Natural Language Processing (NLP)

Linguistic Basics	Text Identification/ Extraction	Text Representation
1. Lemmatization	4. Stop Words	8. Tokenization
2. Stemming	5. Pattern Matching	9. Word Embedding
3. Part of Speech Tagging	6. Sentence Segmentation	10. Bag-of-words/TF-IDF
	7. Named Entity Recognition	

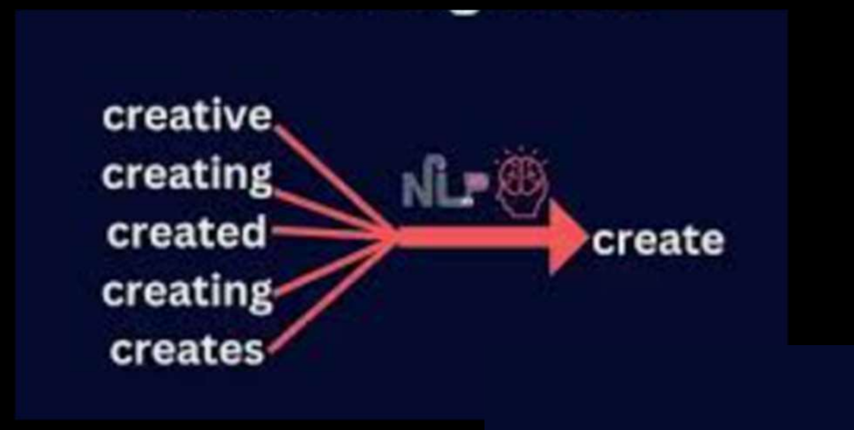
NLP - Stemming

Obtain the base or root form of words by removing letters from the word's end

```
from nltk.stem.porter import *

p_stemmer = PorterStemmer()
words = ["runner", "running", "ran"]
for word in words:
    print(word+' --> '+p_stemmer.stem(word))
```

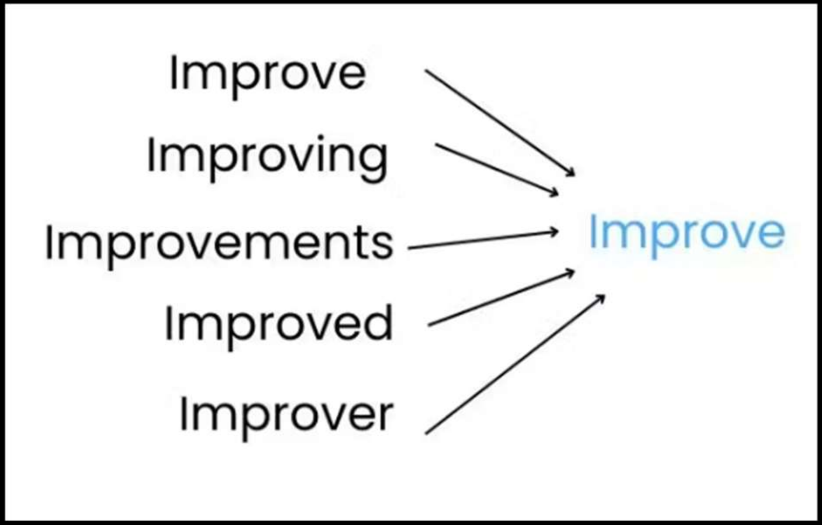
```
runner --> runner
running --> run
ran --> ran
```

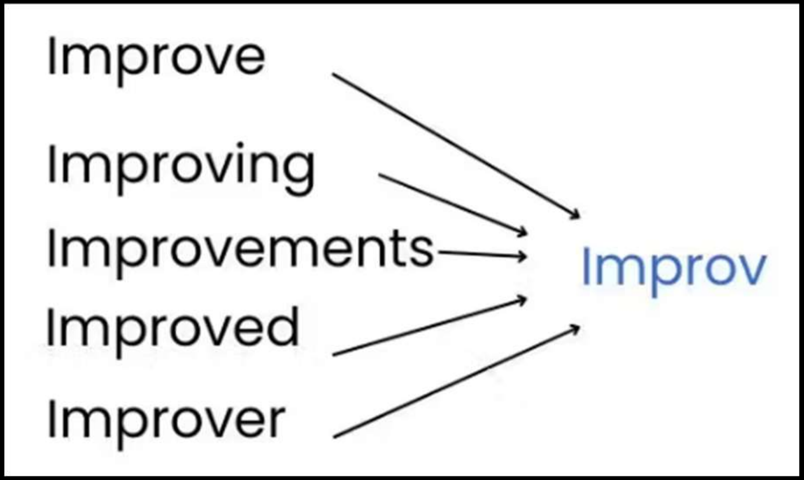


NLP - Lemmatization

lemmatization is a more sophisticated linguistic process that aims to reduce a word to its base or dictionary form

Lemmatization takes into account factors such as part-of-speech (POS) tags and contextual understanding to ensure accurate and meaningful transformations.





