

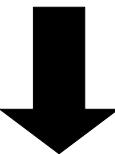
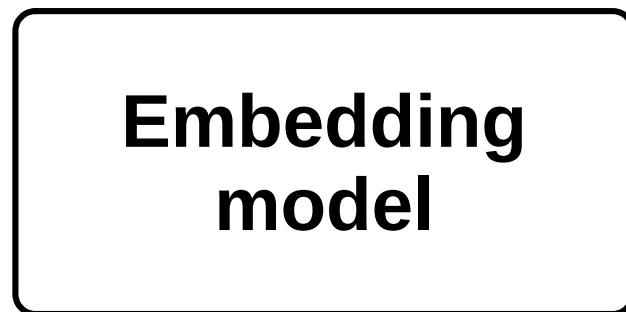
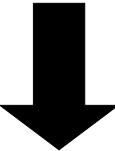
Benchmarking embedding models

Introduction

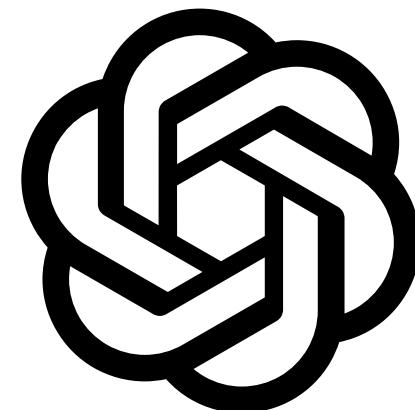
Benchmarking embedding models

- Embedding models **convert text** (or other modalities) to a **dense vector**.
- With embedding models, you can **build RAG and recommendation systems**.
- But **how do you choose an embedding model?**

Hi Cassiopeia! Have you
talked with Andromeda?



[0.69, 0.42, ...]



Benchmarking embedding models

- How do you choose an embedding model?
- You look at **benchmarks!**
- MTEB ranks models based on their performance on **different benchmarks.**

Rank (Bor...)	Model	Zero-shot	Memory U...	Number of P...	Embedding D...	Max Tokens	Mean (T...	Mean (TaskT...	Bitext ...	Classification	Clustering
1	gemini-embedding-001	99%	Unknown	Unknown	3072	2048	68.37	59.59	79.28	71.82	54.59
2	Qwen3-Embedding-8B	99%	28866	7B	4096	32768	70.58	61.69	80.89	74.00	57.65
3	Qwen3-Embedding-4B	99%	15341	4B	2560	32768	69.45	60.86	79.36	72.33	57.15
4	Qwen3-Embedding-0.6B	99%	2272	595M	1024	32768	64.34	56.01	72.23	66.83	52.33
5	gte-Qwen2-7B-instruct	⚠ NA	29040	7B	3584	32768	62.51	55.93	73.92	61.55	52.77
6	Linq-Embed-Mistral	99%	13563	7B	4096	32768	61.47	54.14	70.34	62.24	50.60
7	multilingual-e5-large-instruct	99%	1068	560M	1024	514	63.22	55.08	80.13	64.94	50.75
8	embeddinggemma-300m	99%	578	307M	768	2048	61.15	54.31	64.40	60.90	51.17
9	SFR-Embedding-Mistral	96%	13563	7B	4096	32768	60.90	53.92	70.00	60.02	51.84
10	GritLM-7B	99%	13813	7B	4096	32768	60.92	53.74	70.53	61.83	49.75
11	text-multilingual-embedding-002	99%	Unknown	Unknown	768	2048	62.16	54.25	70.73	64.64	47.84

The MTEB leaderboard on 20/09/2025.

Benchmarking embedding models

- Should we **trust** these public benchmarks?
- You can also create **your own benchmark** with your private data.
- The dataset must be **clean, diverse, and in your language** (or multilingual).

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11	text-multilingual-embedding-002	99%	Unknown	Unknown	768	2048	62.16	54.25	70.73	64.64	47.84

Benchmarking embedding models

In this course, you will:

- Create a **golden dataset**.
- Run **open source** and **proprietary models**.
- Compute **metrics** to grade the models.
- Perform **statistical tests** to prove if a model is better than another.
- **Automate** some steps in the pipeline.
- **Generate tables** to compare the models.

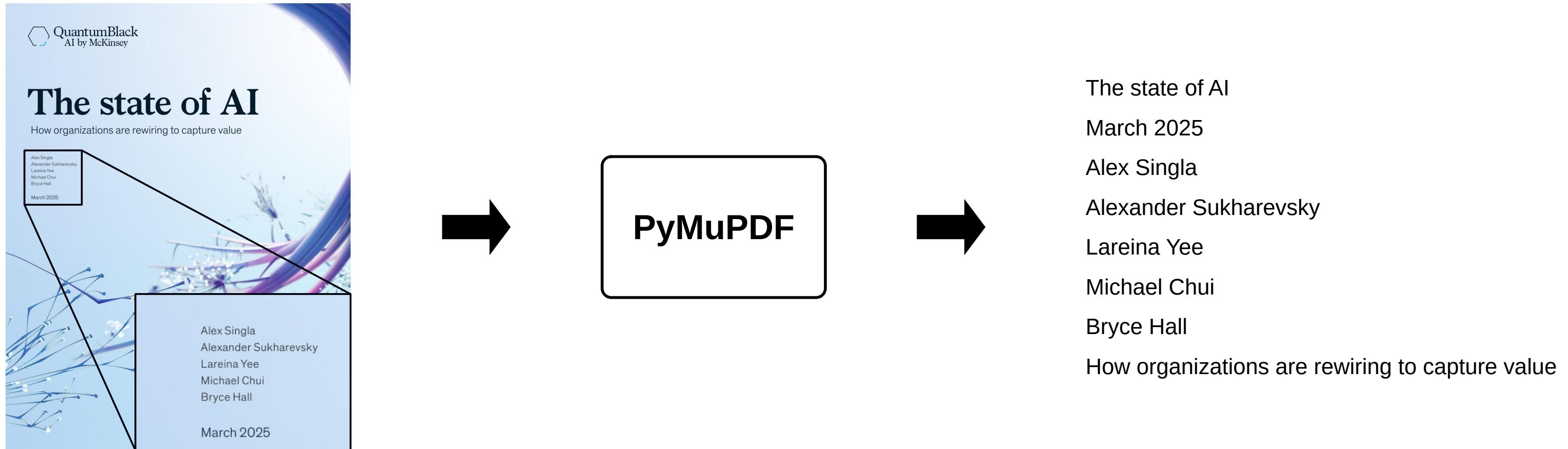
#	Model	mrr	recall@1	recall@5	ndcg@5
a	OpenAI 3-Small	0.780	0.683	0.901	0.804
b	OpenAI 3-Large	0.778	0.681	0.901	0.802
c	Google Gemini-001	0.810 ab	0.725 b	0.927 ab	0.834 ab

Comparing Gemini embedding to OpenAI's embedding models.

Extract text from PDF files

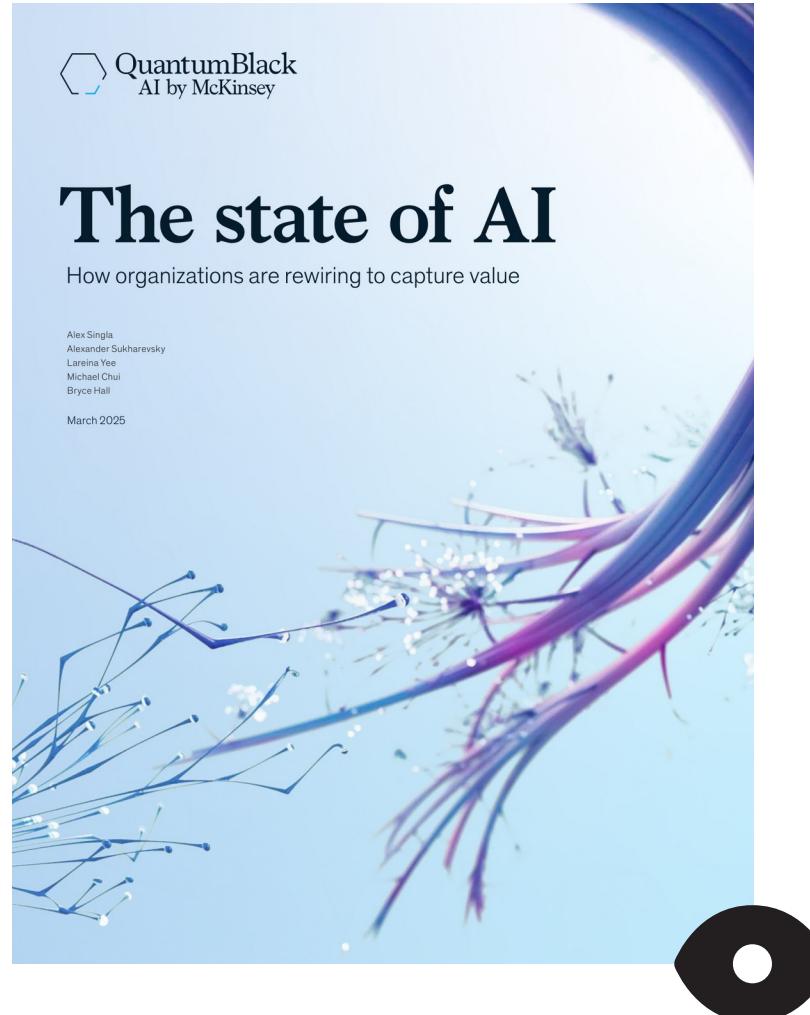
Extract text from PDF files

- Extracting text from PDF files is challenging.
- PDF files can be scanned, have complex layouts, and contain images, tables, etc
- In Python, we can use libraries like [PyMuPDF](#), [PyPDF2](#), and [pdfplumber](#).
- These libraries are ineffective if you want to preserve the structure of the document.



Extract text from PDF files

- We can use vision language (VL) models to parse PDF documents and images.
- VL models can see images



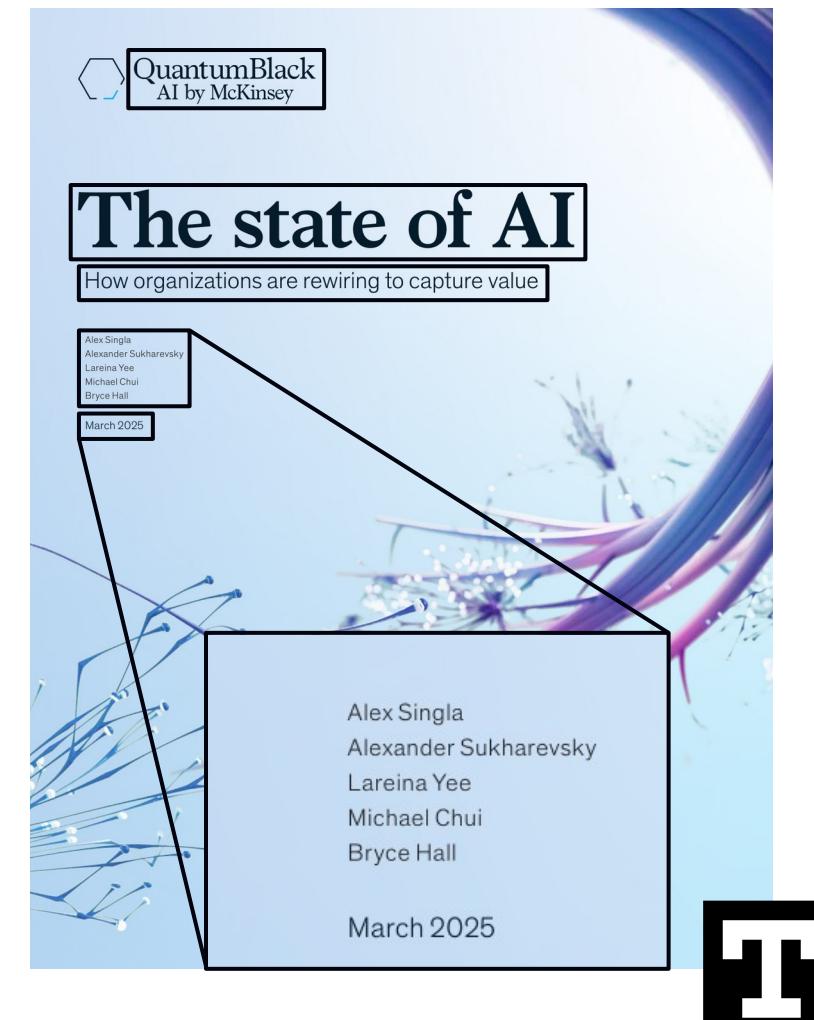
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- VL models can see images, read and understand text.
- The vision and language parts work together to parse the image effectively.



