

La recherche à l'ère de l'IA

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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 not 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.



are
not
the
droids
you

These

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
```



锅 elastic

"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









You Know, for Search







You Know, for **Vector** Search







What is a **Vector**?









Embeddings represent your data Example: 1-dimensional vector

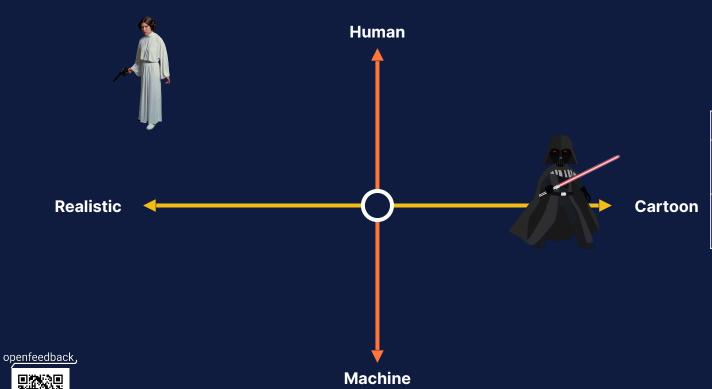


Character	Vector
1	[-1]
	[1]





Multiple dimensions represent different data aspects

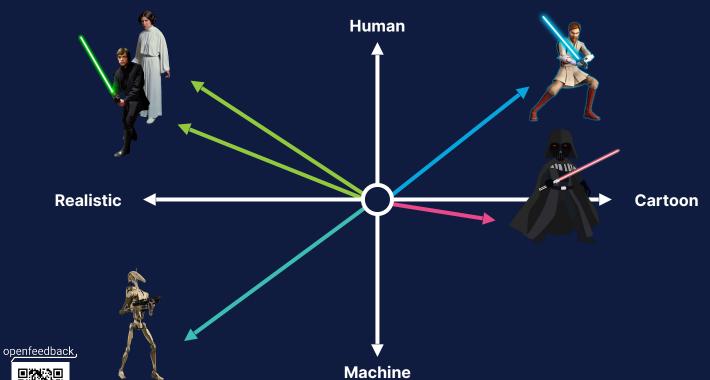


Character	Vector
	[-1,1]
41111	[1,0]





Similar data is grouped together

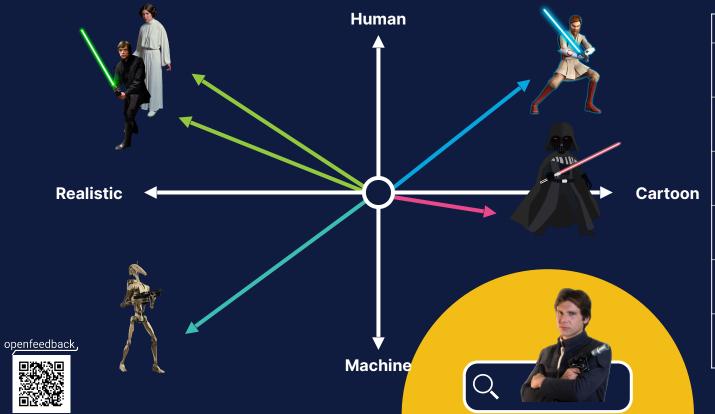


Character	Vector
	[-1.0, 1.0]
anin.	[1.0, 0.0]
, in the second	[-1.0, 0.8]
×	[1.0, 1.0]
₹ The state of th	[-1.0, -1.0]





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



Rank	Result
Query	
1	
2	
3	
4	
5	





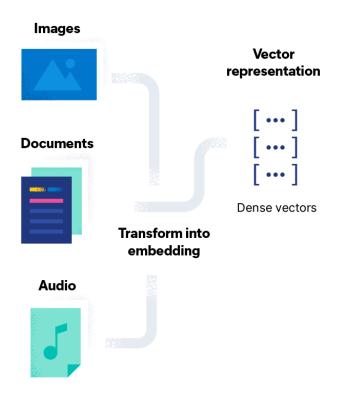
How do you

index vectors?





Architecture of Vector Search



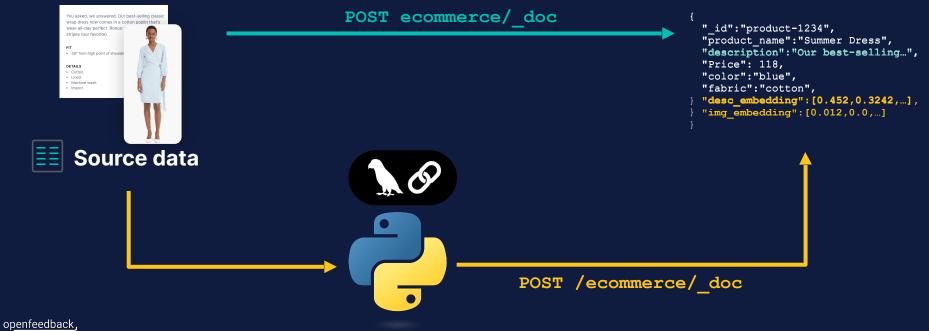
dense_vector field type

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





Data Ingestion and Embedding Generation







With Elastic ML





Source data

openfeedback

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

T /ecommerce/ doc
```



```
## ML Inference pipelines

Inference pipelines will be run as processors from the Enterprise Search Ingest Pipeline

ml-inference-embedding-generation

• Deployed pytorch text_embedding

ml-inference-emational-analysis

• Deployed pytorch text_classification

Learn more about deploying ML models in Elastic ☑
```

```
"_id":"product-1234",

"product_name":"Summer Dress",

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

"Price": 118,

"color":"blue",

"fabric":"cotton",

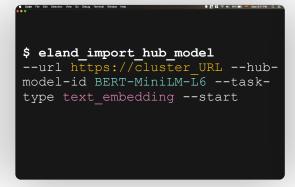
"desc_embedding":[0.452,0.3242,...]
```

