Natural Language Processing

An Introduction

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Introduction

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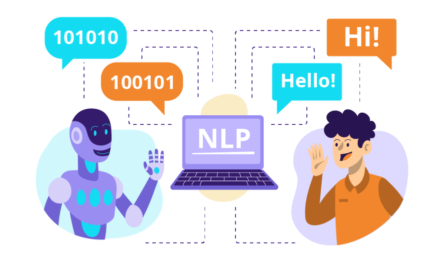
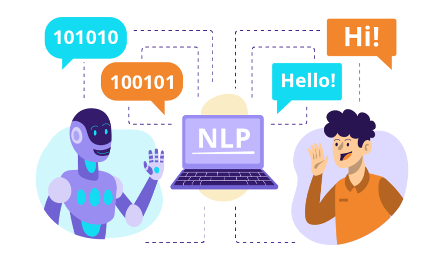
- Collecting feedback on webpages and apps
- Chatting with users and providing answers
- Voice assistants that accomplish a wide variety of tasks

Image: https://techcrunch.com/wp-content/uploads/2018/10/Assistant_1.png

Natural Language Processing



Natural Language Processing



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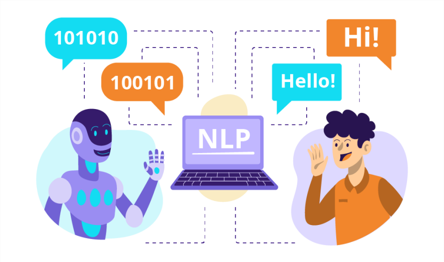

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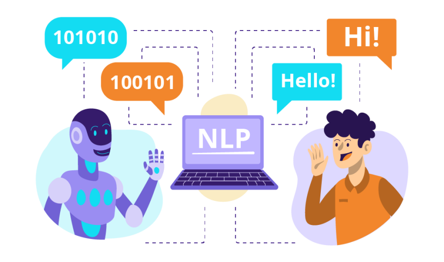

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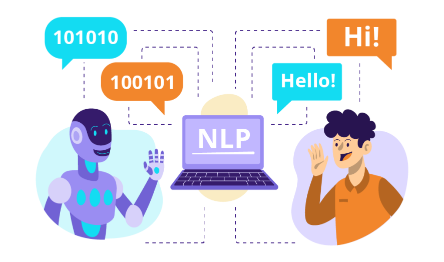

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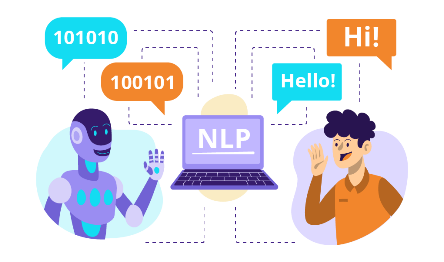

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- Using human language as input
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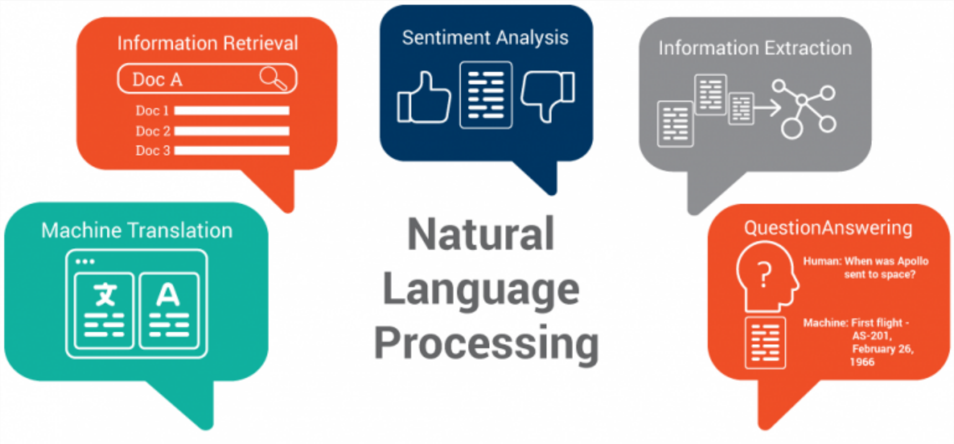
- Represents text as numbers, that Machine Learning models can understand