QuantumBlack
AI by McKinsey

The state of AI
How organizations are rewiring to capture value

Alex Singla
Alexander Sukharevsky
Lareina Yee
Michael Chui
Bryce Hall

March 2025

Extract text from PDF files

- What is the trade-off?
- Let's compare both methods side-by-side.

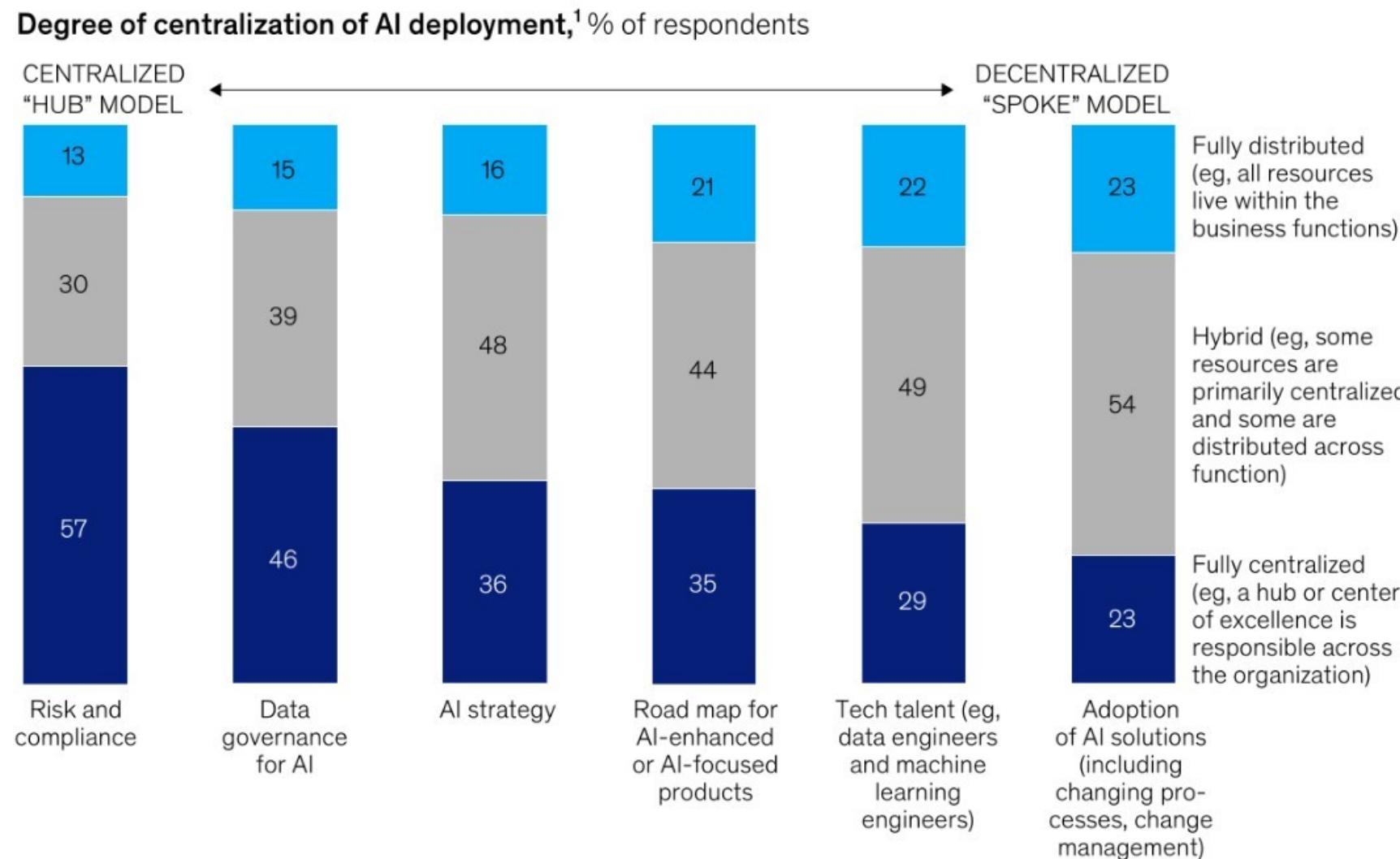
	Python libraries	VL models
Cost	Free	Free / Paid
Scanned input	No	Yes
Resources	Low	High / Low
Preserve structure	No	Yes
Handle complex layouts	No	Yes
Understand the content	No	Yes
Speed	Fast	Slow

Extract text from PDF files

Side-by-side comparison: Test N°1

Exhibit 1

Risk and data governance are two of the most centralized elements of deploying AI solutions, whereas tech talent is often hybrid.



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Source: McKinsey Global Survey on the state of AI, 1,491 participants at all levels of the organization, July 16–31, 2024

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Side-by-side comparison: Test N°1

