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Introduction to Natural Language Processing

Part 1: Word Embeddings

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3rd March 2021

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Objectives

After today's lecture and tutorials you should be able to:

- Know what is **Natural Language Processing (NLP)** and why it's important
- Identify the main algorithms in **text representation learning**
- Spot common **challenges** in NLP and **ethical concerns**
- Gain intuition on what kind of information gets encoded in **word representations** and how it gets shown in the embedding space
- Get familiarised with the use of pre-trained **language models**, how to interpret them and implement them in a simple NLP pipeline

Outline

- *8:30 - 9:00* - **Lecture**
  Word Embeddings: challenges and techniques
- *9:00 - 9:30* - **Practical Work**
  Visualisation of semantic relations
- *9:30 - 9:45* - Break
- *9:45 - 10:30* - **Lecture**
  Language Modelling: deep learning methods for NLP
- *10:30 - 11:00* - **Practical Work**
  Transformer LM Part 1: Exploring a pre-trained model
- *11:00 - 11:15* - Break
- *11:15 - 11:45* - **Practical Work**
  Transformer LM Part 2: Fine-tuning for Sentiment Analysis

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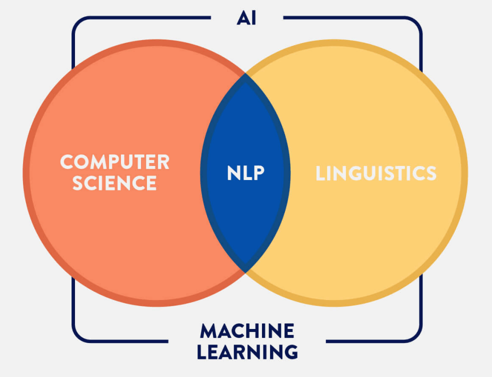
Table of contents

What is NLP?

Natural Language Processing is a sub-field of linguistics, computer science and artificial intelligence, that connects computers and human language.

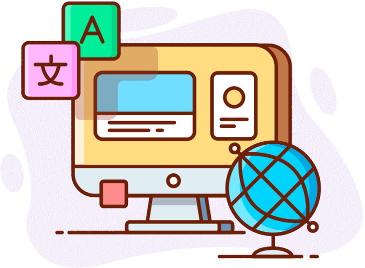
The field has experienced major changes since recent growth of **Deep Learning**.



Why bothering at all with NLP?

Computational encoding of text
opens the gate for:

- Machine Translation



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Computational encoding of text opens the gate for:

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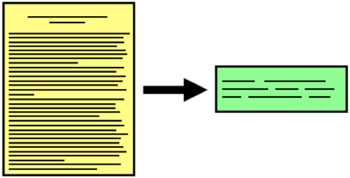
- Natural Language Understanding
- Automatic Text Summarisation



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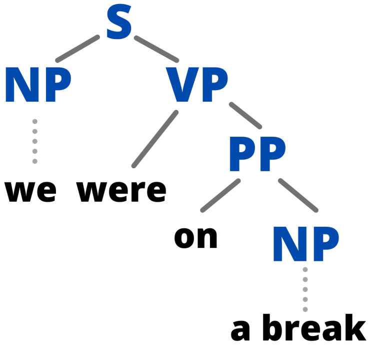

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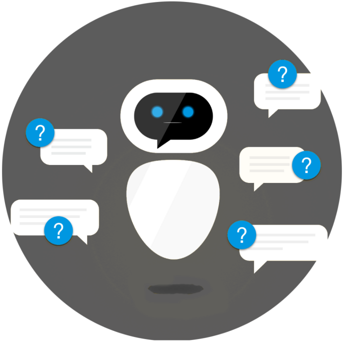
- Natural Language Generation
- Question-Answering



