Welcome! While we wait…

Workshop material

https://github.com/weaviate-tutorials/scalable-ai-workshop

Tell us a little bit about yourself!

Short survey:

https://www.menti.com/al31ja5gtijw

weaviate

How to build scalable AI applications with a vector database

JP Hwang
Developer Educator

Agenda

- Recap: Vector DBs & RAG
- Challenges of scalability
  - Work with a local cluster
  - Apply practical solutions
- Challenges of reliability

Let’s get started

While we wait, go to:

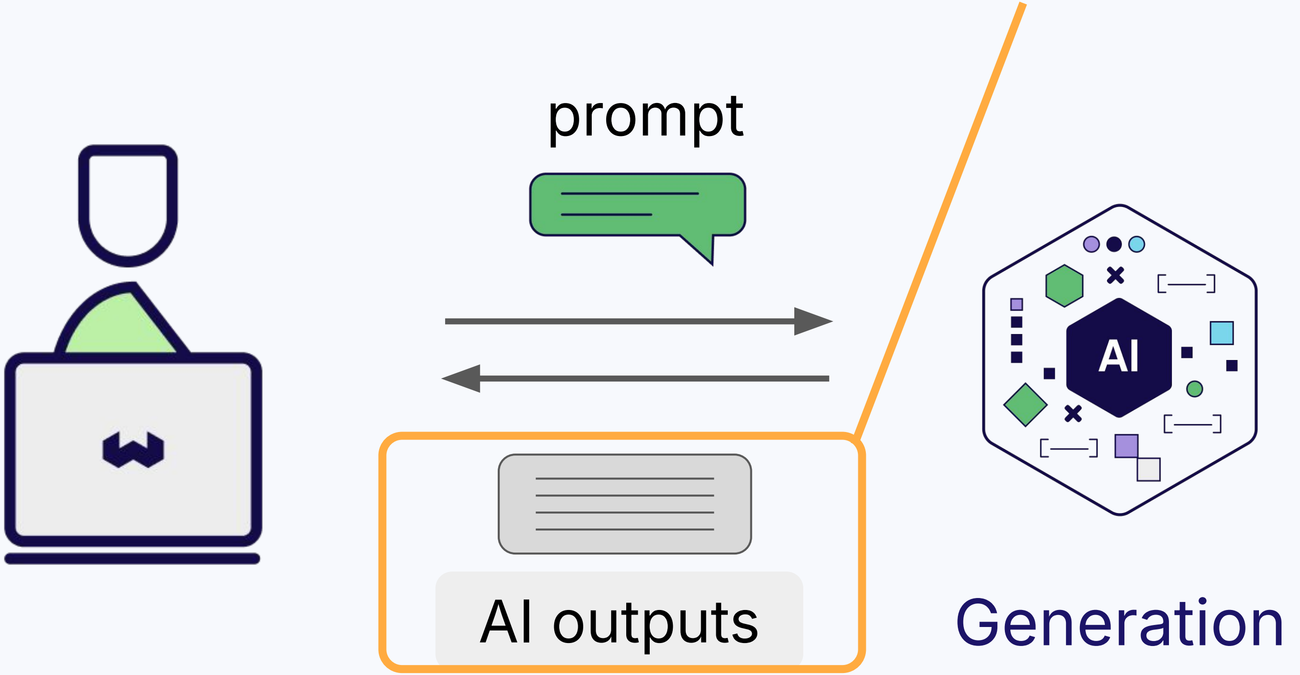
- **https://github.com/weaviate-tutorials/scalable-ai-workshop**

Start on the README instructions

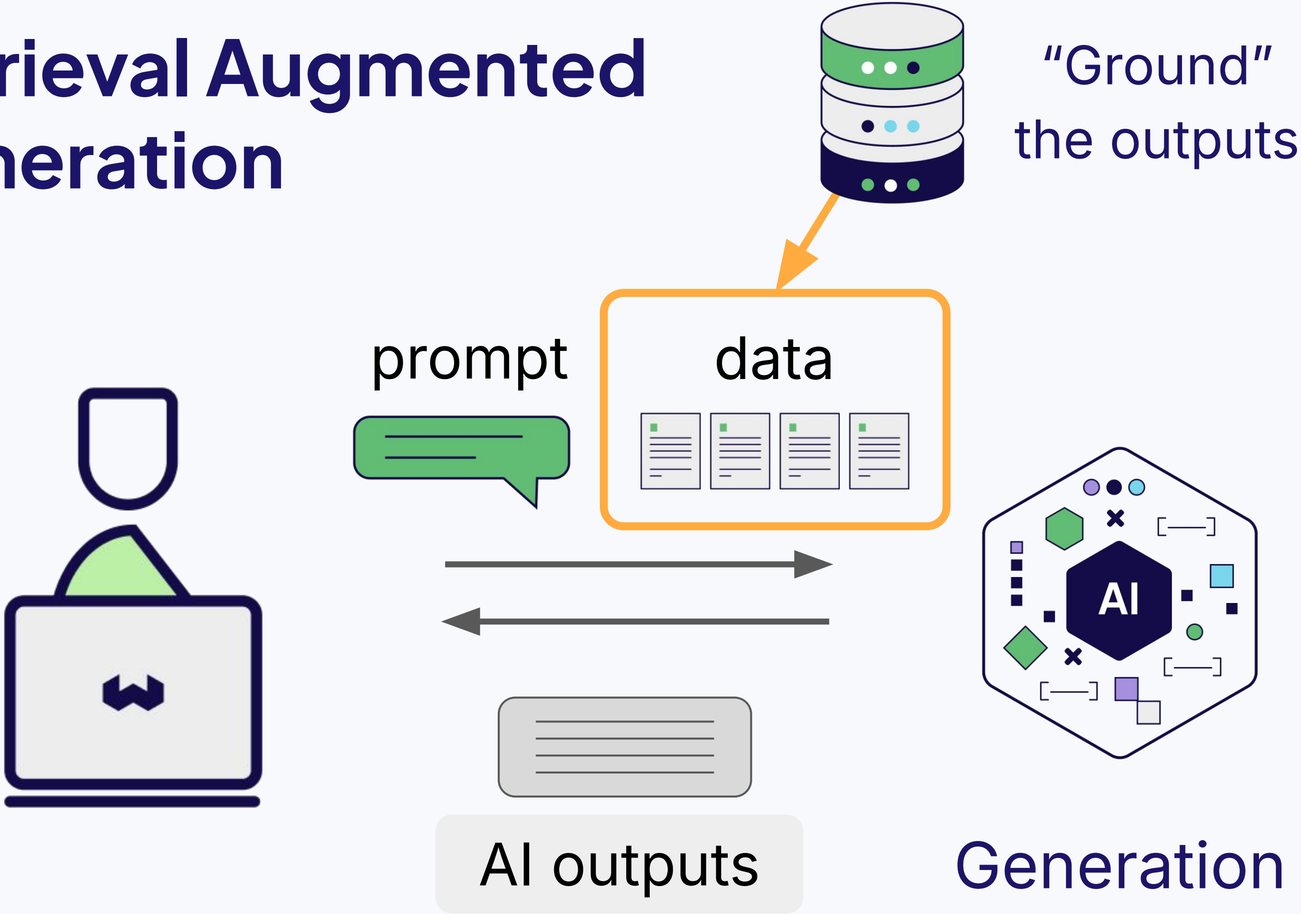
- **Step 1**
- **Step 2**

Recap: Vector DBs & RAG

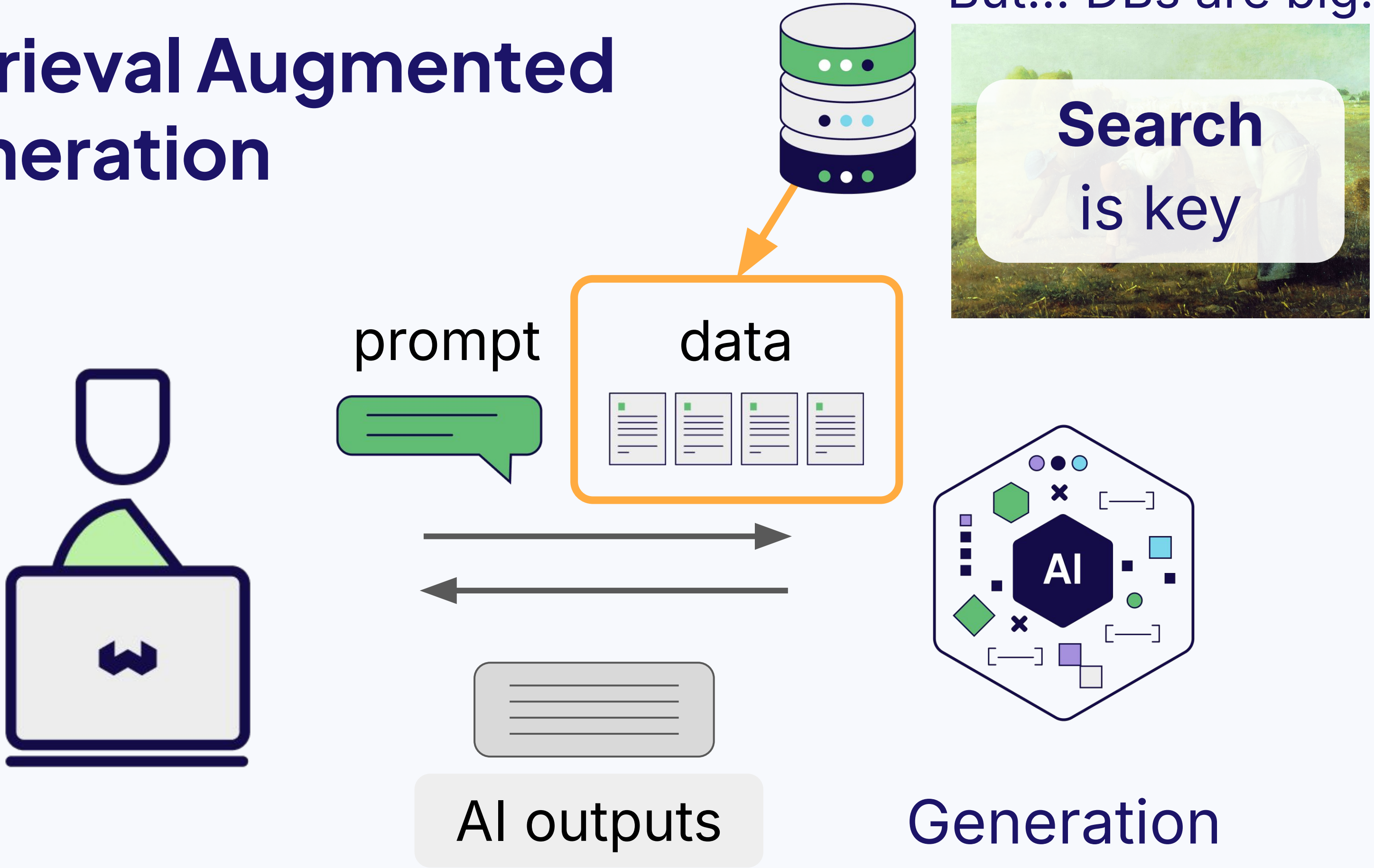
Large Language Model



Retrieval Augmented Generation



Retrieval Augmented Generation



But... DBs are big!

Search

is key

Workshop / Live coding

Challenges of scale

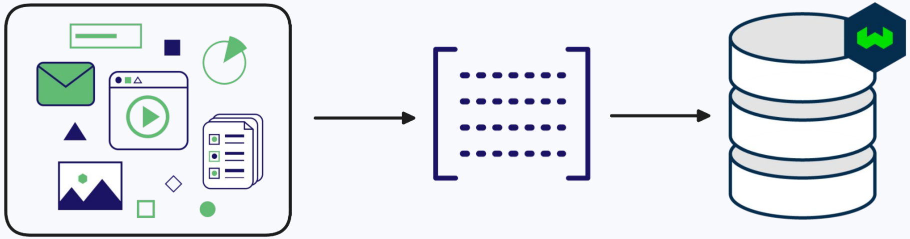
Scale: Considerations

- **Object count**: Memory & storage
- **User count**: Data management & compliance
- **Server load**: Distribute load

