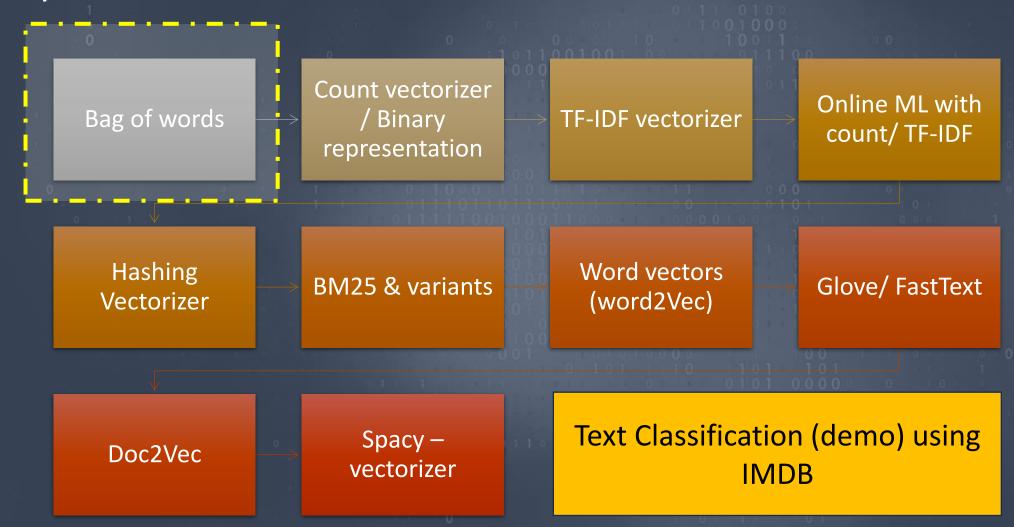
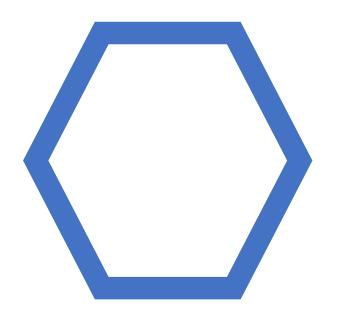


Topics to cover





BOW/Count

"Words in Numbers:

Vectorizer – BOW/Count"

Bag of Words (BoW)



BoW is one of the <u>simplest</u> vectorization techniques.

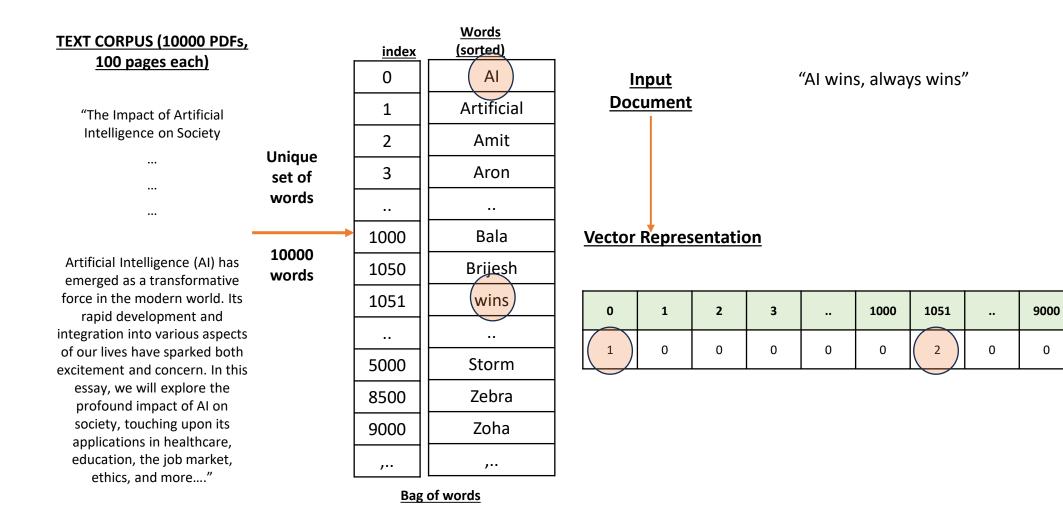


represents a document as a <a href="https://www.nee.go.nee



the value in each element represents the frequency of that word in the document.





