

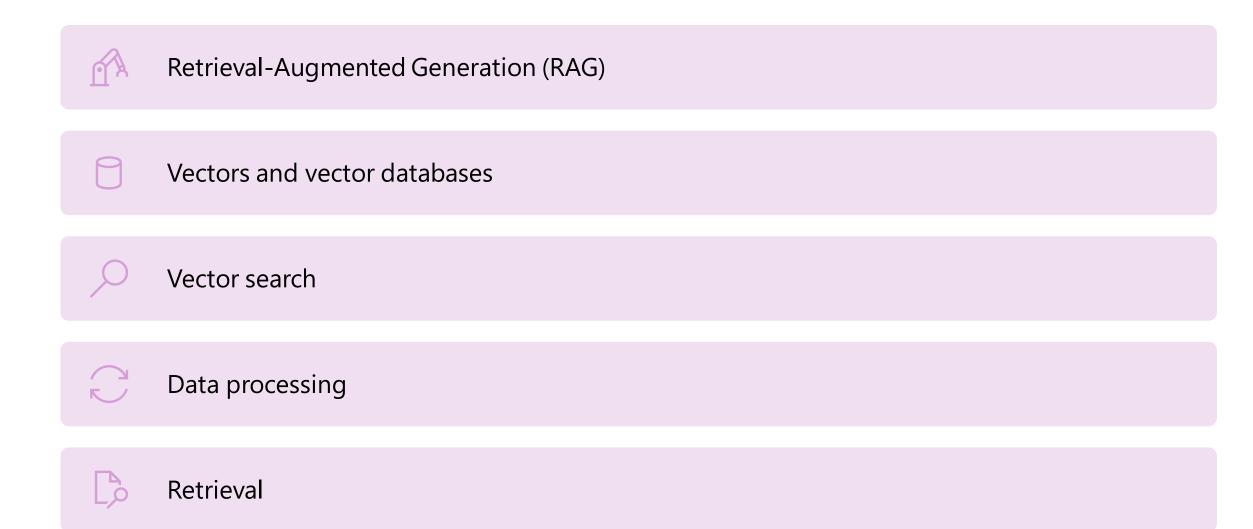
# Search smarter in Generative Al apps

Global Al Bootcamp 2024

Abby Shen

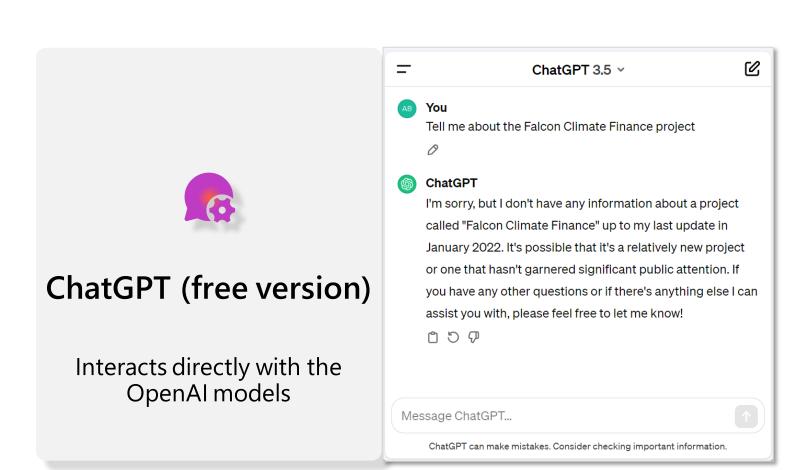


