# WORD REPRESENTATION FOR NATURAL LANGUAGE PROCESSING

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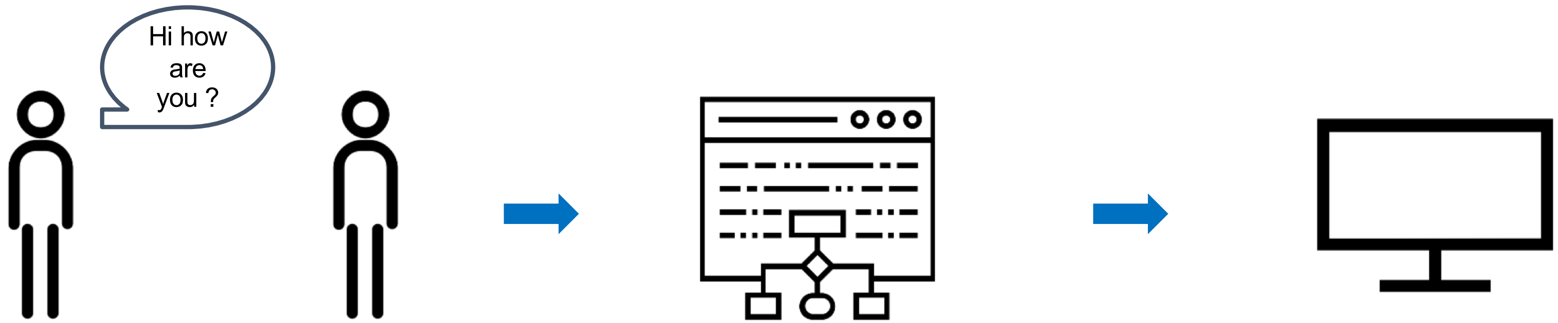
# Natural Language Processing Challenge

Natural Language Processing (NLP) is a field of computer science that **programs computer to process textual information**.




Humans use **symbols** (letters and words) to communicate

Algorithms use **numerical values** to make predictions

Computers use **bits** to compute

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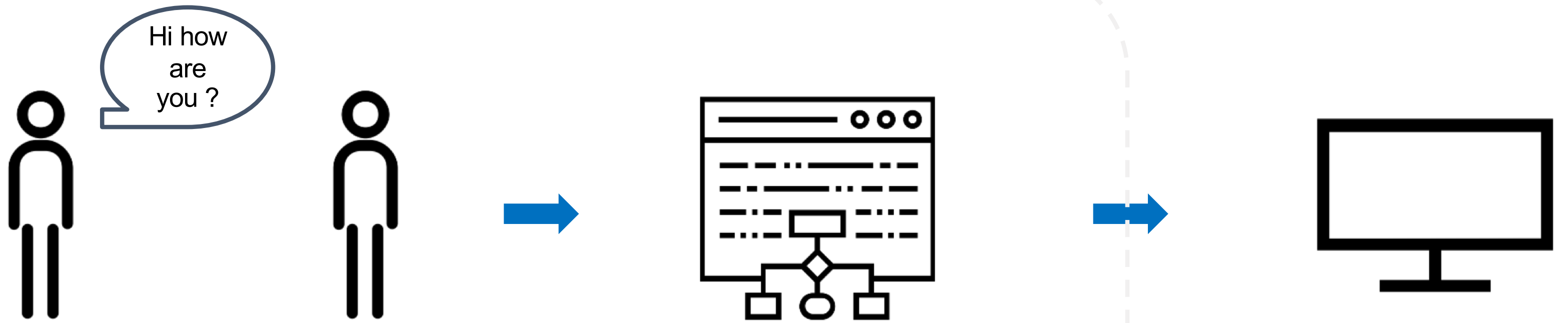


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**Goal:** How can we convert words to numerical values without losing the internal language information of symbols? How can we encode the meaning/semantic of words?