Managing resource requirements

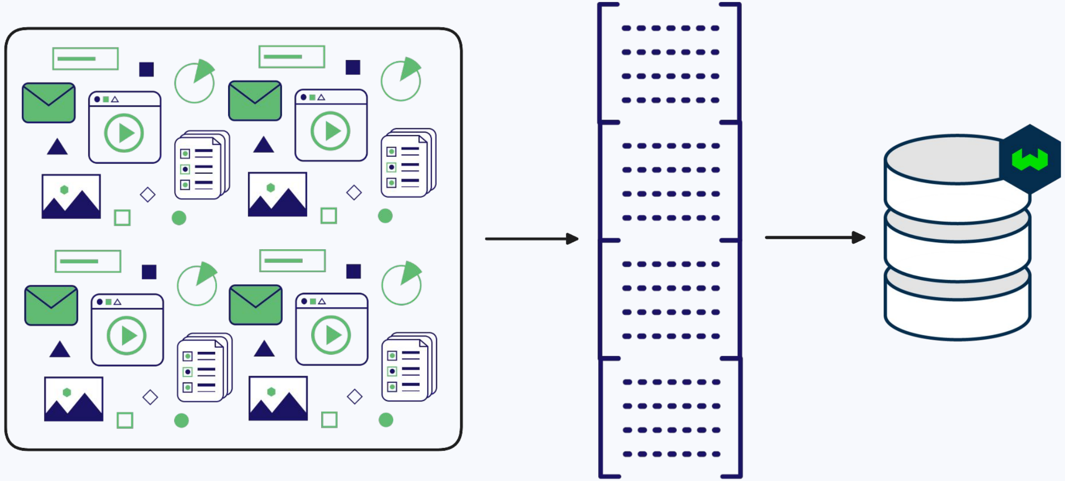
Scale: Solutions

Growth



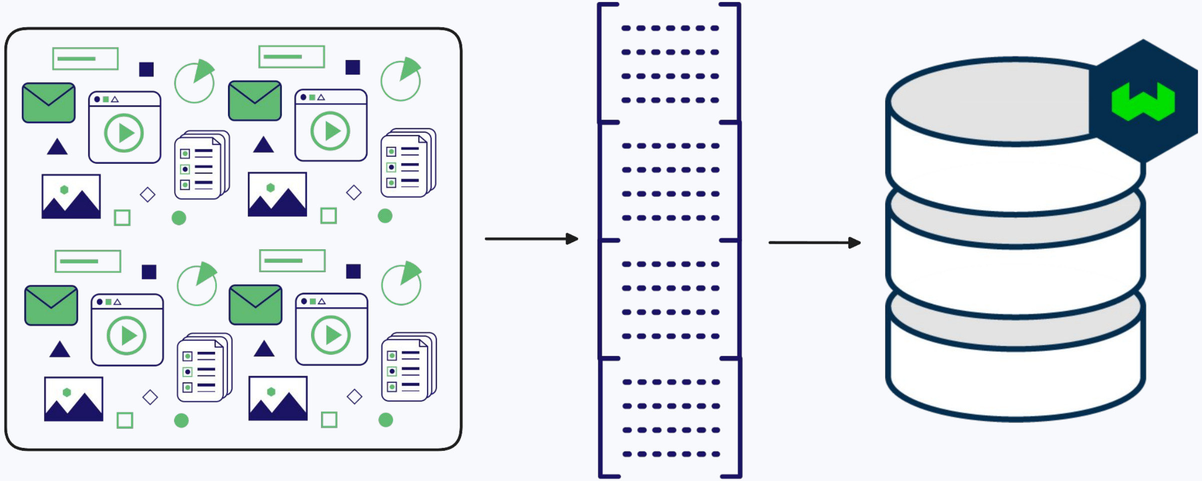
Scale: Solutions

Growth



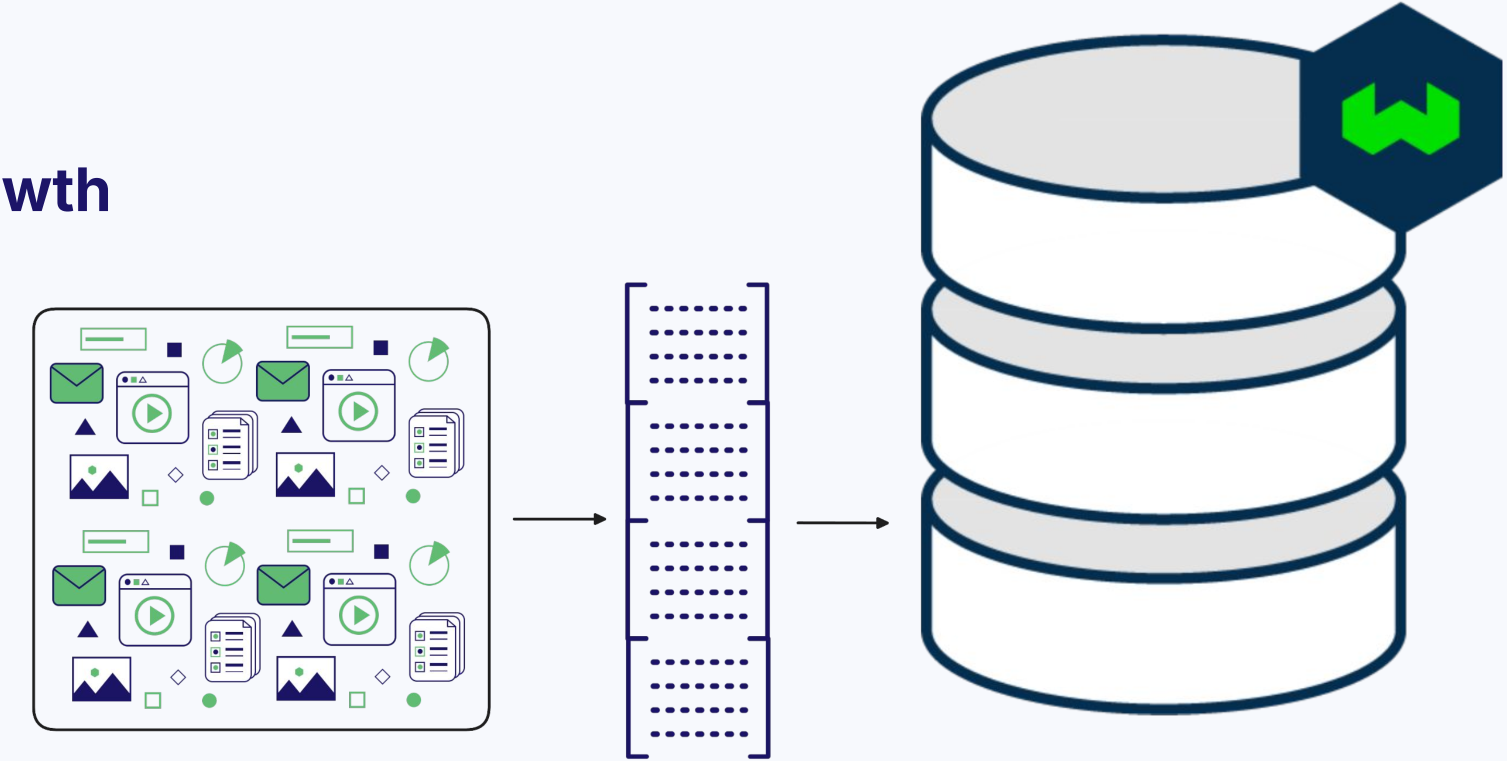
Scale: Solutions

Growth



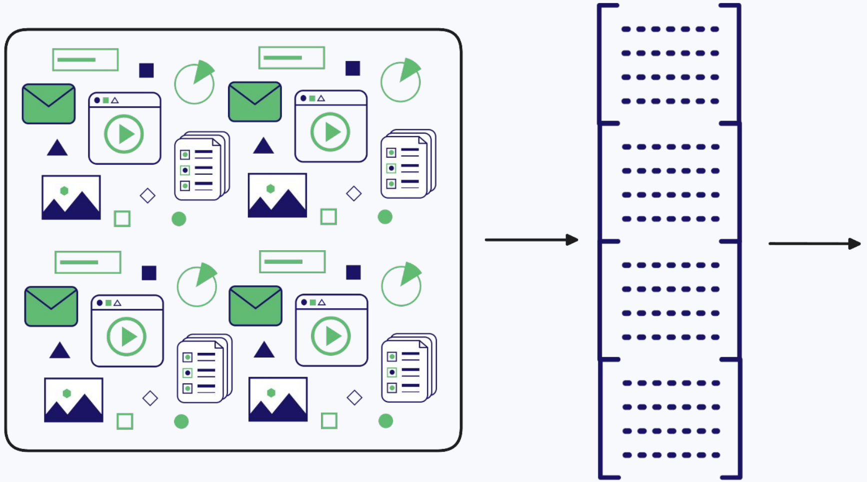
Scale: Solutions

Growth

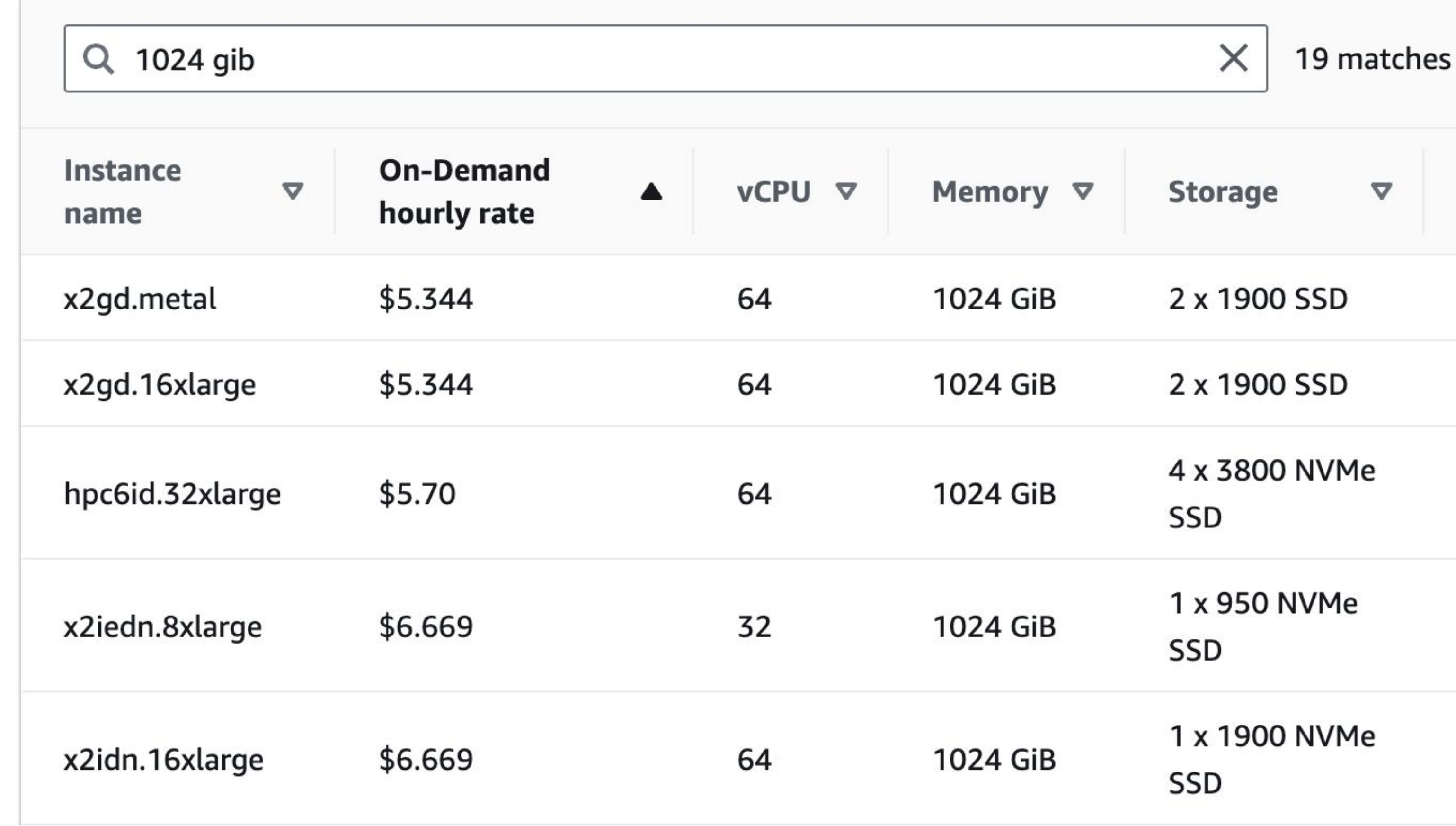


Scale: Solutions

Growth



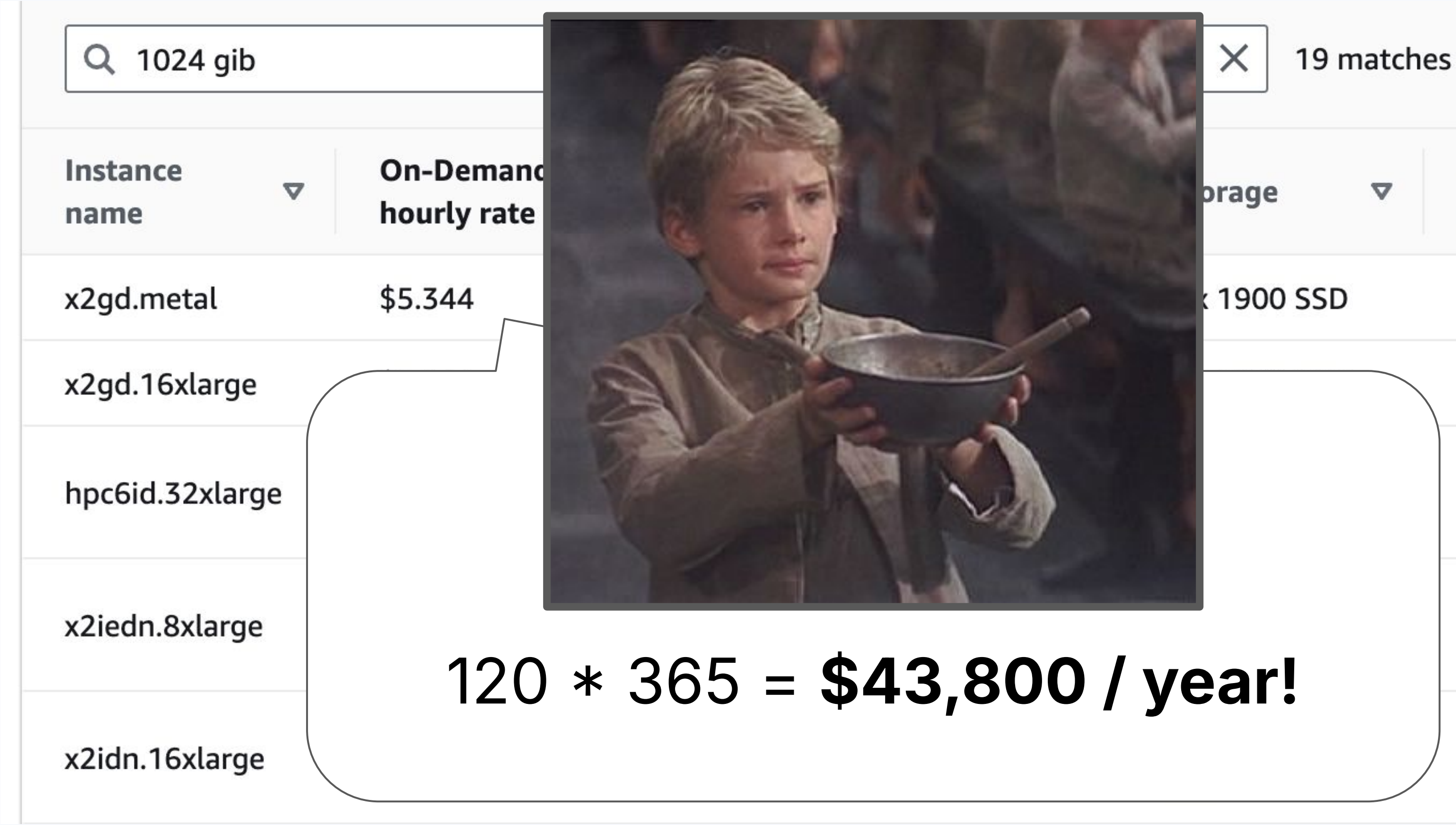
- Single point of failure
- Efficiency
- Upgrades
- Costs



1024 gib ✕ 19 matches

Instance name ▽	On-Demand hourly rate ▲	vCPU ▽	Memory ▽	Storage ▽
x2gd.metal	$5.344	64	1024 GiB	2 x 1900 SSD
x2gd.16xlarge	$5.344	64	1024 GiB	2 x 1900 SSD
hpc6id.32xlarge	$5.70	64	1024 GiB	4 x 3800 NVMe SSD
x2iedn.8xlarge	$6.669	32	1024 GiB	1 x 950 NVMe SSD
x2idn.16xlarge	$6.669	64	1024 GiB	1 x 1900 NVMe SSD

AWS Spot pricing, Nov 2024



1024 gib

19 matches

Instance name	On-Demanc hourly rate	orage
x2gd.metal	$5.344	x 1900 SSD
x2gd.16xlarge		
hpc6id.32xlarge		
x2iedn.8xlarge		
x2idn.16xlarge		

120 * 365 = **$43,800 / year!**

AWS Spot pricing, Nov 2024

Vector indexing options

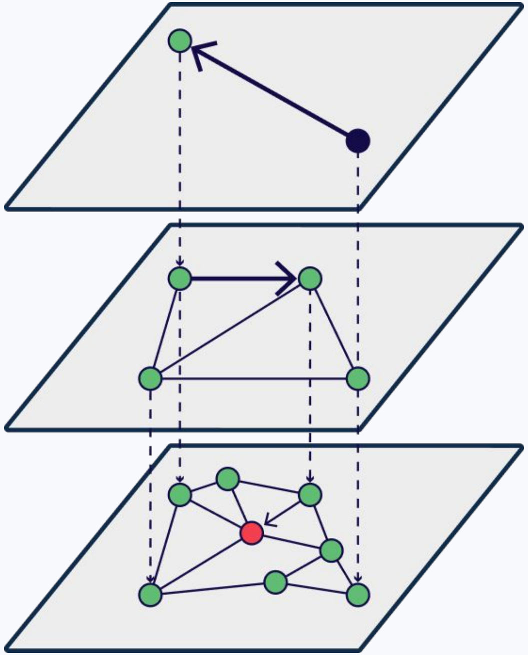
Scale: Solutions

Improve efficiency - indexing

Scale: Solutions

Improve efficiency - indexing

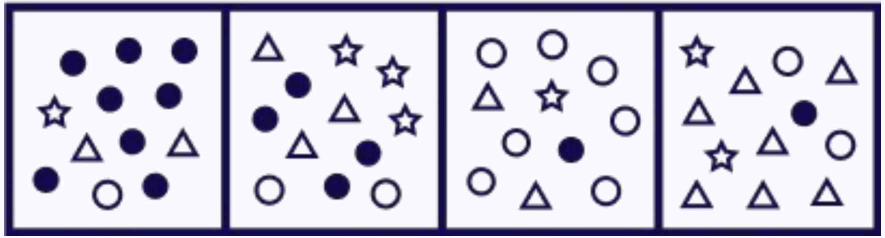
- **HNSW** index (default)



Scale: Solutions

Improve efficiency - indexing

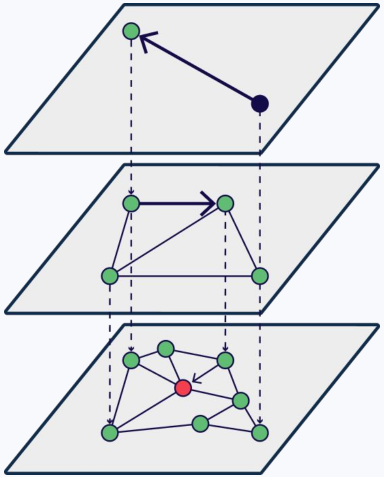
- **HNSW** index (default)
- **Flat** index

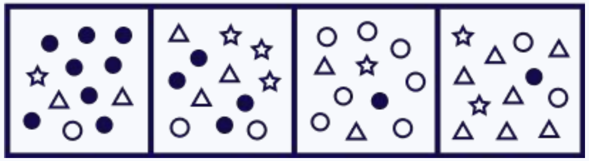


Scale: Solutions

Indexes - comparison

- **HNSW**: fast + scalable
- **Flat**: tiny footprint; ~100k objs





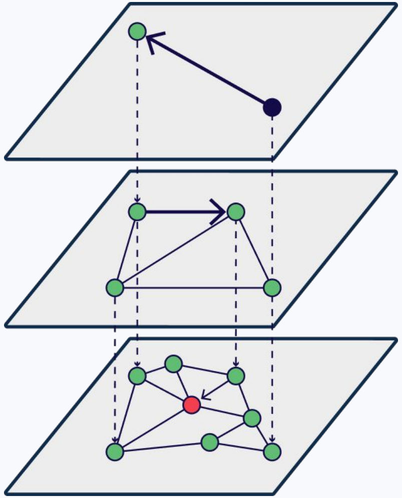
Scale: Solutions

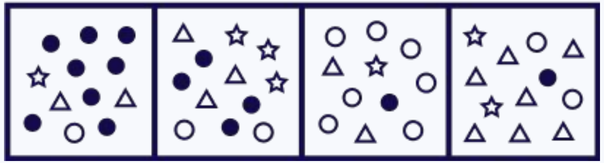
How to choose?

- **Start** with **HNSW**

  (Tune speed / size / accuracy)

- Multi-tenancy?
  - Try **dynamic**

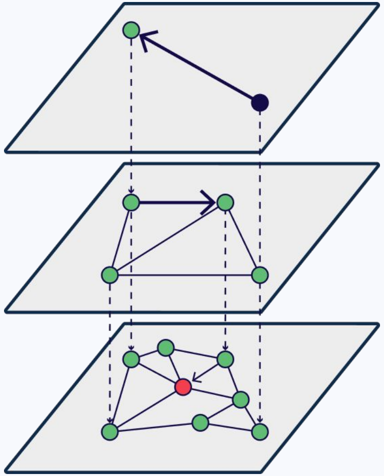


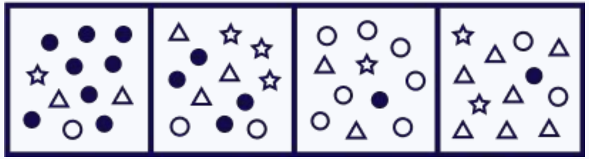


Scale: Solutions

Improve efficiency - indexing

- **HNSW** index (default)
- **Flat** index
- **Dynamic** index
  - Flat → HNSW @ threshold

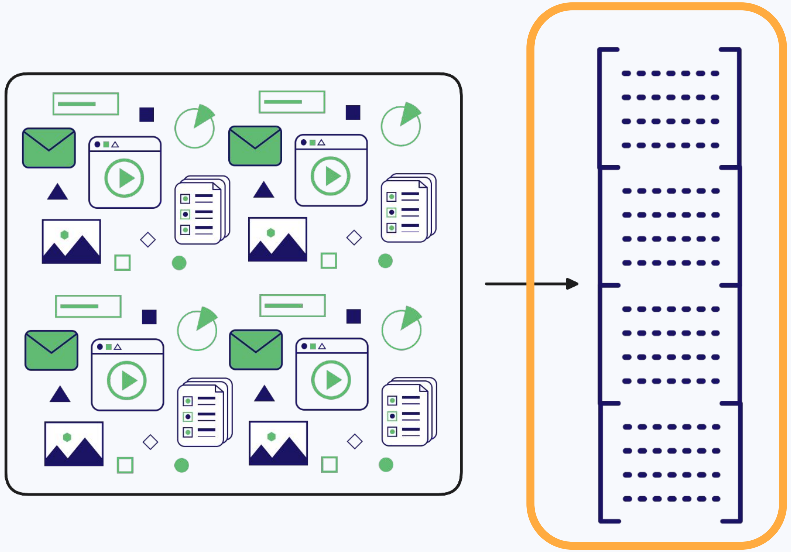




Vector quantization

Scale: Solutions

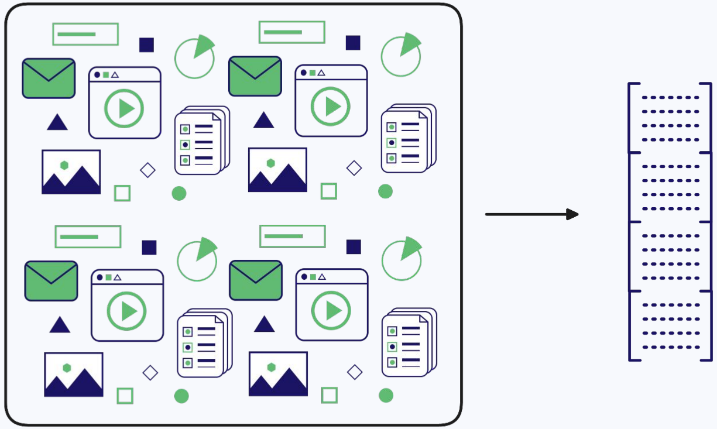
Improve efficiency



Scale: Solutions

Improve efficiency

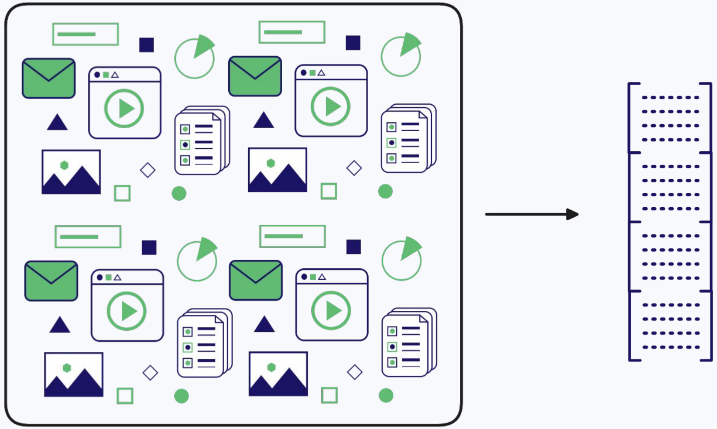
Compression



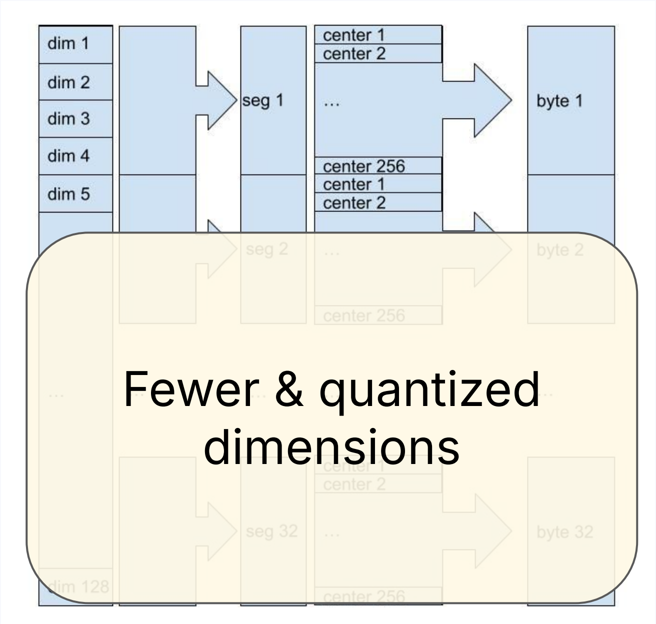
Scale: Solutions

Improve efficiency

Compression



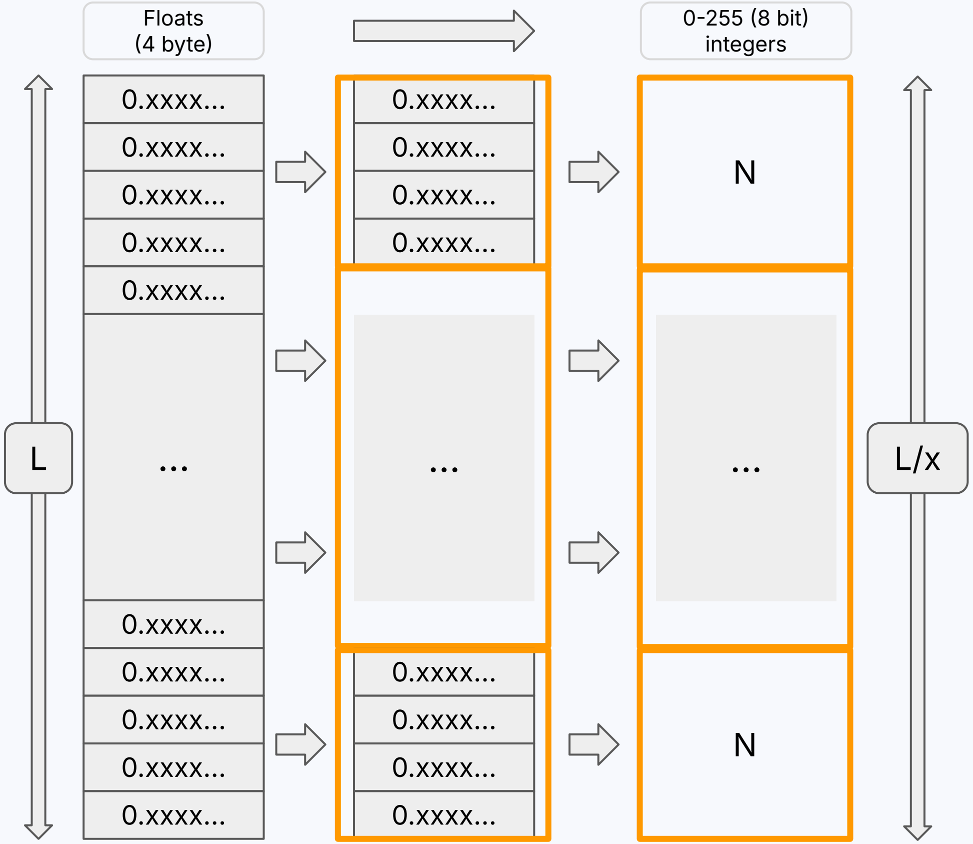
Product quantization



Fewer & quantized dimensions

Customisable compression

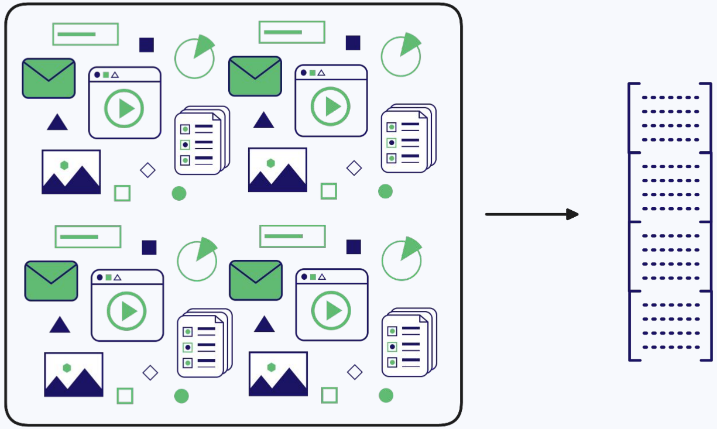
(e.g. 128 floats → 32 bytes: 16x)


Floats
(4 byte)
0-255 (8 bit)
integers
L
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
...
0.xxxx...
0.xxxx...
0.xxxx...
0.xxxx...
N
...
N
L/x

Scale: Solutions

Improve efficiency

Compression



Binary quantization

[-0.1324..., -0.9253...,
0.2389...,
...
0.3249..., 0.2390..., -0.4823...]

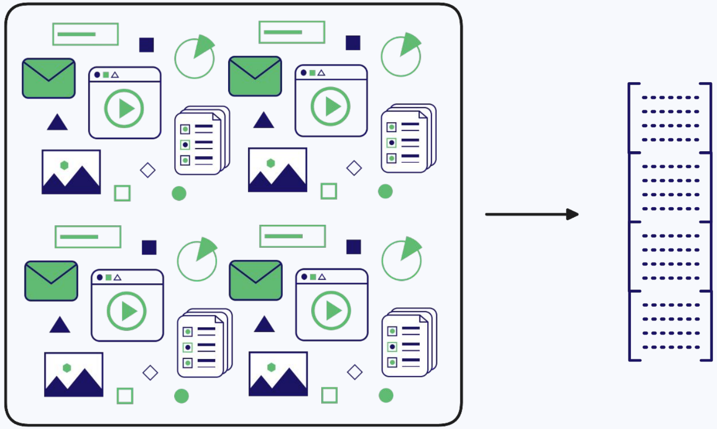
[0, 0, 1, 0, 1, 1,
...
0, 1, 0, 1, 1, 0]

n floats → n bits
(32x reduction)

Scale: Solutions

Improve efficiency

Compression



Scalar quantization

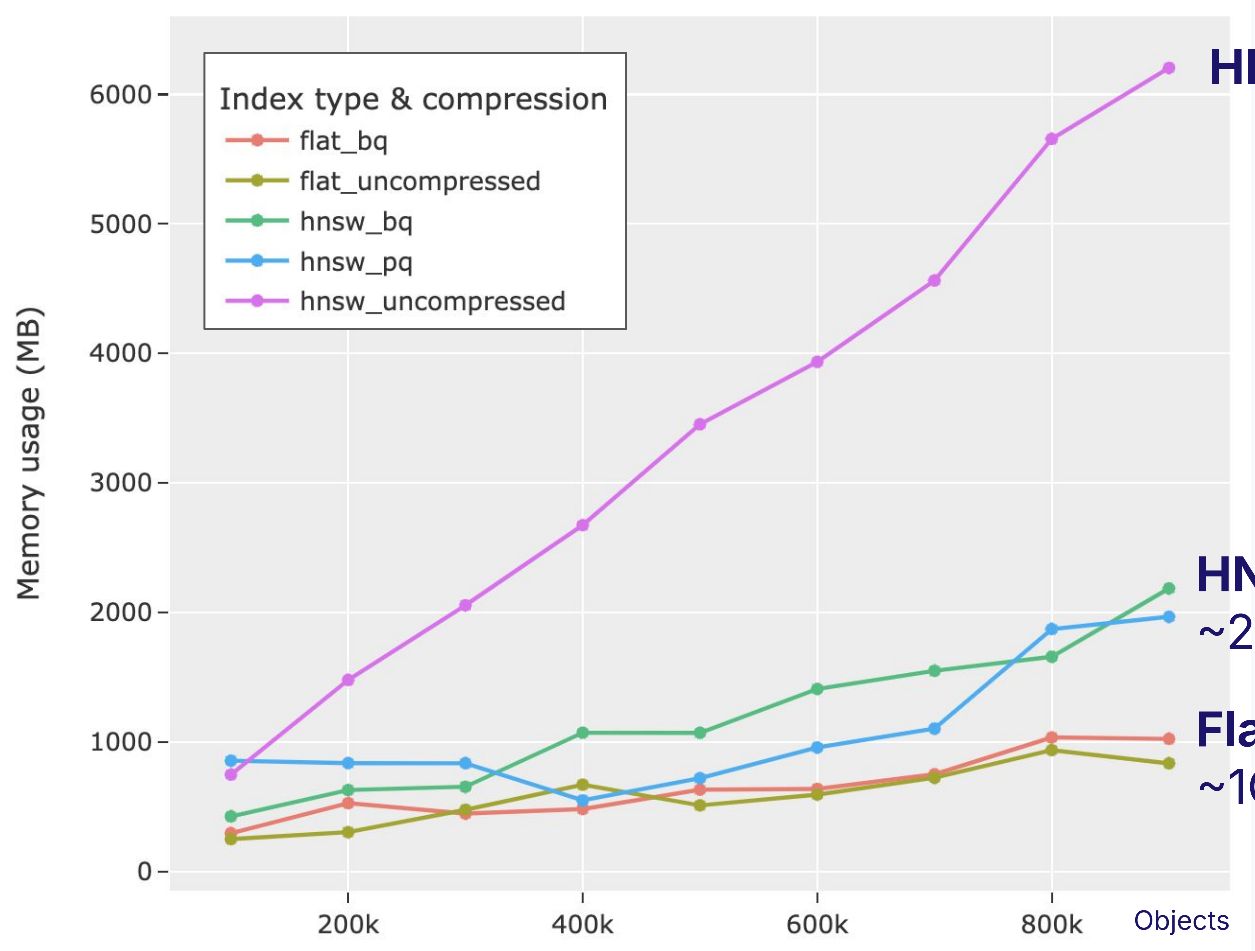
[-0.1324..., -0.9253...,
0.2389...,
...
0.3249..., 0.2390..., -0.4823...]

