

# Natural Language Processing - Search

Recap

## Relevant concepts

- Corpus
- Vocabulary
- Bag of words
- Similarity Measures
- Indexing
- TF-IDF
- Okapi BM25



# Natural Language Processing - Search

How to build a frequency-based search engine ?

# Natural Language Processing - Search

How to build a frequency-based search engine ?

1. Define the corpus
  - a. Define what is the 'document'
  - b. Pre-process data

# Natural Language Processing - Search

How to build a frequency-based search engine ?

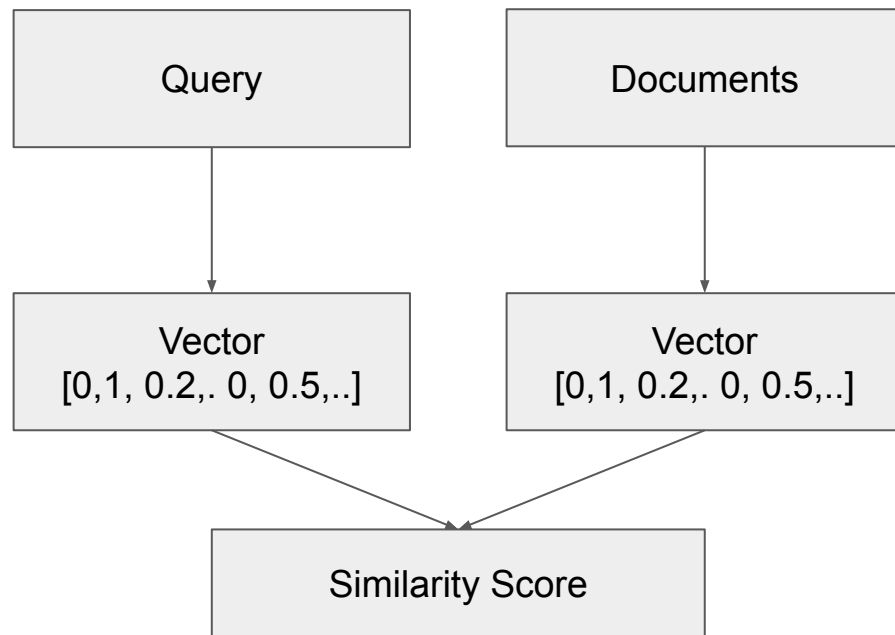
1. Define the corpus
2. Decide on retrieval algorithm
  - a. Bag-of-words + Cosine Similarity
  - b. TF-IDF + Cosine Similarity
  - c. BM25

Computers do not understand text.  
They only understand numbers.

# Natural Language Processing - Search

How to build a frequency-based search engine ?

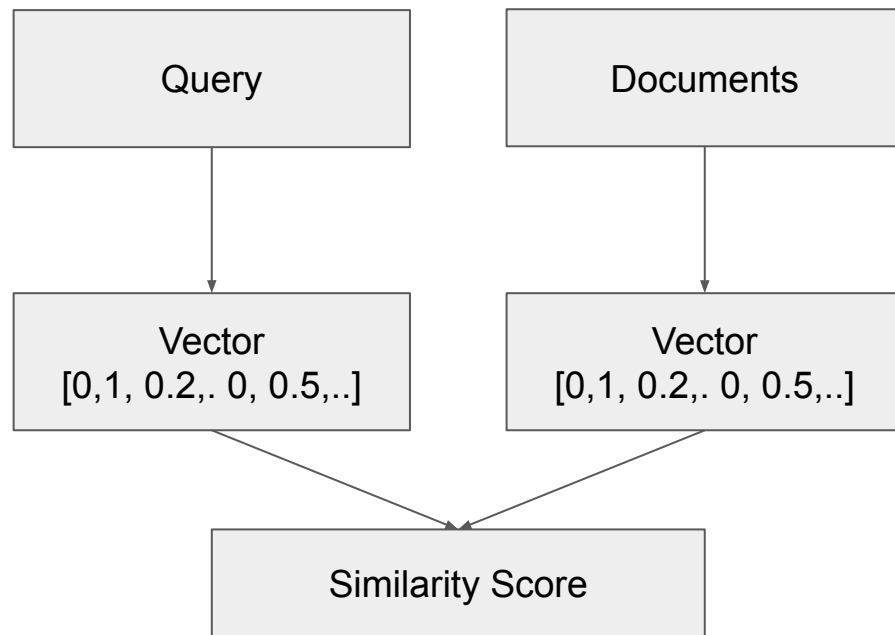
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# Natural Language Processing - Search

How to build a frequency-based search engine ?