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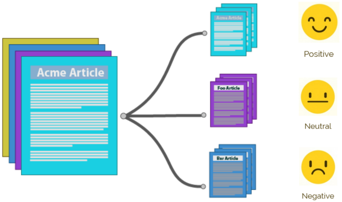
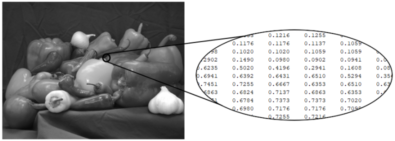
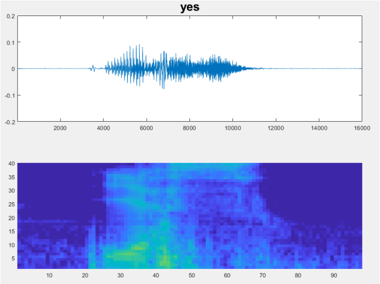


Differences with Image and Audio processing

With both images and audio, we start from a **signal**.
That signal is often of little use without some appropriate pre-processing.





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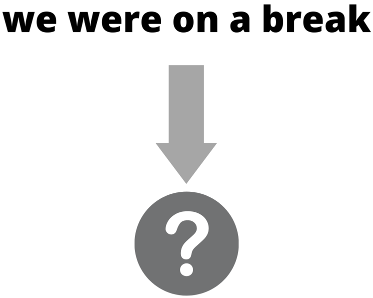
However, this isn't the case for text.

Hence, the **representation learning** process happens from scratch



Differences with Image and Audio processing

One hot-encoding is one possible approach for giving a vector to a word. Let's consider a vocabulary of possible words V with n terms. A one-hot representation for the word w, indexed by i in the vocabulary will correspond to the vector that has only zeros, except for the position i. That way, we can distinguish two different words.

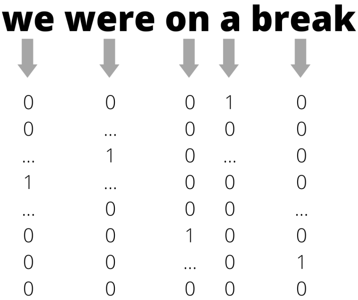
we	were	on	a	break
0	0	0	1	0
0	...	0	0	0
...	1	0	...	0
1	...	0	0	0
...	0	0	0	...
0	0	1	0	0
0	0	...	0	1
0	0	0	0	0

Differences with Image and Audio processing

However, in one-hot encoding we encounter the following problems:

- **Sparsity**: For a vocabulary of 10 thousand words we would have 10 thousand dimensional vectors
- **Lack of information**: the vectors wouldn't encode any semantic information.

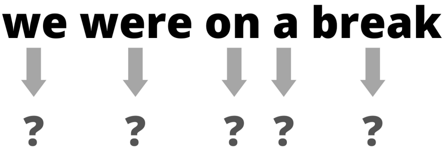
Therefore, we need a better way to construct our vectors.



Word Embeddings

The main idea with **word embeddings** is to create a vector for each word that is:

- **informative**: They encode useful information
- **light-weight**: Lower dimension than the size of the vocabulary
- **easy-to-obtain**: It's expensive to label an entire vocabulary, so we must learn representations automatically and with low computational cost.



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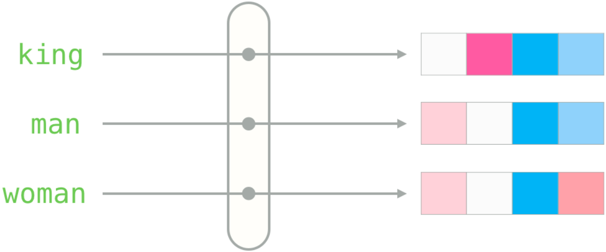

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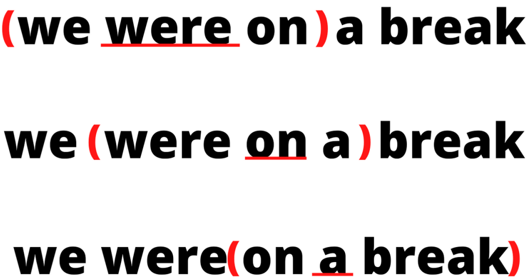
word2vec: Context-Window Methods