↓

[104, 12, 138,
...
152, 138 47]

n floats → n ints
(4x reduction)

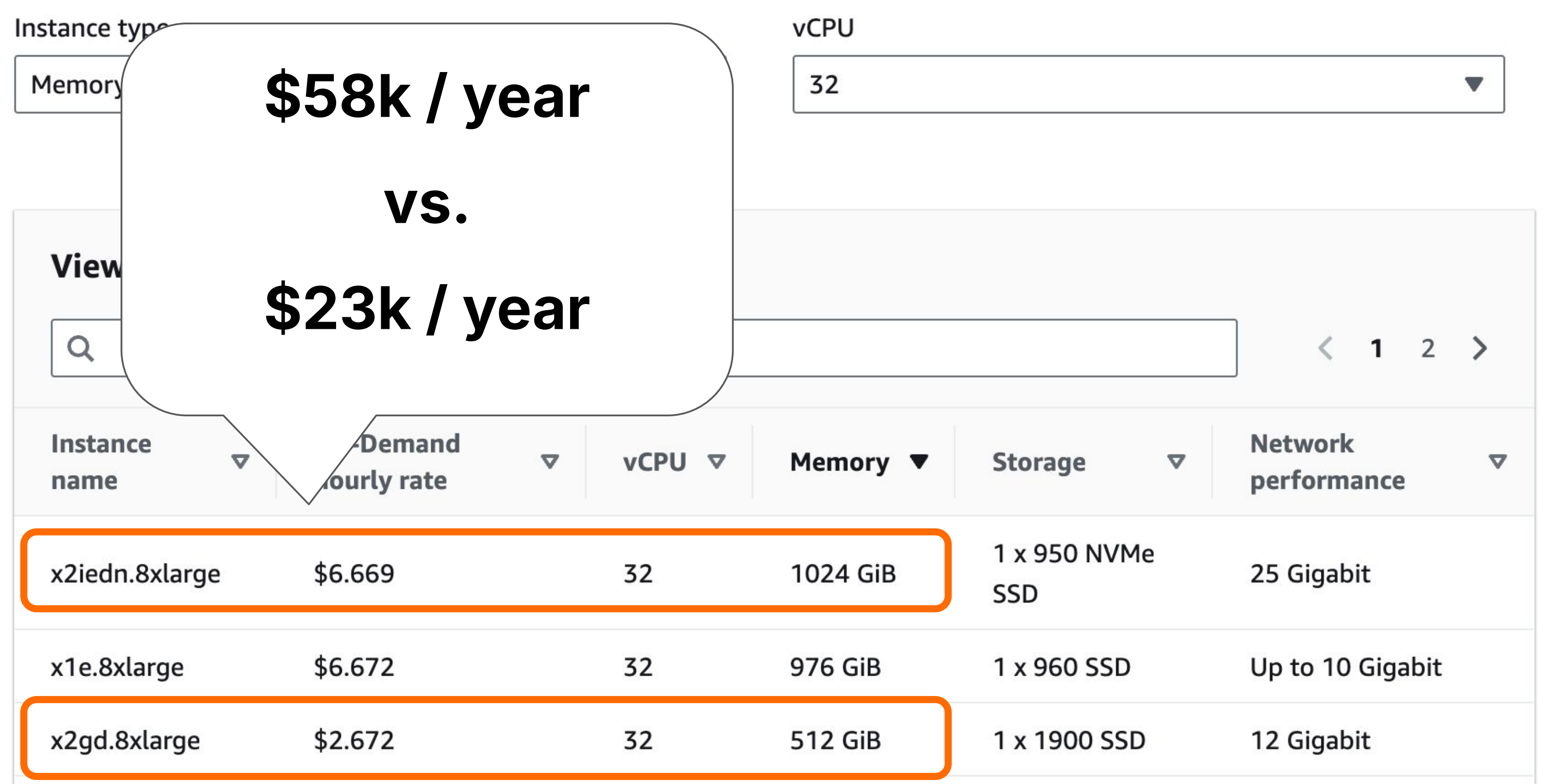
Example: Index type & quantization vs memory footprint



HNSW: ~6GB

HNSW + BQ/PQ: ~2GB

Flat (+BQ): ~1GB



Instance typ

Memory

vCPU

32 ▼

View

1 2

$58k / year

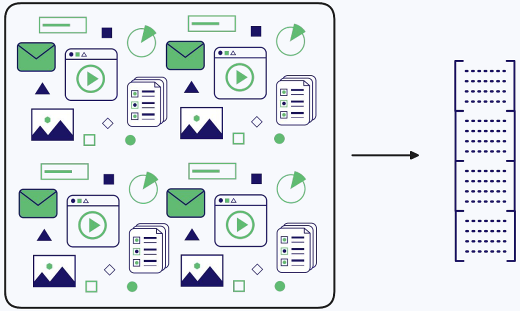
vs.

$23k / year

Instance name ▽	-Demand ourly rate ▽	vCPU ▽	Memory ▼	Storage ▽	Network performance ▽
x2iedn.8xlarge	$6.669	32	1024 GiB	1 x 950 NVMe SSD	25 Gigabit
x1e.8xlarge	$6.672	32	976 GiB	1 x 960 SSD	Up to 10 Gigabit
x2gd.8xlarge	$2.672	32	512 GiB	1 x 1900 SSD	12 Gigabit

AWS Spot pricing, Nov 2024

Scale: Solutions



BQ / PQ / SQ compression

Search **quality** mitigated by over-fetching & rescoring

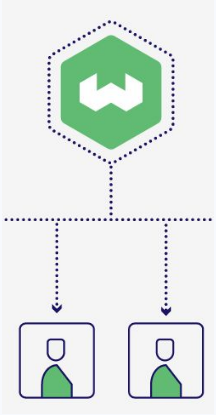
When to use which?

- Generally, try PQ first
- BQ: model-specific

Multi–tenancy

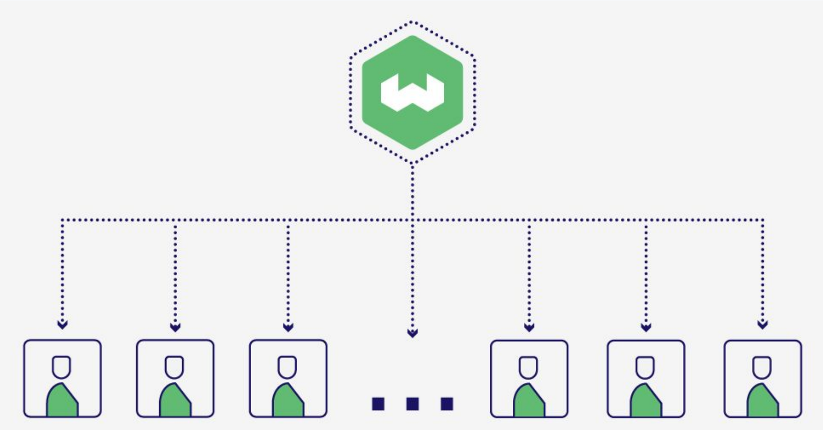
Scale: Solutions

End user growth



Scale: Solutions

End user growth



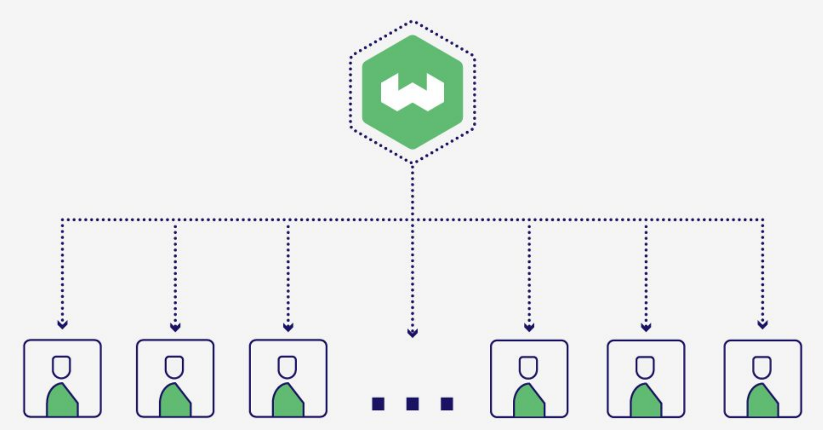
Challenges faced:

- Performance
- Data isolation
- Compliance

Developed: **Multi-tenancy**

Scale: Solutions

End user growth

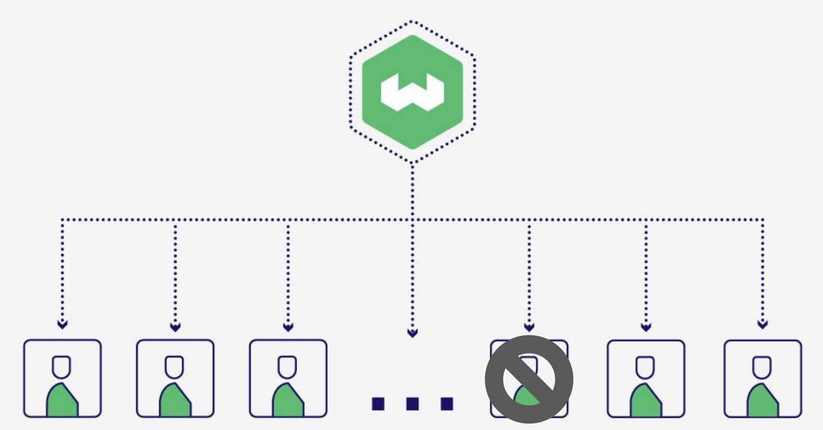


Multi-tenancy implementation

- 1000s per node
- Isolated
- Active/inactive/offloaded tenants

Scale: Solutions

End user growth

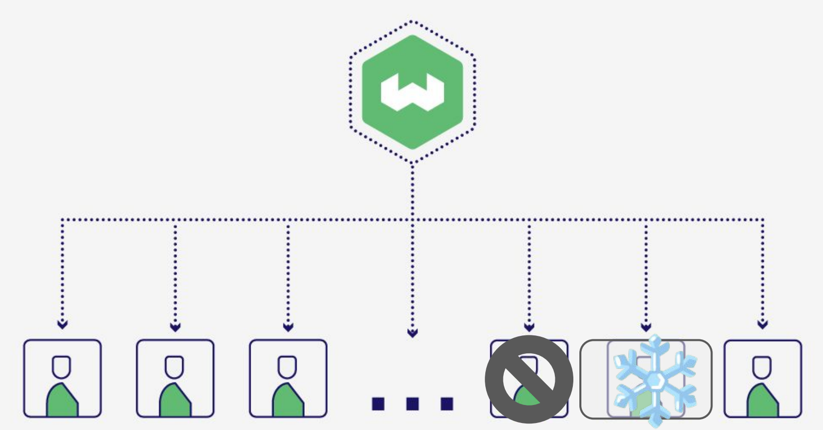


Multi-tenancy implementation

- 1000s per node
- **Isolated** (easy deletion & compliance)
- Active/inactive/offloaded tenants

Scale: Solutions

End user growth



Multi-tenancy implementation

- 1000s per node
- Isolated
- **Active/inactive/offloaded tenants** (efficient)

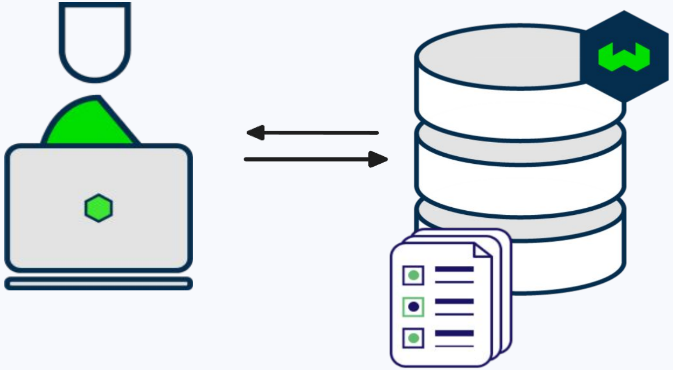
Replication

Reliability: Considerations

- **Robust to errors**: Ensure consistency
- **Downtime**: Reduce disruption
- **Backups**: In case of emergency

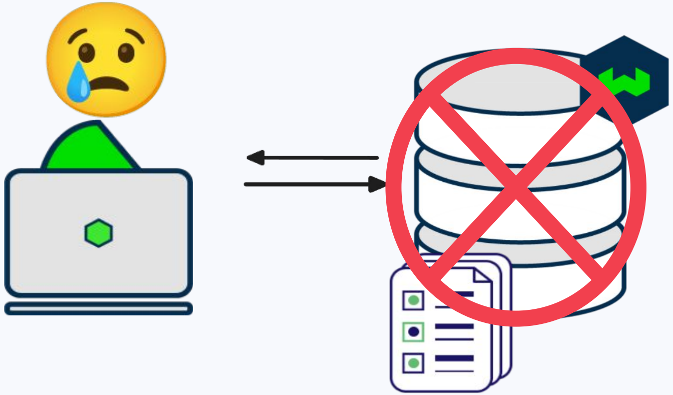
Reliability: Solutions

Happy days



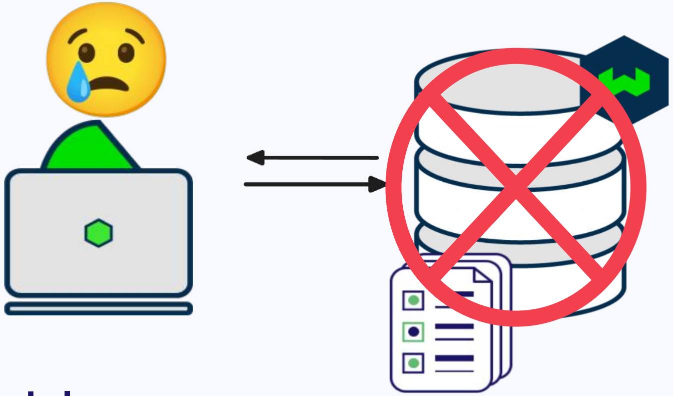
Reliability: Solutions

(Less) Happy days



Reliability: Solutions

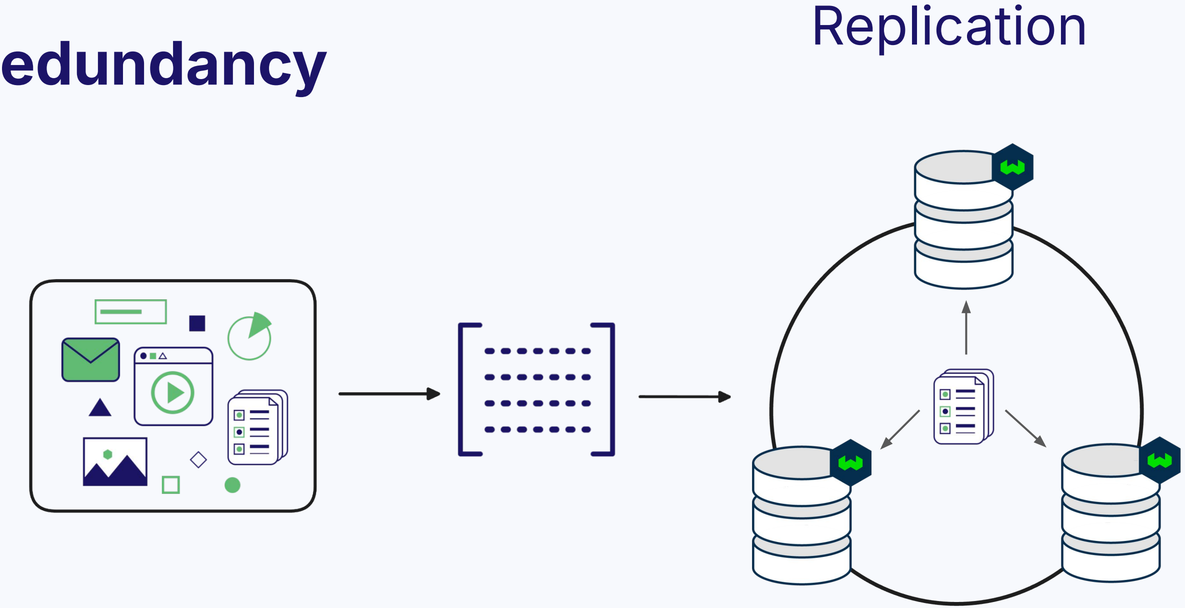
(Less) Happy days



Downtime = inevitable

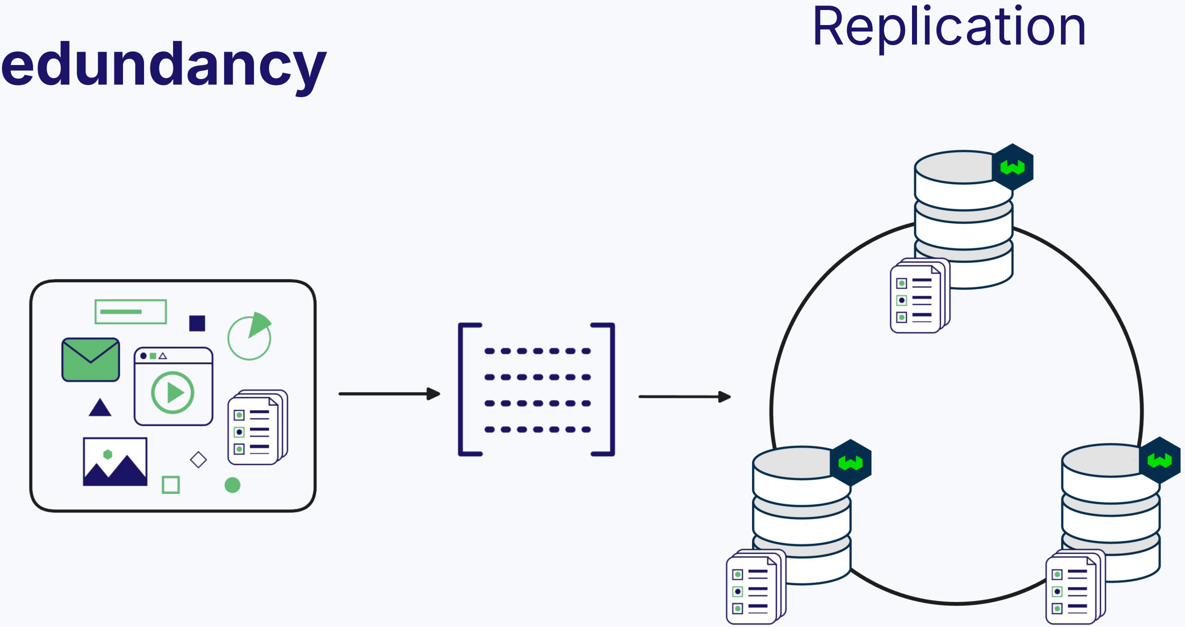
Reliability: Solutions

Provide redundancy



Reliability: Solutions

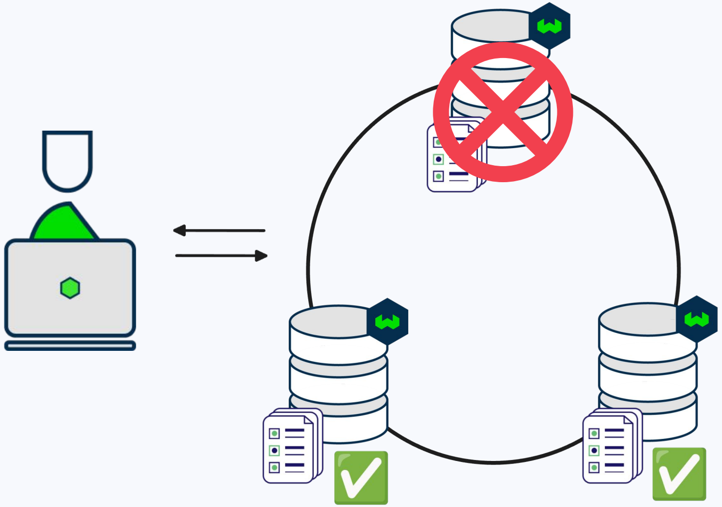
Provide redundancy



Reliability: Solutions

Provide redundancy

Replication



Reliability: Solutions

Provide redundancy

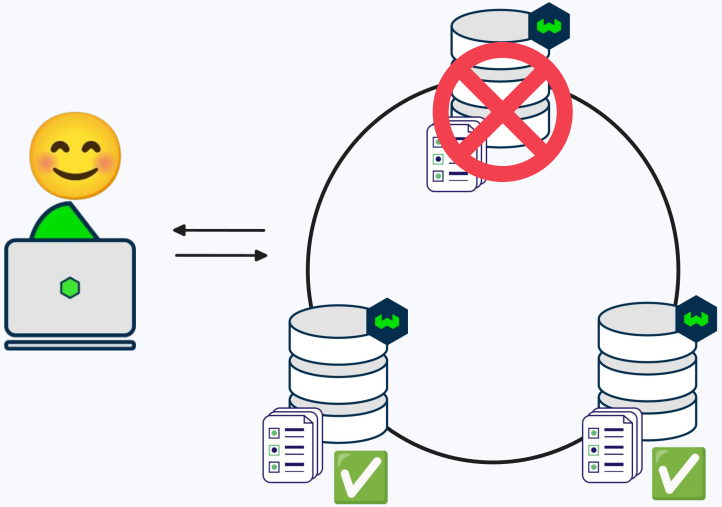
Node-level downtime:

- inevitable

System-level downtime:

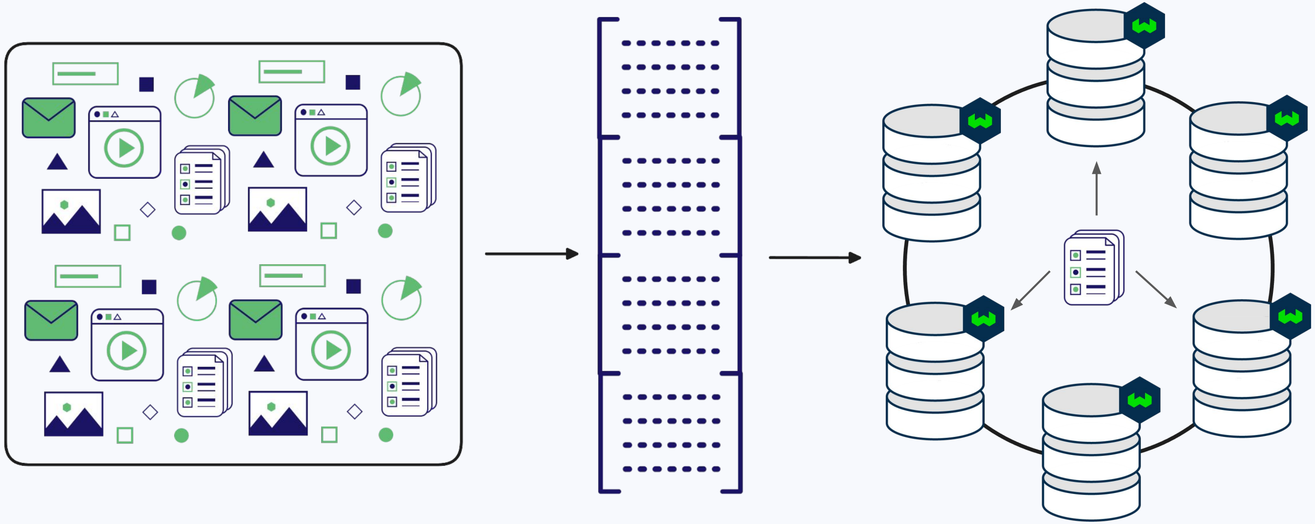
- avoidable!

