

# Natural Language Processing

Artificial Intelligence and Machine Learning for SupTech – Lecture 7



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## Natural Language Processing

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1. What are the main approaches in textual analysis?
2. Going beyond simple word counts
3. How to extract market sentiment?

## Natural Language Processing

### Introduction

### Examples

### NLP Processing Layers

- Morphology

- Syntax

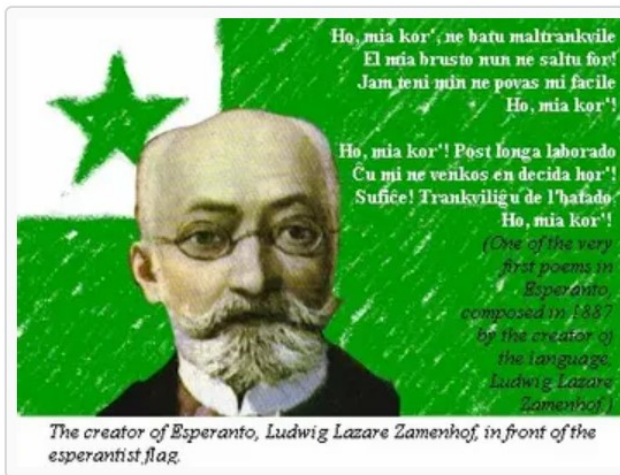
- Semantic

### Wrap-up

- What Is Natural Language Processing (NLP)?
  - NLP is a field of Artificial Intelligence (AI)
  - NLP makes human language intelligible to machines.
  - Combines the power of linguistics and computer science to study the rules and structure of language
- What is NLP used for?
  - Rapid development of applications
  - e.g. automatically categorize email as Promotions, Social, Primary, or Spam
- How does it work?



Gottfried Wilhelm Leibniz (1646 – 1716).









1. Email filters
2. Virtual assistants, voice assistants, or smart speakers
3. Online search engines
4. Predictive text and autocorrect
5. Monitor brand sentiment on social media
6. Sorting customer feedback and Chatbots
7. Natural language generation
8. Machine translation (MT)
9. Finding meaning and sentiment
10. Automatic summarization

## 1. Interchange

- Translation in one-to-one communication (telephone or written correspondence).
- Internet: tweets, blog posts, forums
- Human translation is out of the question (too slow)!
- Any output (even if poor) is better than no output

## 2. Assimilation

- Just to get a rough idea of the content
- Output need not be perfect
- But choice of words should reflect original meaning
- Example Japanese-English translation, for assimilation:

世界中の優秀な頭脳を魅了し、研究に集中できる  
ようなサポート体制の整った環境とはどのような  
ものでしょうか。

- *Attracts the brightest minds in the world, what What are the well-equipped en  
system, such as can concentrate on research*

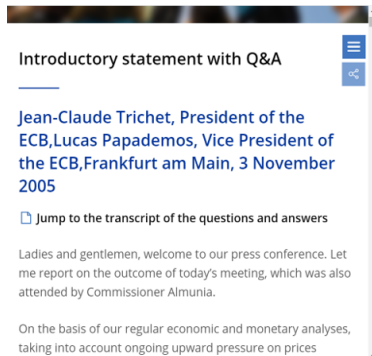
## 3. Disemmination

- Translation output to be distributed for human as-is without changes
- End users will have high expectations! → output must be perfect
- Hard – except for language pairs with huge amount of training data
- Example Russian–English translation, suitable for dissemination:

18 февраля 2015 года Аналитическое  
управление аппарата Совета Федерации  
совместно с экономическим факультетом МГУ  
проводят научный семинар «Реалистическое  
моделирование».

- *February 18, 2015 Analytical Department of the Federation Council in conjunction with the Faculty of Economics of Moscow State University conducted a scientific seminar “The realistic simulation.”*

- Deciphering the meaning of communications has a long history (e.g. Chappell et al. (1997) FOMC)
- Surveys in Loughran and McDonald (2019) and Bholat et al. (2015)
- Various application in Baker et al. (2016), Dim et al. (2021), Engle et al. (2020), Hassan et al. (2020), and Li et al. (2021) in:
  1. forecasting CDS
  2. changes in corporate culture
  3. economic uncertainty
  4. and many, many more ...