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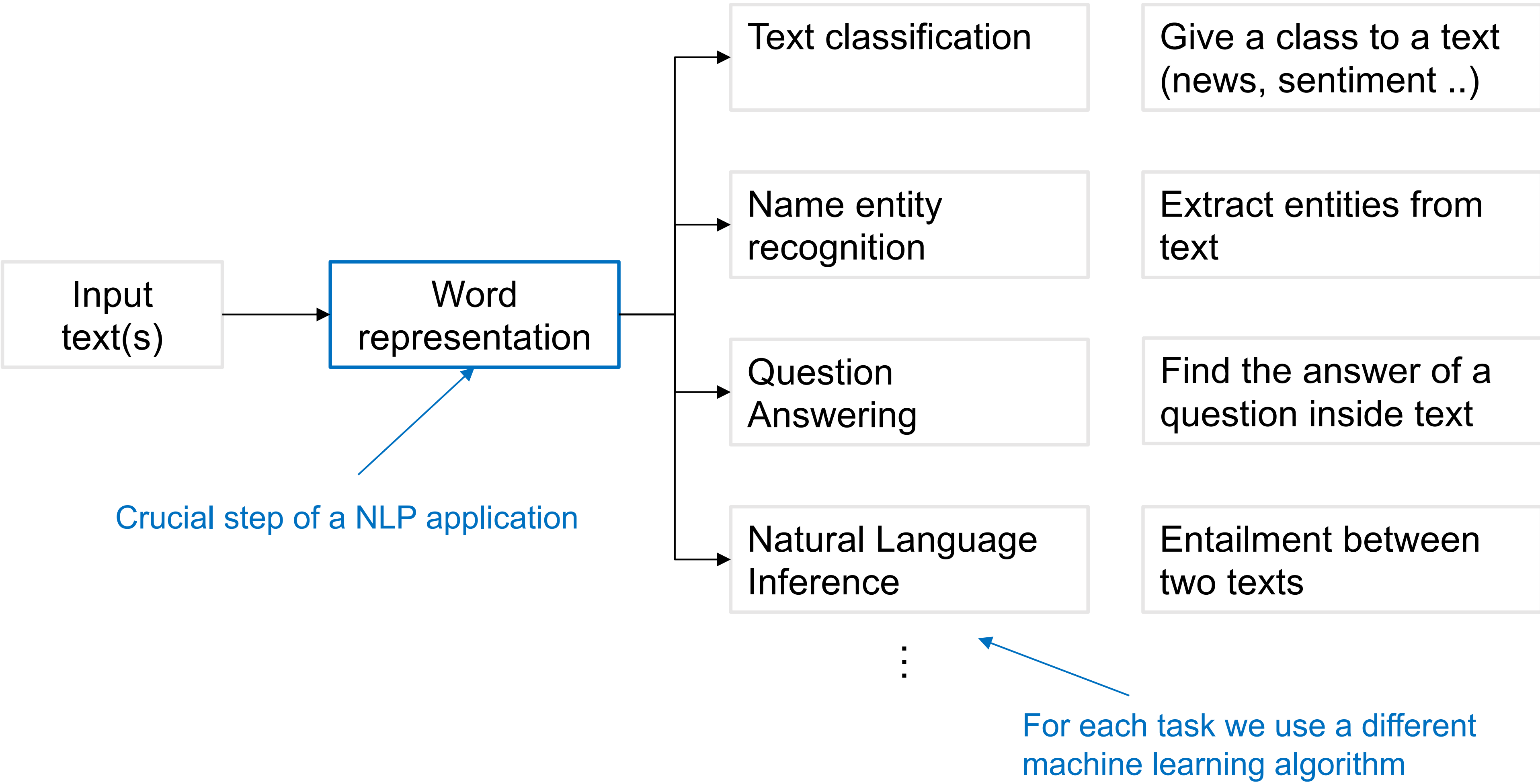
**Feature extraction:** Building derived values intended to be **informative** and **non-redundant.**

# Example of Natural Language Processing Tasks

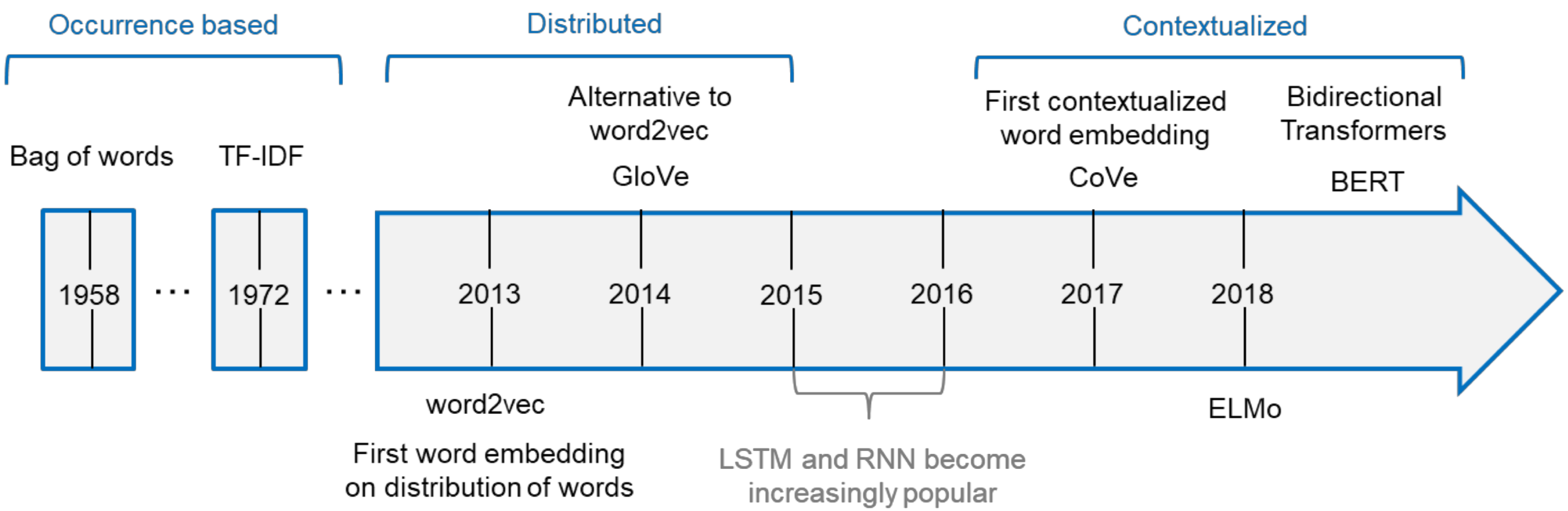


# Different Types of Word Representations

1. **Occurrence based word representation:** words are encoded based on their occurrence count inside a document

2. **Distributed word representation:** word **meanings** are encoded into a vector space thanks to a neural network.