Vs Stemming

Parts Of Speech (POS) Tagging

Part of speech refers to the grammatical category of a word in a sentence, such as noun, verb, adjective, adverb, pronoun, preposition, conjunction, or interjection.

Used to identify named entities and speech recognition

Stop words

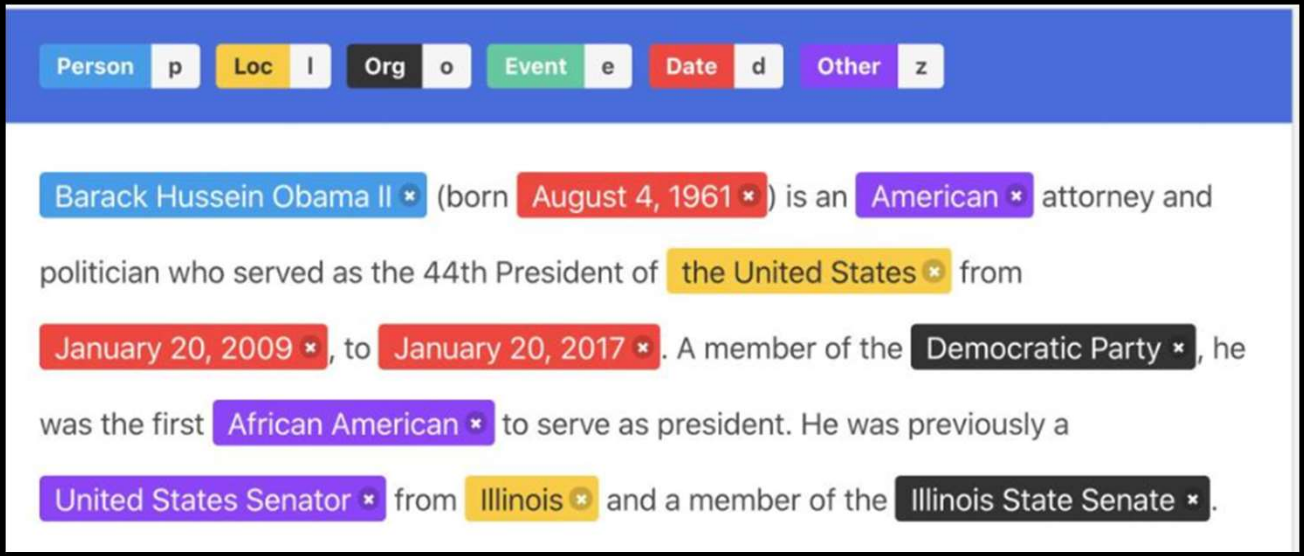
Common words such as “a” and “the” occur so frequently in text that they often do not carry significant meaning compared to nouns, verbs, and modifiers.

Spacy provides a built-in list of approximately 305 English stop words that can be readily utilized.

Named Entity Recognition (NER)

Named Entity Recognition (NER) entails the identification and classification of named entities present in the given text.

Named entities represent recognizable entities : individuals, organizations, locations, dates, numerical expressions, and others.