Replication



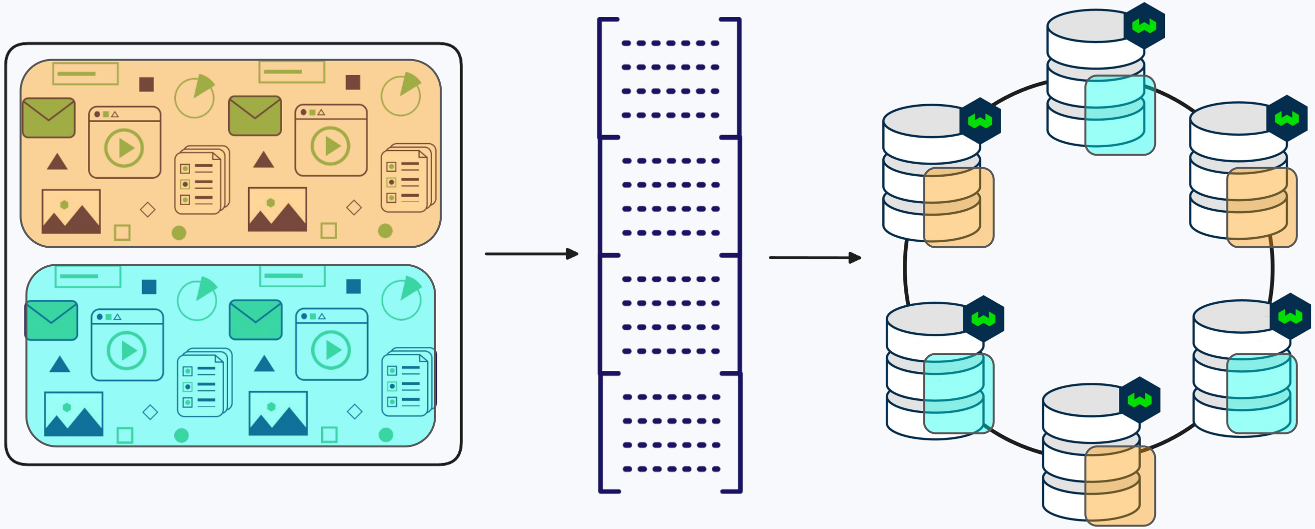
Reliability: Solutions

Sharding + replication



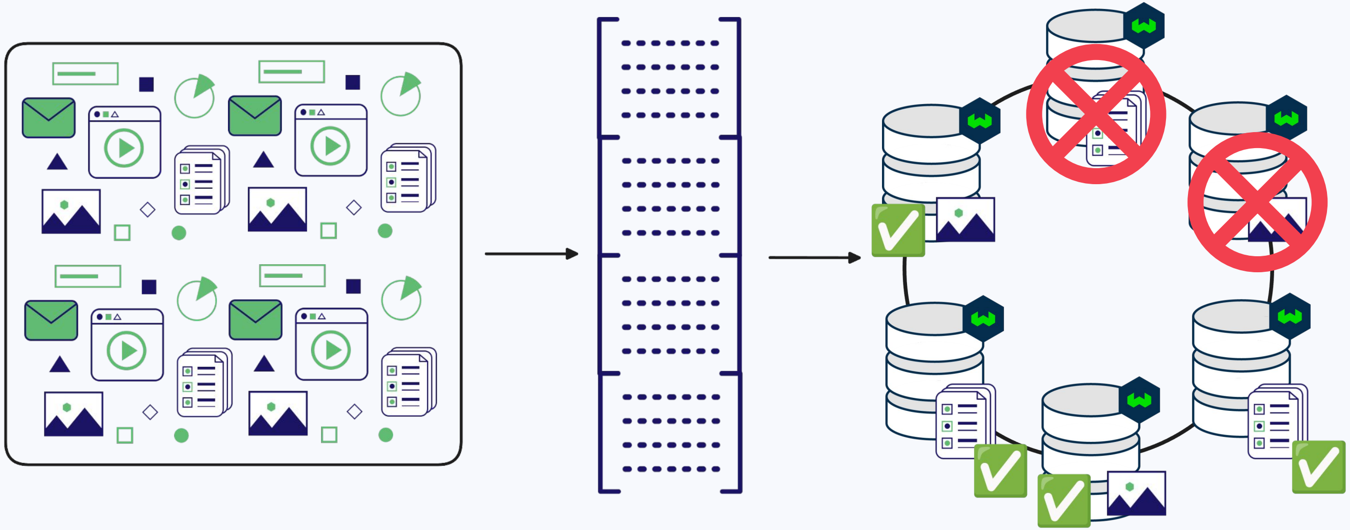
Reliability: Solutions

Sharding + replication



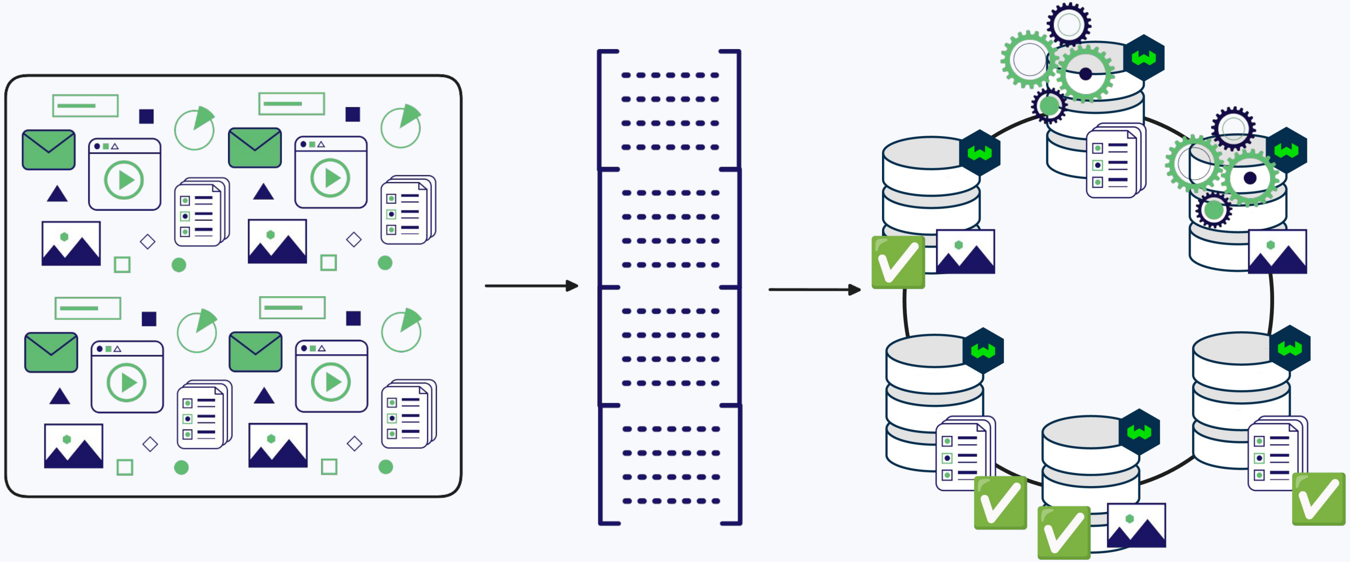
Upgrade: Solutions

Sharding + replication



Upgrade: Solutions

Sharding + replication



Upgrade: Solutions

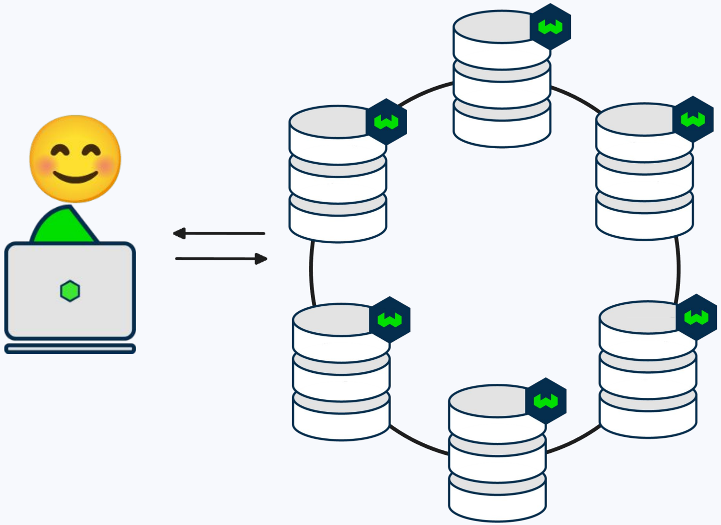
Provide redundancy

“Just works”

for the end user -

with the latest

versions

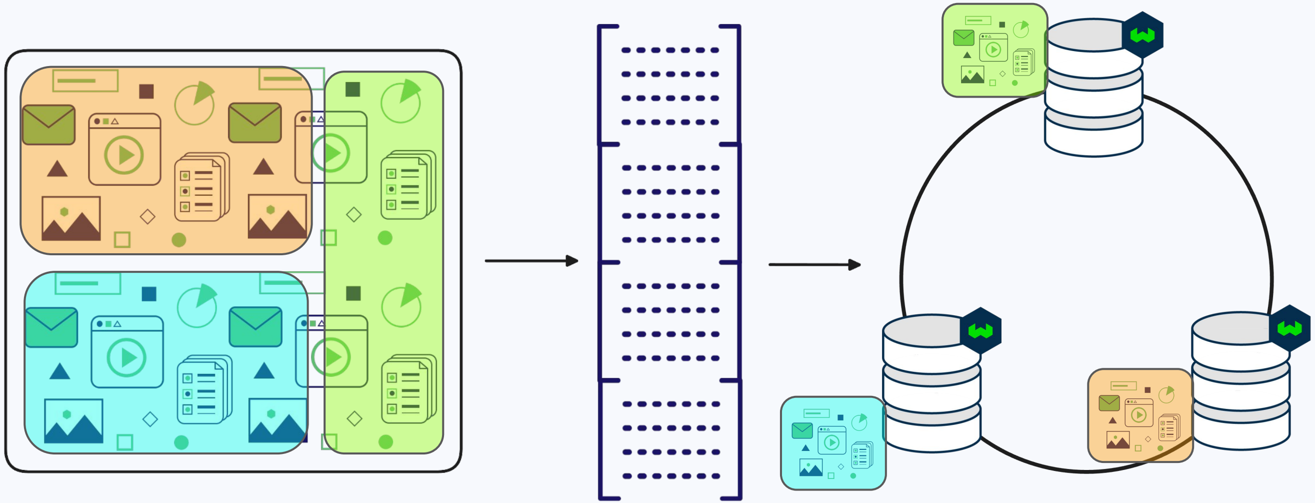


Scaling out

Scale: Solutions

Deal with growth

Horizontal scaling (sharding)



Scale: Solutions

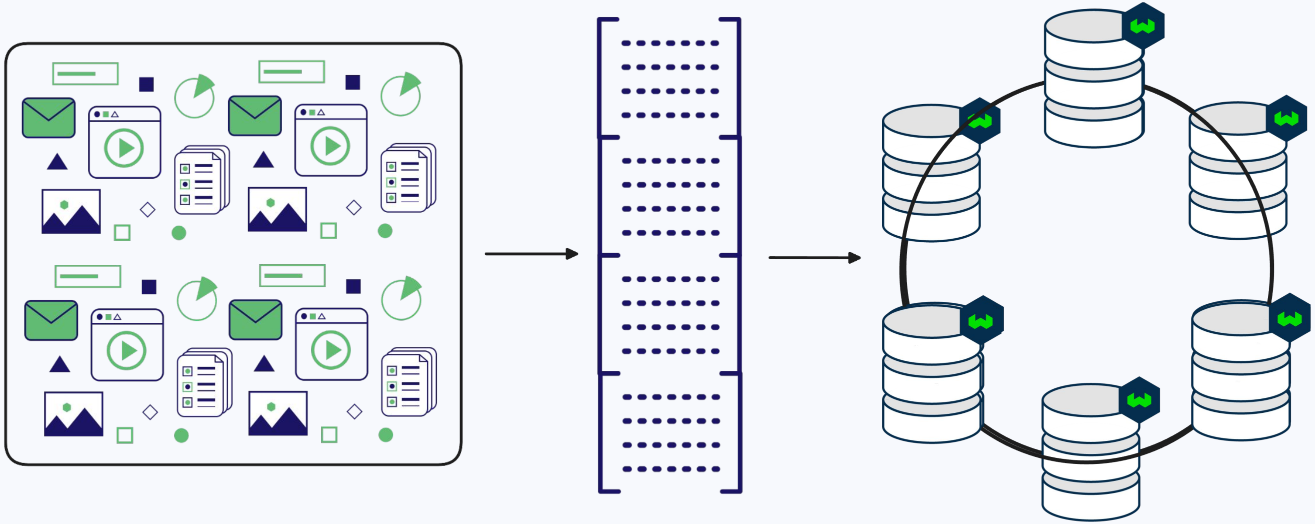
Billion scale

since 2022!

Deal with growth

To scale:

Add more nodes



Scale: Solutions

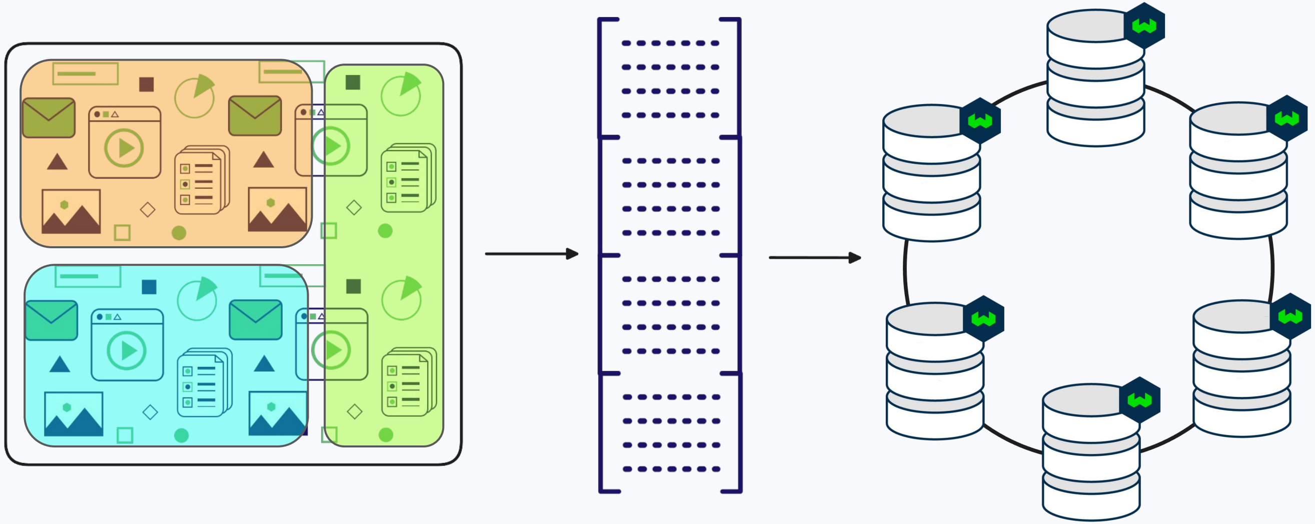
Billion scale

since 2022!

Deal with growth

To scale:

Add more nodes



Billion scale

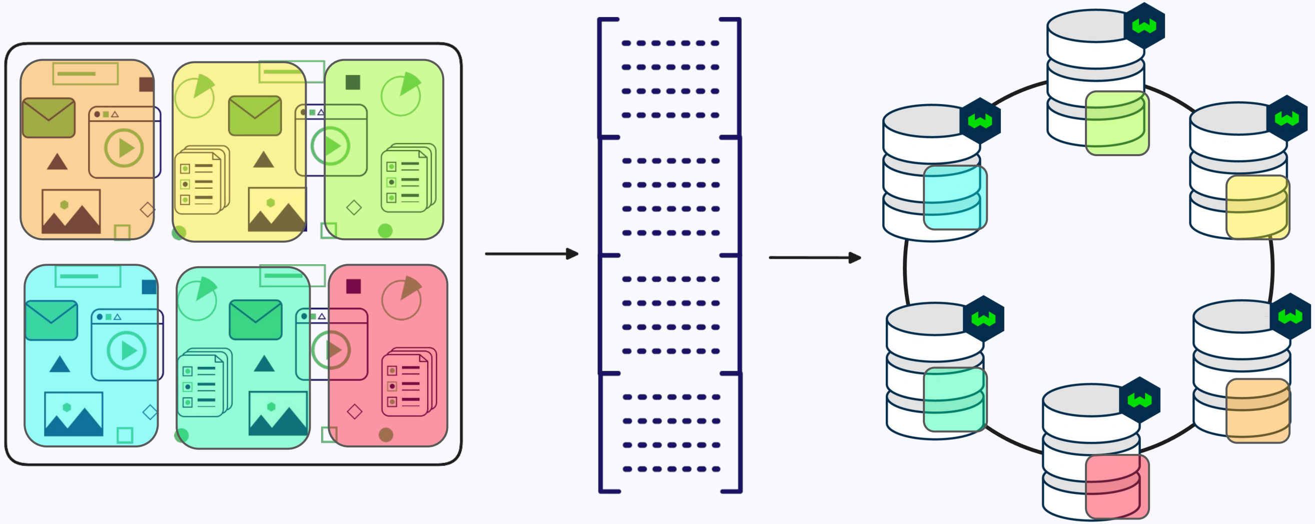
since 2022!

Scale: Solutions

Deal with growth

To scale:

Add more nodes



Available Solutions

Scaling up

Scaling out

Index options

Quantization

Multi-tenancy
(+ tenant states)

Replication

Thank you

Connect with us!

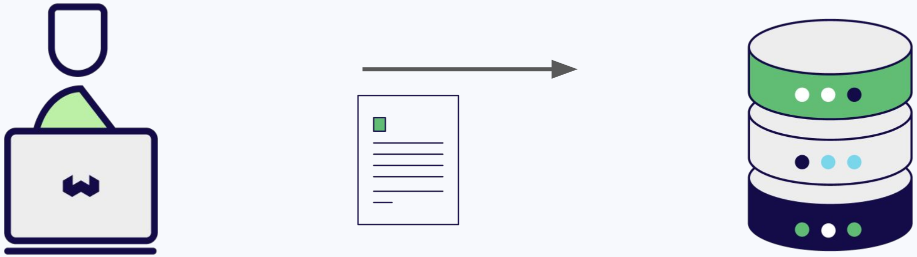
- weaviate.io
- weaviate/weaviate
- weaviate_io

BONUS SLIDES!