PyMuPDF

Exhibit 1

Degree of centralization of AI deployment,¹ % of respondents

McKinsey & Company

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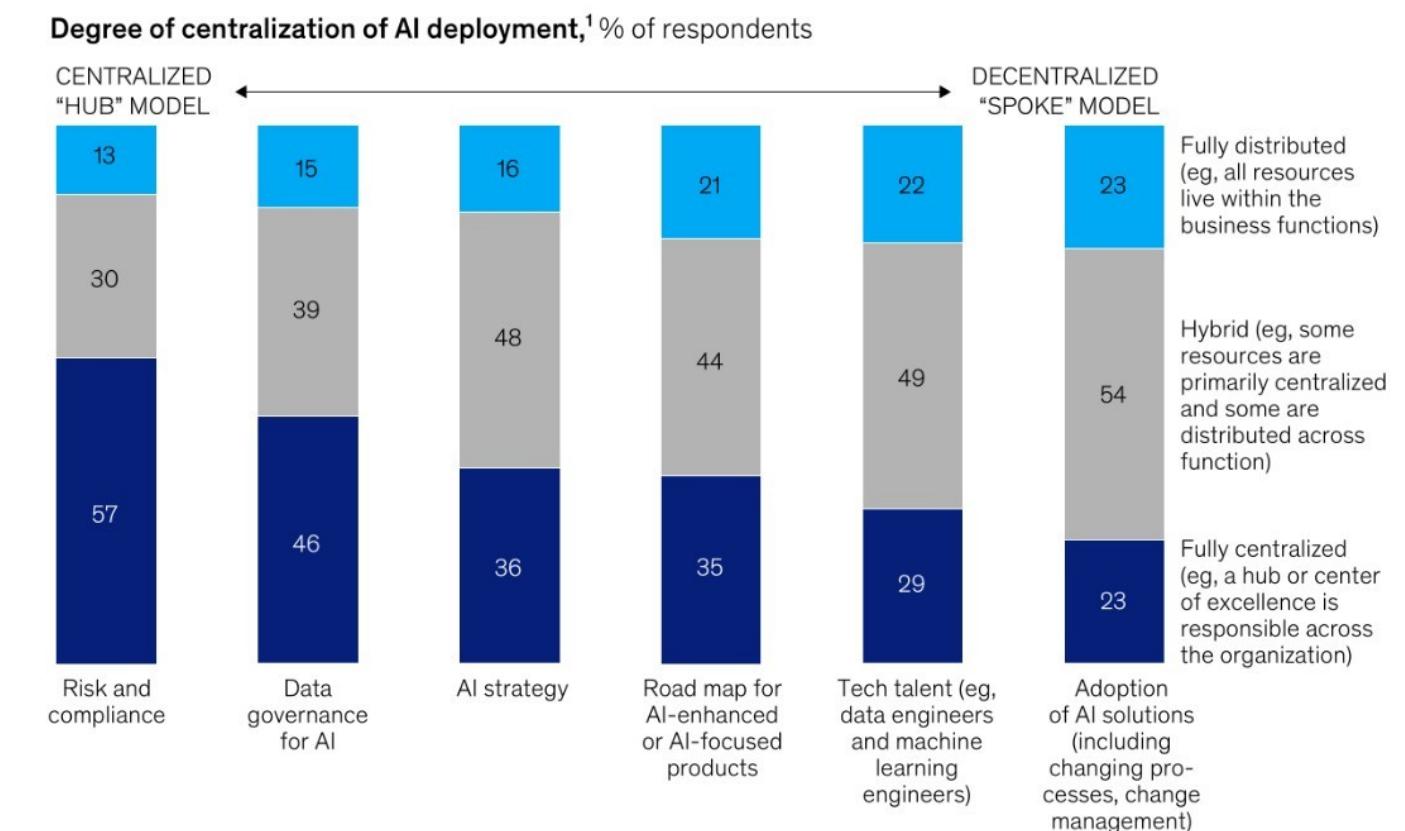
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36
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29
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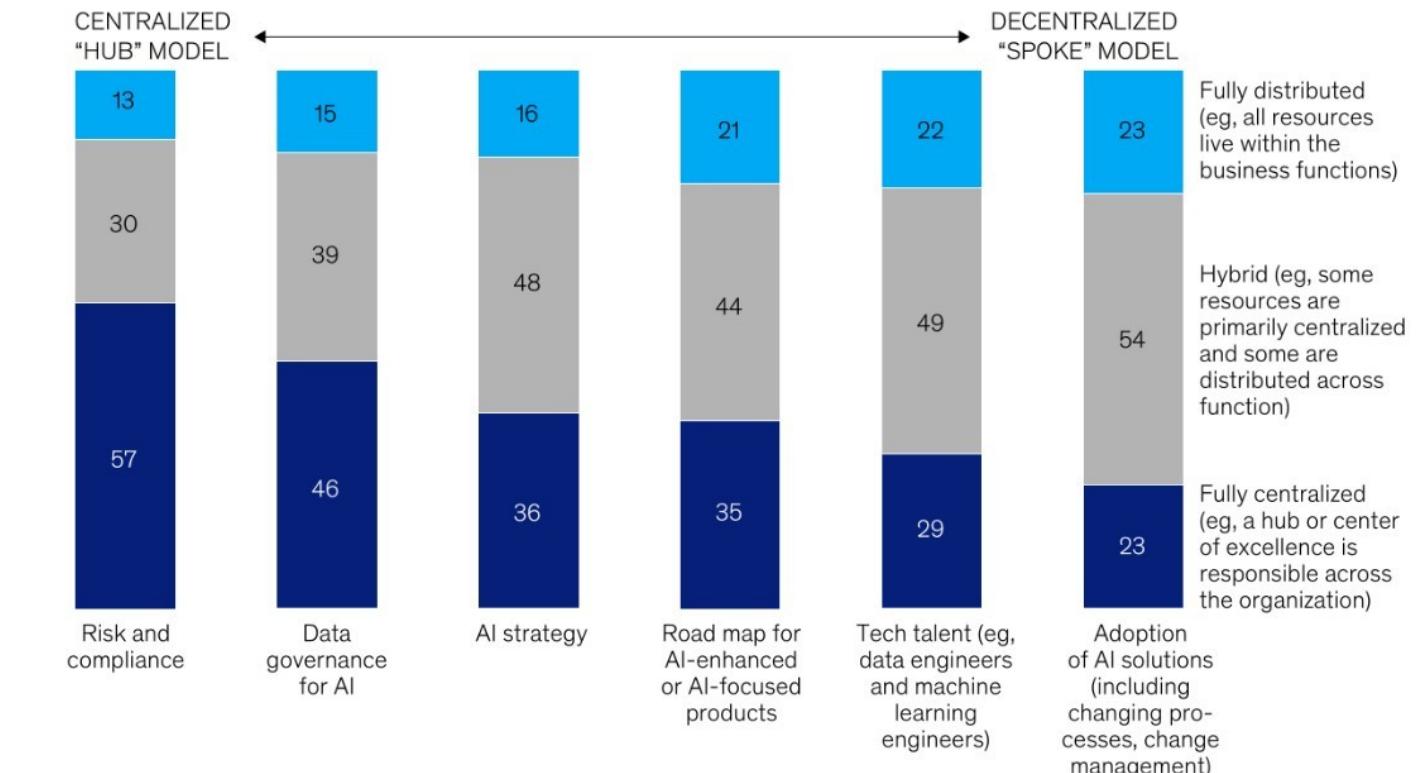
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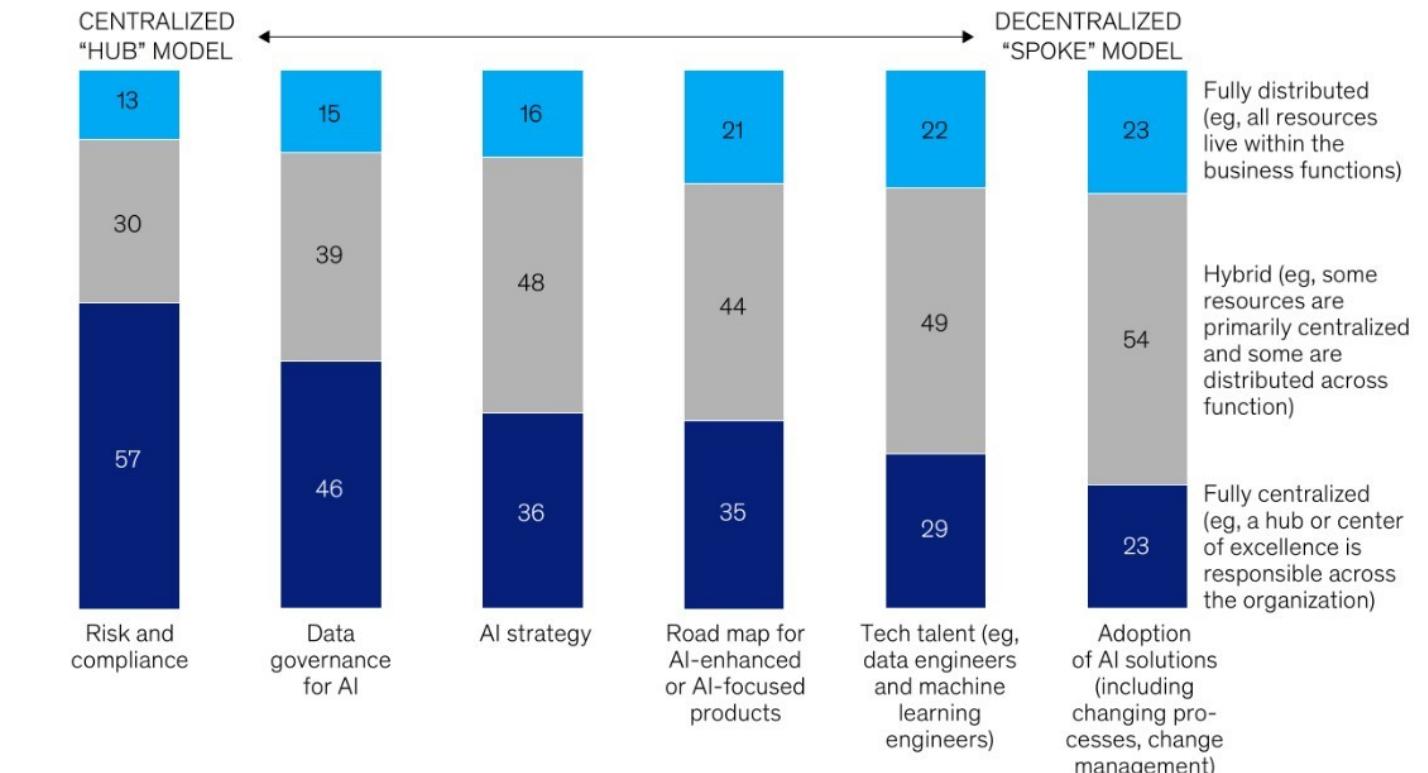
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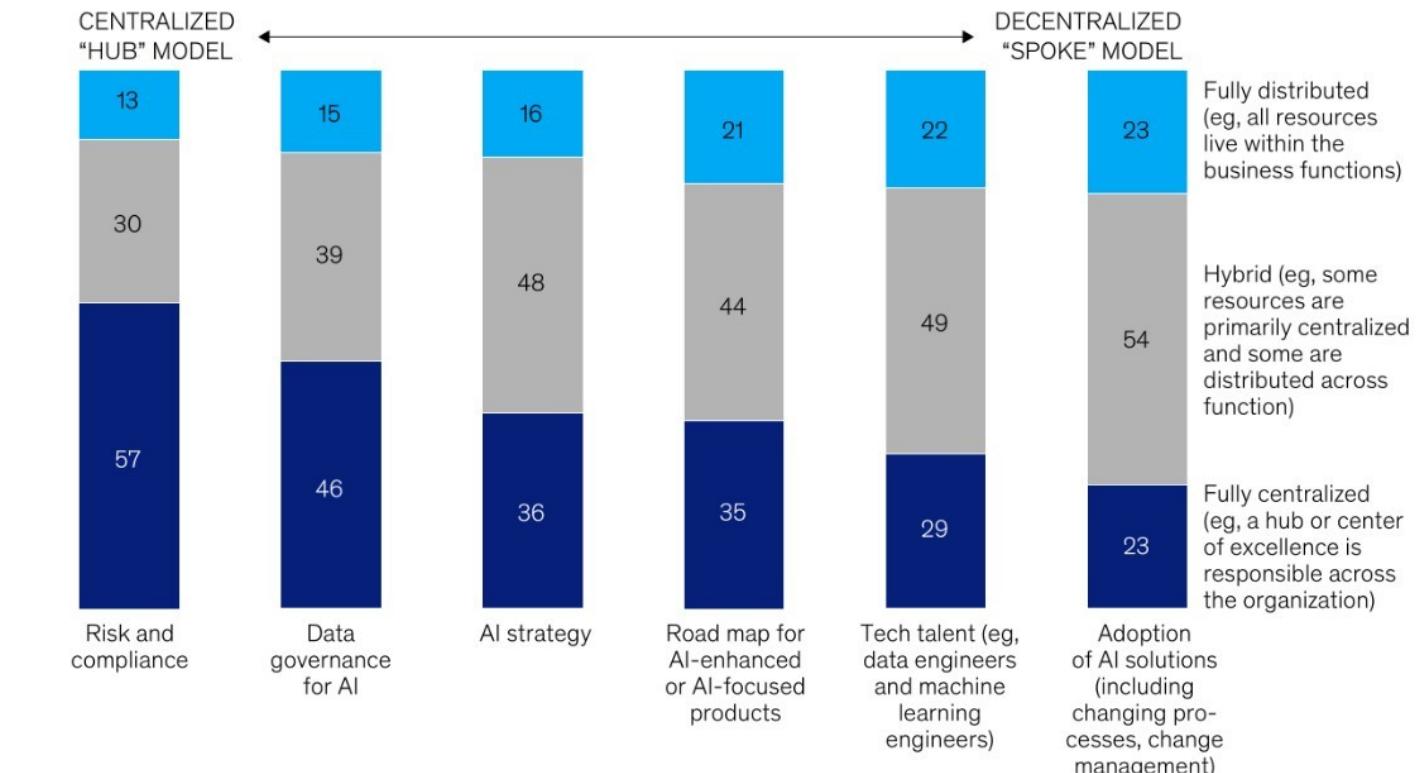
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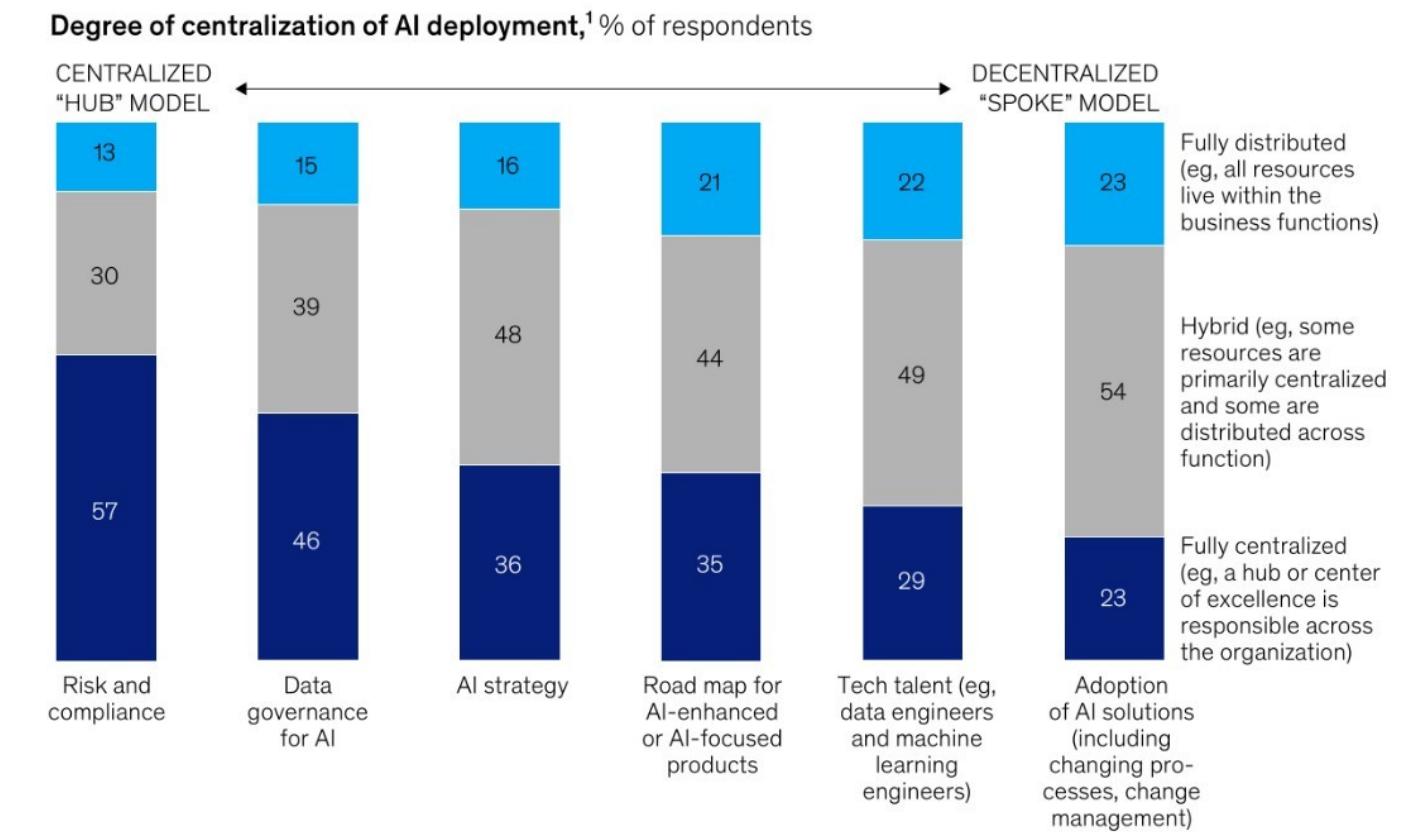
Side-by-side comparison: Test N°1

