A Journey through
Natural Language Process

About me

Lisbon, Portugal

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Lisbon, Portugal

Berlin, Germany

Natural Language Processing Tasks

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"Noam Chomsky, a linguist at MIT, revolutionized cognitive science with his theory of universal grammar in the 1950s."

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Lemmatization/Stemming

Word	Lemma	Stem
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cognitive	cognitive	cognitiv

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Part-of-speech (POS) tagging

Word	POS Tag
Noam	Proper Noun
Chomsky	Proper Noun
,	Punctuation
a	Determiner
linguist	Noun
at	Preposition
MIT	Proper Noun
,	Punctuation
revolutionized	Verb
cognitive	Adjective
science	Noun

Word	POS Tag
with	Preposition
his	Pronoun
theory	Noun
of	Preposition
universal	Adjective
grammar	Noun
in	Preposition
the	Determiner
1950s	Numeral
.	Punctuation

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Syntactic parsing

```
revolutionized (ROOT)
├── nsubj: Chomsky
│   ├── compound: Noam
│   └── appos: linguist
│       ├── det: a
│       └── prep: at
│           └── pobj: MIT
├── dobj: science
│   └── amod: cognitive
├── prep: with
│   └── pobj: theory
│       ├── poss: his
│       ├── prep: of
│       │   └── pobj: grammar
│       │   └── amod: universal
│       └── prep: in
│           └── pobj: 1950s
│               └── det: the
└── punct: .
```

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Natural Language Processing Tasks

Language Analysis

- **Tokenization**: Segmenting text into words, subwords, or character
- **Lemmatization/Stemming**: Reducing words to base/root forms
- **Part-of-speech (POS) tagging**: Classifying words by grammatical categories
- **Syntactic parsing**: Determining grammatical structure of sentences

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Entity	Type
Noam Chomsky	Person
MIT	Organization
theory of universal grammar	Work
1950s	Date

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Relationship Extraction

Entity 1	Relation	Entity 2
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Coreference Resolution

his ⇨ **Noam Chomsky**

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Entity Linking

Entity	Knowledge Base Link (Example)
Noam Chomsky	https://www.wikidata.org/wiki/Q9049
MIT	https://www.wikidata.org/wiki/Q49108
universal grammar	https://www.wikidata.org/wiki/Q728252

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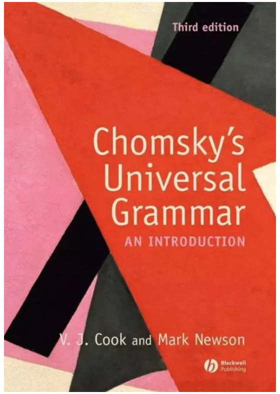

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Semantic Understanding

- **Named entity recognition (NER)**: Identifying and classifying named entities
- **Relation extraction**: Identifying relationships between entities
- **Coreference resolution**: Finding expressions referring to the same entity
- **Entity linking**: Connecting named-entities to knowledge base entries

Natural Language Processing Tasks

Text Classification

- **Text classification**: Categorizing texts by topic, genre, etc.
- **Sentiment analysis**: Determining emotional tone or opinion
- **Hate speech/offensive language detection**: Identifying problematic content
- **Fake news detection**: Identifying misleading information

Document Processing

- **Text summarization**: Extractive summarization or Abstractive summarization
- **Information retrieval**: Finding relevant documents/information
- **Document clustering**: Grouping similar documents

Natural Language Processing - early days

1950s-1980s Rule-Based Approaches

- Relied on hand-crafted rules and pattern matching.
- Linguists would create explicit grammatical rules that computers could follow to parse language.

1980s-1990s: Statistical Methods

- **Hidden Markov Models (HMMs)** became popular for part-of-speech tagging and speech recognition
- **Statistical parsing** used probabilistic context-free grammars
- **N-gram language models** predicted words based on preceding context

2000-2012: Machine Learning Approaches

- **Support Vector Machines (SVMs)** became dominant for many classification tasks
- **Conditional Random Fields (CRFs)** excelled at sequence labeling tasks like NER and POS tagging
- **Maximum Entropy Models** (MaxEnt) were widely used for various classification problems
- **Topic modeling** with Latent Dirichlet Allocation (LDA, introduced 2003)

2000 - 2012: Email SPAM classifier

Subject: `WIN a FREE iPhone NOW!!!`
Body: `Congratulations! You have been selected to win a FREE iPhone. Click here to claim your prize.`

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Text-based features:
- word frequencies, TF-IDF, n-grams

Character-level features:
- exclamation marks, dollar signs, uppercase ratio

Metadata features:
- number of recipients, HTML content, attachments

Structural features
- email length, header format, URL count

Other features
- any of the outcomes of the linguistic analysis (before)

2000 - 2012: Email SPAM classifier

Subject: `WIN a FREE iPhone NOW!!!`
Body: `Congratulations! You have been selected to win a FREE iPhone. Click here to claim your prize.`

Contains the word "free"	1
Contains the word "win"	1
Number of exclamation marks	3
All CAPS words count	3
Number of links	1
Email length (number of words)	15
Sender is in known contacts list	0

Vector: `[1, 1, 3, 3, 1, 15, 0]`

2000 - 2012: Email SPAM classifier

Subject: `Meeting tomorrow`
Body: `Hey, can we reschedule the meeting for the next week? I can't make it this week.`

Contains the word "free"	0
Contains the word "win"	0
Number of exclamation marks	0
All CAPS words count	0
Number of links	0
Email length (number of words)	17
Sender is in known contacts list	1

Vector: `[0, 0, 0, 0, 0, 17, 0]`

2000 - 2012: Email SPAM classifier

Train a classifier based on labeled data

`[1, 0, 2, 1, 0, 25, 1]` - NOT SPAM

`[0, 1, 1, 2, 1, 10, 0]` - SPAM

`[0, 0, 3, 0, 2, 30, 1]` - SPAM

`[1, 1, 0, 1, 0, 40, 0]` - NOT SPAM

`[0, 0, 1, 3, 1, 15, 1]` - NOT SPAM

`[1, 0, 0, 0, 2, 20, 0]` - SPAM

`[0, 1, 2, 1, 1, 35, 1]` - NOT SPAM

`[1, 1, 1, 2, 0, 22, 0]` - SPAM

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- Logistic Regression
- Support Vector Machines
- k-Nearest Neighbors (k-NN)
- Decision Trees / Random Forest
- Naive Bayes
- Gradient Boosting
- XGBoost

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Text ⇒ **Feature Extraction** ⇒ **Feature Vector** ⇒ **Learning Algorithm**

2012 - 2014: From Feature Extraction to Embedding Vectors

- The distributional hypothesis by Harris (1954), states that each language can be described in terms of a distributional structure, i.e., in terms of the occurrence of parts relative to other parts.

