Use cases and applications of LLMs - Lecture 6

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Senior Product Manager, Search (TomTom)
Host of Vector Podcast

Syllabus

Week 1: Introduction to Generative AI and Large Language Models (LLM)

- Introduction to Large Language Models (LLMs) and their architecture
- Overview of Generative AI and its applications in NLP
- Lab: Tokenizers

Week 2: Using LLMs and Prompting-based approaches

- Understanding prompt engineering and its importance in working with LLMs
- Exploring different prompting techniques for various NLP tasks
- Hands-on lab: Experimenting with different prompts and evaluating their effectiveness

Week 3: Evaluating LLMs

- Understanding the challenges and metrics involved in evaluating LLMs
- Exploring different evaluation frameworks and benchmarks
- Hands-on lab: Evaluating LLMs using different metrics and benchmarks

Week 4: Fine-tuning LLMs

- Understanding the concept of fine-tuning and its benefits
- Exploring different fine-tuning techniques and strategies
- Hands-on lab: Fine-tuning an LLM for a specific NLP task

Week 5: Retrieval Augmented Generation (RAG)

- Understanding the concept of RAG and its advantages
- Exploring different RAG architectures and techniques
- Hands-on lab: Implementing a RAG system for a specific NLP task

Week 6: Use cases and applications of LLMs

- Exploring various real-world applications of LLMs in NLP
- Discussing the potential impact of LLMs on different industries
- Hands-on lab: query tables and generate synthetic data

Week 7: Final report preparation

- Students work on their final reports, showcasing their understanding of the labs and the concepts learned.

Outline

- Introduction to Multimodal LLMs
- Key use cases
- Specific applications
- The role of Vector Databases
- Emerging trends in LLMs

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Single modality vs multimodal LLMs

Single-Modality LLMs: Traditional language models, such as GPT-3, are designed to process **only text data**. They excel in natural language understanding and generation tasks but are constrained when tasks involve other data types like images or audio.

Multimodal LLMs: These extend the capabilities of single-modality LLMs by incorporating **multi-domain embeddings** and cross-modal attention mechanisms, enabling them to understand and generate data across multiple modalities (e.g., text, images, audio).

GPT-3 (2020) is a single-modality decoder-only LLM

GPT-4 (2023) is a multimodal LLM (+image-to-text)

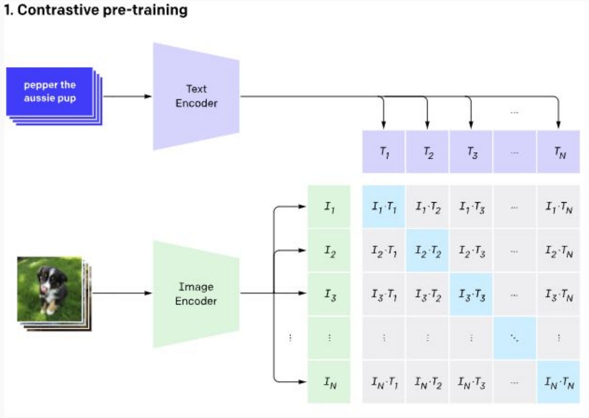
Key Architectural Elements

- **Modality-specific encoders**
  - Multimodal LLMs often use specialized encoders to preprocess each data type (Vision transformers for images, BERT-like encoders for text)
- **Cross-modal fusion**
  - Aligning data from multiple modalities into a shared representation space via attention mechanisms
  - Paper: Radfortd et al., “Learning Transferable Visual Models From Natural Language Supervision” (2021) - CLIP (**C**ontrastive **L**anguage-**I**mage **P**retraining)
- **Pretraining objectives**
  - Image-text alignment (contrastive learning) task
  - Cross-modal generation (decoder-based training)

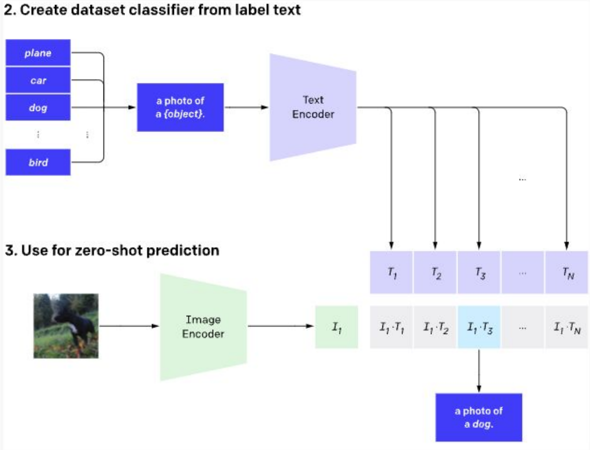
Pretraining objectives

1. **Contrastive Learning**: align embeddings of related data from diff. Modalities in a shared latent space
   a. Bring vectors of image and its caption closer, push unrelated pairs apart
2. **Masked Language Modeling (MLM) and Masked Modality Modeling**
   a. Extend masked token prediction objective to multimodal data
   b. Text: predict randomly masked out tokens, Images: predict masked patches of images using cross-modal information
3. **Image-Text Matching (ITM)**
   a. Trains a model to predict wether a given text and image pair match semantically
4. **Generative Pretraining**
   a. Predict one modality conditioned on another
5. **Multitask Learning Objectives**
   a. Diverse tasks (visual question answering, object detection, text generation)
6. **Alignment Fine-Tuning**
   a. Better alignment between modalities post-training (example: RLHF) on downstream task-specific datasets