PyMuPDF (Continuation)

49
54
13
15
16
21
22
23
Fully centralized
(eg, a hub or center
of excellence is
responsible across
the organization)
Hybrid (eg, some
resources are
primarily centralized
and some are ...)

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Side-by-side comparison: Test N°1

VL model (Gemini 2.5 Pro)

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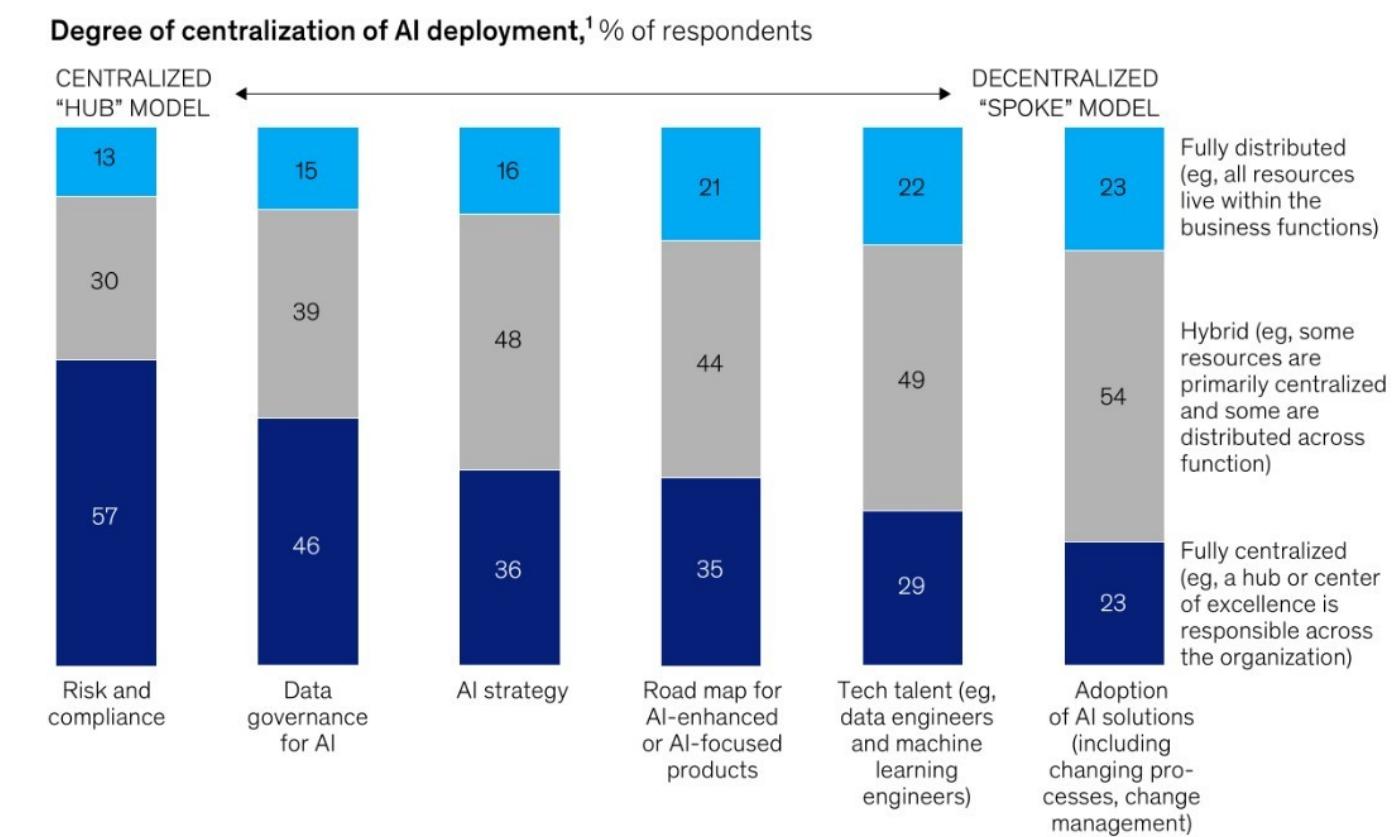
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The six bars are for the following categories, with their respective data breakdowns:

- Risk and compliance:** 57% Fully centralized, 30% Hybrid, 13% Fully distributed.
- Data governance for AI:** 46% Fully centralized, 39% Hybrid, 15% Fully distributed.
- AI strategy:** 36% Fully centralized, 48% Hybrid, 16% Fully distributed.
- Road map for AI-enhanced or AI-focused products:** 35% Fully centralized, 44% Hybrid, 21% Fully distributed.
- Tech talent (eg, data engineers and machine learning engineers):** 29% Fully centralized, 49% Hybrid, 22% Fully distributed.
- Adoption of AI solutions (including changing processes, change management):** 23% Fully centralized, 54% Hybrid, 23% Fully distributed.] ...