https://demos.explosion.ai/displacy-ent

Text representation - tokenization

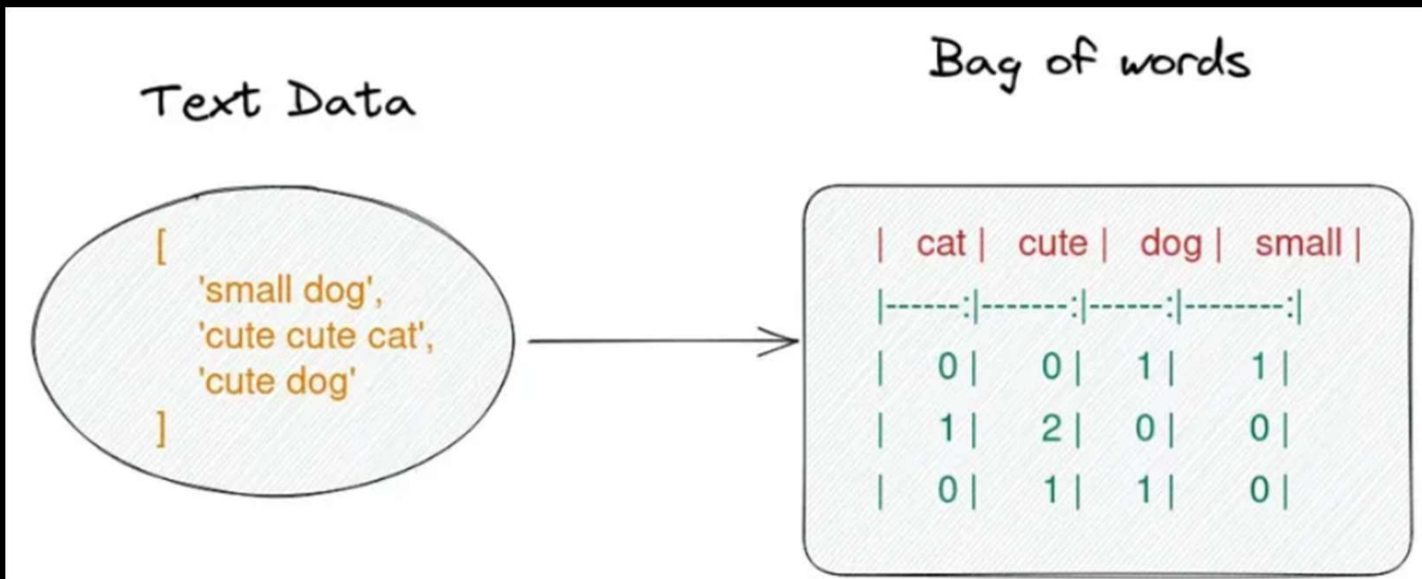
Tokenization involves breaking down the original text into smaller components known as tokens. These tokens can be created based on contiguous sequences of characters or words.

N-gram refers to a consecutive sequence of n items, where an item can be a character or a word.

https://platform.openai.com/tokenizer

Determines the vocabulary of the model

Text representation – Bag of Words



Convers each word into a vector based on the frequency of the text, without considering order

Text representation – TF-IDF

Term Frequence (TF) / Inverse Document Frequency (IDF)

Term Frequency (TF)