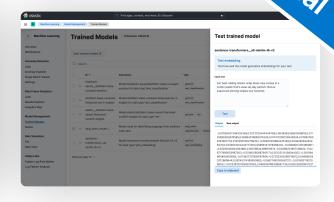


Comm

Eland Imports PyTorch Models















Select the appropriate model

Load it

Manage models

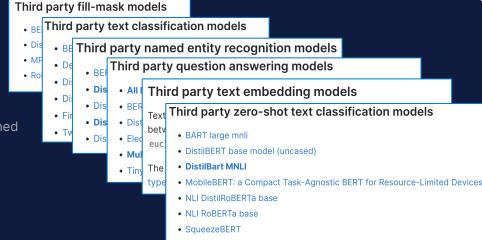


ommerci

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









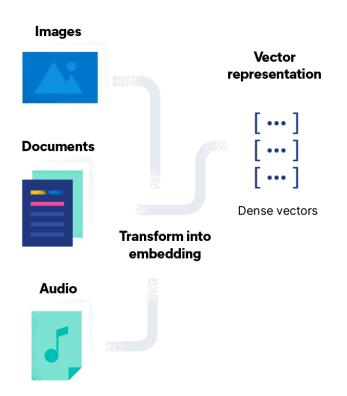
How do you

search vectors?





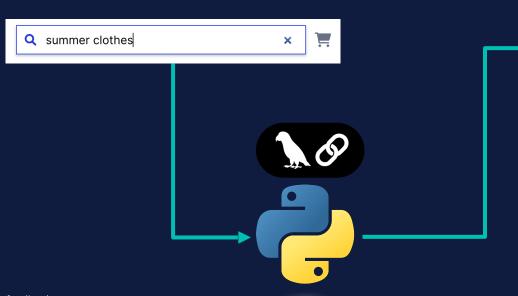
Architecture of Vector Search







knn query



```
GET ecommerce/_search
 "query" : {
    "bool": {
      "must": [{
         "knn": {
           "field": "desc embbeding",
           "query vector": [0.123, 0.244,...]
      }],
      "filter":
        "term": {
          "department": "women"
  "size": 10
```

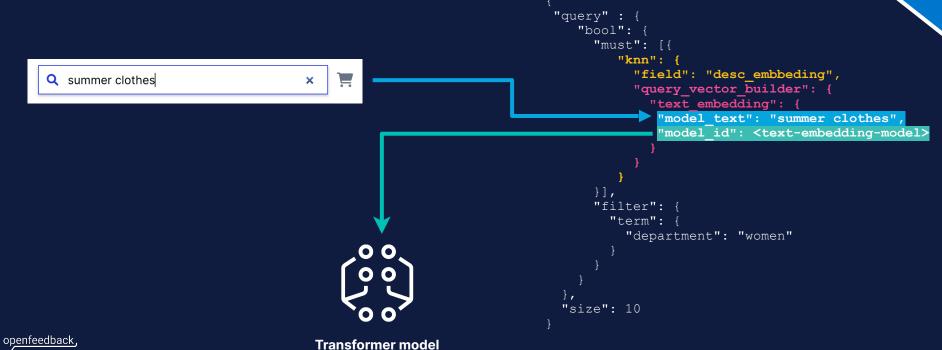
openfeedback,





Commercial Commercial

knn query (with Elastic ML)



