Hybrid Search

Optimizing the R in RAG

Apr 16, 2025

Can’t cover in 45 mins...

1. How lexical search actually works (ask chat GPT about: inverted index, read “Relevant Search” 😉)

2. What is an embedding

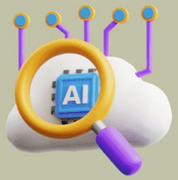
3. Lexical scoring, vector scoring (cosine, euclidean, etc similarities) etc

   Intuitive sense of “close” good enough for today :)

capella

	Traditional Keyword Search	Vector Search
Method	Matches exact words or phrases	Transforms text, audio, and images into numeric representations and matches based on meaning, intent, and context
Speed	May slow down with large and varied data	Fast, even on large and varied data
Relevance of Results	Limited by exact word or phrase match	Highly relevant due to understanding of context and meaning
Flexibility	Primarily text-based search	Enables new classes of search for text, image, and audio

VS



	Traditional (Keyword) Search	Vector Search
SEARCH APPROACH	Keyword-based matching	Semantic/meaning-based matching using vector embeddings
AMBIGUITY HANDLING	Struggles with synonyms, ambiguous language, fuzzy queries	Handles synonyms, ambiguous language, fuzzy queries
SEARCH RELEVANCE CALCULATION	BM25, TF-IDF	Jaccard Similarity, Cosine Similarity, and L2 Distance
SEARCH QUALITY	Depends on exact keyword matching	Semantic relationships => better handles broad queries
SPEED AND IMPLEMENTATION	Fast for simple queries, easy implementation, straightforward usage	Slightly slower, more complicated to implement (if ANN is used)
SCALIBILITY	Challenged by the continuous expansion of content	Better handles huge datasets
COST	Low computational requirements => lower cost	High computational requirements (without ANN) => higher cost

Traditional search vs. vector search

	Traditional (Keyword) Search	Vector Search
SEARCH APPROACH	Matches the exact keywords.	Finds related objects that share similar characteristics.
AMBIGUITY HANDLING	Struggles with ambiguous language and synonyms.	Uses machine learning models to handle synonyms and ambiguous language.
RELEVANCE	Works well for precise queries.	Superior for broad or fuzzy queries.
SPEED AND SCALABILITY	Fast, scales well due to simple index reading.	Less efficient and struggles with scaling due to complex vector calculations.
SEARCH QUALITY	Mostly depends on exact keyword matching.	Uses semantic relationships, thus better handling of broad queries.
COST	Generally less due to lower computational requirement.	Usually higher due to the need for more computing power.

Lexical Search

Key Points:

- **Definition:** Finds documents with exact query words.
- **Core Structure:** Inverted Index → term → list of doc IDs.
  - Example: `"apple"` → [Doc2, Doc5, Doc9]
- **Process:**
  - Tokenize query
  - Lookup tokens in index
  - Retrieve matching docs
  - Apply scoring
- **Scoring Methods:**
  - **TF-IDF:** Weighs term frequency × rarity
  - **BM25:** Length normalization + term frequency saturation
- **Pros:** Fast, explainable
- **Cons:** No semantic understanding (“phone” ≠ “mobile”)

Vector Search

Key Points:

- **Definition:** Matches based on semantic meaning, not exact words.
- **Embedding:** Vector representation of meaning
  - Similar meaning → vectors close together
  - Example: `"dog"` ≈ `"puppy"`, far from `"laptop"`
- **Embedding Generation:** Word2Vec, GloVe, Transformers, etc.
- **Vector Scoring Methods:**
  - **Cosine Similarity:** Angle between vectors
  - **Euclidean Distance:** Straight-line distance
  - **Dot Product:** Magnitude + direction
- **Pros:** Finds synonyms, concept matches (“TV” ≈ “television”)
- **Cons:** Needs embedding computation, slower than lexical search

Also won't cover

1. RRF - Reciprocal Rank Fusion

RRF is Not Enough

NOVEMBER 3RD, 2024

Hybrid search means combining lexical and vector search results into one result listing.

"We'll just use Reciprocal Rank Fusion" I'm sure I've said from time to time.

As if RRF is kind of "a miracle occurs". You get the best of both worlds, and suddenly your search looks incredible.

Take the query `hello to the planet`. Let's say we start with reasonable results from a vector search system (follow along in this notebook)

vector_sim	texts	vector_rank

Assumption: embeddings good first pass search

Embeddings get you *close* but not all the way

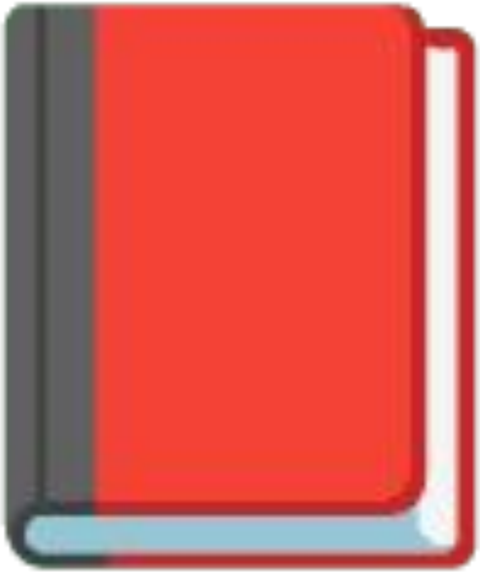
ID	Title	Vector (256? 512? Or more dimensions)
0	mary had a little lamb	[0.9, 0.8, -0.5, 0.75, ..]
1	mary had a little ham	[0.6, 0.4, -0.4, 0.60, ..]
2	a little ham	[-0.2, 0.5, 0.9, -0.45, ..]
3	little mary had a scam	[0.4, -0.5, 0.25, 0.14, ..]
4	ham it up with mary	[0.2, 0.5, 0.2, 0.45, ..]
5	Little red riding hood had a baby sheep?	[0.95, 0.79, -0.49, 0.65, ..]

