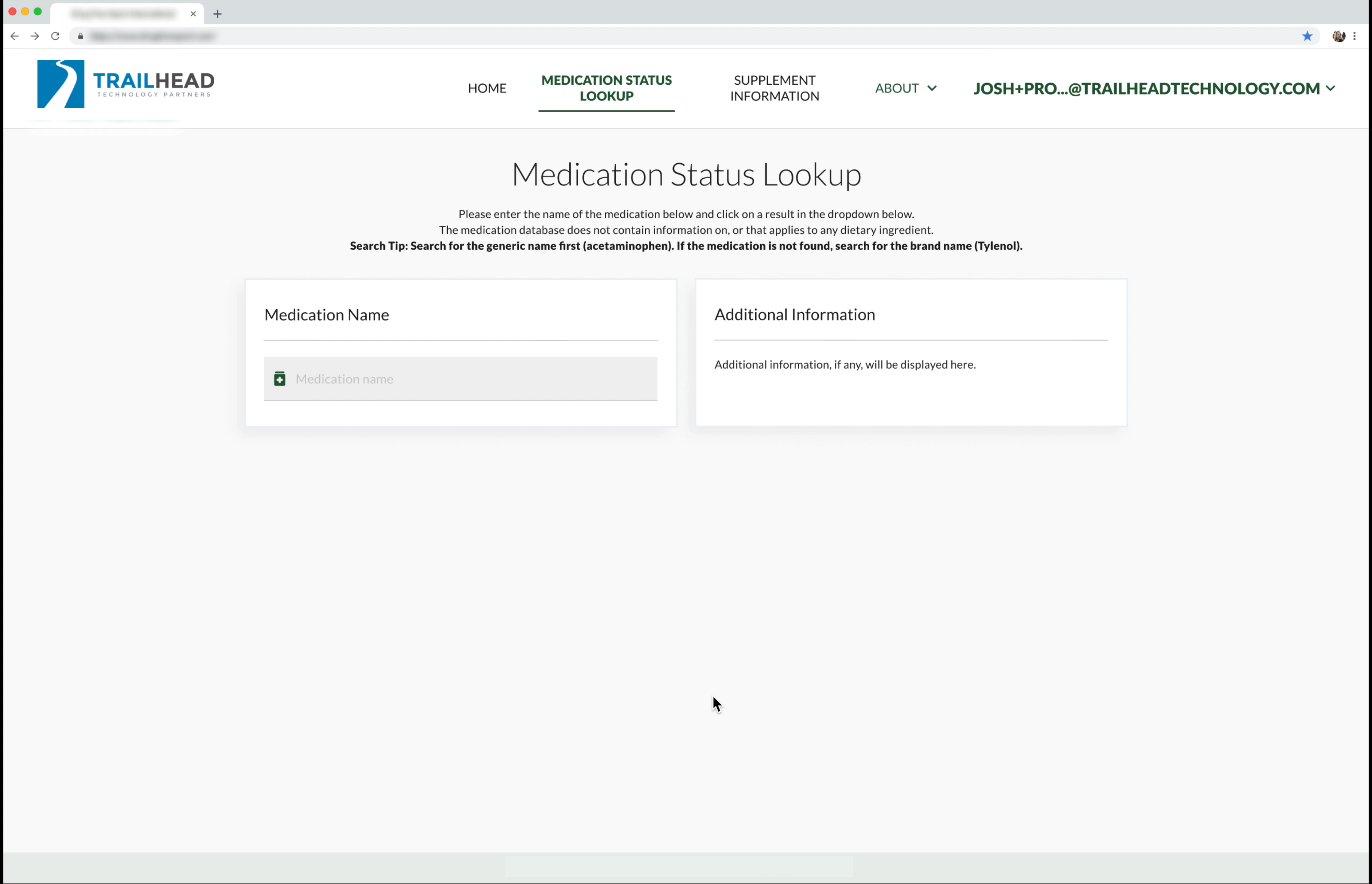
TRAILHEAD
TECHNOLOGY PARTNERS

Warm and Fuzzy

Semantic Search in .NET

Jonathan “J.” Tower



Medication Status Lookup

Please enter the name of the medication below and click on a result in the dropdown below.
The medication database does not contain information on, or that applies to any dietary ingredient.
Search Tip: Search for the generic name first (acetaminophen). If the medication is not found, search for the brand name (Tylenol).

Medication Name

Additional Information

Additional information, if any, will be displayed here.

Learn how to add AI-powered **semantic search** to your **.NET apps**

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Jonathan "J." Tower

Partner & Principal Consultant

TRAILHEAD
TECHNOLOGY PARTNERS

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- ⍰ trailheadtechnology.com/blog
- ⍰ jtowermi
- ⍰ Jonathan “J.” Tower

EXPERT Consultation

bit.ly/th-offer

github.com/trailheadtechnology/api-security

The Evolution of Fuzzy Search

Exact Match

```
SELECT * FROM Products WHERE Name = 'car'
```

User frustration:

“automobile” won’t match “car”
“cra” won’t match ”car”
“ca” won’t match ”car”
“kar” won’t match ”car”

LIKE Queries

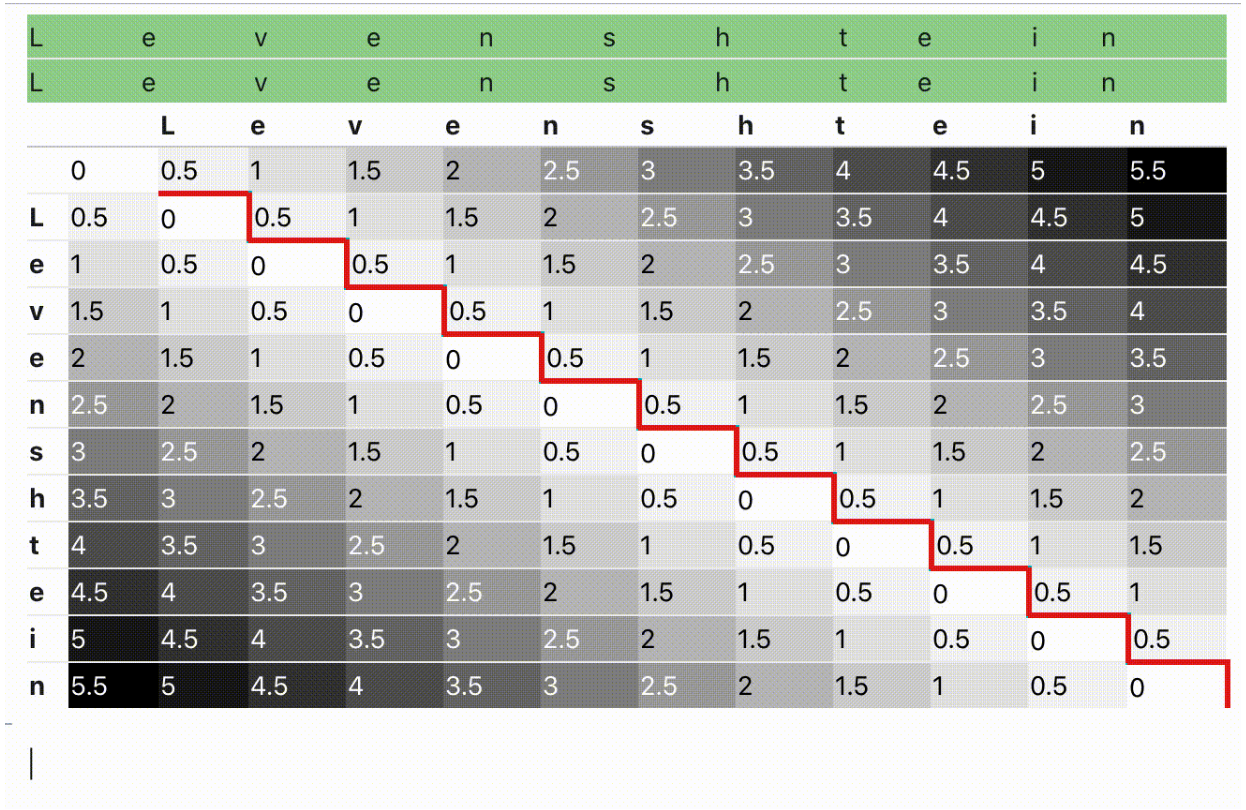
```
SELECT * FROM Products WHERE Name LIKE '%car%’
```

User frustration:

“automobile” won’t match “car”
“cra” won’t match ”car”
“kar” won’t match ”car”

Levenshtein

`Levenshtein("kitten”, "sitting”) = 3`



L e v e n s h t e i n

L e v e n s h t e i n

		L	e	v	e	n	s	h	t	e	i	n
	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5
L	0.5	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
e	1	0.5	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5
v	1.5	1	0.5	0	0.5	1	1.5	2	2.5	3	3.5	4
e	2	1.5	1	0.5	0	0.5	1	1.5	2	2.5	3	3.5
n	2.5	2	1.5	1	0.5	0	0.5	1	1.5	2	2.5	3
s	3	2.5	2	1.5	1	0.5	0	0.5	1	1.5	2	2.5
h	3.5	3	2.5	2	1.5	1	0.5	0	0.5	1	1.5	2
t	4	3.5	3	2.5	2	1.5	1	0.5	0	0.5	1	1.5
e	4.5	4	3.5	3	2.5	2	1.5	1	0.5	0	0.5	1
i	5	4.5	4	3.5	3	2.5	2	1.5	1	0.5	0	0.5
n	5.5	5	4.5	4	3.5	3	2.5	2	1.5	1	0.5	0

Video: Substitution as 1 and cost of deletion or insertion as 0.5

Rules (configurable):

Substitutions cost 1

Deletion or insertion costs 1

Ex:

kitten → **s**itten: 1

sitt**e**n → sitt**i**n: 1

sittin → sittin**g**: 1

Total: 3

Soundex

Creates **4-character code** based on how they **sound**, not how they’re spelled

Rules:

- Keeps the first letter of the word
- Converts the rest into numbers representing consonant sounds
- Drops vowels and silent letters
- Words that sound similar → same code

Ex:
"Smith" → S530
"Smyth" → S530

"Robert" → R163
"Rupert" → R163

From Fuzzy to Semantic Search

Fuzzy Search

Find things that **look similar**

Semantic Search

Find things that **mean the same**

Core Concepts of Semantic Search

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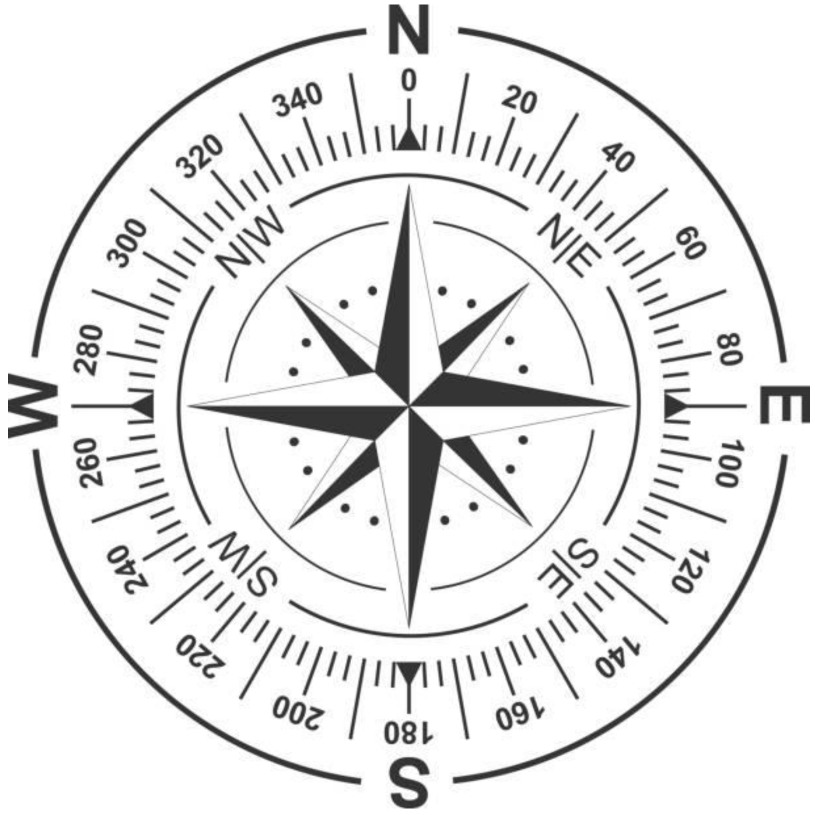
Vectors