- Firth (1957) explored this idea, based on a word context, popularised by the famous quote you "*shall know a word by the company it keeps*"

- Rubenstein and Goodenough (1965) have shown that a pair of words is highly synonymous if their contexts show a relatively high amount of overlap.

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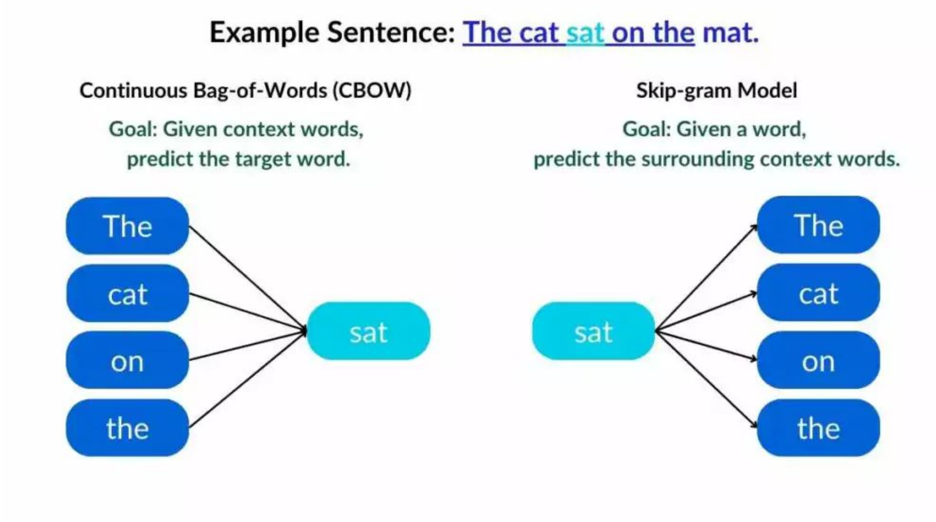
Considering the words "*doctor*" and "*physician*"

- Looking at the contexts in which these words appear, there's significant overlap

- Both frequently co-occur with terms like "patient," "hospital," "treatment," "diagnosis," etc

- This distributional similarity reflects their semantic similarity - they both refer to medical professionals who treat patients

2012 - 2014: From Feature Extraction to Embedding Vectors



CBOW: predicts a target word given its context words:

1. Input: Context words represented as one-hot encoded vectors.
2. Hidden layer: Learns word embeddings by averaging the context word vectors.
3. Output: Predicts the target word.

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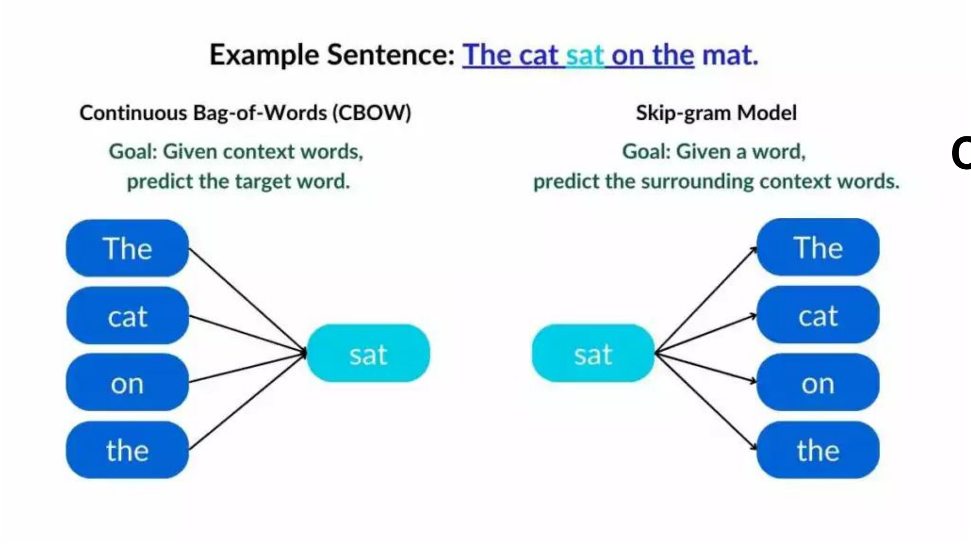

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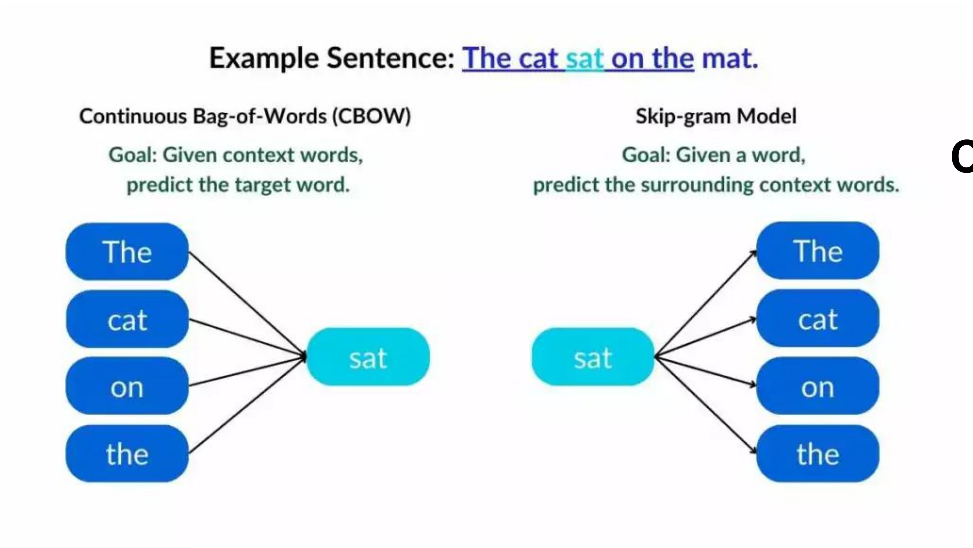

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The resulting embeddings allow for meaningful arithmetic operations on word vectors.
Analogy solving, e.g.: "king - man + woman ≈ queen"