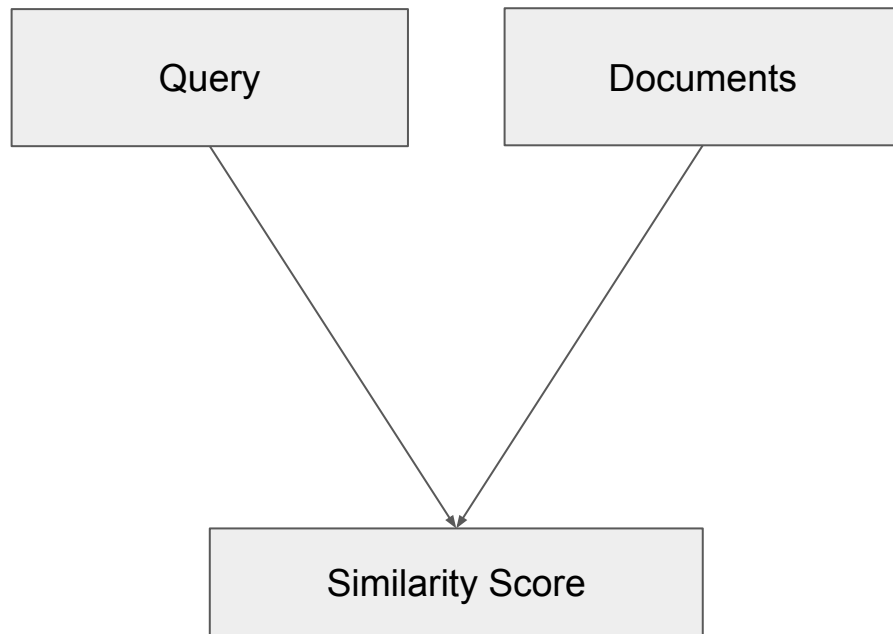
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# Natural Language Processing - Search

How to build a frequency-based search engine ?

1. Define the corpus
2. Decide on retrieval algorithm
  - a. Bag-of-words + Cosine Similarity
  - b. TF-IDF + Cosine Similarity
  - c. **BM25**



# Natural Language Processing - Search

How to build a frequency-based search engine ?

1. Define the corpus
2. Decide on retrieval algorithm
3. Index corpus
  - a. Compute count of words, per corpus and per document
  - b. Create auxiliary vectors



# Natural Language Processing - Search

How to build a frequency-based search engine ?

1. Define the corpus
2. Decide on retrieval algorithm
3. Index corpus
4. That's it

# Natural Language Processing - Search

**Let's compare them.**

How much is pre-processing important ?

How does BoW, TF-IDF and BM25 compare against each other?

# Natural Language Processing - Search

**Let's compare them.**

How much is pre-processing important ?

How does BoW, TF-IDF and BM25 compare against each other?

How can we formally compare them ?

# Natural Language Processing - Search

## Evaluation Metrics

- Precision (at K)
- Recall (at K)
- F1 Score
- NDCG

# Natural Language Processing - Search

## Evaluation Metrics

- Precision (at K)

# Natural Language Processing - Search

## Evaluation Metrics

- Precision (at K)

The diagram illustrates the components of the Precision (at K) metric. It starts with a bullet point 'Precision (at K)' on the left. An arrow points from this text to the equation 'Precision = TP / (TP + FP)' in the center. From the 'TP' in the numerator, an arrow points down to the definition of True Positives. From the 'FP' in the denominator, an arrow points down to the definition of False Positives.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

True Positives  
i.e The system  
classifies something  
as true and they are  
true

False Positives  
i.e The system classifies something as  
true and they are false

