

# Search a new era

David Pilato | @dadoonet



## Elasticsearch

You Know, for Search





## Elasticsearch









## 66

These are not the droids you are looking for.



```
GET / analyze
  "char filter": [ "html strip" ],
  "tokenizer": "standard",
  "filter": [ "lowercase", "stop", "snowball" ],
  "text": "These are <em>not</em> the droids
           you are looking for."
```



"char\_filter": "html\_strip"

These are <em>not</em> the droids you are looking for.



These are not the droids you are looking for.



"tokenizer": "standard"

These are not the droids you are looking for.



```
These
are
not
the
droids
are
looking
for
```



#### "filter": "lowercase"

These these are are not not the the droids droids you you are are looking looking for for



#### "filter": "stop"

```
These
are
not
the
droids
                droids
you
                you
are
looking
                looking
for
```



"filter": "snowball"

droids droid you looking look



```
These are <em>not</em> the droids you are looking for.
{ "tokens": [{
      "token": "droid",
      "start offset": 27, "end offset": 33,
      "type": "<ALPHANUM>", "position": 4
    },{
      "token": "you",
      "start offset": 34, "end offset": 37,
      "type": "<ALPHANUM>", "position": 5
    }, {
      "token": "look",
      "start offset": 42, "end offset": 49,
      "type": "<ALPHANUM>", "position": 7
    } ] }
```





**Semantic** search

**≠** 

**Literal** matches



### Elasticsearch

You Know, for **Vector** Search





What is a **Vector**?







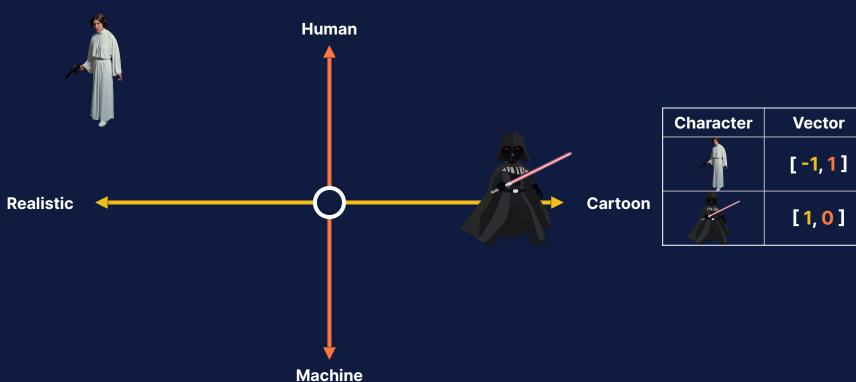
## Embeddings represent your data Example: 1-dimensional vector



Character	Vector
	[-1]
- ville	[1]

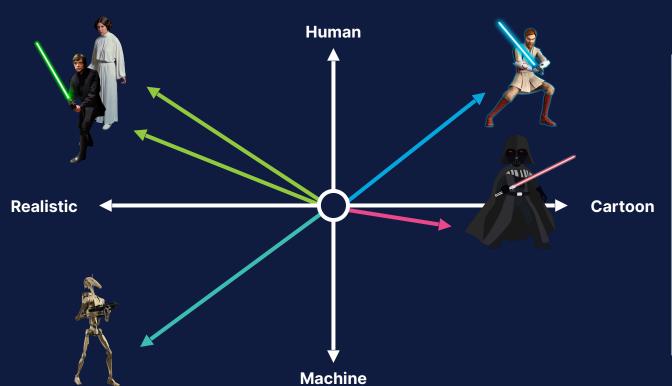


## Multiple dimensions represent different data aspects





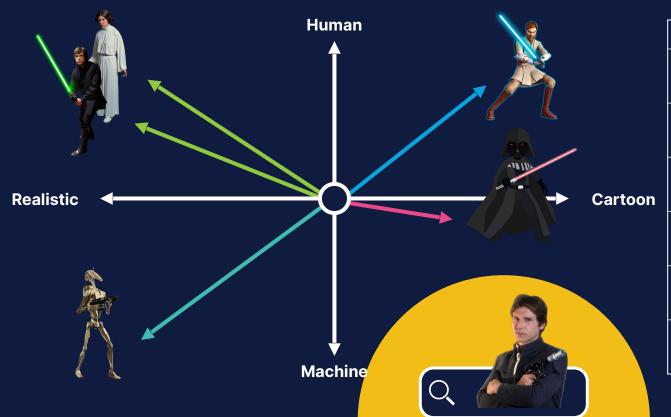
## Similar data is grouped together



Character	Vector
À	[ -1.0, 1.0 ]
.nim	[1.0, 0.0]
, in the second	[ -1.0, 0.8 ]
À	[1.0, 1.0]
A	[ -1.0, -1.0 ]