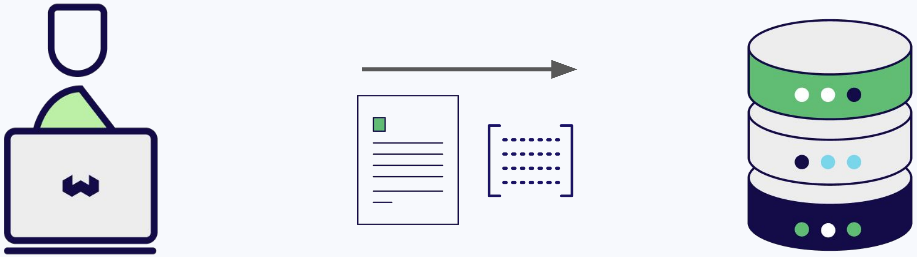
Developer workflow

Ingest data

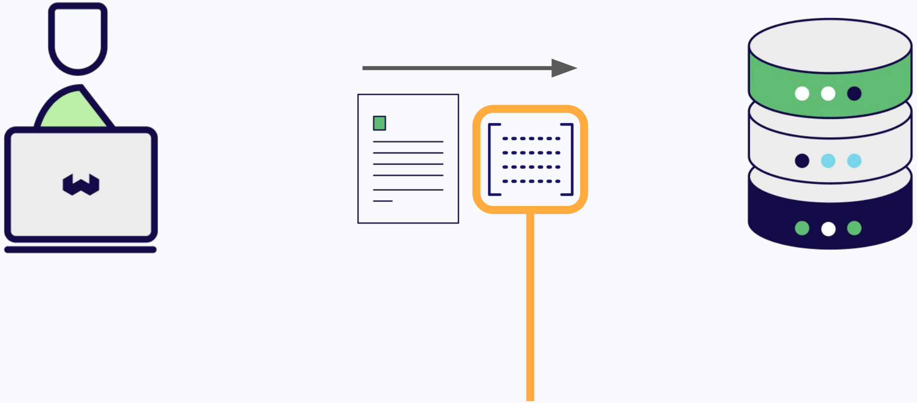
Ingest data



Ingest data

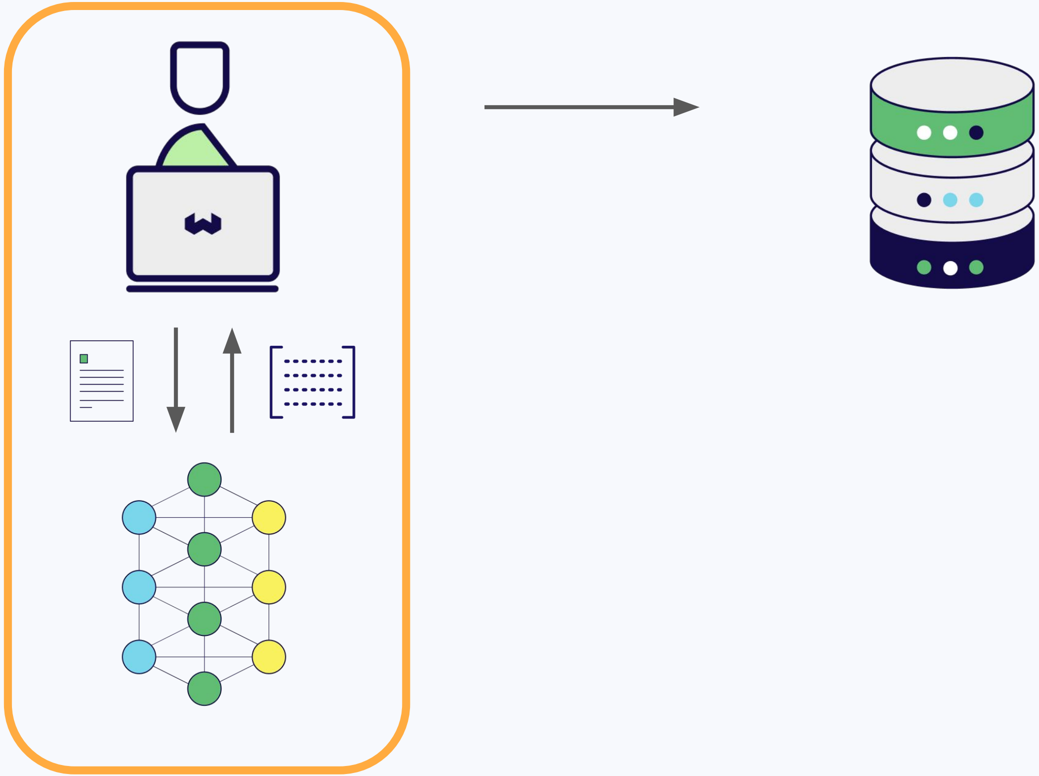


Ingest data

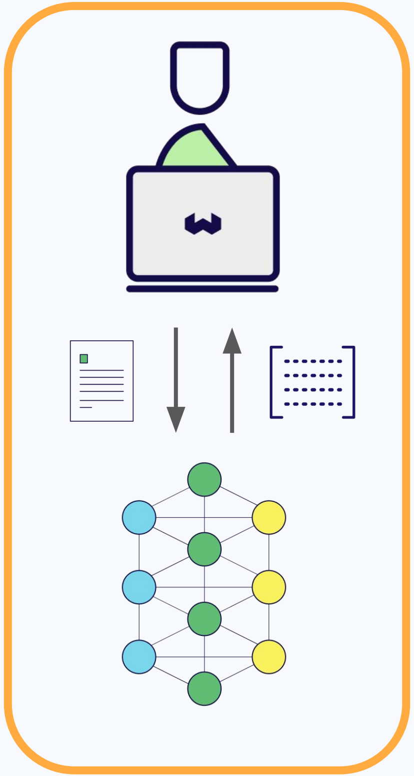


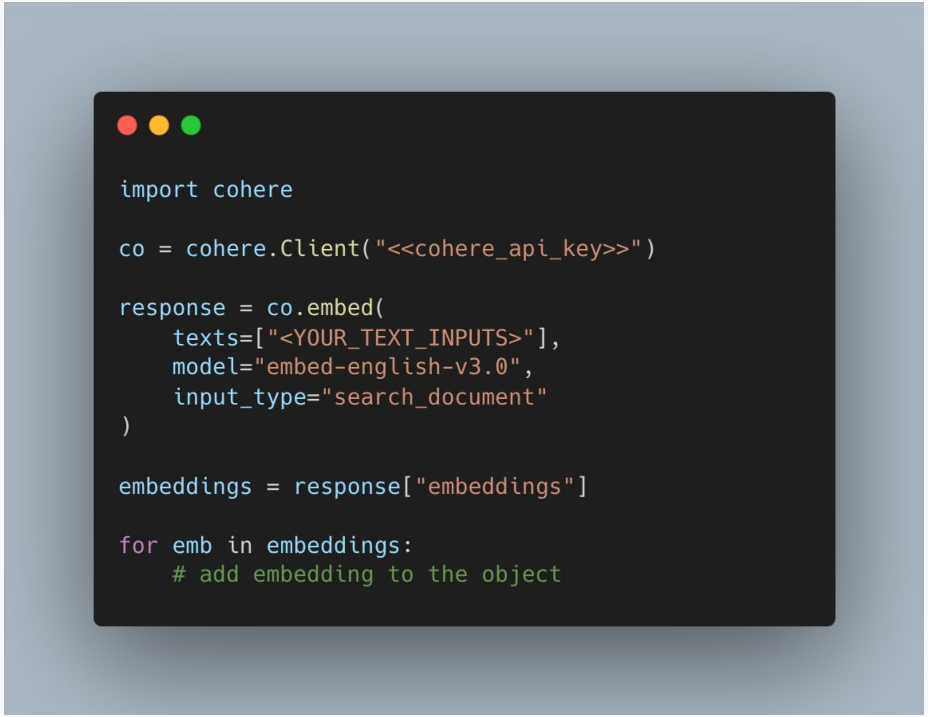
Where do they come from??

Obtain Embeddings



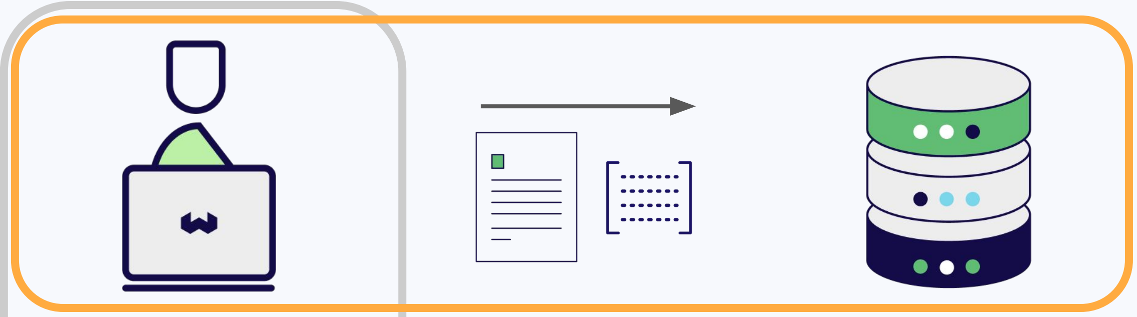
Obtain Embeddings

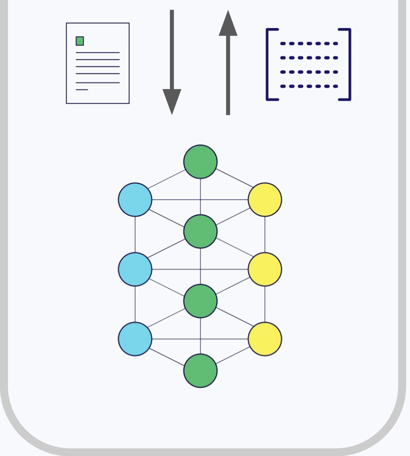


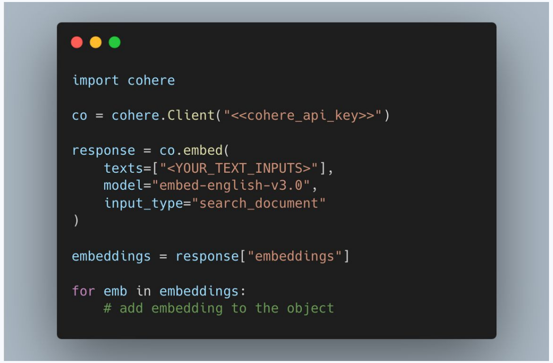


```python
import cohere

co = cohere.Client("<<cohere_api_key>>")

response = co.embed(
    texts=["<YOUR_TEXT_INPUTS>"],
    model="embed-english-v3.0",
    input_type="search_document"
)

embeddings = response["embeddings"]

for emb in embeddings:
    # add embedding to the object
```

Obtain Embeddings

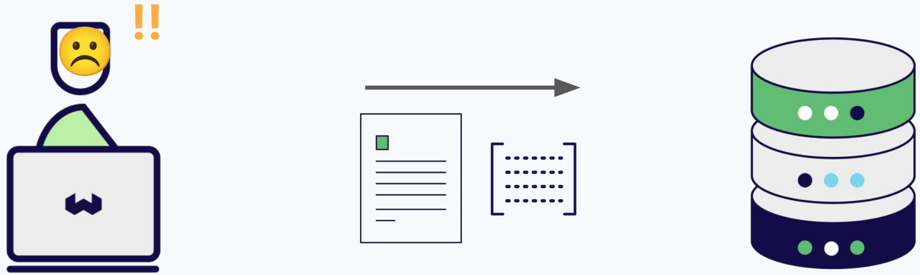


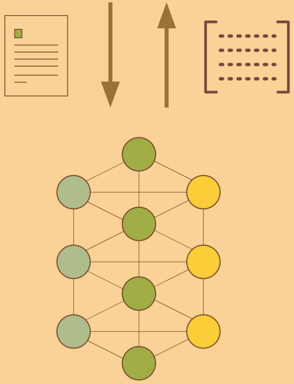


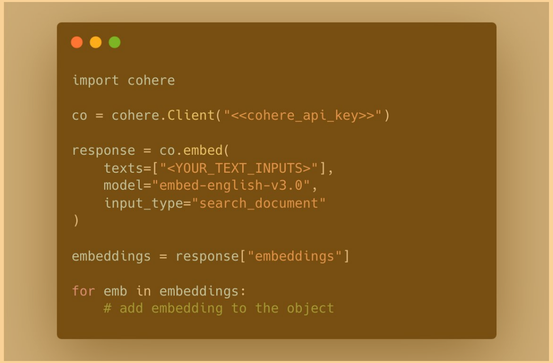


```
import cohere

co = cohere.Client("<<cohere_api_key>>")

response = co.embed(
    texts=["<YOUR_TEXT_INPUTS>"],
    model="embed-english-v3.0",
    input_type="search_document"
)

embeddings = response["embeddings"]

for emb in embeddings:
    # add embedding to the object
```

Overhead







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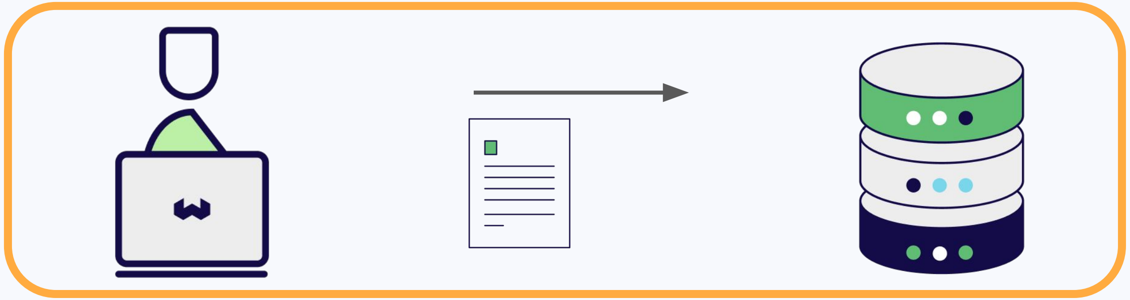
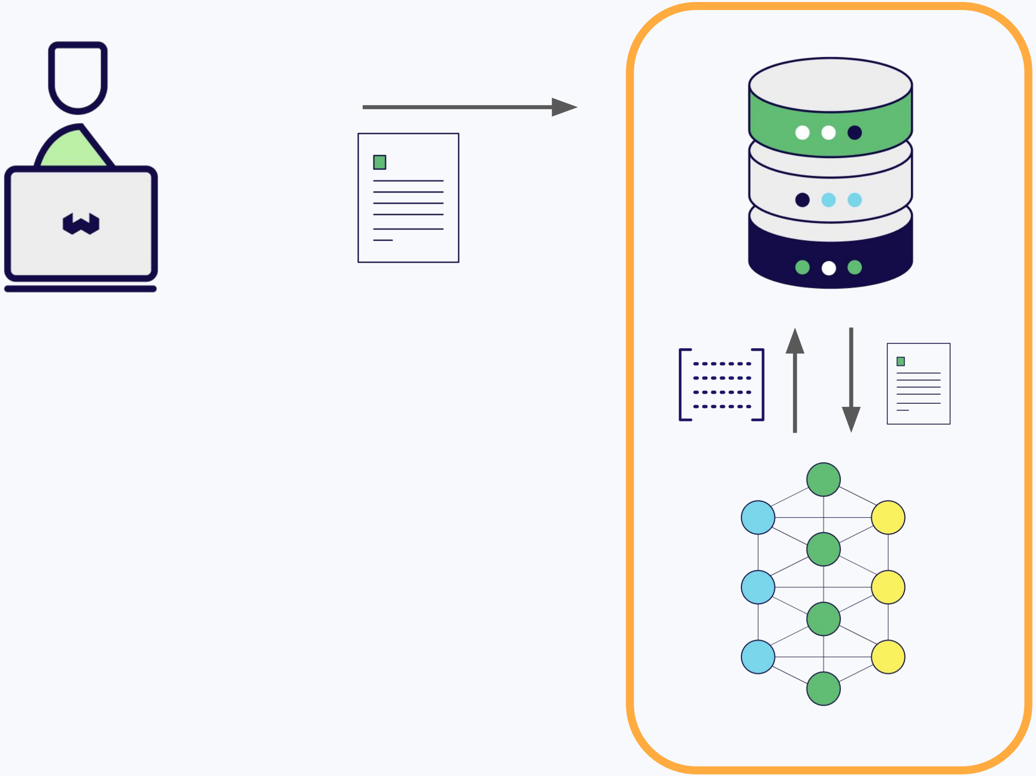
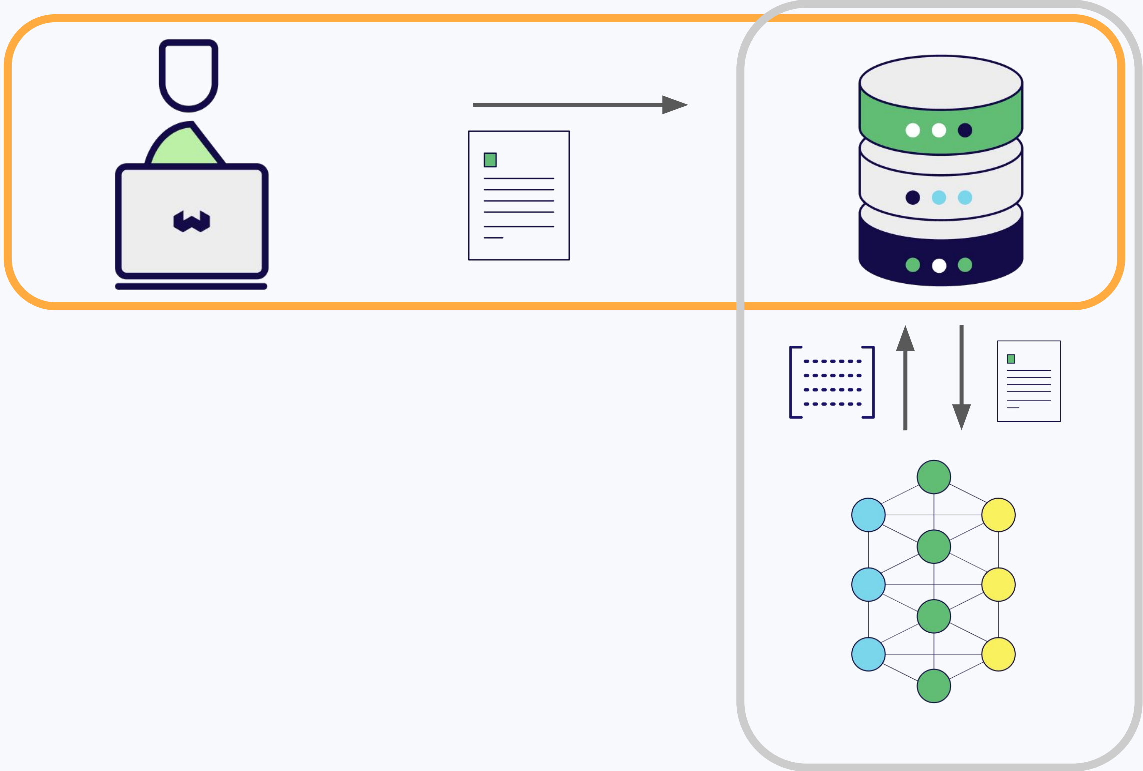
Ingest data



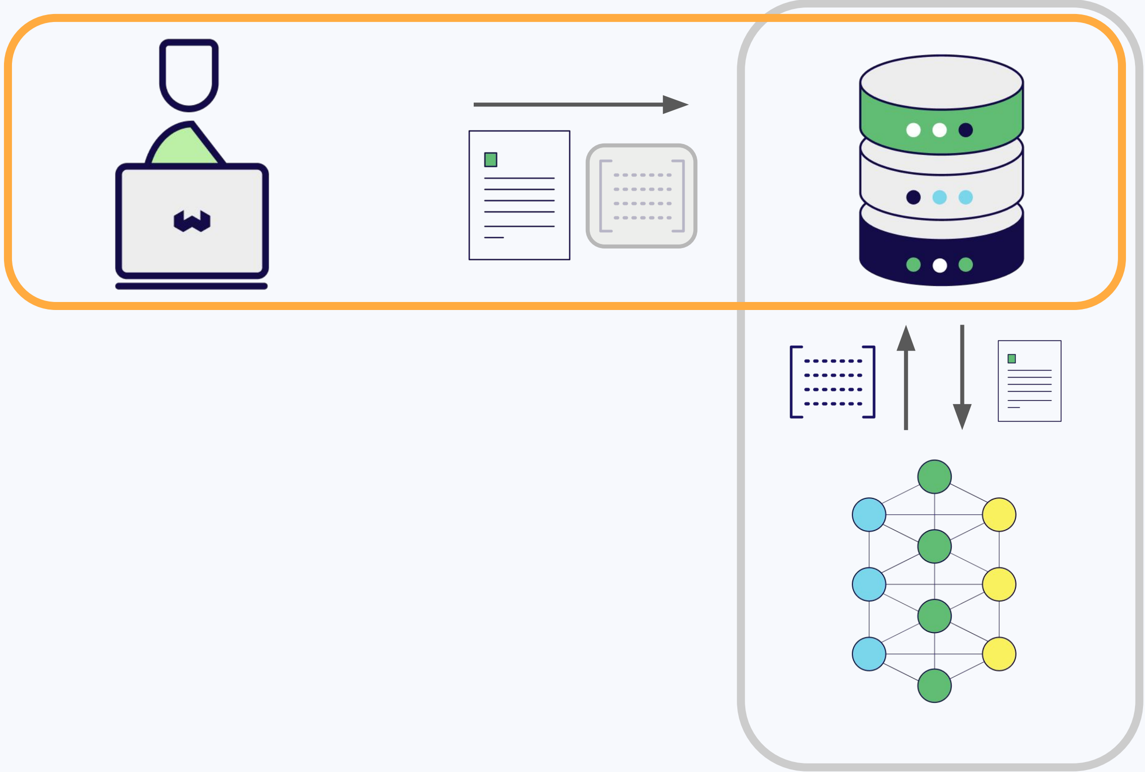
Have Weaviate obtain embeddings



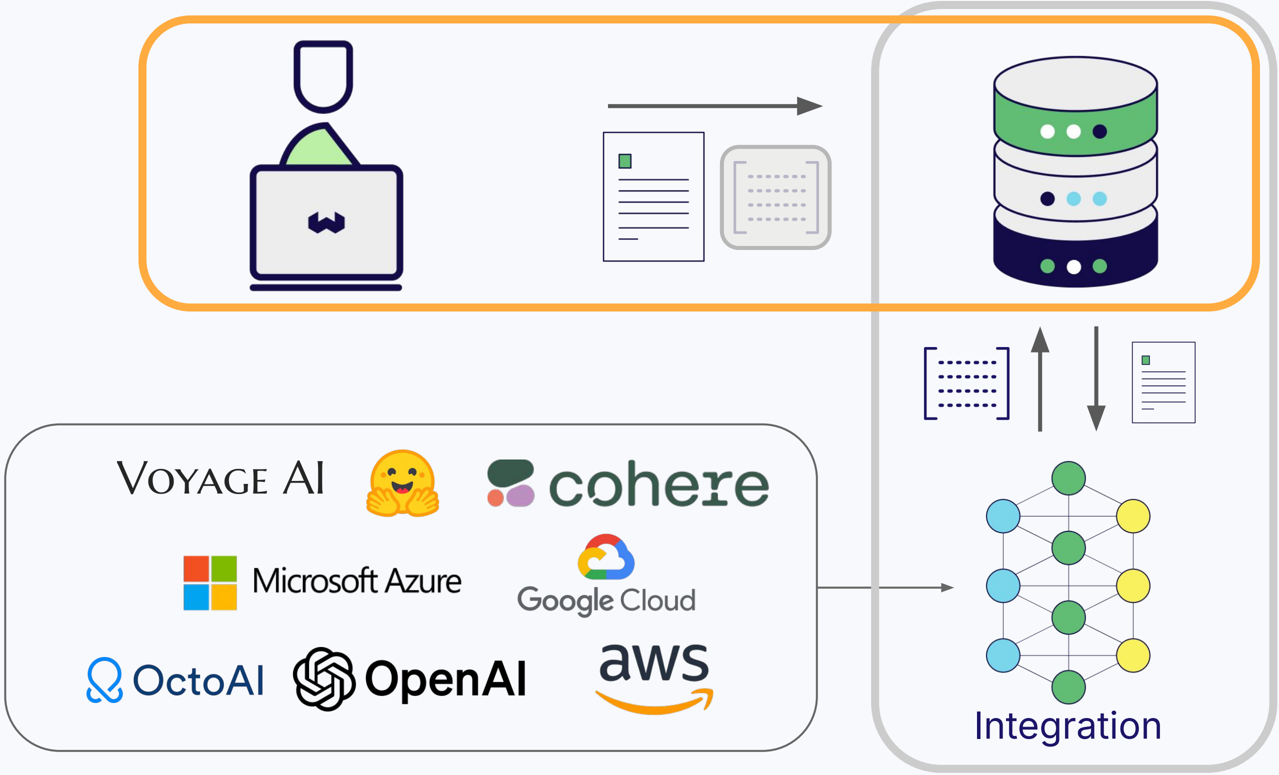
Ingest data (embeddings in background)



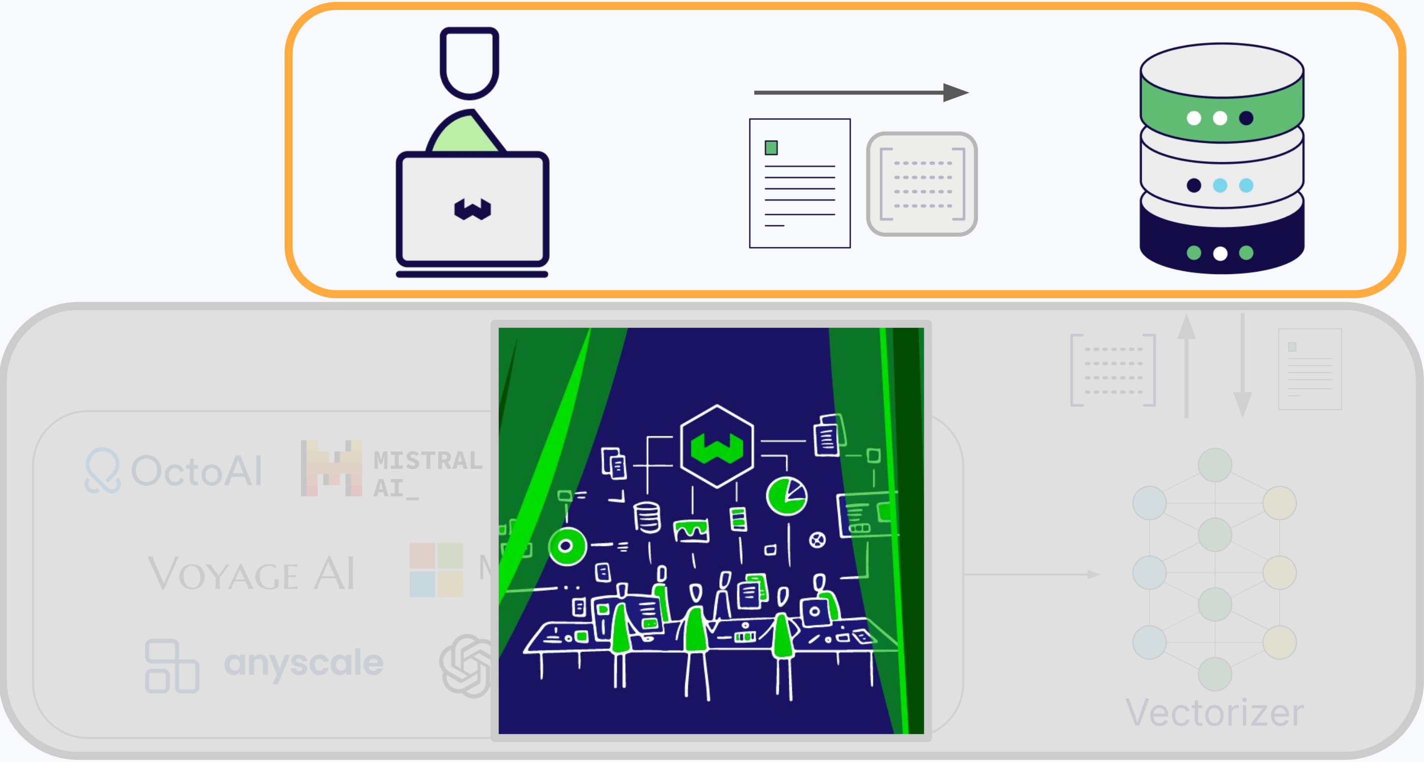
Ingest data (embeddings optional)