# Natural Language Processing - Search

## Evaluation Metrics

- Precision (at K)

Precision =  $TP / (TP + FP)$

All items

True Positives  
i.e The system  
classifies them as true  
and they are true

False Positives  
i.e The system classifies them as true  
and they are false

# Natural Language Processing - Search

## Evaluation Metrics

- Precision (at K)


$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

% of times the system got the true label right



# Natural Language Processing - Search

## Evaluation Metrics

- Precision (at K) is the proportion of recommended items in the top-k set that are relevant



$$\text{Precision at K} = \text{TP at K} / (\text{TP at K} + \text{FP at K})$$

# Natural Language Processing - Search

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Result A	Relevant
Result B	Relevant
Result C	Not Relevant

# Natural Language Processing - Search

## Evaluation Metrics

- Precision (at K) is the proportion of recommended items in the top-k set that are relevant



Precision at K =  $TP \text{ at } K / (TP \text{ at } K + FP \text{ at } K)$       Precision at 3 =  $\frac{2}{3} = 66\%$

Result A	Relevant
Result B	Relevant
Result C	Not Relevant

# Natural Language Processing - Search

## Evaluation Metrics

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Result A	Relevant
Result B	Not Relevant
Result C	Relevant

# Natural Language Processing - Search

## Evaluation Metrics

- Recall (at K)


$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

False Negatives  
i.e The system classifies  
something as false and they  
are true

# Natural Language Processing - Search

## Evaluation Metrics

- Recall (at K) (also known as sensitivity) is the fraction of relevant instances that were retrieved.



Recall at K =  $TP \text{ at } K / (TP \text{ at } K + FN \text{ at } K)$   
Relevant items = 5

Recall at 3 =  $2/2 = 100\%$

Result A	Relevant
Result B	Not Relevant
Result C	Relevant

# Natural Language Processing - Search

## Evaluation Metrics

- Recall (at K) (also known as sensitivity) is the fraction of relevant instances that were retrieved.



Recall at K =  $\text{TP at K} / (\text{All relevant items})$   
Relevant items = 5

Recall at 3 =  $\frac{2}{5} = 40\%$

Result A	Relevant
Result B	Not Relevant
Result C	Relevant

# Natural Language Processing - Search

## Evaluation Metrics

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Recall at K = TP at K / (All relevant items)  
Relevant items = 5

Recall at 3 =  $\frac{2}{5}$  = 40%

Result A	Relevant
Result B	Not Relevant
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# Natural Language Processing - Search

## Evaluation Metrics

- F1 Score is a metric that takes into account both precision and recall to provide a balanced evaluation of a system's performance

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$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

# Natural Language Processing - Search

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... gives more weight to the lower of the two values. This means that if **either precision or recall is low** (i.e., the weaker of the two metrics), **the harmonic mean will also be low**, *reflecting the fact that the system is not performing well in at least one of these aspects*. It penalizes systems that have an extreme imbalance between precision and recall.

# Natural Language Processing - Search

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# Natural Language Processing - Search

## Evaluation Metrics

- Normalized Discounted Cumulative Gain (NDCG)

# Natural Language Processing - Search

## Evaluation Metrics

- Normalized Discounted Cumulative Gain (NDCG) assesses how well the top-ranked items in a list align with the preferences or relevance judgments of users, i.e order matters.

# Natural Language Processing - Search

## Evaluation Metrics

- Normalized **Discounted Cumulative Gain** (NDCG).

$$\text{DCG}_p = \sum_{i=1}^p \frac{rel_i}{\log_2(i+1)} =$$

# Natural Language Processing - Search

## Evaluation Metrics

- Normalized **Discounted Cumulative Gain (NDCG)**.

$$\text{DCG}_p = \sum_{i=1}^p \frac{rel_i}{\log_2(i+1)}$$

DCG<sub>p</sub> is the DCG at position p.



# Natural Language Processing - Search

## Evaluation Metrics

- Normalized **Discounted Cumulative Gain (NDCG)**.

$$DCG_p = \sum_{i=1}^p \frac{rel_i}{\log_2(i+1)}$$

- $DCG_p$  is the DCG at position  $p$ .
- $rel_i$  is the relevance score of the item at position  $i$  in the ranking list (typically a non-negative number, where higher values represent higher relevance).