Image: `https://images.app.goo.gl/C7otX6X8TdFWfYPY7`

NLP Tasks



Information Retrieval
Doc A
Doc 1
Doc 2
Doc 3
Sentiment Analysis
Information Extraction
Machine Translation
文
A
Natural Language Processing
QuestionAnswering
?
Human: When was Apollo sent to space?
Machine: First flight - AS-201, February 26, 1966

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- Each language has grammar, that has complex rules
- And a wide variety of expression

Expression in natural language

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- Lightning made the dog run to its owner

Punctuation

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Usage of stop words

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Concise summarization

- dumb movie
- very scenic place

Preprocessing Methods

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- Earliest NLP techniques had standard pre-processing methods
- Latter models incorporated pre-processing into process flow, doing away the need for separate pre-processing

Natural Language Processing

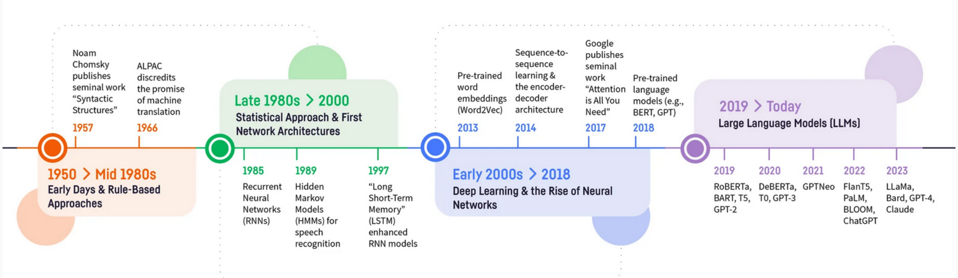

Image: `https://blog.dataiku.com/nlp-metamorphosis`

Some Milestones

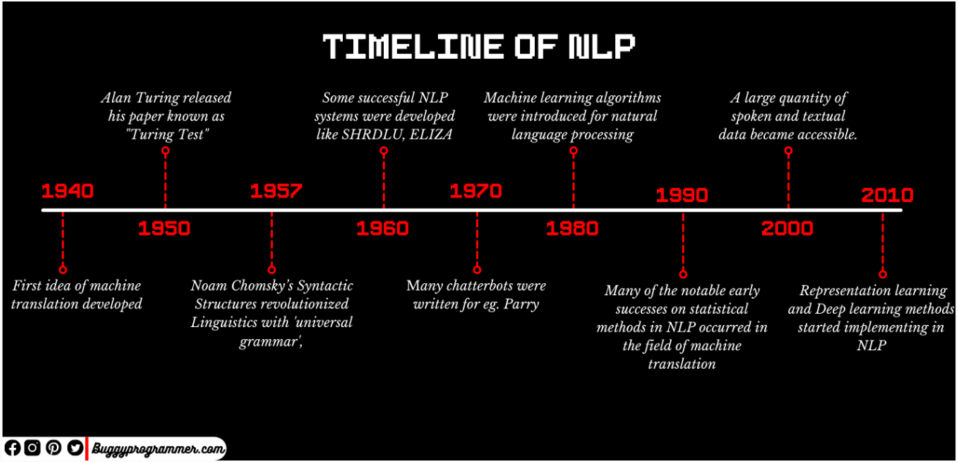

Image: `Buggyprogrammer.com`

Pre-processing Techniques

Earliest NLP techniques relied on reducing the number of unique words needed for the model

- Tokenization
- Stop Word Removal
- Stemming
- Lemmatization
- n-grams

Text pre-processing

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- Lemmatization: Reduces words to their base form
- Tokenization: Splitting longer strings of text into smaller pieces, usually words

Noise removal

Text Strings with html tags	Cleaned Results
Excel 365	Excel 365
Insert multiple blank rows	Insert multiple blank rows
<i>Merge all sheets into one</i>	Merge all sheets into one
Office Tab	Office Tab
Kutools for Excel	Kutools for Excel
www.extendoffice.com	www.extendoffice.com

