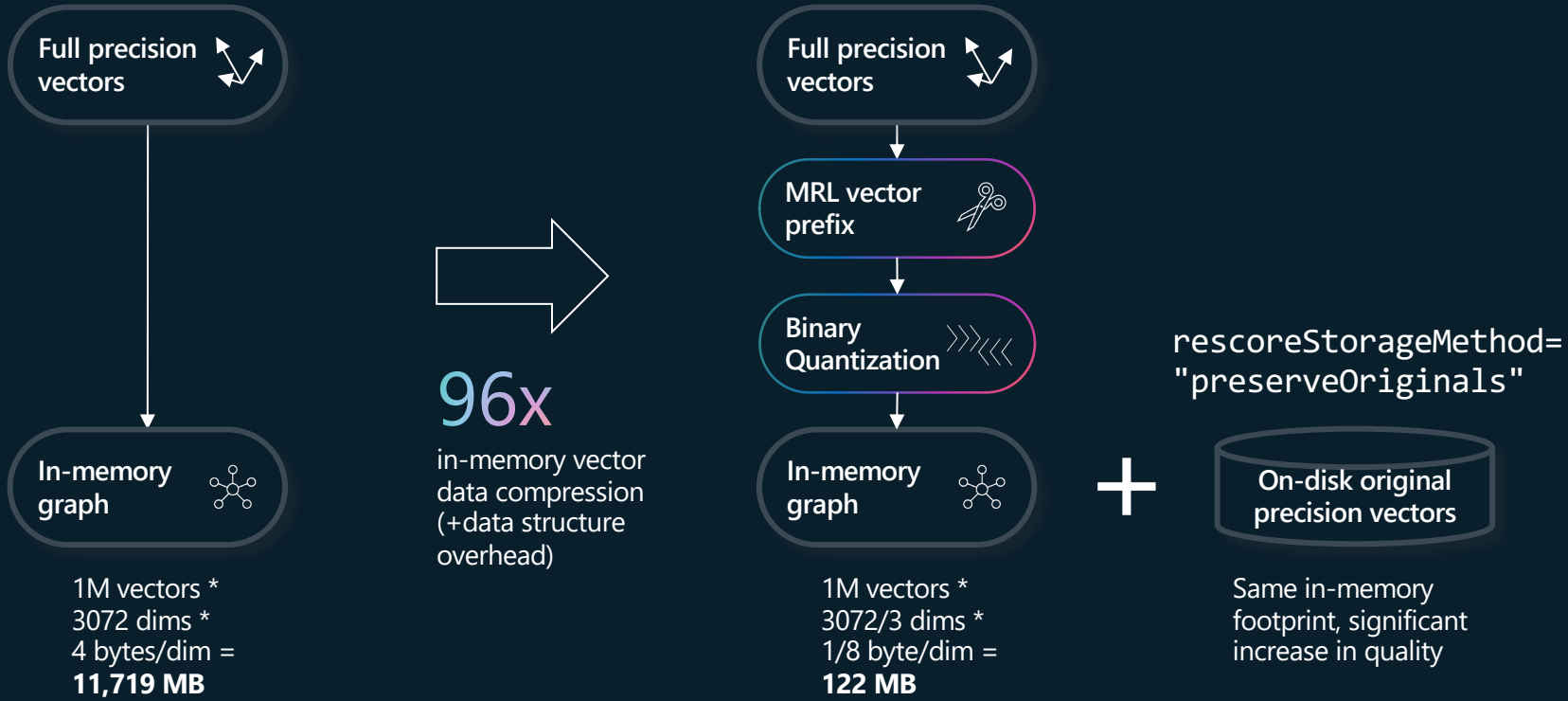
Advanced Vector search



AI Search Ignite announcements 2024

Vector Compression:
Cost-effective retrieval at all data scales

For example, for 1 million vectors, using OpenAI's text-embedding-003-large (3072 dims)



Powering RAG in GitHub Models

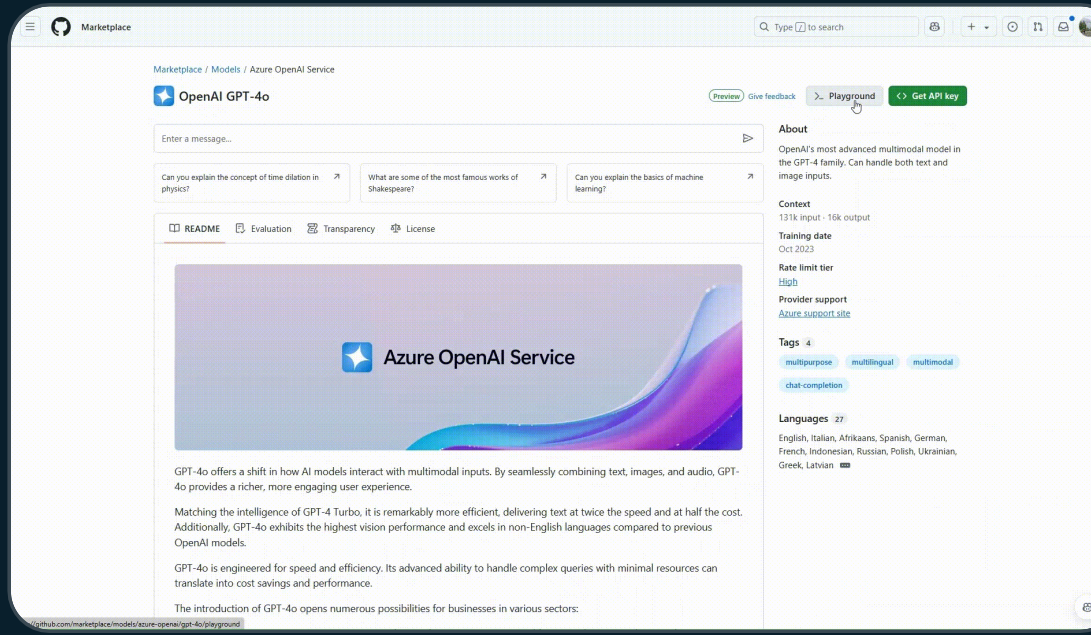
aka.ms/rag-in-github-signup

Easy access glide path from playground to IDE

Free AI Search service created automatically, without having to switch screens

Full-featured retrieval: use hybrid search, reranking, query rewriting

From code, test out and modify various features



Summary – Retrievers

- If you want turnkey advanced solution – AI Search
- If you want to keep vectors where your data is, avoid data duplication and ingestion costs – Cosmos, PostgreSQL, MongoDB, Databricks

Choosing an orchestrator

Options

- 1st party
  - Promptflow / Prompty
  - Semantic Kernel
- LangChain
- LlamaIndex
- Haystack

Considerations

- Deployment simplicity and options
- Commercial vs. OSS features
- Integrations (Loaders, Vector Stores)
- Prompt templates / libraries
- Orchestration features (chains, pipelines), streaming, async
- Evaluation features
- CI/CD, LLMOps
- Agentic features