## ZITEL CORP

The Company has completed the entire process for its non-enterprise software and hardware as of November 30, 1999. The Company has identified and made inquiries of its significant suppliers and large public and private sector customers to determine the extent to which the Company is vulnerable to those third parties' failure to solve their own Year 2000 issues. .

If the Company is unable to generate sufficient cash flow from operations or should management determine it to be prudent, it may attempt to raise additional debt or equity. . There can be no assurance that management will be able to raise additional debt or equity financing.

There can be no guarantee that the systems of other companies or public agencies with which the Company does business will be timely converted, or that failure to convert by another company or public agency would not have a material adverse effect on the Company.

The Company's most likely worst-case Year 2000 scenario would be an interruption in work or cash flow resulting from unanticipated problems encountered with the information systems of the Company, or of any of the significant third parties with whom the Company does business. . The Company believes that the risk of significant business interruption due to unanticipated problems with its own systems is low based on the completion of the Year 2000 project.

RiskFinder and Liu et al. (2018)

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The Company's most likely **worst-case** Year 2000 **scenario** would be an **interruption in work or cash flow** resulting from **unanticipated problems** encountered with the information systems of the Company, or of any of the significant third parties with whom the Company does business. . The Company believes that the **risk** of **significant business interruption** due to **unanticipated problems** with its own systems is **low** based on the completion of the Year 2000 project.

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- DNB used NLP on millions of newspaper articles (36 years of history, de Winter and van Dijk (2021))
- Result: a sentiment indicator that helps improve short run GDP forecasts
- Measures economic activities faster than existing measures from Central Bureau for Statistics.

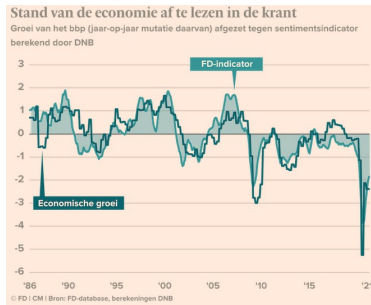
## DNB-onderzoek: het FD voorspelt de economische trend in Nederland

Mathijs Rotteveel Daan Baliegeer 26 mrt '21 21:00

Wie het FD leest, heeft voorkennis. Onderzoek van De Nederlandsche Bank leert namelijk dat het woordgebruik in de krant een voorspellende waarde heeft voor de economie.



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1. **Morphology**: word formation
  - Tokenising
  - Stemming
  - Lemmatising
2. **Syntactic analysis**: identifies the syntactic structure of a text and the dependency relationships between words, represented on a diagram called a **parse tree** (aka **parsing** or **syntax analysis**).
  - Part-of-Speech (POS)
  - Dependency
3. **Semantics**: aims to identify the meaning of language
  - Word Sense Disambiguation (WSD)
  - Sense tagging
4. **Speech**: phonemes
  - Distinct units of sound that distinguish one word from another: e.g. p, b, d, and t in the English words pad, pat, bad, and bat

- Differs markedly between languages
- For English:
  - Inflection: plant → plants, planted, planting ...
  - Derivation: plant → plantation, implant ...
- For Indonesian:
  - Inflection: sakit → sakitnya;  
                  pergi → pergilah
  - Derivation: sakit → pesakit, penyakit, sakitan...

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  - Passers-by did n't go ...
- Related: How to identify **sentence boundaries**?
  - "That's wonderful," he said. 'Have your people call mine. Try to arrange something by 10 a.m. tomorrow."



- **Stem**: reduced form (word stem, base or root form) or a word
- Need not be identical to the morphological root of the word!
- As long as related words map to the same stem
- Usually implemented by **stripping prefix/suffix**
- Example stemming:
  - producer → produc
  - produced → produc
  - producing → produc
  - carresses → carress
  - ponies → **poni**
  - caress → caress
  - cats → cat
- Can have phases/sequences of rules

- 
- **Information Retrieval** – search for documents based on keywords
  - **Stem all words** in documents and **store as index**
  - **Input keyword**: producer → ‘produc’
  - Search documents whose indices contain ‘produc’
  - Results will include documents containing ‘produce’, ‘produced’, ‘producer’ ...