## Vector search ranks objects by similarity (~relevance) to the query



Rank	Result
Query	
1	À
2	, in the second
3	×
4	
5	



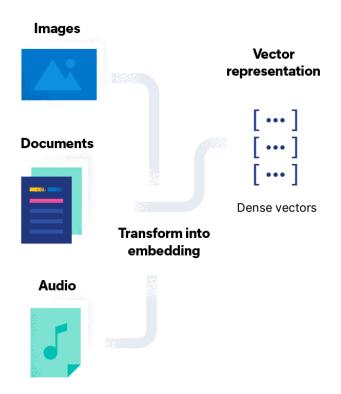


## How do you

index vectors?



#### **Architecture of Vector Search**

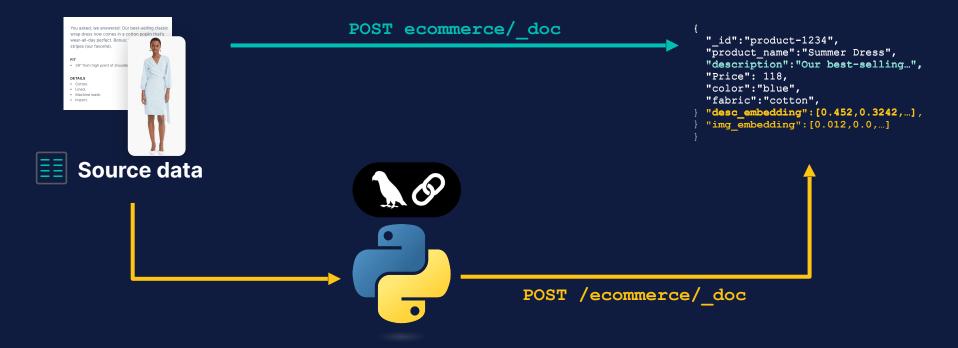


#### dense\_vector field type

```
PUT ecommerce
  "mappings": {
    "properties": {
      "description": {
        "type": "text"
      "desc embedding": {
        "type": "dense vector"
```



#### Data Ingestion and Embedding Generation





#### With Elastic ML





#### Source data

```
{
    "_id":"product-1234",
    "product_name":"Summer Dres
    "description":"Our best-sel
    "Price": 118,
    "color":"blue",
    "fabric":"cotton",
}

POST /ecommerce/_doc
```



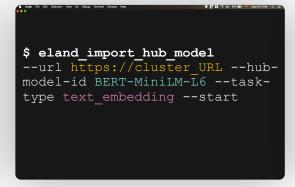
```
"_id":"product-1234",
"product_name":"Summer Dress",
"description":"Our best-selling...",
"Price": 118,
"color":"blue",
"fabric":"cotton",
"desc_embedding":[0.452,0.3242,...]
```

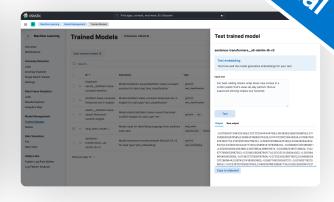


Comm

#### Eland Imports PyTorch Models















Select the appropriate model

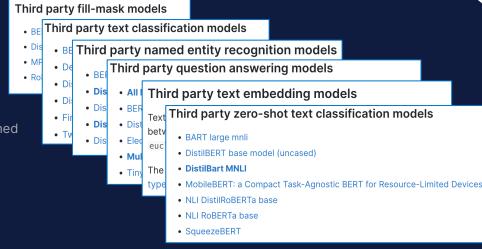
Load it

Manage models



#### Elastic's range of supported NLP models

- Fill mask model
  - Mask some of the words in a sentence and predict words that replace masks
- Named entity recognition model
   NLP method that extracts information from text
- Text embedding model
   Represent individual words as numerical vectors in a predefined
   vector space
- Text classification model
   Assign a set of predefined categories to open-ended text
- Question answering model
   Model that can answer questions given some or no context
- Zero-shot text classification model
   Model trained on a set of labeled examples, that is able to classify previously unseen examples