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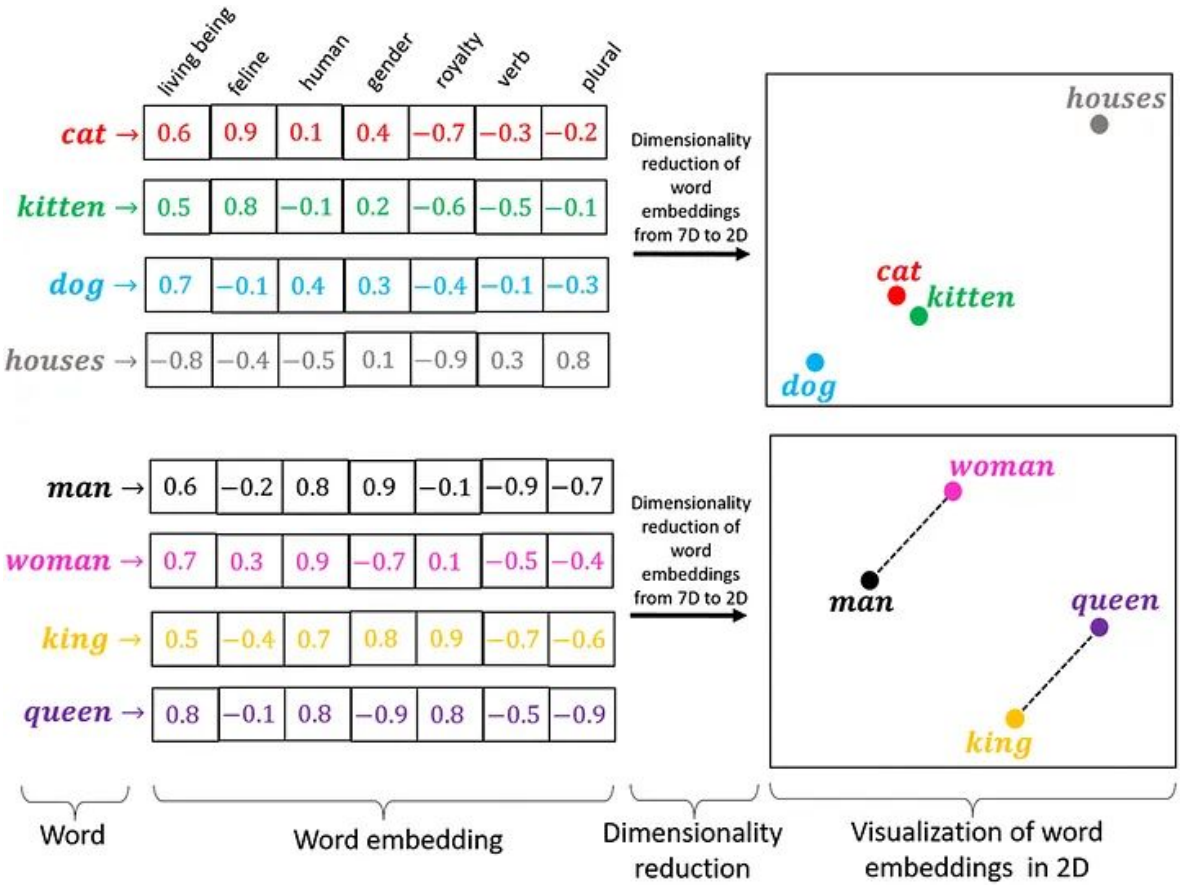

2012 - 2014: From feature extraction to Embedding Vectors

Text → **Feature Extraction** → **Feature Vector** → **ML Learning Algorithm**

2012 - 2014: From feature extraction to Embedding Vectors

Text → Feature Extraction → Feature Vector → ML Learning Algorithm

Text → Word Embeddings → ML Learning Algorithm

2012 - 2014: From feature extraction to Embedding Vectors

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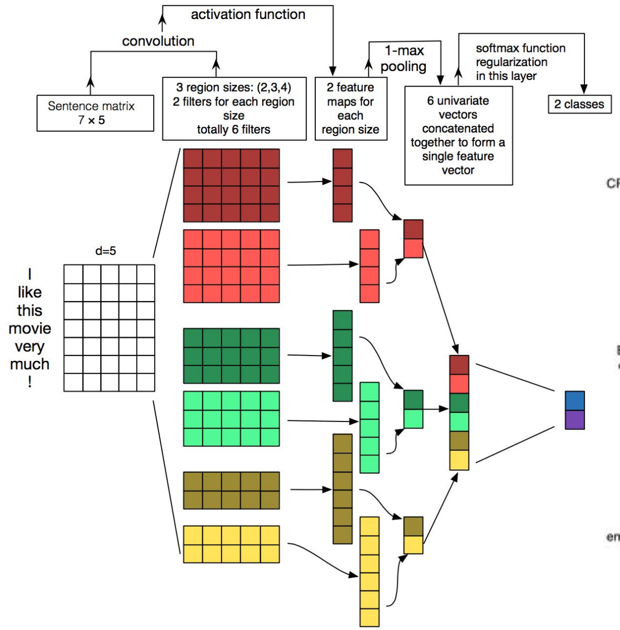
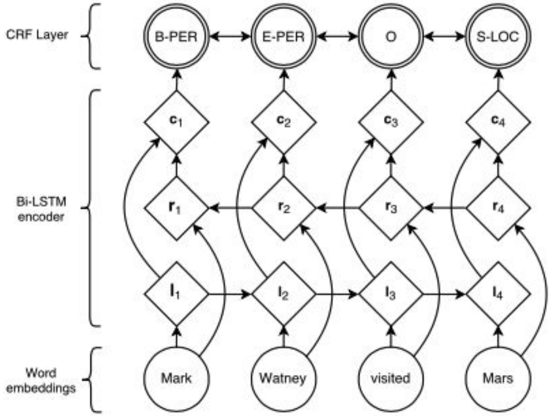
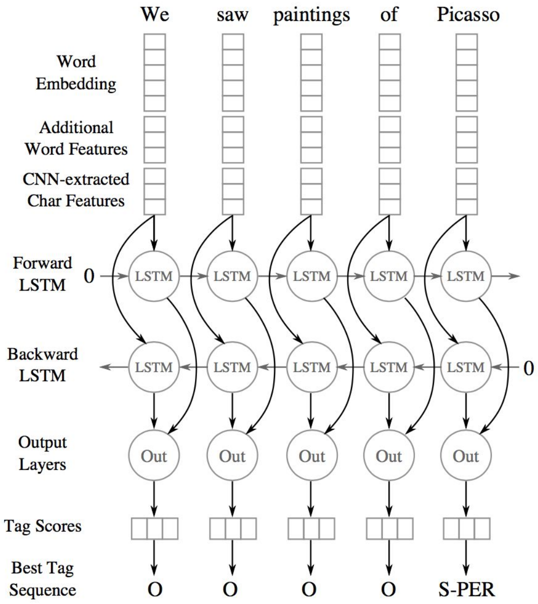
Word Embeddings revolutionised the way almost all NLP tasks can be solved.