## Agenda



## Retrieval-Augmented Generation (RAG)

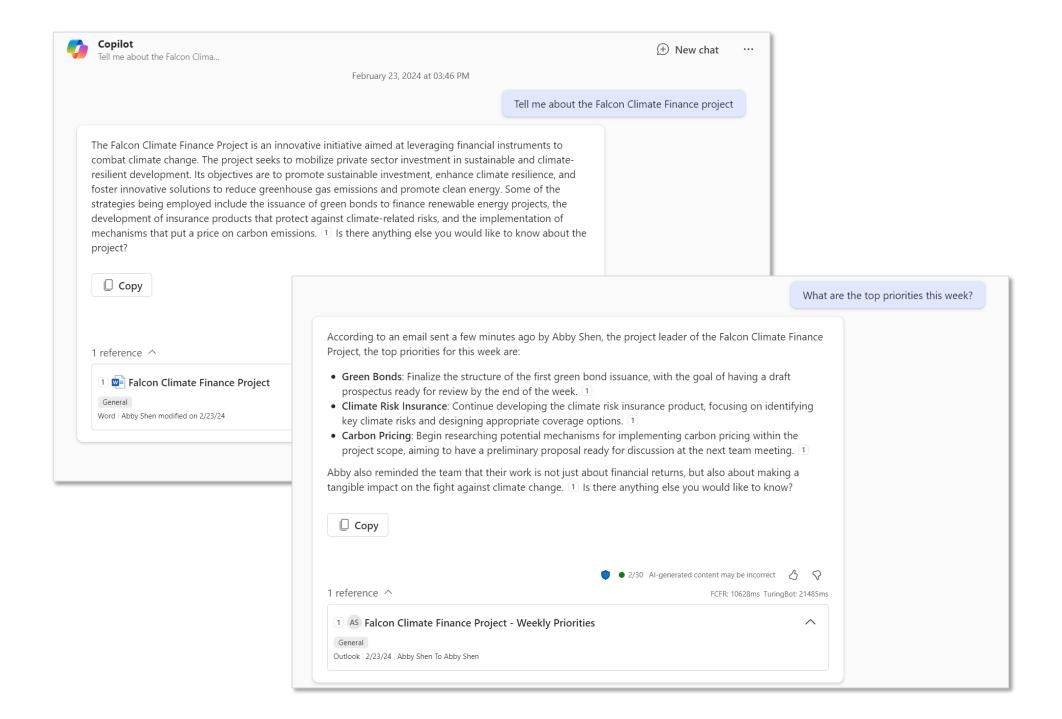
#### What's the difference?