CLIP's architecture



Overview A



Overview B

CLIP pre-trains an image encoder and a text encoder to predict which images were paired with which texts in our dataset. We then use this behavior to turn CLIP into a zero-shot classifier. We convert all of a dataset's classes into captions such as "a photo of a dog" and predict the class of the caption CLIP estimates best pairs with a given image.

```
# image_encoder - ResNet or Vision Transformer
# text_encoder  - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l]       - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t             - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T)  #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

Figure 3. Numpy-like pseudocode for the core of an implementation of CLIP.

https://openai.com/index/clip/

Multimodal LLM examples

- CLIP (encoder-only): text + image (encoder): https://arxiv.org/pdf/2103.00020
- PaliGemma (encoder+decoder) - read and reason about images: https://huggingface.co/blog/paligemma
- ColPali (based on PaliGemma): VLM (Vision Language Model): https://huggingface.co/vidore/colpali-v1.2 - surpass RAG (query-to-text) by adding support for image based document retrieval
- Ichigo (decoder-only): text + speech: Llama that learns to listen: https://github.com/homebrewltd/ichigo?tab=readme-ov-file

PaliGemma

Image

Prompt

What city is this?

Model `paligemma-3b-mix-224` – JAX/FLAX PaliGemma 3B weights, finetuned with 224x224 input images and 256 token input/output text sequences on a mixture of downstream academic datasets. The models are available in float32, bfloat16 and float16 format for research purposes only.

Model

paligemma-3b-mix-224

Decoding

greedy

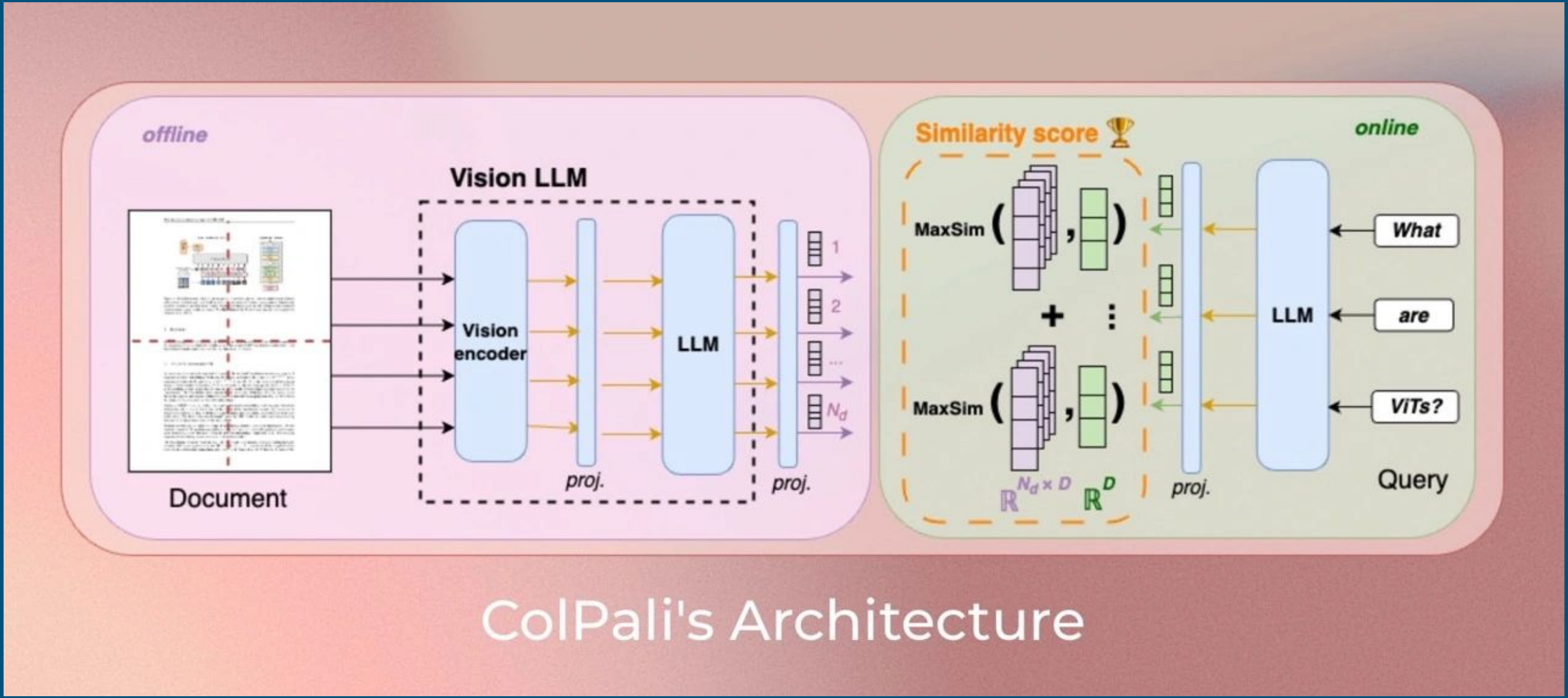
Run

Clear

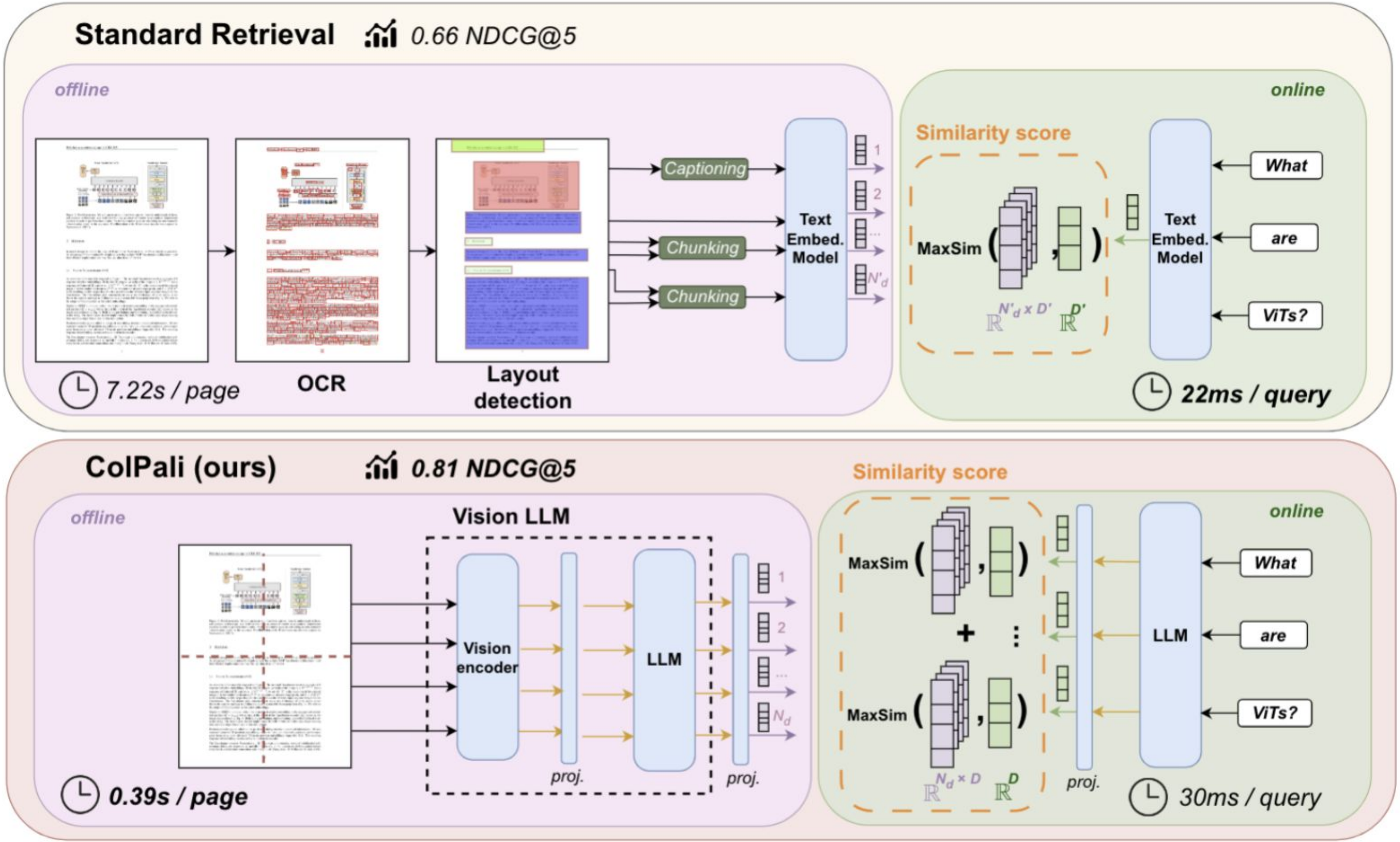
Output

new york

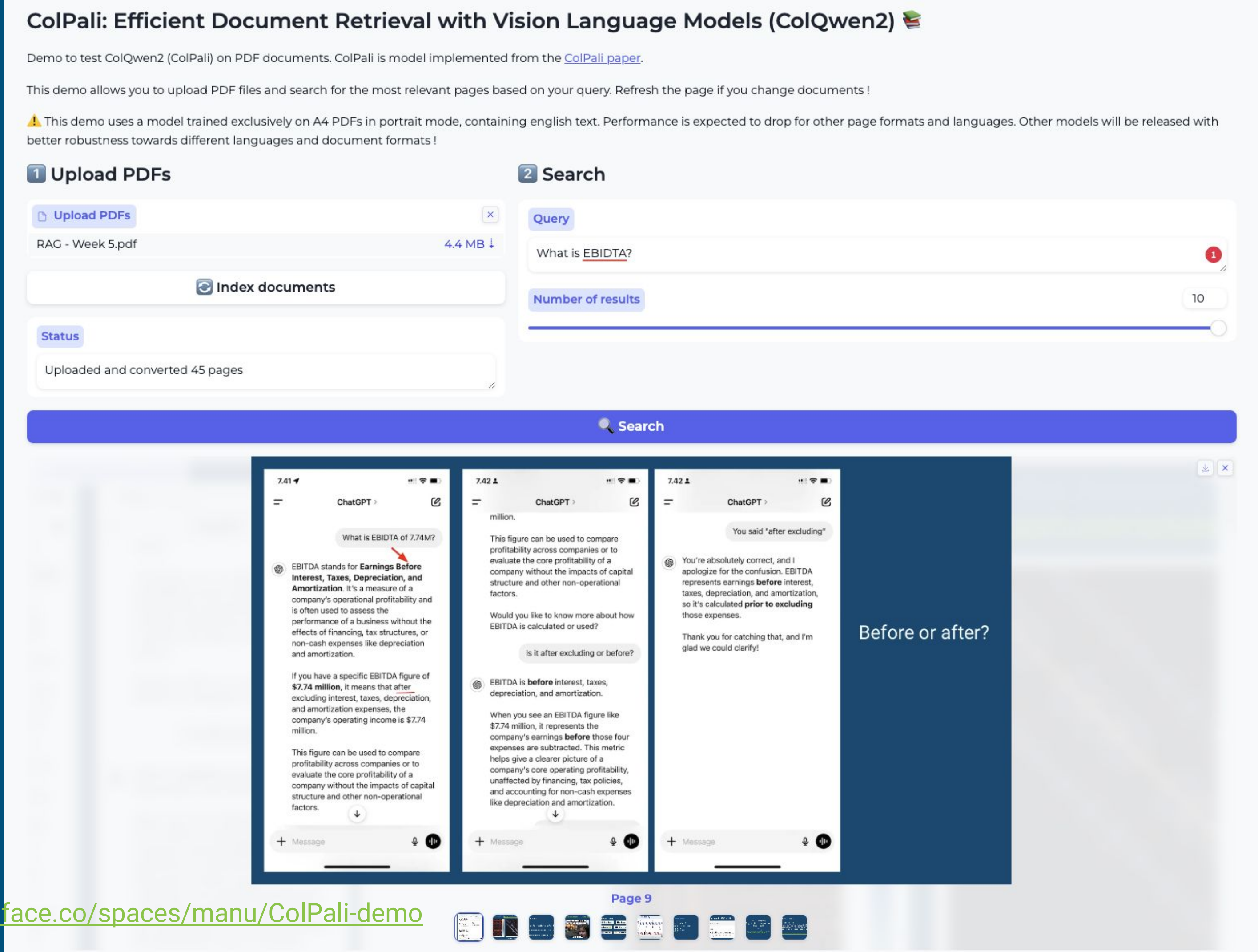
ColPali



offline
Vision LLM
Vision encoder
LLM
proj.
proj.
1
2
...
N_d
Document