GET ecommerce/ search





semantic_text field type

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

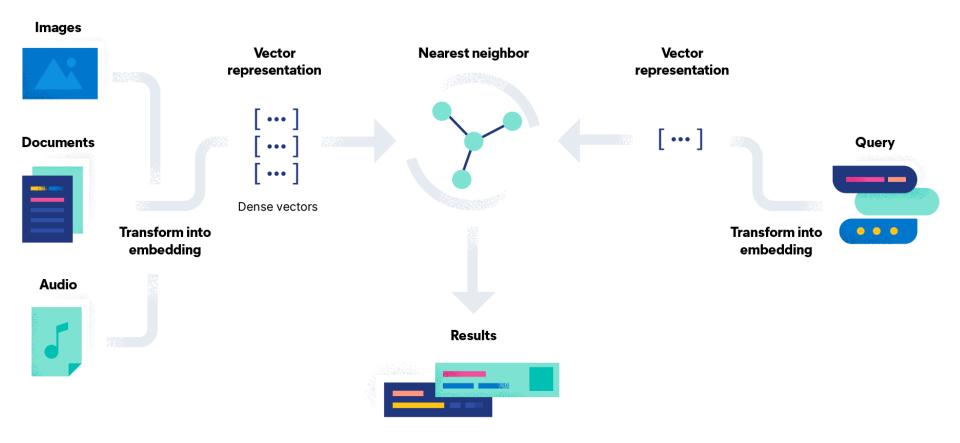
```
PUT ecommerce
{
    "mappings": {
        "properties": {
            "type": "text",
            "copy_to": [ "desc_embedding" ]
        }
        "desc_embedding": {
            "type": "semantic_text",
            "inference_id": "e5-small-multilingual"
        }
    }
}
```

```
POST ecommerce/_doc
{
    "description": "Our best-selling..."
openfeedback,
```



```
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







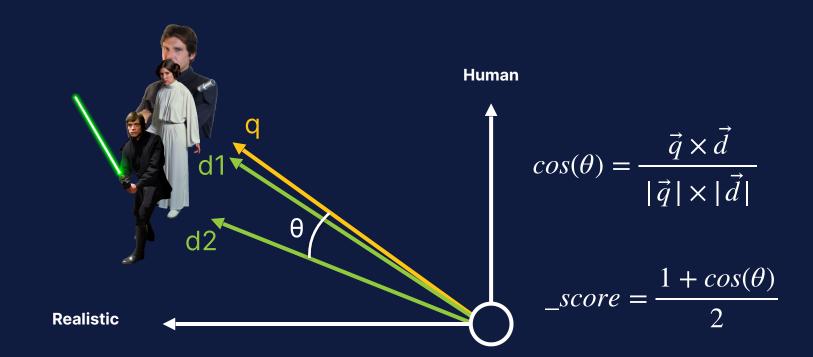


really work?





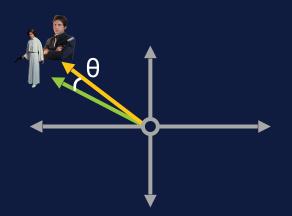
Similarity







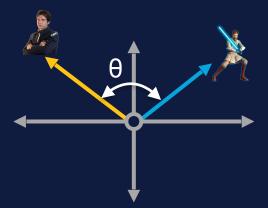
Similarity: cosine (cosine)



Similar vectors

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

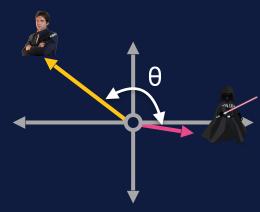
$$_score = \frac{1+1}{2} = 1$$



Orthogonal vectors

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

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



Opposite vectors θ close to 180° $cos(\theta)$ close to -1

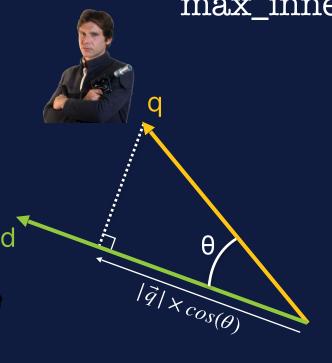
$$_score = \frac{1-1}{2} = 0$$