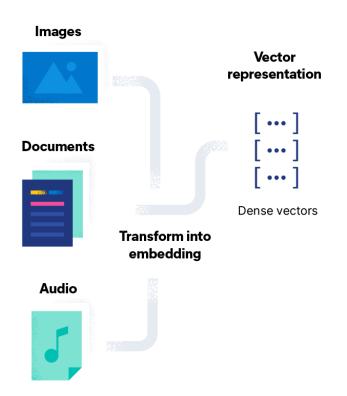


## How do you

search vectors?



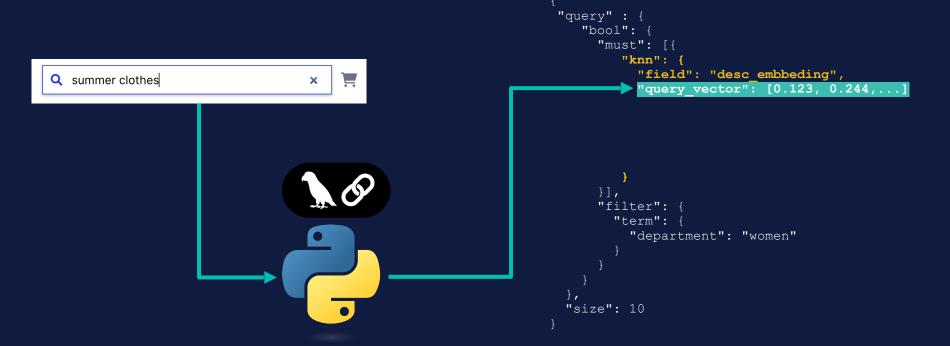
#### **Architecture of Vector Search**







#### knn query



GET ecommerce/\_search



## Commercial Commercial

#### knn query (with Elastic ML)

```
"query" : {
                                                                     "bool": {
                                                                       "must": [{
                                                                           "knn": {
                                                                             "field": "desc embbeding",
summer clothes
                                  ×
                                                                             "query vector builder": {
                                                                               "text embedding":
                                                                                "model text": "summer clothes",
                                                                                "model id": <text-embedding-model>
                                                                       "filter":
                                                                          "term":
                                                                            "department": "women"
                                                                   "size": 10
                                   Transformer model
```

GET ecommerce/ search



#### semantic\_text field type

POST ecommerce/ doc

"description": "Our best-selling..."

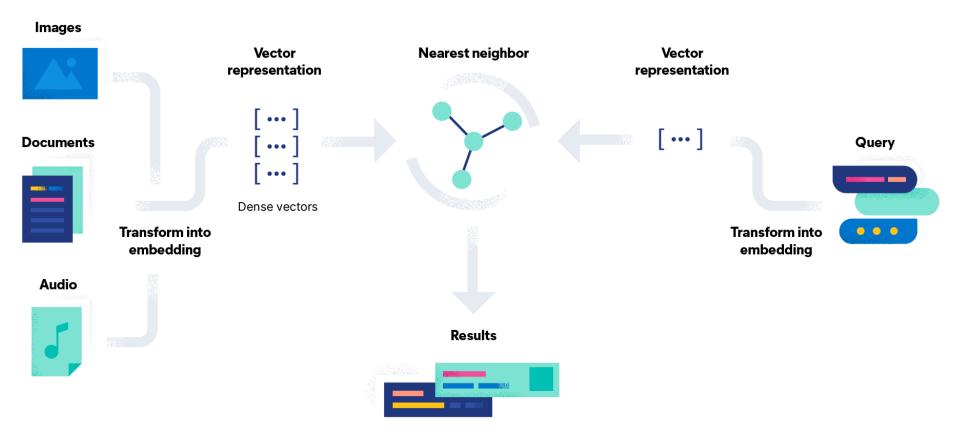
```
PUT /_inference/text_embedding/e5-small-multilingual
{
    "service": "elasticsearch",
    "service_settings": {
        "num_allocations": 1,
        "model_id": ".multilingual-e5-small_linux-x86_64"
    }
}

PUT ecommerce
{
    "mappings": {
        "properties": {
        "type": "text",
        "copy_to": ["desc_embedding"]
    }
}

"desc_embedding": {
        "type": "semantic_text",
        "inference_id": "e5-small-multilingual"
    }
}
```

```
GET ecommerce/_search
{
    "query": {
        "semantic": {
            "field": "desc_embedding"
            "query" : "I'm looking for a red dress for a DJ party"
}}}
```