Similarity score
online
MaxSim
MaxSim
+
$\mathbb{R}^{N_d \times D}$
$\mathbb{R}^{D}$
proj.
LLM
What
are
ViTs?
Query
ColPali's Architecture



Standard Retrieval
0.66 NDCG@5
offline
OCR
Layout detection
Captioning
Chunking
Chunking
Text Embed. Model
7.22s / page
online
Similarity score
MaxSim
What
are
ViTs?
22ms / query
ColPali (ours)
0.81 NDCG@5
offline
Vision LLM
Vision encoder
LLM
proj.
proj.
0.39s / page
Similarity score
online
MaxSim
MaxSim
LLM
What
are
ViTs?
proj.
30ms / query



https://huggingface.co/spaces/manu/ColPali-demo

Video LLMs: Video-LLaMA

An Instruction-tuned Audio-Visual Language Model for Video Understanding

The Vision-Language Branch in the Video-LLaMA framework is designed to enable Large Language Models (LLMs) to understand visual inputs from videos. **1** It consists of several components:

1. Pre-trained Image Encoder: Extracts features from individual video frames.
2. Position Embedding Layer: Injects temporal information into the video frames.
3. Video Q-Former: Aggregates frame-level representations and generates visual query tokens.
4. Linear Layer: Projects the output video representations into the same dimension as the text embeddings of LLMs.

The Vision-Language Branch processes the visual content of videos and transforms it into a format that LLMs can use to generate text conditioned on the video content.

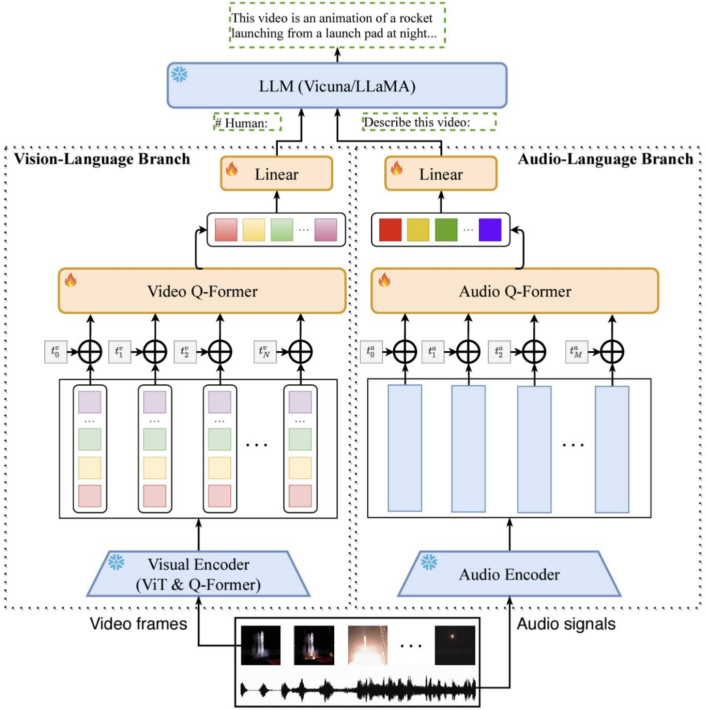
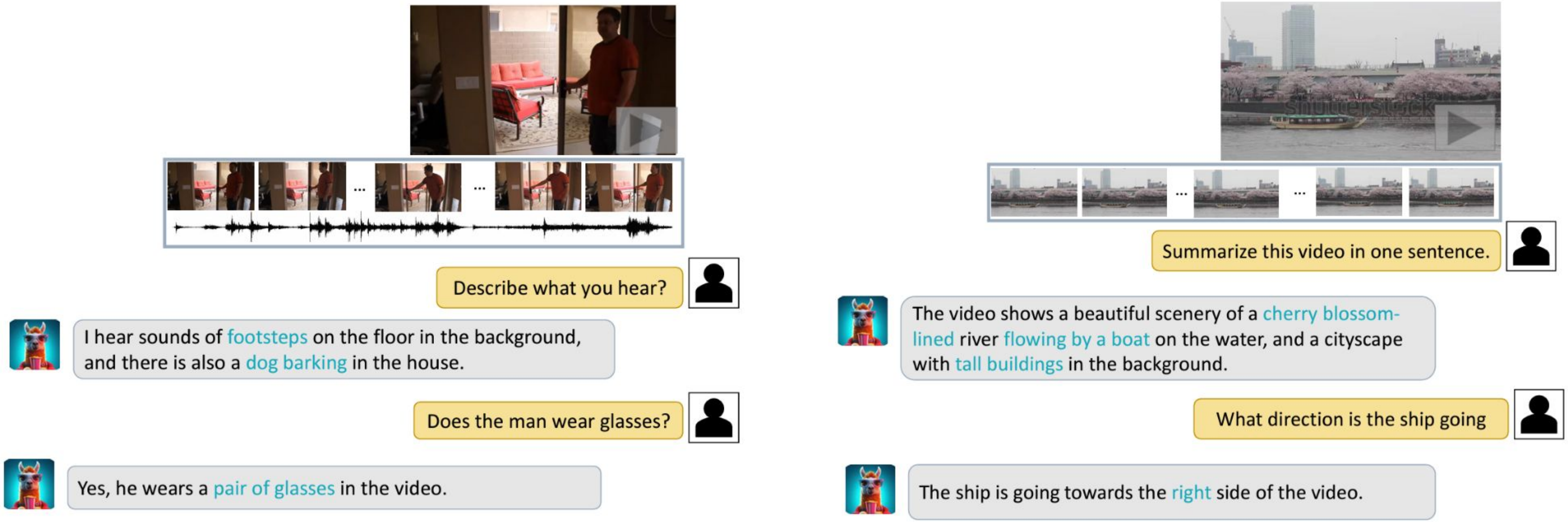


Figure 1: Overall architecture of Video-LLaMA.

https://arxiv.org/pdf/2306.02858

October, 2023 - Alibaba Research

Video-LLaMA: examples



(a) A case that Video-LLaMA answers the questions based on the background sound and visual content of the video

(b) A case showing Video-LLaMA's ability to identify actions over time.

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Use cases

- AI chat assistant in the specific domain, like finance
- Support automation
- Documentation search (RAG)