Embeddings

Cosine Differences

Vectors



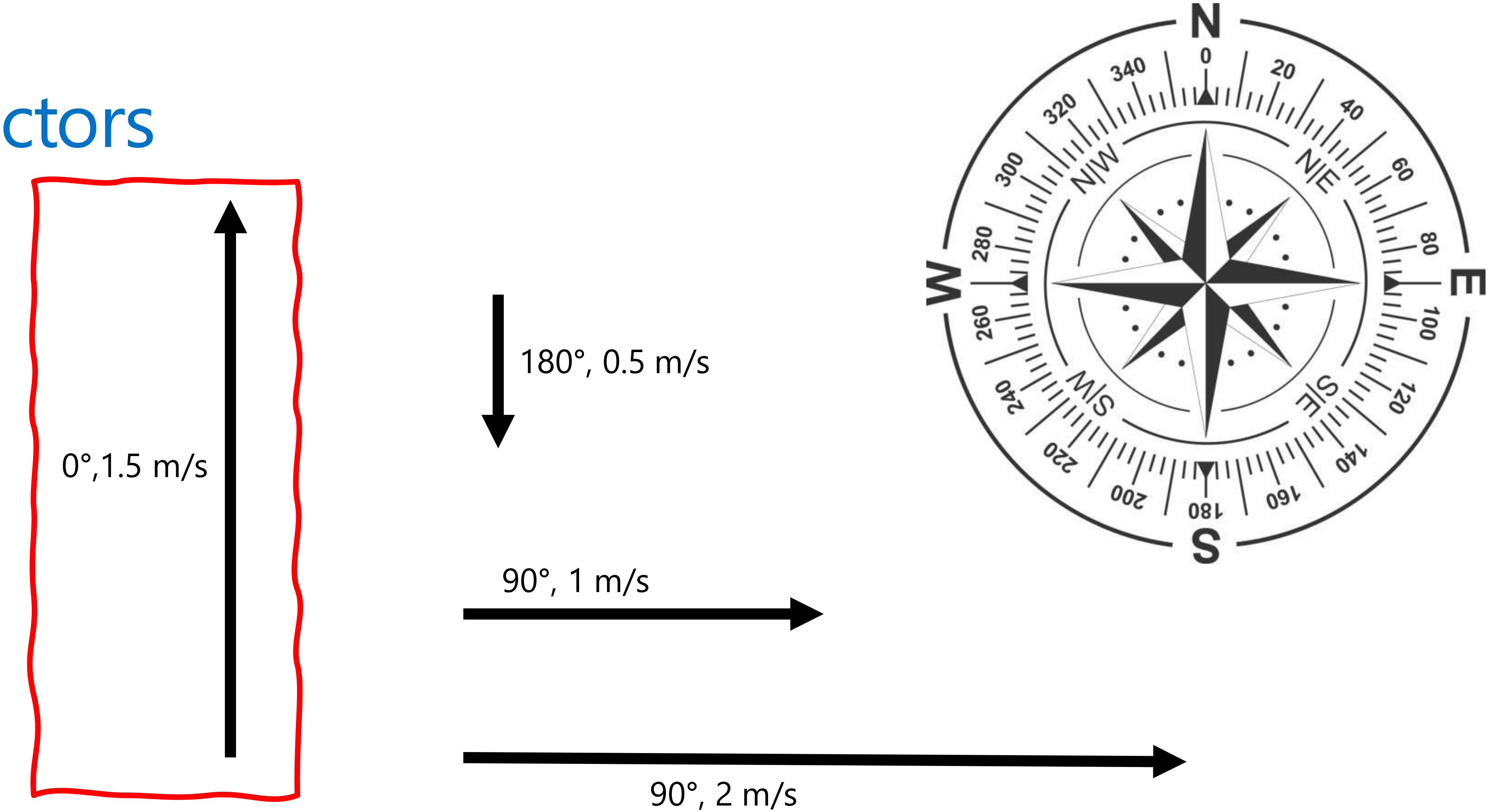
180°, 0.5 m/s

0°,1.5 m/s

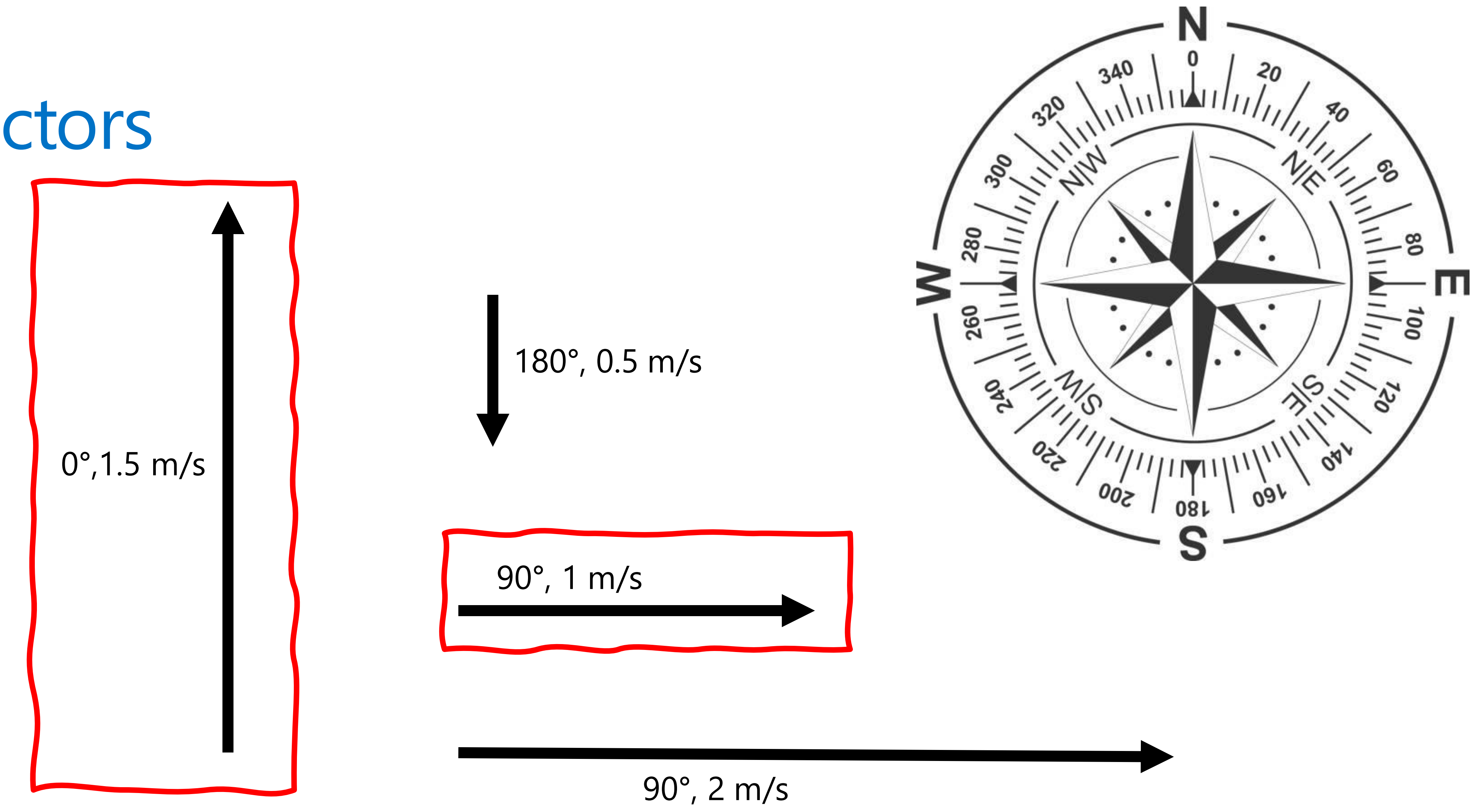
90°, 1 m/s

90°, 2 m/s

Vectors


0°,1.5 m/s
180°, 0.5 m/s
90°, 1 m/s
90°, 2 m/s
N
0
20
40
60
80
E
100
120
140
160
180
S
200
220
240
260
W
280
300
320
340
N/E
S/E
S/W
N/W

Vectors



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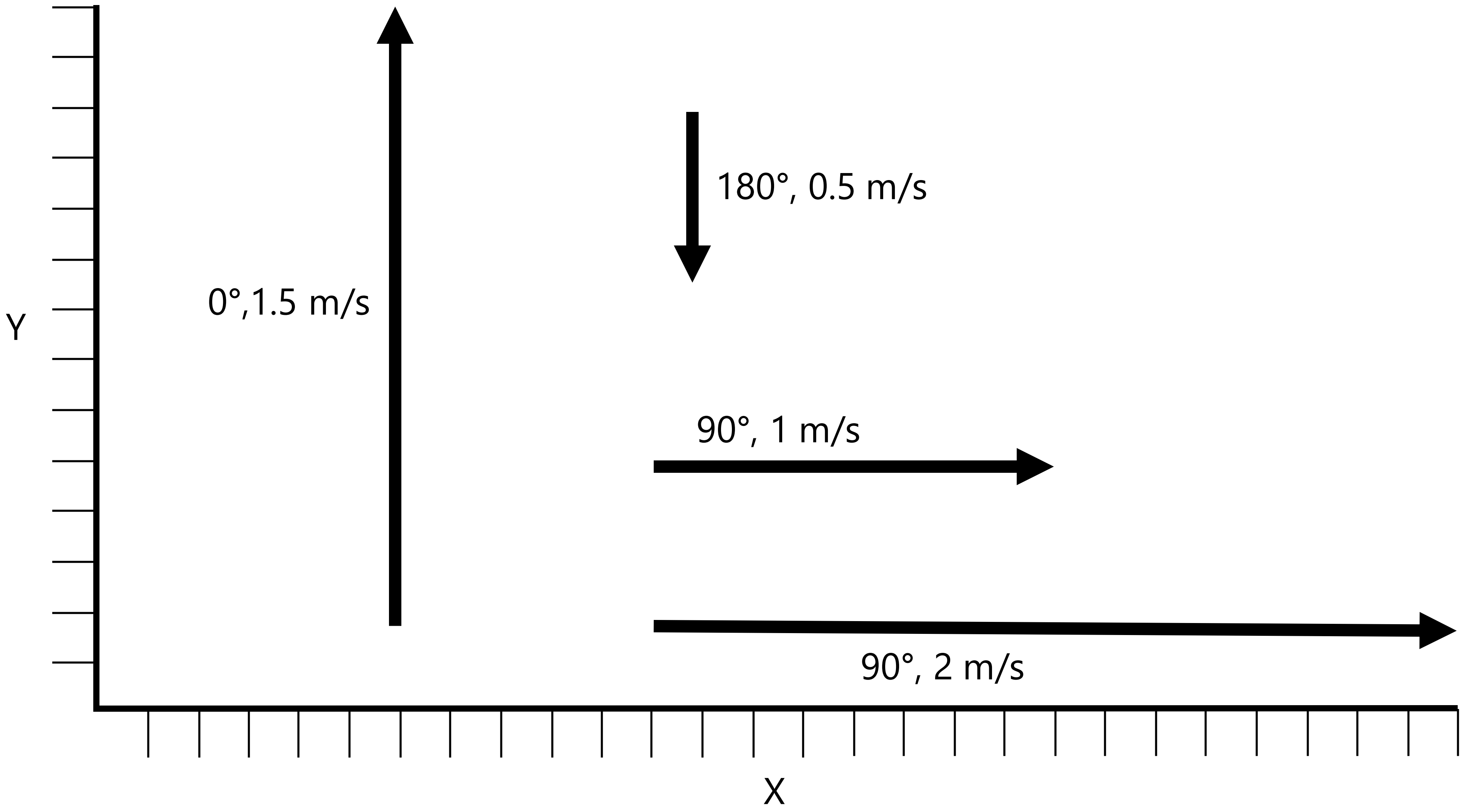

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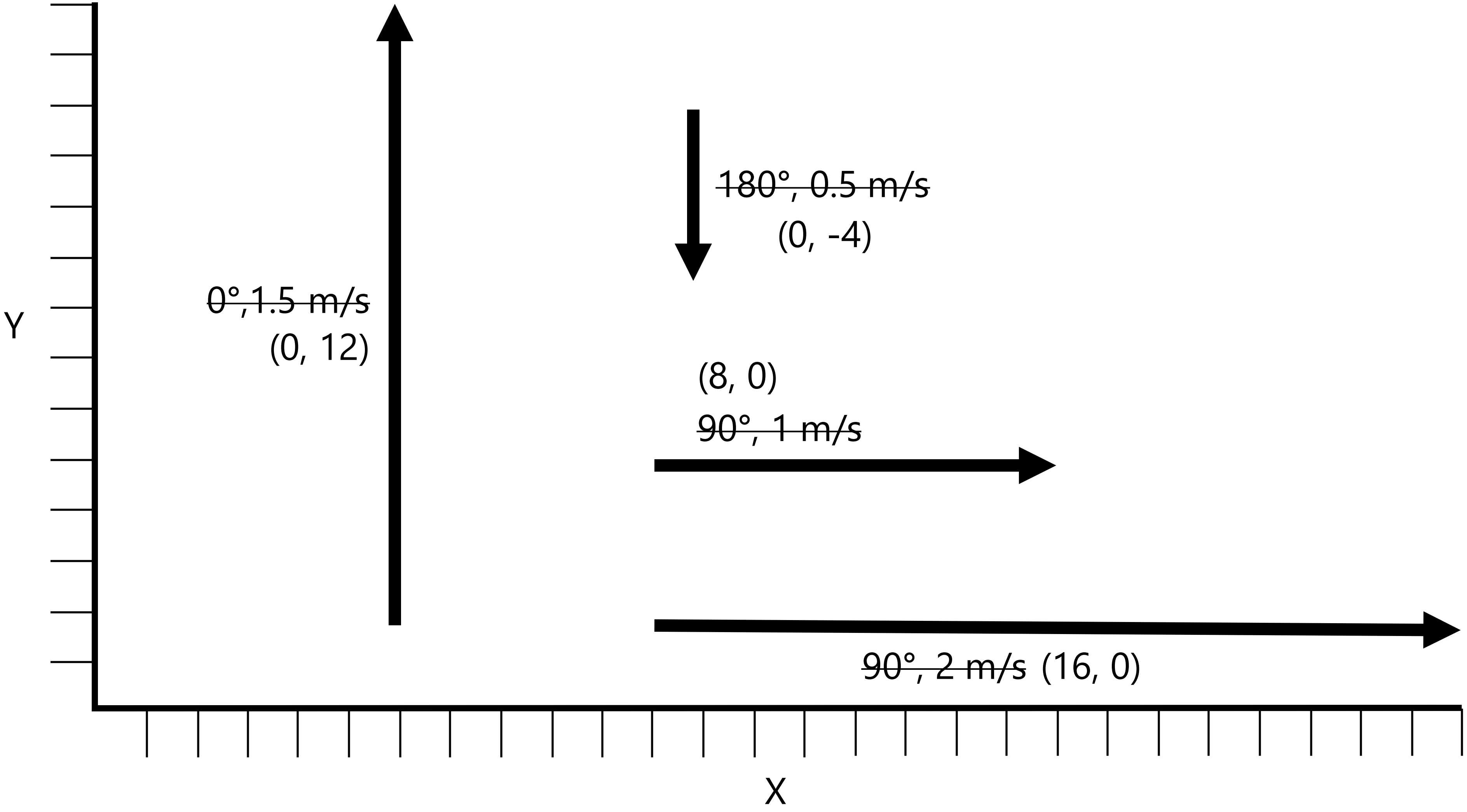