Ingest data (with provider integrations)



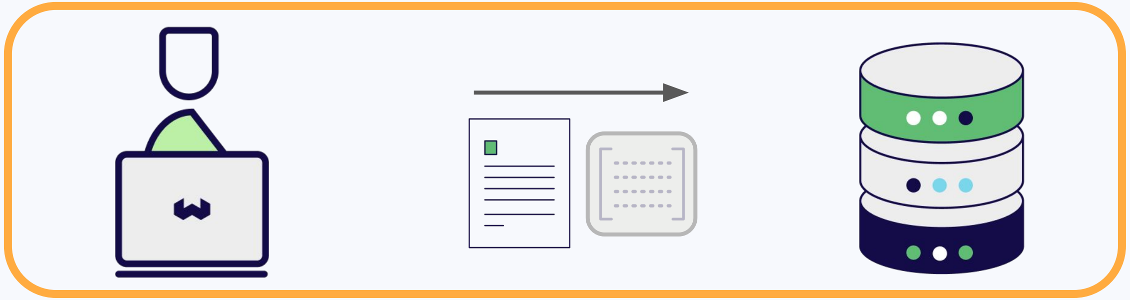
Simplified Experience



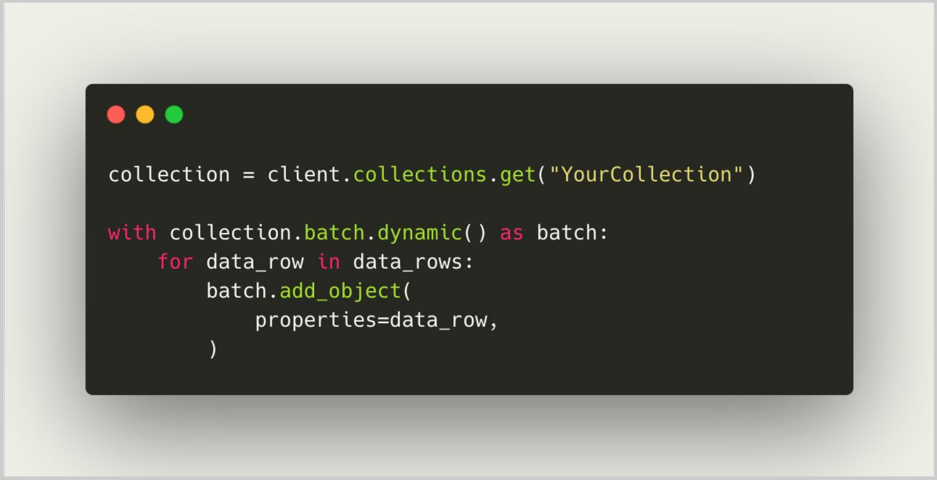
User experience

Under the hood

Simplified Experience



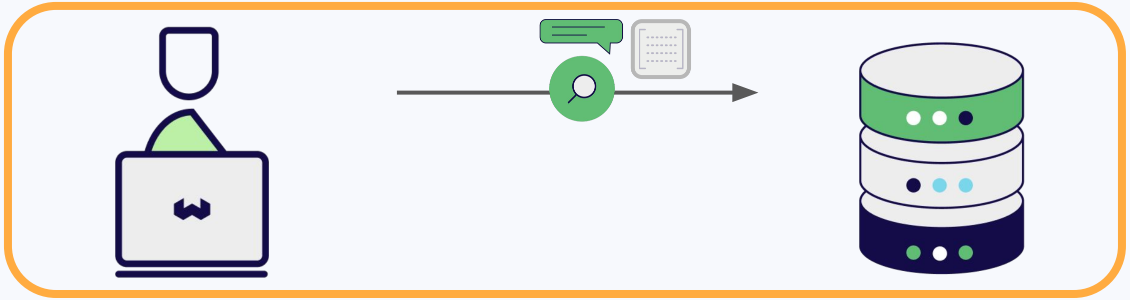
User experience



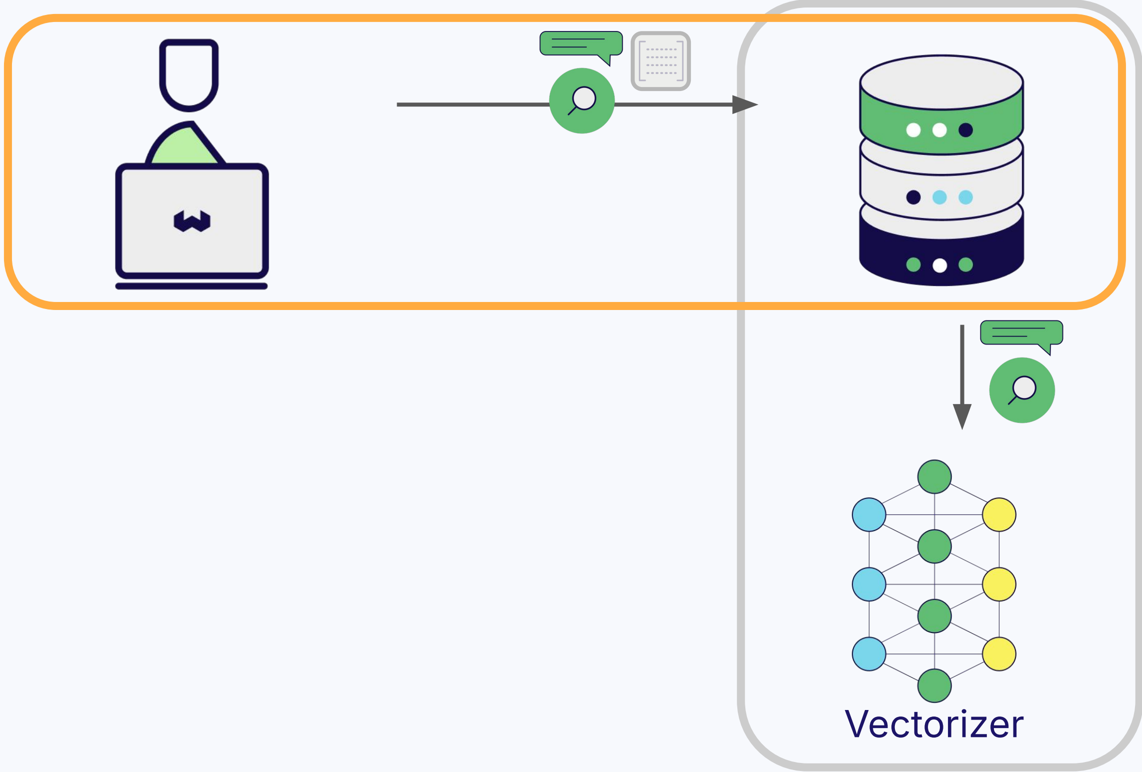
```
collection = client.collections.get("YourCollection")

with collection.batch.dynamic() as batch:
    for data_row in data_rows:
        batch.add_object(
            properties=data_row,
        )
```