Image: https://images.app.goo.gl/vmivtWRWVkSGGLJW6

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- “This is SPARTA” $\rightarrow$ “this is sparta”

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- Have to choose appropriate stop words to remove

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- Text simplification, improved model performance and standardization

Stemming example

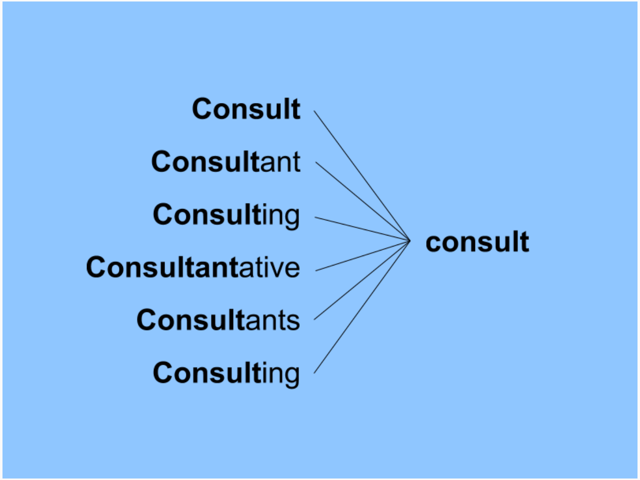

Image: `https://images.app.goo.gl/gRobrUoMPV3xNKA16`

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Lemmatization

- Uses vocabulary and morphological analysis of words
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- Example: Stemming 'saw' might return 's', while Lemmatization will return 'see' or 'saw' based on whether the token was used as verb or noun

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Lemmatization example

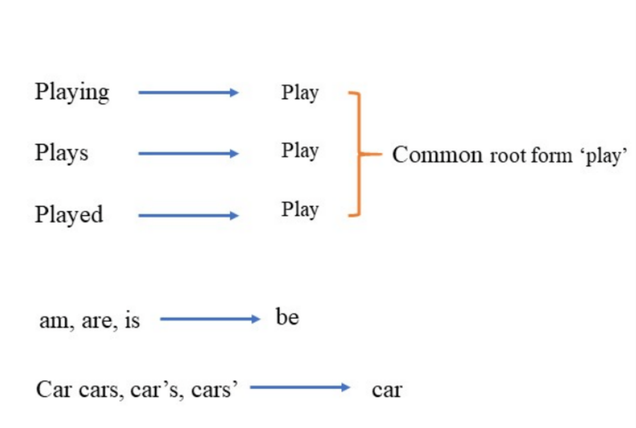

Image: https://github.com/Learn-Write-Repeat/Open-contributions/blob/master/B2-NLP/Amey_Nlp_Lemmatization_stemming.md

Stemming vs. Lemmatization

Stemming commonly collapses derivationally similar words, while Lemmatization only collapses different inflectional form of a lemma.

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- Needs care to ensure that meaning is not lost

Tokenization methods - NLTK

Natural Language Toolkit is an open source Python library for NLP. Has interfaces for different corpora like WordNet

Image: https://neptune.ai/blog/tokenization-in-nlp

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  - Separates based on phrase splitting punctuations like ?!

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  - Can merge required words into single tokens for analysis

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- Choice of tokenization governed by applications
- Each tokenizer might have slight differences in the way words are broken

An example

Original text : Alice in wonderland

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```
Alice was beginning to get very tired of sitting by her sister on the bank, and of
     having nothing to do. Once or twice she had peeped into the book her sister
    was reading, but it had no pictures or conversations in it, "and what is the
    use of a book," thought Alice, "without pictures or conversations?"
```

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Word tokenize: Alice in wonderland

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```
['Alice', 'was', 'beginning', 'to', 'get', 'very', 'tired', 'of', 'sitting', 'by',
    'her', 'sister', 'on', 'the', 'bank', ',', 'and', 'of', 'having', 'nothing', '
    to', 'do', '.', 'Once', 'or', 'twice', 'she', 'had', 'peeped', 'into', 'the', '
    book', 'her', 'sister', 'was', 'reading', ',', 'but', 'it', 'had', 'no', '
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```

An example

Stemming: Alice in wonderland

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```
beginning : begin

very : veri

tired : tire

sitting : sit

having : have
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Word stemming: Alice in wonderland