#### **Architecture of Vector Search**



#### **Choice of Embedding Model**

### **Start with Off-the Shelf Models**

- Text data: Hugging Face (like Microsoft's E5)
- Images: OpenAl's CLIP

#### **Extend to Higher Relevance**

- Apply hybrid scoring
- Bring Your Own Model: requires expertise + labeled data



## Problem training vs actual use-case



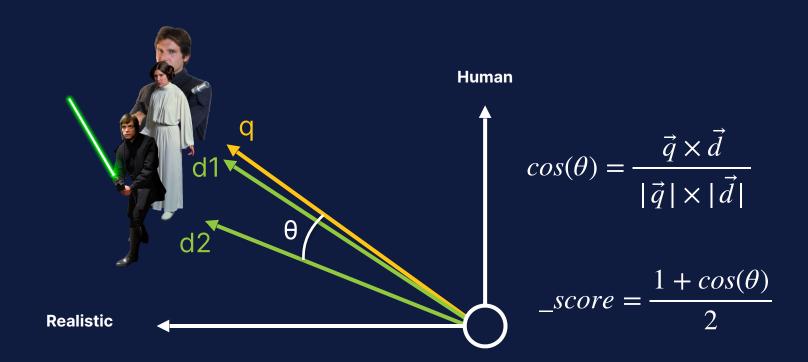




really work?



#### Similarity





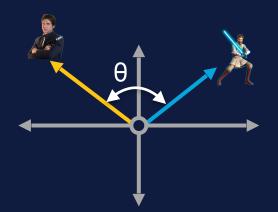
#### Similarity: cosine (cosine)



#### Similar vectors

 $\theta$  close to 0  $cos(\theta)$  close to 1

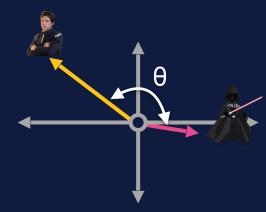
$$\_score = \frac{1+1}{2} = 1$$



#### **Orthogonal vectors**

θ close to 90°  $cos(\theta)$  close to 0

$$\_score = \frac{1+0}{2} = 0.5$$



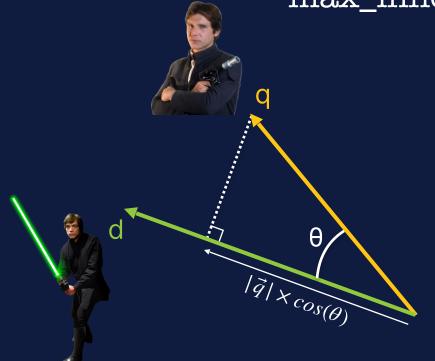
## Opposite vectors $\theta$ close to 180°