Replacing the feature extraction/engineering with embeddings which could then be fed as input to different neural network architectures

2014 - 2017: Embeddings and Neural Networks for NLP







- **Averaging:** created a single vector representation for the entire document by summing up the embeddings of each word and dividing by the number of words
- **Pooling Operations**: Instead of simple averaging, some approaches used other pooling operations like max-pooling or min-pooling over the word embeddings in a document

2014 - 2017: Embeddings and Neural Networks for NLP

Word Embeddings Limitations

- *“I deposited 100 EUR in the **bank**.”* vs *“She was enjoying the sunset on the left **bank** of the river.”*
- **bank** has the same embedding vector
- Couldn't capture polysemy, no contextual understanding of words in sentences

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RNN/LSTM Limitations (dominant models but faced several challenges)

Sequential Processing Bottleneck: Processing words one-by-one, making parallelization difficult

Long-range Dependency Problems: Difficulty capturing relationships between distant words

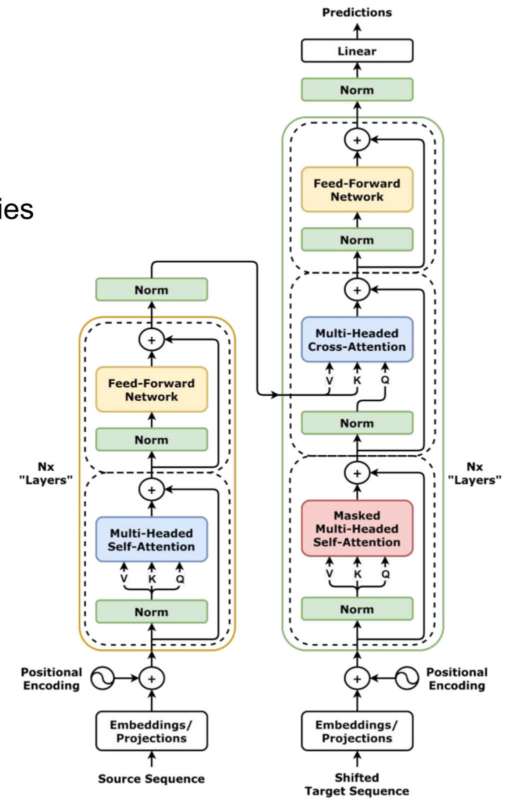
2017 - 2018: Transformer and BERT

2017 paper "Attention Is All You Need"

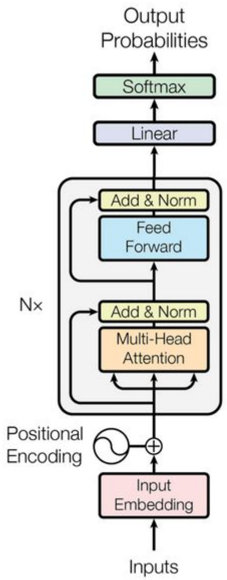
- **Self-Attention Mechanism**:
  - Each word can "attend" to all other words, capturing long-range dependencies
- **Parallelizable computation:**
  - no sequential processing
- **Contextual Representations**:
  - same word gets different embeddings in different contexts

Transformer architecture consists of two main building blocks:

- an encoder
- a decoder



2017 - 2018: Transformer and BERT



"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"

- **Pre-Training**
  - Predicting words that have been randomly masked out of sentences
  - Determining whether sentence B could follow after sentence A in a text passage
  - Wikipedia (approximately 2.5 billion words)
  - Google's BooksCorpus (approximately 800 million words)
  - Resulted in good initial word representations embeddings

- **Fine-Tuning**
  - Model is fine-tuned to learn a specific task initialised from the pre-trained model parameters
  - BERT achieved good benchmarks results in several NLP tasks

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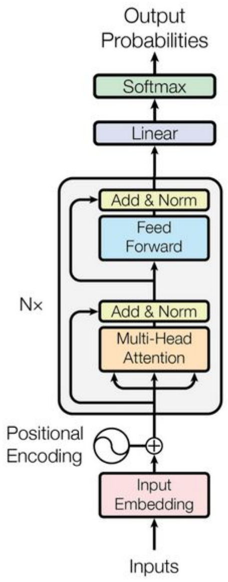

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BERT become a powerful feature extractor!

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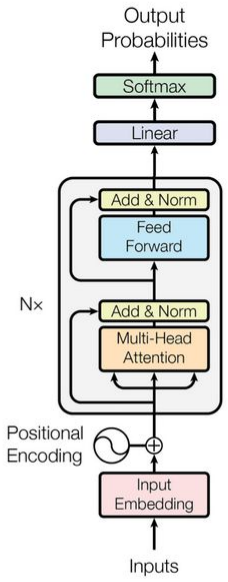

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Text ⇨ **Word Embeddings** ⇨ **Neural Networks**

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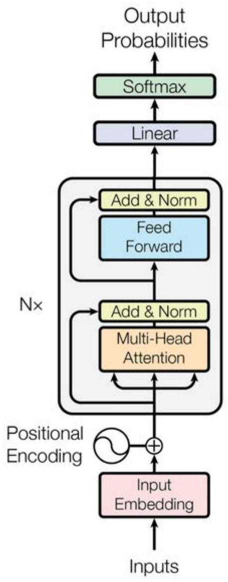

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Text ⇨ **BERT Pre-Trained Encoder Transformer** ⇨ **Linear Layer**