```
['alic', 'wa', 'begin', 'get', 'veri', 'tire', 'sit', 'sister', 'bank', ',', 'noth
    ', '.', 'onc', 'twice', 'peep', 'book', 'sister', 'wa', 'read', ',', 'pictur',
    'convers', ',', '``', 'use', 'book', ',', "''", 'thought', 'alic', ',', '``', '
    without', 'pictur', 'convers', '?', "''"]
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Word Representation

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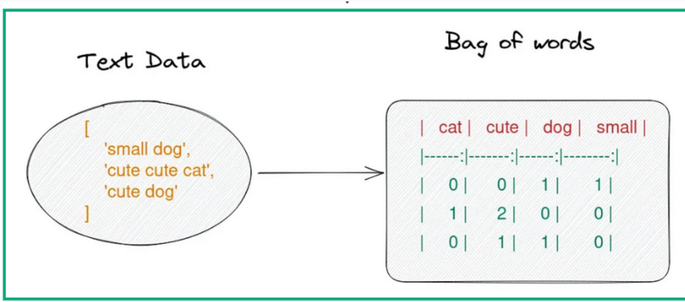

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Term Frequency X Inverse Document Frequency

$$w_{x,y} = tf_{x,y} \times log(\frac{N}{df_x})$$

Text1: Basic Linux Commands for Data Science
Text2: Essential DVC Commands for Data Science

	basic	commands	data	dvc	essential	for	linux	science
Text 1	0.5	0.35	0.35	0.0	0.0	0.35	0.5	0.35
Text 2	0.0	0.35	0.35	0.5	0.5	0.35	0.0	0.35

Image: https://www.kdnuggets.com/wp-content/uploads/awan_convert_text_documents_tfidf_matrix_tfidfvectorizer_3.png

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- These techniques are typically used for Sentiment Analysis

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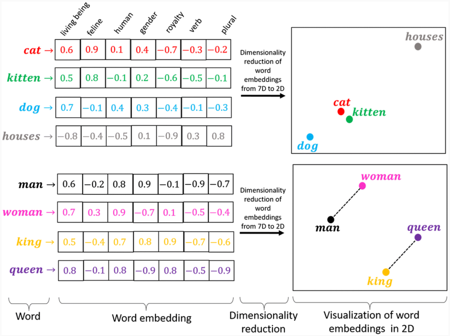