 $cos(\theta)$  close to -1

$$\_score = \frac{1-1}{2} = 0$$



# Similarity: Dot Product (dot\_product or max\_inner\_product)



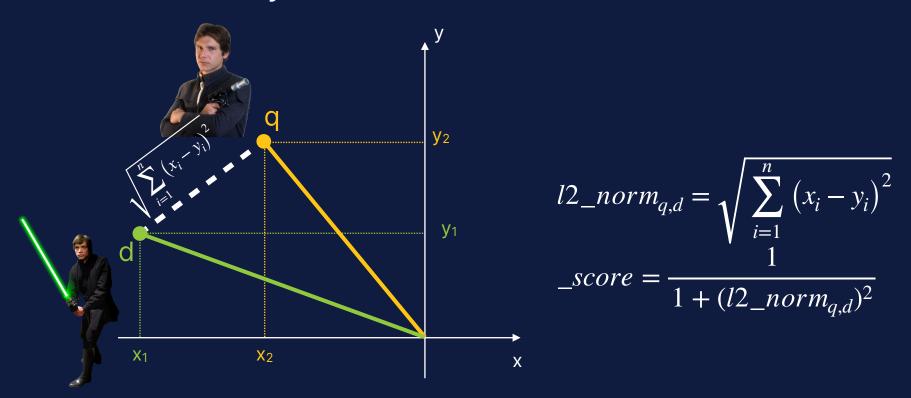
$$\vec{q} \times \vec{d} = |\vec{q}| \times cos(\theta) \times |\vec{d}|$$

$$\_score_{float} = \frac{1 + dot\_product(q, d)}{2}$$

$$\_score_{byte} = \frac{0.5 + dot\_product(q, d)}{32768 \times dims}$$



#### Similarity: Euclidean distance (12\_norm)







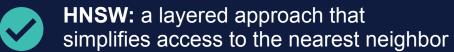
**Brute Force** 

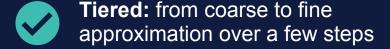




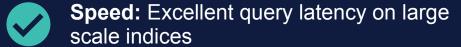
## Hierarchical Navigable Small Worlds (HNSW)

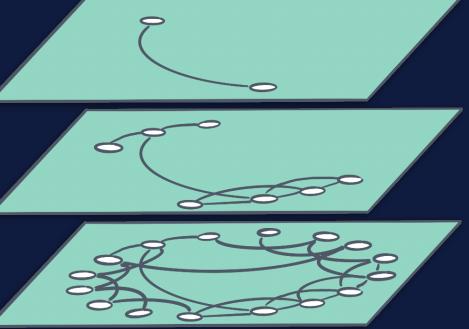
#### One popular approach













#### Scaling Vector Search

#### **Vector search**

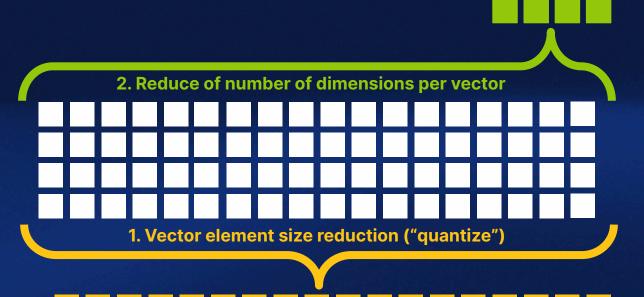
- 1. Needs lots of memory
- 2. Indexing is slower
- 3. Merging is slow

\* Continuous improvements in Lucene + Elasticsearch

#### **Best practices**

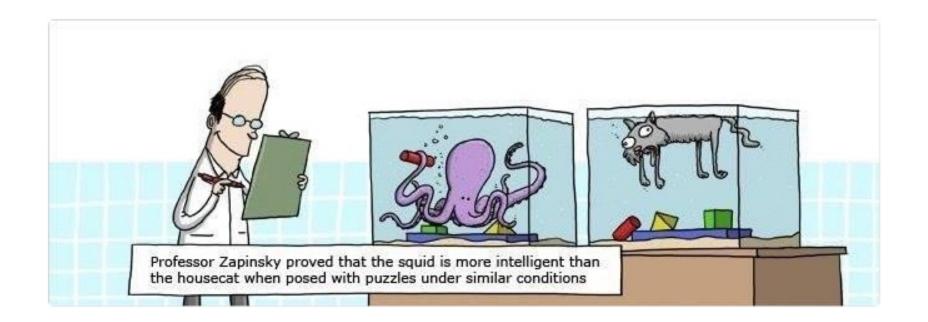
- 1. Avoid searches during indexing
- 2. Exclude vectors from \_source
- 3. Reduce vector dimensionality
- 4. Use byte rather than float