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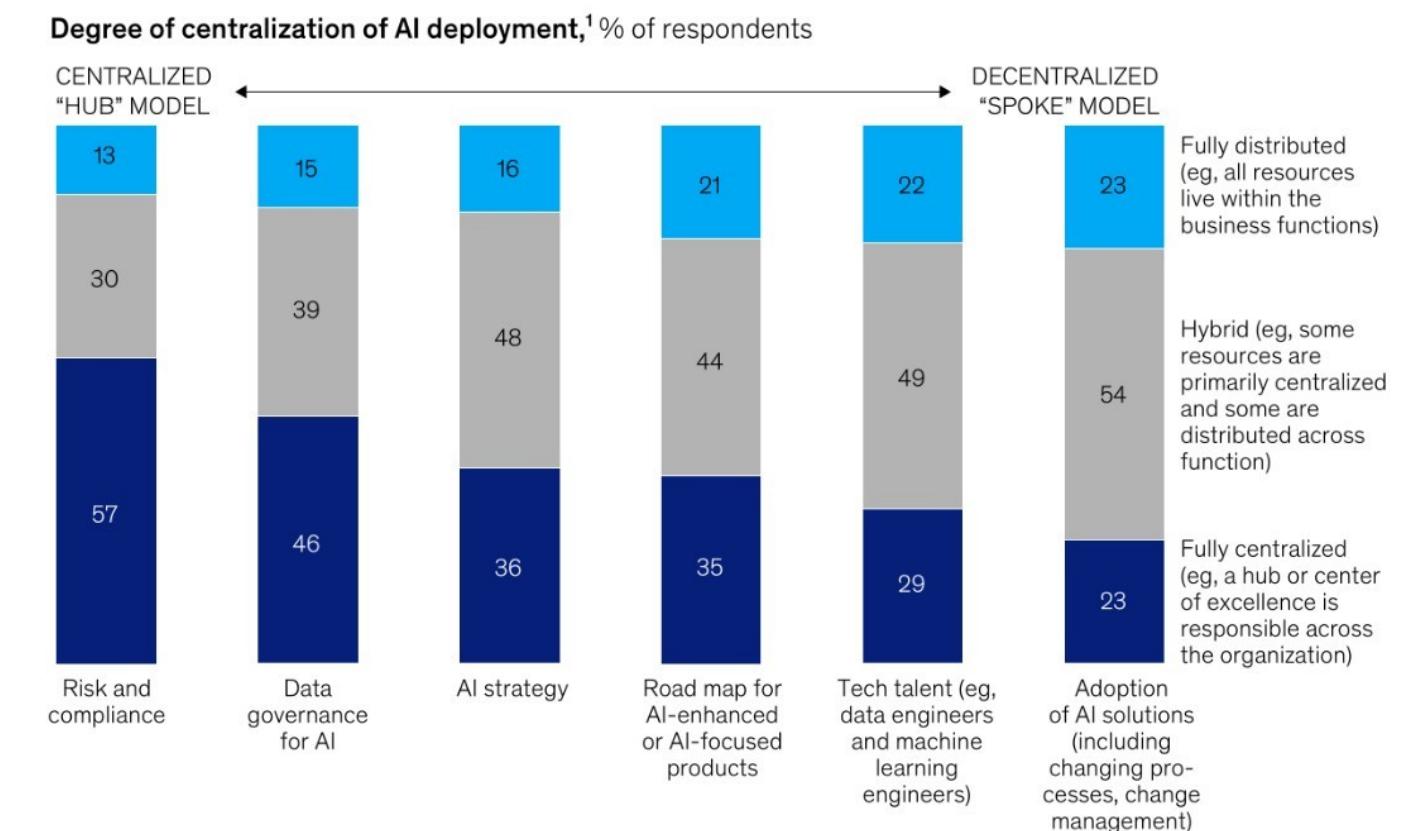
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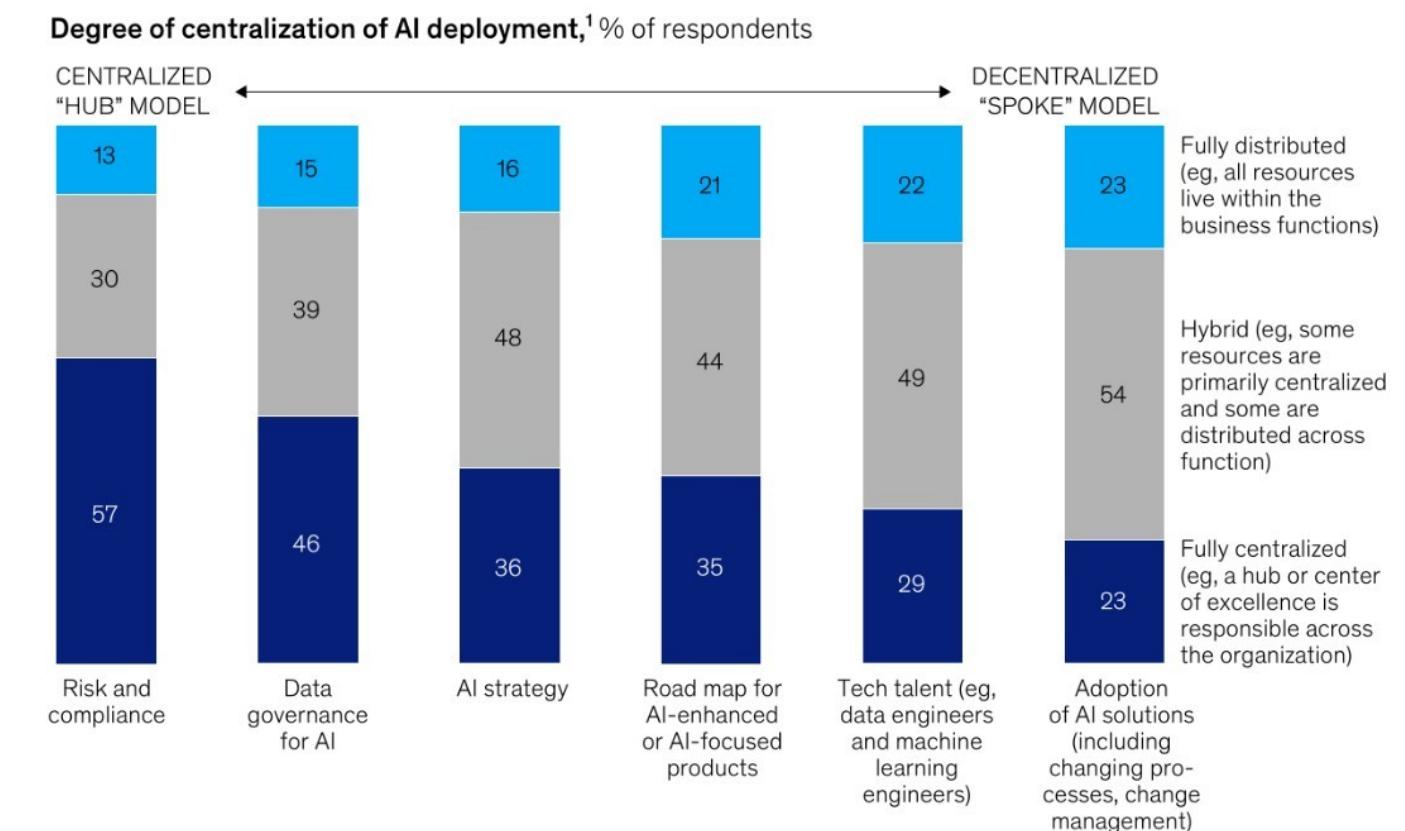
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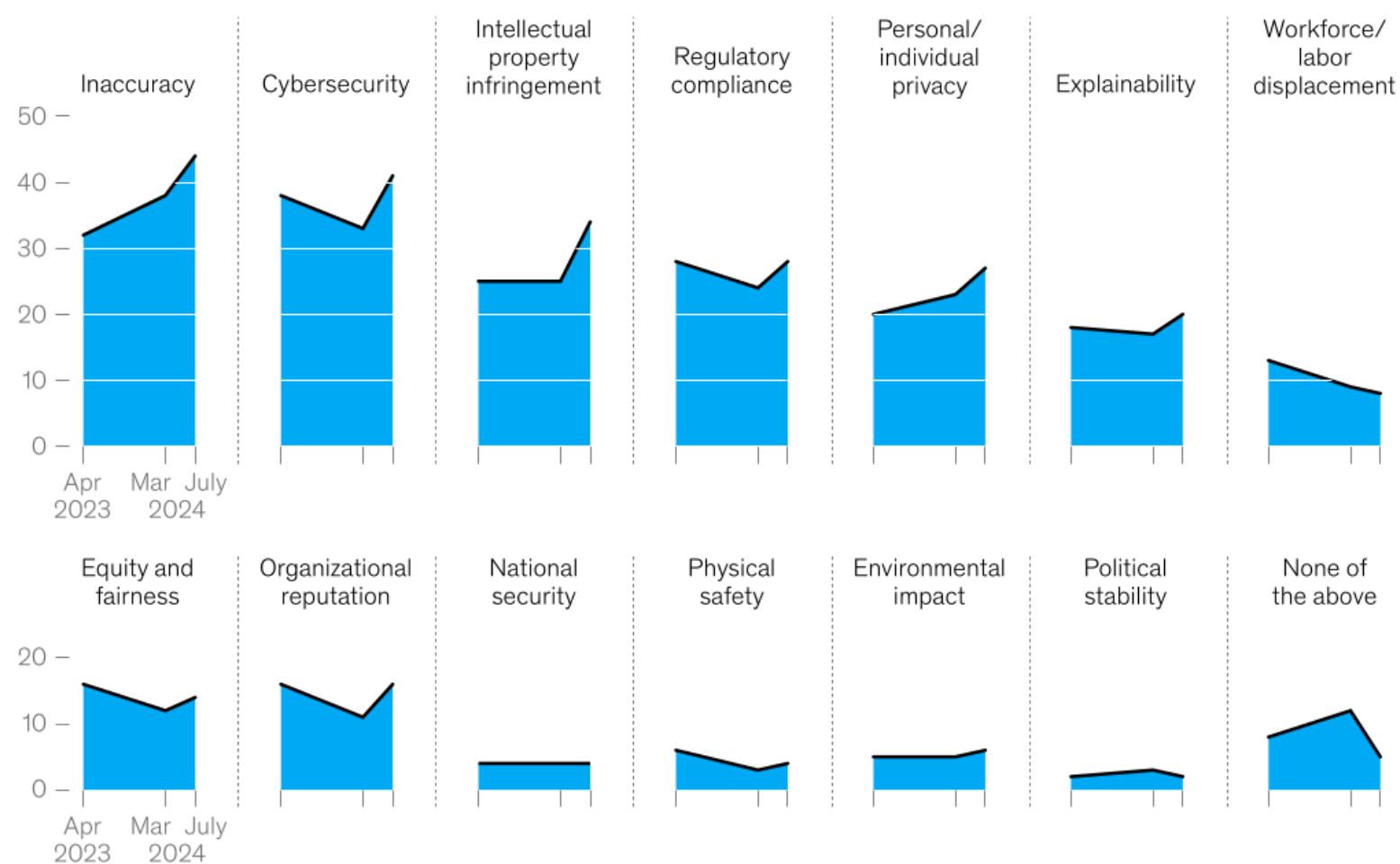
Extract text from PDF files

Side-by-side comparison: Test N°2

Exhibit 3

Respondents report increasing mitigation of inaccuracy, intellectual property infringement, and privacy risks related to use of gen AI.

Gen-AI-related risks that organizations are working to mitigate,¹ % of respondents



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Extract text from PDF files

Side-by-side comparison: Test N°2

PyMuPDF

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McKinsey & Company

0
10
20
30
40
50

0
10
20

...

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Side-by-side comparison: Test N°2

VL model (Gemini 2.5 Pro)

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Image of a series of **14 area charts** arranged in **two rows of seven**. The charts show the percentage of respondents working to mitigate various generative AI-related risks over time, from **April 2023 to July 2024**.

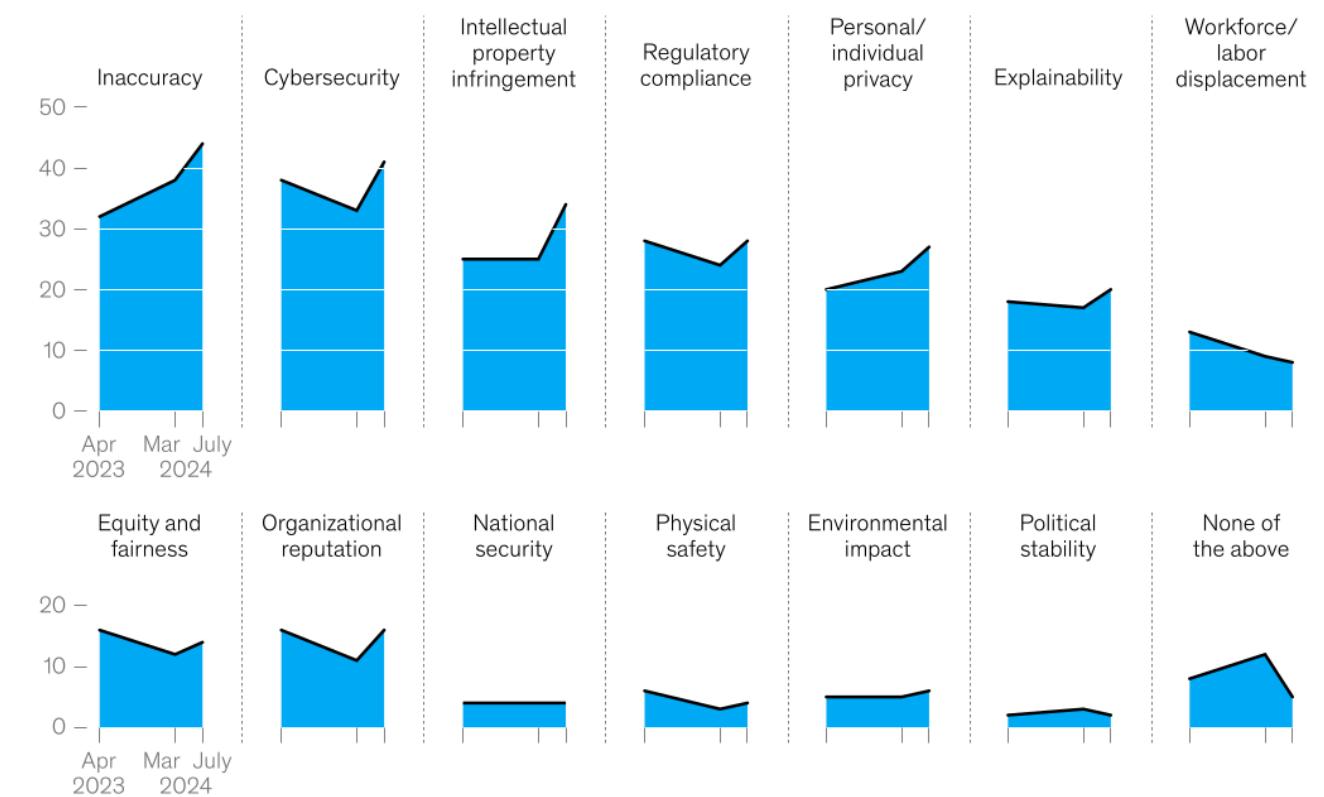
The charts in the **top row** have a **y-axis ranging from 0 to 50**. The charts are:

- * Inaccuracy: Shows a **significant increasing trend**, starting around **32%** in April 2023 and rising to approximately **45%** by July 2024.
- * Cybersecurity: Shows a **slight overall decrease**, starting near **38%** in April 2023 and ending around **35%** in July 2024, with a dip in between.
- * Intellectual property infringement: Shows a **clear increasing trend**, starting at about **25%** in April 2023 and rising to roughly **35%** in July 2024.
- * Regulatory compliance: Shows a **slight downward trend**, starting at about **28%** in April 2023 and ending around **25%** in July 2024.
- * Personal/individual privacy: Shows an **increasing trend**, starting from approximately **22%** in April 2023 and rising to about **28%** by July 2024.
- * Explainability: Shows a **slight increase**, starting from about **18%** in April 2023 and ending around **20%** in July 2024 ...