# Natural Language Processing - Search

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- Log is used to produce a smooth reduction

# Natural Language Processing - Search

## Evaluation Metrics

- Normalized **Discounted Cumulative Gain (NDCG)**.

The premise of DCG is that **highly relevant documents appearing lower in a search result list should be penalized** as the graded relevance value is reduced logarithmically proportional to the position of the result.

# Natural Language Processing - Search

## Evaluation Metrics

- **Normalized Discounted Cumulative Gain (NDCG).**

$$\text{nDCG}_p = \frac{\text{DCG}_p}{\text{IDCG}_p}$$

Diagram illustrating the components of NDCG:

- $\text{IDCG}_p = \sum_{i=1}^{|REL_p|} \frac{rel_i}{\log_2(i+1)}$ 
  - ↑ represents the list of relevant documents (ordered by their relevance) in the corpus up to position  $p$ .
  - ↓ ideal discounted cumulative gain

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*How can we formally compare them ?*

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- Recall at K
- F1 Score at K
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# Natural Language Processing - Search

## **Semantic Search**

... is a search technique that focuses on understanding the meaning and context of user queries to provide more relevant search results.

# Natural Language Processing - Search

## Semantic Search

... is a search technique that focuses on understanding the meaning and context of user queries to provide more relevant search results.

- Goes beyond keyword matching.
- Utilizes Natural Language Understanding (NLU).
- Aims for contextual accuracy.



# Natural Language Processing - Search

## Semantic Search

... is a search technique that focuses on understanding the meaning and context of user queries to provide more relevant search results.

- **Aims for contextual accuracy.**

# Natural Language Processing - Search

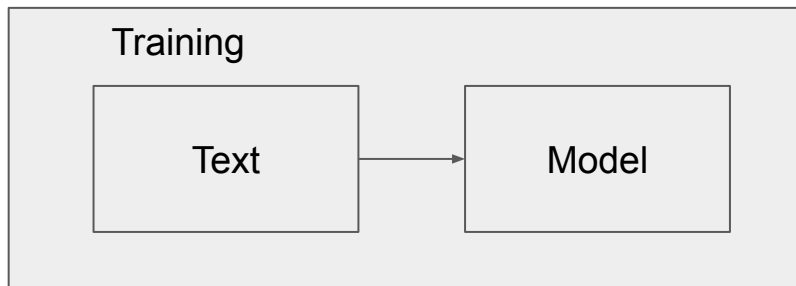
## **Semantic Search**

Word Embeddings (dense vectors)