- **Lemma:** base form of a word or term that is used as the formal dictionary entry for the term.
- Lemmatising can be seen as a special form of stemming
  - Stemming: outputs do not need to be real words
  - Lemmatising: outputs are genuine words used as headwords in dictionaries

(1) *Input: banks raised rates to fight inflation*  
*Lemmas: bank raise rates to fight inflation*

- Stemming is much faster than lemmatising
- But lemmatising is essential for many NLP tasks
- Would lemmatising be required for Chinese?

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Morphology

Syntax

Semantic

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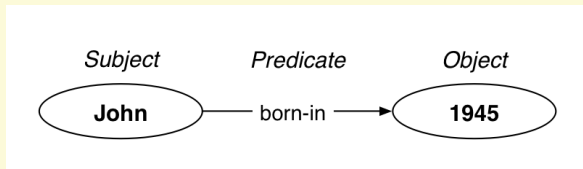
- Grammatical rules and structures are known
  - Syntactic processing: extract structure of phrase/sentences
1. Part-of-Speech (POS)
  2. Parsing

- **Part-of-speech (PoS) tagging**: add a speech category to each token within a text.
  - Common PoS tags are **verb**, **adjective**, **noun**, **pronoun**, etc
  - PoS tagging is useful for identifying relationships between words → understand the meaning of sentences

(2) *Input: banks raised rates to fight inflation*  
POS-tags: NNS VBD NNS TO VB NN

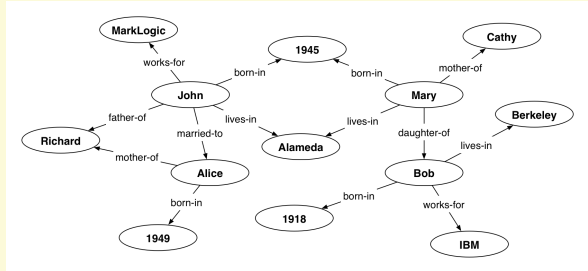
Tag	Description
NN	Noun, singular or mass
NNS	Noun, plural
VB	Verb, base form
VBD	Verb, past tense
VBG	Verb, gerund or present participle
...	...

- The base of linked data is the **Resource Description Format (RDF)** [more info](#)
- Framework for describing resources on the world wide web
- Can be queried with **SPARQL**





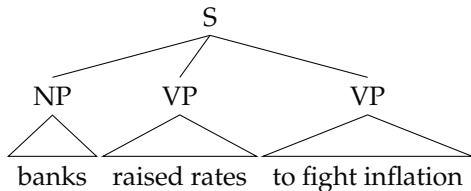
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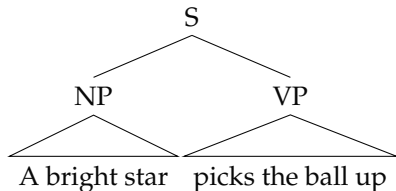
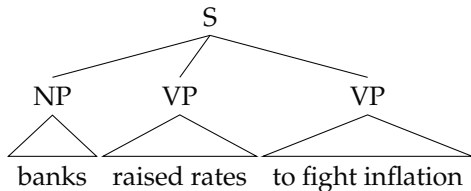
- Given an utterance, assign the most likely POS tag to each word token
- Current libraries quite stable now (for English):  $\sim 96\%$  accuracy
- Different languages may have different sets of POS Tagsets
- English: [Penn Treebank \(PTB\)](#) tagset is widely adopted

- Sentences/clauses are made up of **phrases** following grammar/syntax rules
- Some examples:
  - Noun phrase (NP): 'a bright star', 'cats', 'stars and moons'
  - Verb phrase (VP): 'ran', 'picks the ball up'
  - Clause/sentence (S): NP VP 'a bright star picks the ball up'
- A syntactically correct sentence **doesn't have to makes sense!**

- Identify the **noun phrases**, **verb phrases** etc but do not go into the internal structure



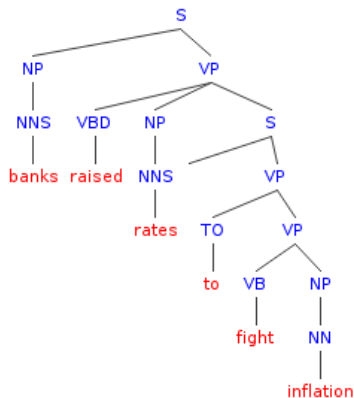
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- Fully building the clauses and relations in a sentence
- Syntactic **parse tree**:

‘Banks raised rates to fight inflation’

```
(S
  (NP (NNS banks))
  (VP (VBD raised)
    (NP (NNS rates))
    (S
      (VP (TO to)
        (VP (VB fight)
          (NP (NN inflation)))))))
```



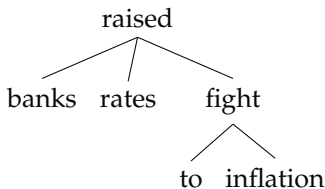
- **Dependency Parsing:** uncover the way the words in a sentence are connected. A dependency parser, therefore, analyzes how **head words** are related and modified by other words too understand the syntactic structure of a sentence:

```
nsubj(raised, banks)
root(ROOT, raised)
dobj(raised, rates)
aux(fight, to)
vmmod(raised, fight)
dobj(fight, inflation)
```

‘Banks raised rates to fight inflation’

- ‘banks’ is subject of ‘raised’
- ‘rates’ is object of ‘raised’
- ...

Parsing is more difficult than POS-tagging



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- 
- The meaning conveyed by the text
  - Hard!
  - How to represent 'meaning'?
  - Still an open question in artificial intelligence, cognitive science, psychology...
  - Lots of on-going research

- **Word Sense Disambiguation (WSD)**: Depending on their context, words can have different meanings (a.k.a. **Sense-tagging**). Take the word “book”, for example:
  - You should read this **book**; it’s a great novel!
  - You should **book** the flights as soon as possible.
  - You should close the **books** by the end of the year.
  - You should do everything by the **book** to avoid potential complications.
- Main techniques for WSD:
  1. **knowledge-based (or dictionary approach)**: tries to infer meaning by observing the dictionary definitions of ambiguous terms within a text
  2. **supervised approach**: based on natural language processing algorithms that learn from training data
- Can be used for **Synonym Expansion**: Search for ‘wizard’ would also retrieve documents containing ‘sorcerer’, ‘magician’

- **Stop words**: Words that are ignored in NLP tasks (e.g. function words in a sense-tagging task). Filters out **high-frequency words** that **add little value** to a sentence, for example, **which, to, at, for, is**, etc.
  - How to identify stop words?
    - Open-class words (content words): nouns, verbs, adjectives, adverbs
    - Closed-class words (function words): determiners, pronouns, conjunctions, infinitives...
    - Stop words are the residual
- ...so WSD needs POS-tagging and lemmatisation first

## Senses of bank.n in WordNet

1. sloping land (especially the slope beside a body of water)
2. a financial institution that accepts deposits and channels the money into lending activities
3. a long ridge or pile
4. ...

(3) *Input: banks raised rates to fight inflation*  
*Sense-tags: bank.n.2 raise.v.13 rates.n.1 fight.v.1 inflation.n.1*

- Label each sense in the input with a concept tag  
(Example below uses WordNet–SUMO mapping)

(4)	<i>Input:</i>	<i>banks</i>	<i>raised</i>	<i>rates</i>	<i>to fight</i>	<i>inflation</i>
	Sense-tags:	bank.n.2	raise.v.13	rates.n.1	fight.v.1	inflation.n.1
	Concept tags:	CORPORATION	INCREASING	TAX	VIOLENTCONTEST	INCREASING

- **Named Entity Recognition (NER)**: one of the most popular tasks in semantic analysis and involves extracting entities from within a text. Entities can be names, places, organizations, etc. **Relationship extraction**, another sub-task of NLP, goes one step further and finds relationships between two nouns. For example, in the phrase “Susan lives in Los Angeles,” a person (Susan) is related to a place (Los Angeles) by the semantic category “lives in.”
- Coreference resolution
  - ‘The cat climbed onto the chair. It yawned and slept.’