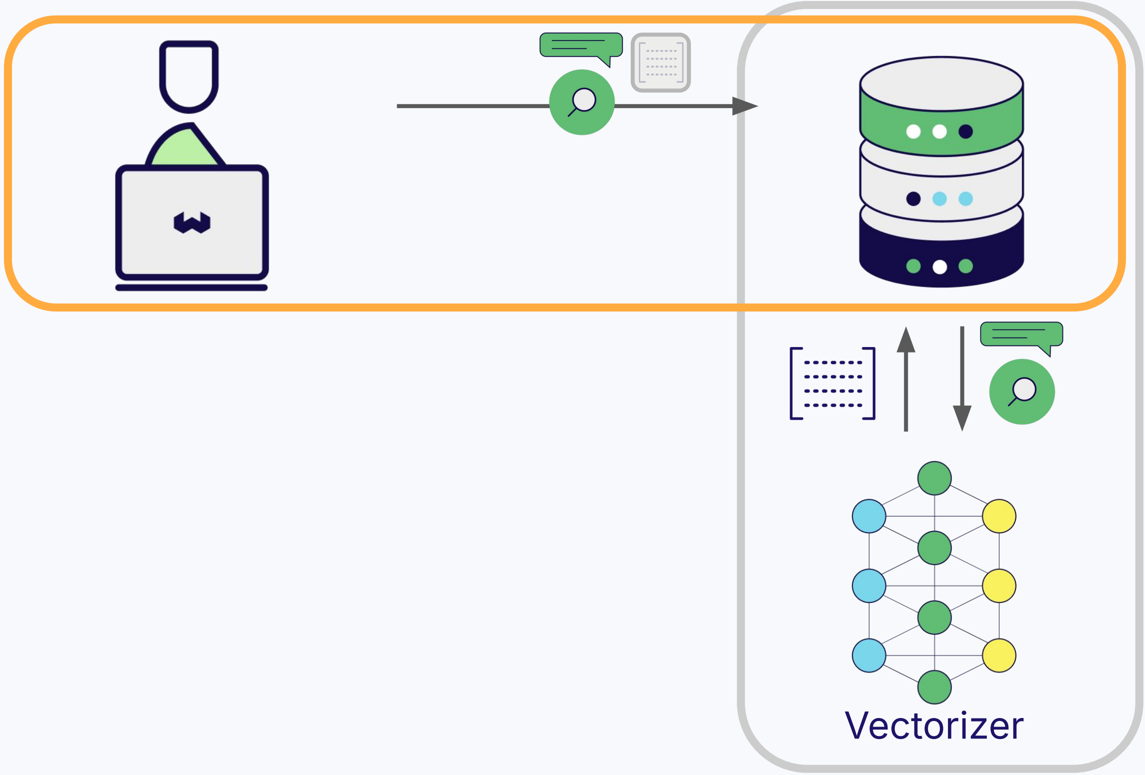
Query



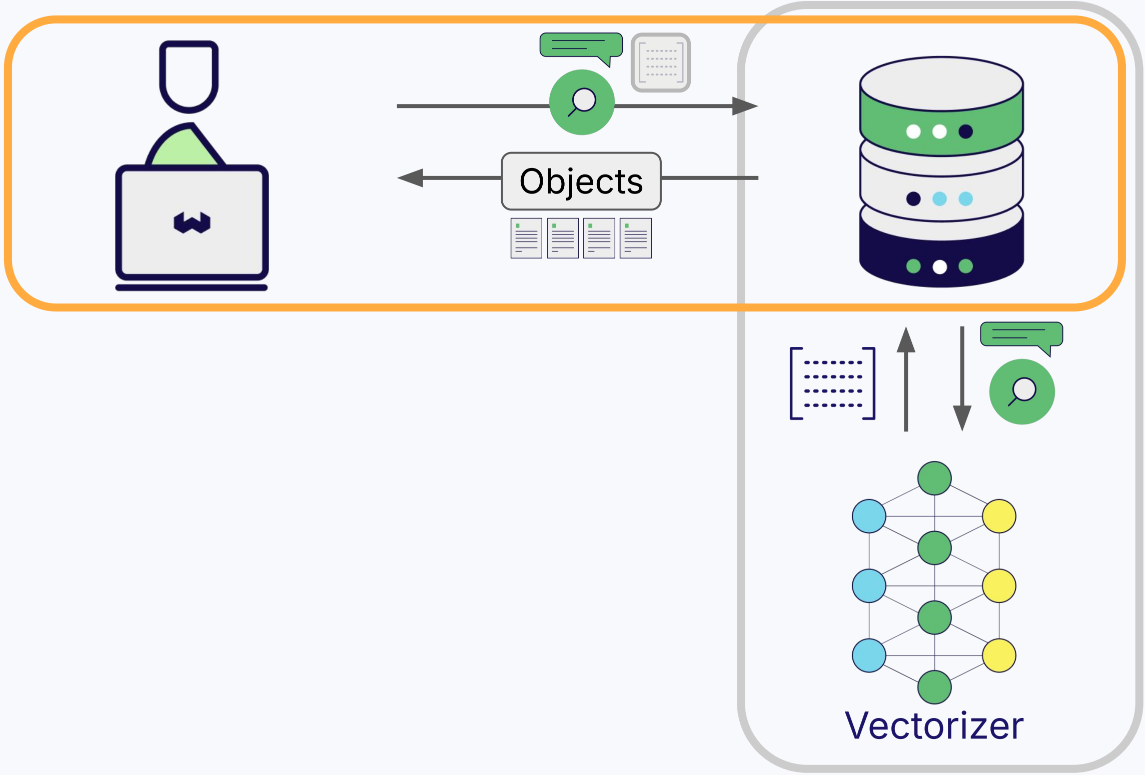
Query



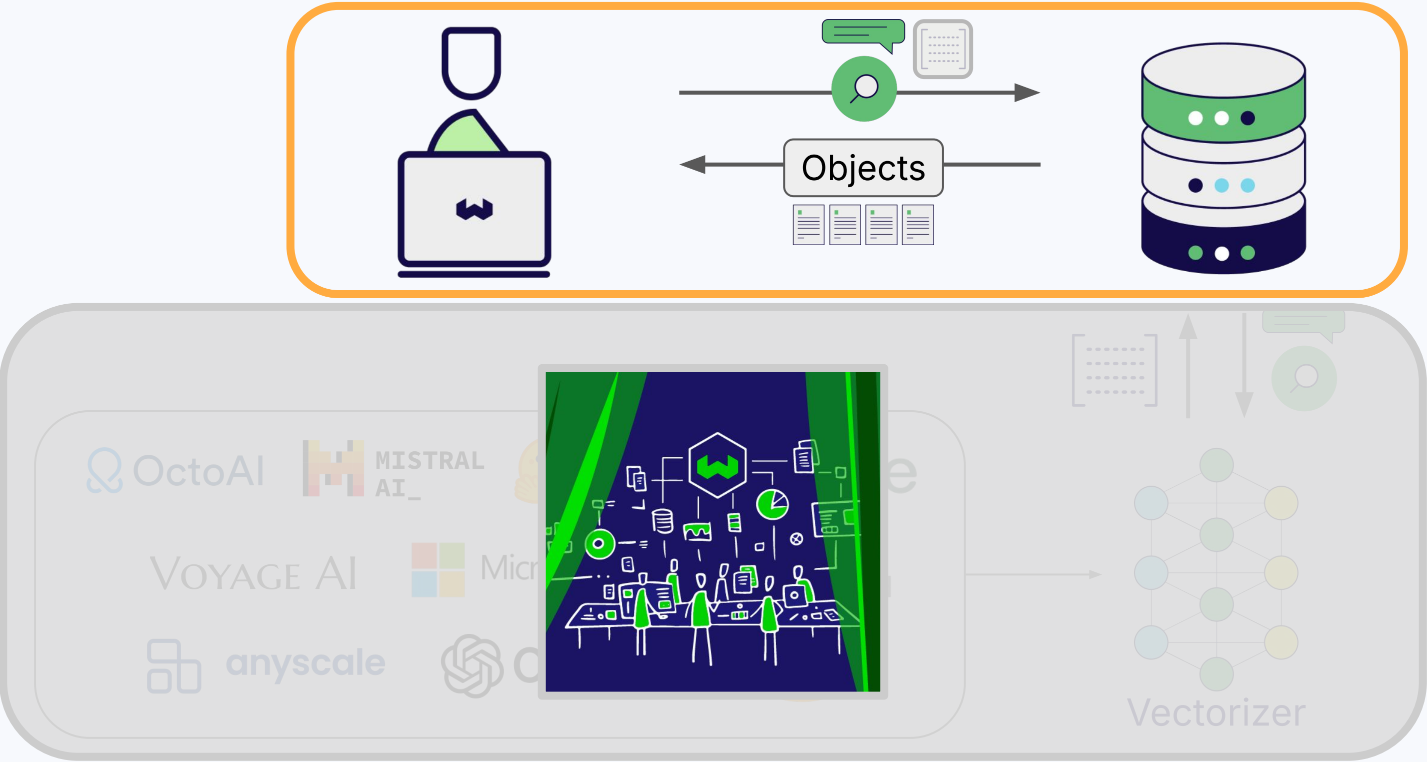
Query



Query



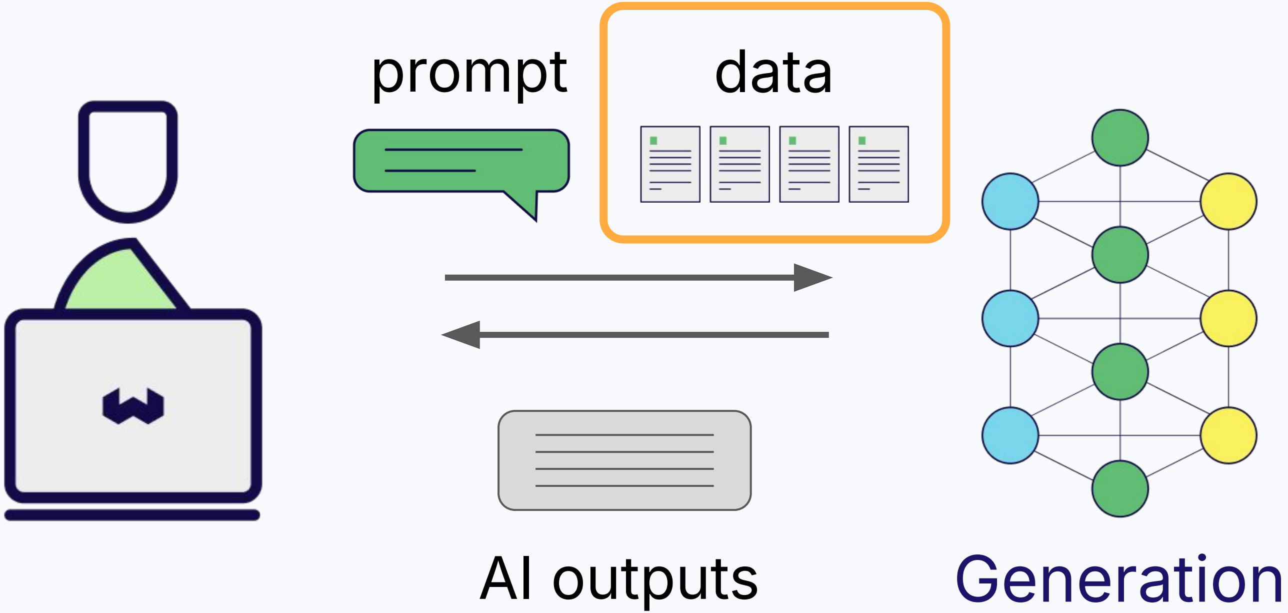
Query



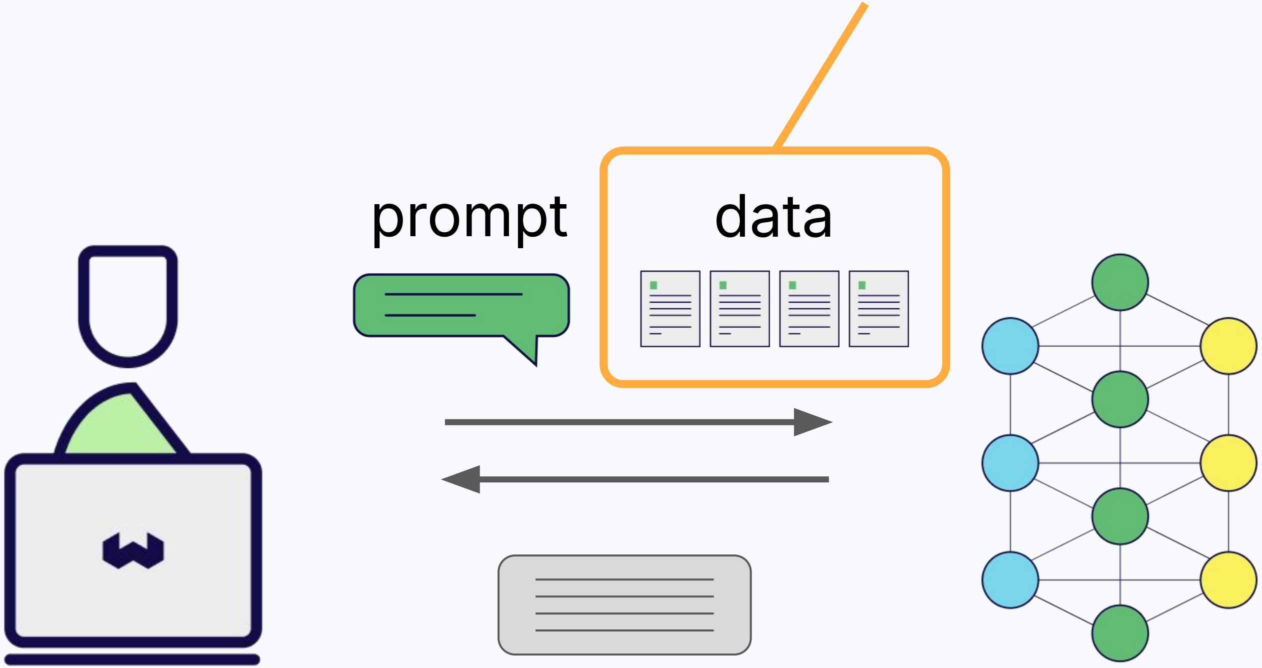
User experience

Under the hood

RAG



RAG



Must be relevant

prompt

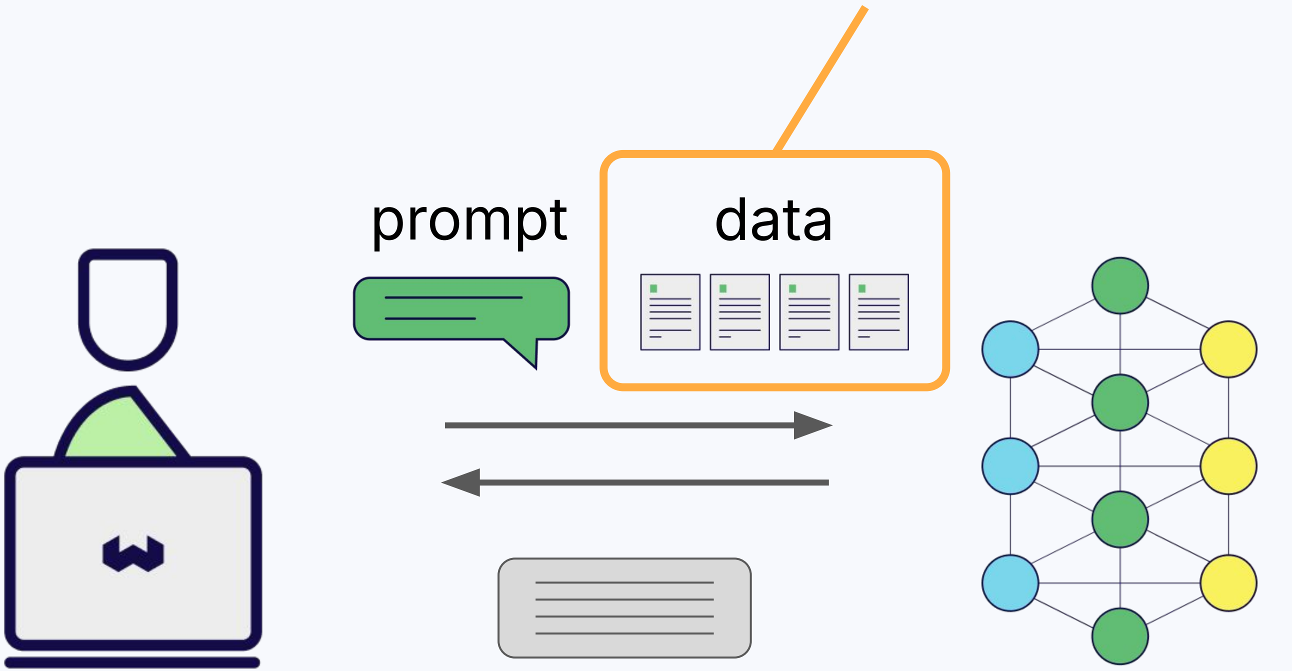
data

AI outputs

Generation

RAG

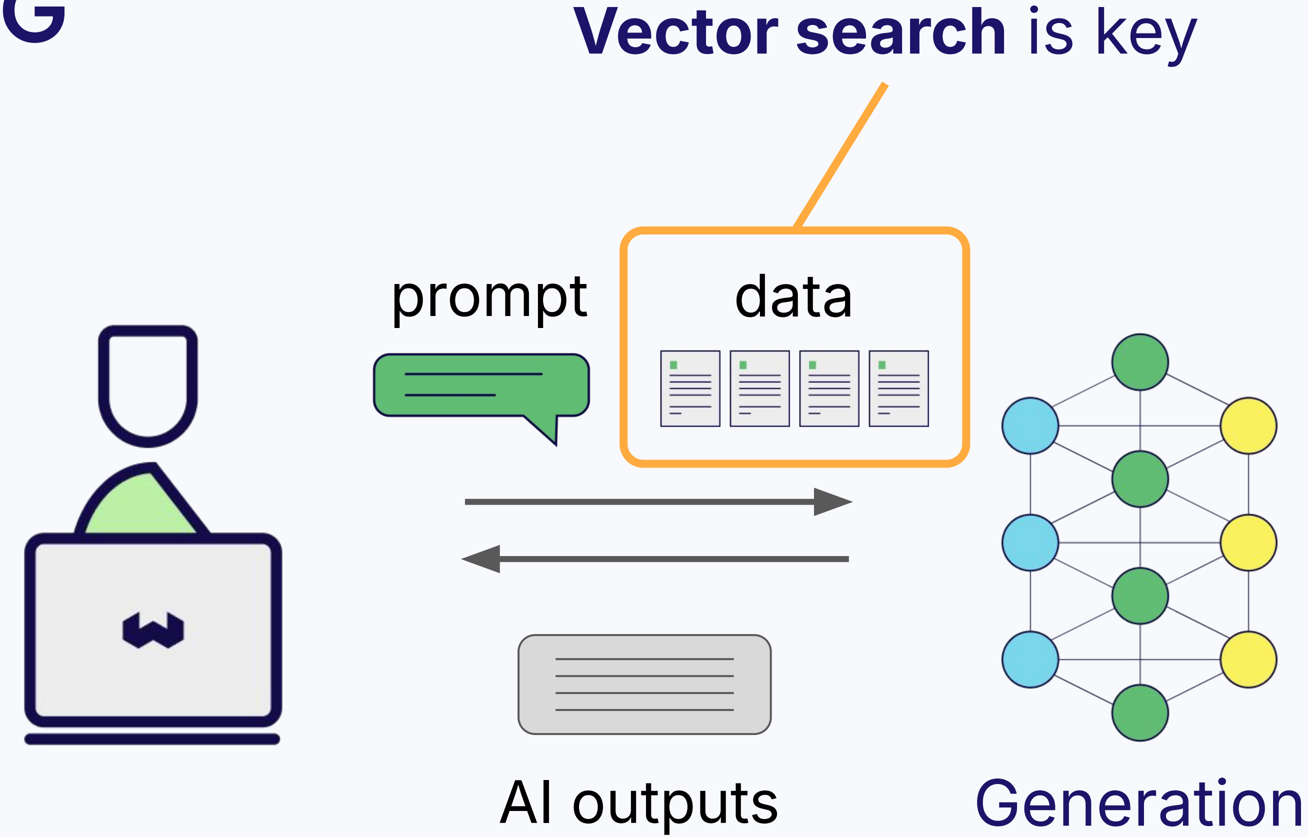
Search is key



AI outputs

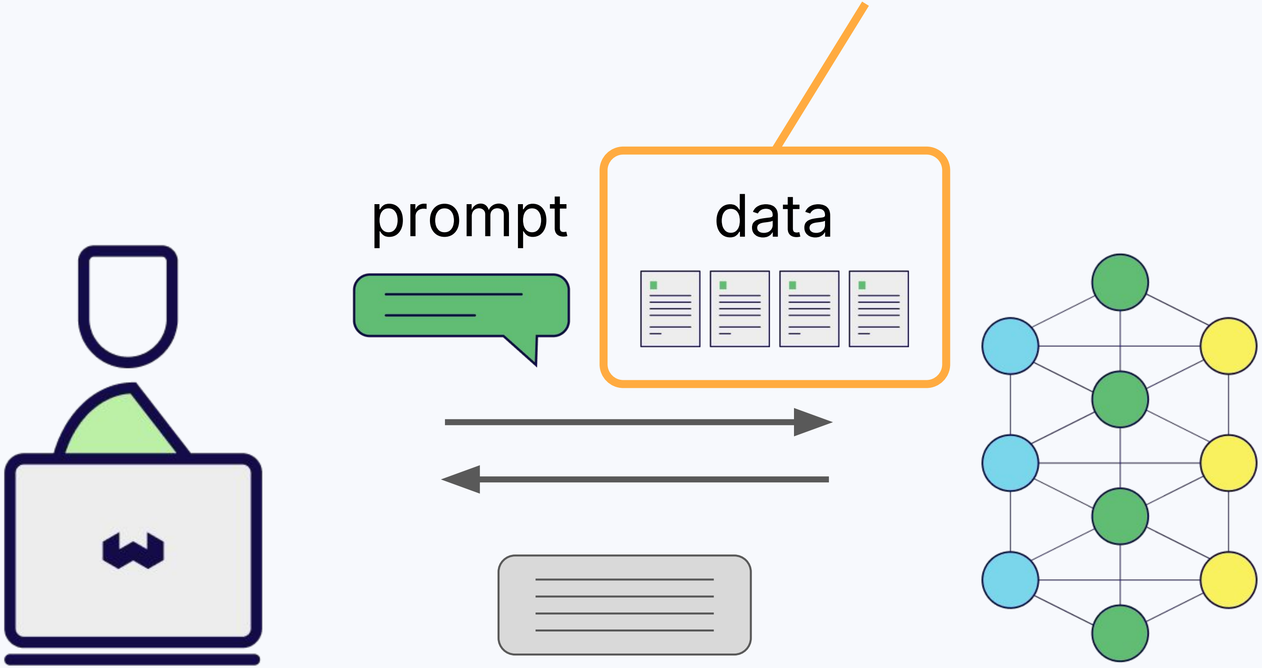
Generation

RAG



RAG

Vector search: relevance search



prompt

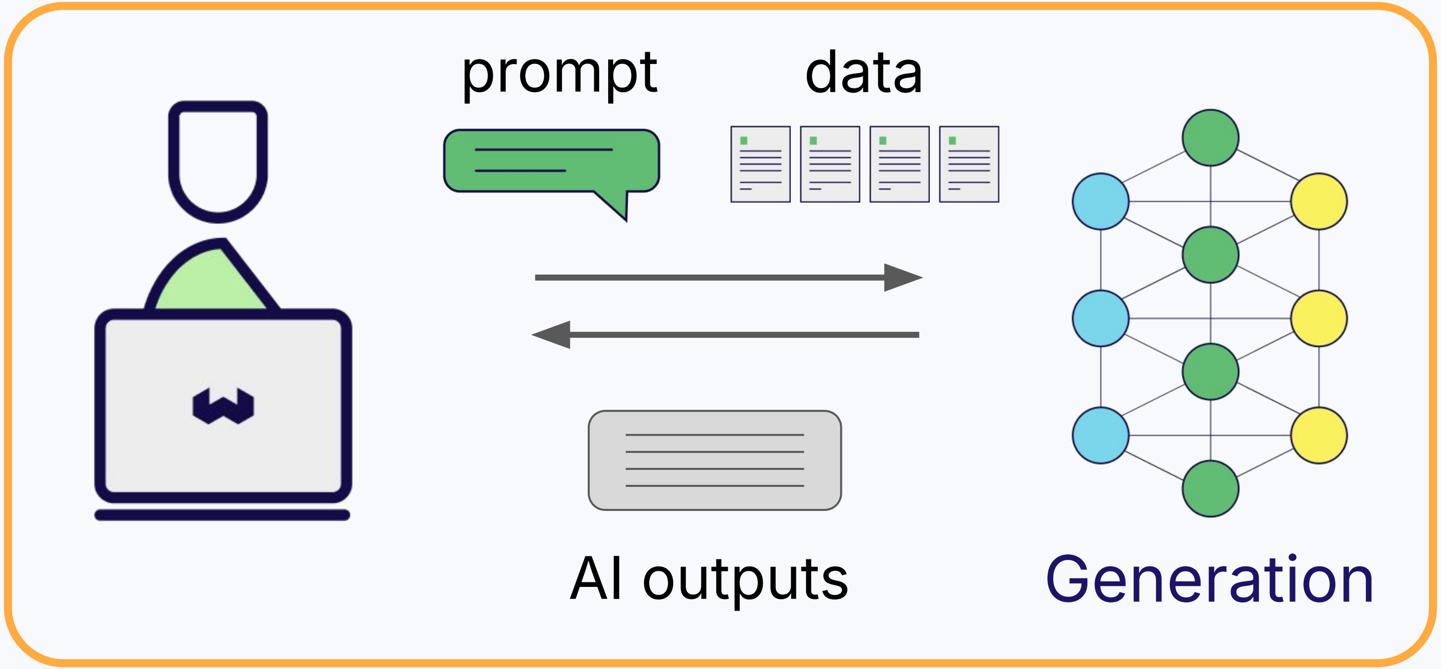
data

AI outputs

Generation

RAG

Why **vector search** is hot



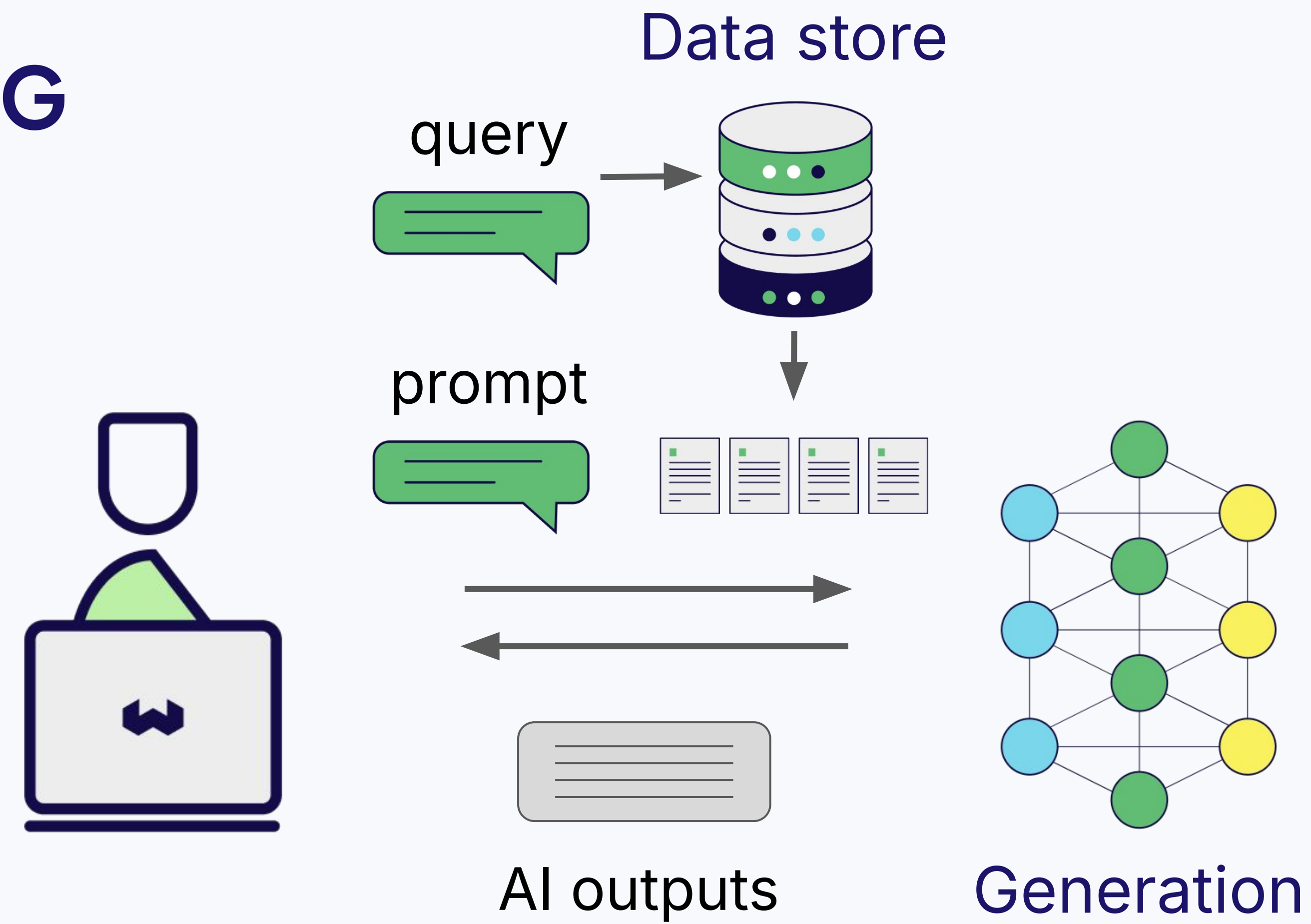
prompt

data

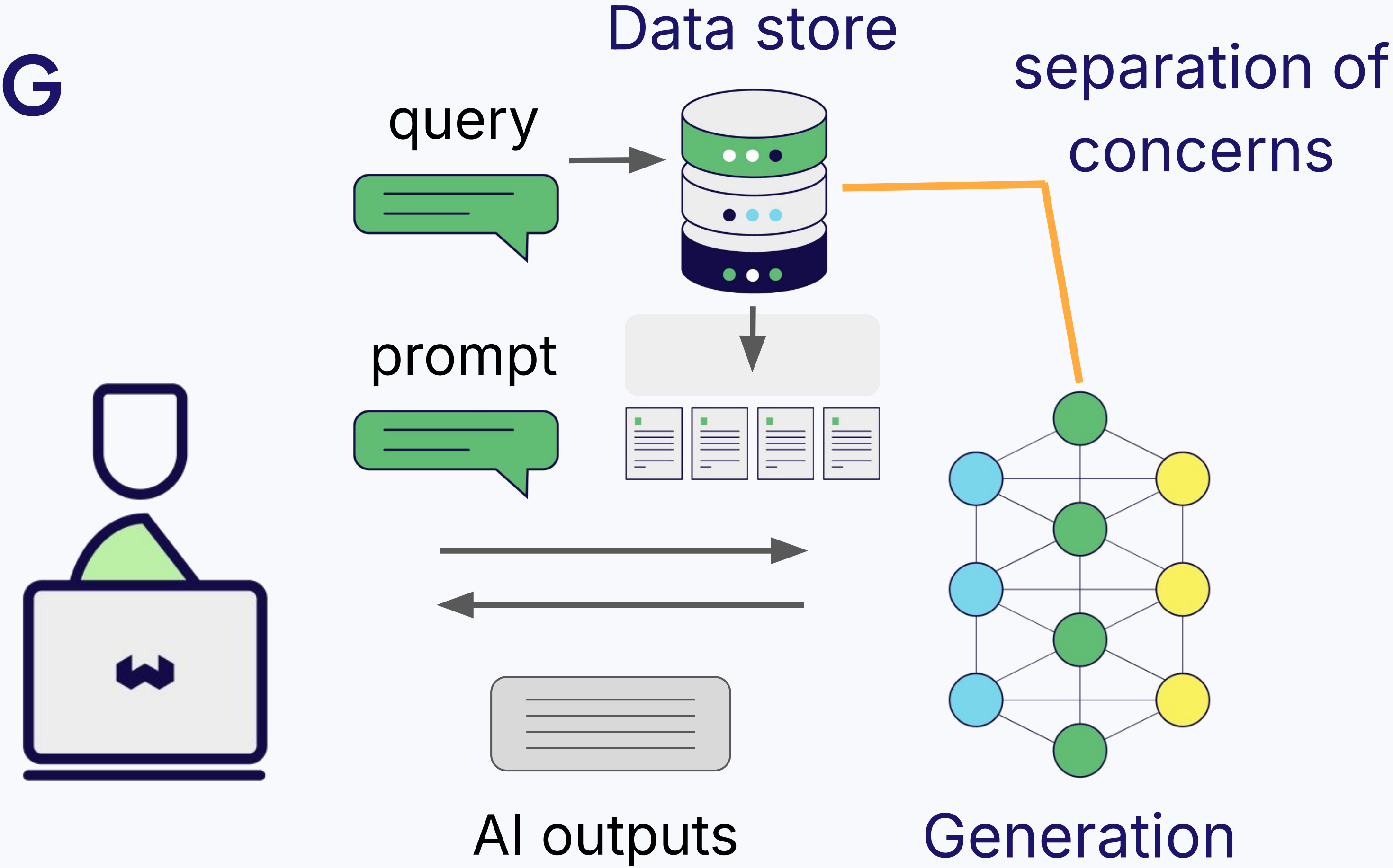
AI outputs

Generation

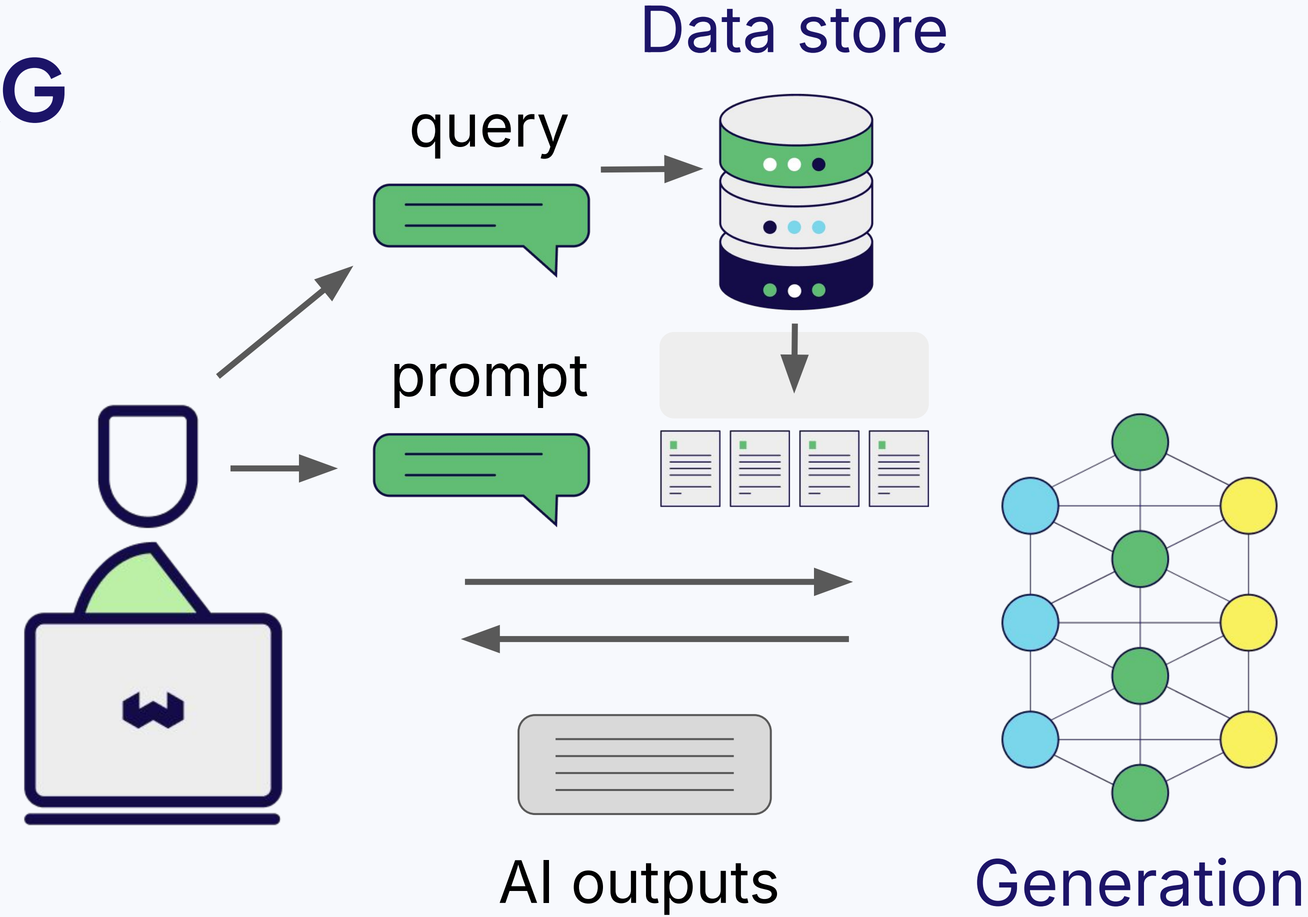
RAG



RAG


Data store
query
separation of concerns
prompt
AI outputs
Generation

RAG