Similarity: Dot Product (dot_product or max_inner_product)



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

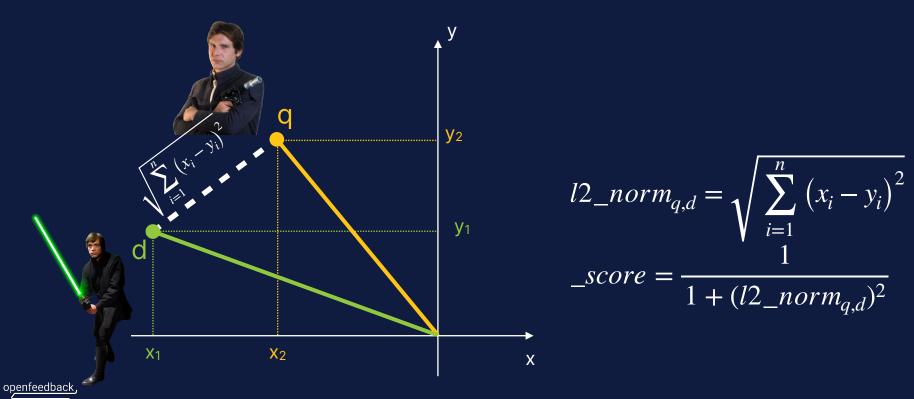
$$_score_{float} = \frac{1 + dot_product(q, d)}{2}$$

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





Similarity: Euclidean distance (12_norm)







Brute Force



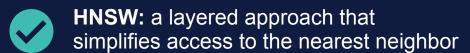


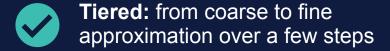




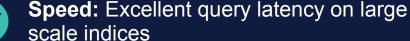
Hierarchical Navigable Small Worlds (HNSW)

One popular approach





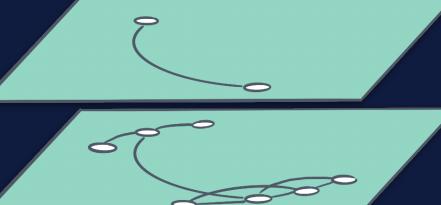












Scaling Vector Search

Vector search

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

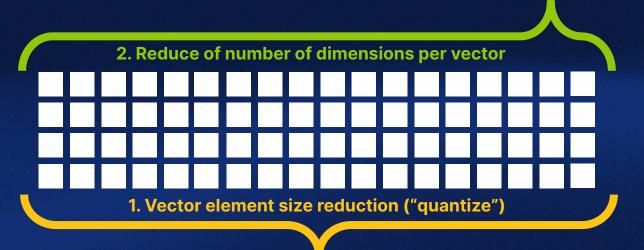
Best practices

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



^{*} Continuous improvements in Lucene + Elasticsearch

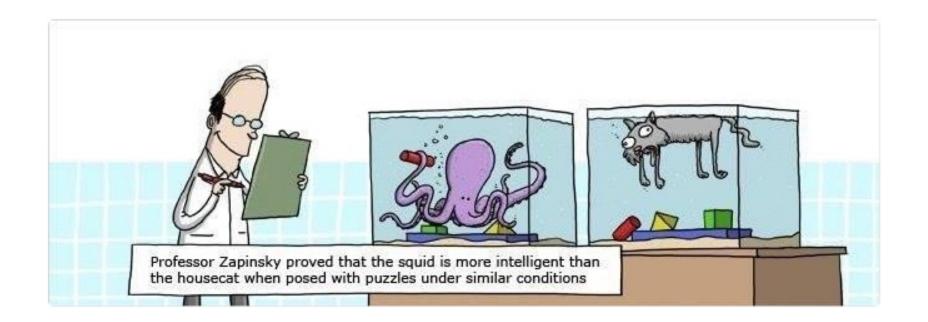
Reduce Required Memory







Benchmarketing









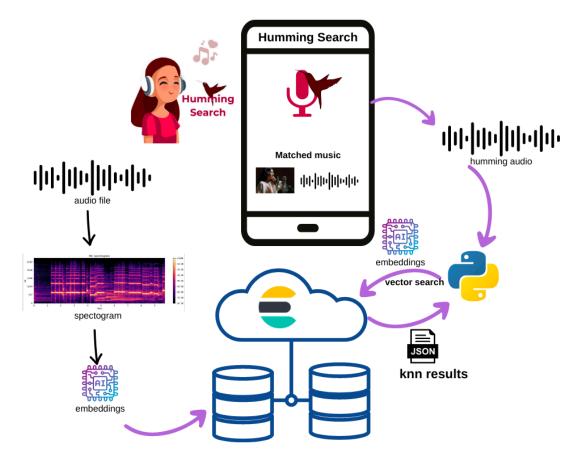
https://djdadoo.pilato.fr/











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



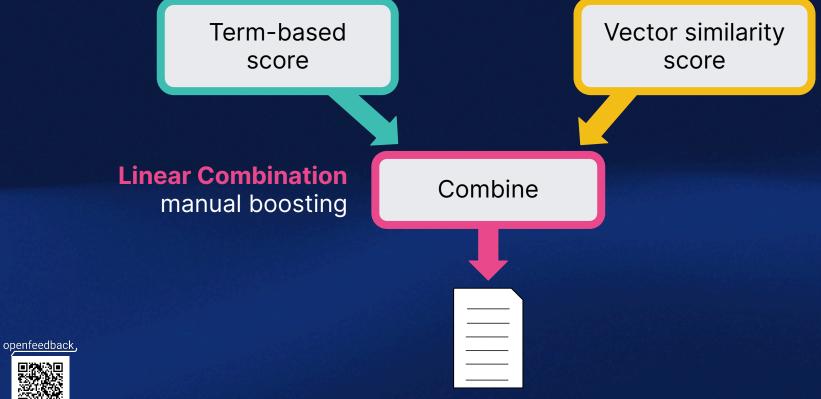


You Know, for **Hybrid** Search





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, ... }
openfeedback
```