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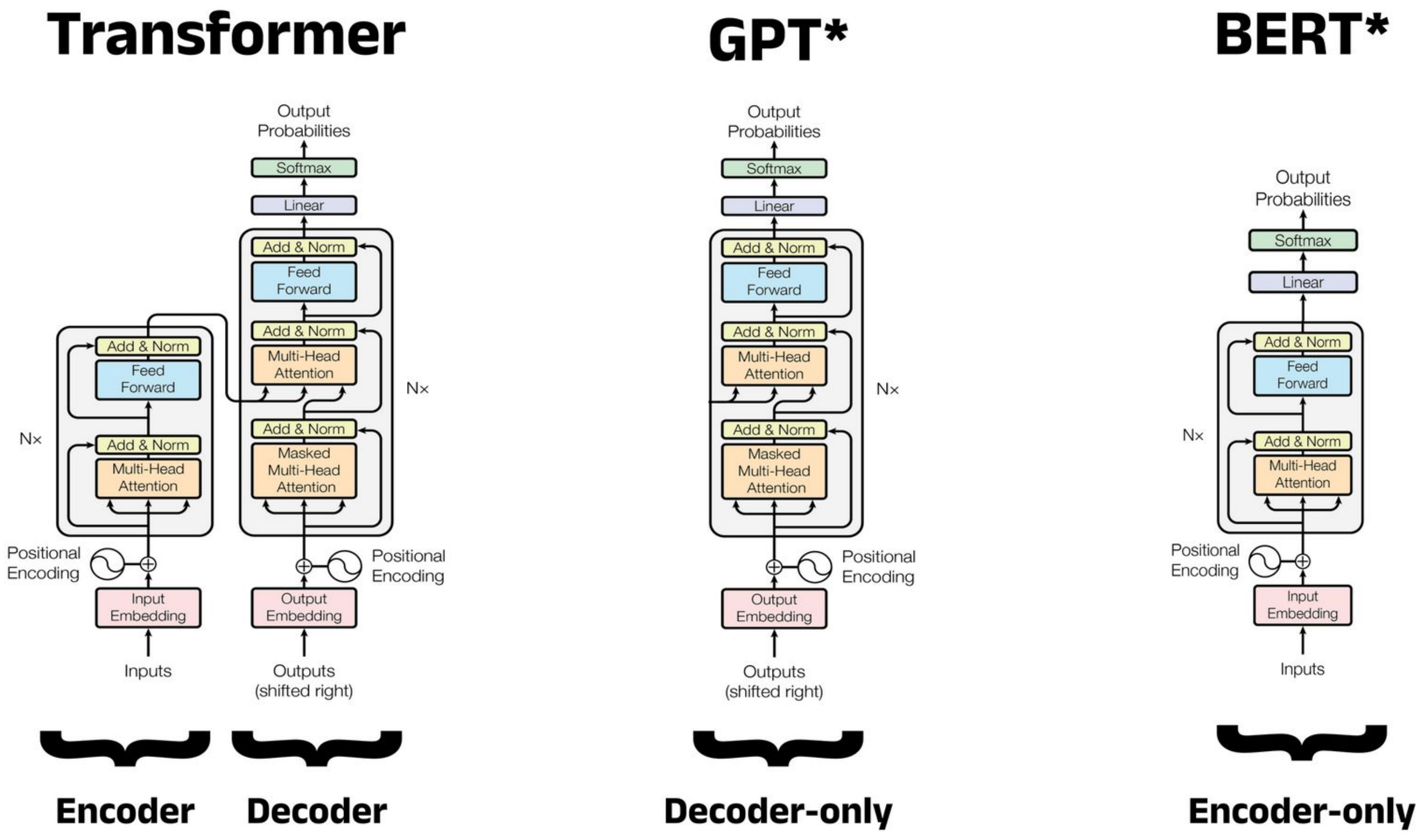

2019 - 2022: Pre-Training and Scaling

The BERT-like models: **(encoder)**

- Bidirectional context
- Task-specific fine-tuning
- Discriminative tasks

Generative models: **(decoder)**

- Unidirectional (autoregressive) prediction
- Scaling compute and parameters
- Zero/few-shot capabilities through prompting to solve tasks

2019 - 2022: Pre-Training and Scaling

2019:

- **RoBERTa** (Facebook): Robustly optimized BERT pre-training approach **(encoder)**
- **ALBERT** (Google): A Lite BERT with parameter reduction techniques while maintaining performance **(encoder)**
- **DistilBERT** (HuggingFace): Knowledge distillation for creating smaller, faster models **(encoder)**
- **T5** (Google): Text-to-Text Transfer Transformer unifying NLP tasks into a text-to-text format **(seq2seq)**
- **GPT-2** (OpenAI): 1.5B parameter model shows surprising zero-shot abilities; initially "too dangerous" for full release **(decoder)**

2020:

- **GPT-3 (OpenAI):** a language model with 175 billion parameters, demonstrating remarkable abilities in text generation, coding, and creative tasks **(decoder)**

2021:

- **CLIP (OpenAI):** Contrastive Language-Image Pre-training bridging text and visual understanding **(multimodal)**
- **CodeX (OpenAI):** Code generation model fine-tuned on GitHub repositories, precursor to GitHub Copilot **(decoder)**
- **FLAN (Google):** Instruction-tuned model demonstrating improved few-shot learning capabilities across diverse tasks **(decoder)**

2022 Onwards: Decoder-Centric Generative AI

Large Language Models

- **ChatGPT** (November 2022): OpenAI's conversational interface built on GPT-3.5 that mainstream audiences adopted rapidly
- **GPT-4** (March 2023): Multimodal capabilities with significantly improved reasoning
- **LLaMA** (February 2023): Meta's open-source LLM series that catalyzed open-source development
- **Claude** models (2023-2024): Anthropic's models focused on helpfulness and harmlessness

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Multimodal Generative Models

- **DALL-E 2** (April 2022) and **DALL-E 3** (2023): Text-to-image generation with improved coherence
- **Stable Diffusion** (August 2022): Open-source text-to-image model that revolutionized accessibility
- **Midjourney** (2022-2023): Text-to-image service with distinctive aesthetic quality

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2023-2025: emerging trends - what's next?

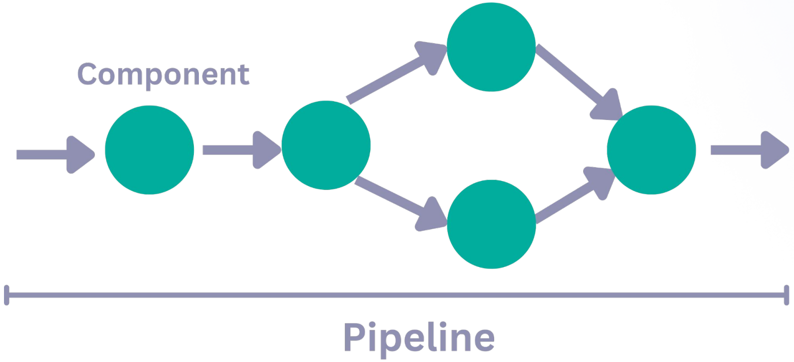
- **Tool Use**: Models effectively leveraging external tools and APIs to extend capabilities
- **Agentic Systems**: LLMs orchestrating complex tasks with planning capabilities
- **Local Deployment**: Smaller, more efficient models running on personal devices