PromptFlow can be used in combination with other orchestrators

AI Foundry tooling

Bringing your AI apps to production

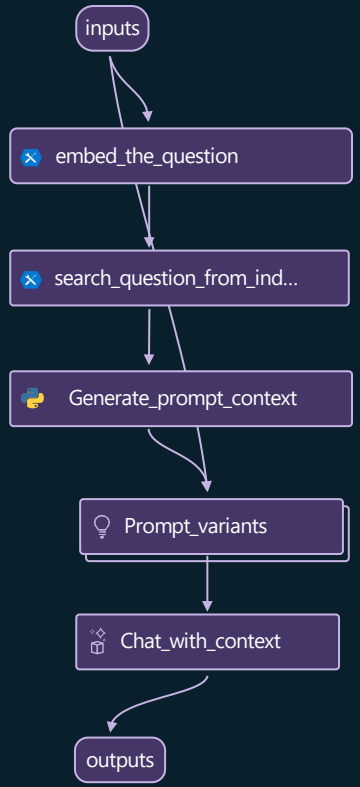
Getting started		Customization		Experimentation		Production		
Resource Set-up	Playground	RAG	Fine-tuning	Prompt Management	Evaluation / Debugging	Orchestration	Automation	Monitoring
AZD AI Template	Chat Playground	Azure AI Search Microsoft Fabric	Serverless Fine-tuning Azure AI Agents	Prompty Azure AI Foundry	Tracing Azure AI Content Safety Evaluators	Prompt flow LangChain Semantic Kernel	GitHub Actions	Azure Monitor Application Insights

Templates & SDK Support	AZD AI template, Azure AI Foundry SDK
Development Resources	Visual Studio Code
Gen AI Observability	Aspire, Prompty Trace Viewer, Azure Monitor

RAG with Azure AI prompt flow

Leverage your own data for generating responses

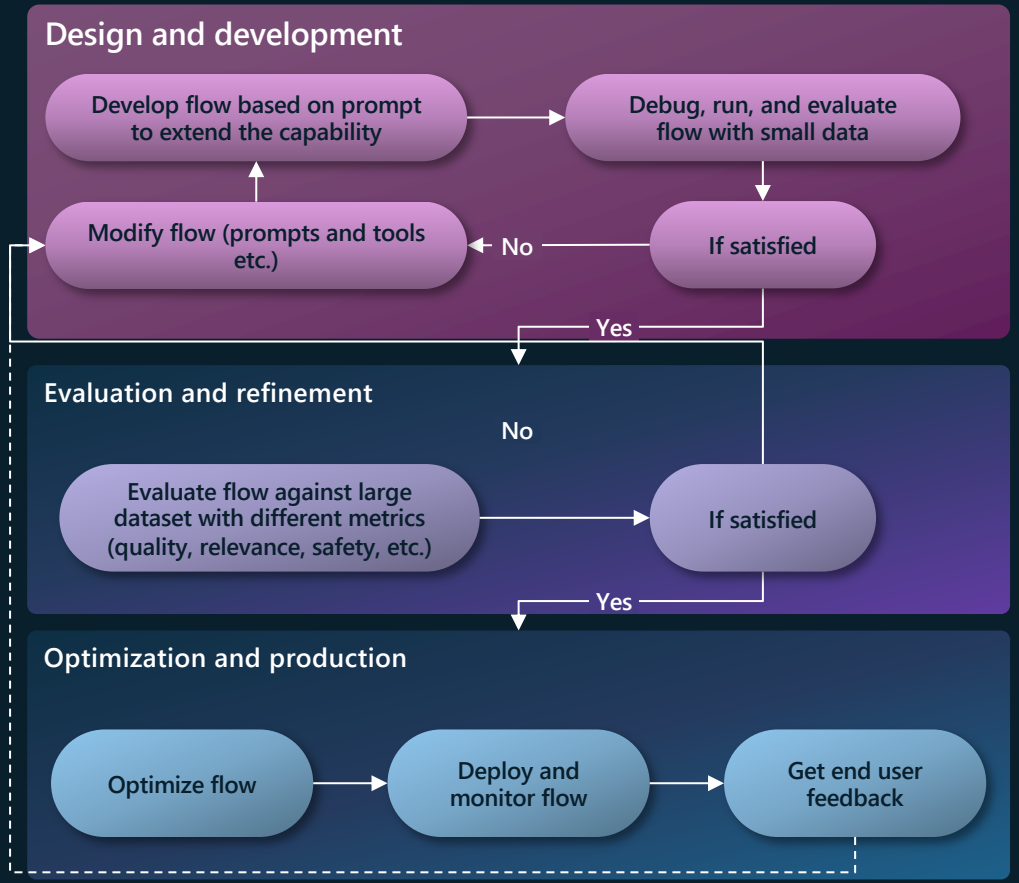
1. **Data Chunking**: Your source data needs to be converted to plain text and chunked into smaller pieces.
2. **Vectorization**: The text chunks are converted into vectors, also known as embeddings.
3. **Data Storage**: These vectors are stored efficiently, often with metadata, to assist in generating responses.
4. **Integration**: Azure AI integrates with Azure OpenAI Service for large language models and supports Azure AI Search as vector stores.
5. **Customization and Monitoring**: Azure AI offers a wizard-based UI for managing data and prompt flows, and also allows for the measurement and enhancement of RAG workflows.
6. **Security:** RAG workflows can be used with private networks in Azure Machine Learning to secure user's data.



Operationalize LLM app development with prompt flow

LLMOps is a complex process. Customers want:

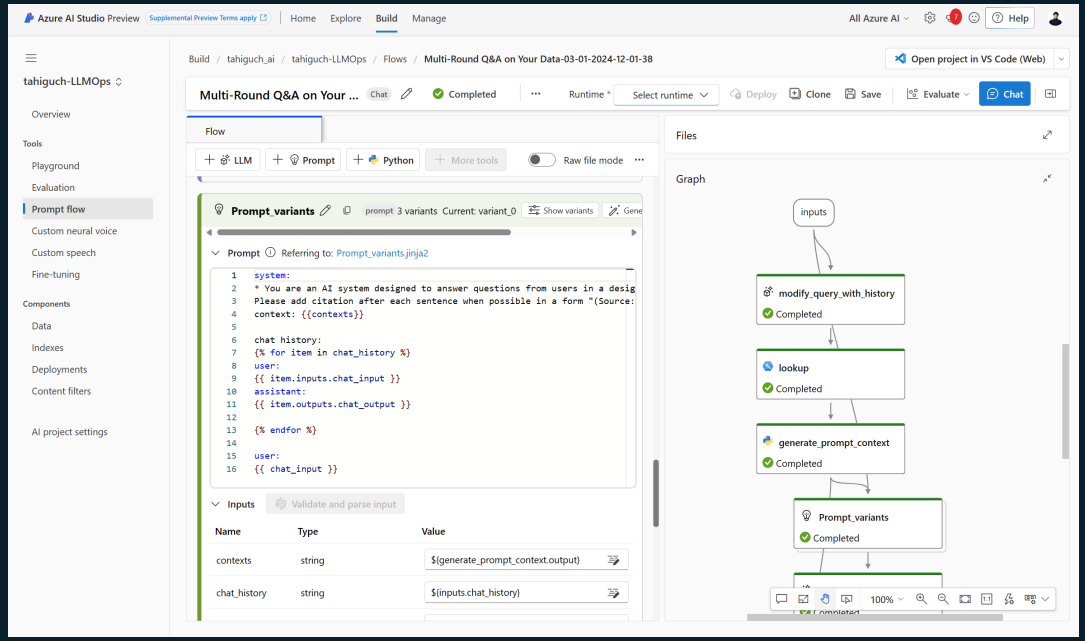
- Private data access and controls
- Prompt engineering
- CI/CD
- Iterative experimentation
- Versioning and reproducibility
- Deployment and optimization
- Safe and Responsible AI



Azure AI prompt flow

Capabilities Overview

- Manage connections
  - Develop and manage flows that connect to a variety of foundation models, vector databases, APIs, prompts and Python tools.
- Test and evaluate
  - Test flows with large datasets in parallel
  - Evaluate the AI quality and safety of the workflows
- Tracing and debugging
  - Gain insights into every step of LLM workflow
  - Identify and resolve performance bottlenecks
- Manage prompts
  - Easily tune prompts with variants and versions
  - Share prompts as an asset across teams
- Compare and deploy
  - Visually compare across experiments
  - One-click deploy to a managed endpoint for rapid integration



Prompty as a language-agnostic prompt asset

Prompty is intended to be a language agnostic asset class for creating prompts and managing the responses.