#### Reduce Required Memory





## Benchmarketing







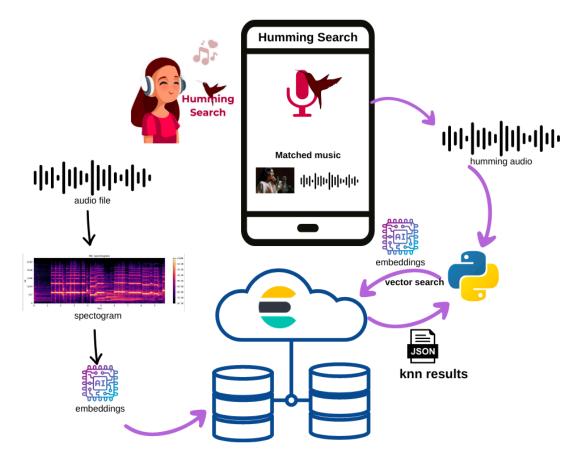


https://djdadoo.pilato.fr/









https://github.com/dadoonet/music-search/

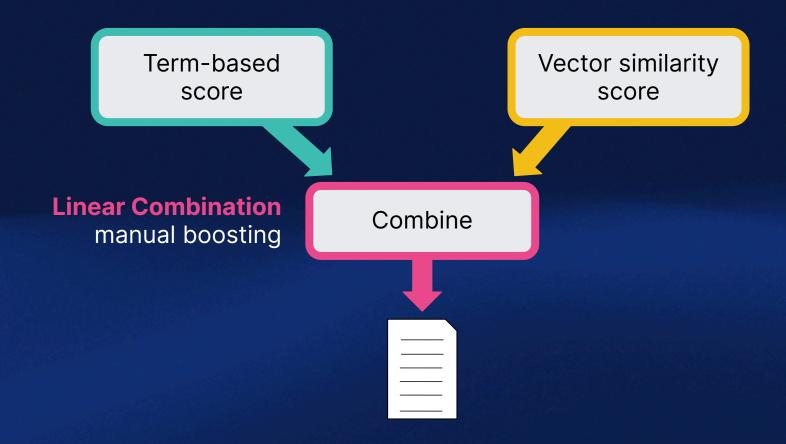


# Elasticsearch

You Know, for **Hybrid** Search



## **Hybrid scoring**





```
GET ecommerce/_search
  "query" : {
    "bool" : {
      "must" : [{
        "match":
          "description": {
            "query": "summer clothes",
            "boost": 0.1
                                                       summer clothes
        "knn": {
          "field": "desc embbeding",
          "query vector": [0.123, 0.244,...],
          "boost": 2.0,
          "filter":
            "term": {
              "department": "women"
                                                 pre-filter
      }],
      "filter" : {
        "range" : { "price": { "lte": 30 } }
                                                         post-filter
```



```
PUT starwars
  "mappings": {
    "properties": {
      "text.tokens": {
        "type": "sparse vector"
          "These are not the droids you are looking for.",
          "Obi-Wan never told you what happened to your father."
             GET starwars/ search
                "query":{
                   "sparse vector": {
                     "field": "text.tokens",
                     "query vector": { "lucas": 0.50047517,
                                       "ship": 0.29860738,
                                       "dragon": 0.5300422,
                                       "quest": 0.5974301, ... }
```