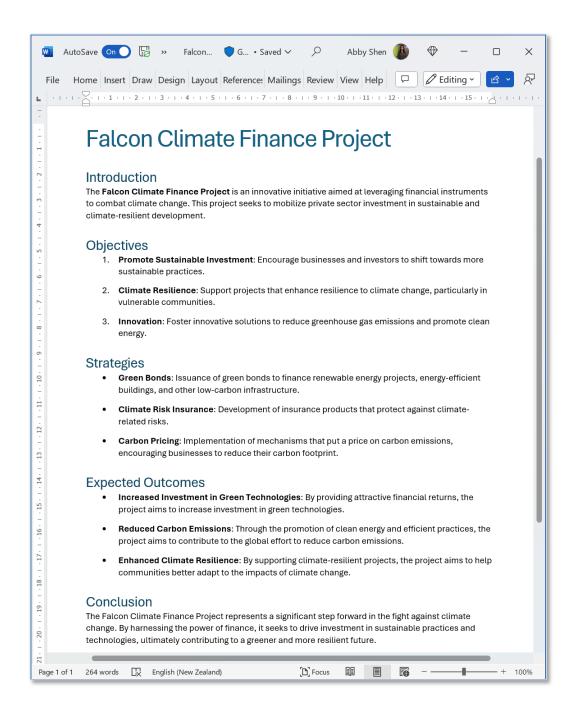


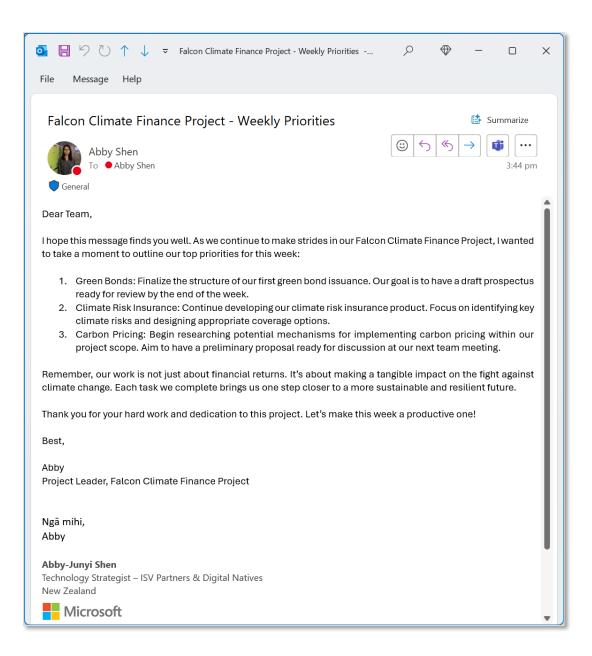


M365 Copilot

Grounded in your M365 data









Summarize my recent Teams messages from this week about Falcon Climate Finance

#### October 18, 2023 at 05:27 PM

Summarize my recent Teams messages from this week about Falcon Climate Finance

Here is a summary of your recent Teams messages from this week about Falcon Climate Finance:

- · You, Isaiah Langer, and Joni Sherman had a conversation yesterday afternoon where you shared the Project Update and Media Campaign Impact Report. Isaiah shared the FCF budget and Deepak Sadan shared the Falcon Climate Finance Q3 presentation. Joni Sherman shared the Press Release Draft and Isaiah shared the Stakeholder Feedback on Carbon Offset Report. You also shared the Climate Offset Report PDF. 1
- Deepak Sadan mentioned taking the lead on community relations and building trust with local communities. You asked Isaiah for a comprehensive breakdown of the Q3 progress metrics for Falcon Climate Finance, including carbon offset statistics and financial overviews, as well as projections for Q4 and potential impact estimates for upcoming initiatives. You also mentioned ensuring Deepak has all the necessary resources for community engagement efforts.
- Isaiah mentioned that the 550 MW solar project can offset approximately 2.42 million tonnes of CO2 annually, equivalent to taking half a million cars off the road every year. You suggested leveraging the Biweekly Communications Strategy Sync platform to share updates with other teams. 1
- · Deepak Sadan mentioned the importance of teamwork and ensuring local communities understand and benefit from the solar project. You emphasized the importance of emphasizing Falcon Climate Finance's commitment to sustainability and community welfare in the narrative. 1



1 reference V

● 1/30 Al-generated content may be incorrect 🖒 🛇







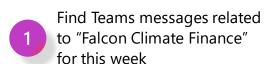
What are the Q3 progress metrics for Falcon Climate Finance?

Ask a work question or use / to reference people, files, and more











Render results and propagate references

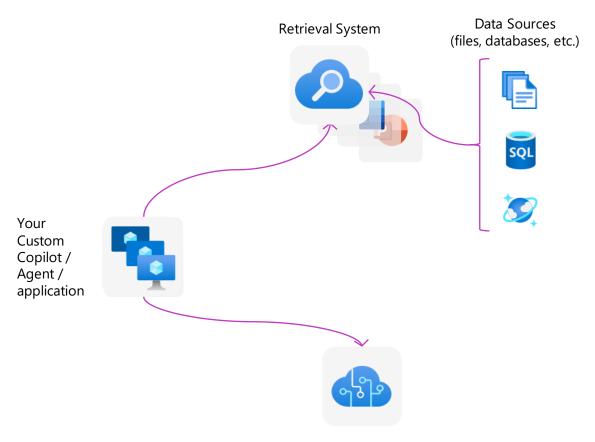


#### Build prompt with:

- Instructions Context
  - Retrieved content



## RAG – Retrieval Augmented Generation



Large Language Model

## Robust retrieval for RAG apps

· Responses only as good as retrieved data

- Keyword search recall challenges
  - "vocabulary gap"
  - · Gets worse with natural language questions
- Vector-based retrieval finds documents by semantic similarity
  - Robust to variation in how concepts are articulated (word choices, morphology, specificity, etc.)