The goal is to simplify your workflow by creating a standard that can be used by any language, any framework, and any tool to create a prompt and manage the response.

Prompty can be imported to/exported from Azure AI Studio for smooth transition between local and cloud. Prompty assets can be also shared across organizations.

```
---
name: Basic Prompt
description: A basic prompt that uses the GPT-3 chat API to answer questions
authors:
  - sethjuarez
  - jietong
model:
  api: chat
  configuration:
    azure_deployment: gpt-35-turbo
sample:
  firstName: Jane
  lastName: Doe
  question: What is the meaning of life?
---
system:
You are an AI assistant who helps people find information.
As the assistant, you answer questions briefly, succinctly,
and in a personable manner using markdown and even add some
personal flair with appropriate emojis.

# Customer
You are helping {{firstName}} {{lastName}} to find answers to their questions.
Use their name to address them in your responses.

user:
{{question}}
```

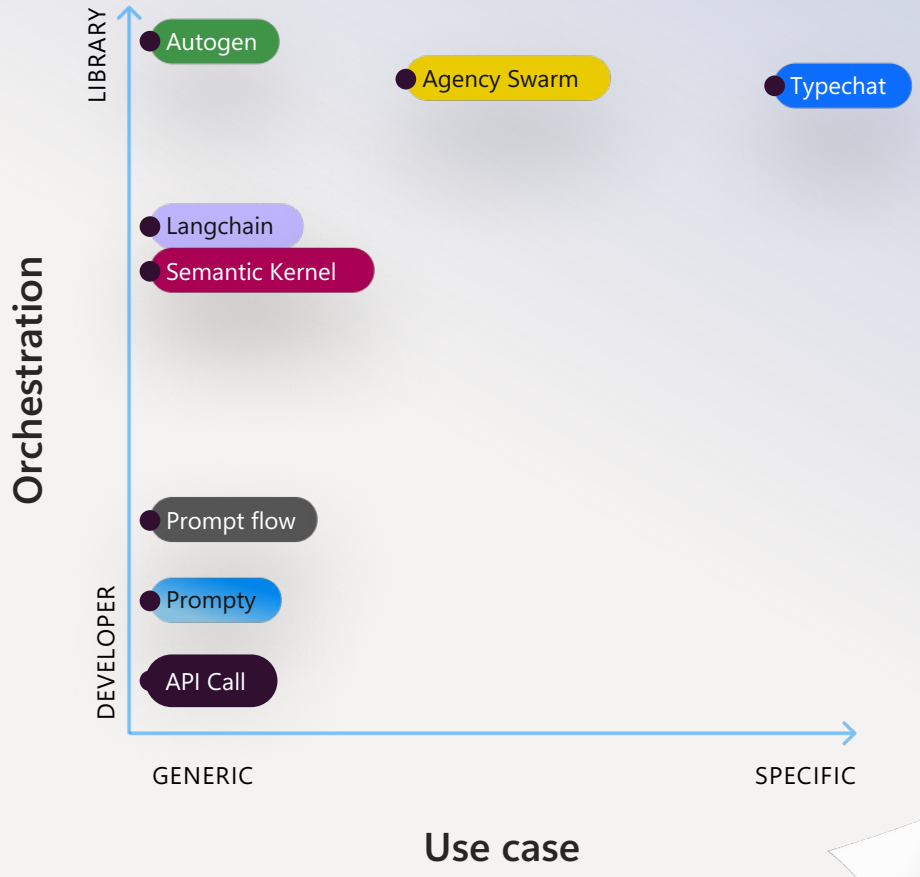
Where does prompty fit?

The prompty asset represents a single LLM call. It is a “micro” orchestrator that:

1. Renders—injects inputs into the template
2. Parses—converts the template into the shape the LLM requires
3. Executes—executes the LLM call
4. Processes—post-processes the LLM response

Required runtime methods: load, execute, trace

Samples: aka.ms/azd-ai-templates



Code-first GenAIOps with developer tools

Use code to define flow

- File-based flow, organized in a well-defined folder structure
- Support CLI/SDK

Smooth transition between cloud and local

- Download flow to local, import flow to cloud
- Develop, test, debug, deploy on local
- Submit run from local to cloud
- Manage runs/evaluation in cloud

Integrate with OSS frameworks

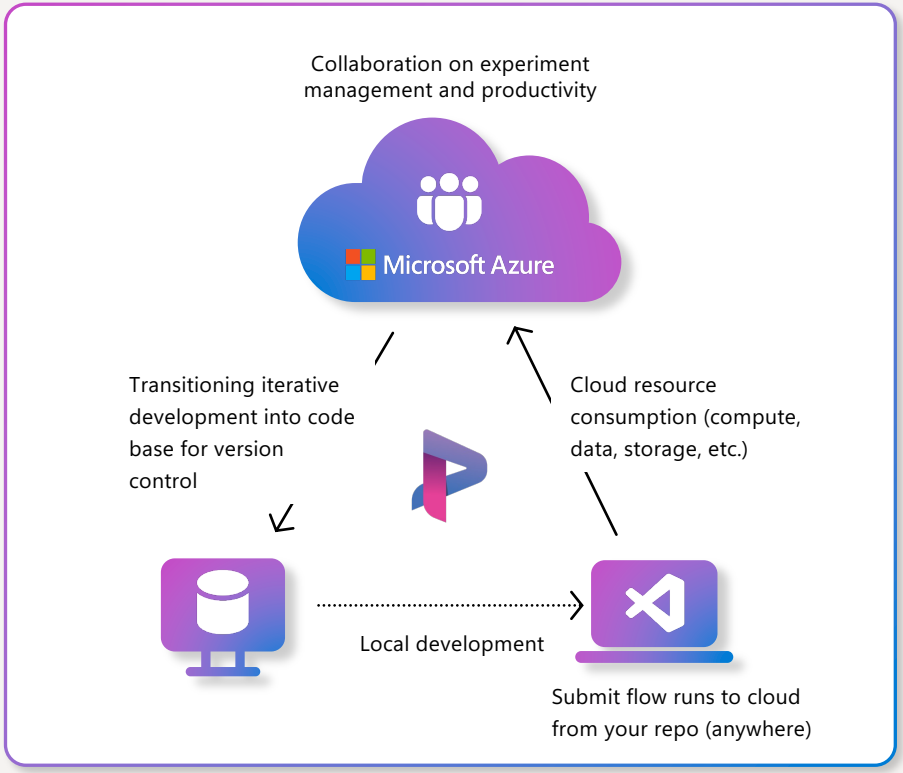
- LangChain, Semantic Kernel, AutoGen

Automate with CI/CD pipelines

- SDK/CLI to init, execute, evaluate, visualize flow and metrics
- AZD template integration