- GAR (Generative AI Augmented Retrieval)
- Ask LLM to parse input text, detect sentiment and output the colour sequences of words in a JSON format
- Query tables in natural language (lab)
- Synthetic data (for quality evaluations)

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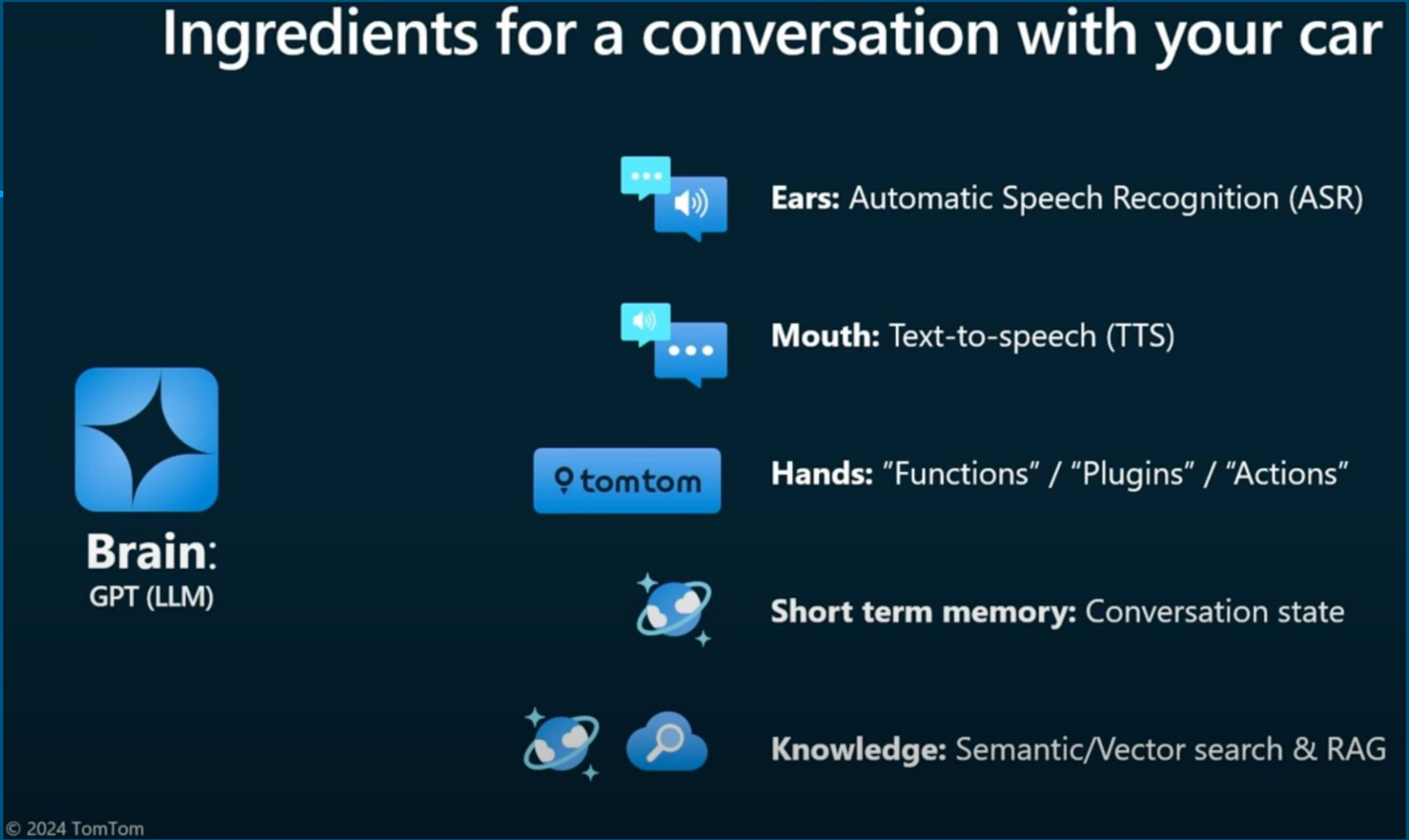
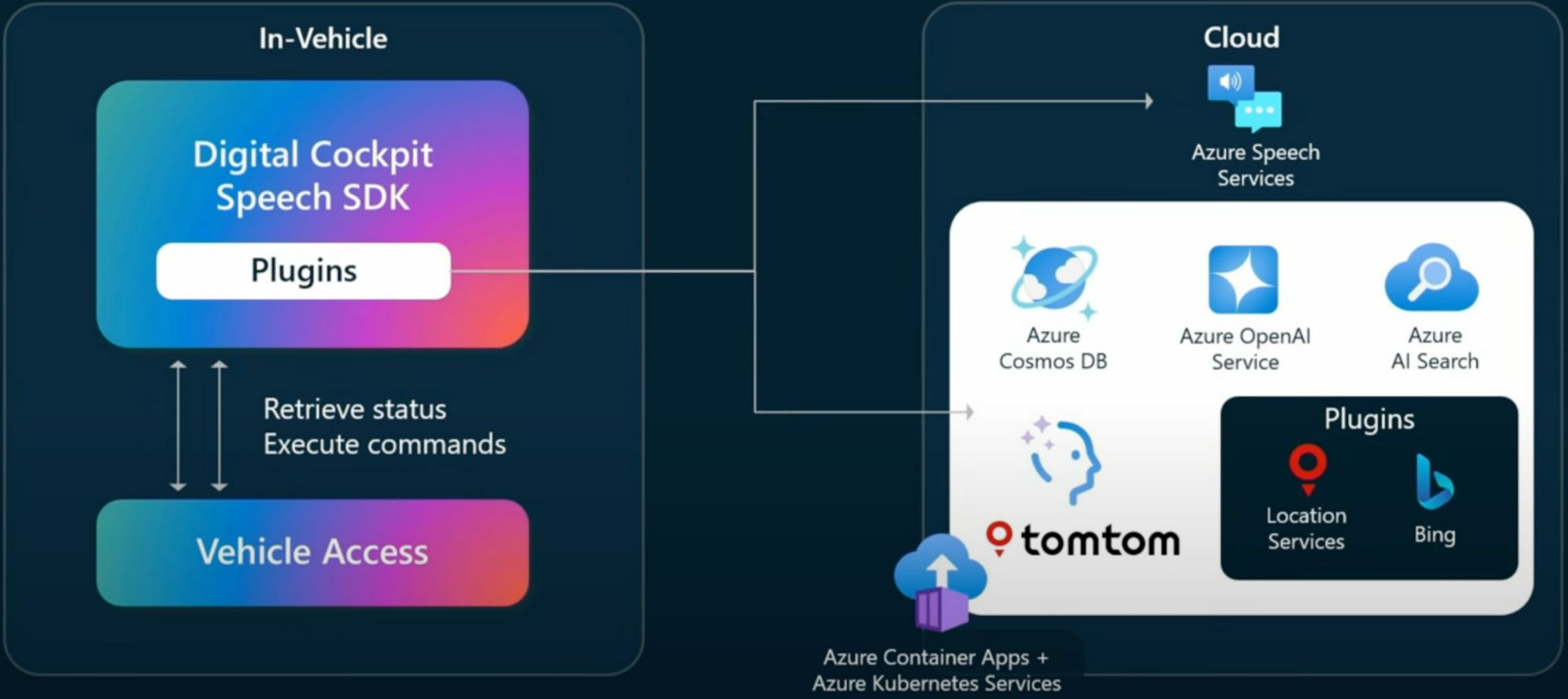
TomTom's IVA: Intelligent Vehicle Assistant


Ingredients for a conversation with your car
Ears: Automatic Speech Recognition (ASR)
Mouth: Text-to-speech (TTS)
tomtom
Hands: "Functions" / "Plugins" / "Actions"
Brain:
GPT (LLM)
Short term memory: Conversation state
Knowledge: Semantic/Vector search & RAG
© 2024 TomTom

Architecture

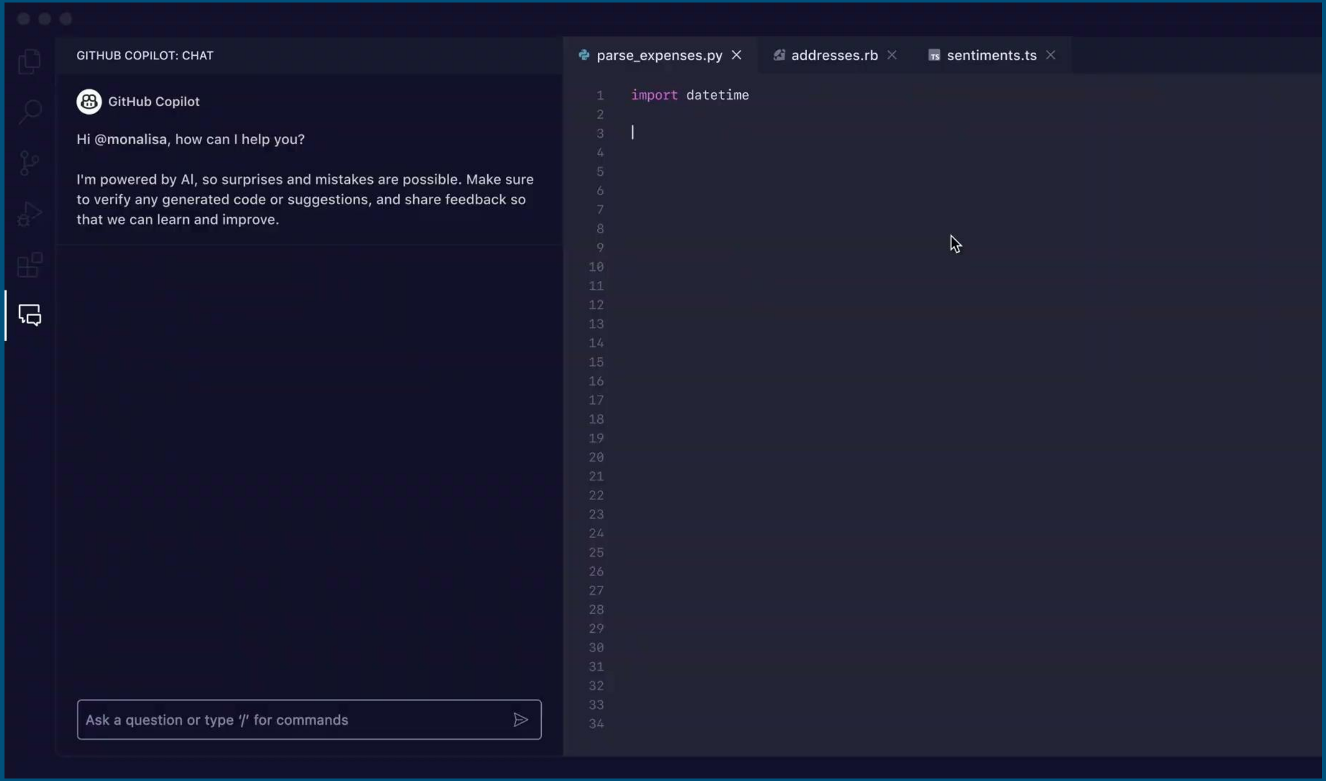


BabyAGI

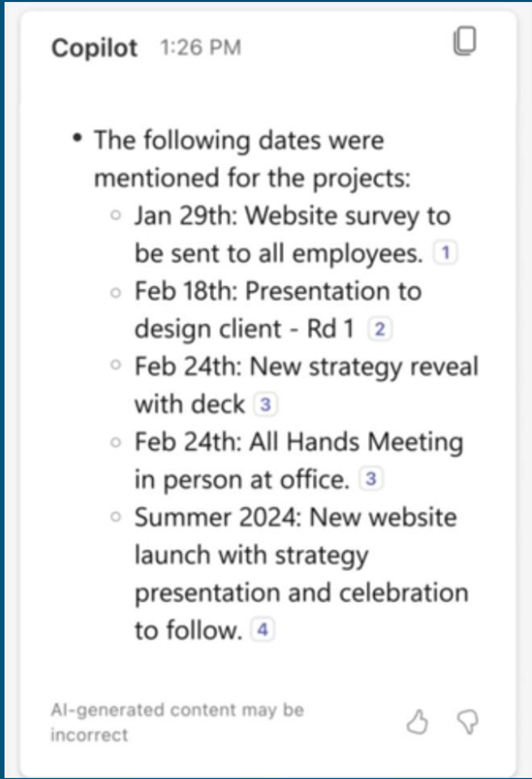
https://github.com/yoheinakajima/babyagi by Yohei Nakajima, Venture Capitalist at Untapped Capital

Code assistant

- Use LLM to analyze and complete code
- LLMs: GPT, Codex (https://openai.com/index/openai-codex/)
- Also in the race: Cursor



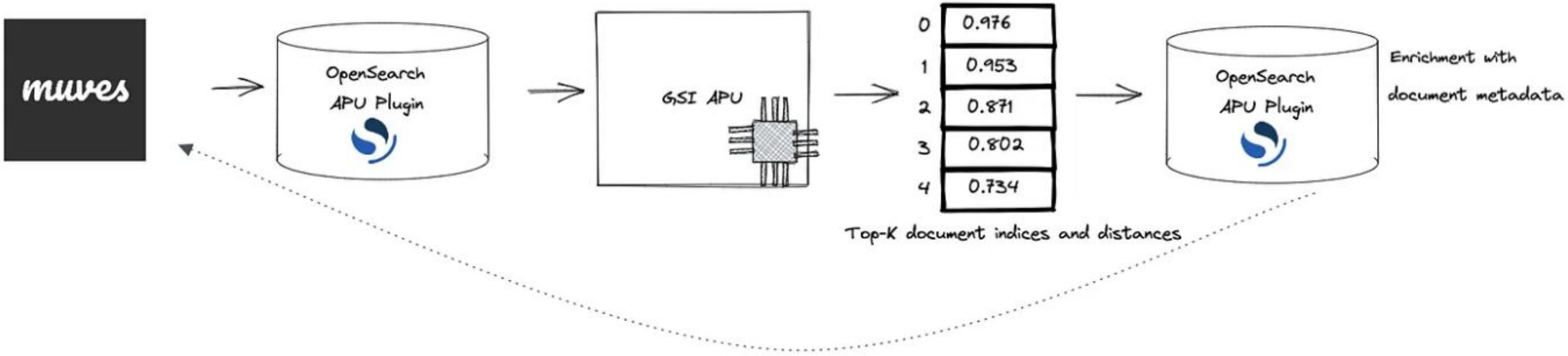
Copilot for work (beyond coding)



- Summarize meetings, extract action points, deadlines
- Get latest updates from a person (emails, chats, files)
- Get key points from documents and presentations

https://copilot.cloud.microsoft/en-US/prompts?ocid=copilot_akams_copilotlab

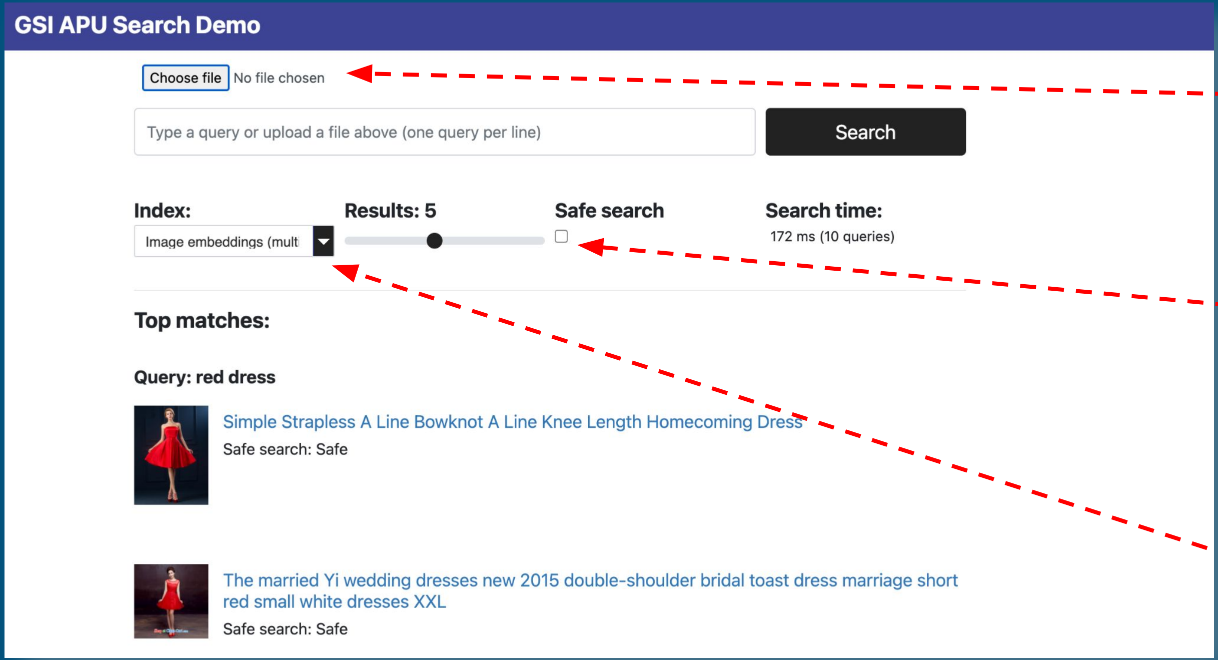
Better e-commerce with multilingual and multimodal vector search with HW acceleration



Muves — APU query workflow for neural search scenarios

https://blog.muves.io/multilingual-and-multimodal-vector-search-with-hardware-acceleration-2091a825de78

The demo contains filtering based on safe search, batch search functionality and different indices



You can submit a text file with multiple queries (one query per line)

You can filter results and show only Safe results

Select between 3 indices / search types: Image embeddings (APU), text embeddings (APU) and pure keyword (OpenSearch)