#### **Example**

#### **Question:**

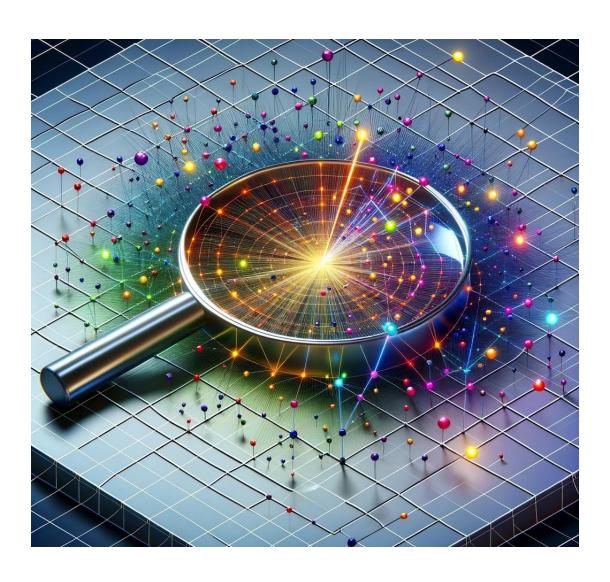
"Looking for lessons on underwater activities"

#### Won't match:

"Scuba classes"
"Snorkeling group sessions"

## Vectors and vector databases

#### **Vectors**



#### Vector representations

- · Models that encode item -> vector
- · Similar items map to close vectors
- · Sentences, images, graphs, etc.

#### Vector search

- Find K closest vectors given a "query" vector
- Search exhaustively or through approximations

#### **Vectors**

```
D ~
        client.embeddings.create(input="hello, world", model="ada002").data[0].embedding 🗑
      ✓ 3.1s
[18]
     [-0.016783414408564568,
      -0.00672766612842679,
      -0.02743067592382431,
      -0.046463146805763245,
      -0.01095276977866888,
      0.01014025043696165,
      -0.013910342939198017,
      -0.004839369561523199,
      -0.018681460991501808,
      -0.028366699814796448,
      0.028990715742111206,
      0.0197994876652956,
```

## **Vector similarity**

Query:

'The new movie is awesome'

#### Data:

['The dog plays in the garden',
 'This recent movie is so good',
 'The new movie is awesome']

The new movie is awesome The new movie is awesome The new movie is awesome

The dog plays in the garden
This recent movie is so good
The new movie is awesome

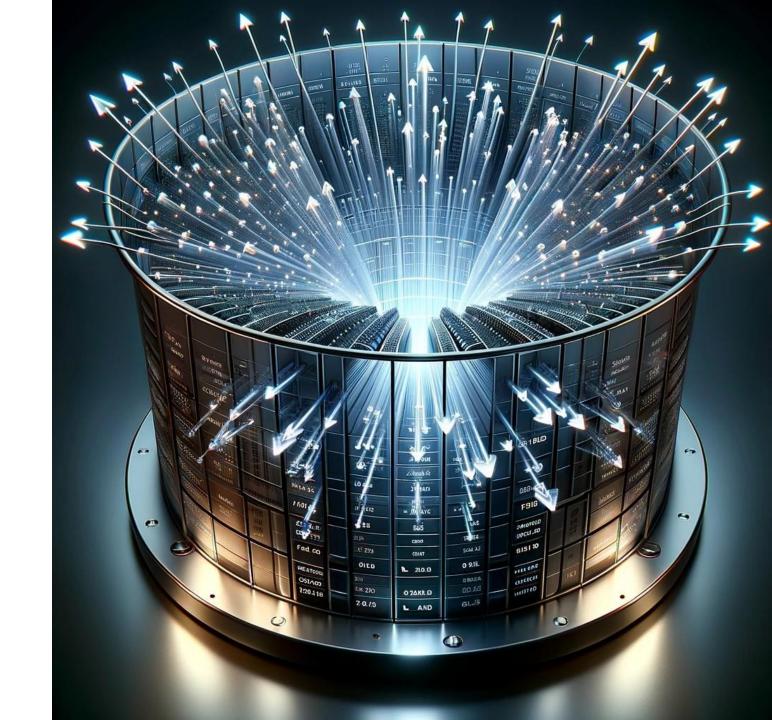
Score: 0.7488

Score: 0.9191

Score: 1.0000

#### **Vector databases**

- Durably store and index vectors and metadata at scale
- Various indexing & retrieval strategies
- Combine vector queries with metadata filters
- · Enable access control



#### **Azure Al Search**

Feature rich, enterprise-ready vector database Data and platform integration

State-of-the-art retrieval system



## **Azure Al Search**

Feature-rich vector database

Ingest any data type, from any source

Seamless data & platform integrations State-ofthe-art search ranking Enterpriseready foundation