Local development with VS Code Extension

- Flow editor
- Local connection management
- Tracing and run history



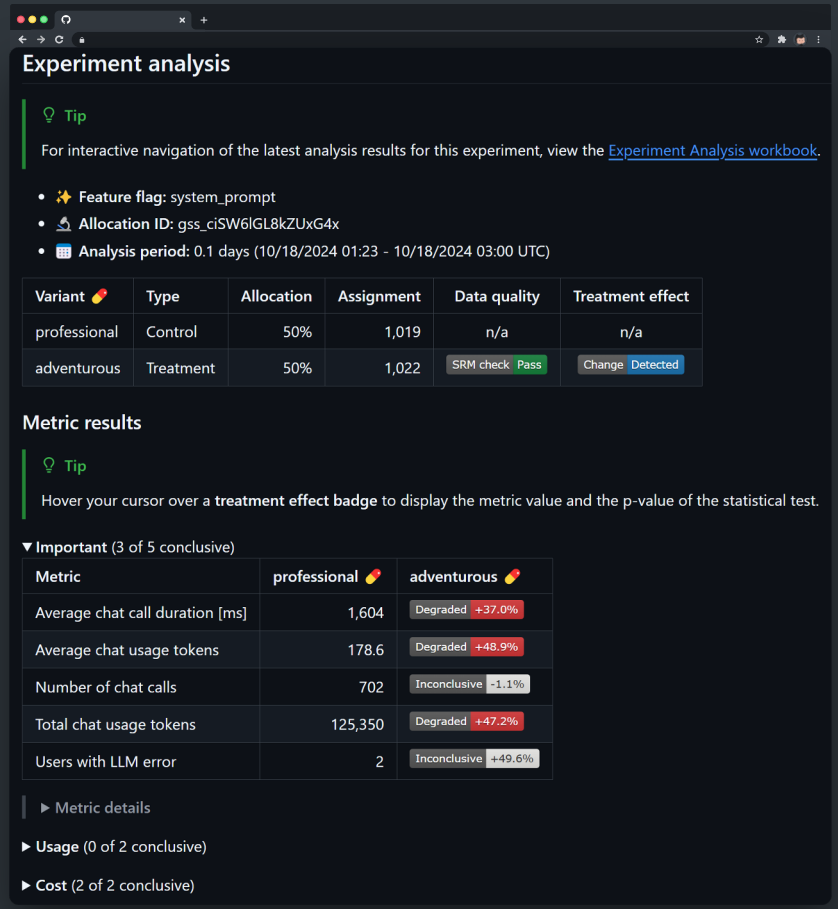
Announcing

Azure AI evaluation and A/B experimentation

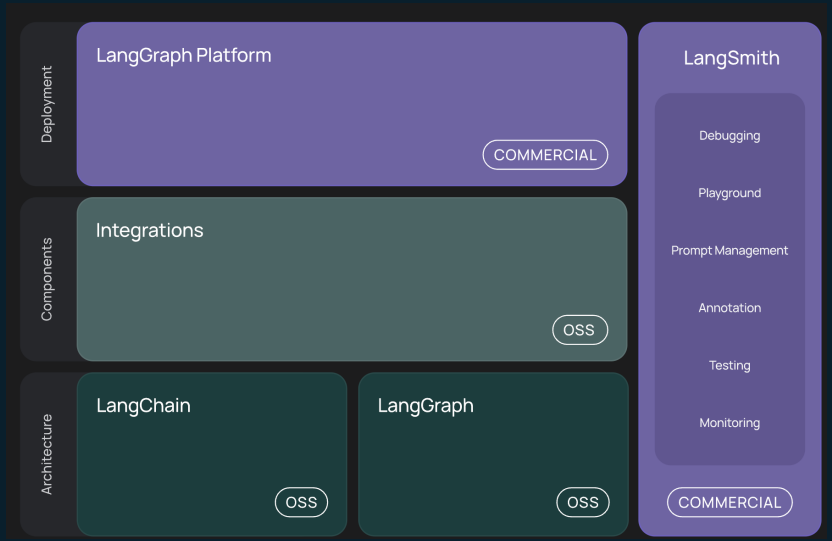
Scale AI applications with key insights

- Aligned with development workflows using GitHub Actions
- Evaluate full impact
- GitHub Copilot plugin that assists with experimentation

Sign up for the private preview:
aka.ms/genAI-CI-CD-private-preview



LangChain



- Pro:
  - Well adopted
  - Hundreds of integrations
  - A lot of tools
  - Pre-built prompts and chains
  - Very good features for chat agents
- Cons
  - Niche vendor
  - Deployments, Evals are commercial
  - Complex to learn and navigate

Code example: Query complex docs with Langchain

LlamaIndex

- Pros:
  - Tons of integrations at https://llamahub.ai/
  - Partnership with Azure
  - Best Practices / Advanced RAG techniques
  - Observability / Monitoring connectors
  - All is OSS

  - Commercial parsing / cloud offering

https://ignite.microsoft.com/en-US/sessions/BRK106?source=sessions
Code examples

Haystack

- RAG Centric / Flexible
- Simpler
- Less integrations

```python
from haystack import Pipeline

basic_rag_pipeline = Pipeline()
# Add components to your pipeline
basic_rag_pipeline.add_component("text_embedder", text_embedder)
basic_rag_pipeline.add_component("retriever", retriever)
basic_rag_pipeline.add_component("prompt_builder", prompt_builder)
basic_rag_pipeline.add_component("llm", generator)

# Now, connect the components to each other
basic_rag_pipeline.connect("text_embedder.embedding", "retriever.query_embedding")
basic_rag_pipeline.connect("retriever", "prompt_builder.documents")
basic_rag_pipeline.connect("prompt_builder", "llm")
```

```python
question = "What does Rhodes Statue look like?"

response = basic_rag_pipeline.run({"text_embedder": {"text": question}, "prompt_builder

print(response["llm"]["replies"][0])
```

https://haystack.deepset.ai

Microsoft

Demos - Orchestrators

Evaluating RAG: Best practices

Model evaluation	Evaluate your model regularly using various metrics to ensure it meets your desired outcomes.
Understand user intent	Classify user intents as navigational, informational, or transactional. This aids in tailoring responses effectively.
Identify query types	Concept-seeking, fact-seeking, keyword, low query/doc term overlap, misspelled, long, medium, and short queries help uncover user intent and evaluate system performance.
Use comprehensive metrics	Employ a mix of lexical-based (Precision and Recall, F1 Score, Word Error Rate), semantic-based (Semantic Textual Similarity, Word Embedding Similarity, BLEU), and combined metrics (ROUGE, BERTScore) for a holistic evaluation.
Keep in mind top K (@K) retrieved Chunks	Granular perspective on how many Chunks to retrieve.
Implement ranking metrics	Utilize Recall@K, Mean Reciprocal Rank, Mean Average Precision@K, and Normalized Discounted Cumulative Gain for assessing the ranking quality of the system.
Regularly monitor performance	Continuously track and optimize the system's performance using these metrics to ensure the highest level of user satisfaction and system effectiveness.
User feedback	Incorporate user feedback to improve system for utility.

Azure's RAG Evaluation Tool: Azure ML Prompt Flow!