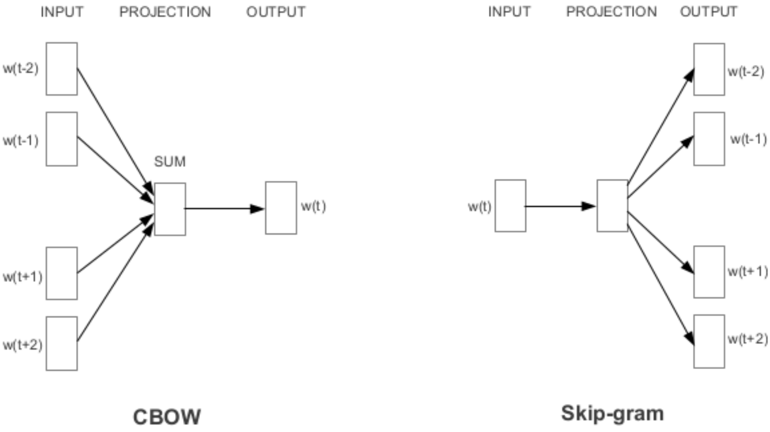
This section is based on **word2vec** by Mikolov et al. 2013 [1]. It is one of the most widely used pre-trained models for creating word vectors. They propose two architectures that are based on **context windows**[1].



[1] Figure shows examples of context windows of length 3 with the centre word underlined

word2vec: Context-Window Methods

They are also called **Log-linear** models since they use a Log-linear classifier as training objective.



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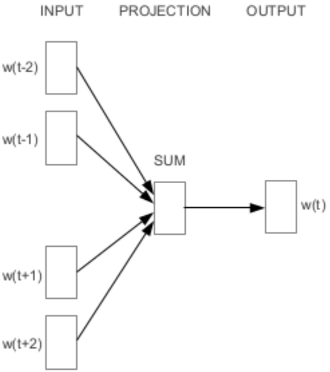
Continuous Bag-of-Words

In **CBOW**:

1. We take the **context words**. It's a bag-of-words, so order doesn't matter.
2. We project them in the **embedding space**
3. We **sum** the representations
4. We use that continuous representation of context to **predict the centre word.**



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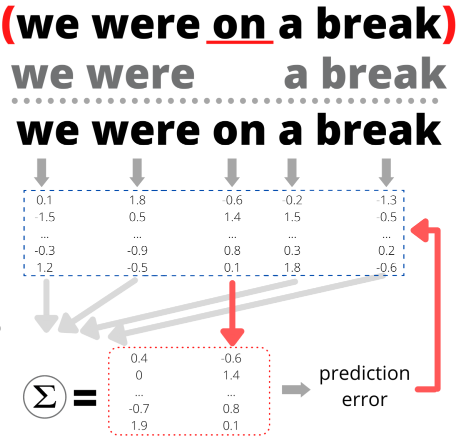


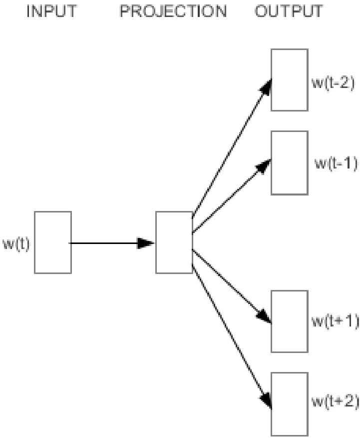
For our previous example, with context window of length 5, we would have

Skip-Gram

In **Skip-Gram**:

1. We take the **centre word**.
2. We project it in the **embedding space**
3. We **predict the context words** given the centre word representation.

This is roughly equivalent to compare centre and context words pairwise.