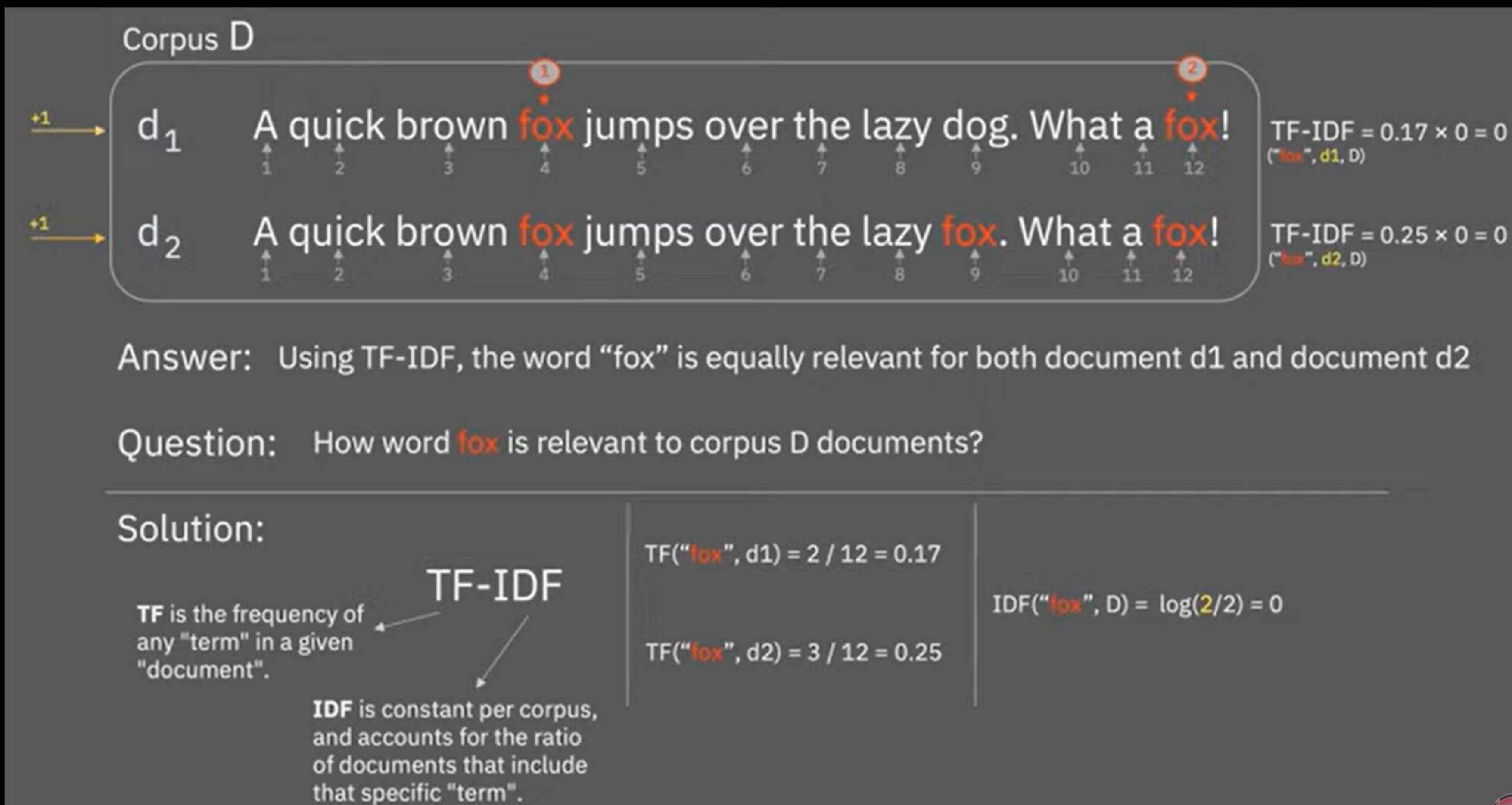
This measures how frequently a term (word) appears in a document. It assigns a higher weight to words that occur more frequently within the document.

Inverse Document Frequency (IDF)

This part measures how unique or rare a term is across all documents.
It assigns a higher weight to words that appear less frequently across the corpus but provide more unique or informative content within a document.

Text representation – TF-IDF

Term Frequence (TF) / Inverse Document Frequency (IDF)



Limitations of BoW and TF/IDF

BoW and TF-IDF are traditional text representation techniques, they have major limitations:

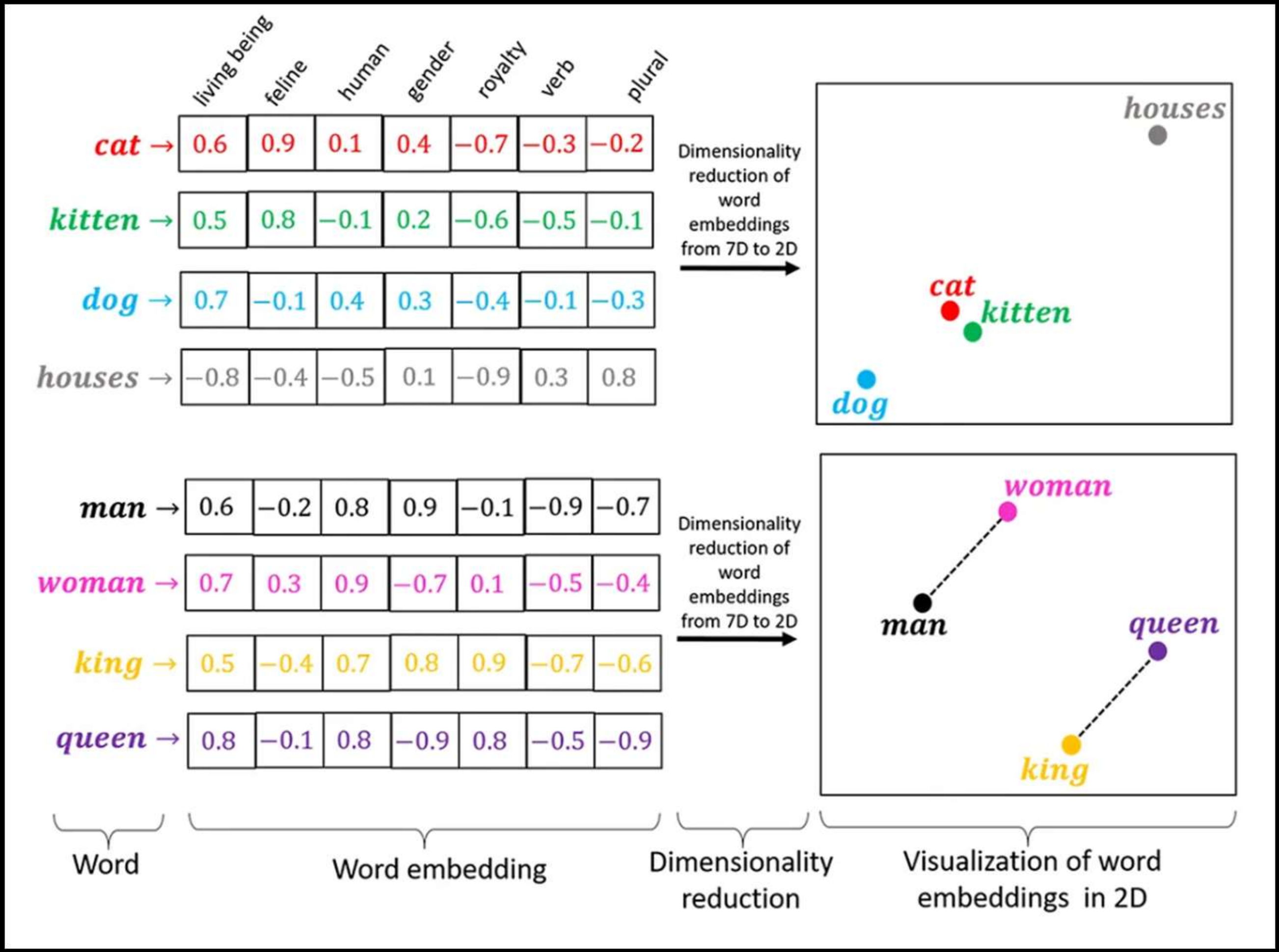
No Semantic Meaning, cannot capture similarity
Represent text as sparse vectors where each word is a separate dimension.
For example, "king" and "queen" have no relationship in BoW/TF-IDF.

High Dimensionality (Sparse Representation)
If a vocabulary has 100,000 words, each document is a 100,000-dimensional vector, making computations inefficient.

No Context Awareness
BoW & TF-IDF treat all occurrences of a word the same, regardless of sentence structure.

No Word Order Information
BoW and TF-IDF ignore word order, so "I love cats" and "Cats love me" have the same representation.

Vectors and Embeddings



Video: Vectors and Embeddings

Word2vec (Google 2013)

Solves many of the issues with previous approaches

Word2Vec is a

- Neural network-based model for learning word embeddings
- Introduces word embeddings: dense vector representations of words that capture their semantic meaning based on the context they appear in.
- It transforms words into high-dimensional numerical vectors, allowing words with similar meanings to have similar vector representations.

A major breakthrough in NLP

How Word2vec (Google 2013) solves these issues?

Dense Vector Representations

Represents words as low-dimensional dense vectors
(e.g., 300 dimensions instead of 100,000).

Captures Semantic Meaning
Similar words have similar vector representations:
king - man + woman ≈ queen

Learns Context from Word Usage
Uses CBOW (Continuous Bag of Words) and Skip-gram to learn relationships based on nearby words.

Handles Synonyms and Similarity
Places similar words close in vector space, making it useful for NLP tasks.

A major breakthrough in NLP

Training the word2vec model

CBOW (Continuous Bag Of Words)

Predicts center word from context

Skip-gram

Predicts context from the center word

How Word2vec learns Symantec meaning and relationship?

Self supervised learning

Skip-gram Model
Given a word, it predicts surrounding words.
Example: From "The cat sits on the mat," the model learns that "cat" is often surrounded by words like "sits," "on," and "mat."
This helps capture the semantic meaning of "cat."

Continuous Bag of Words (CBOW) Model

Given surrounding words, it predicts the missing word.
Example: Given "The ___ sits on the mat," the model predicts "cat."