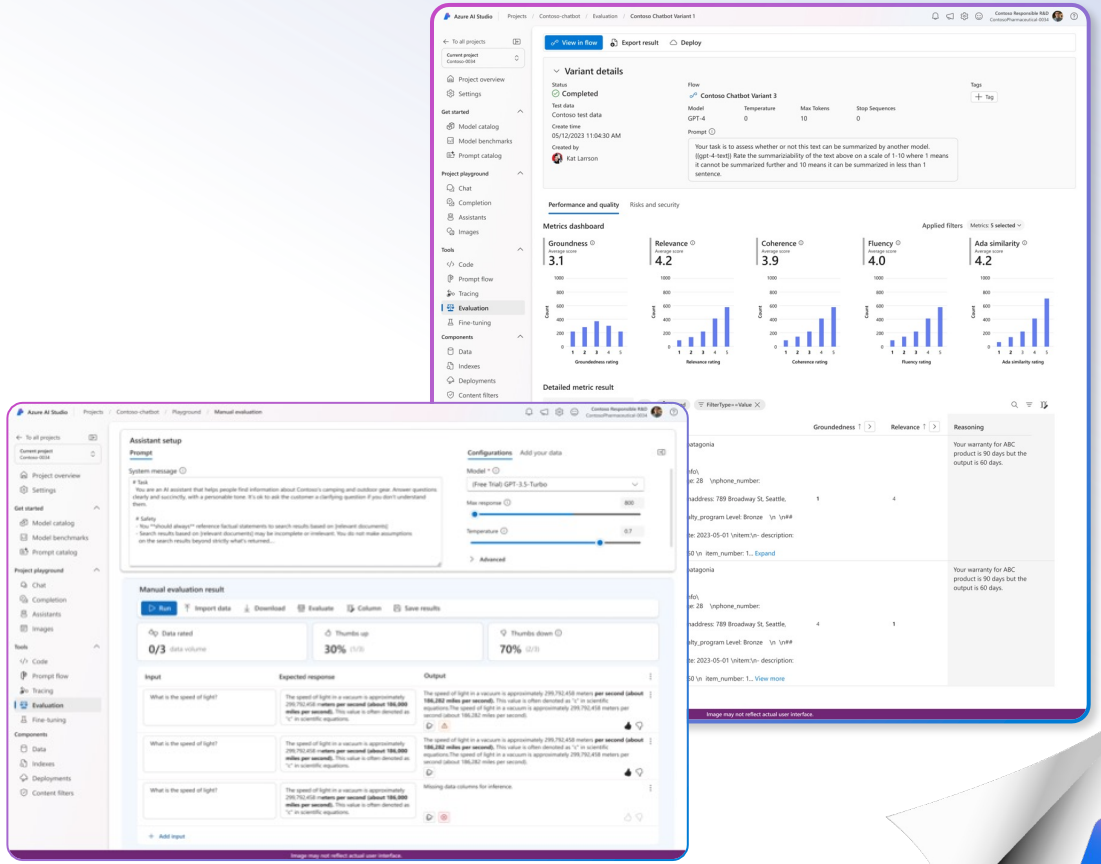
Built-in and custom evaluations

Built-in evaluations quickly and comprehensively assess the generated outputs of an AI application, streamlining feedback for continuous improvement.

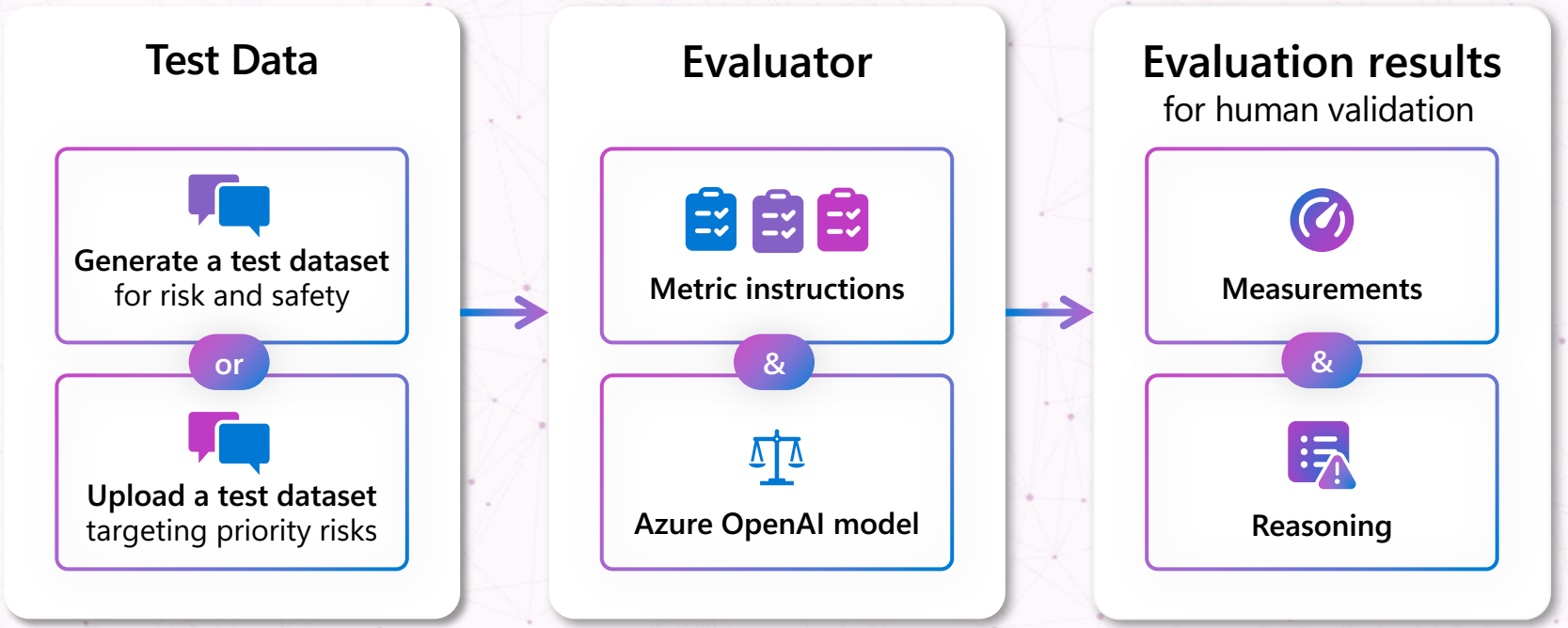
Quickly and continuously iterate on your application and track the impact of ongoing changes by manually rating model outputs as you go.

Try evaluation in prompt flow:
https://aka.ms/2024-brk141

Streamline model and app evaluations



Assess your app with AI assistance in Azure AI Studio



aka.ms/Evaluators_Blog

GitHub Action Evaluation

Operationalize and monitor workflows

Promptflow Evaluation Results

	request	gpt_relevance	gpt_fluency	gpt_coherence	gpt_groundedness
0	Write an article about the latest camping trends and what folks are doing in the winter	4	5	5	5
1	Write an article about the best kind of tents for snow camping	1	5	5	5
2	Write an article about the best kind of hiking shoes	5	5	5	5

Averages scores:

	0
gpt_relevance	3.33333
gpt_fluency	5
gpt_coherence	5
gpt_groundedness	5

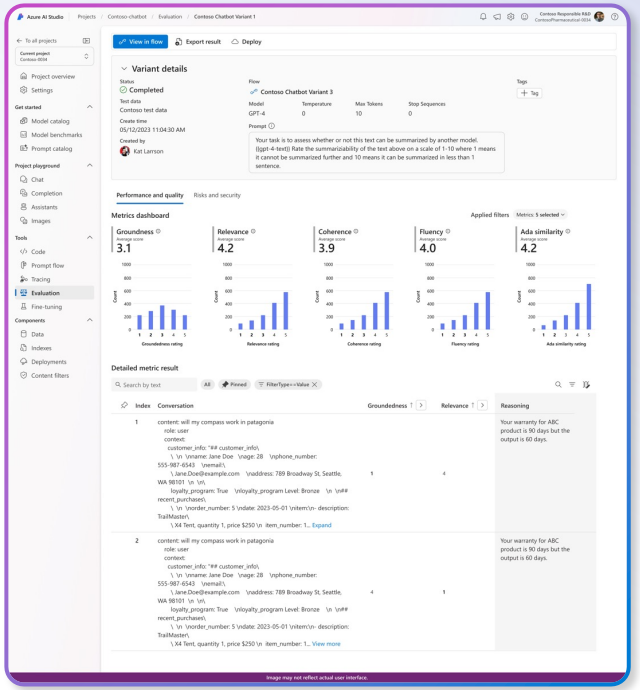
Image may not reflect actual user interface.