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Word Embeddings

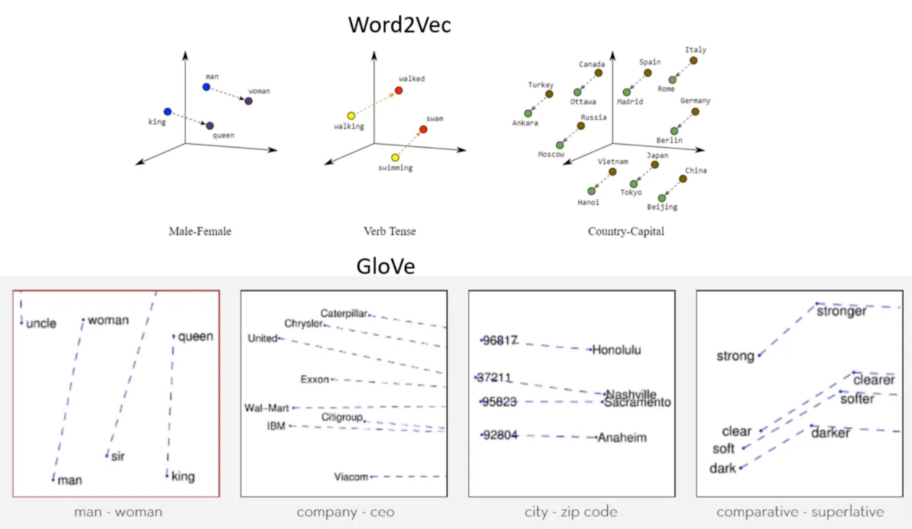

Image: `https://towardsdatascience.com/word-embeddings-for-nlp-5b72991e01d4`

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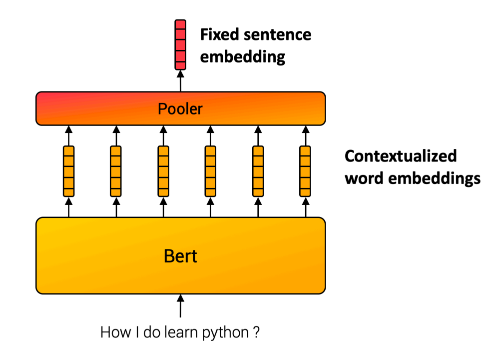

Image: `https://images.app.goo.gl/rVMefeyEKT8jnsBBA`

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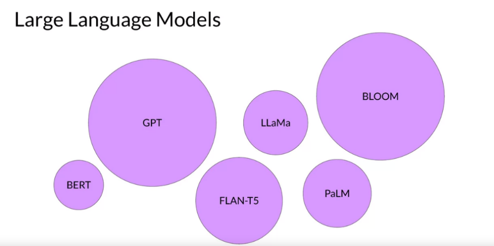
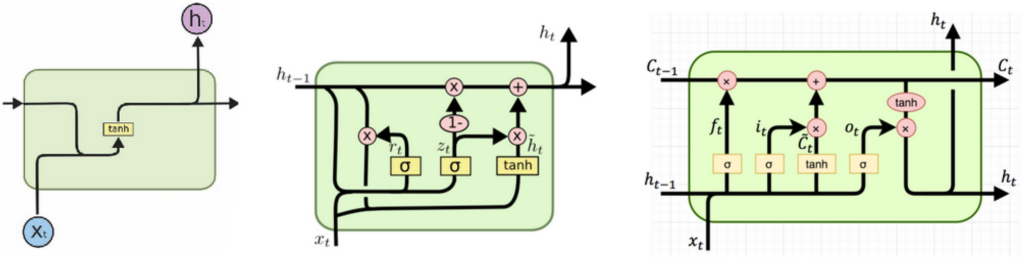


NLP Models

Basic NLP Models



Basic architectures of RNN, GRU and LSTM cells

- RNN: Recurrent Neural Network
- GRU: Gated Recurrent Unit
- LSTM: Long Short-Term Memory

https://medium.com/@saurabh.rathor092/simple-rnn-vs-gru-vs-lstm-difference-lies-in-more-flexible-control-5f33e07b1e57

Transformers

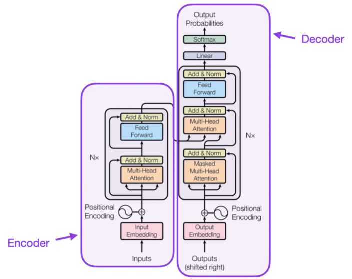


Figure 1: The Transformer - model architecture.

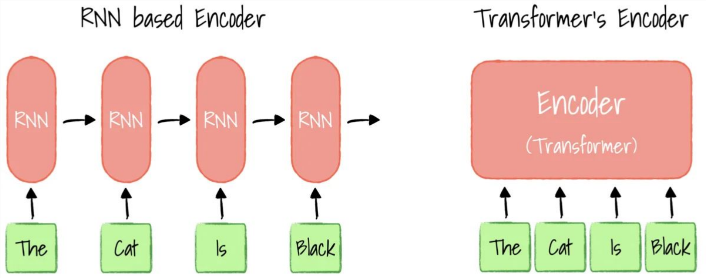


Image: `https://jinglescode.github.io/2020/05/27/illustrated-guide-transformer/`

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Image: https://medium.com/mlearning-ai/3-llm-architectures-f527ed781ba9

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- Large Language Models use their own tokenizers and embeddings
- Minimal pre-processing required to use LLMs for NLP tasks
- However, LLMs are computationally heavy - may not be required for simple tasks

Thank you.