Haystack by deepset

Haystack Introduction

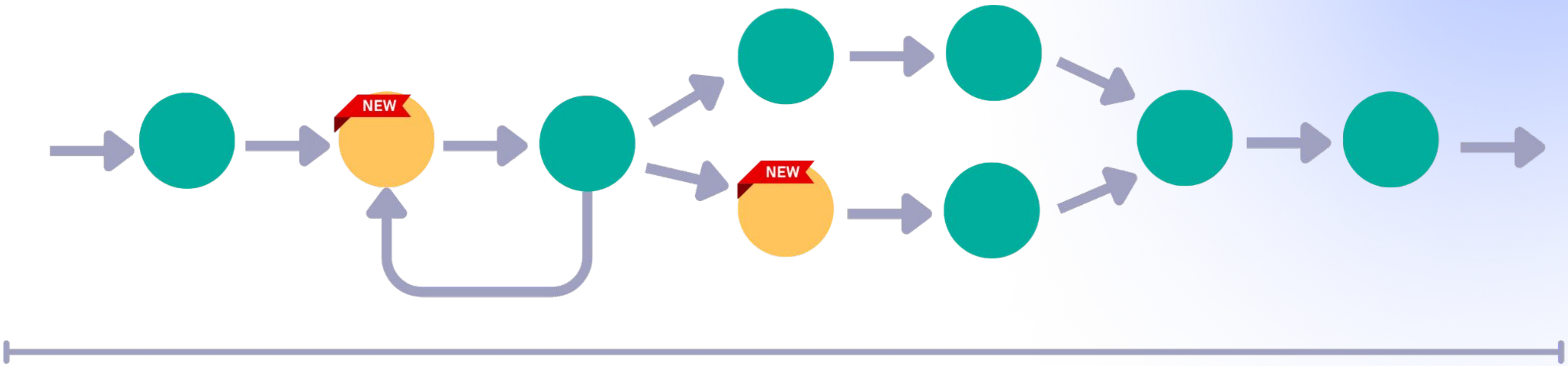
Haystack
by deepset

- Open-source AI orchestration framework by deepset
- deepset AI Platform is built on Haystack
- Provides the tools that Python developers need to build real world, agentic AI systems
- Building blocks: Components & Pipelines