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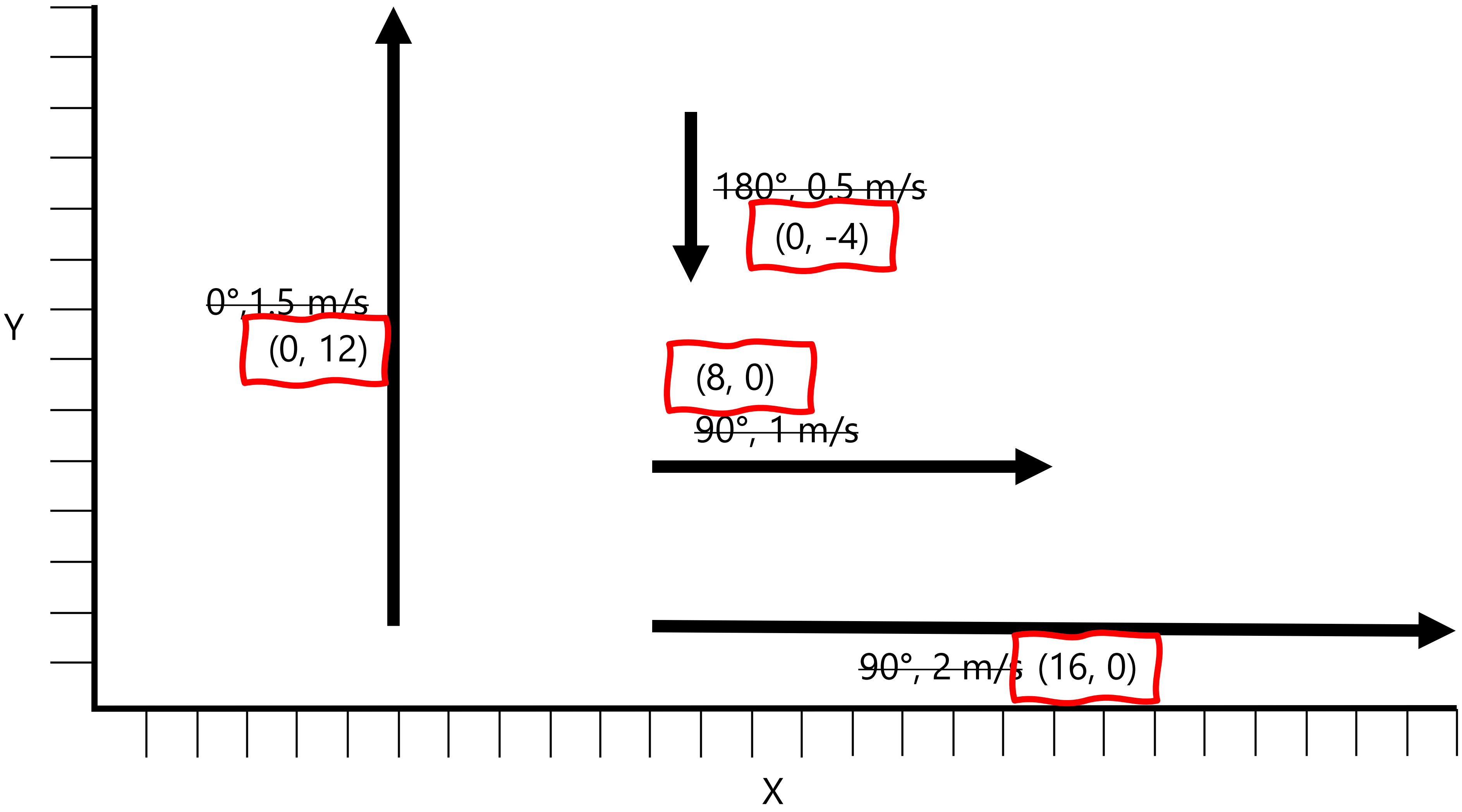
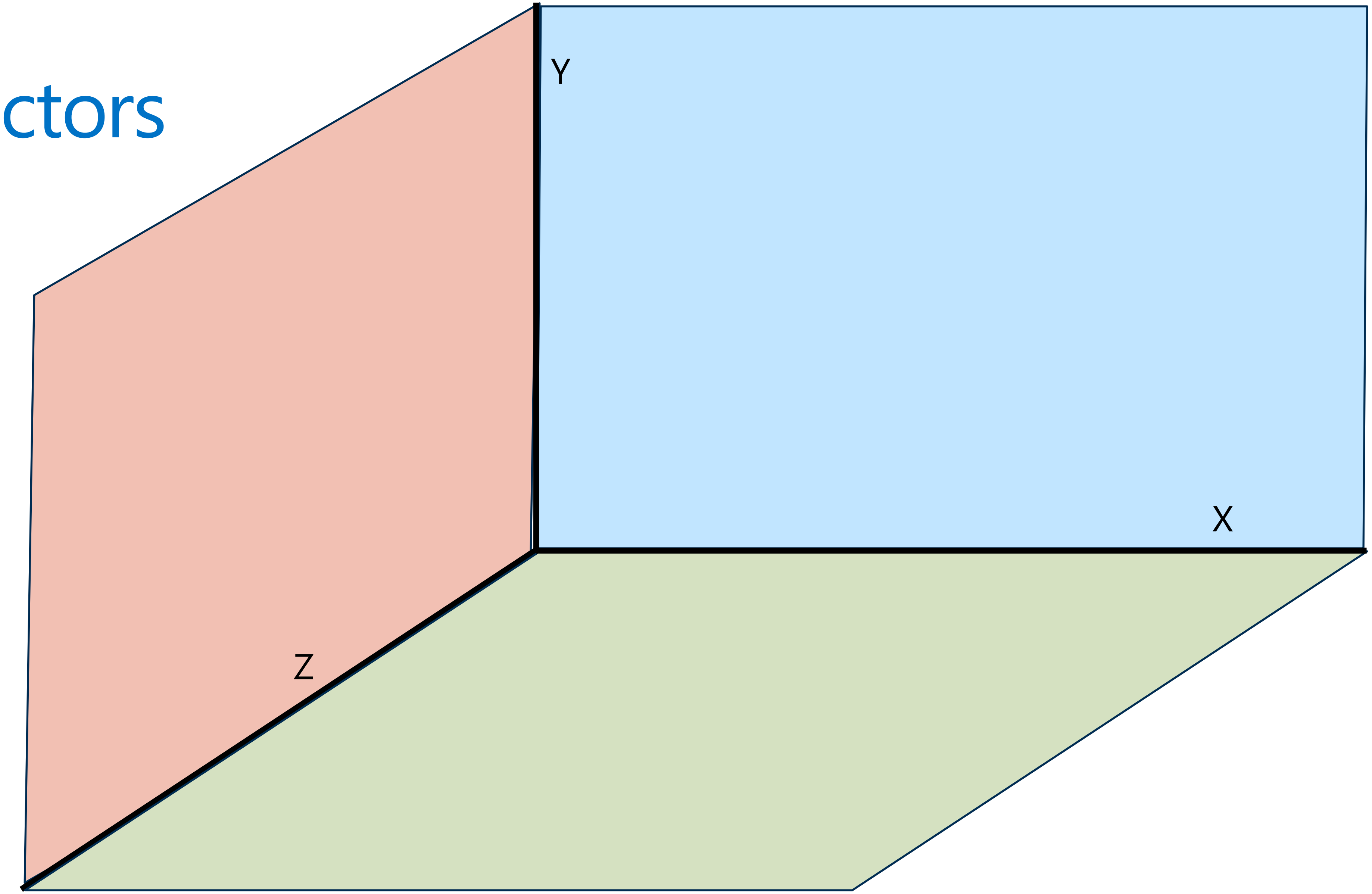


3D Vectors



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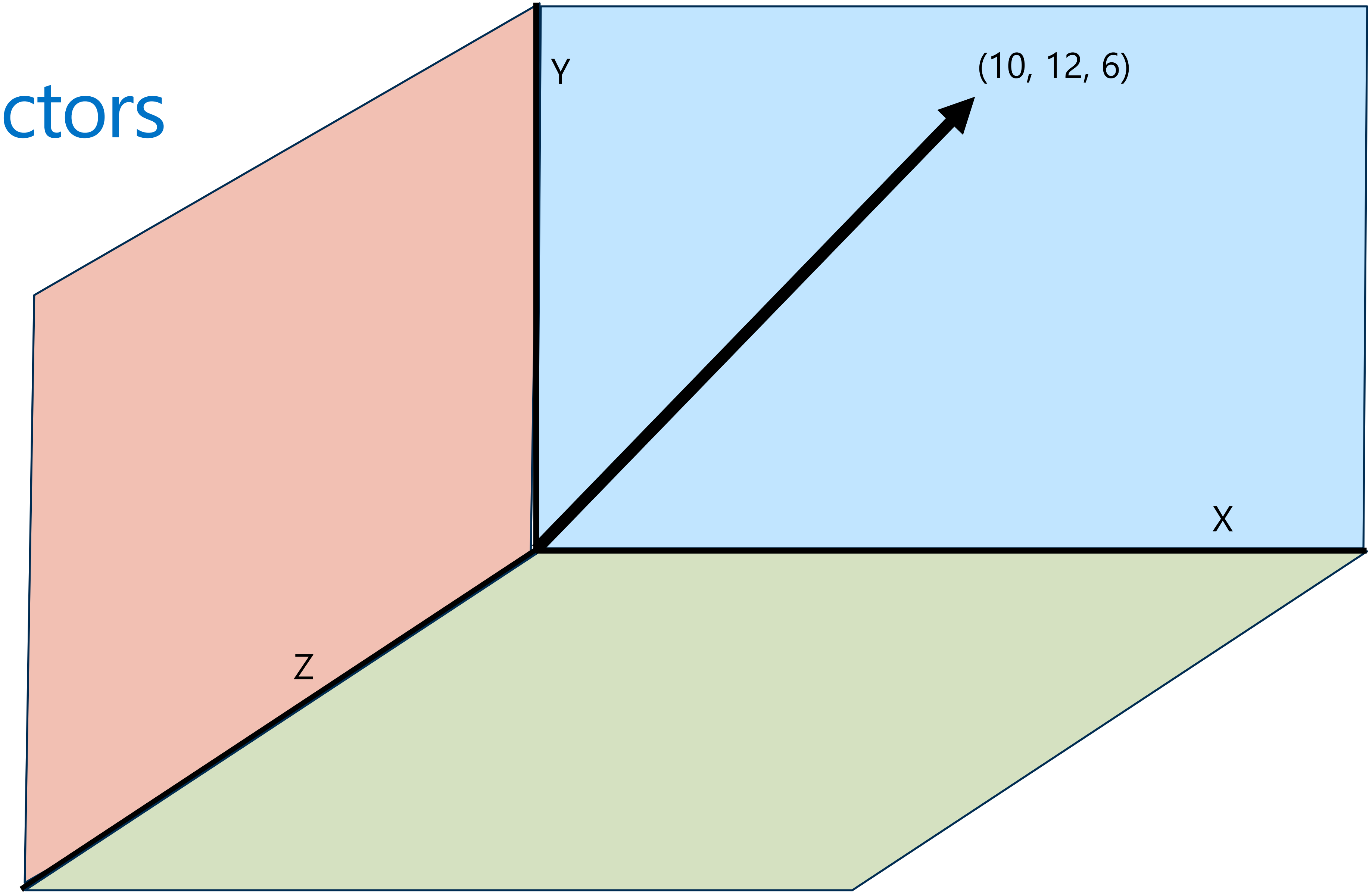

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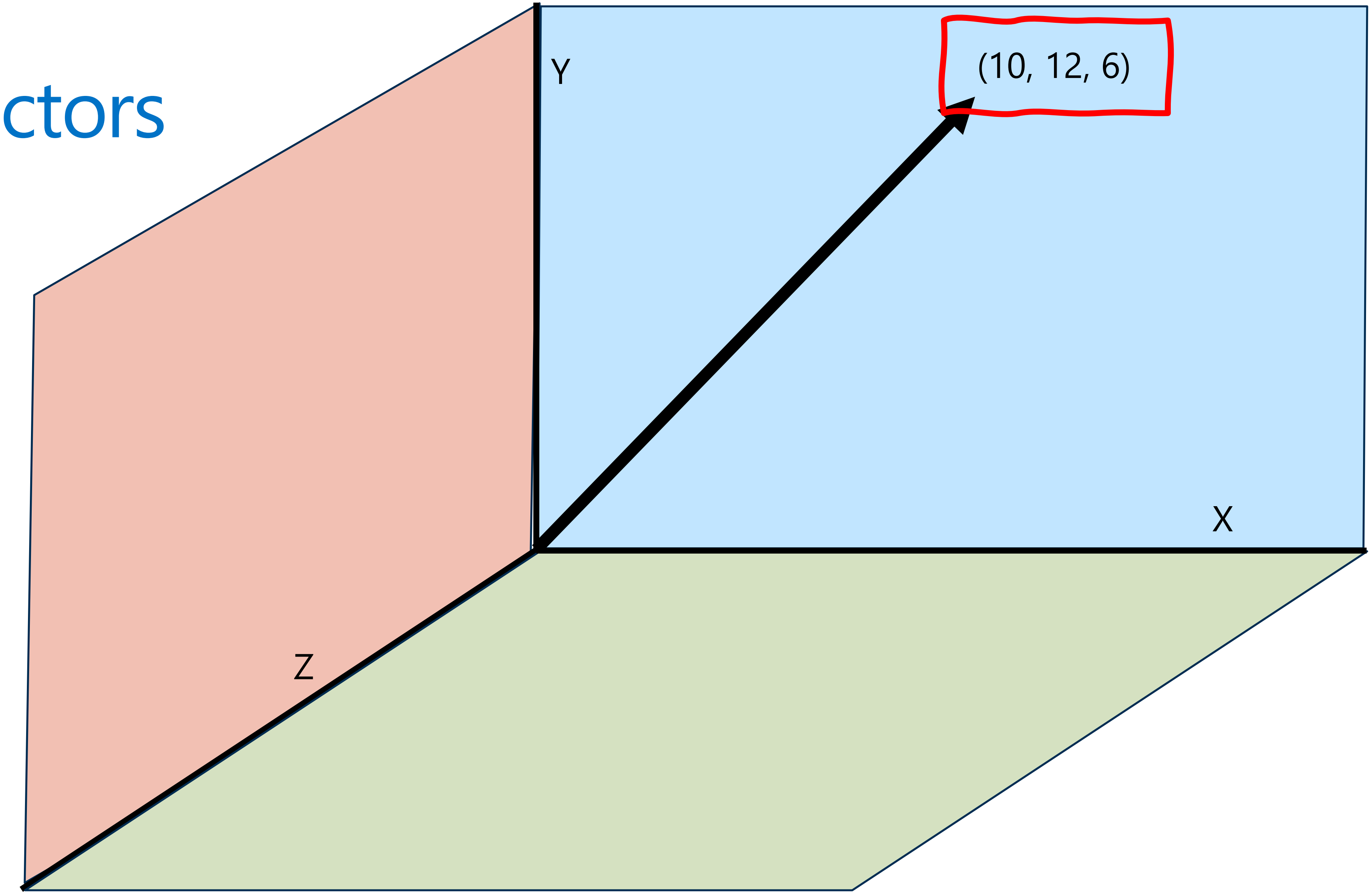
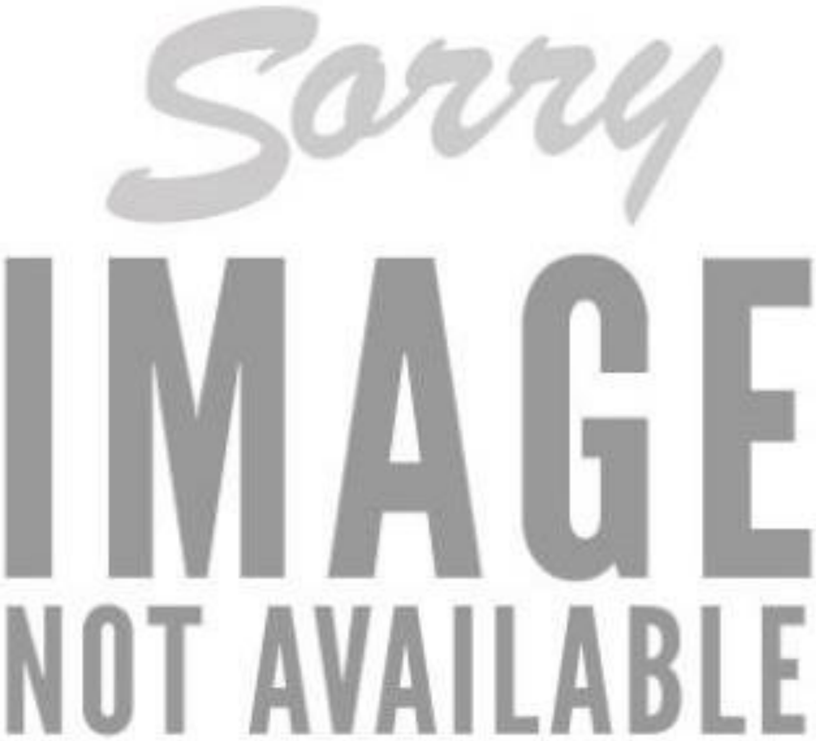


4D+ Vectors



4D+ Vectors

Dimensions	Sample Vector
2	(10, 12)
3	(10, 12, 6)
4	(10, 12, 6, 4)
5	(10, 12, 6, 4, 10)
6	(10, 12, 6, 4, 10, 3)
7	(10, 12, 6, 4, 10, 3, 144)
N	…

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N	…

LLMS: 384 to 3,000 dimensions

Embeddings

Storing meaning using vectors

An **embedding** is just a **vector** that points in a direction **representing meaning**

The **closer** two embeddings point in the **same direction**, the more **similar their meaning**

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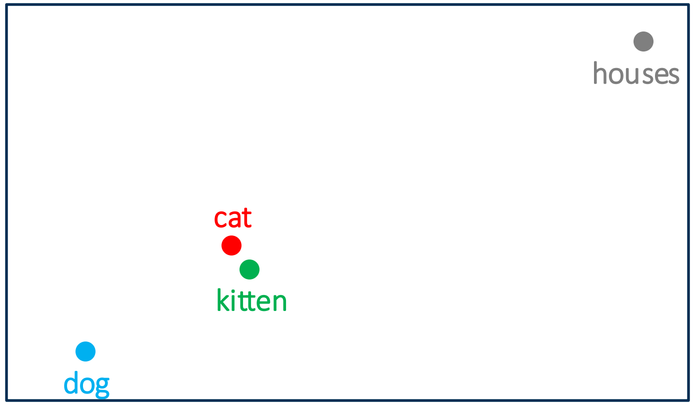
Embeddings

	Living being	Feline	Human	Gender	Royalty	Verb	Plural
cat →	0.6	0.9	0.1	0.4	-0.7	-0.3	-0.2
kitten →	0.5	0.8	-0.1	0.2	-0.6	-0.5	-0.1
dog →	0.7	-0.1	0.4	0.3	-0.4	-0.1	-0.3
houses →	-0.8	-0.4	-0.5	0.1	-0.9	0.3	0.8

Simplified for Visualization



man →	0.6	-0.2	0.8	0.9	-0.1	-0.9	-0.7
woman →	0.7	-0.3	0.9	-0.7	0.1	-0.5	-0.4
king →	0.6	-0.4	0.7	0.8	0.9	-0.7	-0.6
queen →	0.8	-0.1	0.8	-0.9	0.9	-0.5	-0.9