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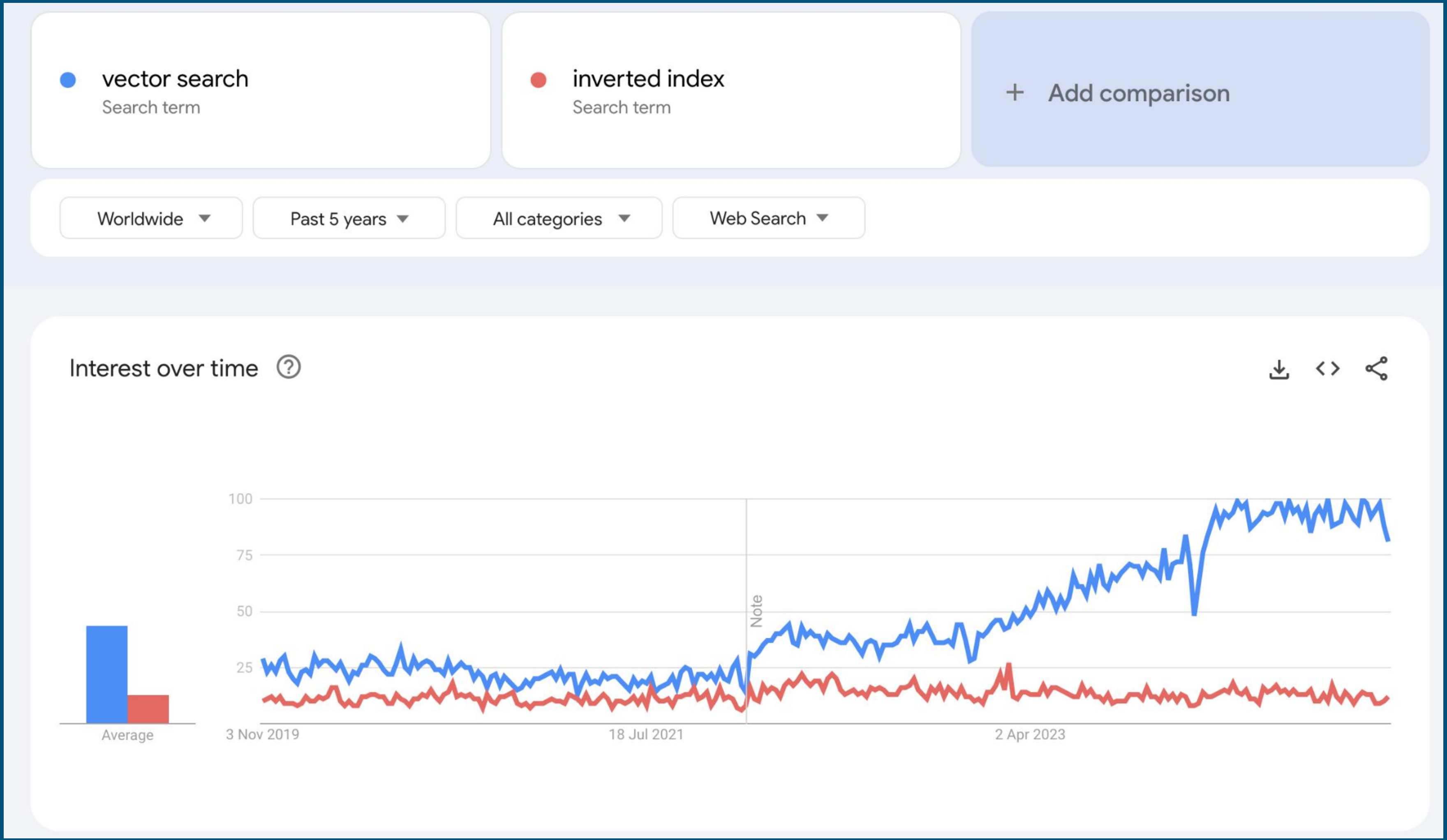
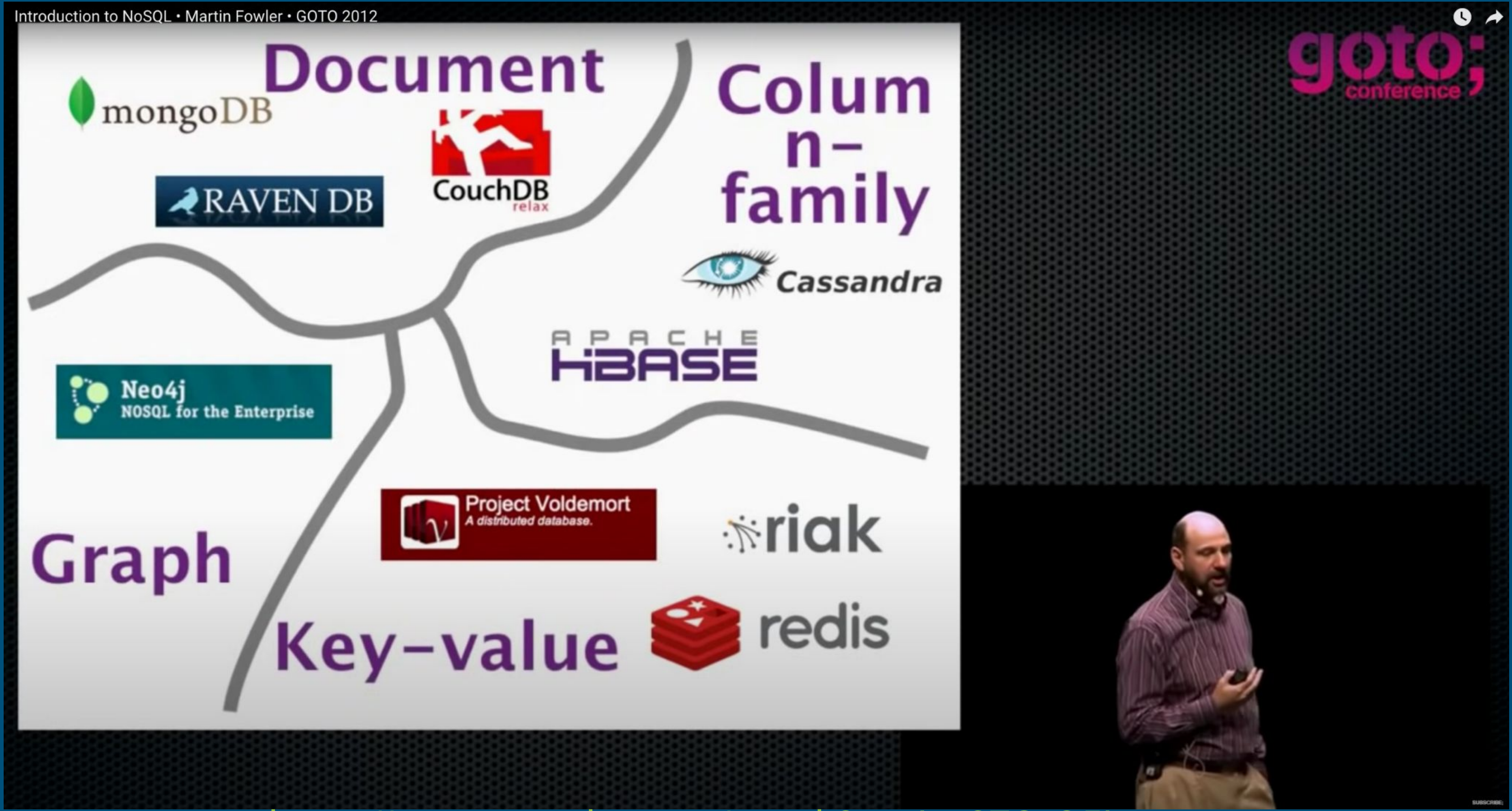
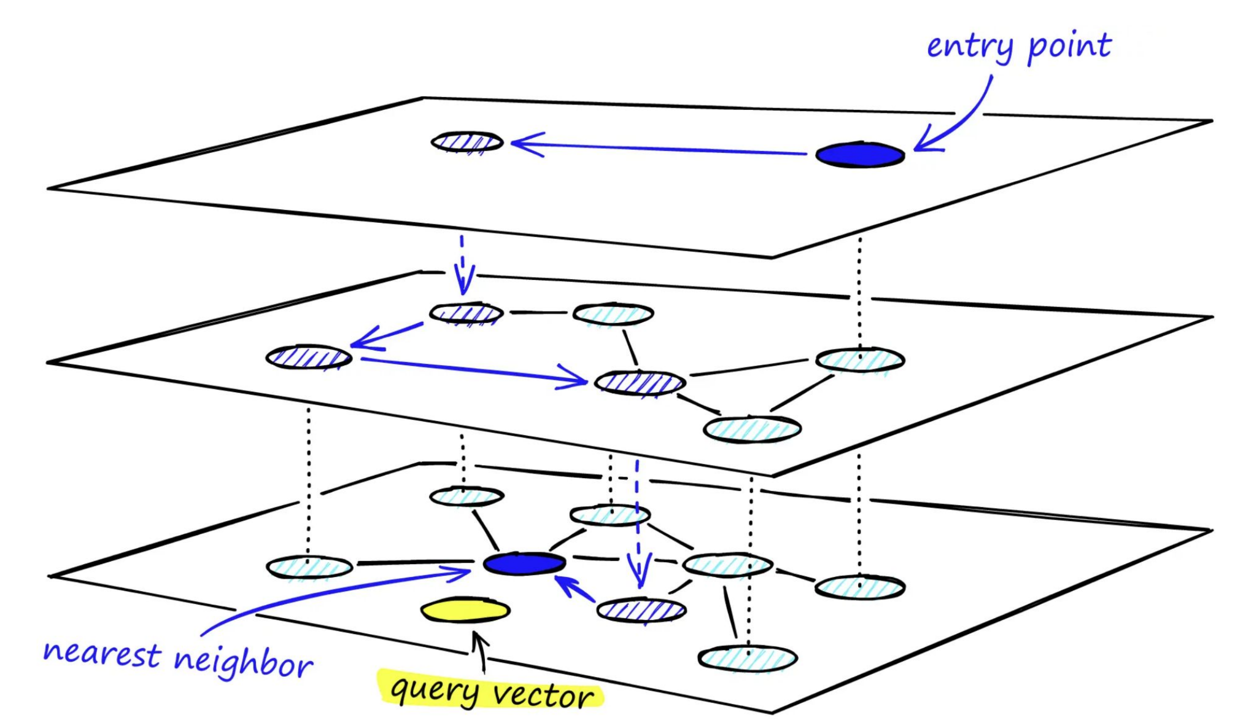


https://trends.google.com/trends/explore?date=today%205-y&q=vector%20search,inverted%20index&hl=en-GB



https://www.youtube.com/watch?v=qI_g07C_Q5I

Vector search algorithms: HNSW



The search process through the multi-layer structure of an HNSW graph.

https://www.pinecone.io/learn/series/faiss/hnsw/

Not All Vector Databases Are Made Equal

A detailed comparison of Milvus, Pinecone, Vespa, Weaviate, Vald, GSI and Qdrant

Dmitry Kan Oct 2 · 7 min read ★

While working on this blog post I had a privilege of interacting with all search engine key developers / leadership: Bob van Luijt and Etienne Dilocker (Weaviate), Greg Kogan (Pinecone), Pat Lasserre, George Williams (GSI Technologies Inc), Filip Haltmayer (Milvus), Jo Kristian Bergum (Vespa), Kiichiro Yukawa (Vald) and Andre Zayarni (Qdrant)

This blog is discussed on HN: https://news.ycombinator.com/item?id=28727816

Update: Vector Podcast launched!

Not All Vector Databases Are Made Equal

· 7 min read · Oct 2, 2021 · View story

121K	46K
Views	Reads

https://dmitry-kan.medium.com/milvus-pinecone-vespa-weaviate-vald-gsi-what-unites-these-buzz-words-and-what-makes-each-9c65a3bd0696

Smaller Vector DB players: 71% are Open Source

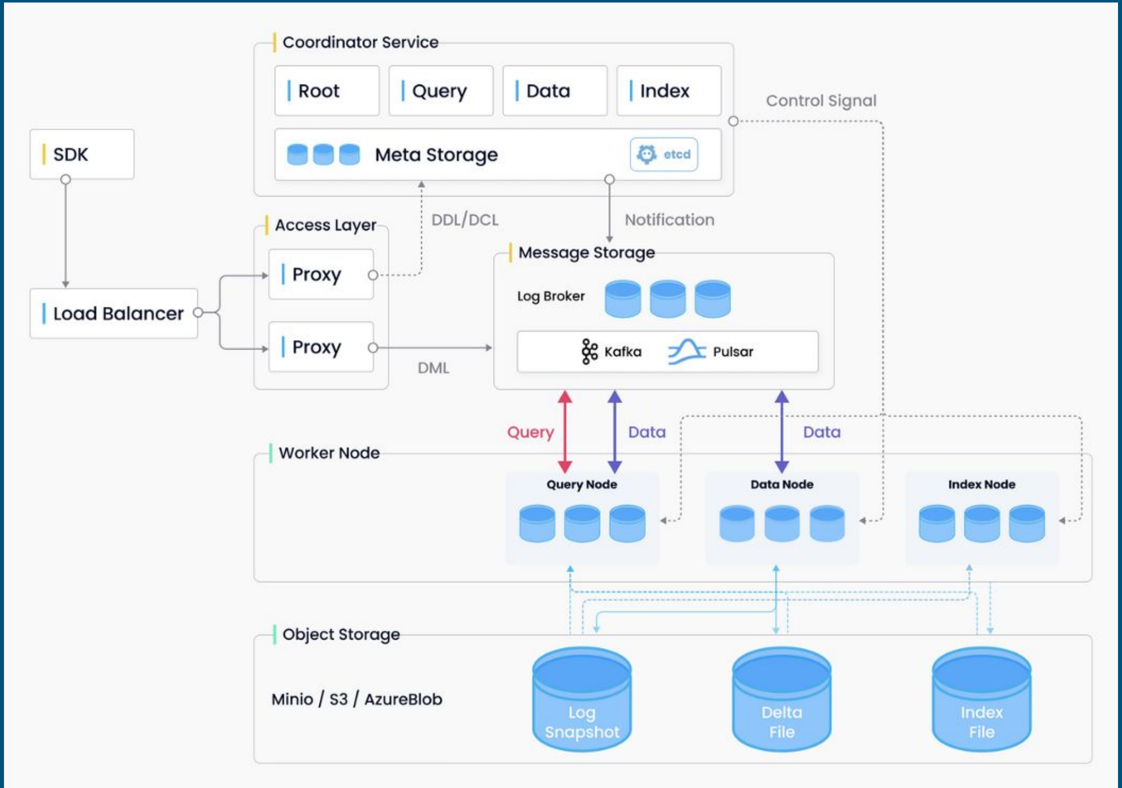
Company	Product	Cloud	Open Source: Y/N	Algorithms
Weaviate	Weaviate	Y	Y (Go)	custom HNSW
Pinecone	Pinecone	Y	N (Rust)	FAISS + own
GSI	APU chip for Elasticsearch / Opensearch	N	N	Neural hashing / Hamming distance
Qdrant	Qdrant	Y	Y (Rust)	HNSW (graph)
Yahoo!	Vespa	Y	Y (Java, C++)	HNSW (graph)
Ziliz	Milvus	N	Y (Go, C++, Python)	FAISS, HNSW
Yahoo!	Vald	N	Y (Go)	NGT

Milvus

🌍 milvus.io
💡 self-hosted vector database
🤖 open source

Value proposition:

- attention to scalability: (re)indexing and search