#### **ELSER**

#### Elastic Learned Sparse EncodER

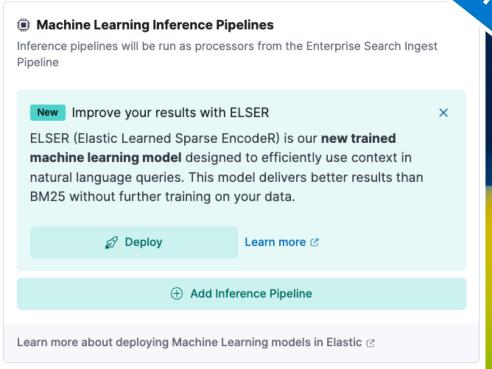
commercial commercial

#### sparse\_vector

Not BM25 or (dense) vector

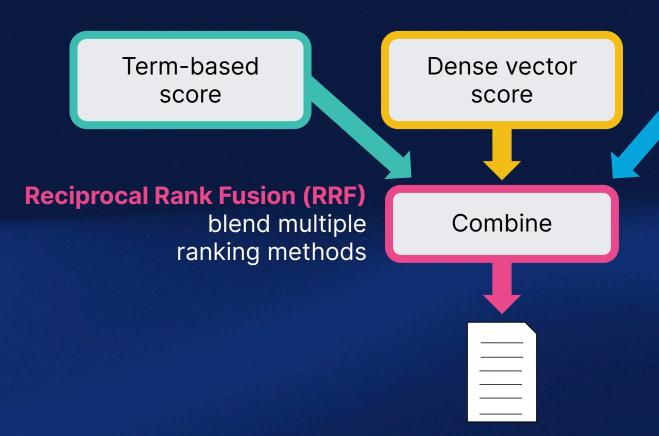
Sparse vector like BM25

Stored as inverted index





## **Hybrid ranking**



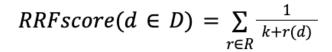
Sparse vector score



#### Reciprocal Rank Fusion (RRF)

Dense Vector							
Doc	Score	r(d)	k+r(d)				
Α	/1	1	61				
В	<b>ø</b> .7	2	62				
С	0.5	3	63				
D	0.2	4	64				
E	0.01	5	65				

BM25							
Doc	Score	r(d)	k+r(d)				
С	1,341	1	61				
Α	739	2	62				
F	732	3	63				
G	192	4	64				
Н	183	5	65				



D - set of docs

R - set of rankings as permutation on 1..|D|

k - typically set to 60 by default



Doc	RRF Score	
Α	1/61 + 1/62 = 0,0325	
С	1/63 + 1/61 = 0,0323	
В	1/62 = 0,0161	
F	1/63 = 0,0159	
D	1/64 = 0,0156	



```
GET index/ search
  "retriever": {
    "rrf": {
     "retrievers": [{
          "standard" { "query": {
              "match": {...}
          "standard" { "query": {
              "sparse vector": {...}
          "knn": { ... }
```