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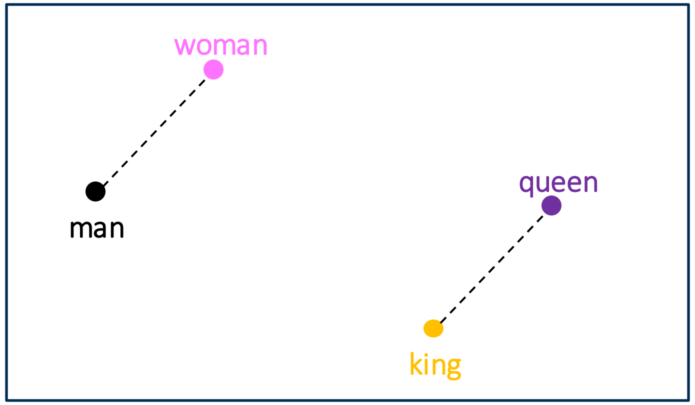

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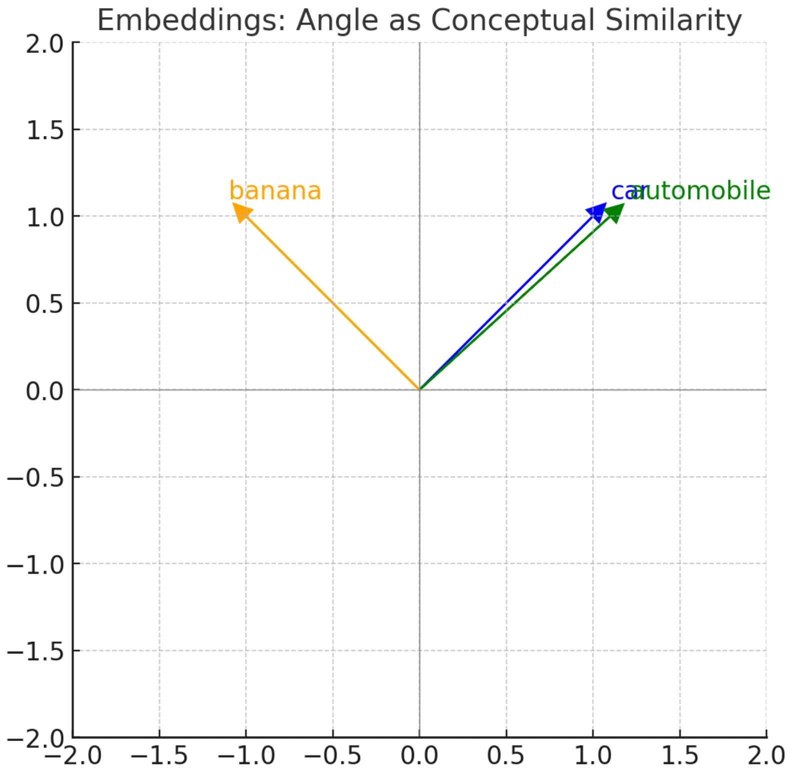
Cosine Similarity

$$\text{cosine similarity} = \cos(\theta) = \frac{A \cdot B}{||A||\,||B||}$$



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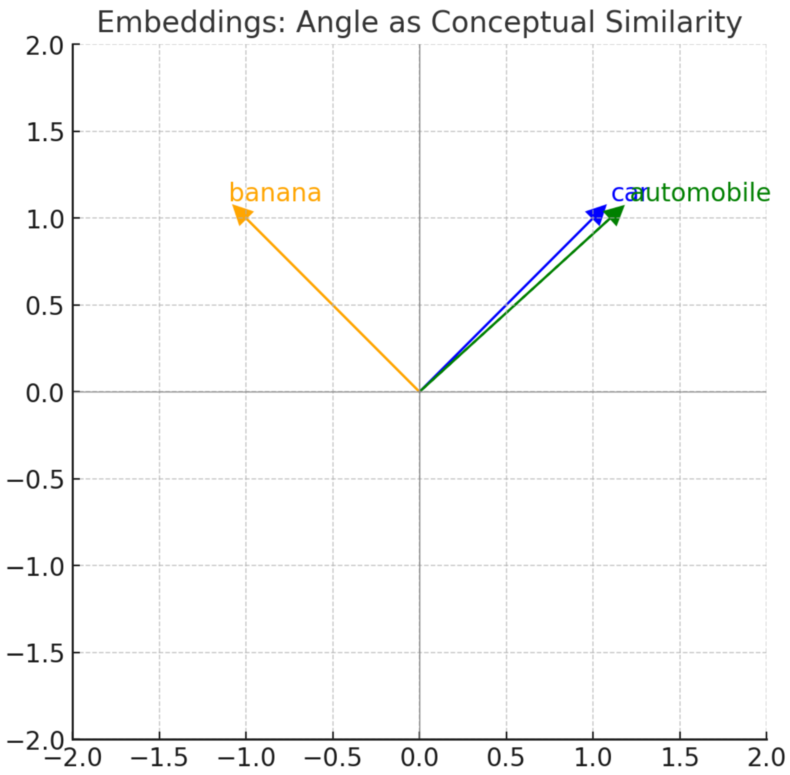

$$A = [2, 3], \quad B = [4, -1]$$

$$A \cdot B = (2 \times 4) + (3 \times -1) = 8 - 3 = 5$$

$$||A|| = \sqrt{2^2 + 3^2} = \sqrt{4 + 9} = \sqrt{13} \approx 3.606$$

$$||B|| = \sqrt{4^2 + (-1)^2} = \sqrt{16 + 1} = \sqrt{17} \approx 4.123$$

$$||A|| \times ||B|| \approx 3.606 \times 4.123 \approx 14.85$$

$$\cos(\theta) = \frac{5}{14.85} \approx 0.34$$

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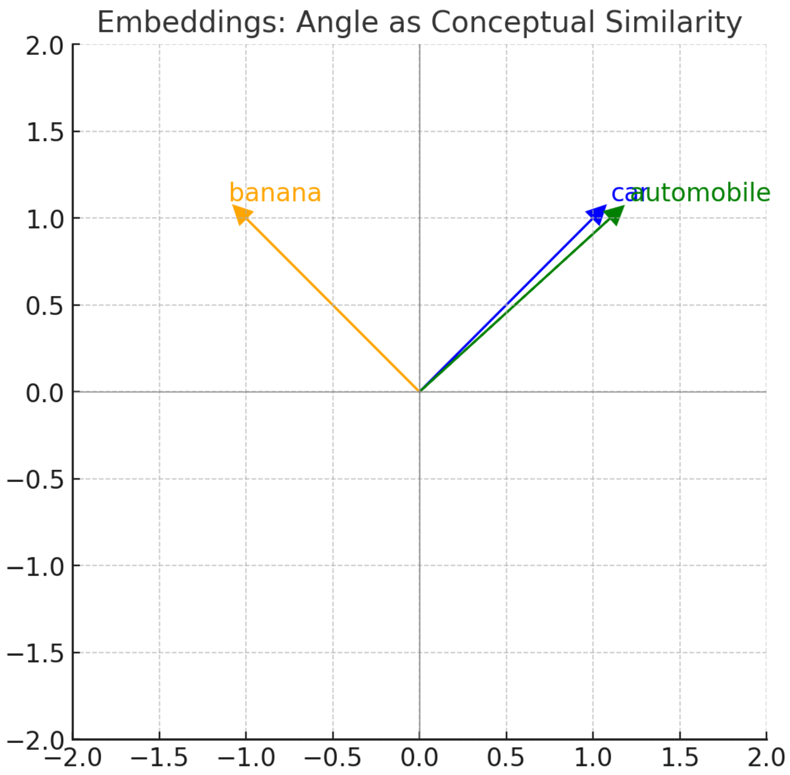

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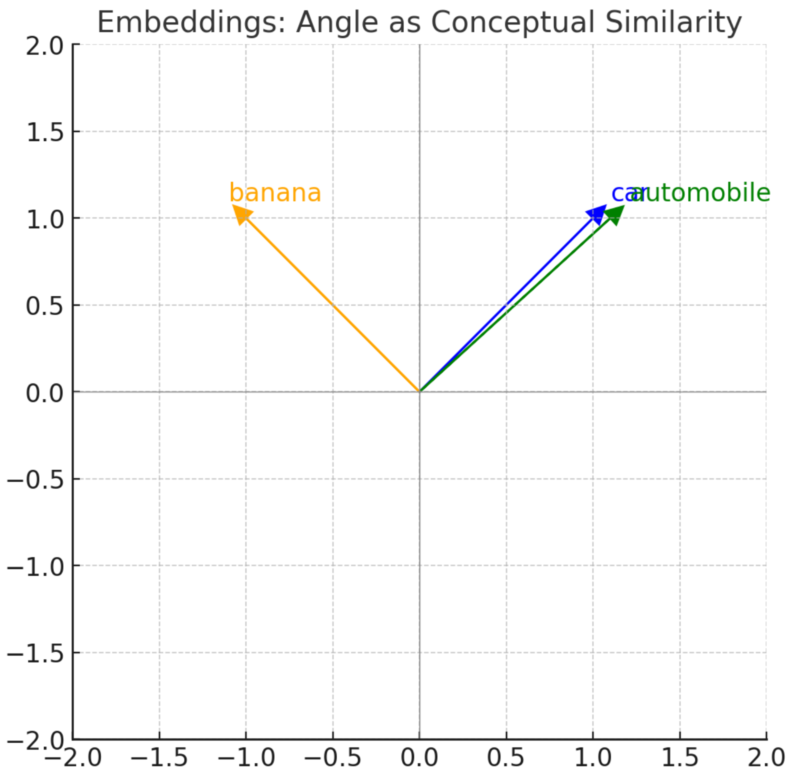

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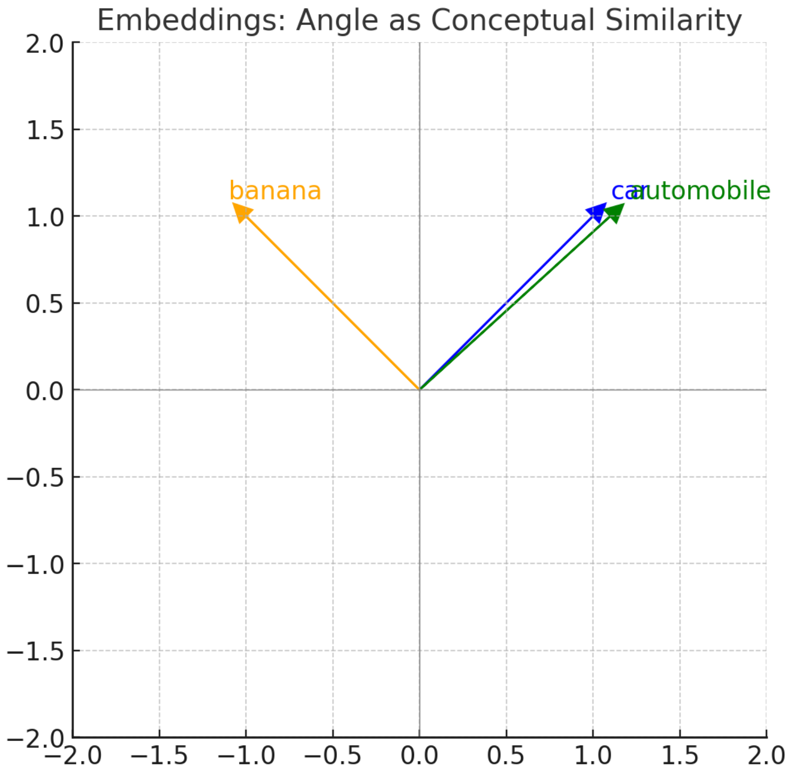

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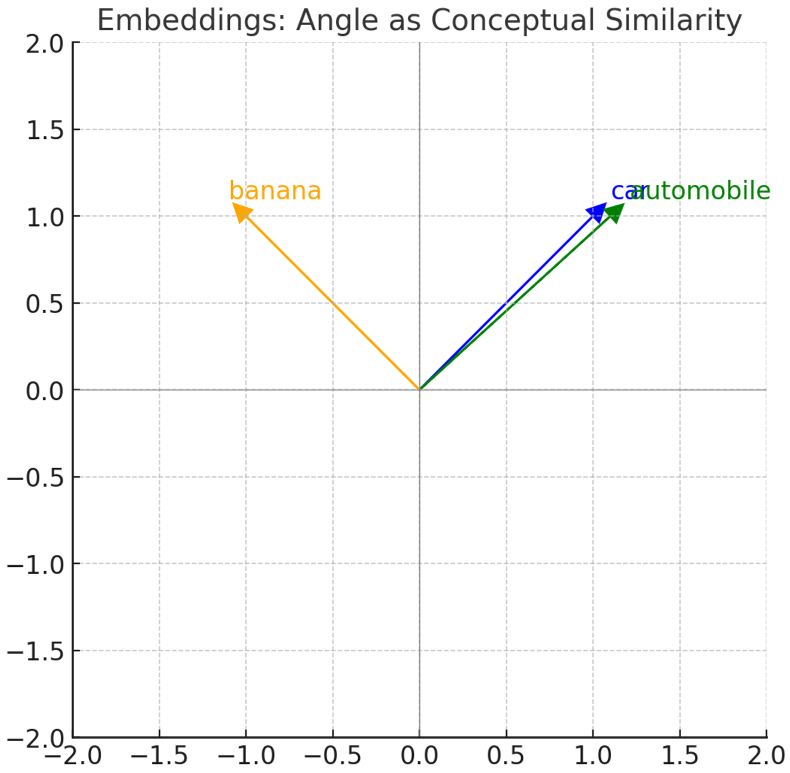

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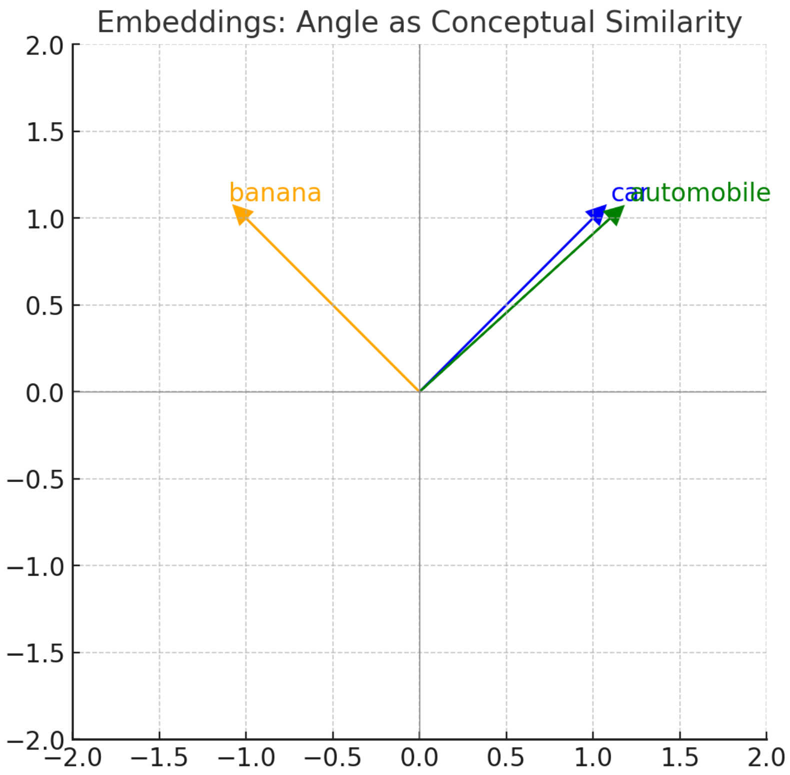