Similar!

(despite sharing few terms)

Chunked

You’ve chunked your data into a meaningful “search document” with important metadata:



```
{
    “Book_title”: “Nursery Rhymes”
    “Section”: “Mary Had a Little
    Lamb”
    “Text”: “...”

}
```

Embedding for *whole document*

We want an embedding capturing as much of the document as is reasonable

```
text_concatted = data['product_name'] + ' -- ' + data['product_description']
embedding = model.encode(text_concatted)
```

(Not just a title embedding)

Embedding is ~ two-towerable

Short text (ie queries) and long text (paragraphs) can be mapped in similarity space

QUERY: Kid story about sheep

Document:

Mary had a little lamb, little lamb, little lamb.

Mary had a little lamb, its fleece was white as snow.

And everywhere that Mary went. Mary went. Mary went.

And everywhere that Mary went, the lamb was sure to go.

It followed her to school one day, school one day, school one

Similar

Bonus: embedding is a two tower model!

Query Features

- Query embedding
- Query

Document Features

- Name
- Description
- Product image embedding
- ???

(Biencoder,
learned on
labeled data)

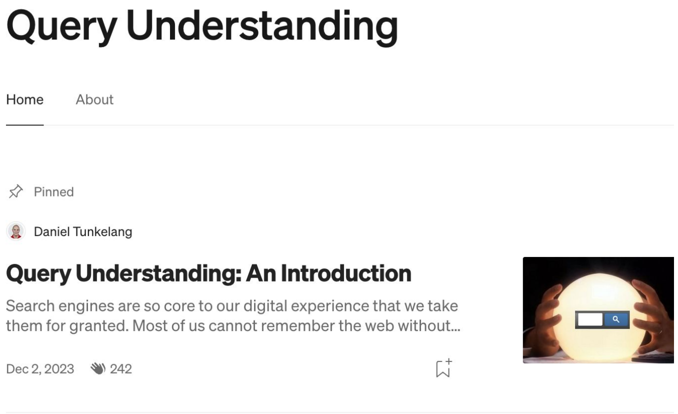
After embedding we boost/rerank/...

Exact name match?

- Move these to the top!

Query mentions color?

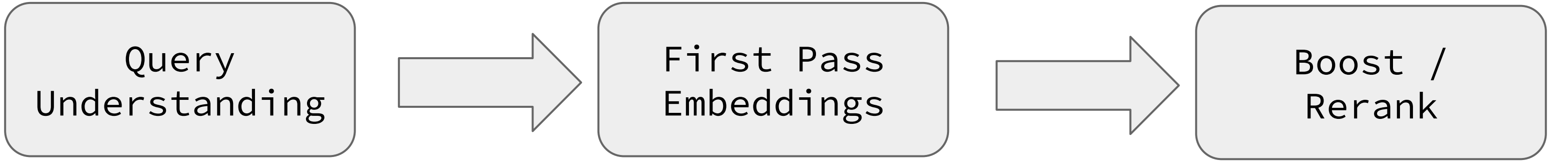
- Ensure color matches boosted



(Different query types == different treatments!)

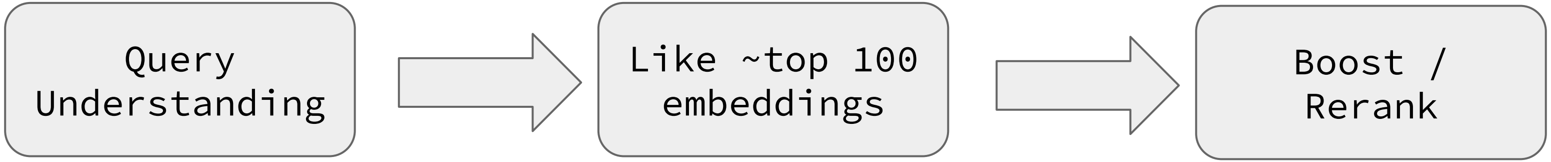
http://queryunderstanding.com

Ideal:

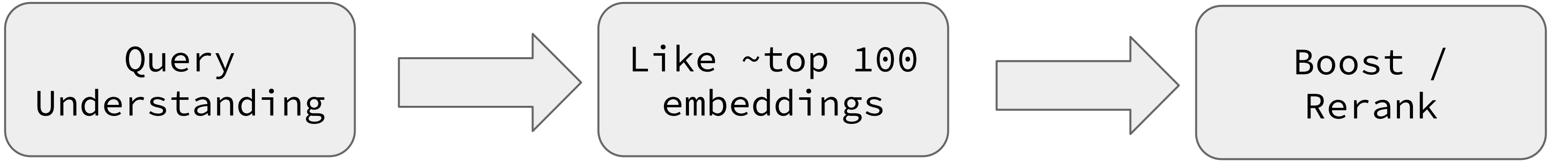


(depending on needs of query)

Reality:

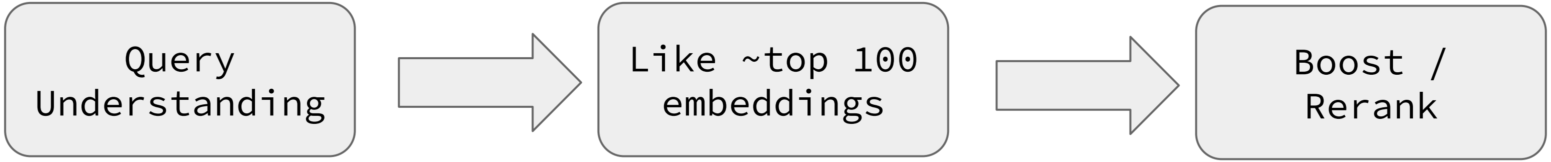


Reality:



(Do we have the right
top 100 to boost?)