ELSER

Elastic Learned Sparse EncodER

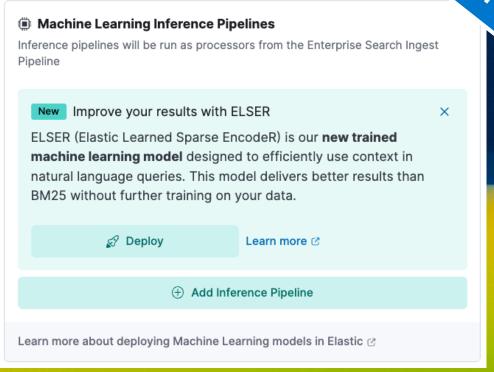
commercial commercial

sparse_vector

Not BM25 or (dense) vector

Sparse vector like BM25

Stored as inverted index





Hybrid ranking

Term-based score

Dense vector score

Sparse vector score

Reciprocal Rank Fusion (RRF)
blend multiple
ranking methods

Combine

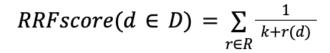




Reciprocal Rank Fusion (RRF)

Dense Vector							
Doc	Score	r(d)	k+r(d)				
Α	h	1	61				
В	ø .7	2	62				
С	0.5	3	63				
D	0.2	4	64				
E enfeedback	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": { ... }
openfeedback
```

Commun.

Hybrid Ranking