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  - ANIMATE OBJECT  $\xrightarrow{\text{capable-of}}$  ‘yawn’, ‘sleep’
  - $\therefore$  ‘It’ = ‘the cat’

- **Text Classification** Text classification aims to understand the meaning of unstructured text and organizing it into predefined categories (**tags**). One of the most popular text classification tasks is **sentiment analysis**, which aims to categorize unstructured data by sentiment.
  - Other classification tasks: **intent detection**, **topic modeling**, and **language detection**.

```
1  from nltk.sentiment.vader import SentimentIntensityAnalyzer
2  sentences = [
3      "VADER is smart, handsome, and funny.",          # positive sentence
4      "VADER is smart, handsome, and funny!",          # punctuation emph., adj. intensity
5      "VADER is very smart, handsome, and funny.",      # booster words
6      "VADER is VERY SMART, handsome, and FUNNY.",      # emphasis for ALLCAPS
7      "VADER is VERY SMART, handsome, and FUNNY!!!",    # many signals, adj. intensity
8      "VADER is VERY SMART, really handsome, and INCREDIBLY FUNNY!!!", # booster
9      "The book was good.",                              # positive sentence
10     "The book was kind of good.",                       # qualified pos., adj. intensity
11     "The plot was good, but unconvincing characters and the dialog is not great.",
12                                     # mixed negation sentence
13     ...
14 ]
15 paragraph = "It was one of the worst movies I've seen, despite good reviews. \
16 Unbelievably bad acting!! Poor direction. VERY poor production. \
The movie was bad. Very bad movie. VERY bad movie. VERY BAD movie. VERY BAD
movie!"
```

- Biggest challenge in NLP is simply that human language is ambiguous
- Even humans struggle to analyze and classify human language correctly.
  - Sarcasm, humour, ...
- Natural language processing and powerful machine learning algorithms (often multiple used in collaboration) are improving, and bringing order to the chaos of human language

- [SMMRY](#): Summarize my text in [7] sentences.
- [TextBlob](#) is a Python library with a simple interface to perform a variety of NLP tasks. Built on the shoulders of NLTK and another library called Pattern, it is intuitive and user-friendly, which makes it ideal for beginners. Learn more about how to use TextBlob and its features
- [Natural Language Toolkit \(NLTK\)](#) is a suite of libraries for building Python programs (Bird et al. (2009)). It is the most popular Python library for NLP, has a very active community behind it, and is often used for educational purposes
- [SpaCy](#) is a free open-source library for advanced natural language processing in Python. It has been specifically designed to build NLP applications that can help you understand large volumes of text
- [MonkeyLearn](#) is a SaaS platform that lets you build customized NLP models to perform tasks like sentiment analysis and keyword extraction

- Choosing one package over another is often not clear cut as it depends on the circumstances. Your choice could depend on:
  - **Focus**. NLTK sees things holistically, while spaCy is known for its granular approach. NLTK == used to develop complex NLP functions via different [stemming libraries](#). Used by researchers to build something from scratch. spaCy == single stemmer and good fit for app builders
  - **Processing**. NLTK takes strings as input and returns lists of them as output. spaCy is object-oriented: every function returns objects as output. With NLTK, developers have to check out the documentation on a regular basis, while spaCy allows for easy exploration.
  - **Performance**. NLTK considerably slower than spaCy: the latter was written in Cython from scratch. Also, spaCy exceeds NLTK with regard to **part-of-speech** tagging and **word tokenization**.
- Nice [spaCy](#) and [NLTK](#) tutorials

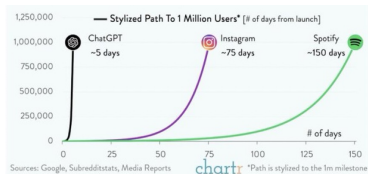


## Bi-directional Encoder Representations from Transformers

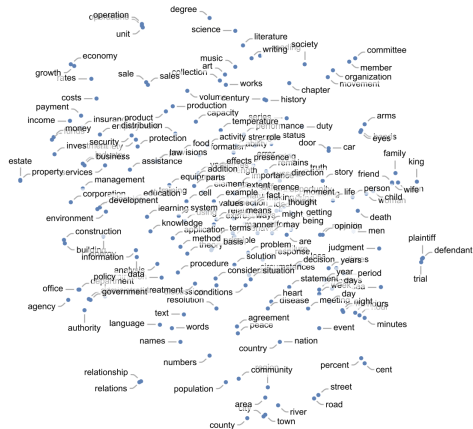
- BERT was trained on 2500M words in Wikipedia and 800M from books.
- BERT reads the sentence from left to right but also from right to left
- BERT encodes the sentence to a vector so that we can work with It
- BERT uses an **attention mechanism** to use the context of the use of a word
- Other language models Generative Pre-trained Transformers: GPT-3 and OPT-175B