Reality:

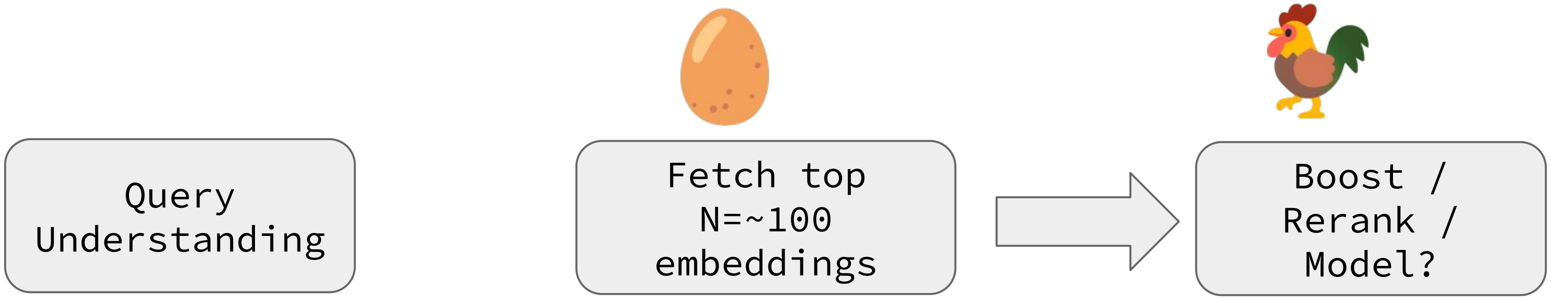


Need to filter this to
“good” 100 or so

Chicken and egg problem:

If I want to boost exact product name matches here..

Chicken and egg problem:



Must retrieve good product name matches from vector index…

…if I want to boost exact product name matches here

Chicken and egg problem:

The good product name matches better be in the candidates!

~2021 vector DB

```
SELECT * FROM <search_engine>
```

No WHERE!

👎 Can't guarantee product name matches promoted

```
ORDER BY vector_similarity(query_embedding, title_embedding)
LIMIT 100
```

2025 vector DB (search engine)

```
SELECT * FROM <search>

WHERE [trowel] in product_name

     ...

ORDER BY vector_similarity(query_embedding, title_embedding)
LIMIT 100
```

BEFORE vector_similarity
Get candidates matching
“trowel”

👍 Now I have matches!

~2025 era vector DB (search engine)

```
SELECT * FROM <search>

WHERE [trowel] in product_name

    ...

ORDER BY vector_similarity(query_embedding, title_embedding)
LIMIT 100
```

BEFORE vector_similarity
Get candidates matching
“mary”

🚨 *How does your vector DB **pre**-filter? Can you do this at scale?*

… and “where” could be *anything*

Search for “garden trowel”

```
SELECT * FROM <search>
WHERE “lawn_and_garden” in department
     AND “trowel” in item_type
     AND (garden in title OR garden in description OR
          trowel in title OR trowel in description)
ORDER BY vector_similarity(query_embedding, title_embedding)
LIMIT 100
```

Somehow we turn the query to this dept / item type

… and “where” could be *anything*

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ORDER BY vector_similarity(query_embedding, title_embedding)
LIMIT 100
```

And also match query terms in tokenized title/description

… and “where” could be *anything*

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```

And also match query terms

(yes you search nerds, I’m ignoring BM25 and lexical scoring for now)

Practically: there’s a vector index

We can reasonably get top K...

Search for “garden trowel”

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     AND “trowel” in item_type

     AND (garden in title OR garden in description OR

          trowel in title OR trowel in description)

ORDER BY vector_similarity(query_embedding, title_embedding)
LIMIT 100
```

Get top 100 from this set via an index
(otherwise we scan all results to score them)

There’s more than one “top K” we care about

What about “pure” vector matches?

```
SELECT * FROM <search>

WHERE “lawn_and_garden” in department

     AND “trowel” in item_type

     AND (garden in title OR garden in description OR

          trowel in title OR trowel in description)

ORDER BY similarity(query_embedding, title_embedding)
LIMIT 100
```

100 from this set

```
UNION ALL

SELECT * FROM <search>

WHERE “lawn_and_garden” in department

     AND “trowel” in item_type

ORDER BY similarity(query_embedding, title_embedding)
LIMIT 100
```

There’s more than one candidate set

What about “pure” vector matches?