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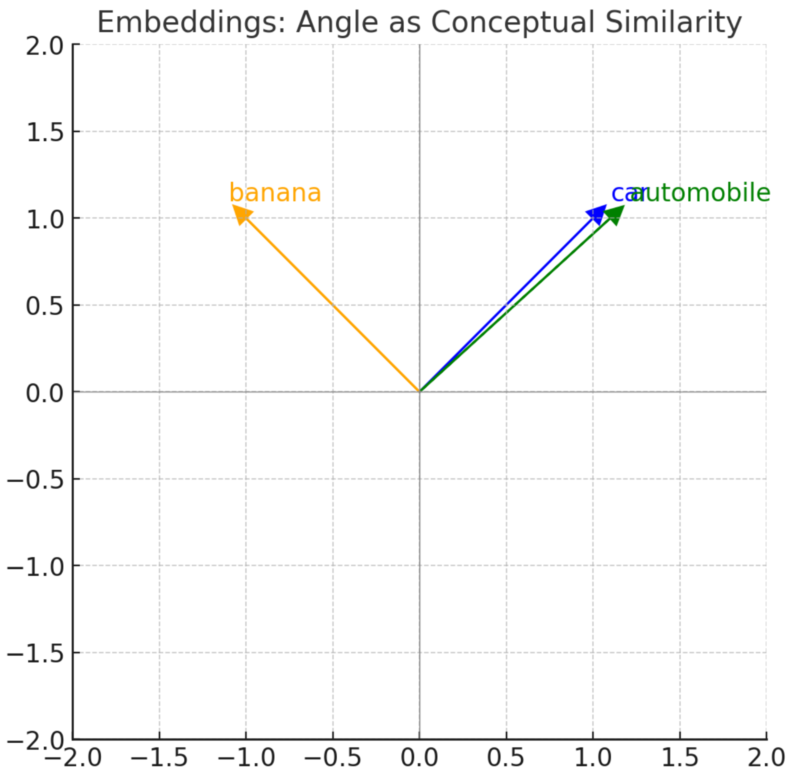

cos(0°) = 1 → perfect match

cos(90°) = 0 → no relation

cos(180°) = -1 → opposite

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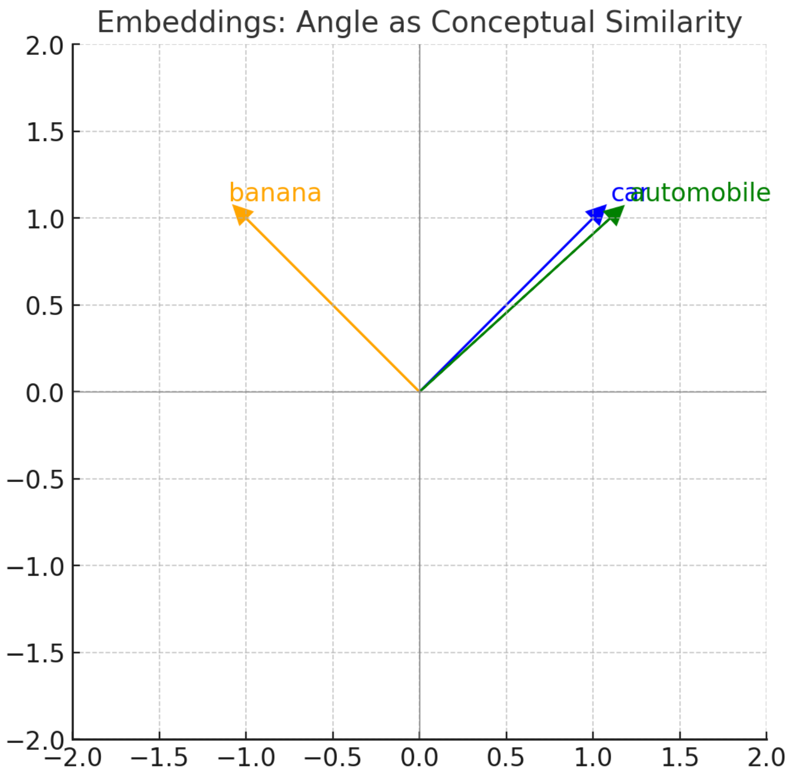

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cos(180°) = -1 → opposite

“car” → vector A

“automobile” → vector B

Their angle is tiny → high similarity

“car” vs. “banana” → angle ~90° → not related.

Semantic Search Tools in the .NET Ecosystem

Frameworks & Libraries

Microsoft.Extensions.AI

Semantic Kernel

ML.NET

Frameworks & Libraries

⭐ Microsoft.Extensions.AI

Semantic Kernel

ML.NET

Embedding Models

OpenAI API

Ollama

Hugging Face

Embedding Models

OpenAI API

⭐ Ollama

Hugging Face

Vector Databases

Cosmos DB

Redis

Qdrant

Pinecone,
Weaviate, Milvus

NOTE: SQL Server 2025 includes a vector data type

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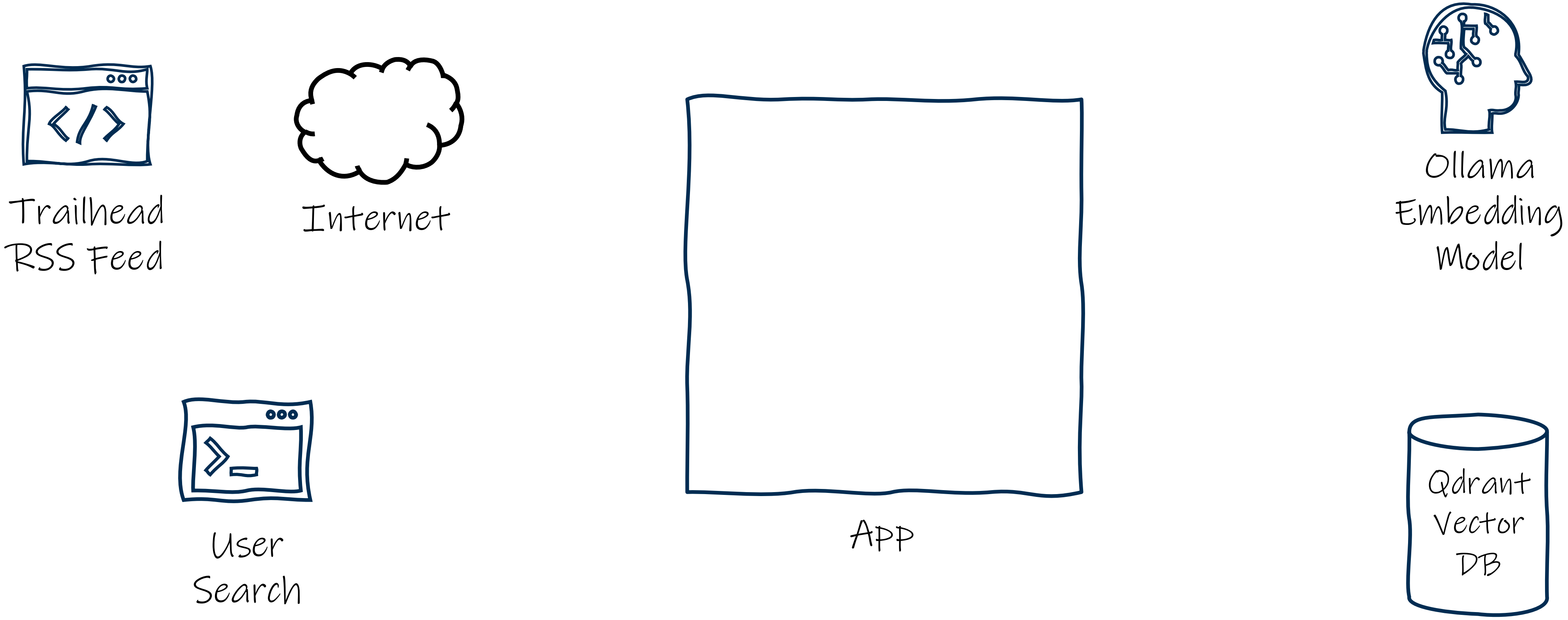
Cloud Services

Azure AI Search

ElasticSearch

Implementing Semantic Search in .NET

Semantic Search Process



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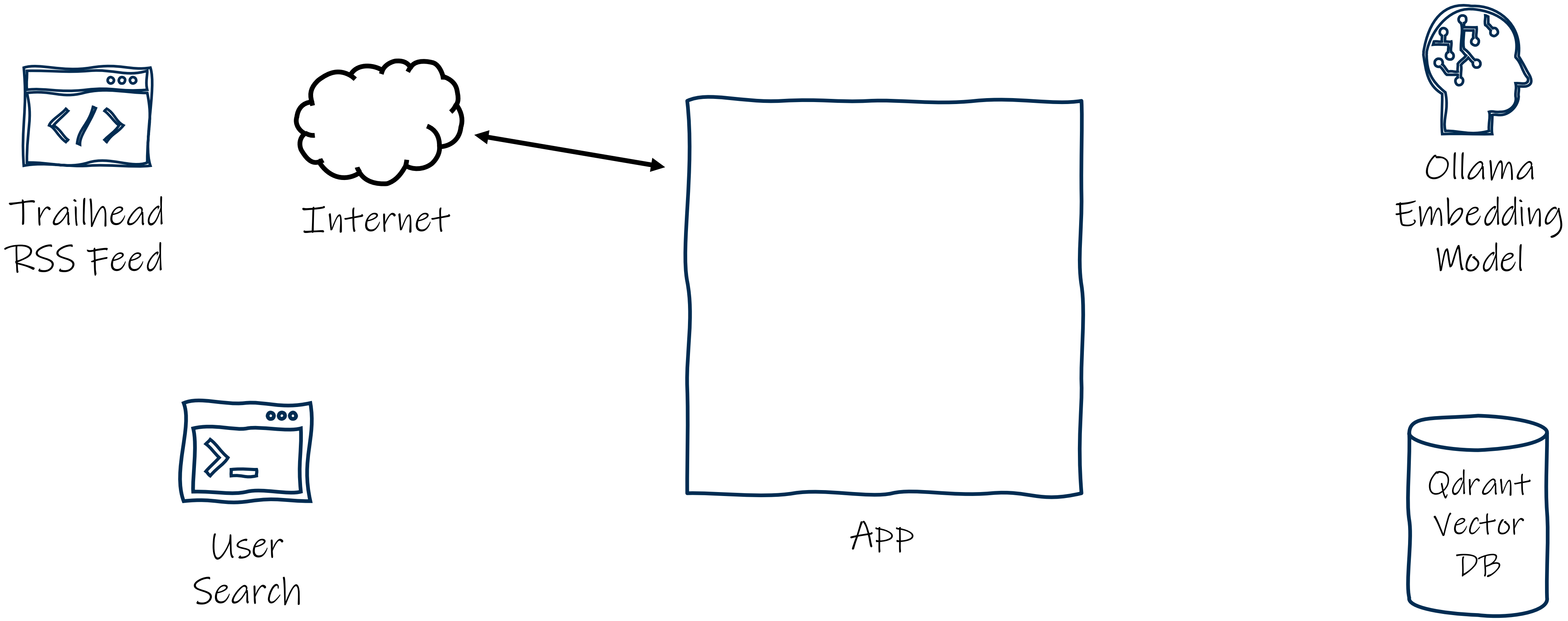

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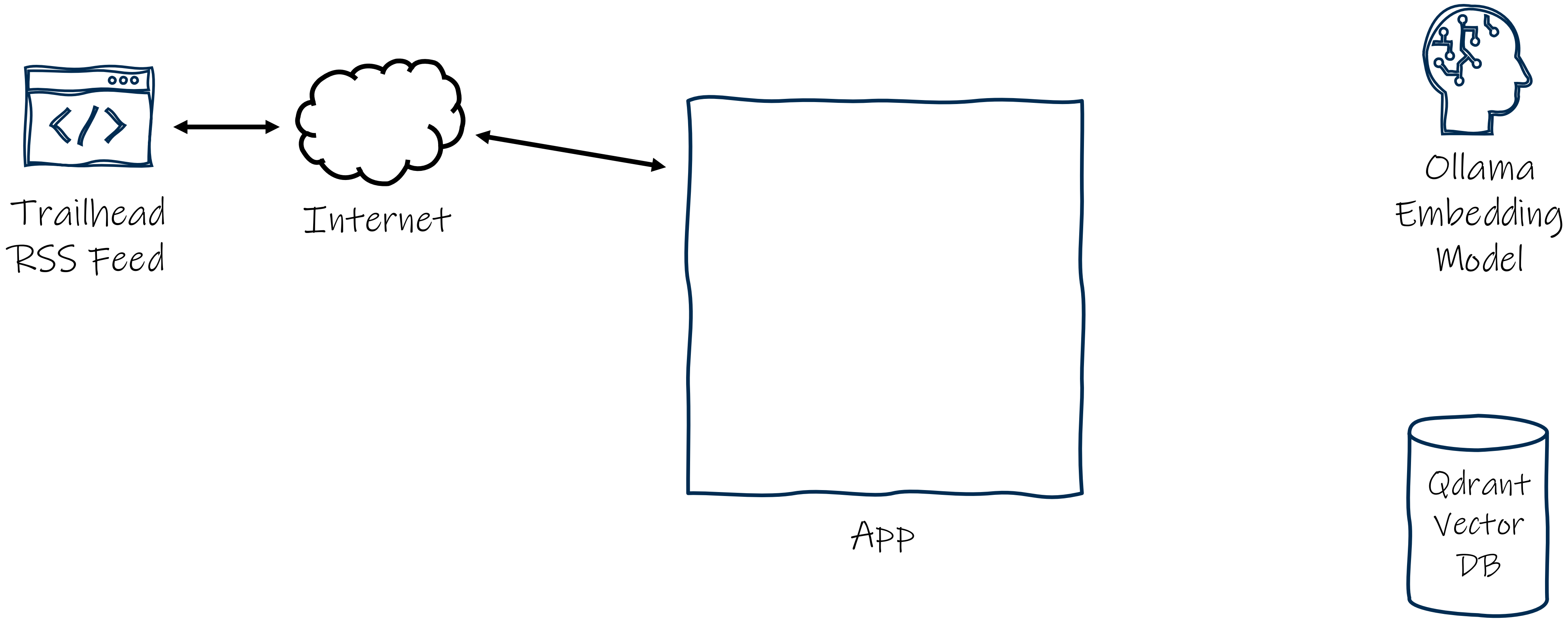

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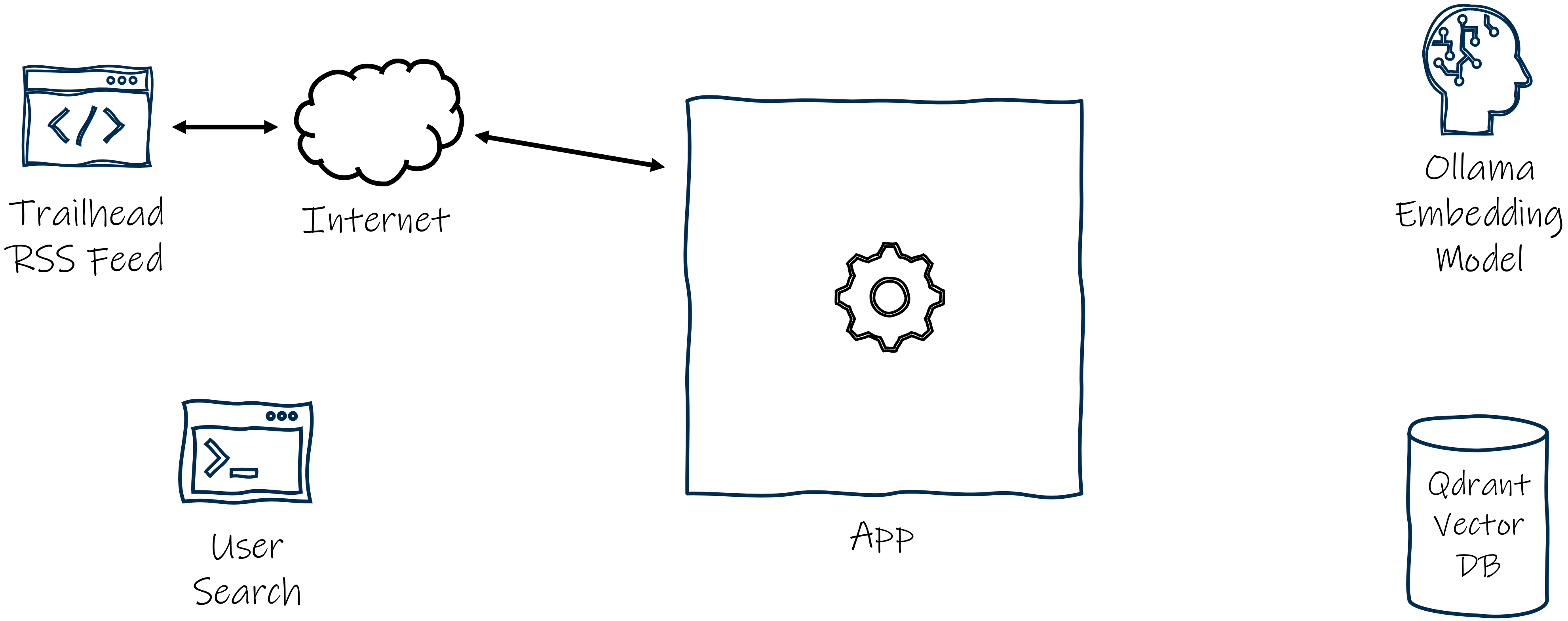