Vector search

Azure Al Search in Azure Al Studio

Integrated vectorization (Public Preview)

Semantic ranker

## Azure Al Search: vector search

### Vector search in Azure Al Search



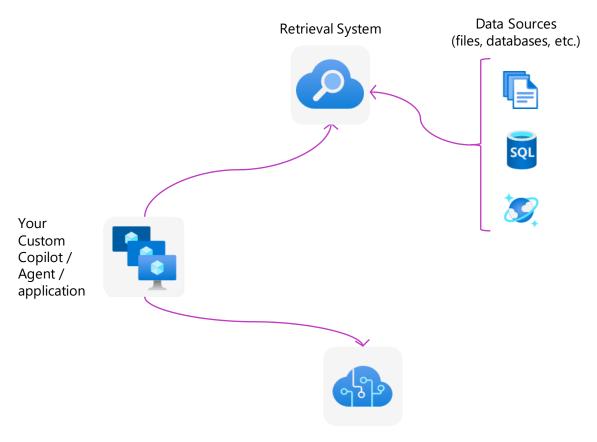


· Comprehensive vector search solution

- Enterprise-ready
  - → scalability, security and compliance

 Integrated with Semantic Kernel,
 LangChain, LlamaIndex, Azure OpenAl Service, Azure Al Studio, and more

## RAG – Retrieval Augmented Generation



Large Language Model

## Rich vector search query capabilities

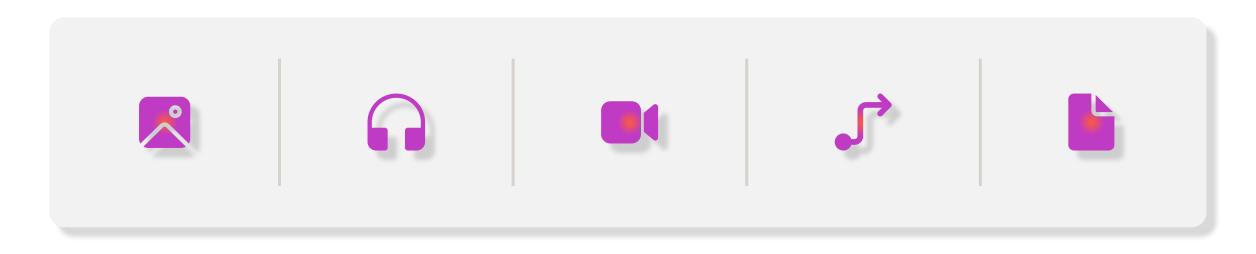
#### Filtered vector search

- Scope to date ranges, categories, geographic distances, etc.
- Rich filter expressions
- Pre-/post-filtering
  - Pre-filter: great for selective filters, no recall disruption
  - Post-filter: better for low-selectivity filters, but watch for empty results

#### **Multi-vector scenarios**

- Multiple vector fields per document
- Multi-vector queries
- Can mix and match as needed

## Not just text



- · Images, sounds, graphs, and more
- · Multi-modal embeddings e.g., images + sentences in Azure Al Vision
- Still vectors → vector search applies
- RAG with images with GPT-4 Turbo with Vision





C 0a9b0b18-030 4-41a2-8367-1 55479b77985. png

€ 8c9044bf-e9cb

-4c15-a977-93

4533055792.p



png

€ 0b0e0e52-e3b

f-4bf7-b1e1-3

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2 1a8555cc-a1e4 -4fae-9624-8e acfbe64bc8.pn g



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png

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png





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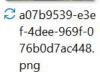