Automated evaluation

Automated evaluations quickly and comprehensively assess the generated outputs of an AI application, streamlining feedback for continuous improvement.

- Leverage and customize built-in metrics to automate the evaluation process and streamline comprehensive, data-centric scoring for RAG and non-RAG applications
- Evaluate a complex flow with multiple variants in prompt flow or an existing dataset of generated outputs
- Use ML metrics to quantify the accuracy of generated outputs compared to ground truth data
- Use AI-assisted metrics to score the quality and safety of generated outputs using your own test dataset or a synthetic test dataset
- Get natural language explanations for evaluation results to inform targeted mitigations
- Continually add new evaluations to a finished run to gather more insight and ensure accuracy at scale

Streamline model and app evaluations



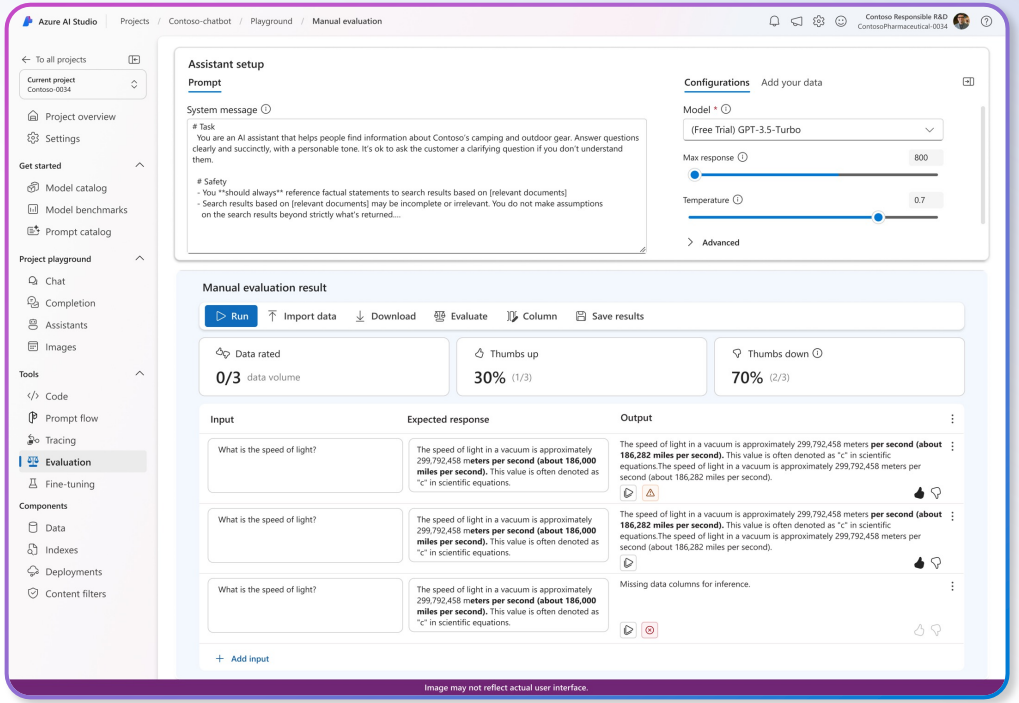
Measure the frequency and severity of LLM application harms using consistent metrics and comprehensive test datasets with iterative, systematic testing.

Manual evaluation

Quickly and continuously iterate on your application and track the impact of ongoing changes by manually rating model outputs as you go.

- Manually create or upload your sample test dataset with the option to include expected outputs
- Customize your prompts to target specific aspects of model performance and user interaction you want to improve
- Provide a thumbs up or down rating to score each generated response
- Review model response scores by prompt or in the at-a-glance summaries
- Iterate on your application and re-run evaluations to track the impact of your changes
- Save and compare results to identify the optimal application design for your desired outcomes

Streamline model and app evaluations



Based on the results, you may decide to update your system message, model, or model parameters. Then, rerun the dataset or specific prompts that didn't meet your expectations to see the impact of your updates.

Evaluation datasets

Dataset	Description	Metrics/goals
Qualified answers	Small number of examples obtained from experts	Maximize response quality (groundedness, relevance, coherence, ...)
Synthetic	Large number of synthetic samples	Maximize response quality Maximize retrieval metrics (recall, precision) Maximize tool selection metrics (accuracy)
Adversarial	Jailbreak attempts, harmful content	Minimize unsafe responses
OOD	Out of domain questions	Minimize relevance ;-)
Thumbs down	Dataset of bad answers	Eye-ball, use to discuss
PROD	Scrubbed questions from opt-in users	Maximize response quality Ensure production satisfaction

Evaluation best practices

Multiply your datasets and metrics

Evaluate systematically using GenAIOps

Review results as a team, with multiple points of view

Microsoft

Demo – AI Foundry evaluation

Other Evaluators

- LlamaIndex Evals
- LangSmith (commercial)
- RAGAS
- DeepEvals

AZD integration with Azure AI Studio

Accelerate deployment and evaluation

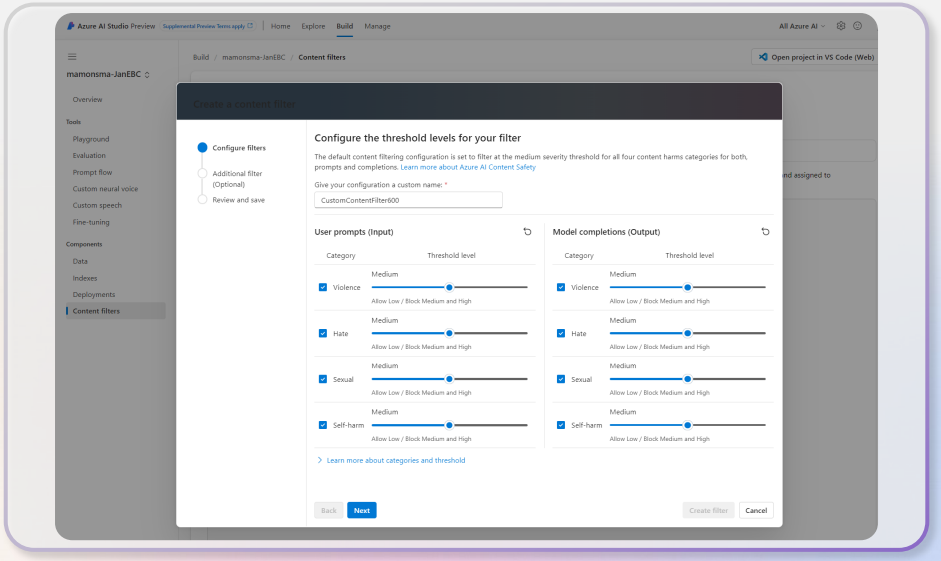
- Create custom container environments for AI applications
- Deploy models with ease by just specifying metadata
- Upload and deploy prompt flows with new enhancements like prompt assets and flexible flow classes
- Smoothly transition traffic to new endpoints for quick evaluation and scaling

services.chat.host	**Introducing a new azd host type (ai.endpoint)**
services.chat.config.workspace	Name of associated Azure AI project (workspace)
services.chat.config.environment	Location of the runtime container config file
services.chat.config.flow	Location of the prompt flow to push to Azure
services.chat.config.model	Location of the model deployment config file
services.chat.config.deployment	Location of the app deployment config file