Data store

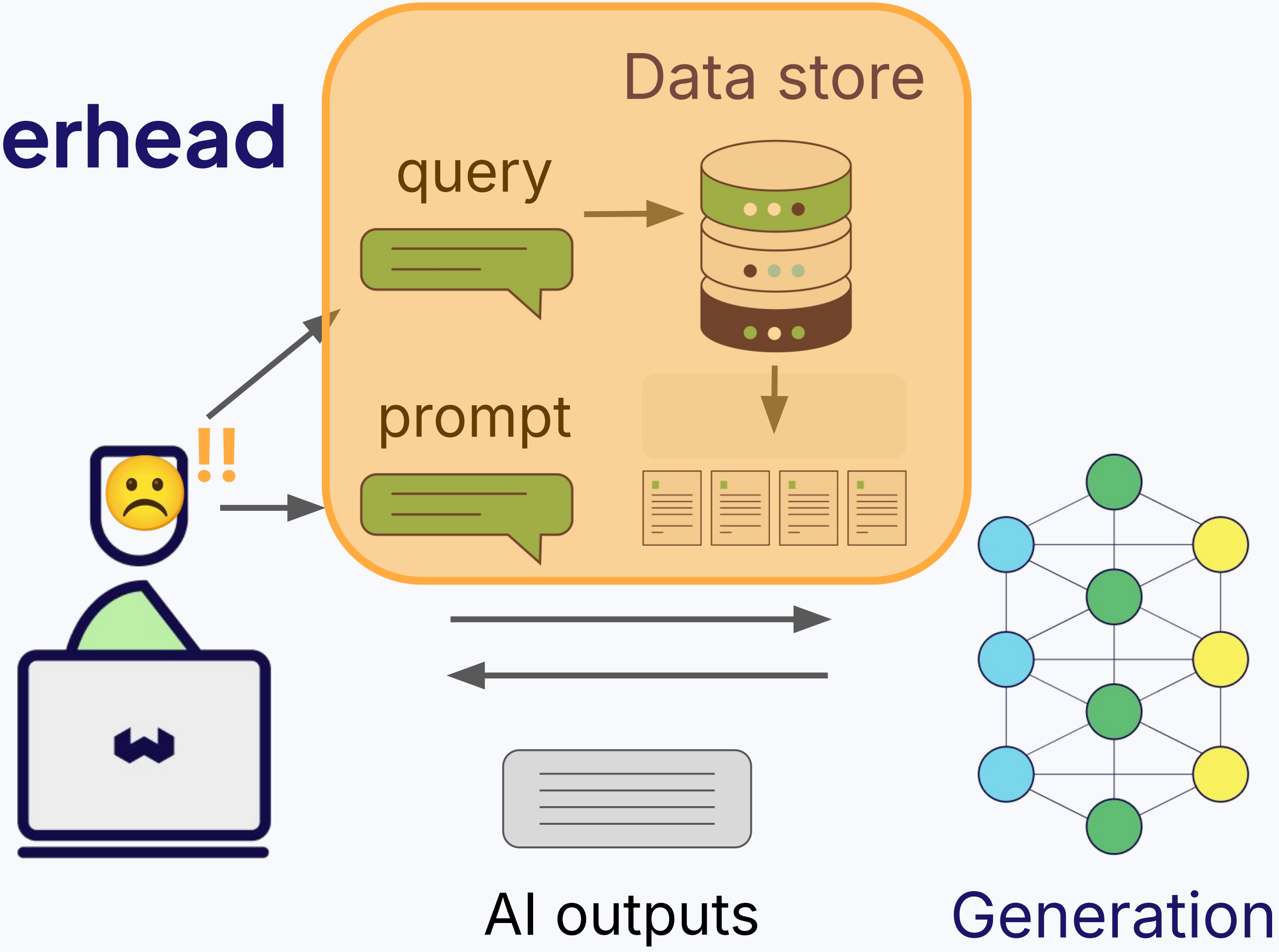
query

prompt

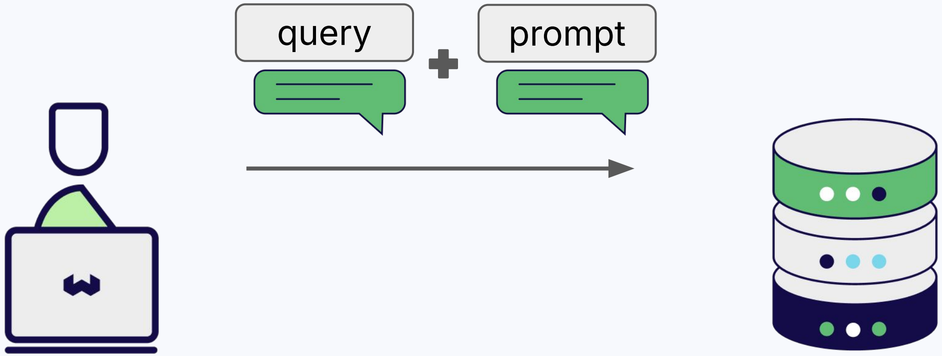
AI outputs

Generation

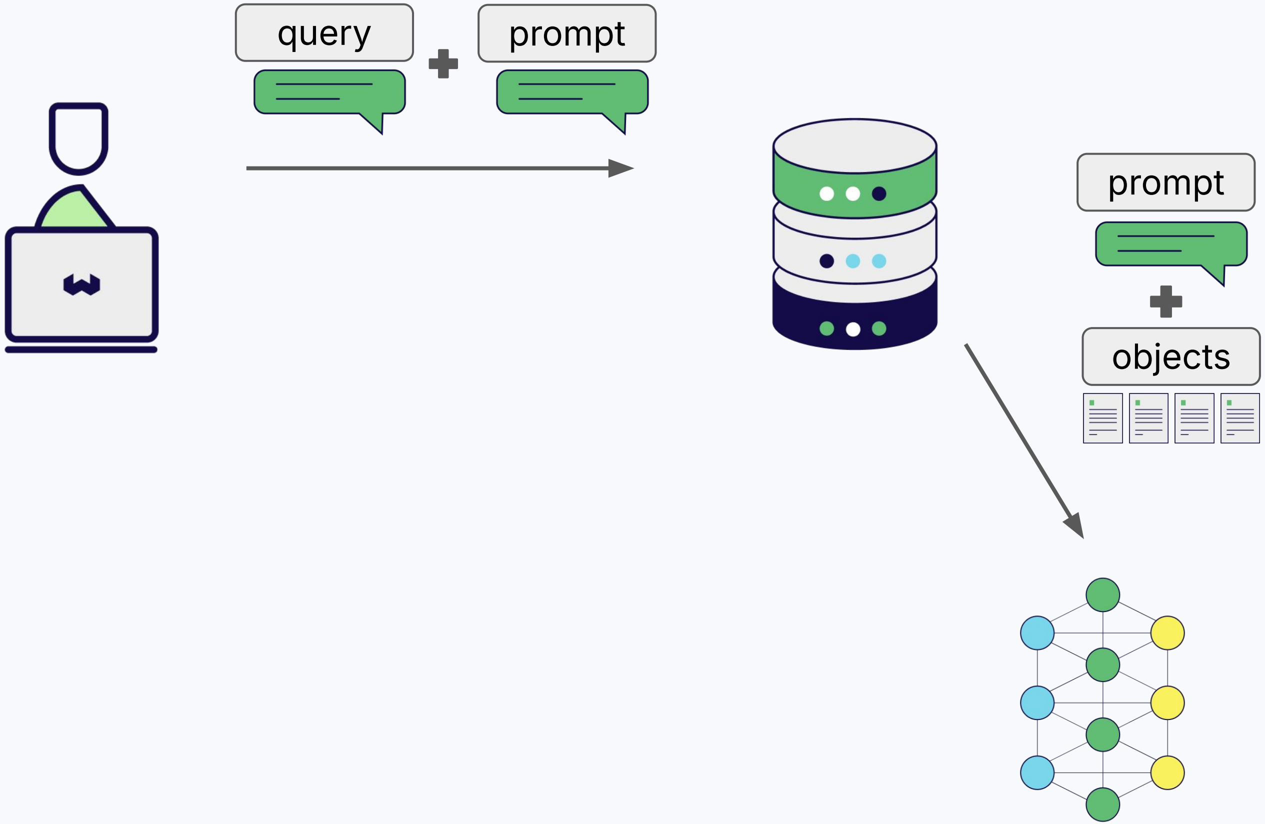
Overhead



RAG



RAG



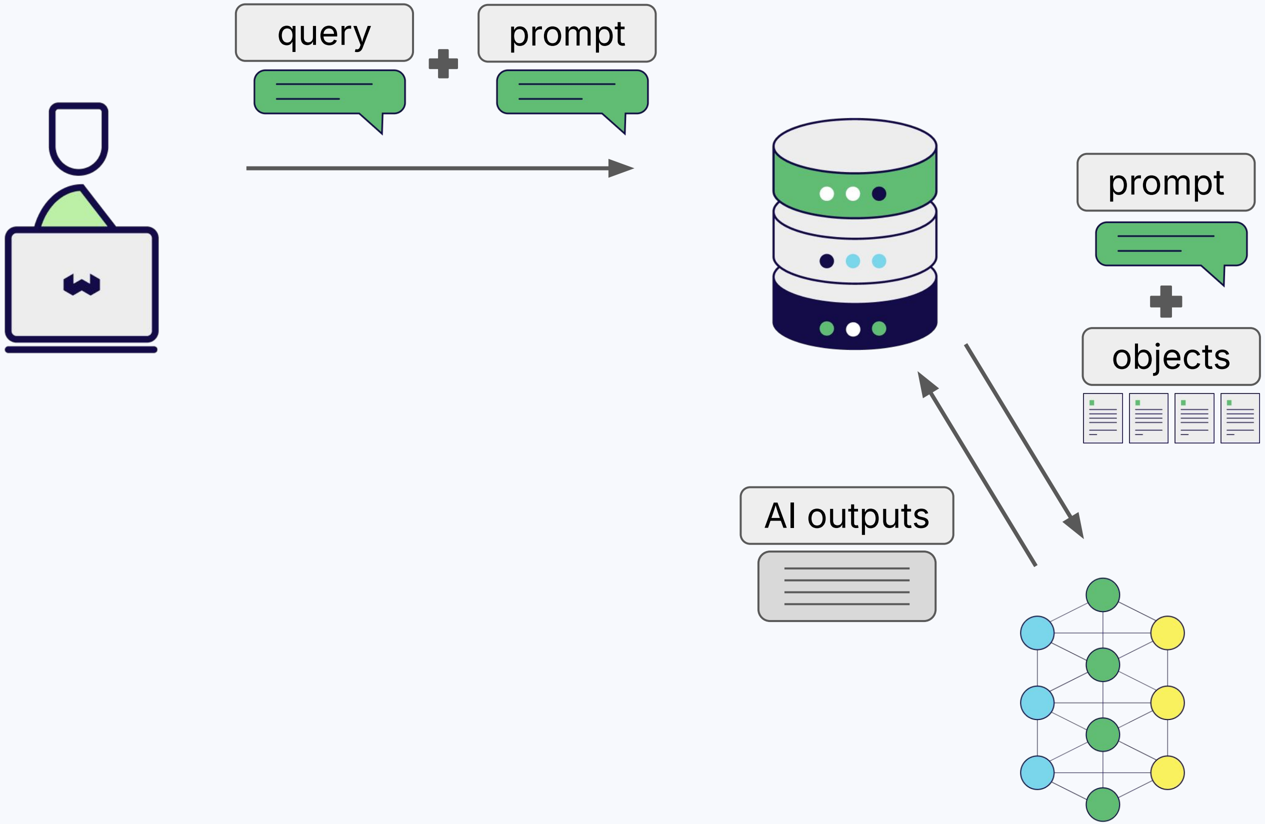
query

prompt

prompt

objects

RAG



query

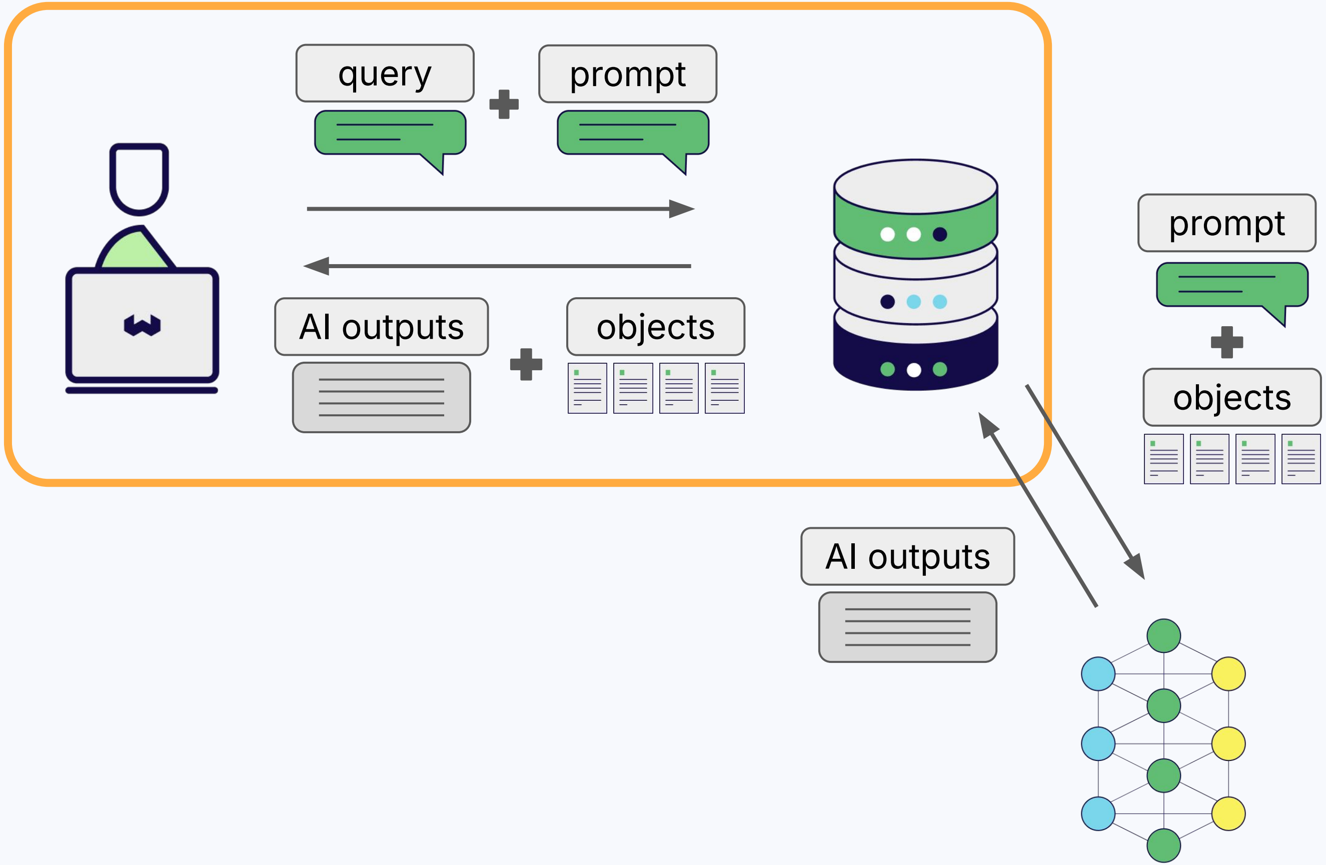
prompt

prompt

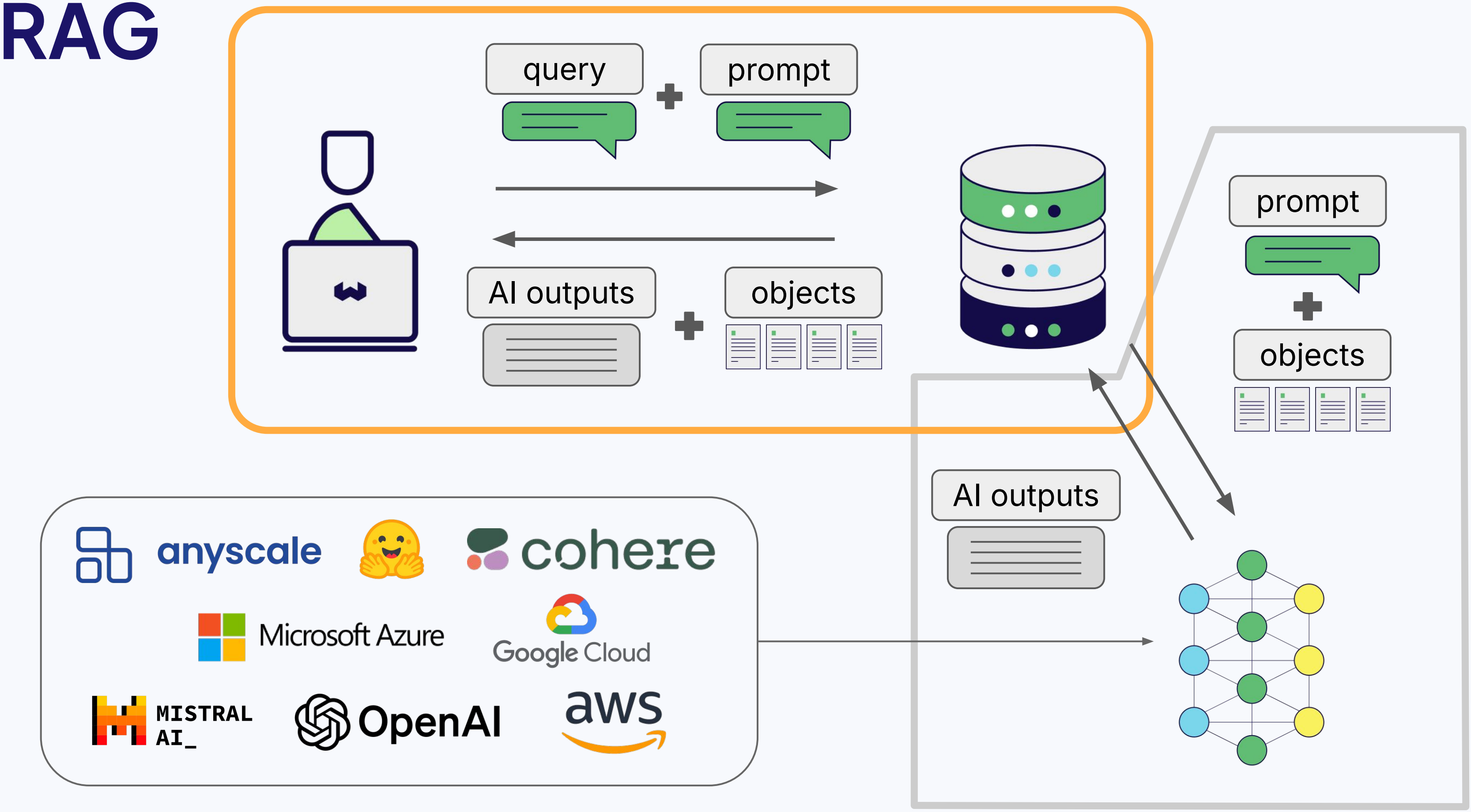
objects

AI outputs

RAG



RAG



query

prompt

AI outputs

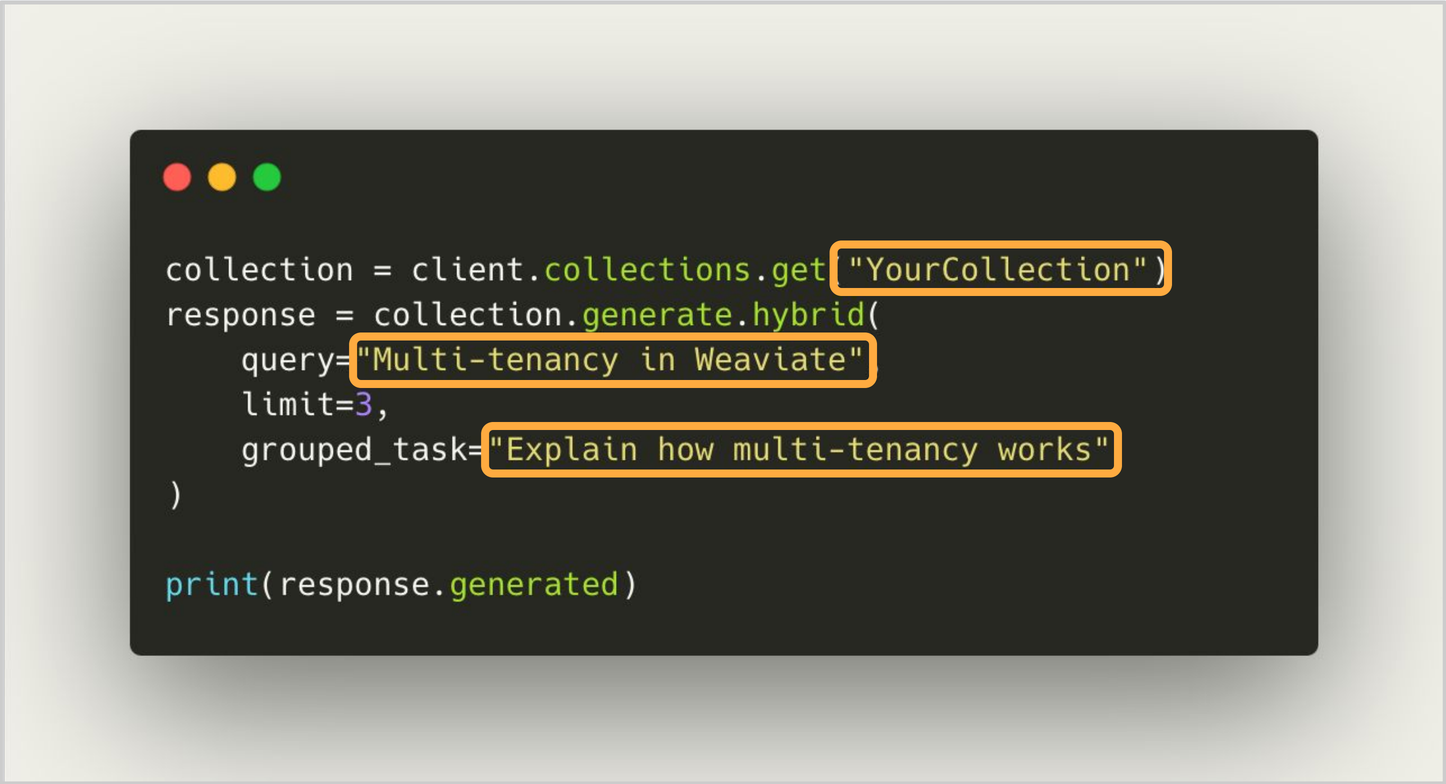
objects

prompt

objects

AI outputs

Simplified Experience



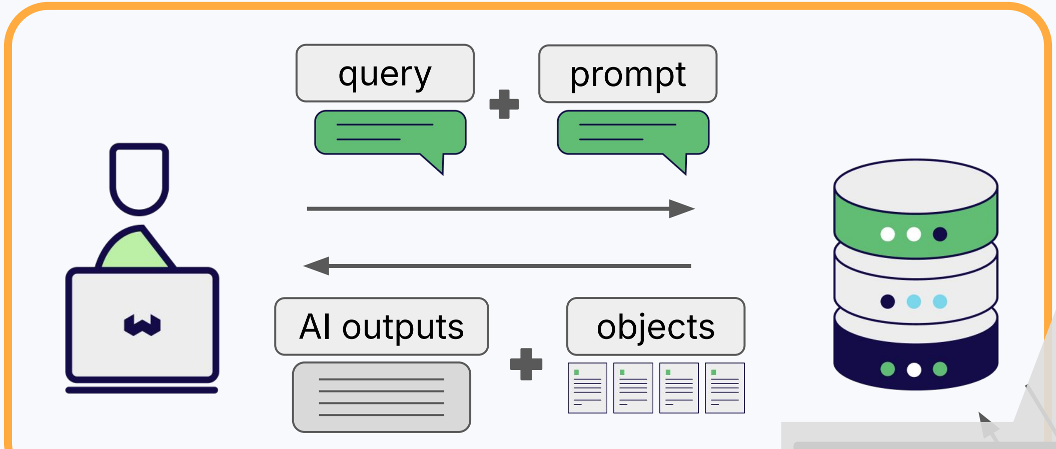
```
collection = client.collections.get("YourCollection")
response = collection.generate.hybrid(
    query="Multi-tenancy in Weaviate",
    limit=3,
    grouped_task="Explain how multi-tenancy works"
)

print(response.generated)
```

User experience (RAG)

RAG

User experience



anyscale

cohere

Microsoft Azure

Google Cloud

MISTRAL AI_

OpenAI

aws