BM25f

Sparse Vector

.

Dense Vector





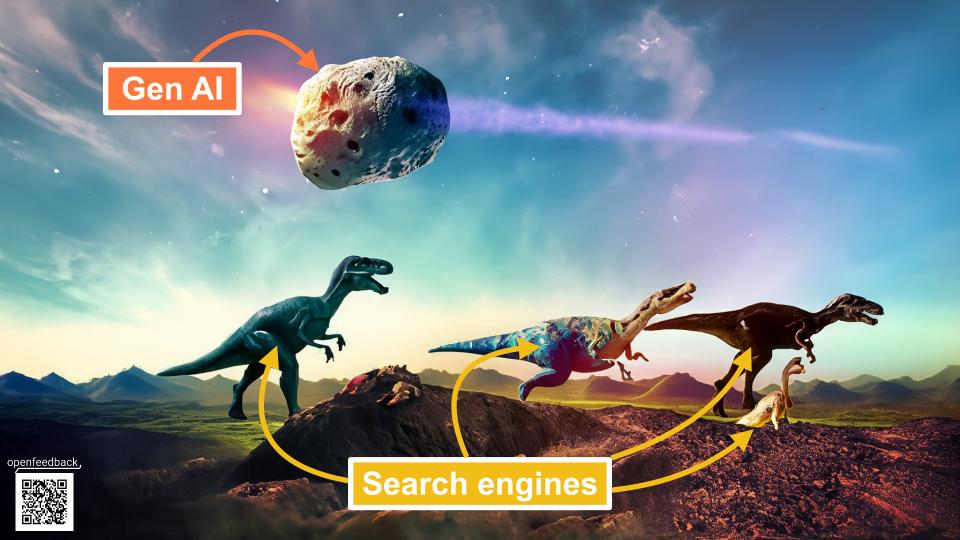


ChatGPT

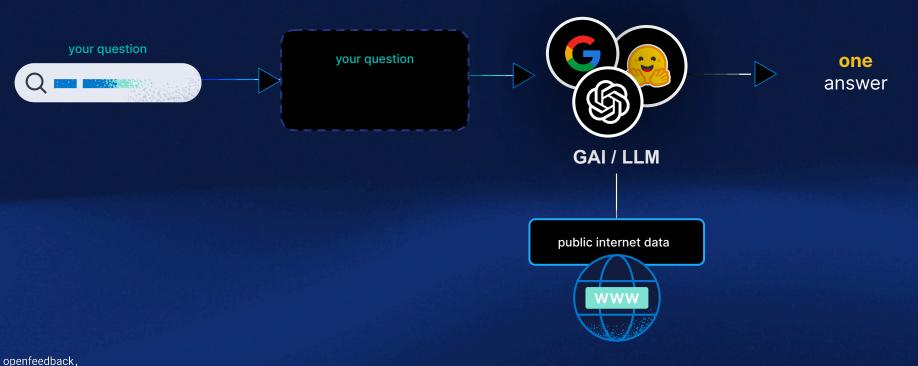
Elastic and LLM





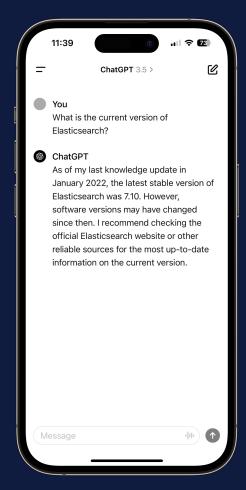


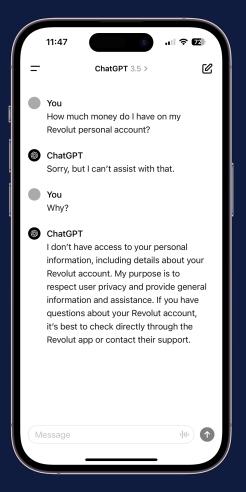
LLM: opportunities and limits









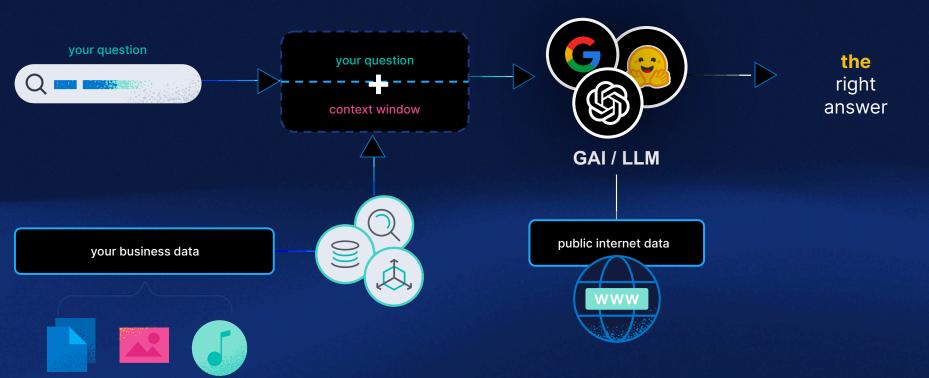








Retrieval Augmented Generation

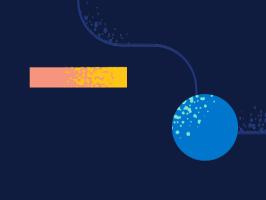


images

documents

audio





Demo

Elastic Playground





Home

Online banking

Enviroment setup

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

openfeedback,







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