- ability to index data with multiple ANN algorithms to compare their performance for your use case



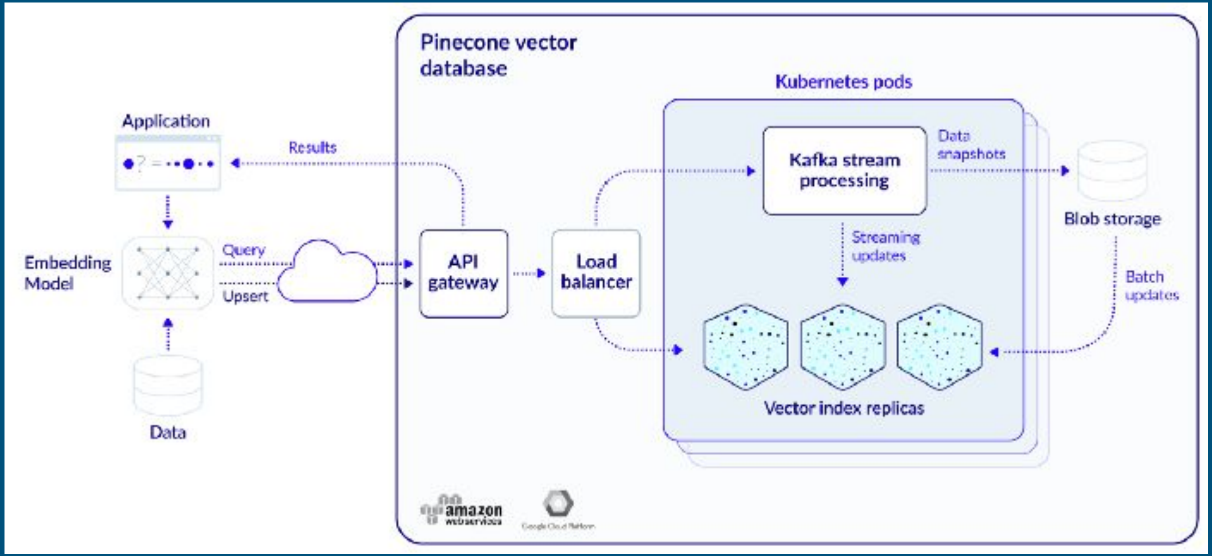
milvus

Pinecone

🌍 pinecone.io
💡 managed vector database
🤖 close source

Main features:

- Fully managed vector database
- Single-stage filtering capability: search for your objects (sweaters) + filter by metadata (color, size, price) in one query



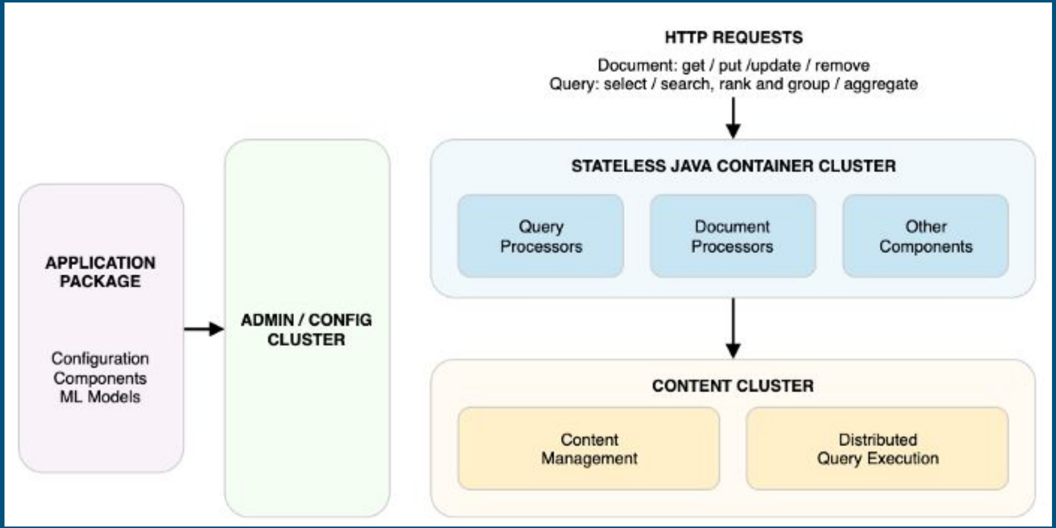
Pinecone

Vespa

🌍 vespa.ai/
💡 managed / self-hosted
🤖 Code: open source

Value proposition:

- low-latency computation over large data sets
- stores and indexes your data so that queries, selection and processing over the data can be performed at serving time
- customizable functionality
- deep data structures geared towards deep-learning like data science, like Tensors

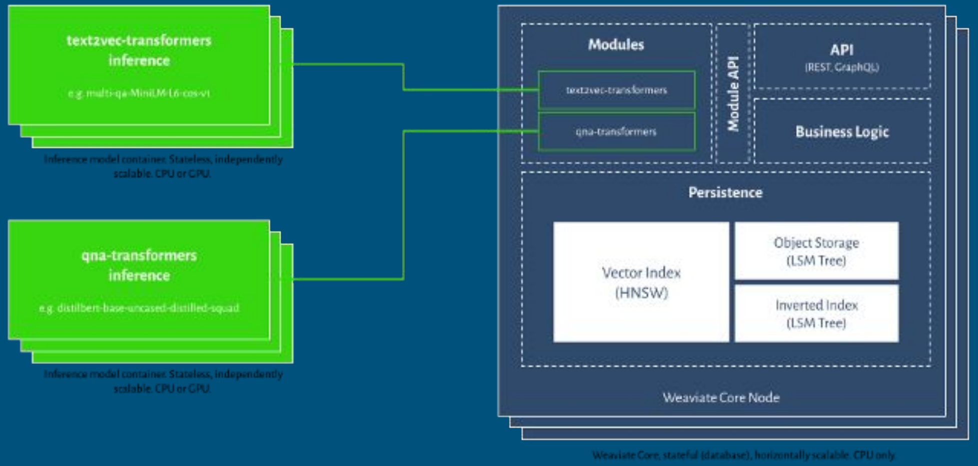


Weaviate

🌍 semi.technology/developers/weaviate/current/
💡 managed / self-hosted
🤖 open source

Value proposition:

- Expressive query syntax
- Graphql-like interface
- combo of vector search, object storage and inverted index
- Wow-effect: Has an impressive question answering component

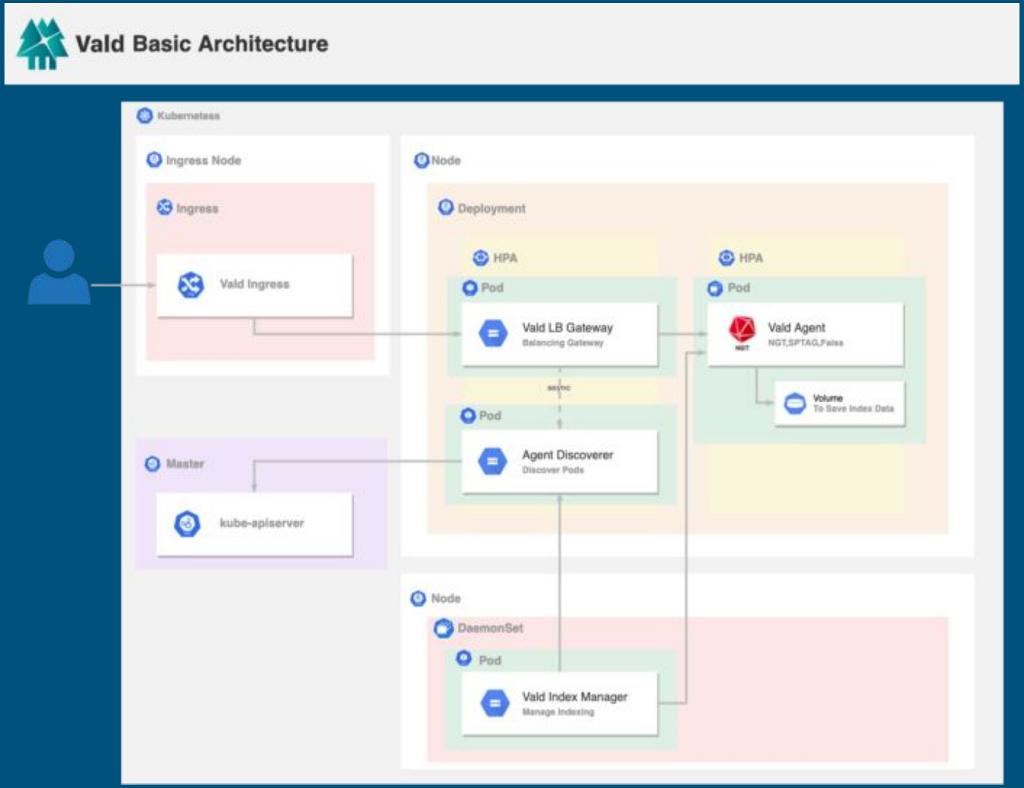


Vald

🌍 Link: vald.vdaas.org/
💡 Type: Self-hosted vector database
🤖 Code: open source

Value proposition:

- Billion-scale
- Cloud-native architecture
- Fastest ANN Algo: NGT
- Custom reranking / filtering algorithm plugins



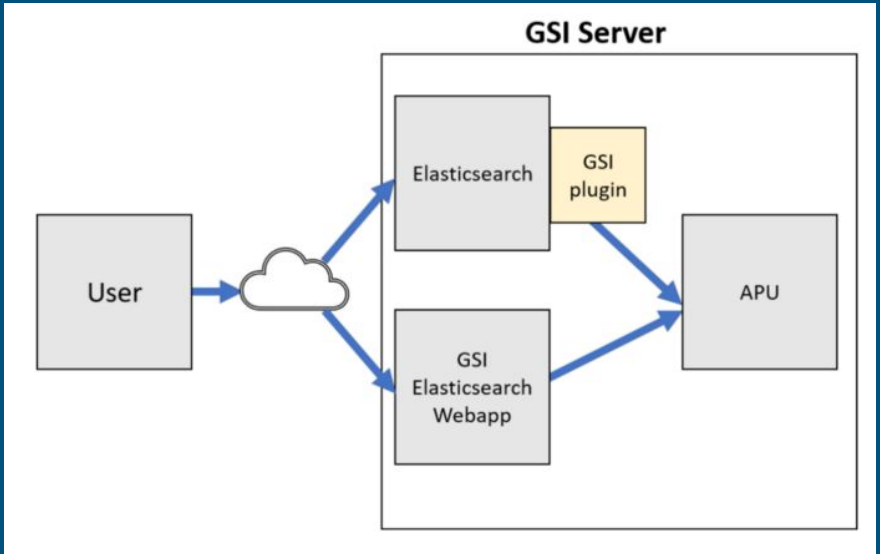
Vald

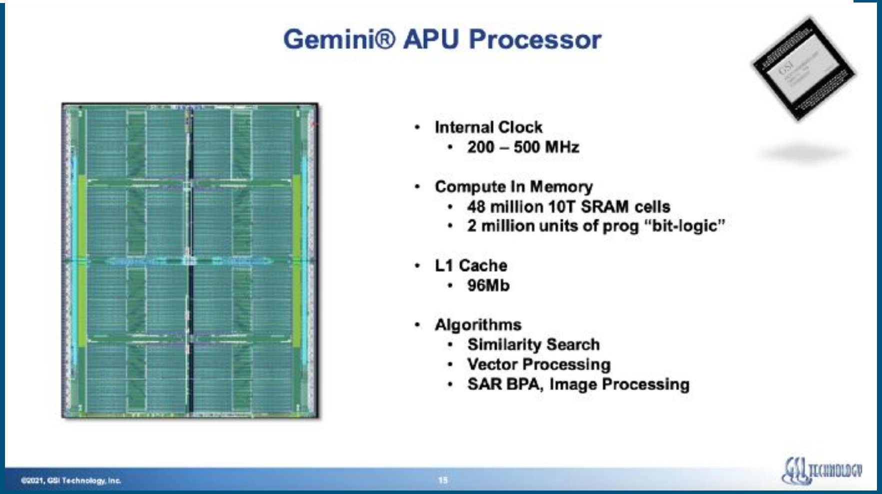
GSI APU

🌍 Link: gsitechnology.com/APU
💡 Type: Vector search hardware backend for your Elasticsearch / OpenSearch
🤖 Code: close source

Value proposition:

- Billion-scale
- Extends your Elasticsearch / OpenSearch capabilities to similarity search
- On-prem / hosted APU board hosted cloud backend



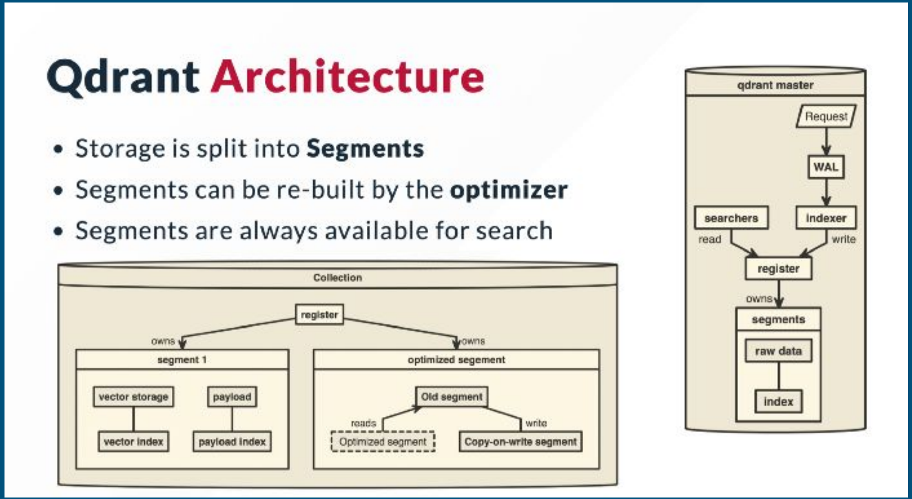


Qdrant

🌍 qdrant.tech/
💡 self-hosted vector database + Cloud
🤖 open source

Value proposition:

- The vector similarity engine with extended filtering support
- dynamic query planning and payload data indexing
- string matching, numerical ranges, geo-locations, and more
- Metric Deep Learning



Semantic frameworks / layers: 57% Open Source

Company	Product	Open Source: Y/N	Focus
Deepset.ai	Haystack	Y	NLP, neural search
Jina.AI	Jina, Hub, Finetuner	Y	NLP, CV, ASR
Featureform	Feature store, EmbeddingHub	Y	All AI verticals
ZIR.AI	AI search platform	N	NLP
Hebbia.AI	Knowledge Base	N	NLP -> Finance
Rasa.ai	Virtual assistants	Y	NLP
Muves.io	Multilingual vector search	N	Multilingual search, multimodality

Vector Search Pyramid

user interface

Application business logic: neural / BM25, symbolic filters, RAG, ranking

Encoders: BERT, Clip, GPT3… + Mighty — 25%

Neural frameworks: Haystack, Jina.AI, Vectara, Hebbia.AI, txtai … — 43%

Vector Databases: Milvus, Weaviate, Pinecone, GSI, Qdrant, Vespa, Vald, Elastiknn… — 71%

KNN / ANN algorithms: HNSW, PQ, IVF, LSH, Zoom, DiskANN, BuddyPQ … — 100%

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Reasoning LLMs

- Self-replay: rStar (Microsoft Asia)
- Slower, but more accurate models, like QwQ-32B-Preview by team Qwen (Alibaba Research) - 32.5B parameters, 32000 prompt capacity: https://techcrunch.com/2024/11/27/alibaba-releases-an-open-challenger-to-openais-o1-reasoning-model/

rStar: Self-play muTuAl Reasoning

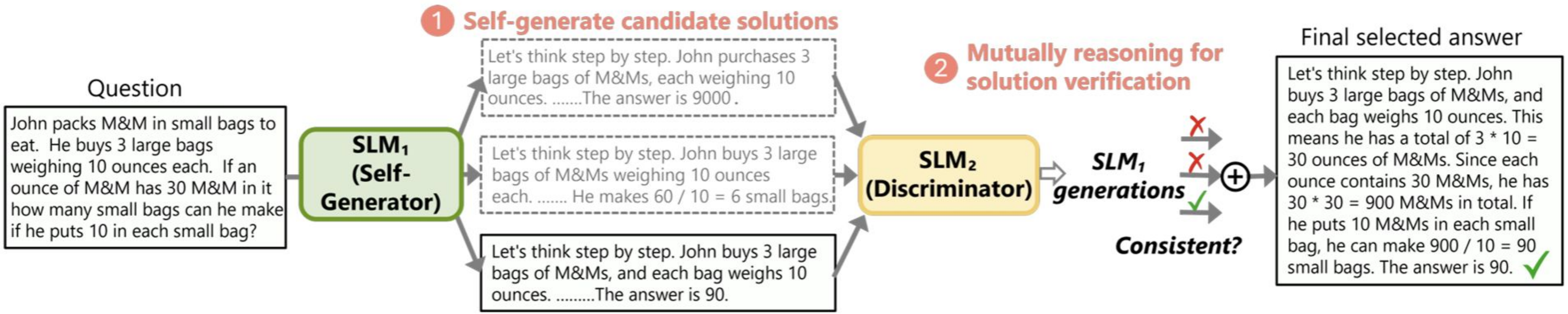

Figure 2: Our self-play mutual reasoning is a generation-discrimination process: (1) a self-generator augments the target SLM to generate candidate reasoning trajectories using MCTS; (2) the discriminator uses another SLM to provide unsupervised feedback on each trajectory based on partial hints; (3) based on this feedback, the target SLM decides a final reasoning trajectory as the solution.

https://arxiv.org/pdf/2408.06195v1

Lab!

1. Continue working on the RAG app, if you are still not done
2. Improve query_tables.py with:
   a. Loading all sections to avoid hard-coding a section with tables
   b. Test the capabilities of reasoning with table data: can it sum up numbers or do some other calculation?
3. Implement code in synthetic_data.py: generate variants of queries with misspellings and test them
4. Optional: set up, run and test: https://github.com/DAMO-NLP-SG/LLM-Sentiment

For 2 and 3 consult week-6/README.md

Group session

Think about a field of life that deserves to be improved with LLMs.

- Can you come up with a solution to this?
- What are the expected benefits?
- What is the risk of model hallucination / inaccuracy / bias / misuse and what is the mitigation?
- Why does it matter? Broader impact on society or individuals

Examples of fields: Healthcare, Education, Transportation, Social Media, Customer Service

Be prepared to present

- The field you chose
- The problem and your LLM-based solution
- A potential risk and how it could be mitigated

Further study

- Ichigo paper: https://arxiv.org/pdf/2410.15316
- MSFT's GraphRAG: https://microsoft.github.io/graphrag/
- GraphRAG with Neo4j: demo https://neo4j.com/labs/genai-ecosystem/rag-demo/
- Book code: Building LLM applications: https://github.com/PacktPublishing/Building-LLM-Powered-Applications/tree/main
- rStar paper: https://arxiv.org/pdf/2408.06195v1 code: https://github.com/zhentingqi/rStar
- GitHub Copilot: https://github.blog/ai-and-ml/github-copilot/inside-github-working-with-the-llms-behind-github-copilot/

Further study

- ColPali demo: https://huggingface.co/spaces/manu/ColPali-demo
- Podcast episode with the Cursor team: https://lexfridman.com/cursor-team/
- Improved video LLM: https://arxiv.org/pdf/2311.18445v1
- Vector Podcast on YouTube: https://www.youtube.com/c/VectorPodcast
- Vector Podcast on Spotify: https://open.spotify.com/show/13JO3vhMf7nAqcpvIlgOY6
- Vector Podcast on Apple Podcasts: https://podcasts.apple.com/us/podcast/vector-podcast/id1587568733