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SELECT * FROM <search>

WHERE “lawn_and_garden” in department

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ORDER BY similarity(query_embedding, title_embedding)
LIMIT 100
```
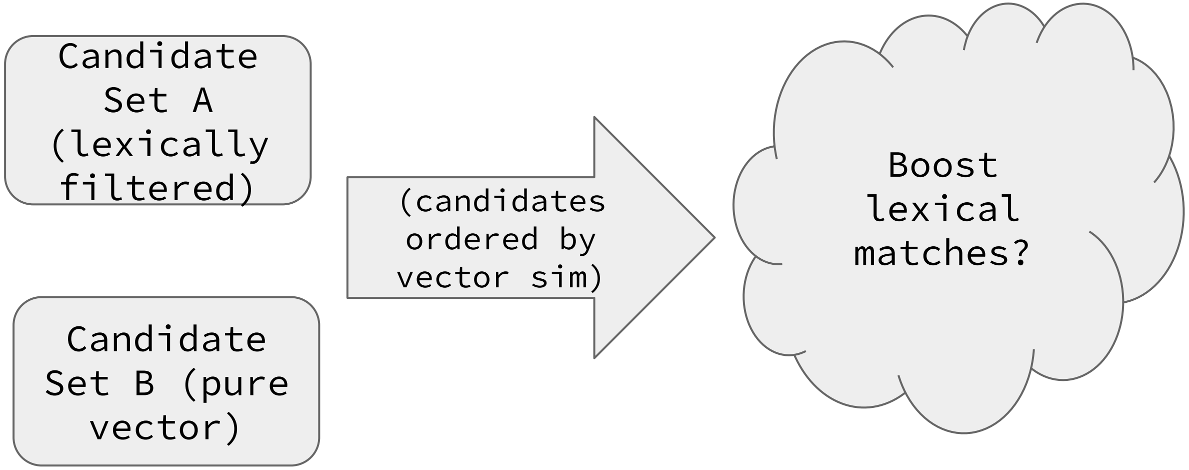
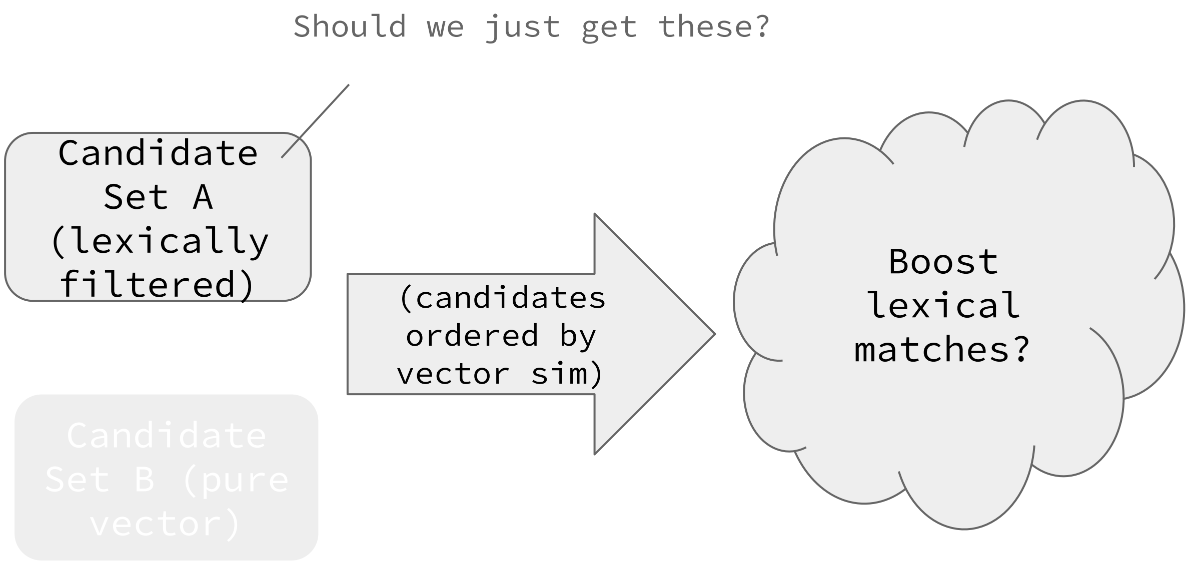