3. **Contextualized word representation:** the meaning of words **inside their context** is encoded into a vector space thanks to a neural network



# Some NLP Jargon

**Definitions:**

- *Corpus:* a collection of documents (written text) on which the analysis is performed
- *Document:* a part of the corpus
- *Vocabulary:* a set or subset of the words of the **corpus**

**Example:** A corpus could be a full book. In this case the documents would be its paragraphs.

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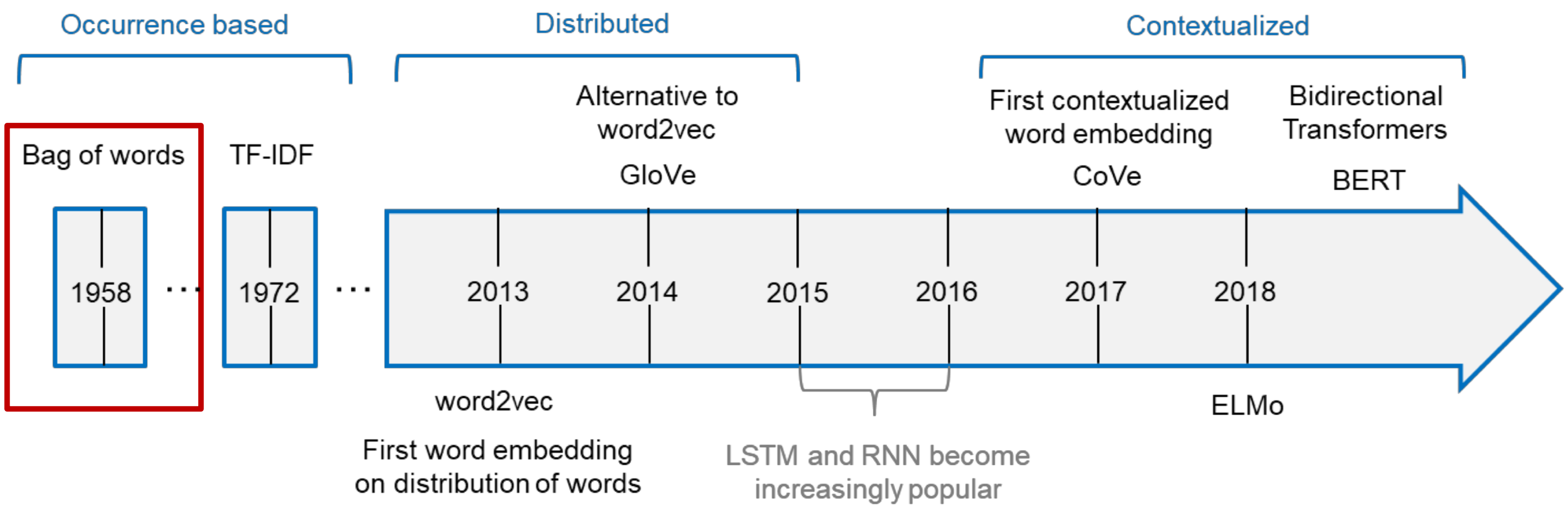


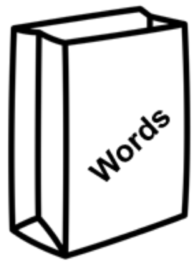
# Occurrence Based Word Representation

**Bag of Words (BoW):**

Each document is represented as a vector that counts the occurrence of words in it

How to construct the bag?

1. Define a vocabulary from **the corpus**
2. Create the vector that represents the document by counting the words of the vocabulary that belongs to the document.




**Example:** Given the following corpus of two documents:

1. John likes to watch movies. Mary likes movies too.
2. John likes to watch football.

Vocabulary:

"John"
"likes"
"to"
"watch"
"movies"
"Mary"
"too"
"football"

$$BoW_1 = \begin{bmatrix} 1 \\ 2 \\ 1 \\ 1 \\ 2 \\ 1 \\ 0 \\ 0 \end{bmatrix} \qquad BoW_2 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