Trailhead RSS Feed

Internet

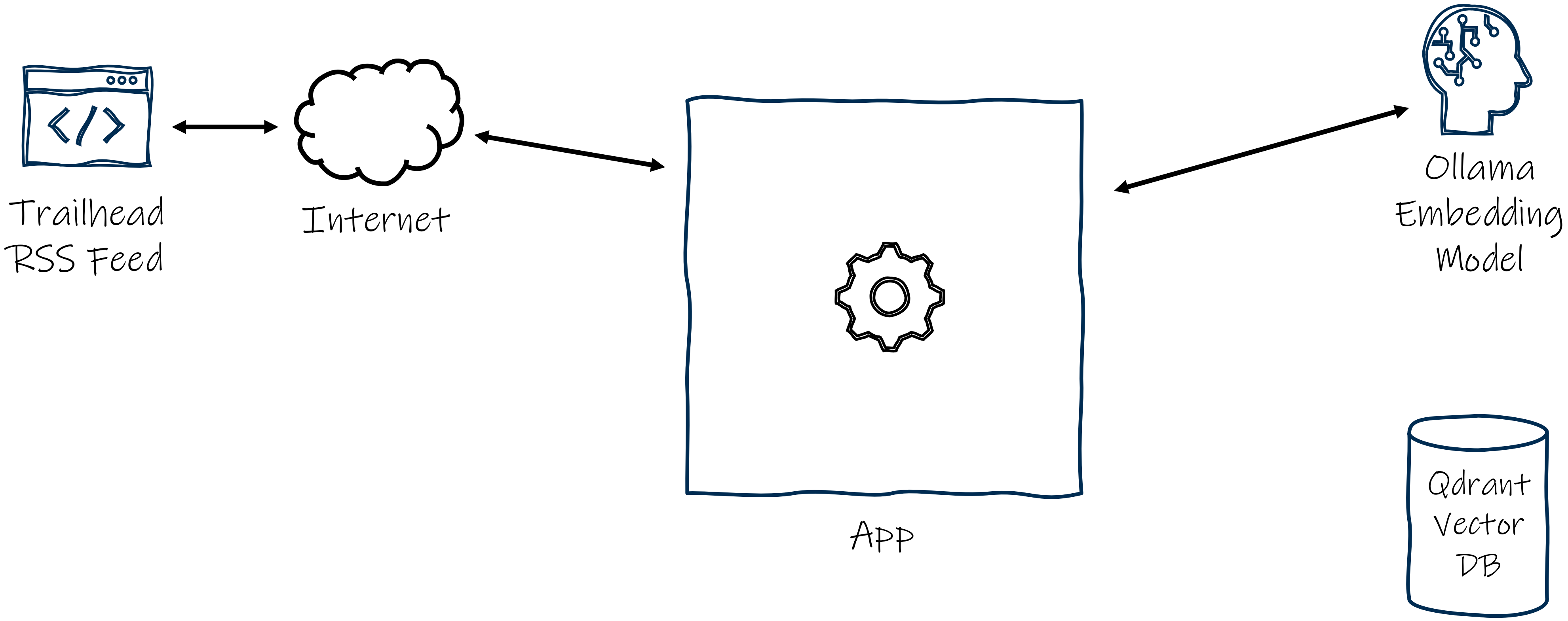
App

Ollama Embedding Model

User Search

Qdrant Vector DB

Semantic Search Process



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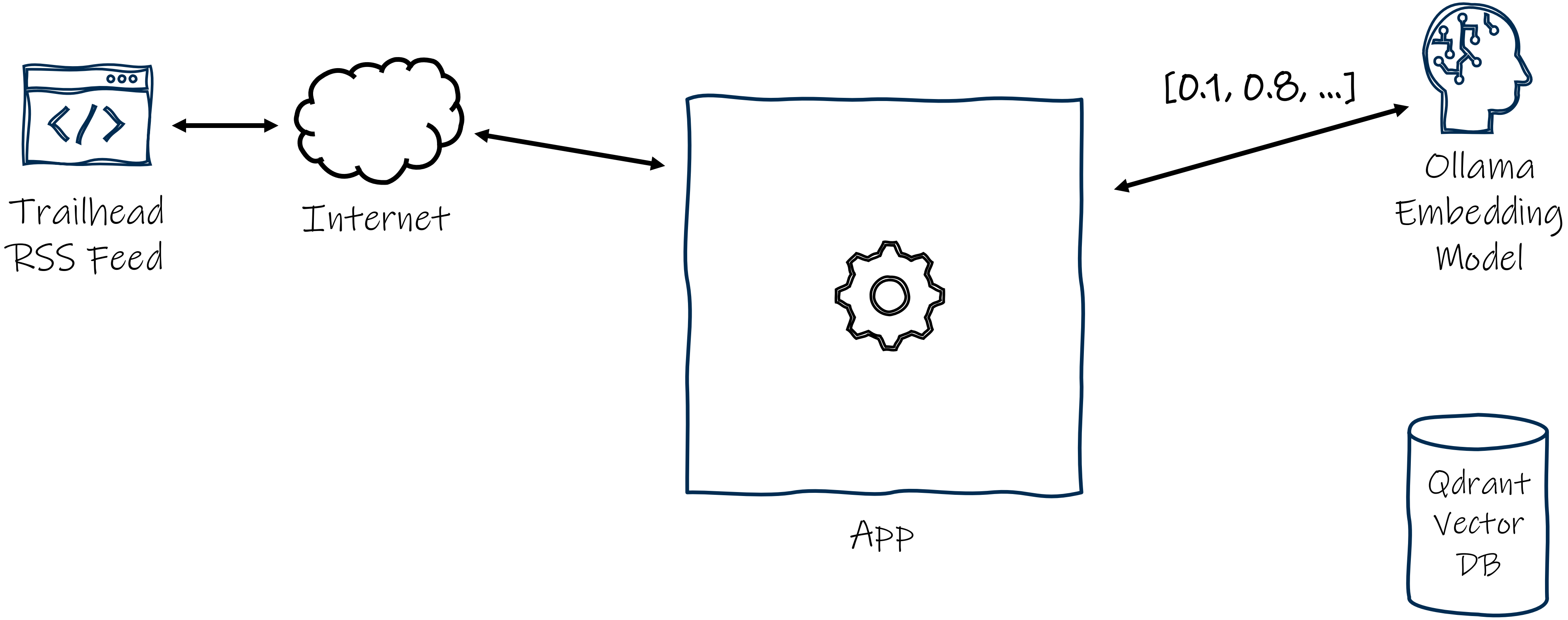

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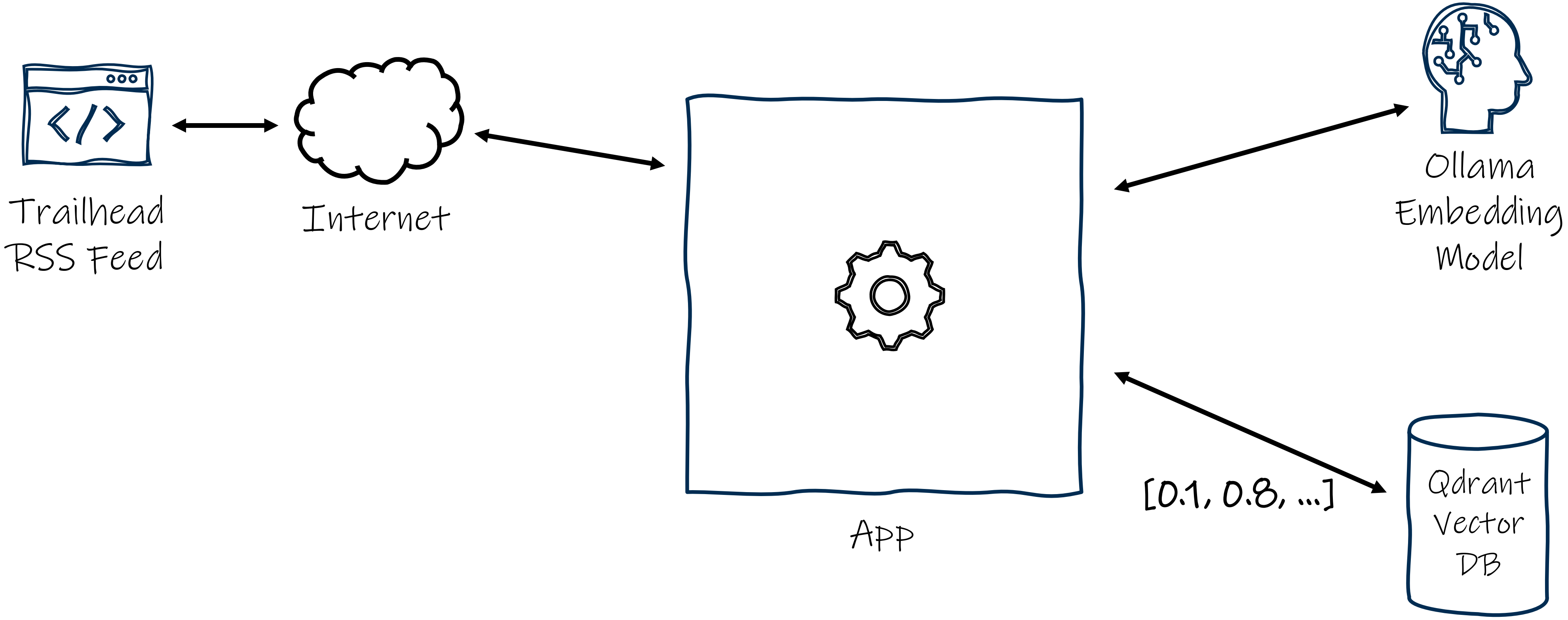

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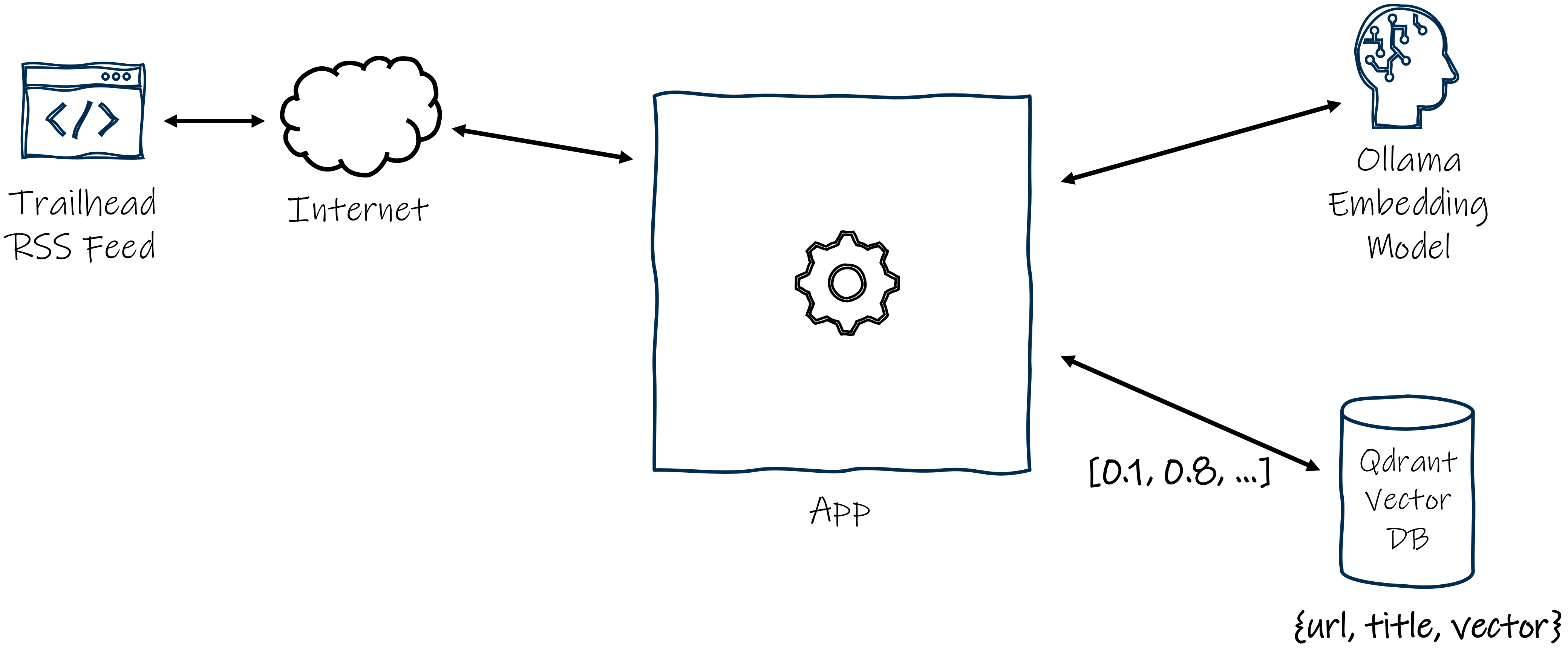

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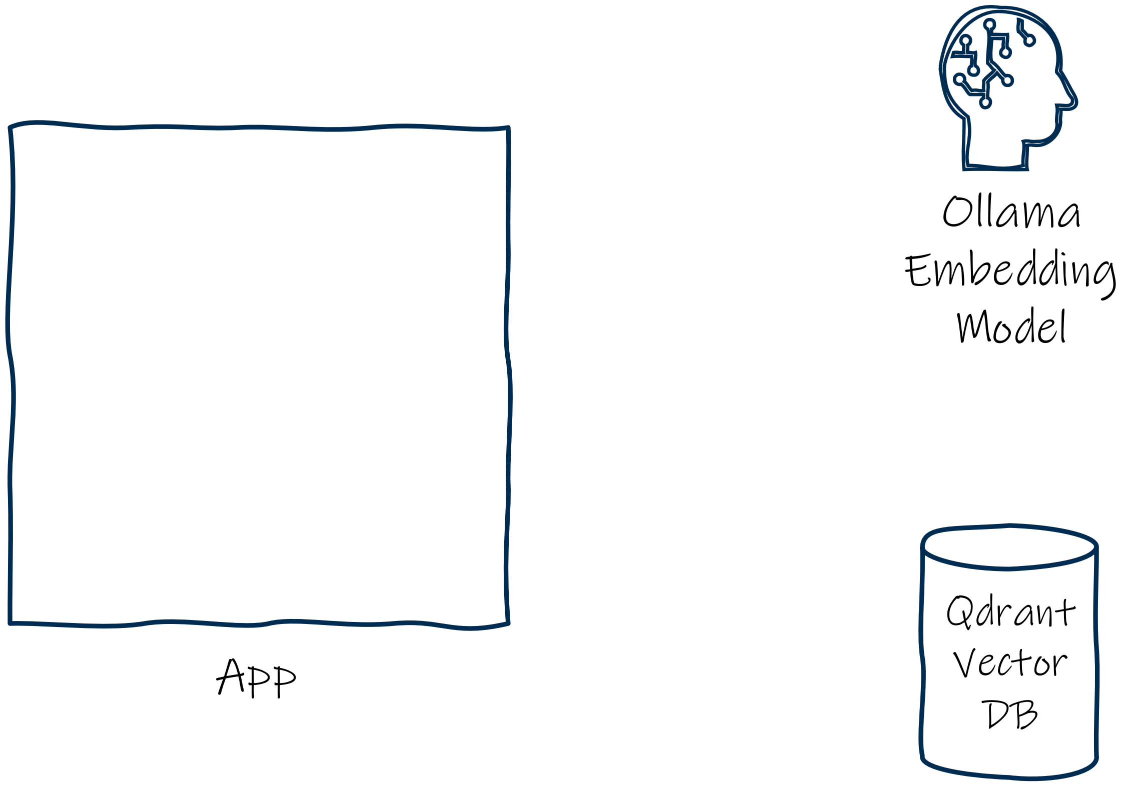