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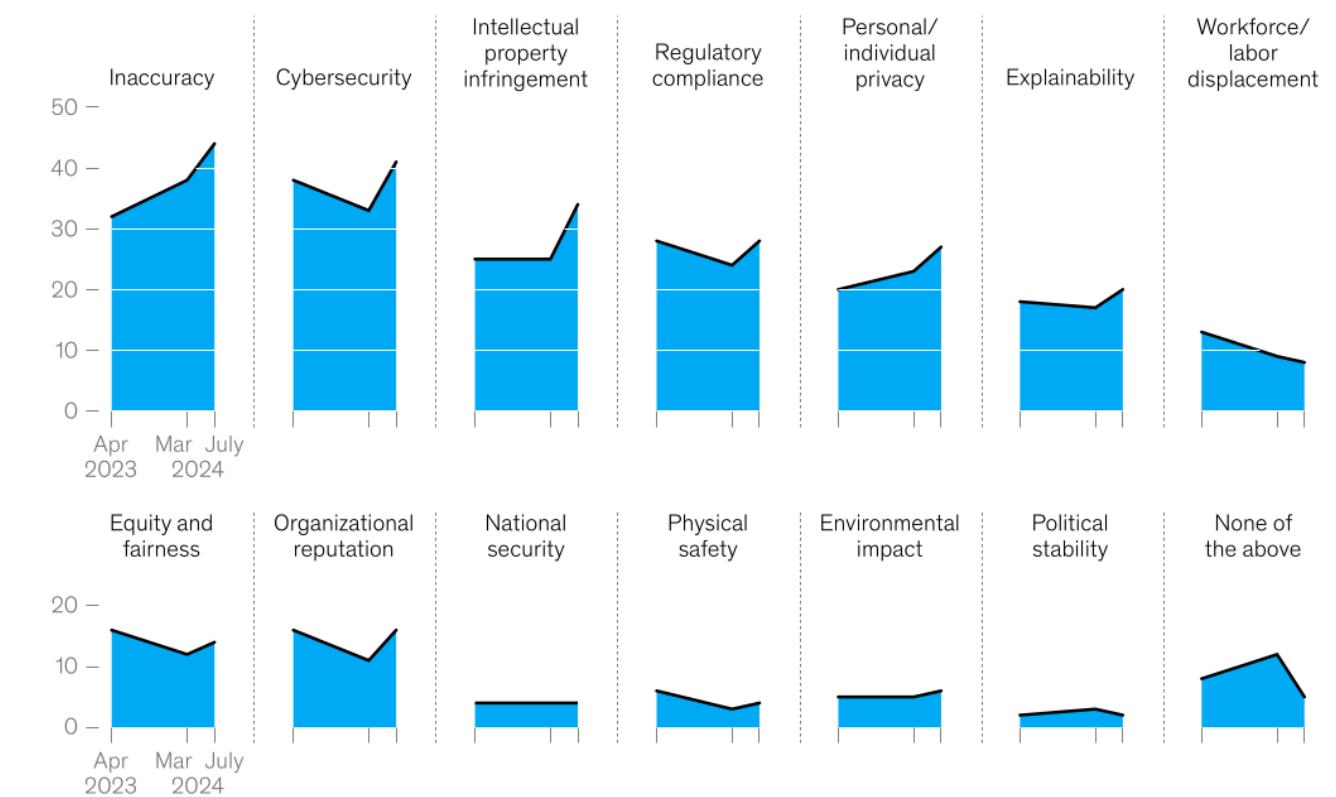
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Extract text from PDF files

- VL models will help you create high quality datasets by:
 - **Annotating** images.
 - Describing tables or outputting them in **Markdown**.
 - **Preserve the layout**.
 - **Extract only what you need** from the documents.
 - Working with **scanned** documents.

Extract text from PDF files

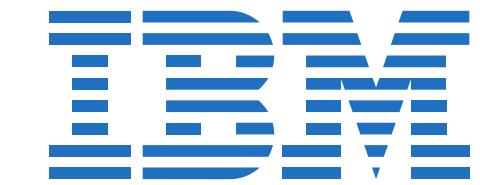
- What model should you use?
- Use proprietary and open models through the API. **Cheaper!**
- Host the models in your own servers. **Expensive!!!**

Proprietary models

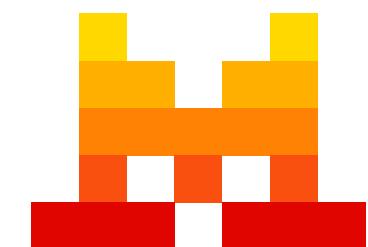
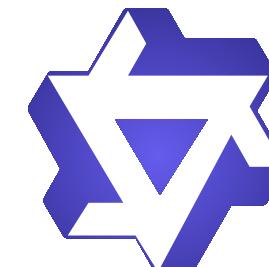


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Open models



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Extract text from PDF files

- Keep track of the best models with these leaderboards:
 - OpenVLM leaderboard.
 - Intelligent document processing leaderboard.

Evaluation Dimension

<input checked="" type="checkbox"/> Avg Score	<input checked="" type="checkbox"/> Avg Rank	<input checked="" type="checkbox"/> MBench_V11	<input checked="" type="checkbox"/> MMStar	<input type="checkbox"/> MME	<input checked="" type="checkbox"/> MMMU_VAL	<input checked="" type="checkbox"/> MathVista	<input checked="" type="checkbox"/> OCRBench	<input checked="" type="checkbox"/> AI2D	<input checked="" type="checkbox"/> HallusionBench	<input type="checkbox"/> SEEDBench_IMG	<input checked="" type="checkbox"/> MMVet	<input type="checkbox"/> LL
<input type="checkbox"/> RealWorldQA	<input type="checkbox"/> POPE	<input type="checkbox"/> ScienceQA_TEST	<input type="checkbox"/> SEEDBench2_Plus	<input type="checkbox"/> MMT-Bench_VAL	<input type="checkbox"/> BLINK							

Model Name

Input the Model Name (fuzzy, case insensitive)

Model Size

<4B 4B-10B 10B-20B 20B-40B >40B

Model Type

API OpenSource

Unknown

Rank	Method	Param (B)	Language Model	Vision Model	Eval Date	Avg Score	Avg Rank	MBench_V11	MMStar	MMU_VAL	MathVista	OCRBench	AI2D
1	SenseNova-V6-5-Pro				2025/09/03	82.2	6.12	87.3	76.1	77	82.8	885	90.2
2	CongRong-v2.0				2025/05/20	80.7	4.88	88.1	75.3	75.6	76.8	927	90
3	SenseNova-V6-Pro				2025/05/05	80.4	7.12	88	73.7	70.4	76.9	895	89.2
4	Gemini-2.5-Pro				2025/04/07	80.1	9.25	88.3	73.6	74.7	80.9	862	89.5
5	JT-VL-Chat-V3.0				2025/08/04	79.9	11.88	87.5	82.1	68.7	72.8	950	88.3
6	GPT-5-20250807				2025/08/14	79.9	18.25	86.6	75.7	81.8	81.9	807	89.5
7	InternVL3-78B	78.4	Qwen2.5-72B	InternViT-6B-v2.5	2025/04/14	79.1	8.75	87.7	73.4	72.2	79	908	89.8
8	BlueLM-2.6-3	3			2025/09/01	78.4	19.62	86.4	80.1	62.4	82.3	881	86.1

Leaderboard

RANK	MODEL	COST	AVG	KIE	VQA	OCR	CLASSIFICATION	LONGDOCBENCH	TABLE
1	gemini-2.5-pro-preview-06-05 (reasoning: low)	-	82.32	78.92	86.29	78.54	99.31	68.57	82.28
2	gemini-2.5-pro-preview-03-25 (reasoning: low)	1.113	82.04	79.66	85.99	81.18	99.18	66.69	79.51
3	gemini-2.5-flash-preview-04-17	0.133	81.00	77.99	85.16	78.9	99.05	69.08	75.82
4	claude-3.7-sonnet (reasoning: low)	1.748	79.99	76.09	83.47	69.19	98.92	75.93	91.23
5	o4-mini-2025-04-16	2.595	78.56	75.43	87.07	72.82	99.14	66.13	70.76
6	gpt-4.1-2025-04-14	1.583	78.05	72.68	80.37	75.64	99.27	66	74.34
7	gemini-2.0-flash	0.022	77.62	77.22	82.03	80.05	99.1	56.01	71.32
8	gpt-5-2025-08-07 (reasoning: low)	-	76.18	72.19	87.72	73.76	99.40	67.79	56.25
9	gpt-4o-2024-08-06	1.979	75.40	71.83	79.08	74.56	95.74	66.9	64.3
10	claude-sonnet-4	0.959	75.15	71.91	82.51	64.09	98.88	40.06	93.44
11	InternVL3-38B-Instruct	-	72.77	70.31	74.82	66.31	98.84	68.30	58.03
12	gemini-2.5-flash-lite-preview-06-17	0.0555	71.73	77.20	76.28	77.12	98.88	42.36	58.55
13	llama-4-maverick(400B-A17B)	0.058	70.80	73.3	80.1	70.66	98.84	27.74	74.15
14	gpt-4o-mini-2024-07-18	2.990	69.95	70.03	72.86	72.43	98.41	55.48	50.47
15	gemma-3-27b-it	-	69.71	72.81	66.85	54.75	98.49	72.95	52.38
16	qwen2.5-vl-72b-instruct	0.242	68.48	76.11	80.1	69.61	99.01	37.47	48.58
17	gpt-4-nano-2025-04-14	0.071	64.56	66.25	74.08	67.09	87.34	27.89	50.83
18	mistral-small-3.1-24b-instruct	0.02	61.50	63.73	71.5	51.01	91.86	29.23	61.64
19	gpt-4o-2024-11-20	1.868	60.08	70.91	75.6	74.91	14.38	63.95	60.74
Pending	qwen2.5-vl-32b-instruct	Pending	Pending	79.63	81.36	Pending	98.71	75.62	77.46
Pending	mistral-medium-3	Pending	Pending	74.21	80.02	69.05	98.39	Pending	70.21

1. Cost represents the average cost in cents per requests for each model.
 2. The score for each task in the leaderboard is the average across all the datasets for the corresponding task.
 3. We compute edit distance accuracy for all tasks and datasets except classification where we compute exact match, and table extraction where we use GITS. Please check our paper for more details.

Dividing text into chunks

Divide text into chunks

- How do we **divide** the extracted text?
- Dividing the text **programmatically** is not a good idea.

The chart shows two models of centralization: a "**CENTRALIZED 'HUB' MODEL**" on the left and a "**DECENTRALIZED 'SPOKE' MODEL**" on the right. The chart has six vertical stacked bars, each representing a different aspect of AI deployment. The legend on the right explains the color coding for the segments of each bar: a dark blue segment represents "**Fully centralized** (eg, a hub or center of excellence is responsible across the organization)", a gray segment represents "**Hybrid** (eg, some resources are primarily centralized and some are distributed across function)", and a light blue segment represents "**Fully distributed** (eg, all resources live within the business functions)".

The six bars are for the following categories, with their respective data breakdowns:

1. **Risk and compliance:** 57% Fully centralized, 30% Hybrid, 13% Fully distributed.
2. **Data governance for AI:** 46% Fully centralized, 39% Hybrid, 15% Fully distributed.
3. **AI strategy:** 36% Fully centralized, 48% Hybrid, 16% Fully distributed.

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 - We use **large language models (fast)**, but needs supervision.