Commercial

Hybrid Ranking

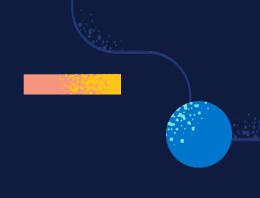


BM25f

Sparse Vector

Dense Vector

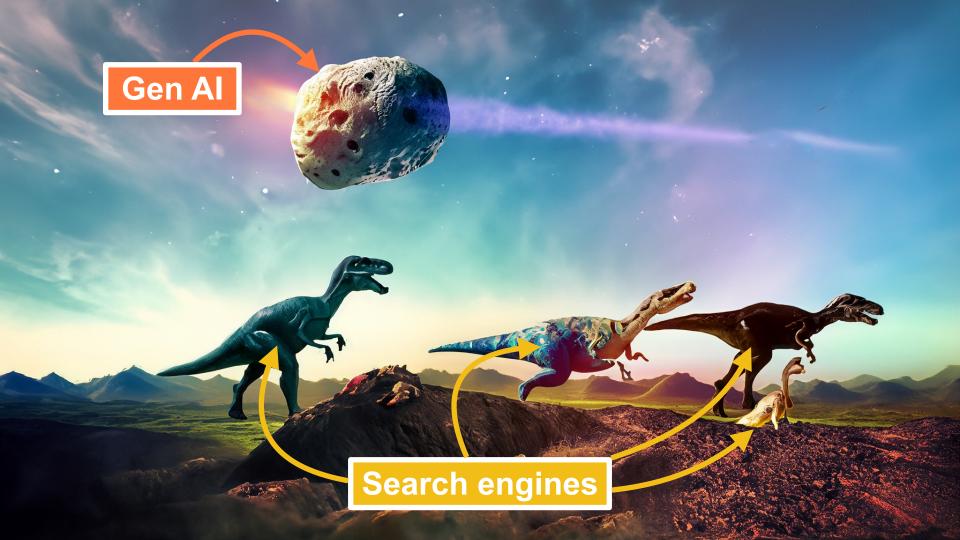




# **ChatGPT**

Elastic and LLM

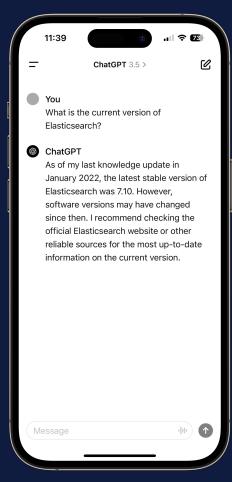


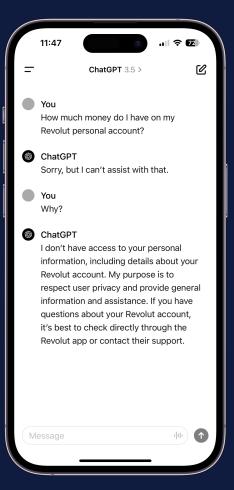


## LLM: opportunities and limits



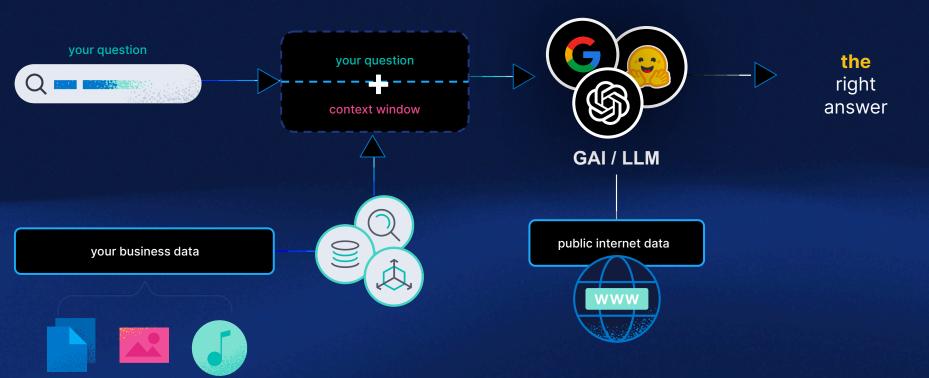








## Retrieval Augmented Generation



images

documents

audio





# Demo

Elastic Playground



me Transaction search Financial summary Customer support

#### Search your transactions:

This search is not enabled by Elastic and reflects the kirt of functionality available to customers today.

#### Submit

Date	Account	Description	Value	Opening balance	Closing balance
18/06/24	EL03-130981-Transmission	Inbound payment made from EL03-130981-Transmission, St.james's Plac (STJ): 864dce1b-bb95-47d5-87dd- 7d02f3b10c3f	7419.0	-825.0	6594.0
18/06/24	EL03-130981-Transmission	Purchase at merchant: Southeastern Grocers, LLC, location: Fayetteville,AR	82.0	6594.0	6512.0
18/06/24	EL03-130981-Transmission	Purchase at merchant: Müller Holding Ltd. & Co. KG, location: Glendale, AZ	188.0	6512.0	6324.0
17/06/24	EL03-130981-Transmission	Payment made from EL03-130981-Transmission to Elwood Erickson, Mitie Grp. (MTO): d37085fc-1382-4593-9cb8-26e5526bd9a0	533.0	20.0	-513.0
17/06/24	EL03-130981-Transmission	Payment made from EL03-130981-Transmission to Classie Johns, Barclays (BARC): 75b603a2-1c1b-45e9-a7ec- 4a551bf98a8d	312.0	-513.0	-825.0
16/06/24	EL03-130981-Transmission	Purchase at merchant: E-MART Inc., location: Fayetteville,AR	31.0	51.0	20.0
14/06/24	EL03-130981-Transmission	Purchase at merchant: Dick's Sporting Goods, Inc., location: Montgomery,AL	182.0	329.0	147.0
14/06/24	EL03-130981-Transmission	Purchase at merchant: Valor Holdings Co., Ltd., location: Louisville,KY	96.0	147.0	51.0
13/06/24	EL03-130981-Transmission	Purchase at merchant: The Save Mart Companies, location:	34.0	363.0	329.0



# Elasticsearch

You Know, for **Semantic** Search





# Search a new era

David Pilato | @dadoonet



Part of Accenture