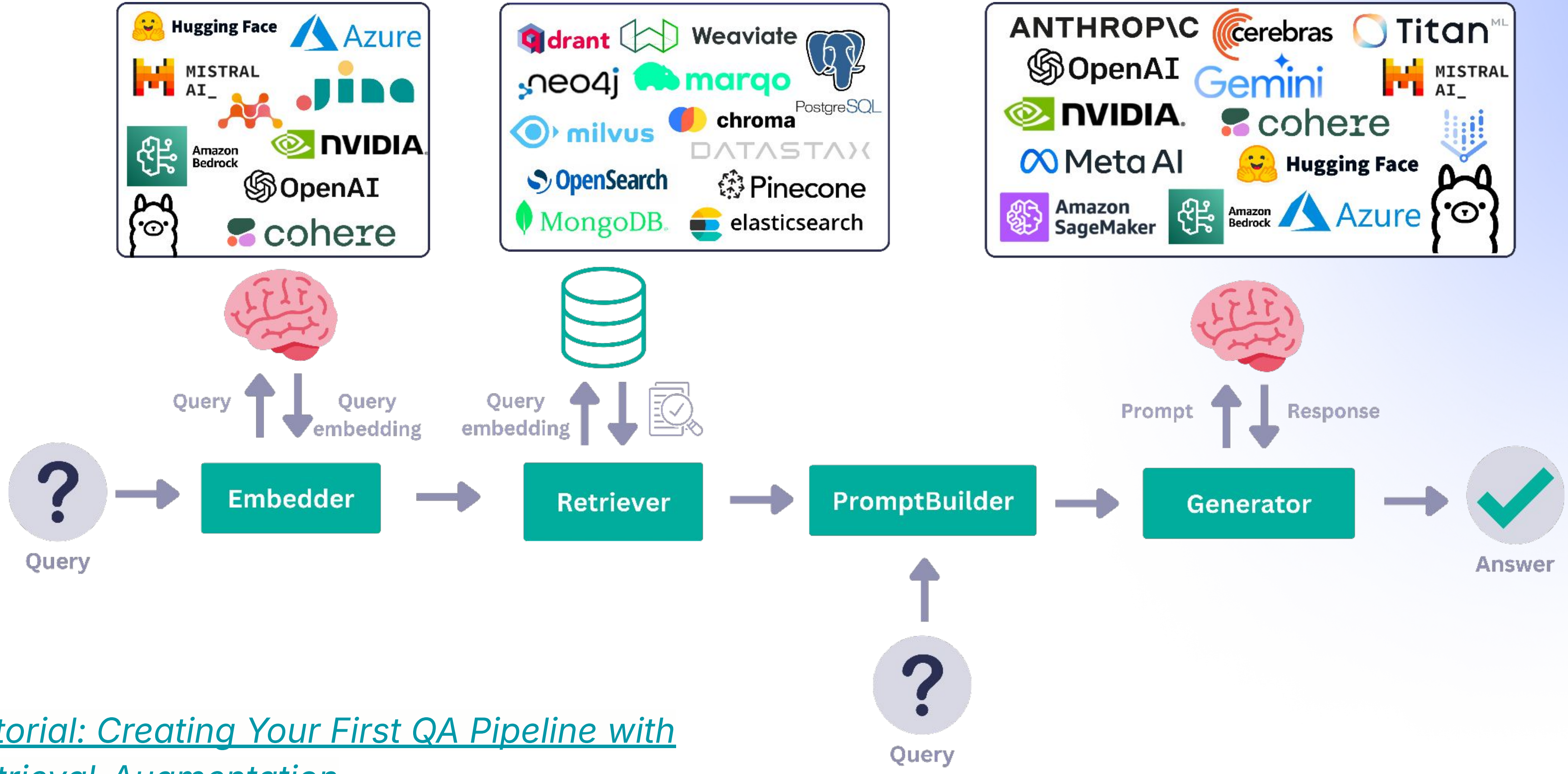


Haystack
by deepset

Pipelines → Assemble components into workflows

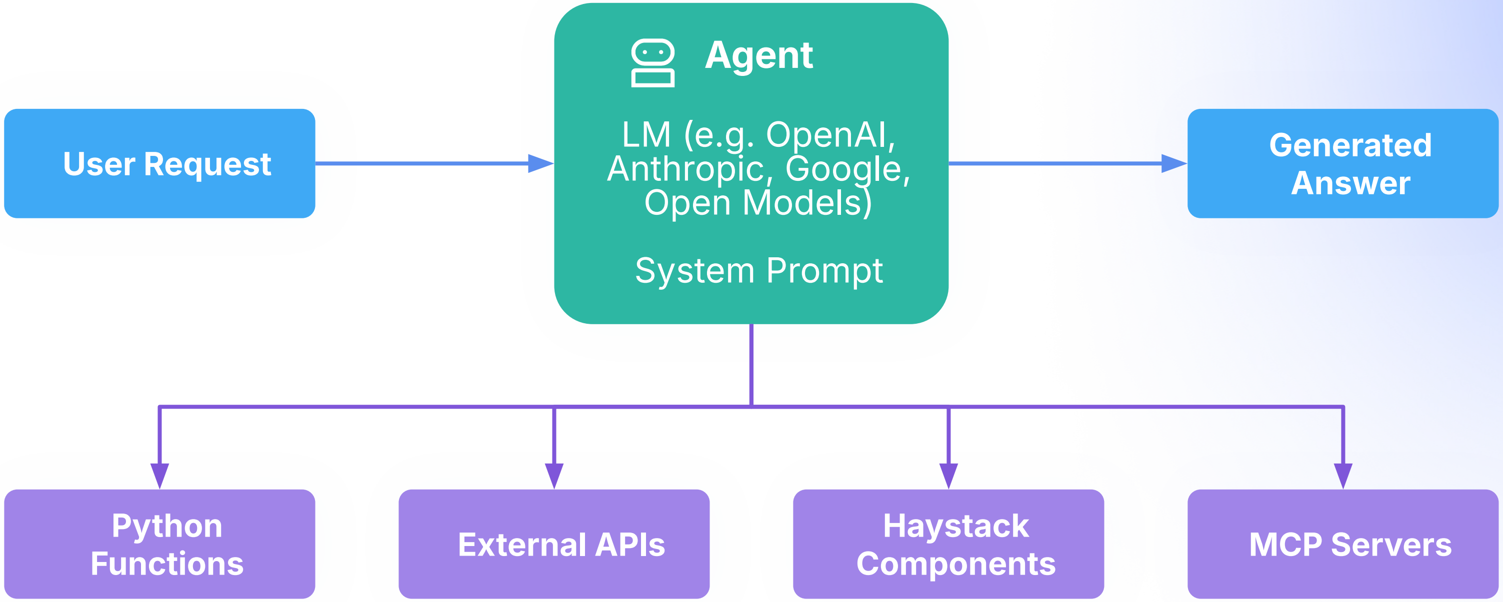


Retrieval Augmented Generation



[Tutorial: Creating Your First QA Pipeline with Retrieval-Augmentation]()

Haystack Agents



Haystack Use Cases

- RAG - Web RAG
- Converting, preprocessing, embedding, indexing
- Text-to-SQL Pipeline
- Advanced Retrieval (Hybrid, Sentence Window Retrieval, HyDE)
- Conversational & Chat Systems
- Agent (ReAct, Self Reflection, Multimodal, Multi-Agent)

Build with Haystack

pip install haystack-ai

haystack.deepset.ai

- Get Started
- Documentation
- Haystack Integrations
- Haystack Cookbook
- Haystack Tutorials
- Haystack Demos

Discord community

datacamp

Building AI Agents with Haystack

Haystack Demos

- https://itinerary-agent.deepset.ai/
- https://huggingface.co/spaces/deepset/autoquizzer
- https://huggingface.co/spaces/bilgeyucel/captionate

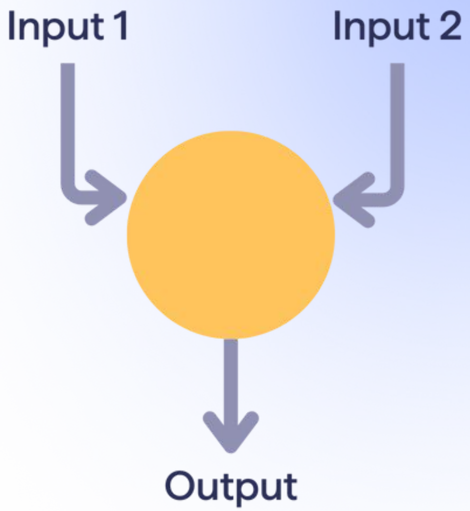
Extra

Components

```python
from haystack import component

@component
class Component:

  @component.output_types(output=str)
  def run(input_1: str, input_2: str):
    return {"output": ""}
```



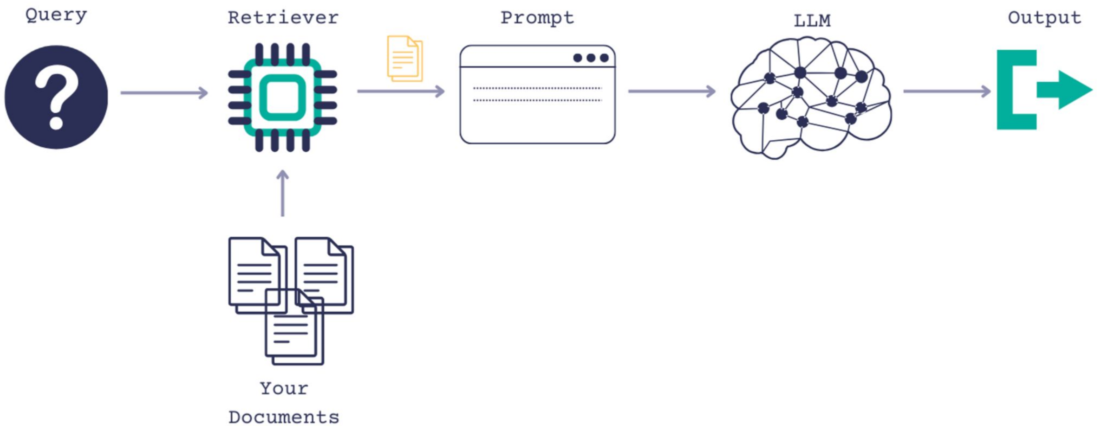
Haystack: RAG and Agents framework

2021~2022 - Retrieval-Augmented Generation (RAG): Combining generation with external knowledge retrieval

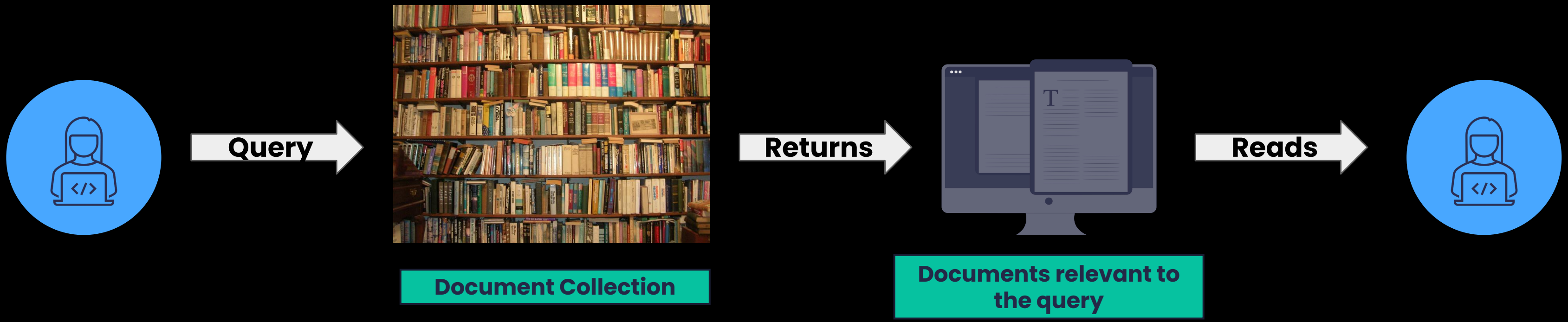
1. **Retrieval-Based Systems**: fetch relevant documents from a DB based on a query.