C f8a023c8-169c -443a-b0bb-b 63409d7933f. png



png





## Azure Al Search: data processing

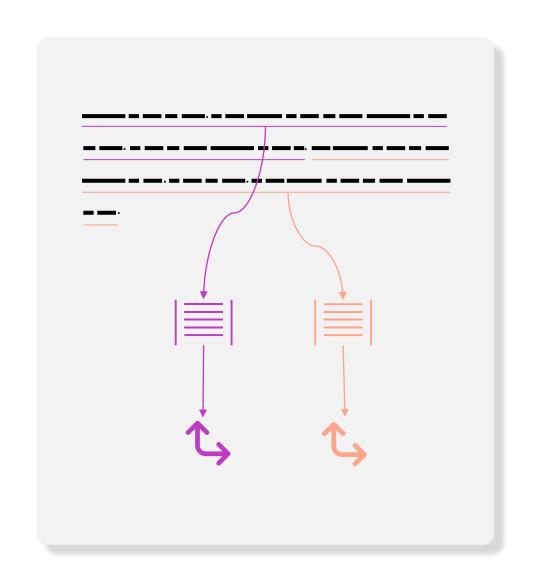
## Data preparation for RAG applications

#### **Chunking**

- Split long-form text into short passages
  - · LLM context length limits
  - · Focused subset of the content
  - Multiple independent passages
- Basics
  - · ~200–500 tokens/passage
  - Maintain lexical boundaries
  - Introduce overlap
- Layout
  - · Layout information is valuable, e.g., tables

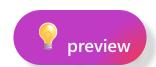
#### **Vectorization**

- · Indexing-time: convert passages to vectors
- · Query-time: convert queries into vectors



## Integrated vectorization

End-to-end data processing tailored to RAG





















## Data source access

- Blob Storage
- ADLSv2
- SQL DB
- CosmosDB
- ..
- + Incremental change tracking

## File format cracking

- PDFs
- Office documents
- JSON files
- ...
- + Extract images and text, OCR as needed

#### Chunking

- Split text into passages
- Propagate document metadata

#### Vectorization

- Turn chunks into vectors
- OpenAl embeddings or your custom model

#### Indexing

- Document index
- Chunk index
- Both

## Even poke around with it!

```
Microsoft Azure (Preview)

    Search resources, services, and docs (G+/)

                                                                                                                                 (2) Copilot
Home > ignitedemo | Indexes >
ignite5 ...
                                                                                                           Query options
                                                                                                                                Search
tent
Results
          "@odata.context": "https://ignitedemo.search.windows.net/indexes('ignite5')/$metadata#docs(*)",
    3
           "@search.answers": [],
           "value": [
    4
               "@search.score": 0.014925372786819935,
               "@search.rerankerScore": 2.6010262966156006,
               "@search.captions": [
                   "text": "## Description\r \r The SkyView 2-Person Tent is a lightweight, durable, and easy-to-assemb
   10
                   "highlights": ""
   11
   12
   13
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   14
   15
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               "chunk": "# SkyView 2-Person Tent\r\n\r\n## Introduction\r\nThank you for purchasing the SkyView 2-P
   16
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   17
   18
               "vector": [
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   20
                 0.012547161,
   21
                 0.00448874,
   22
                 -0.016556391,
   23
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   24
                 0.023109687,
   25
                 -0.018088158,
```

## Retrieval



State of the art re-ranking model

Highest performing retrieval mode

New pay-go pricing

Multilingual capabilities

Includes extractive answers, captions and ranking

## Improving relevance

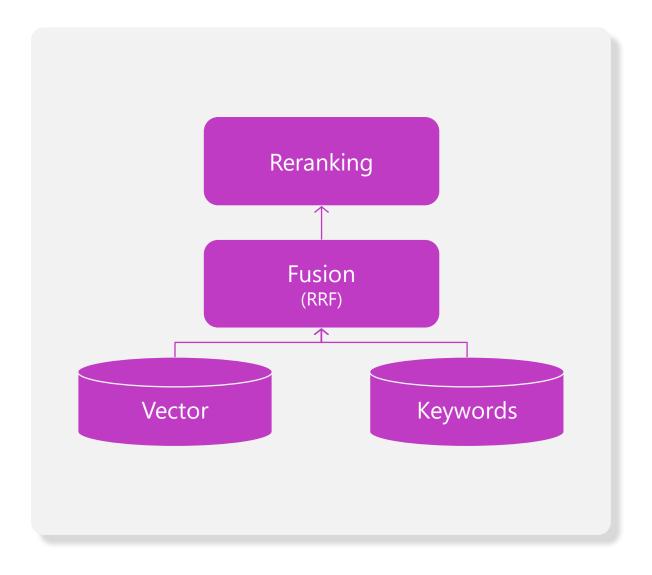
All information retrieval tricks apply!