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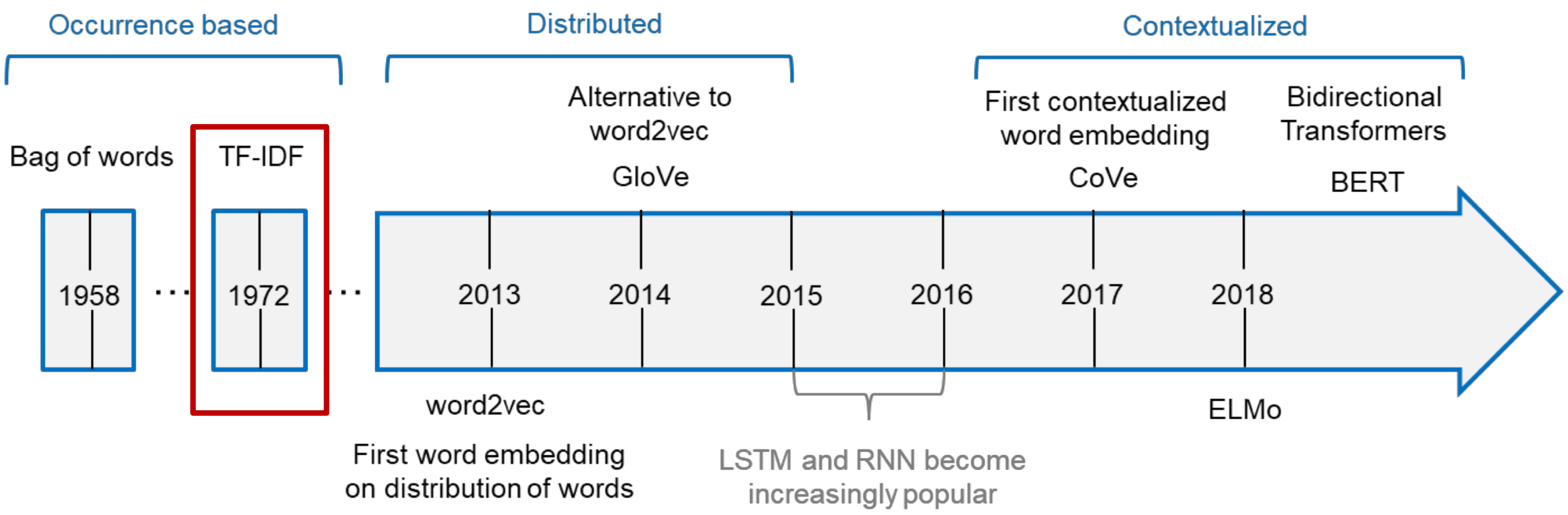

# Occurrence Based Word Representation

**Term Frequency – Inverse Document Frequency (TF - IDF):**

BoW computes the **frequency** of words to define their importance

**Issue:** It is **not necessarily the most frequent words that are the most important**. We have to take into account **rare** words across the corpus

→ Instead of using the frequency of BoW, TF-IDF uses another score which solves this problem:

$\boxed{tfidf(w,d) = tf(w,d) \times idf(w,C)}$ $w$ is a word, $d$ a document and $C$ the corpus

$$\begin{cases} tf(w,d) & \text{Term frequency of word } w \text{ inside document } d \text{ (similar to Bow)} \\ idf(w,C) & \text{Measure of \textbf{how rare} word } w \text{ is \textbf{across all documents}} \end{cases}$$

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$w$ is a word, $d$ a document and $C$ the corpus

$$\begin{cases} tf(w,d) = \dfrac{n_w}{|d|} \\ idf(w,C) = \log\left(\dfrac{|D|}{1+|d \in D : w \in d|}\right) + 1 \end{cases}$$

The score is divided by the number of documents which contain word $w$

The log function lowers the scaling for really frequent words

# Occurrence Based Word Representation

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We have to take into account **rare** words across the corpus

**Example:**
1. John likes to watch movies. Mary likes movies too.
2. John likes to watch football.

Vocabulary: "John" "likes" "to" "watch" "movies" "Mary" "too" "football"

$$BoW_2 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \qquad tfidf_2 = \begin{bmatrix} 1/5 \text{ x } (\log(2/(1+2))+1) \\ 1/5 \text{ x } (\log(2/(1+2))+1) \\ 1/5 \text{ x } (\log(2/(1+2))+1) \\ 1/5 \text{ x } (\log(2/(1+2))+1) \\ 0 \\ 0 \\ 0 \\ 1/5 \text{ x } (\log(2/(2))+1) \end{bmatrix} = \begin{bmatrix} 0.12 \\ 0.12 \\ 0.12 \\ 0.12 \\ 0 \\ 0 \\ 0 \\ 0.2 \end{bmatrix}$$

The TF – IDF scores focus on the word "football" because it is rare in the corpus

# Occurrence Based Word Representation

**Tricks to improve the models:**

- **N-grams**: Build a vocabulary that is a combination of successive words

  **Example:** It might be more useful for the model to consider "New York" as one term instead of two

- **Stemming/Lemmatization**: Keep only the root form of the inflected words

  **Example:** Inside documents it might be useful to aggregate the score of "playing", "play", "played" to a single term "play"

- **Stop words removal**: Remove commonly used words from vocabulary when building the BoW or TFIDF vector