Antares is a bright star, you
can see it during summer in
the constellation Scorpius

Text input

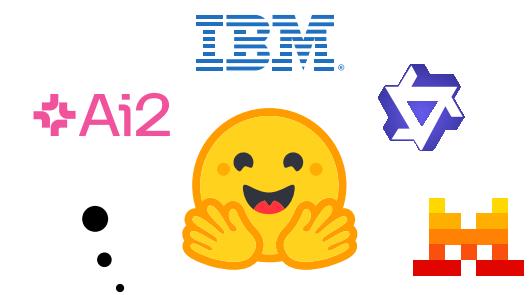
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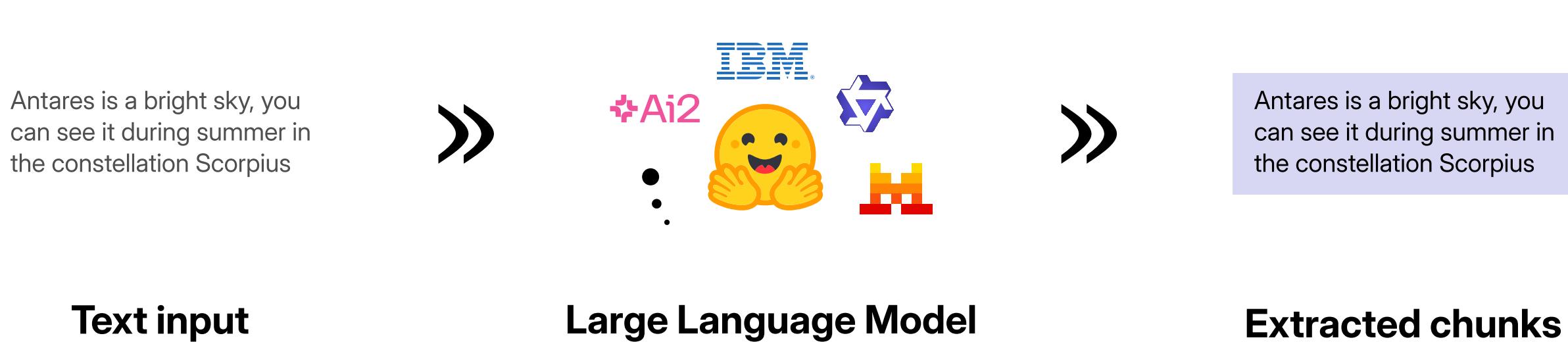
Text input



Large Language Model

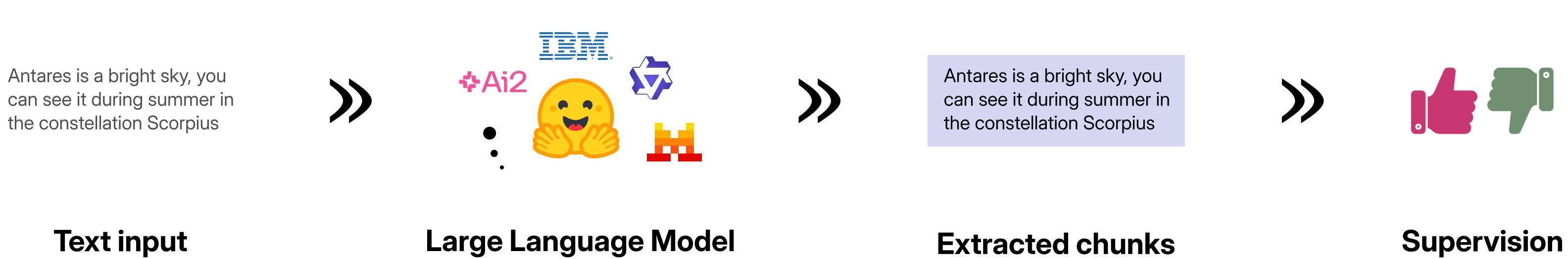
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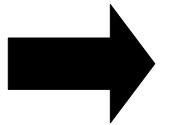


Generating question answer pairs

Generate question-answer pairs

- Generate questions that can be answered by a chunk of text.
- A chunk can answer one or more questions.
- A question can be answered by one or more chunks.

bitsandbytes enables accessible large language models via k-bit quantization for PyTorch. **bitsandbytes** provides **three main features** for dramatically reducing memory consumption for inference and training: **8-bit optimizers**, **LLM.int8()** or **8-bit quantization**, and **QLoRA** or **4-bit quantization**.



Q.1/ What is the primary purpose of the bitsandbytes library?
Q.2/ What are the three main features bitsandbytes provides for reducing memory consumption?

Text chunk

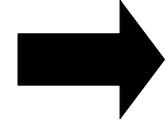
Questions

Text embeddings

Text embeddings

- A text embedding model **converts text into a numerical representation.**
- This numerical representation is a **dense vector containing n values.**

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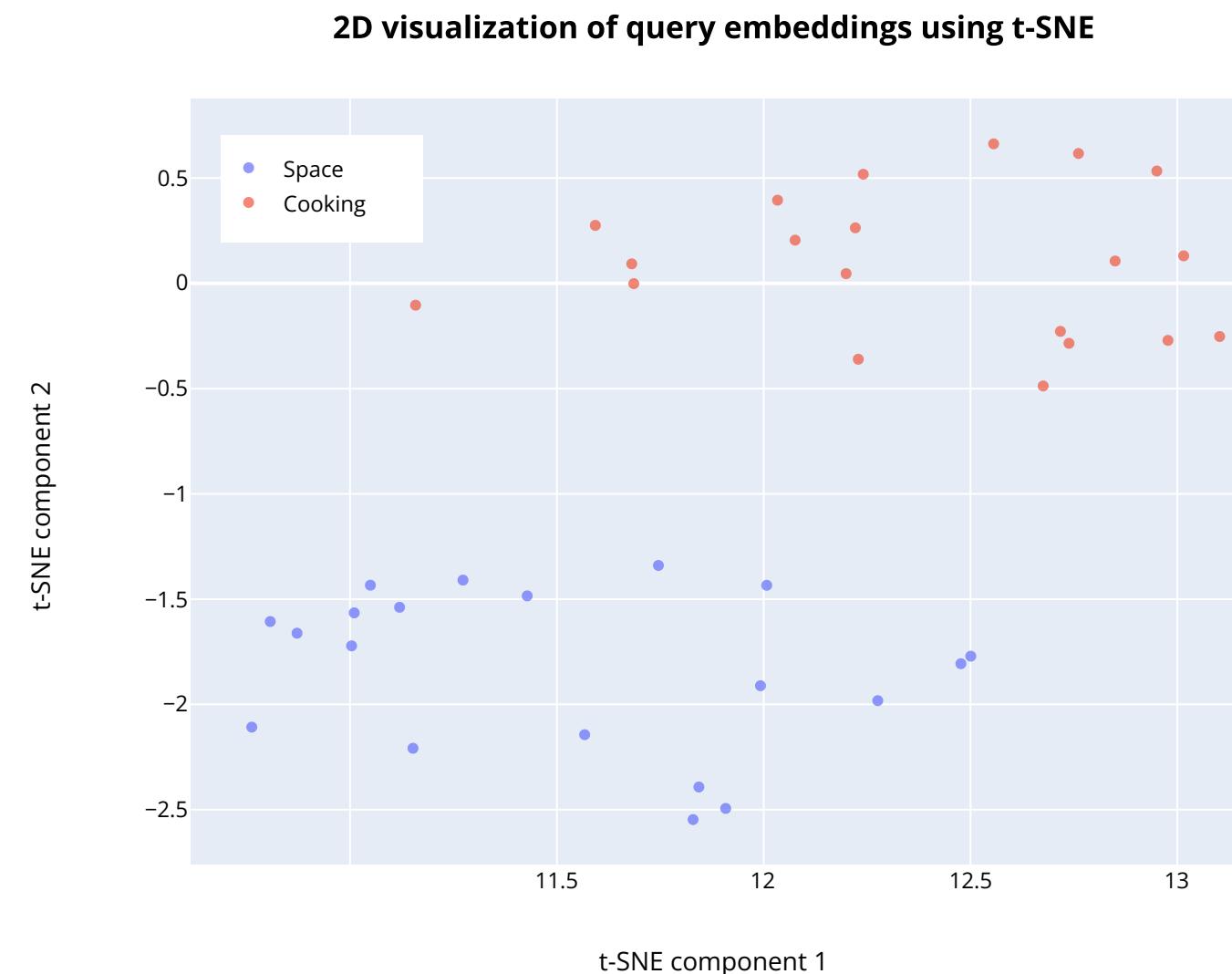
[0.58, 0.99, -0.1, 1, 0.03, ..., 0.69]

Text chunk

Dense vector

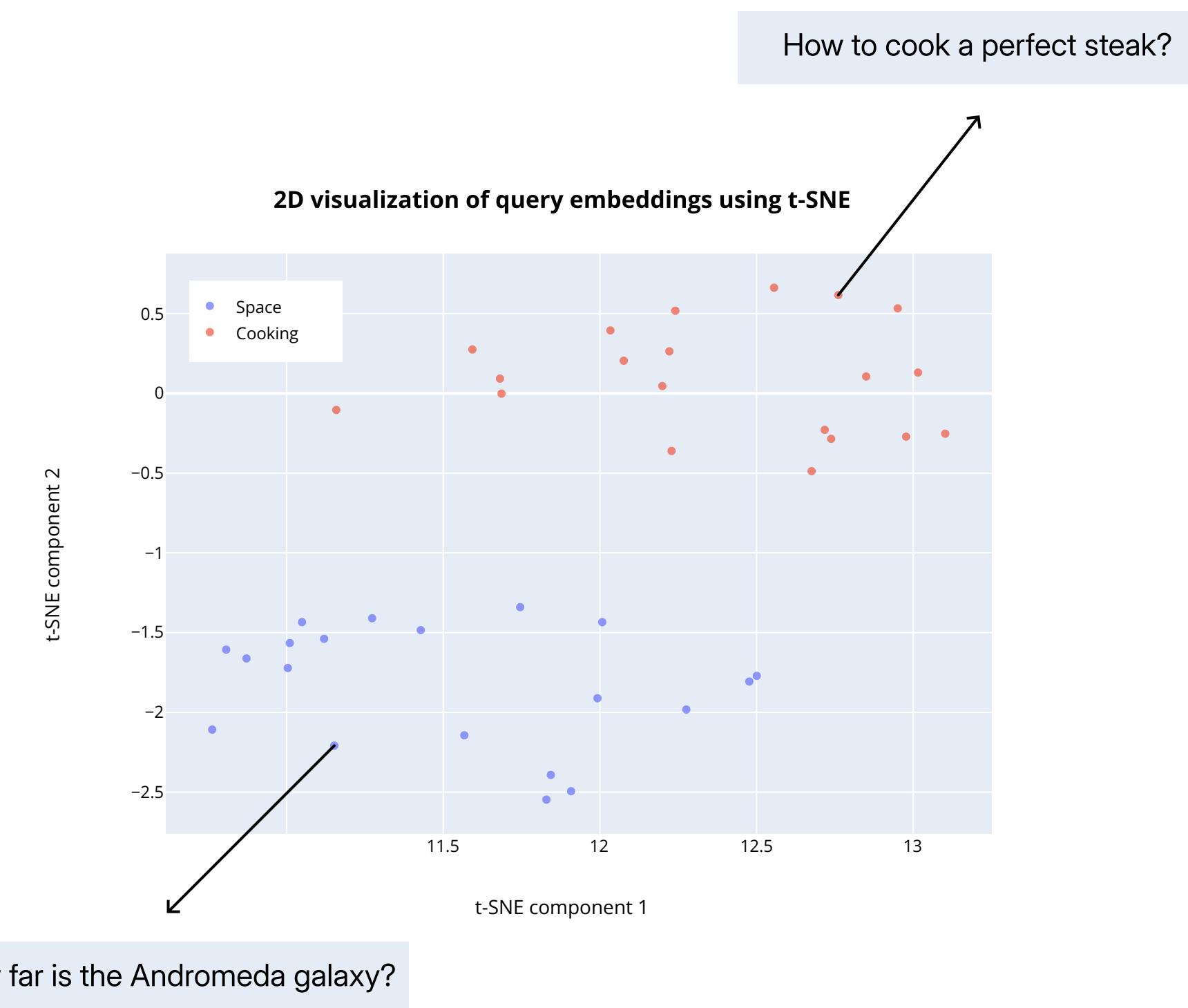
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Text embeddings

- A text embedding model **converts text into a numerical representation**.
- That numerical representation is a **dense vector with n values**.
- What is the purpose?
- Does the size of the dense vector matter?