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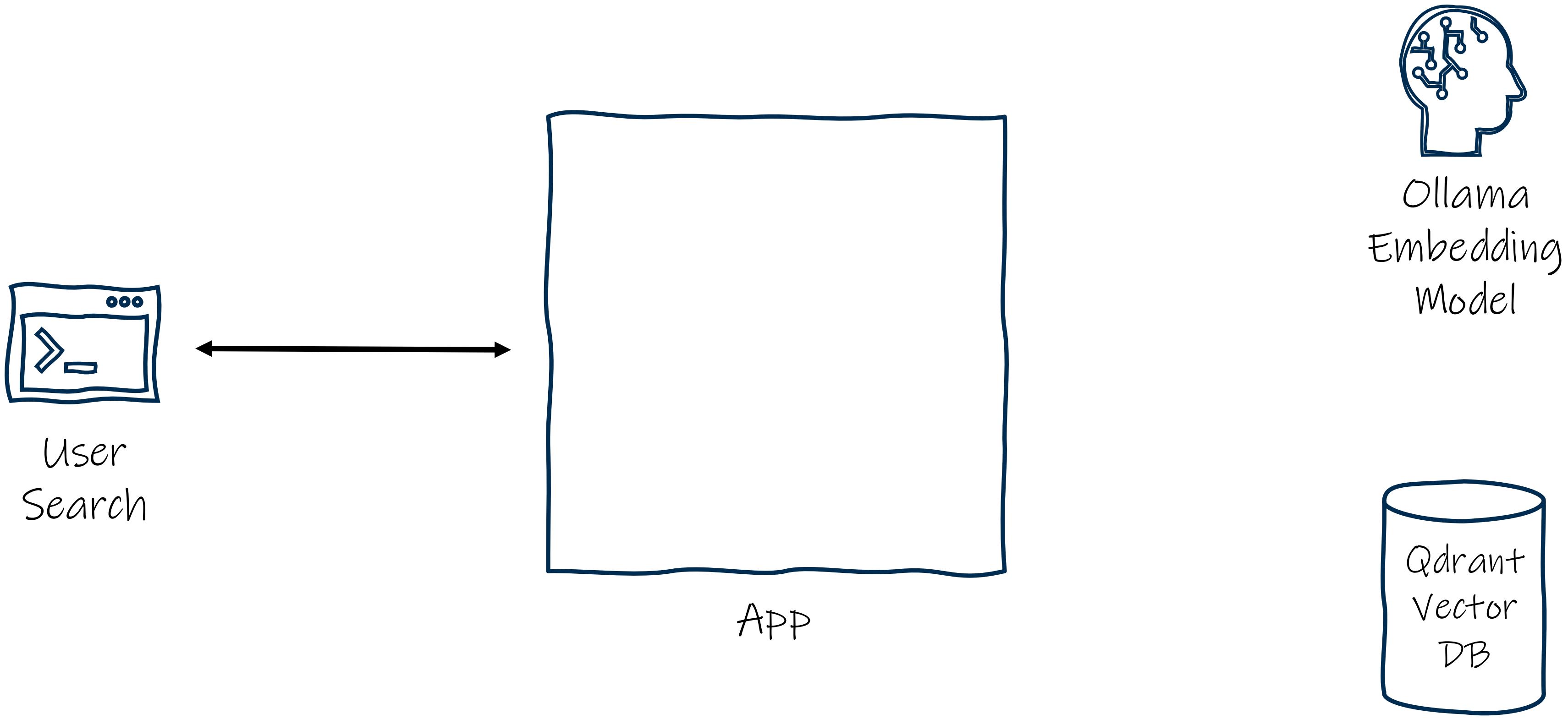

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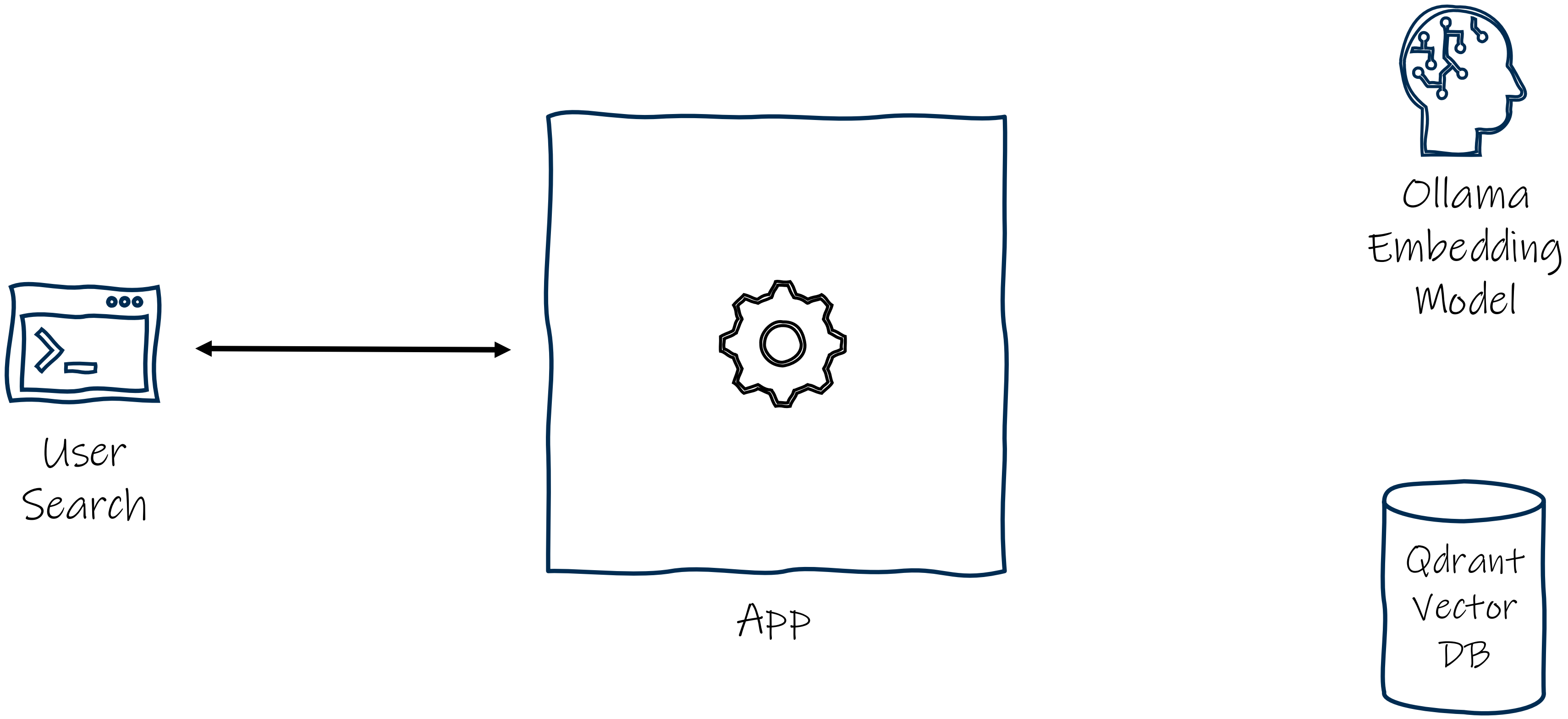

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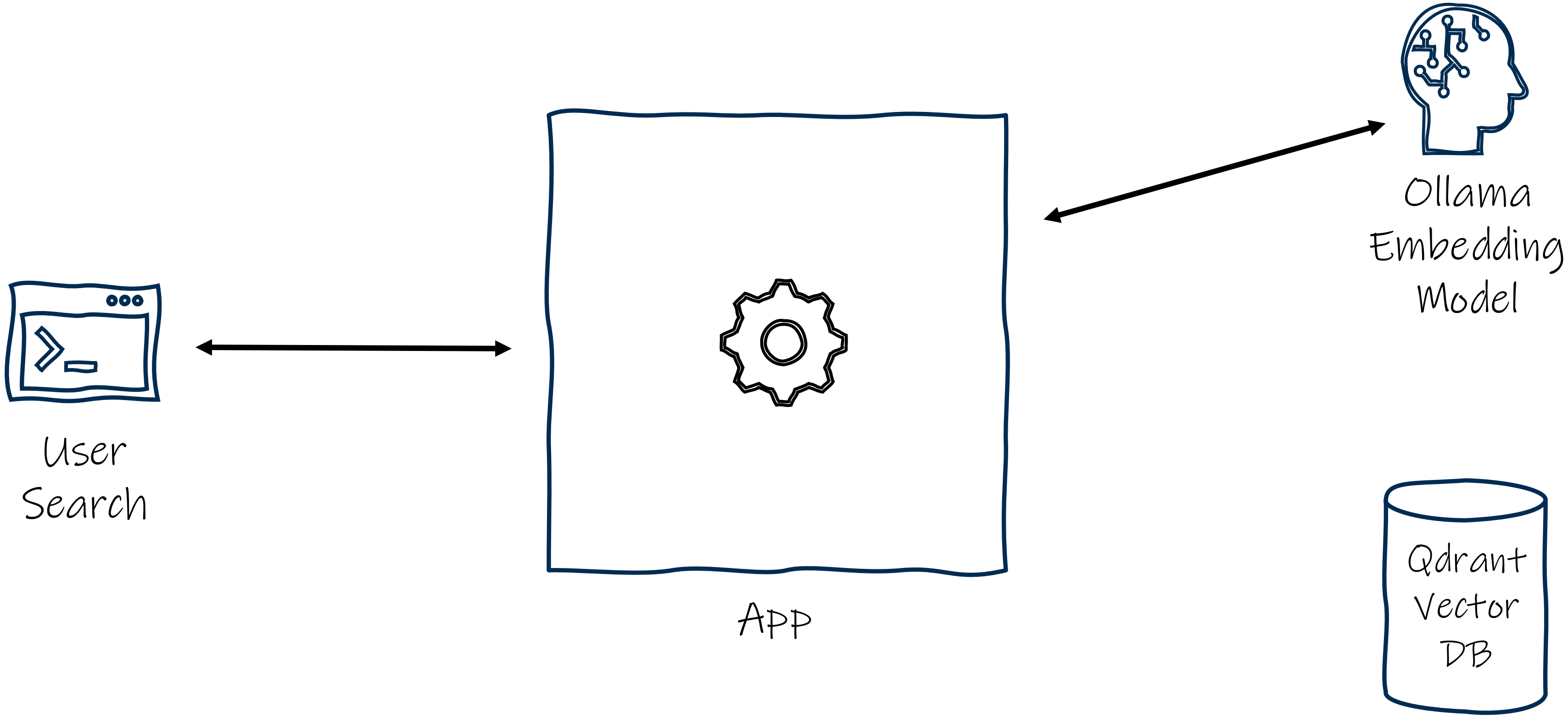

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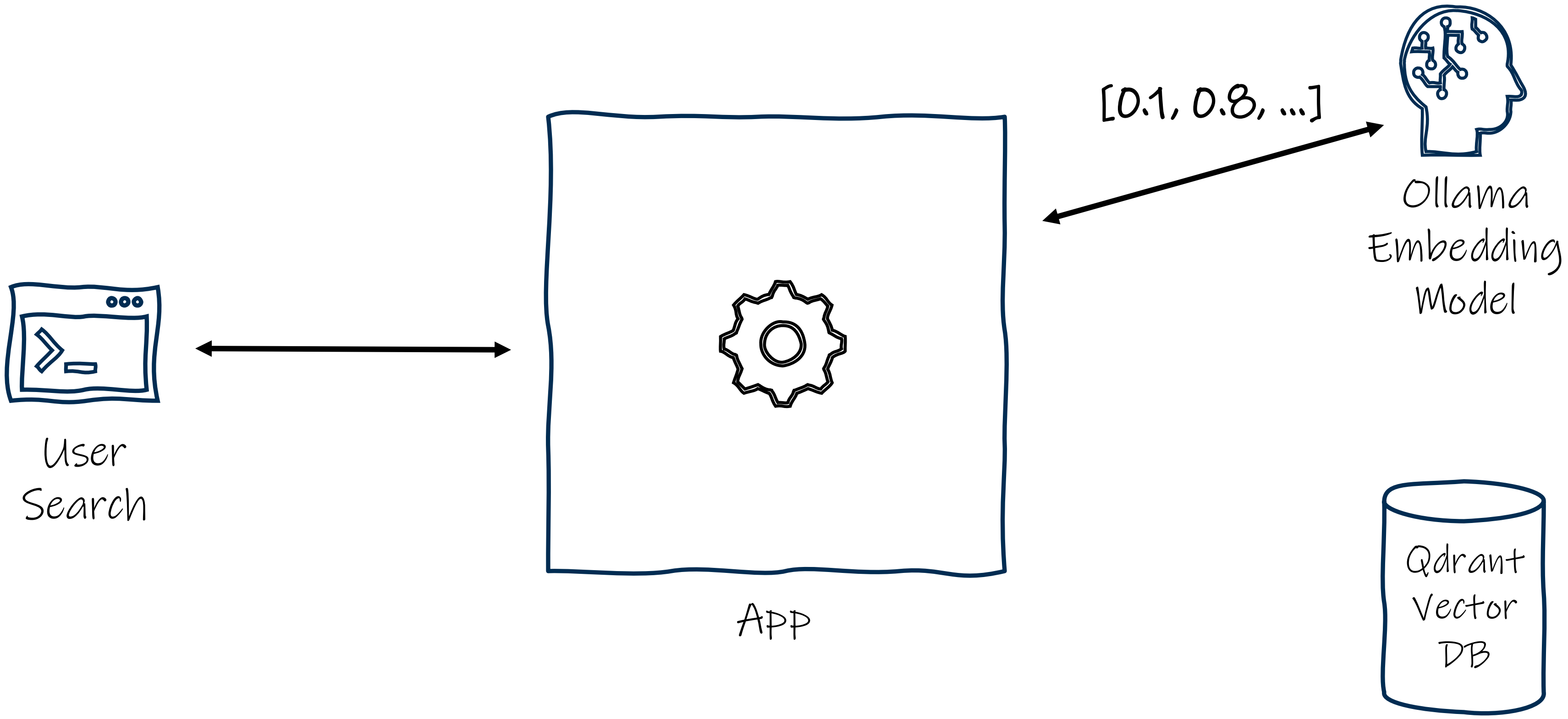