  **Example:** Words such as "to", "and", "a" or "what" etc. do not give much information about documents

# Occurrence Based Word Representation

**Pros and cons:**

| Pros | Cons |
|---|---|
| • Really easy to compute<br>• Fast to compute as calculation are straightforward | Does not capture:<br>• Position in text<br>• Semantic<br>For big corpus the size of the vocabulary can be an issue |

Occurrence based word representations are

- Really good for text classification
- particularly bad at text comparison because they work as keyword matching and don’t consider the semantic of words

**To solve more complex NLP tasks we need models that work at a semantic level in order to catch synonyms.**

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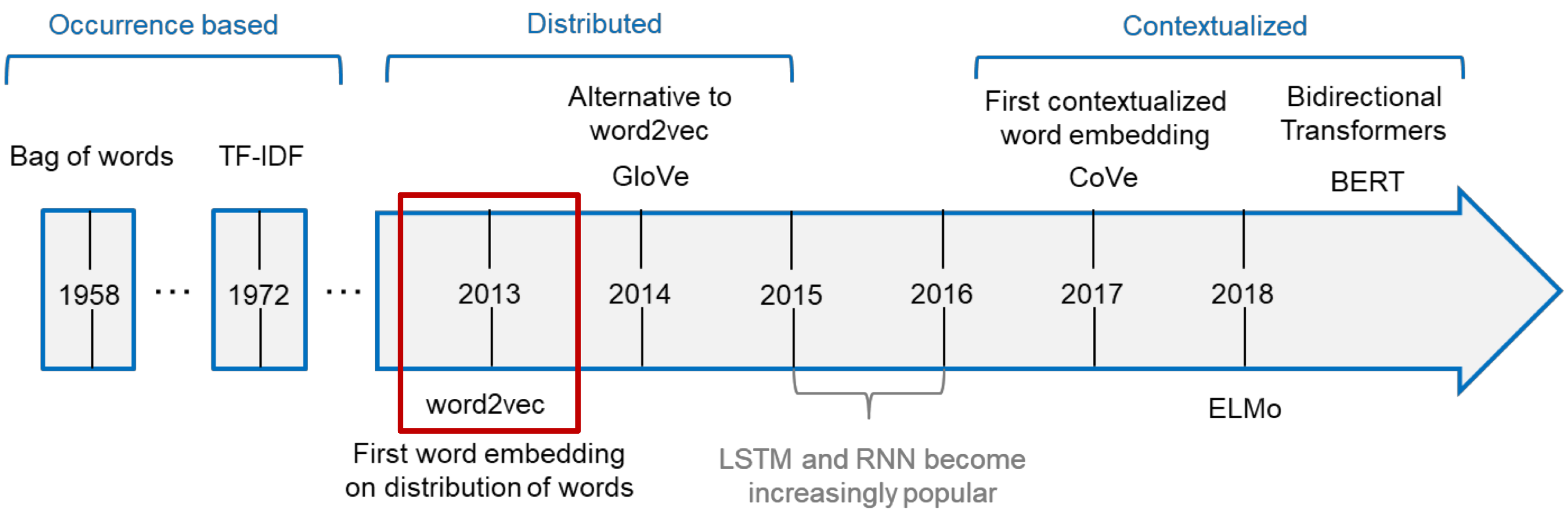


# Distributed Word Representation

**The intuition behind word embedding:**

A word embedding encodes **the meaning** of words into a vector of numerical values

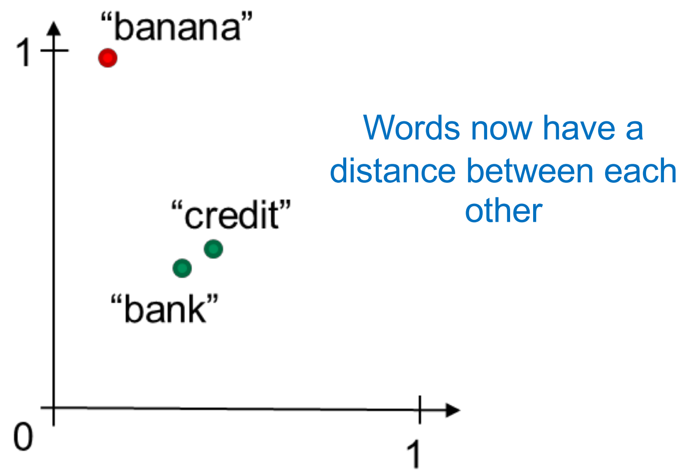
The model learns from analyzing the **context** in which words appear.