Dimension	Advantages	Disadvantages
Large	<ul style="list-style-type: none">• Captures nuances in semantic information• Distinguishes finer details within the data	<ul style="list-style-type: none">• Requires more computational resources for processing• Needs increased storage space for the vectors• Results in increased latency in vector databases
Small	<ul style="list-style-type: none">• Requires few computational resources• Enables faster processing• Reduces storage costs• Achieves low latency	<ul style="list-style-type: none">• May not capture as much semantic detail as larger embeddings

Text embeddings

- A text embedding model **converts text into a numerical representation.**
- That numerical representation is a **dense vector with n values.**
- What is the purpose?
- Does the size of the dense vector matter?

Model	Output dimension
Qwen3-Embedding-0.6B	1024
Qwen3-Embedding-4B	2560
Qwen3-Embedding-8B	4096
all-MiniLM-L6-v2	384
Gemini embedding 001	3072
text-embedding-3-small	1536
text-embedding-3-large	3072

Text embeddings

- A text embedding model **converts text into a numerical representation.**
- That numerical representation is a **dense vector with n values.**
- What is the purpose?
- Does the size of the dense vector matter?

Model	Output dimension	Size of 10k vectors (MB)
Qwen3-Embedding-0.6B	1024	39
Qwen3-Embedding-4B	2560	98
Qwen3-Embedding-8B	4096	156
all-MiniLM-L6-v2	384	14
Gemini embedding 001	3072	117
text-embedding-3-small	1536	59
text-embedding-3-large	3072	117

Text embeddings

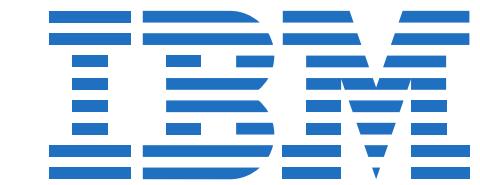
- You can use both open and closed-source models.
- There are many great open-source models that you can use without having a powerful device.

Proprietary models

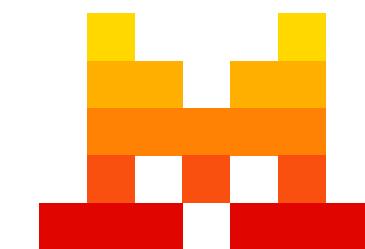
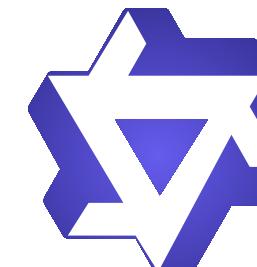
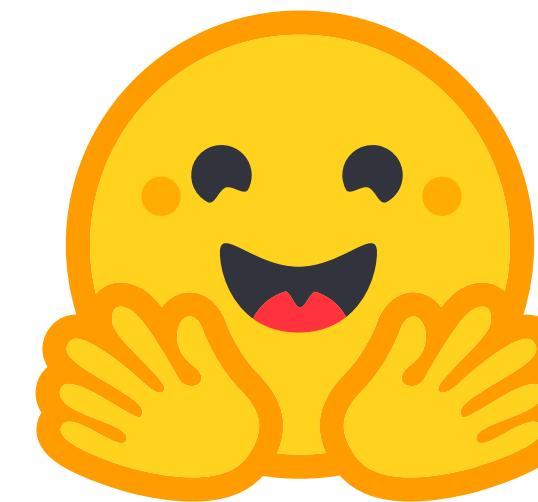


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Open models



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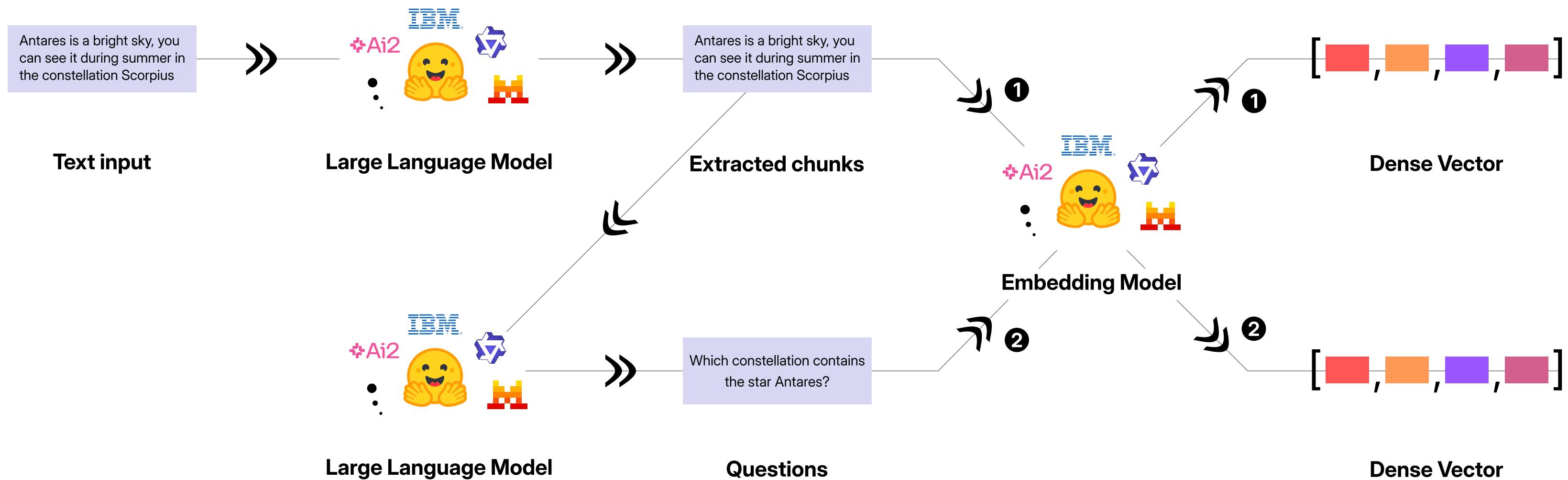
Text embeddings

- You can use both open and closed-source models.
- There are many great open-source models that you can use without having a powerful device.
- Use the [MTEB leaderboard](#) to get a quick look at the best embedding models.

Summary											
	Model	Zero-shot	Memory U...	Number of P...	Embedding D...	Max Tokens	Mean (T...	Mean (TaskT...	Bitext ...	Classification	
1	llama-embed-nemotron-8b	99%	28629	7B	4096	32768	69.46	61.09	81.72	73.21	
2	gemini-embedding-001	99%	Unknown	Unknown	3072	2048	68.37	59.59	79.28	71.82	
3	Qwen3-Embedding-8B	99%	28866	7B	4096	32768	70.58	61.69	80.89	74.00	
4	Qwen3-Embedding-4B	99%	15341	4B	2560	32768	69.45	60.86	79.36	72.33	
5	Qwen3-Embedding-0.6B	99%	2272	595M	1024	32768	64.34	56.01	72.23	66.83	
6	gte-Qwen2-7B-instruct	⚠ NA	29040	7B	3584	32768	62.51	55.93	73.92	61.55	
7	Linq-Embed-Mistral	99%	13563	7B	4096	32768	61.47	54.14	70.34	62.24	
8	multilingual-e5-large-instruct	99%	1068	560M	1024	514	63.22	55.08	80.13	64.94	
9	embeddinggemma-300m	99%	578	307M	768	2048	61.15	54.31	64.40	60.90	
10	SFR-Embedding-Mistral	96%	13563	7B	4096	32768	60.90	53.92	70.00	60.02	
11	text-multilingual-embedding-002	99%	Unknown	Unknown	768	2048	62.16	54.25	70.73	64.64	

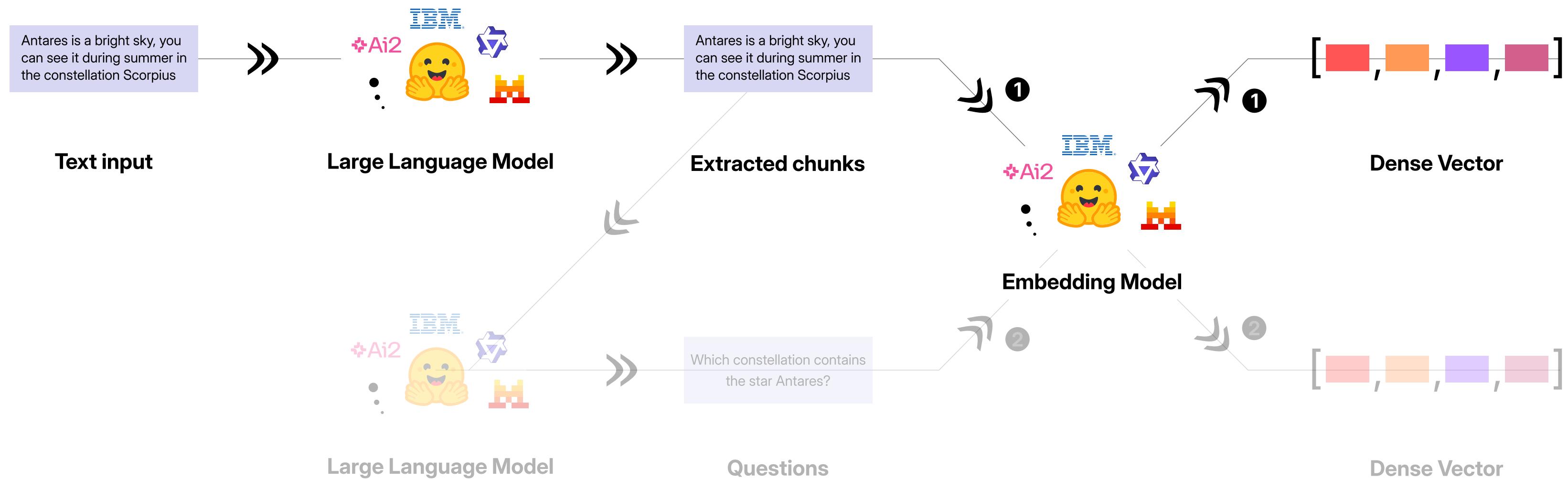
Text embeddings

- Here is the updated pipeline.



Text embeddings

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Text embeddings

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