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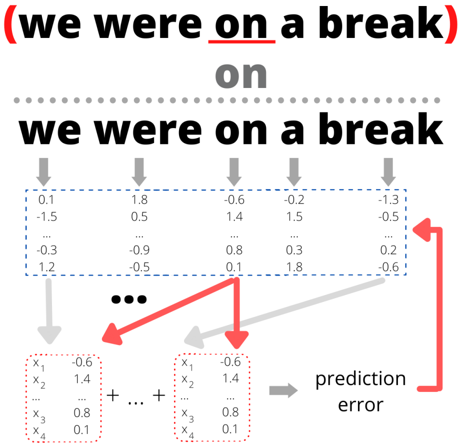
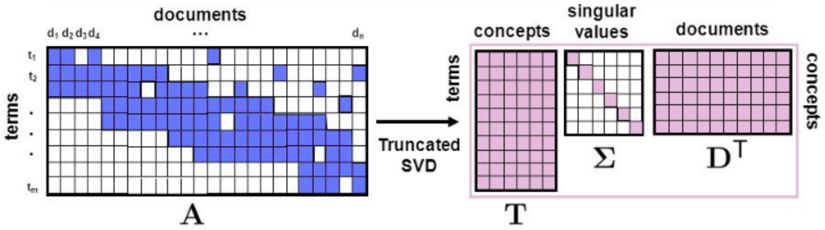


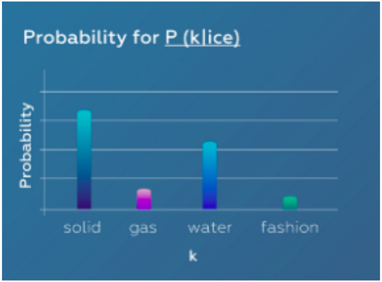
Matrix Factorisation: count-based models

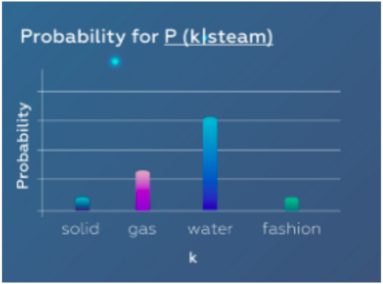
Count-based models take advantage of **word co-occurrence matrices**. Latent semantic analysis is one example in which matrix decomposition is used to grasp **statistical information** of terms and documents [2]. However, these methods generally **do not reflect semantic relations** in the same way word2vec does.



GloVe: a Hybrid Method

Global Vectors (**GloVe**) proposed by Pennington et al. seek to use statistical information while keeping the benefits of Skip-Gram [3]. For two words, they proceed by making the dot product of their embeddings equal to the logarithm of the **words' probability of co-occurrence** from the count matrix. To understand this, let's consider an example[2] with the words ICE and STEAM:

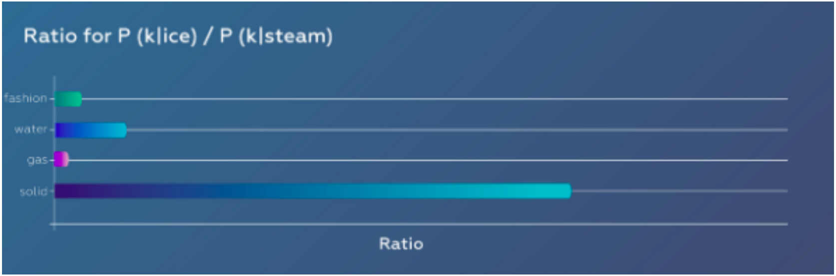




[2] Illustrations from: https://medium.com/@sciforce

GloVe: a Hybrid Method

Since both ICE and STEAM are related to WATER and unrelated to FASHION, these two words might be considered as **noise** when comparing them. The important information rather relies in the respective thermodynamic states.



GloVe implicitly causes the **vector differences** to correlate with **ratios of probabilities of co-occurrence.** This encodes more fine-grained **semantic relations** than pure context sharing.