2. **LLMs**: generate responses based on the input query using the language model.

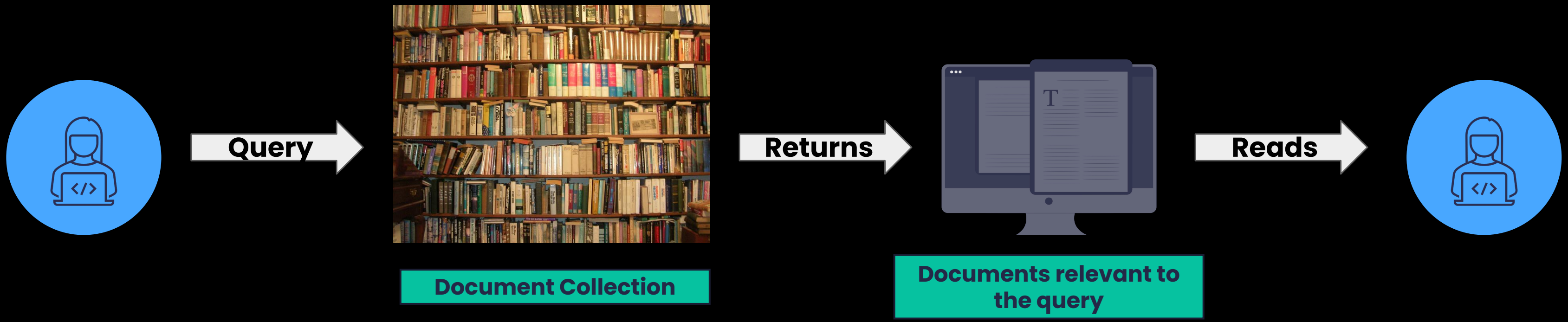
3. **Retrieval-Augmented Generation (RAG)**: RAG combines the strengths of both approaches. It first retrieves relevant documents or passages based on the query and then uses these retrieved pieces of information to generate a more informed and accurate response. This helps in grounding the generated responses in factual information, reducing hallucinations, and improving overall accuracy.



From classic Information Systems to RAG



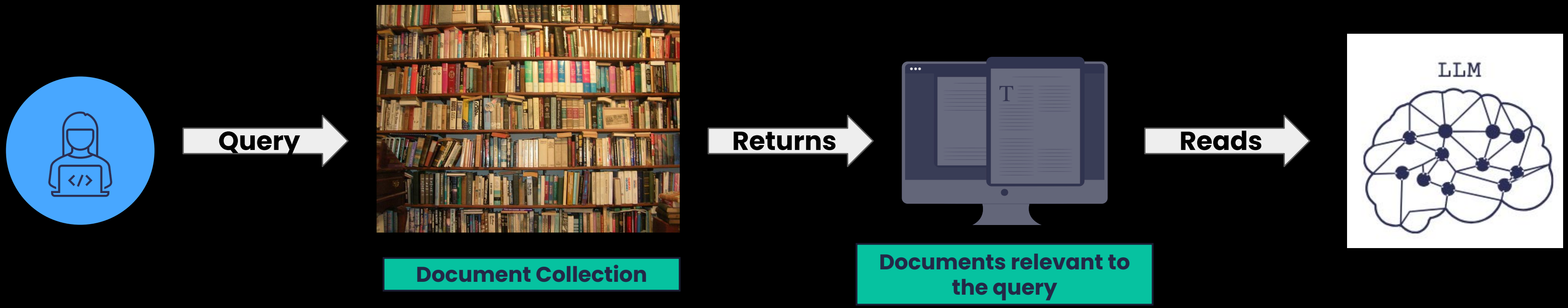
From classic Information Systems to RAG



- Return a list of documents or snippets, requiring users to read through multiple results to find the information they need

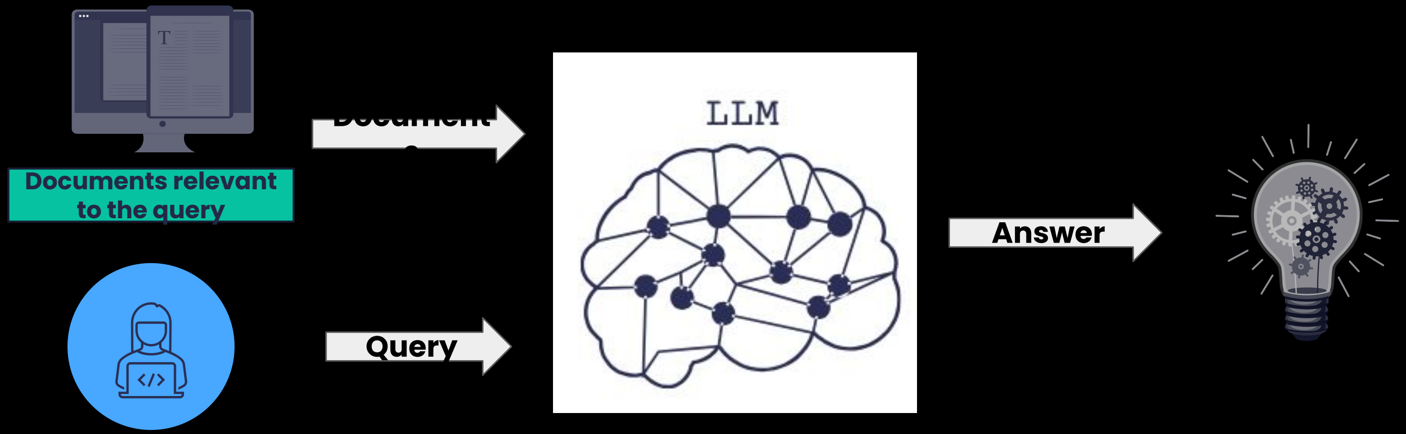
- A complex or nuanced query requires a deeper understanding of the context and relationships between different pieces of information

From classic Information Systems to RAG



- What if, instead the user sifting through the results, we build a prompt composed by retrieved snippets together with the query and feed it to an LLM?

From classic Information Systems to RAG



2012 - 2014: From Feature Extraction to Embedding Vectors