#### Complete search stacks do better:

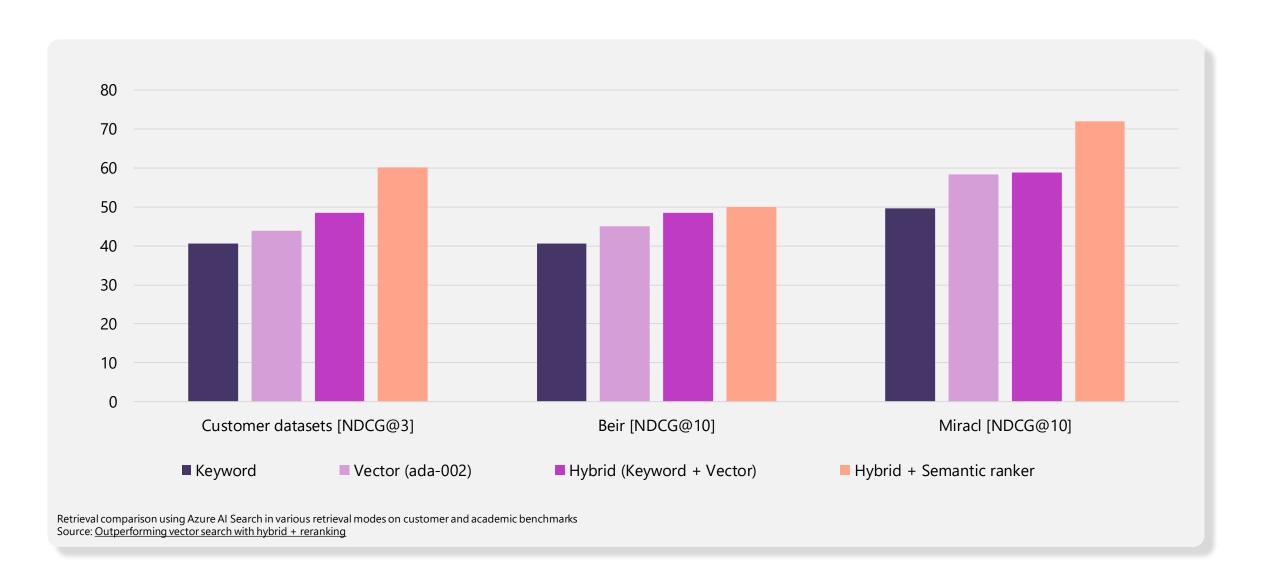
- Hybrid retrieval (keywords + vectors) > pure-vector or keyword
- Hybrid + Reranking > Hybrid

#### Identify good & bad candidates

- Normalized scores from Semantic ranker
- Exclude documents below a threshold



### Retrieval relevance across methods



## Impact of query types on relevance

	Q	Q	Q	Q
Query type	Keyword [NDCG@3]	Vector [NDCG@3]	Hybrid [NDCG@3]	Hybrid+ Semantic ranker [NDCG@3]
Concept seeking queries	39	45.8	46.3	59.6
Fact seeking queries	37.8	49	49.1	63.4
Exact snippet search	51.1	41.5	51	60.8
Web search-like queries	41.8	46.3	50	58.9
Keyword queries	79.2	11.7	61	66.9
Low query/doc term overlap	23	36.1	35.9	49.1
Queries with misspellings	28.8	39.1	40.6	54.6
Long queries	42.7	41.6	48.1	59.4
Medium queries	38.1	44.7	46.7	59.9
Short queries	53.1	38.8	53	63.9

Source: Outperforming vector search with hybrid + reranking

RAG at scale

Powering massive, missioncritical RAG workloads with Azure Al Search

## Azure OpenAl Service

aka.ms/aoaiservice



#### Search smarter!



Learn more about Azure Al Search

https://aka.ms/AzureAlSearch



Explore Azure Al Studio for a complete RAG development experience

https://aka.ms/AzureAlStudio



Dig more into quality evaluation details and why Azure AI Search will make your application generate better results

https://aka.ms/ragrelevance