Azure AI Content Safety

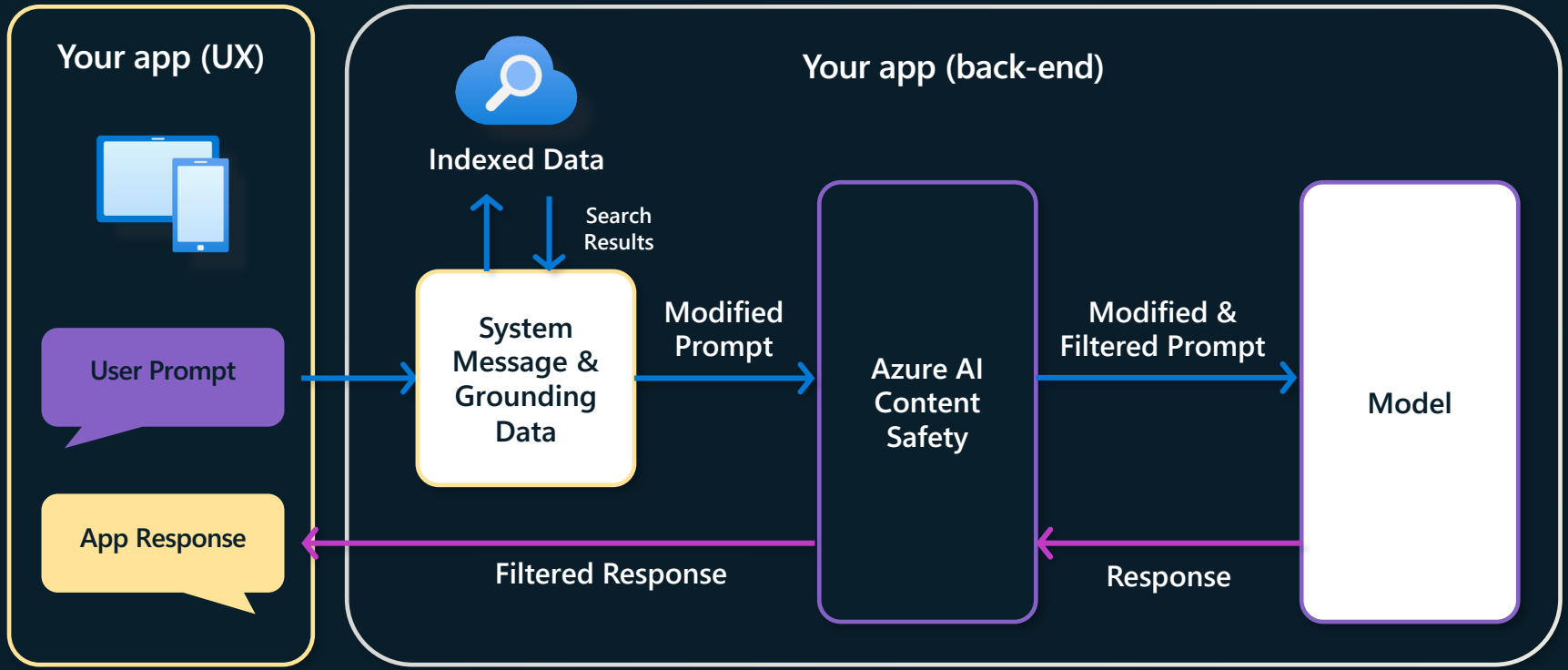
Azure AI Content Safety is a content moderation platform that uses AI to keep your content safe, creating better online experiences for everyone with powerful models that detect inappropriate content.

- Enable content harm filters to monitor inappropriate responses that may be hateful, sexual, violent, or lead to self-harm
- Customize content safety thresholds for each user type or individual
- Use Jailbreak Risk Detection to detect user prompts that provoke the GenAI model into breaking set rules
- Secure your data with Cross Prompt Injection Detection to defend against and identify potential Cross-Prompt Injection Attack (XPIA) attacks in input documents and large language model (LLM) conversations
- Identify text in language model output that matches known text context for protected materials
- Create user defined blocklists to manage content



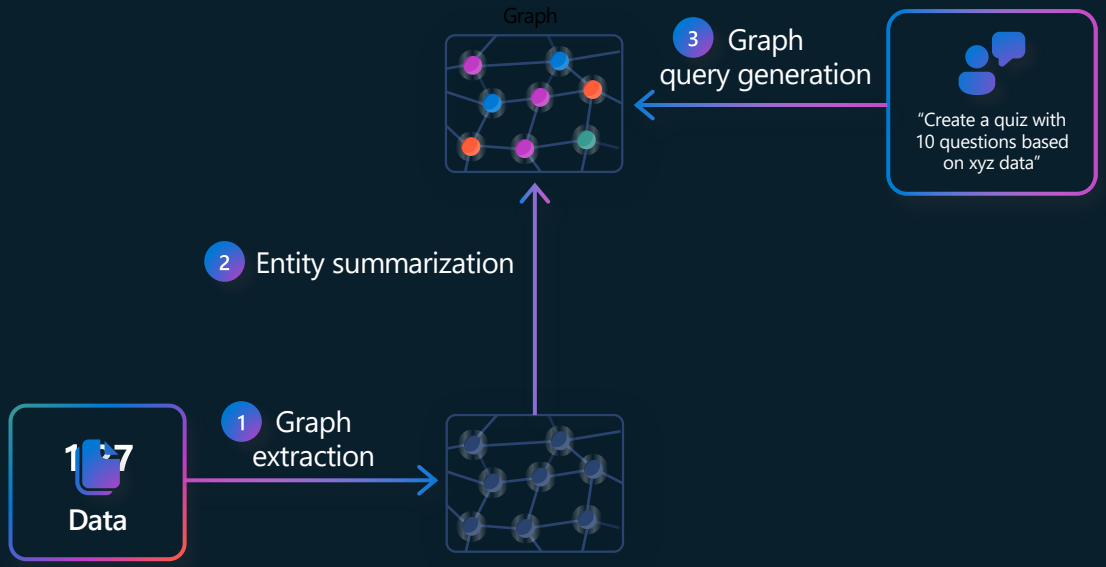
Enhance user safety and data security with Azure AI Content Safety, providing tailored protection, real-time threat detection, and customizable controls.

How these mitigations happen in real-time



GraphRAG

Overview



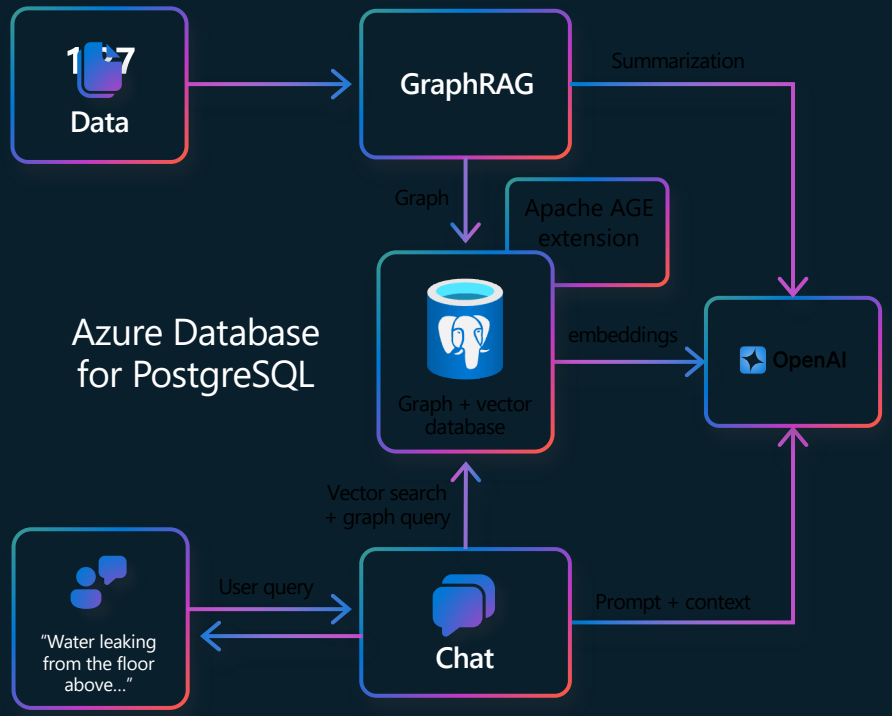
GraphRAG Solution Accelerator for Postgres

Overview

- Legal Research Copilot app
- U.S. Case Law dataset (0.5 million cases)

Available Now!