“two words that appear in the same context have similar meanings / are close to each other”

**Mathematically:** We want map words to vectors such that words that share **common contexts in the corpus** are **close neighbors in the vector space**

Word embedding in 2D

| | |
|---|---|
| “bank” | (0.4, 0.4) |
| “credit” | (0.46, 0.48) |
| “banana” | (0.15, 0.98) |



# Distributed word representation

**Training Data:** What does the model takes as input to learn the vector representation?

Input word → Word embedding model → Prediction of its context

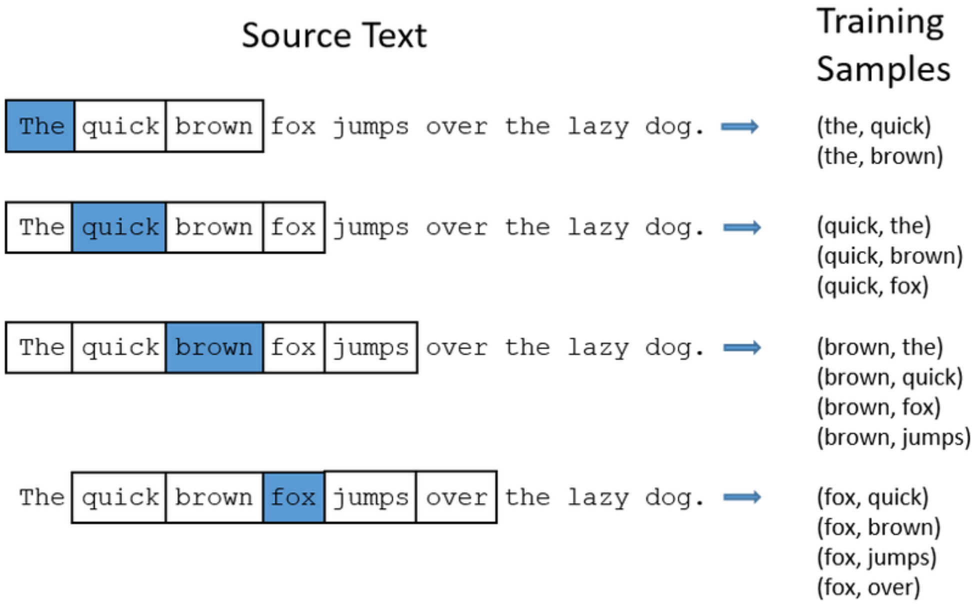
→ We need **training samples (input word, context)** in order to teach the model how to predict the context in which the input word appears

Where can we find numerous different contexts for words?

# Distributed word representation

**Training Data:** What does the model takes as input to learn the vector representation?

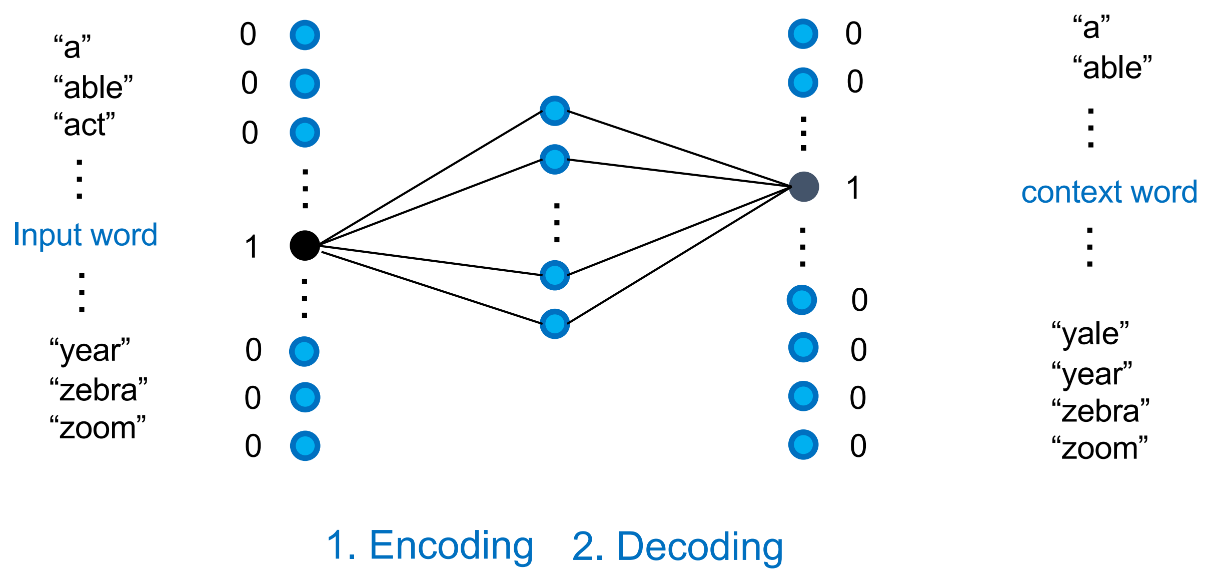
We use a **sliding window** over many **Wikipedia articles** to construct pairs (word, context).