# Natural Language Processing - Search

## Semantic Search

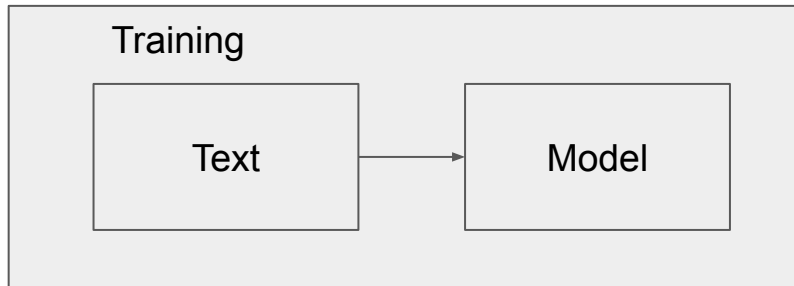
Word Embeddings



# Natural Language Processing - Search

## Semantic Search

### Word Embeddings

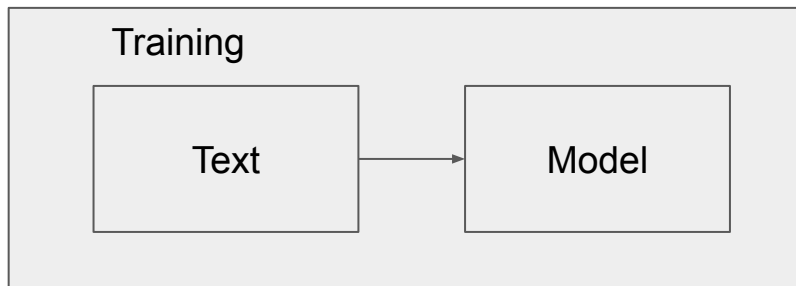


- Word2Vec
- GloVe
- CBOW
- Skipgram
- ...
- Transformers

# Natural Language Processing - Search

## Semantic Search

### Word Embeddings

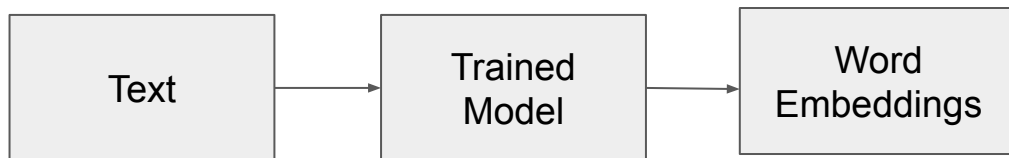


- Predict context i.e words around another
- Predict next word  
(next token prediction)
- Predict missing word  
(masked token token prediction)

# Natural Language Processing - Search

## Semantic Search

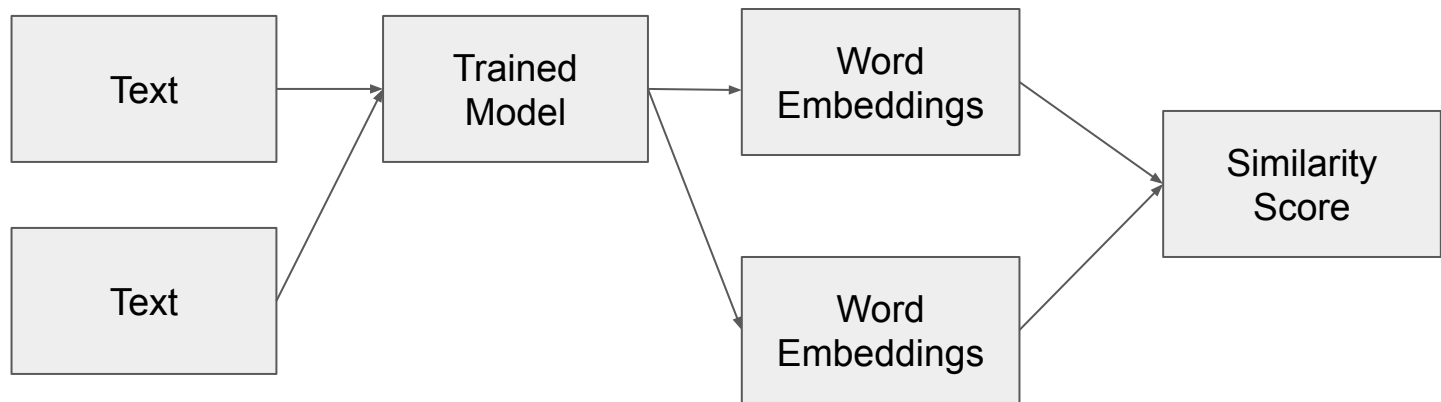
Word Embeddings



# Natural Language Processing - Search

## Semantic Search

Word Embeddings



# Natural Language Processing - Search

## Semantic Search

Key players

spaCy



Hugging Face

 OpenAI

... and much more



# Natural Language Processing - Search

## Semantic Search

Key players

spaCy



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# Natural Language Processing - Search