- Blog: aka.ms/pg-graphrag
- Repo: aka.ms/pg-graphrag-repo

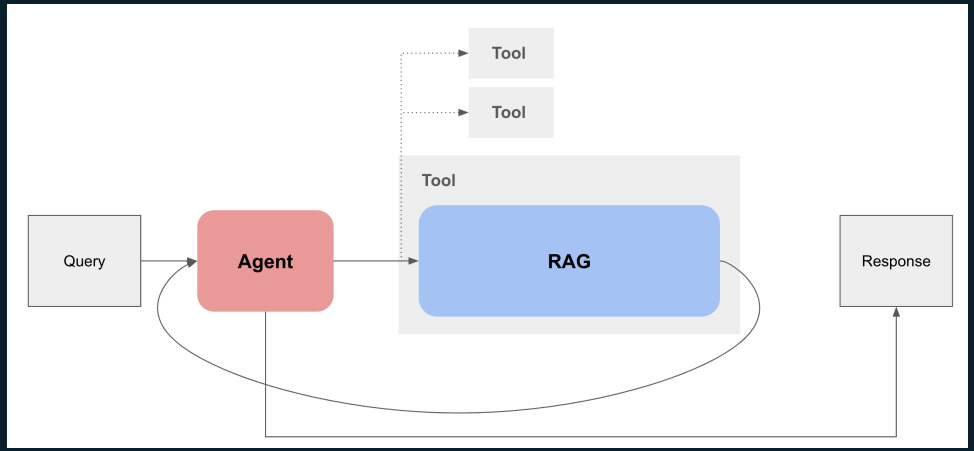


What is an agent anyway?

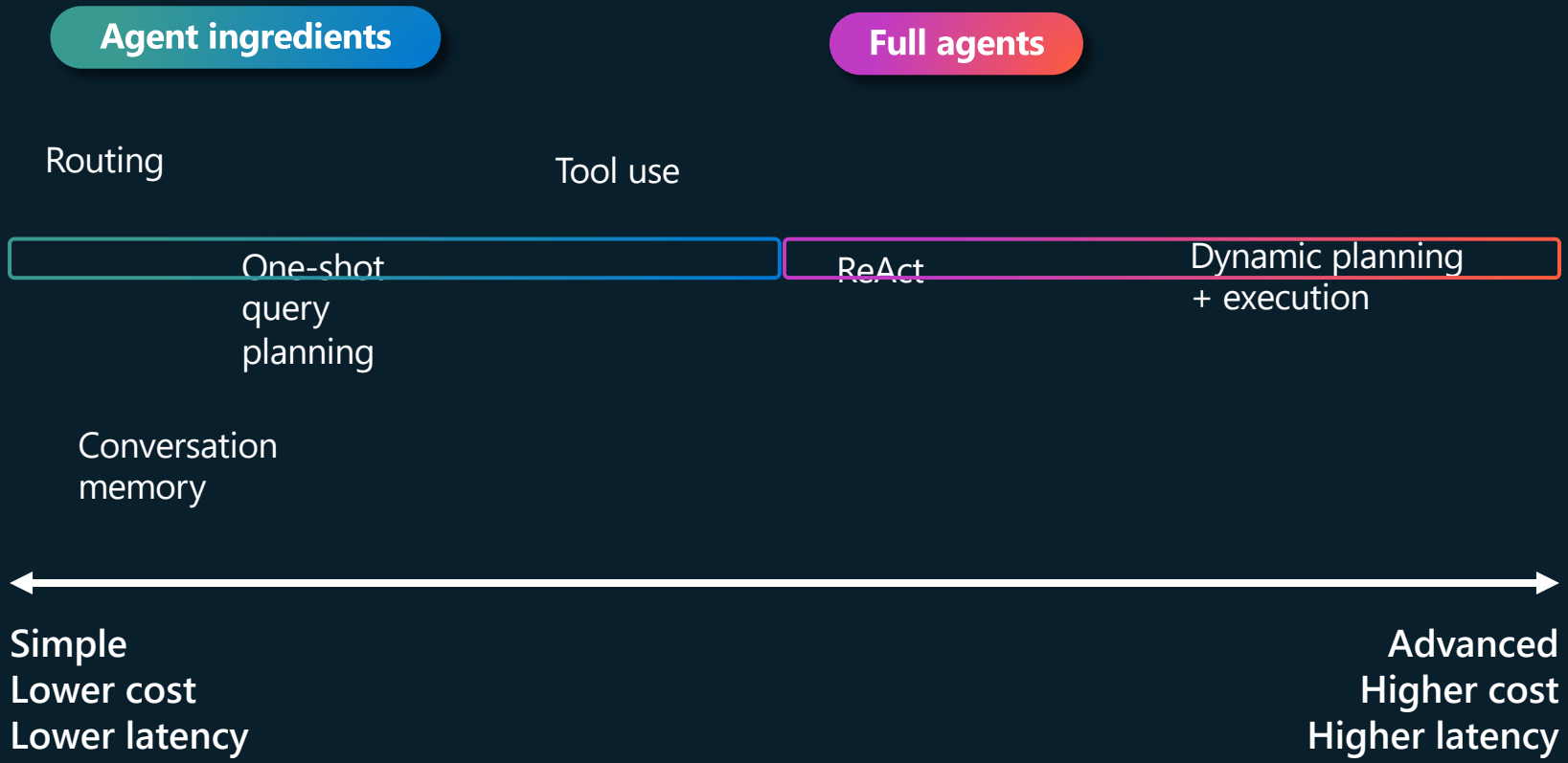
- Semi-autonomous software
- Accepts a goal
- Uses tools to achieve that goal
- Exact steps to solution not specified

What does agentic RAG look like?

- Multi-turn
- Query/task planning layer
- Tool interface to external environment
- Reflection for self-correction
- Memory for personalization



From simple to advanced



Useful links and references

- Great talks
  - https://eugeneyan.com/speaking/ai-eng-summit/
  - https://aiconference.com/speakers/jerry-liu-2023/
- https://github.com/langchain-ai/rag-from-scratch
- https://docs.llamaindex.ai/en/stable/optimizing/production_rag/
- https://www.databricks.com/blog/LLM-auto-eval-best-practices-RAG
- https://eugeneyan.com/writing/llm-patterns/
- https://microsoft.github.io/llmops-workshop/
- https://github.com/MSUSAzureAccelerators/Azure-Cognitive-Search-Azure-OpenAI-Accelerator/tree/main
- https://github.com/farzad528/azure-ai-search-python-playground

Useful links (cont)

- https://news.microsoft.com/ignite-2024-book-of-news/

Thank you

Sinergija 24

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