# Distributed word representation

**Model Architecture:** How do we transform the meaning of words into vectors of real values?

→ We use a Neural Network as an auto-encoder




3. Maximize the probability of predicting the good context
→ Adjust the vector values

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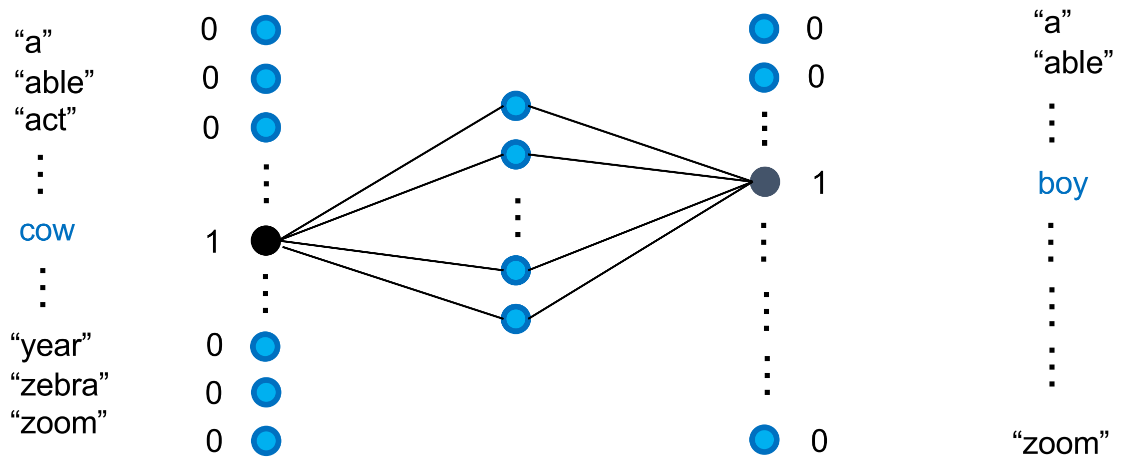

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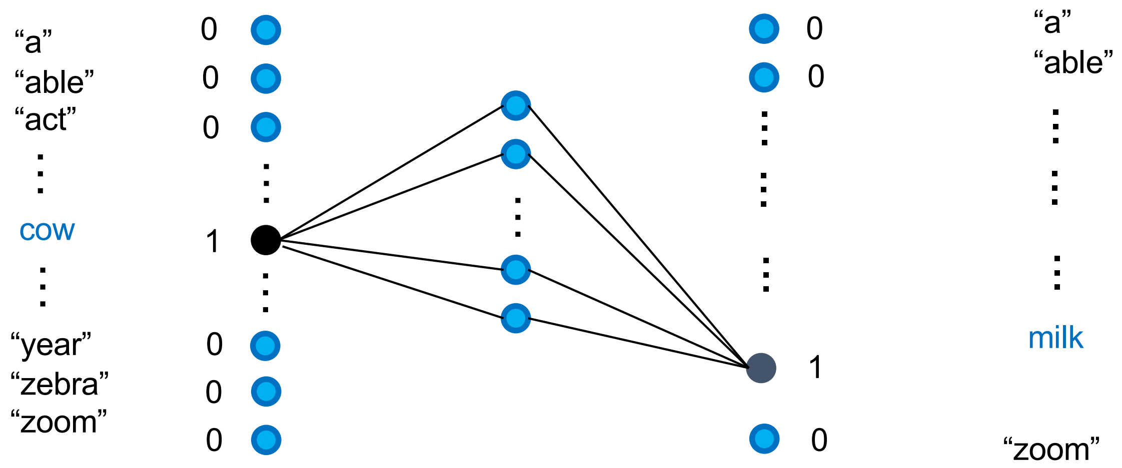

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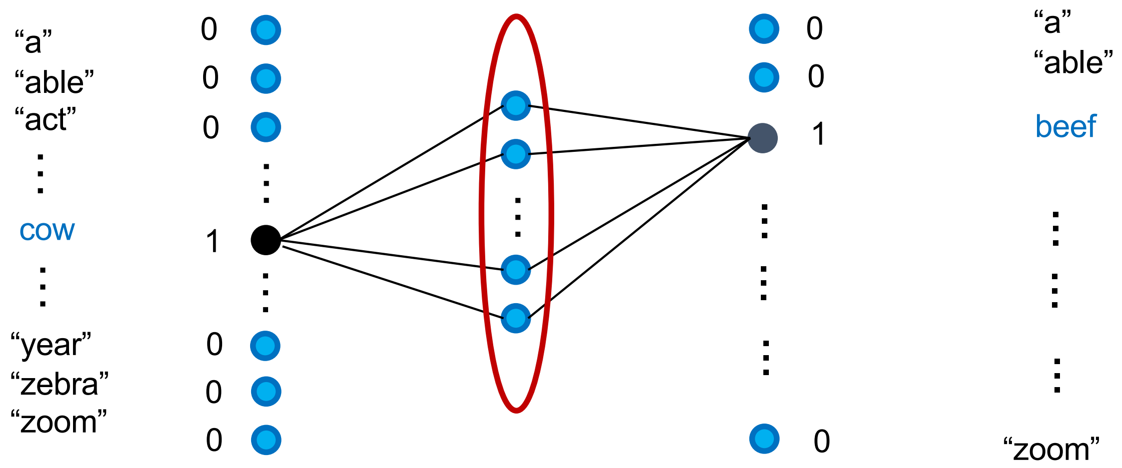



By showing the network enough pairs (input, context) we can condensate the information of the various context in which the word appears in order to **encode its meaning.**

Thanks to the encoding decoding mechanism the model is able to predict different context words from the **same input words** → encoded vectors contains the semantic of the word.