**Semantic Search**

**+**

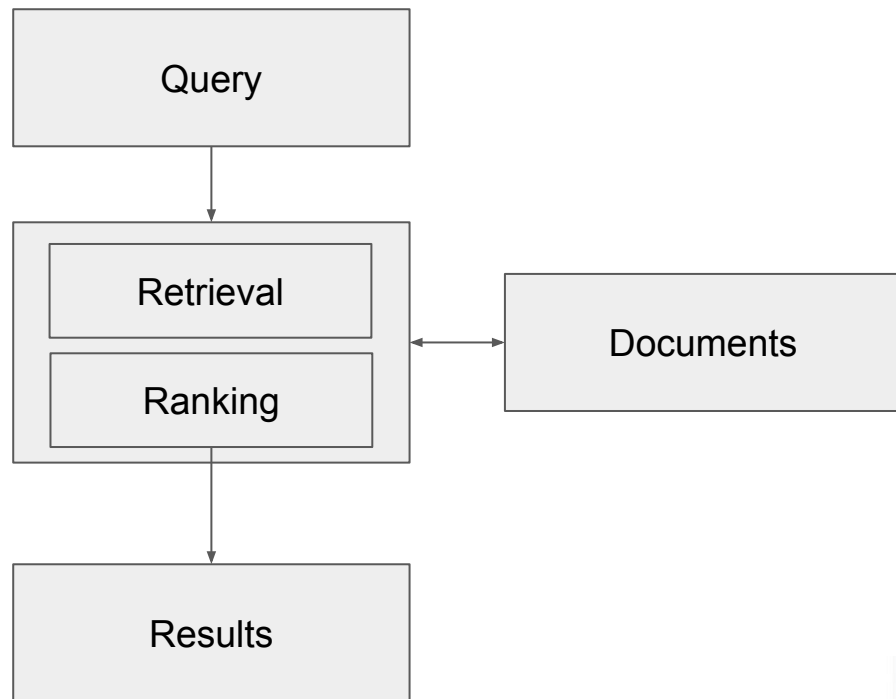
**Generative AI**

**=**

**Retrieval Augmented Generation (RAG)**

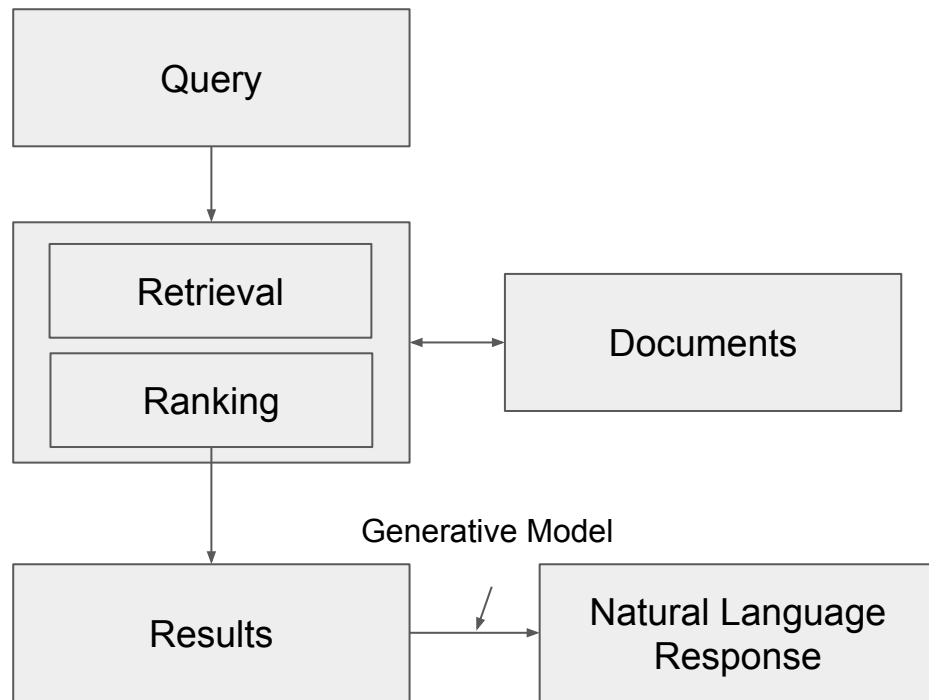
# Natural Language Processing - Search

**Semantic Search**  
**+**  
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# Natural Language Processing - Search

**Semantic Search**  
**+**  
**Generative AI**  
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**Retrieval Augmented Generation (RAG)**