Incorporating Knowledge

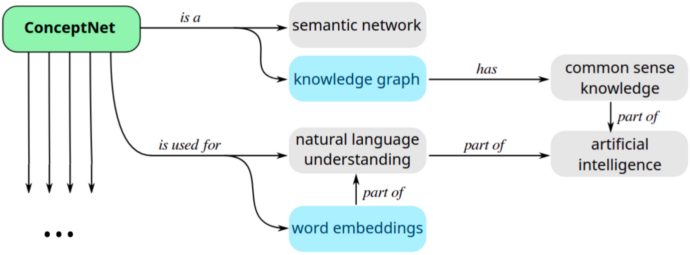
It is also possible to learn vectors in a (semi) supervised way. Here are two examples:

- **Retrofitting** is an algorithm that **fine tunes** pre-trained embeddings by minimising the distance between representations of words that are adjacent to each other in a **semantic graph** [4].

Incorporating Knowledge

It is also possible to learn vectors in a (semi) supervised way. Here are two examples:

- **Numberbatch** embeddings incorporate common sense knowledge from **ConceptNet**[3] by incorporating it using Retrofitting [5]. It is also partly built using a combination of word2vec and GloVe algorithms.



[3] http://www.conceptnet.io/

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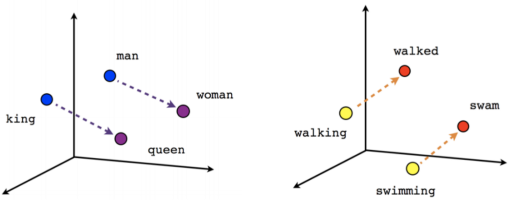
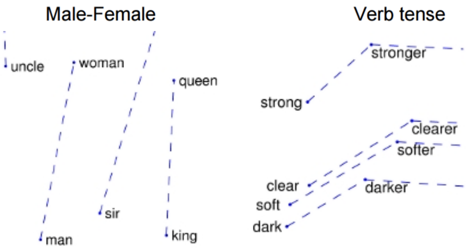
Semantic Regularities

Due to the way they are constructed, both word2vec (top) and GloVe (bottom) have shown to exhibit **linear substructures** [3, 6].

We'll further explore their embedding capacity in the practical session using Principal Component Analysis (**PCA**)





Drawbacks

Learning word representations comes at a cost:
Representing words as a point in an Euclidean space might not fully encode natural uncertainties in language such as **multiple senses** and **affective semantics.** Some works have tried with more complex embedding spaces.

Furthermore, drawing vectors from large corpora is dangerous since they can hide **stereotyped representations** [7]. A possible solution is debiasing vectors[8], which is done with Numberbatch[a].

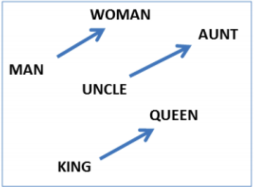
[a] http://blog.conceptnet.io/posts/2017/conceptnet-numberbatch-17-04-better-less-stereotyped-word-vectors/

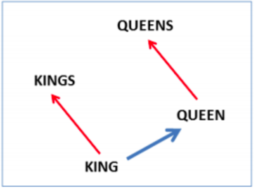
In a Nutshell

- word2vec uses context windows for learning word representations by either predicting the centre word (CBOW) or the context words (Skip-Gram)
- GloVe also incorporates co-occurrence probabilities from a term-document count matrix.
- Vectors can then be fine-tuned using semantic information, like Numberbatch does.
- NLP consists of many useful applications for which representation learning is the departing point
- However, we need to be aware of the possible harmful data encoded in pre-trained vectors

Visualisation of semantic relations

Objectives: You should gain intuition on what kind of information gets encoded in word representations and how to visualise it.
To do: You will code a **PCA visualisation of semantic relations** using Numberbatch. They can base their algorithm in an example given with countries and capitals.
Bonus task: Interested students may implement a simple semantic evaluation for word embeddings.





References I

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