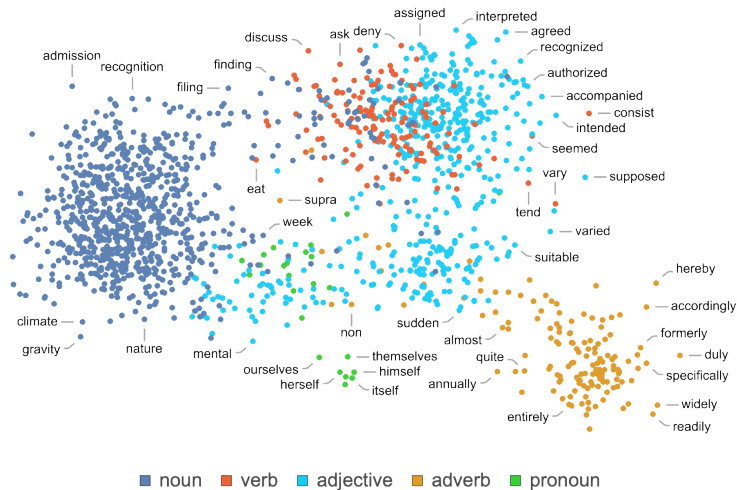
- Incredibly fast pick-up
- ChatGPT has an uncanny performance
- Especially useful for writing code and generating boiler plate text
- It passed the Bar and passed the US medical licensing exam

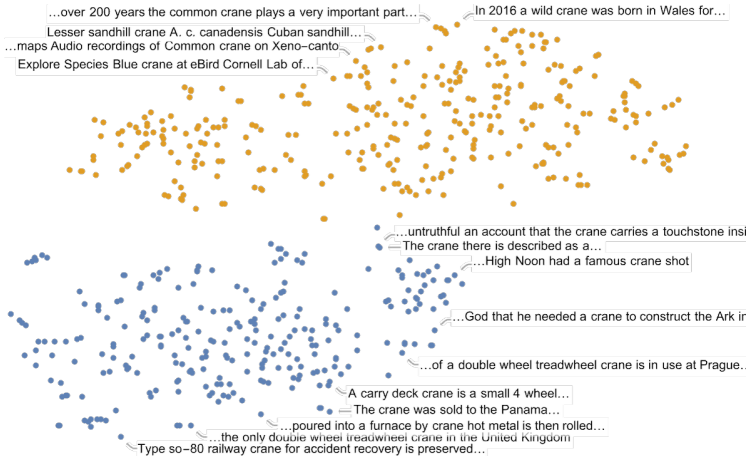


# How does GPT work?



Source: Wolfram





Source: Wolfram

1. **Effects on employment:** will change types of jobs not yet touched by automation
2. **Hallucinating:** ChatGPT has the tendency to authorotively make up stuff
3. **Bias:** it's trained on what is on the internet in 2021. The internet is not representatieve or inclusive
4. **Fake news:** makes it very cheap and convincing to generate disinformation. See Frankurter's article "On Bullshit" (**Frankurt1986**)
5. **Boring:** it generates the most probable text. This is often middle of the road

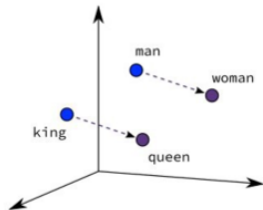
See [Matt Turck's blog](#) for further discussion

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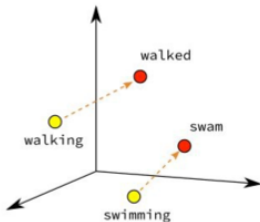
In this lecture we covered:

1. some examples of Natural Language Processing (NLP)
2. a discussion of the different building blocks needed (e.g. tokenization, lemmatization, etc.)
3. how to use these methods to extract the right information from textual input

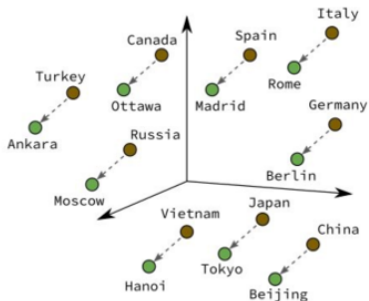
# What are word vectors?



Male-Female









Verb Tense



Country-Capital



- [Ivan Habernal](#)
- [Natural Language Processing \(NLP\): What Is It and How Does it Work?](#)
- [BERT NLP Model Explained for Complete Beginners](#)

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