```
UNION ALL

SELECT * FROM <search>

WHERE “lawn_and_garden” in department

     AND “trowel” in item_type

ORDER BY similarity(query_embedding, title_embedding)
LIMIT 100
```

\+ 100 from this set

With squiggly lines...



Why do we do it this way?



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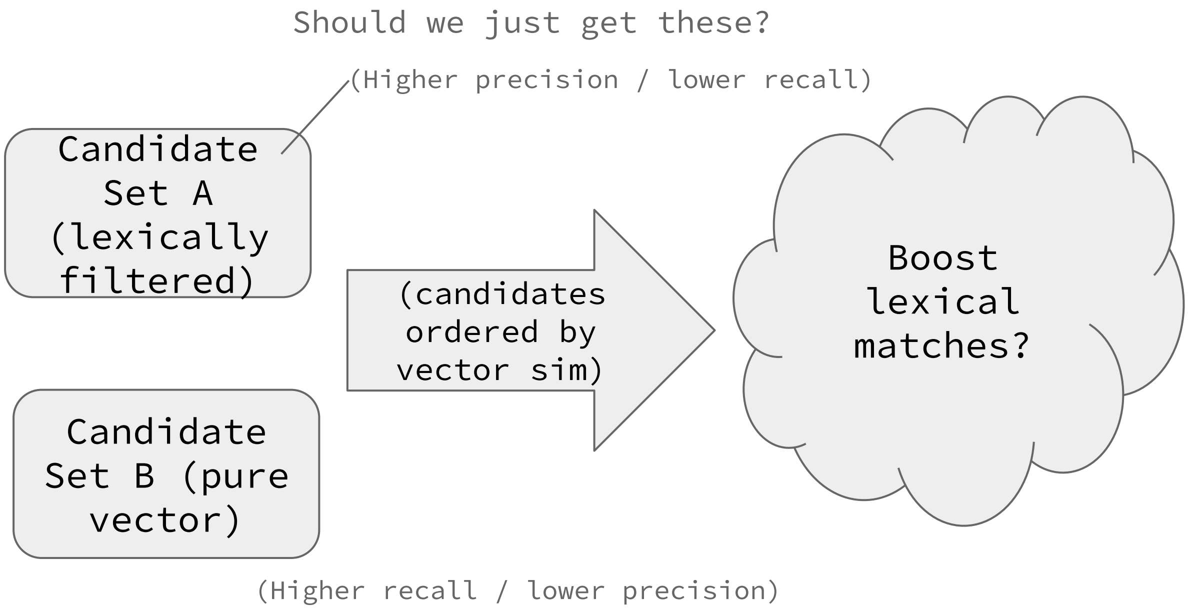
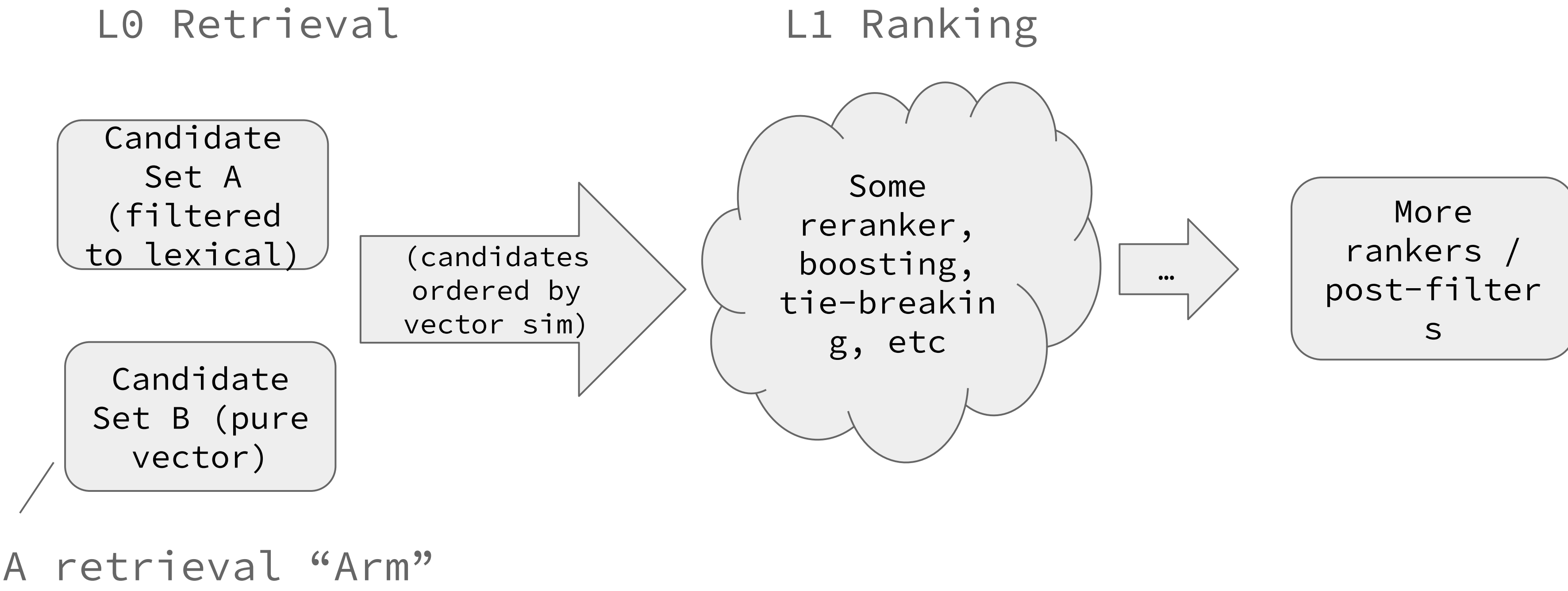
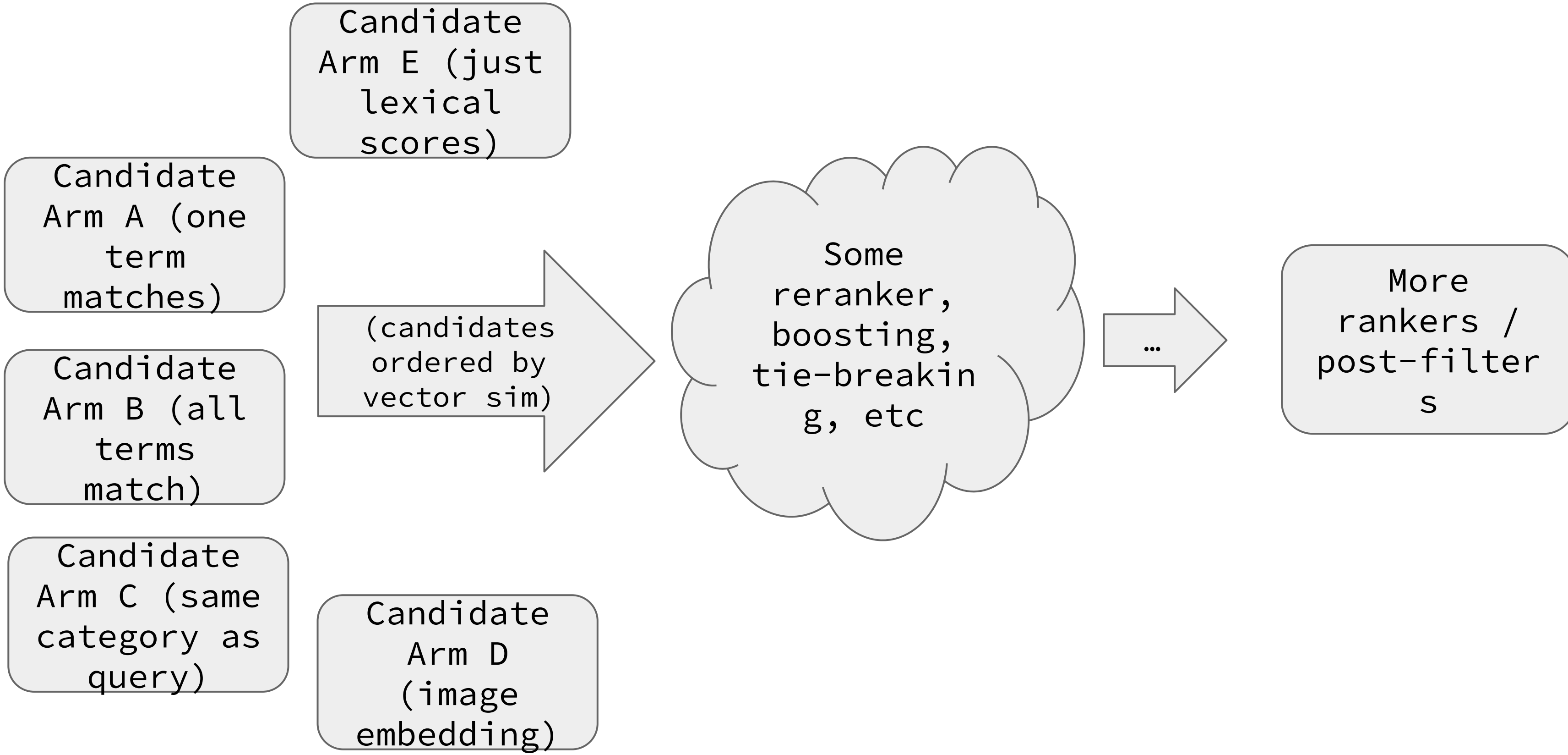


With squiggly lines…

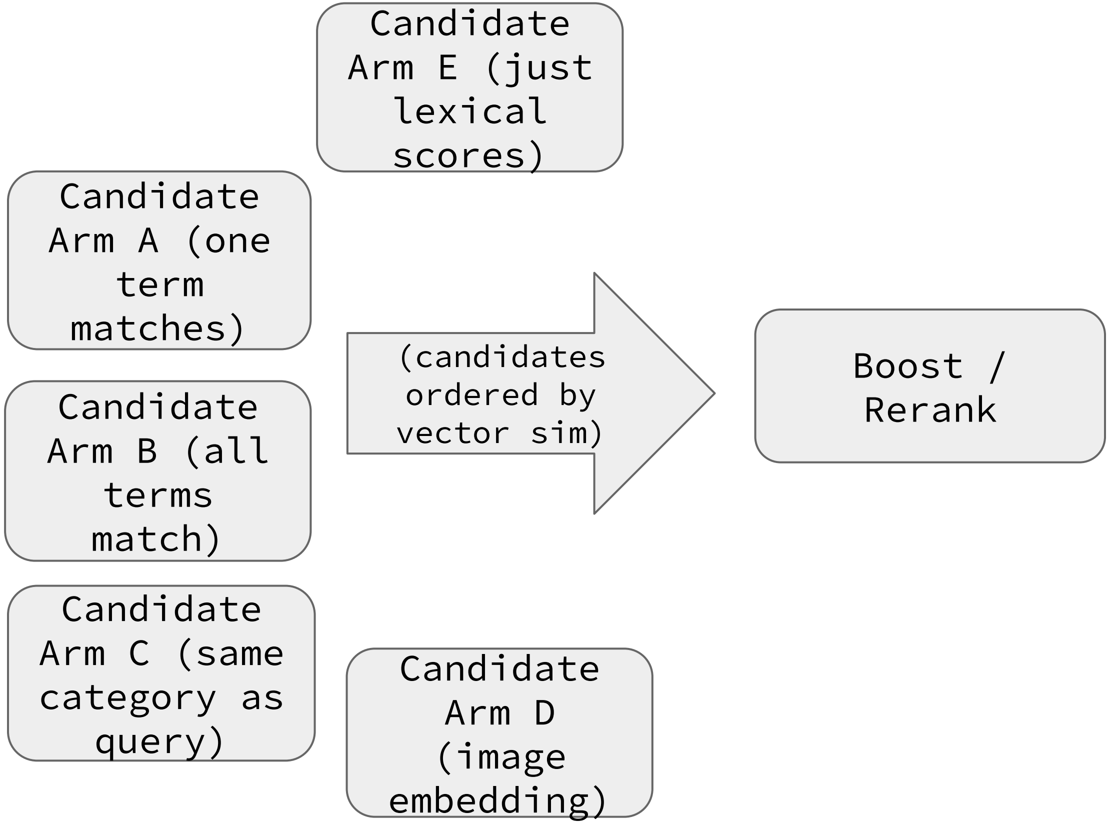


And many retrieval arms

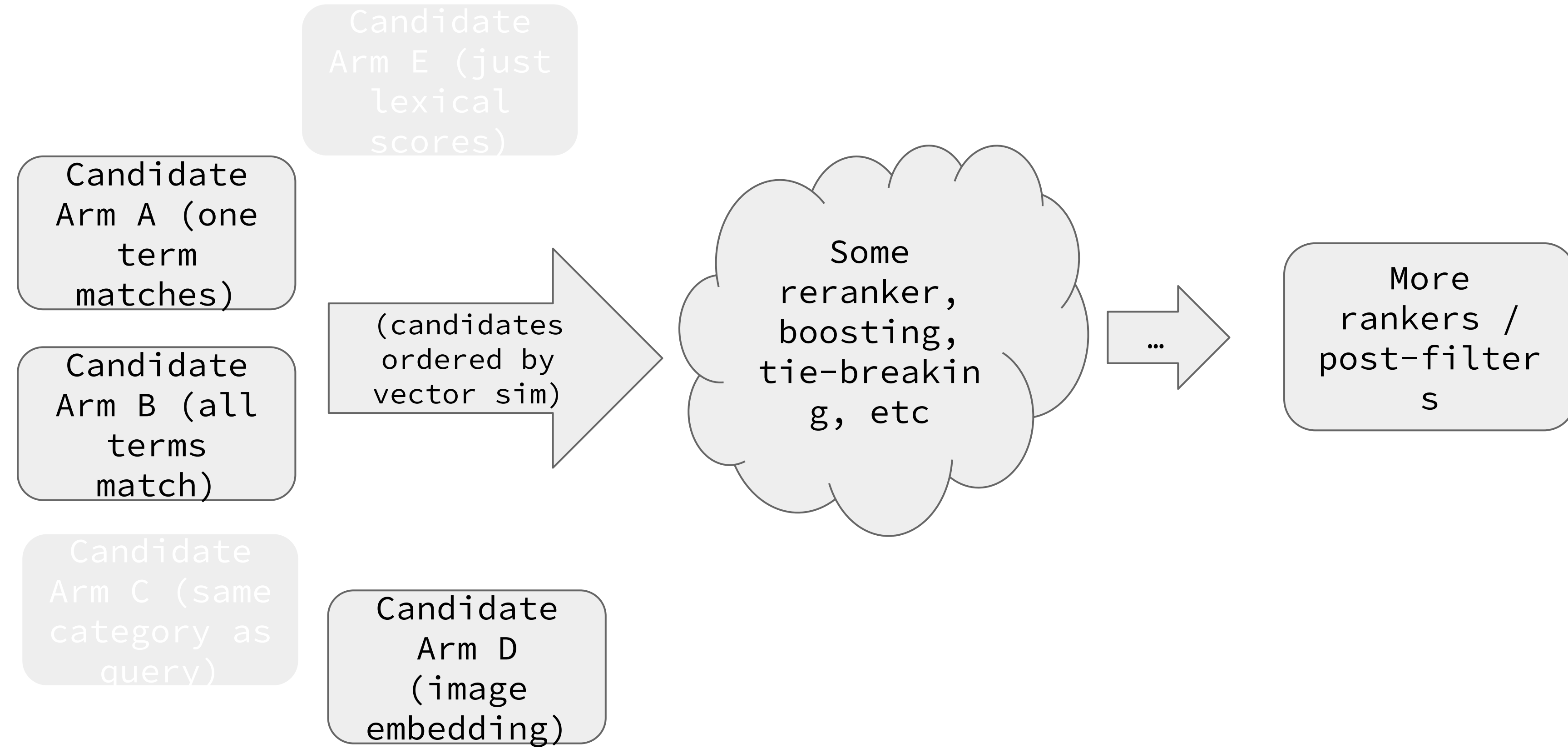