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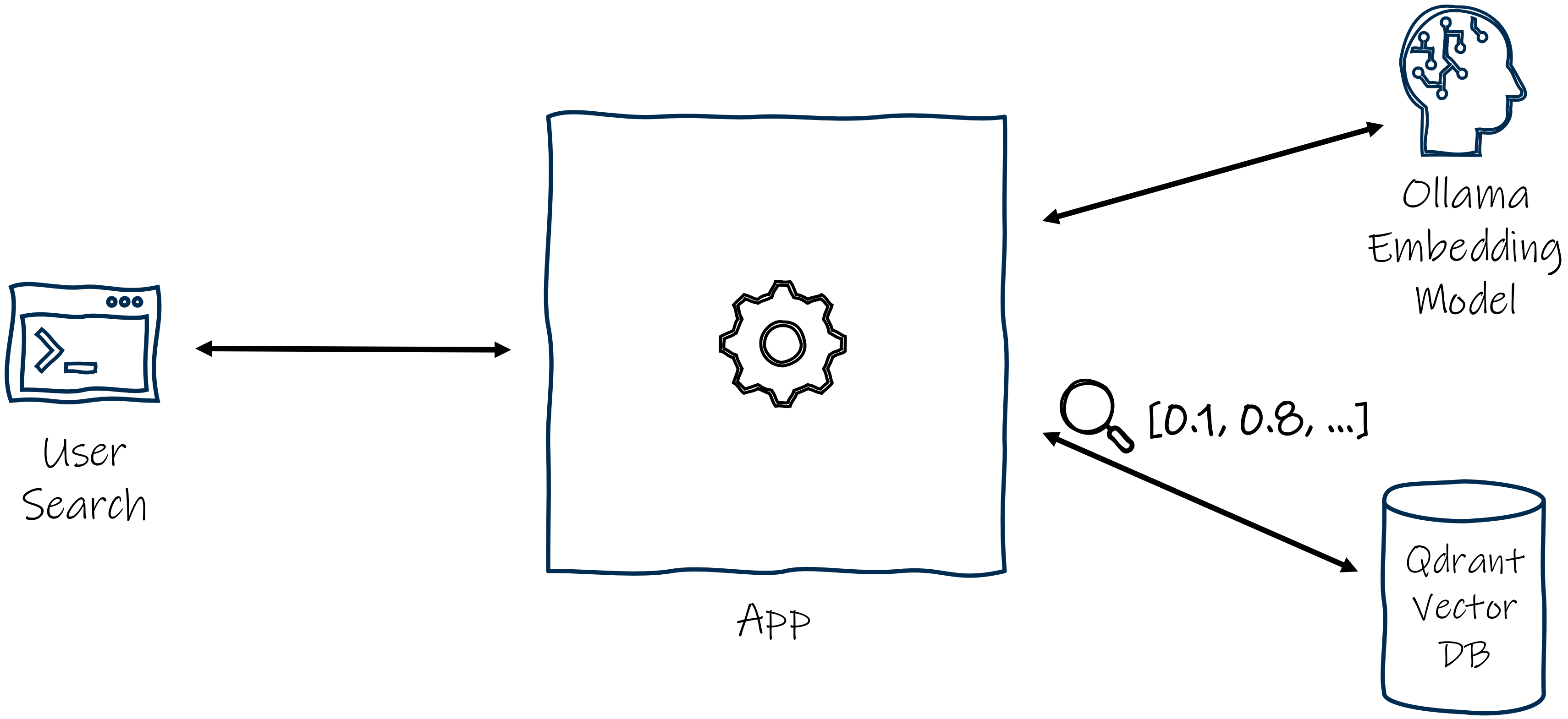

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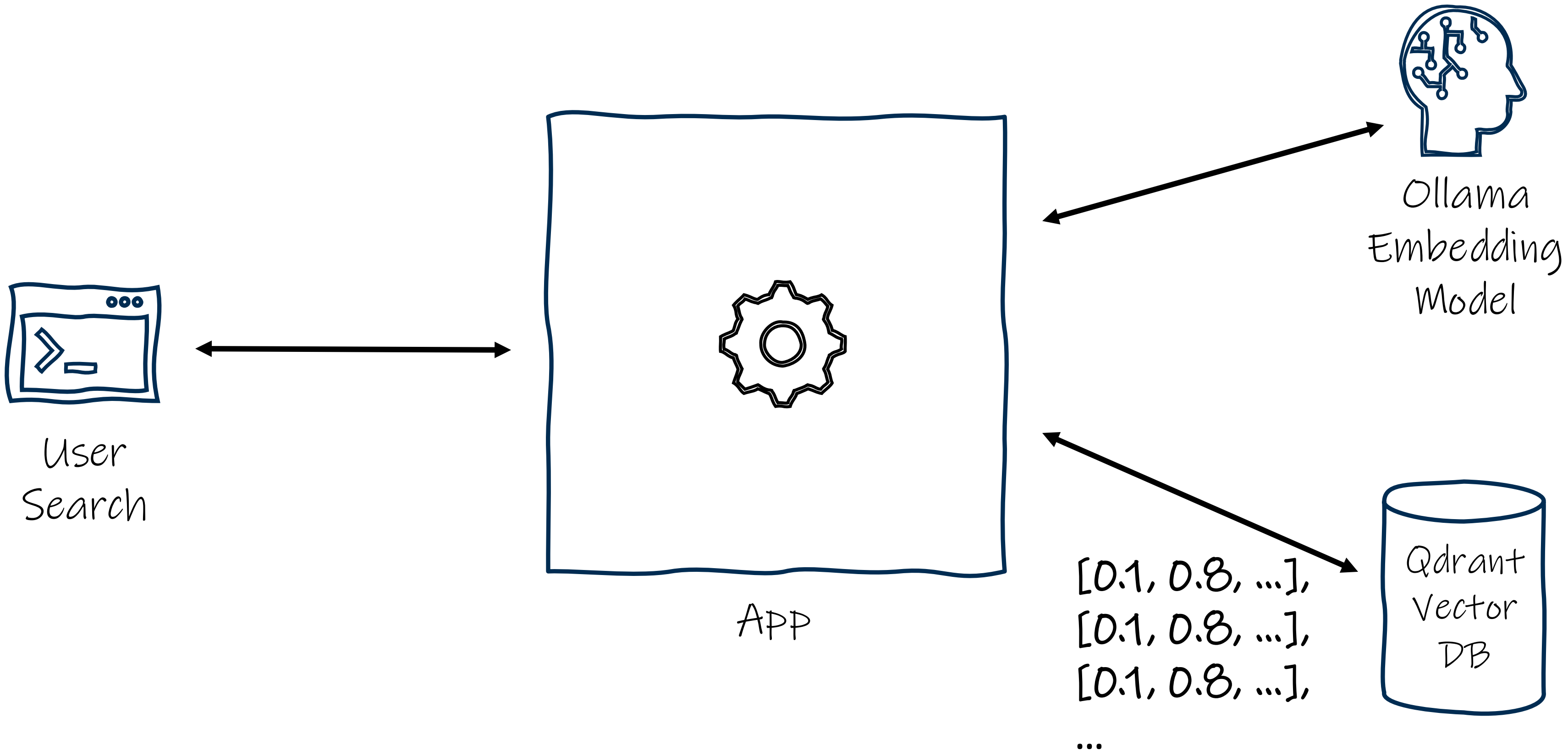

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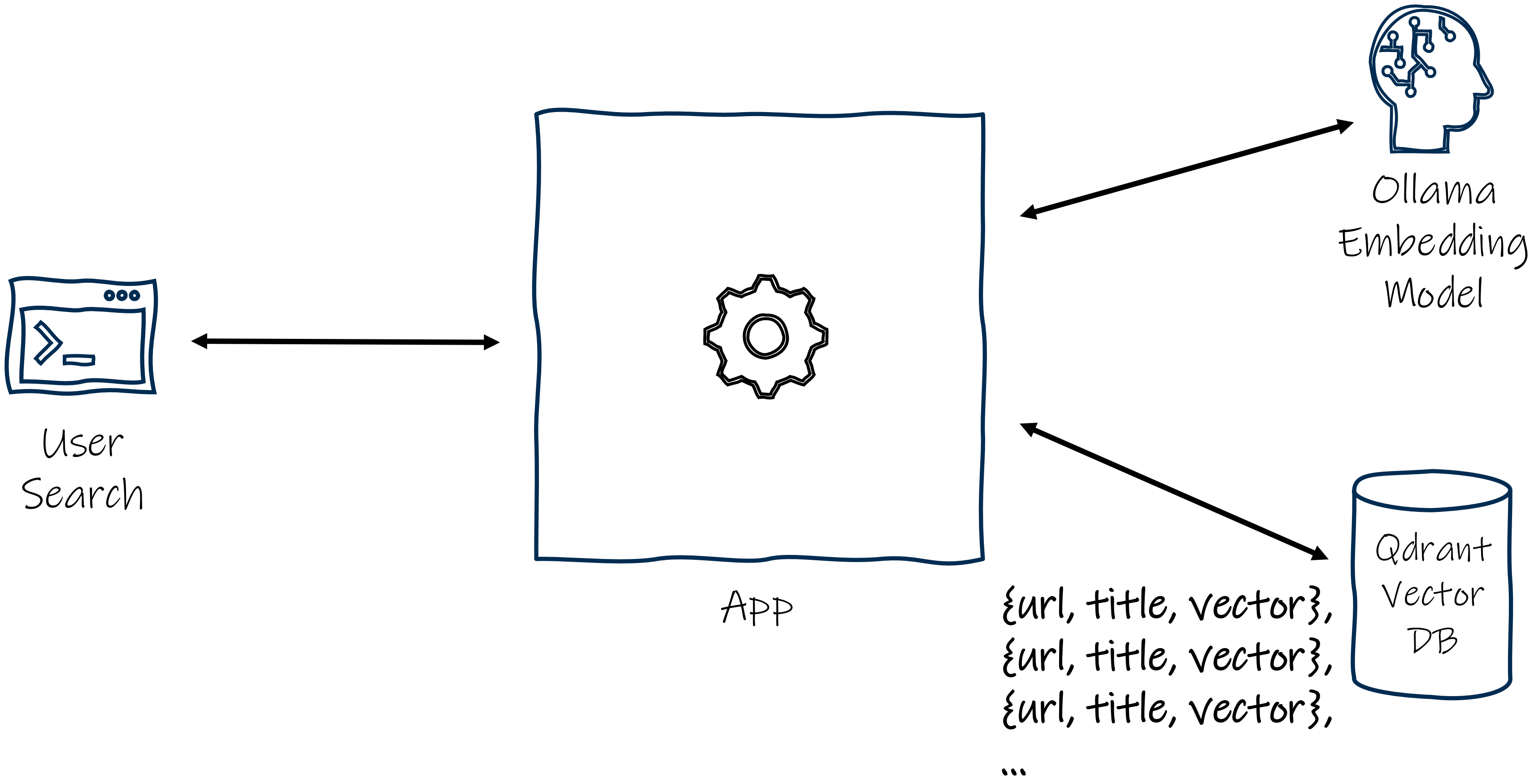
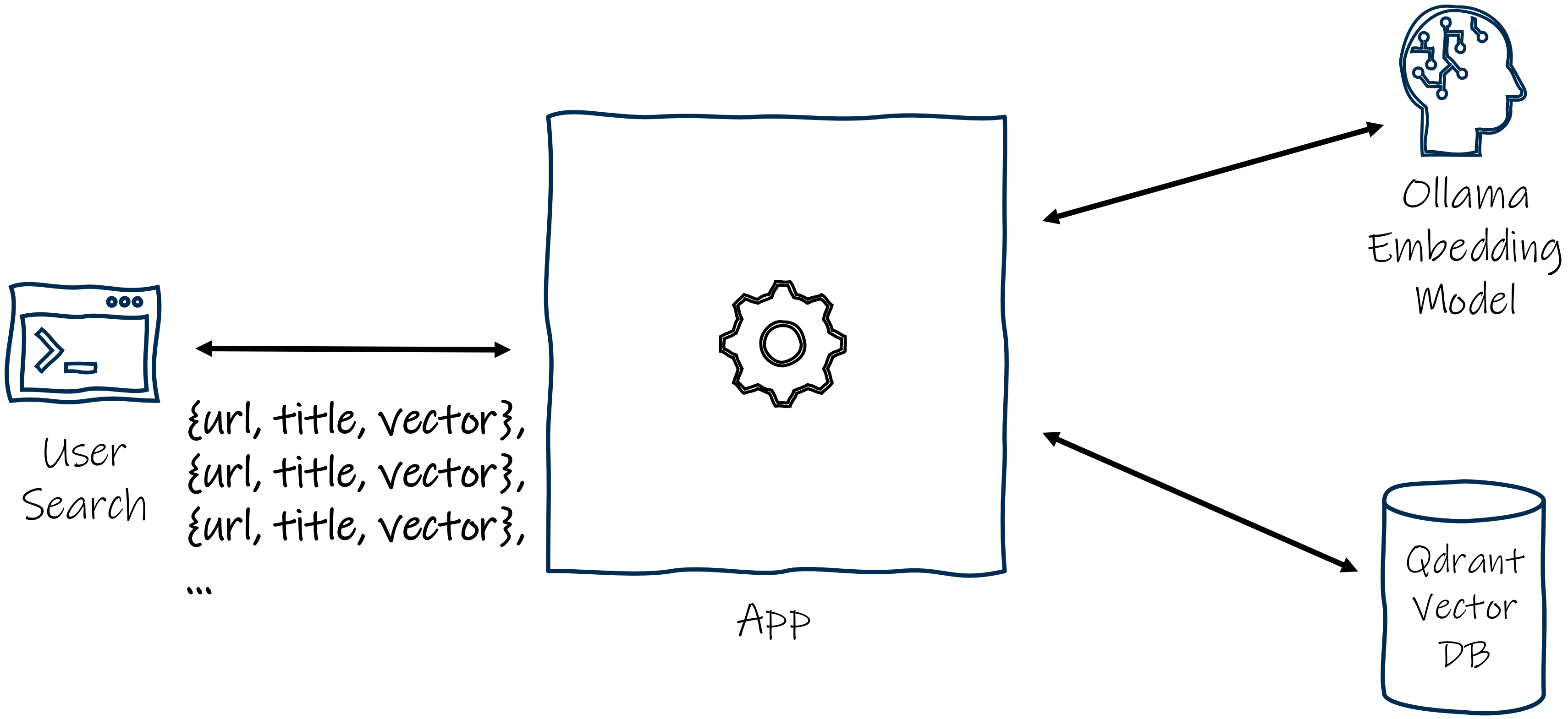


Semantic Search Process



LIVE DEMO

TRAILHEAD
TECHNOLOGY PARTNERS

Practical Considerations

Cost & Latency Trade-Offs

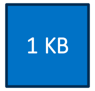
Option	Cost	Latency
Local (Ollama)	✅ low	⚠️ medium
OpenAI/Azure	⚠️ higher	✅ low
Hybrid	⚖️ balanced	⚖️ balanced

Scalability & Storage

Store in a Vector DB

Index Vectors

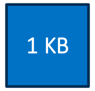
Scalability & Storage



1 KB

1 vector = 1 KB

Scalability & Storage



1 vector = 1 KB

1M vectors = GBs

Quality & Model Choice

Type	Pros	Cons	Use Cases
Small embeddings (384–768 dims)	✅ Fast ✅ Cheap ✅ Lower storage	⚠ Less nuance ⚠ Lower accuracy	Quick search, lightweight apps, prototyping
Large embeddings (1024–3000 dims)	✅ Higher accuracy ✅ Captures subtle meaning	⚠ More compute ⚠ Higher storage/cost	Production search, nuanced queries, RAG
Domain-specific models	✅ Tuned for specific language (legal, medical, finance, etc.) ✅ Often best results	⚠ May miss general queries ⚠ Limited availability	Specialized industries, enterprise apps

When NOT to Use Semantic Search

Tiny Datasets

Structured Lookups

Strict Regulatory environments

Summing Up

1. Semantic search **searches meaning**, not just words or parts of words
2. Powered by **vectors** and **embeddings**
3. Many **tools exist** such MEAI, Ollama, Azure OpenAI API, Qdrant, etc.
4. Balance tradeoffs of **local vs hosted** models.

Thanks! Questions?

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EXPERT

Consultation

bit.ly/th-offer

github.com/trailheadtechnology/api-security