# Distributed word representation

**Illustration of Word Embedding capabilities**

**Semantic similarity:** Let’s ask the model what are the closest words to “bnp”:

```
> embedding_model.(positive=[bnp'], topn=3)
```

| Word | Similarity |
|---|---|
| paribas | 0.78 |
| khaleda | 0.54 |
| awami | 0.53 |
| societe | 0.51 |
| barclays | 0.48 |

BNP PARIBAS


Often written “bnp” on Wikipedia ☺

# Distributed word representation

**Illustration of Word Embedding capabilities**

**Linear operation:** We can do basic operations on word vector to recover semantic information

**Example:** “woman”+”king” – “man”=“queen”

“paris”+”spain” - “france”=“madrid”

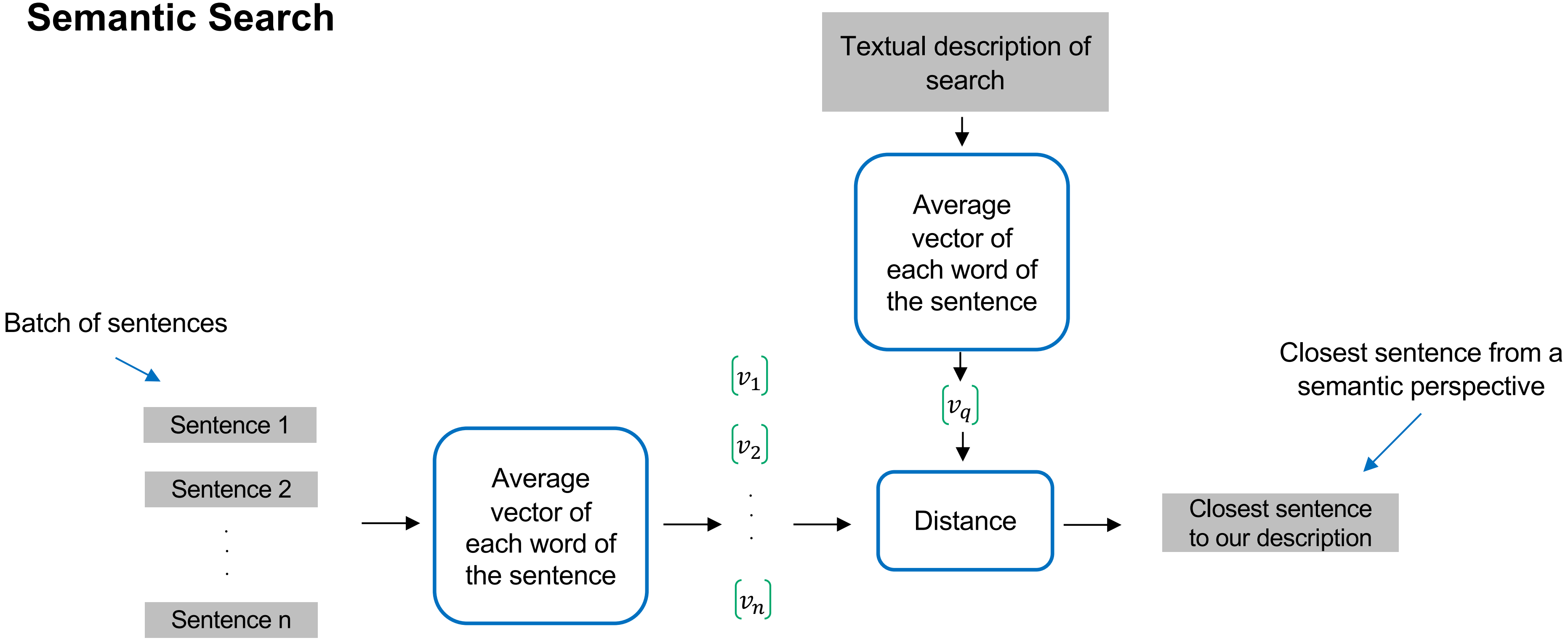
→ This means that we can combine the word of a sentence to compute its representation by taking the average vector of all the words of the sentence

→ We can do **semantic search** inside text

# Distributed word representation

## Illustration of Word Embedding capabilities

### Semantic Search



# Distributed word representation

| Pros | Cons |
| --- | --- |
| • Distance in vector space allow to compare text at a semantic level | • Harder to implement<br>• Encode a single vector for each word and thus a single meaning |

Word embedding are

- Less efficient for text classification when using simple models
- Very powerful for text comparison (Question answering, Natural Language Inference)

# Conclusion

- Word representation are constantly getting better allowing to encode abstract information about language such as the meaning of word
- This does not mean that we should replace the old by the new → Occurrence based word representation works great for text classification
- It is important to adapt the word representation to the NLP application we want to consider