L0
Retrieval Arms
🥚🥚🥚🥚🥚

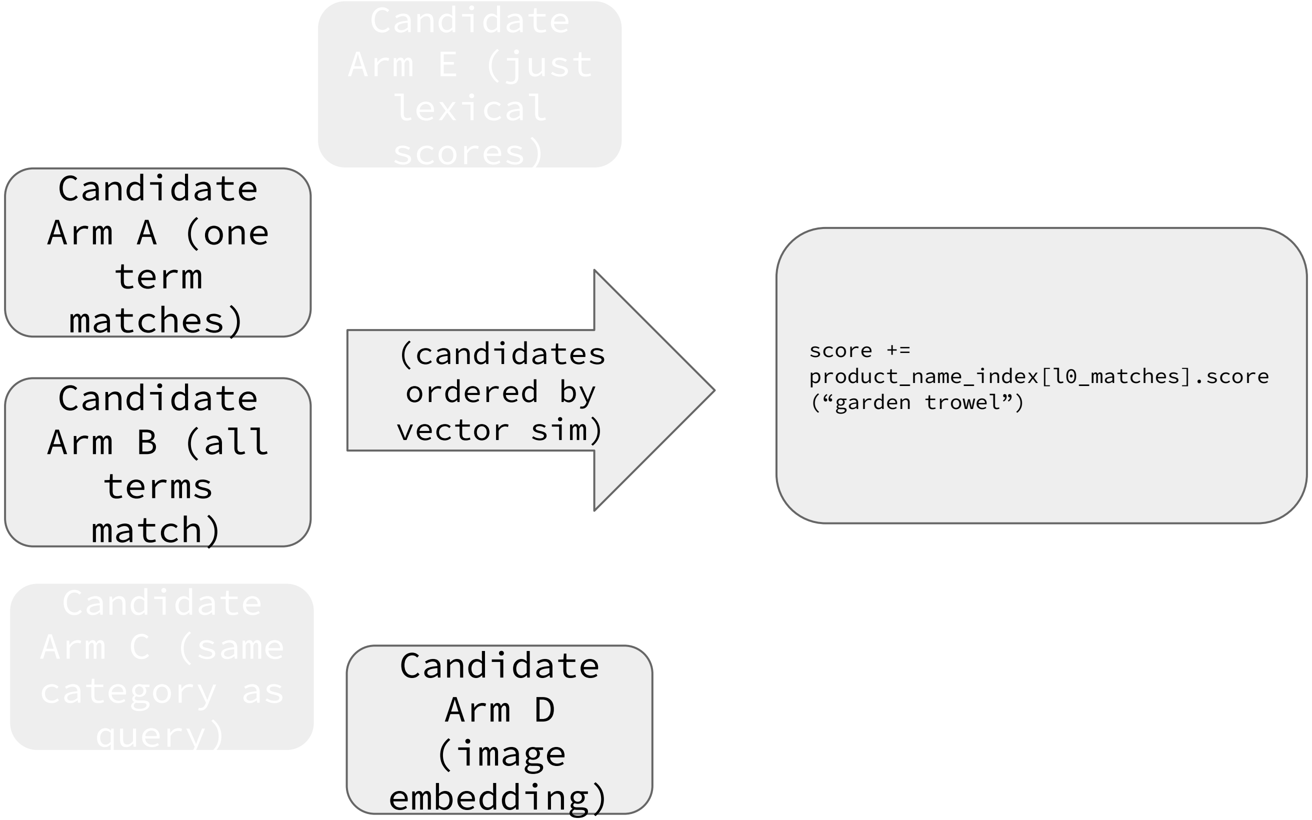
L1
boost/reranking
🐓



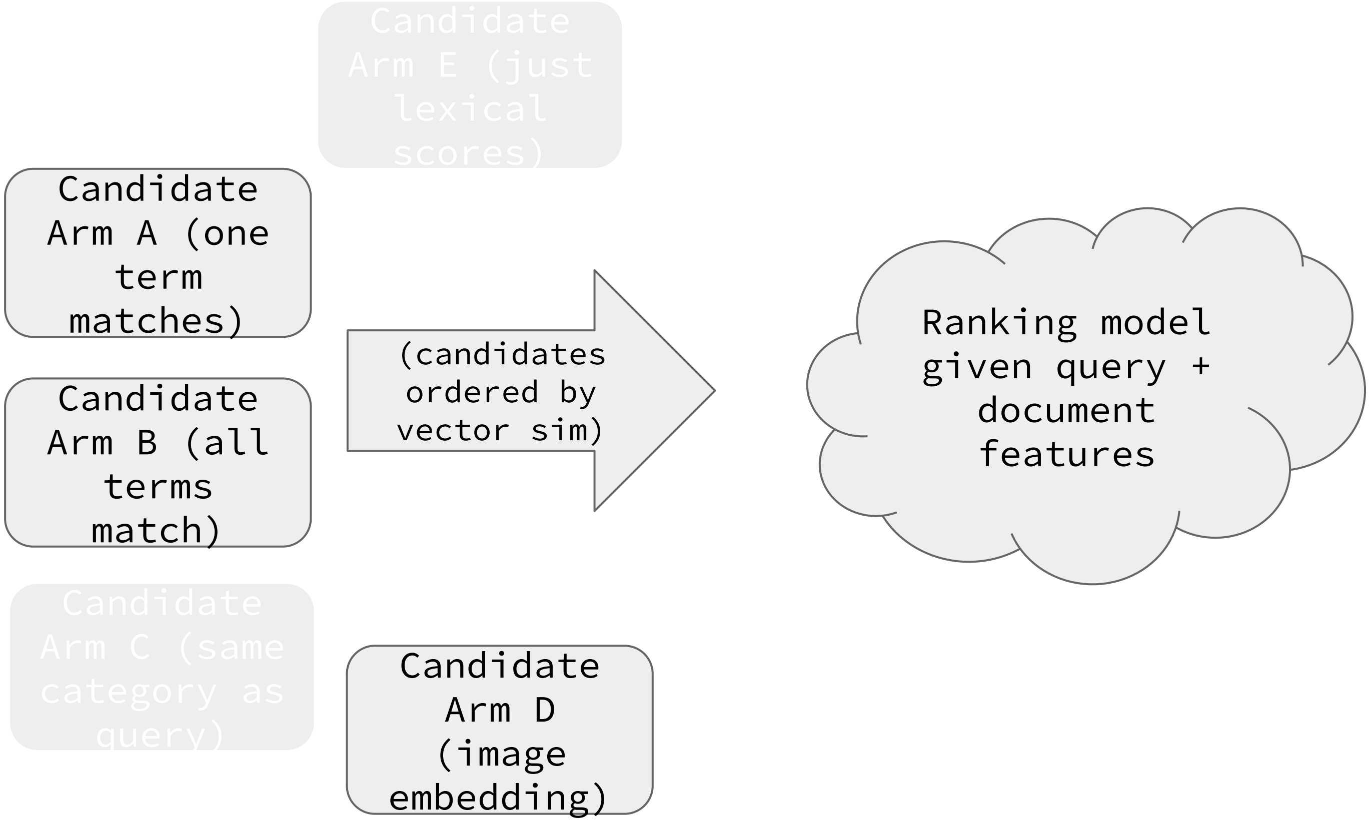
Or depending on the query



Then the boost



Or a model


Candidate Arm E (just lexical scores)
Candidate Arm A (one term matches)
Candidate Arm B (all terms match)
Candidate Arm C (same category as query)
Candidate Arm D (image embedding)
(candidates ordered by vector sim)
Ranking model given query + document features

That’s the theory at least

https://colab.research.google.com/drive/1HmWdKON-wxHMQCnig0hVA3u0-OX1I2Ph