# Natural Language Processing - Search

**Semantic Search**

**+**

**Generative AI**

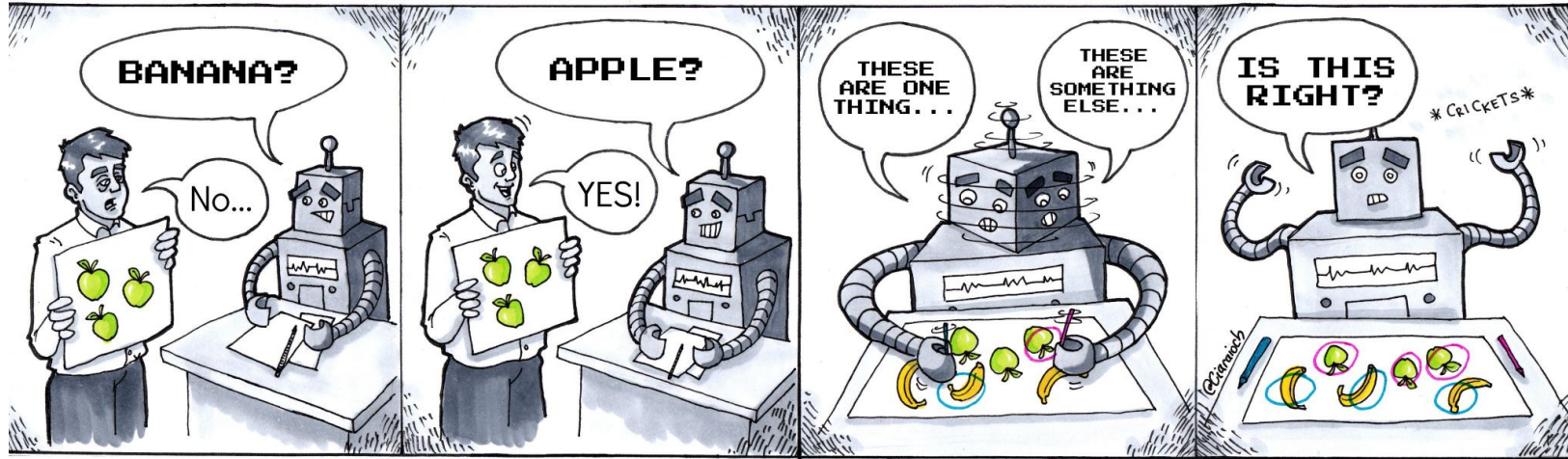
**=**

**Retrieval Augmented Generation (RAG)**



# Natural Language Processing

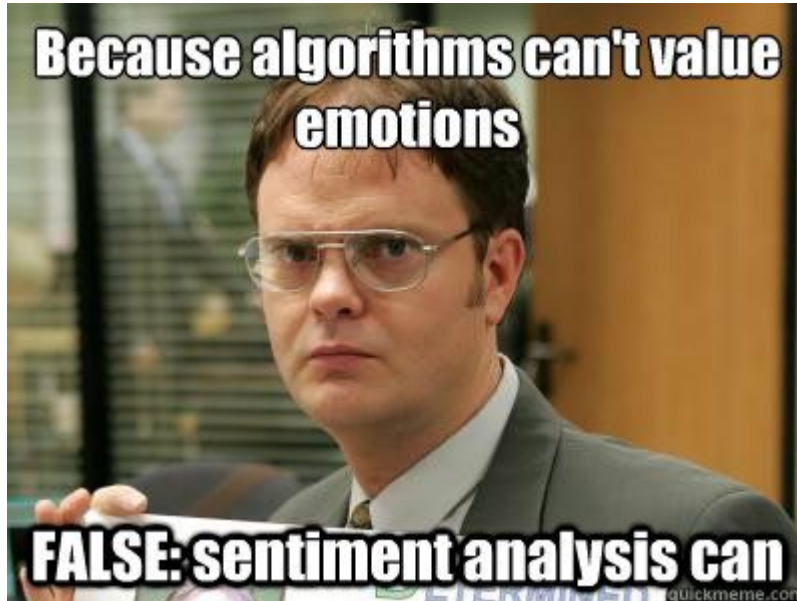
Next up:



**Supervised Learning**

**Unsupervised Learning**

# Natural Language Processing



# Natural Language Processing