Intuition of BOW

Why we need corpus for BOW



Vocabulary and Lexicon

A corpus is the foundation for creating a <u>comprehensive</u> vocabulary or lexicon.

includes a <u>vast array of words and</u> phrases



Statistical Analysis:

calculating word frequencies for <u>next</u> word predictions

<u>collocations</u> (words that tend to appear together)

<u>n-grams</u> (sequences of N words).

Example - BOW

- Let's say we have two documents:
 - Document 1: "I love machine learning."
 - Document 2: "Machine learning is fascinating, and I enjoy it."
- We create a BoW representation by considering the unique words in both documents:
 - Vocabulary: ["I", "love", "machine", "learning", "is", "fascinating", "and", "enjoy", "it"]

- We then create vectors for each document based on word frequency:
 - Document 1 BoW: [1, 1, 1, 1, 0, 0, 0, 0, 0]
 - Document 2 BoW: [1, 0, 1, 1, 1, 1, 1, 1, 1]



Word Frequency: represents a document as a <u>vector</u> where each element corresponds to a <u>unique word</u> in the vocabulary and the value in each element represents the <u>count</u> (or sometimes a <u>binary</u> indication of presence/absence) of that word in the document.



Order Ignored: BoW completely ignores the order of words within a document.

Vocabulary: BoW requires a <u>pre-defined vocabulary</u>, which is created by collecting all <u>unique</u> words across the entire corpus of documents.

The vocabulary size determines the <u>dimensions</u> of the BoW vectors.

Sparse Representation: BoW vectors are typically <u>sparse</u>, especially in large vocabularies, because most documents only contain a subset of the words in the vocabulary.

This sparsity can be <u>computationally efficient</u> but may require specialized data structures for storage.



Scalability: BoW is scalable to <u>large datasets</u> and can be applied to a wide range of text analysis tasks, including <u>document classification</u>, <u>sentiment analysis</u>, and information retrieval.



Text Preprocessing: Before applying BoW, text preprocessing steps like tokenization (splitting text into words or tokens), stop word removal (excluding common and uninformative words), and stemming (reducing words to their base form) are often performed to improve the <u>quality of representations</u>.

- **Document Similarity:** BoW can be used to measure the <u>similarity</u> between documents by calculating the <u>cosine similarity</u> or other distance metrics between their corresponding vectors.
- Dimensionality: The dimensionality of BoW vectors can be quite high, especially for large vocabularies or extensive corpora.
- This high dimensionality can impact computational resources and may require techniques like dimensionality reduction.



Bag of N-grams: While BoW is typically based on individual words (unigrams), it can be extended to include multi-word sequences (<u>n-grams</u>) to capture more context. For example, "New York" might be treated as a single feature.



Application Flexibility: BoW is versatile and can be used in various NLP tasks, is particularly suitable for tasks where word frequency information is essential but may not perform well on tasks requiring understanding of word order and semantics.



Baseline Model: BoW often serves as a <u>baseline</u> or **starting point** for more complex NLP models.

Illustrations (BOW)

Documents:

- Document 1: "I love programming."
- Document 2: "Programming is fun."
- Document 3: "Coding is interesting."

Step by step



Step 1: Tokenization

Tokenize each document by breaking it into individual words and converting them to lowercase, removing punctuation.

Document 1: ["i", "love",
"programming"]

Document 2: ["programming",
"is", "fun"]

Document 3: ["coding", "is", "interesting"]



Step 2: Vocabulary Construction

Create a vocabulary by considering all unique words across the documents.

Vocabulary: ["i", "love",
"programming", "is", "fun",
"coding", "interesting"]



Step 3: Bag-of-Words Representation

Represent each document as a binary vector, where the values correspond to the presence (1) or absence (0) of each word in the vocabulary.

Document 1: [1, 1, 1, 0, 0, 0, 0]

Document 2: [0, 0, 1, 1, 1, 0, 0]

Document 3: [0, 0, 1, 1, 0, 1, 1]

Explanation



Document 1:

"i" is present, so the first element is 1.

"love" is present, so the second element is 1.

"programming" is present, so the third element is 1.

The rest of the elements are 0 because those words are not present.



Document 2:

"programming" is present, so the third element is 1.

"is" is present, so the fourth element is 1.

"fun" is present, so the fifth element is 1.

The rest of the elements are 0 because those words are not present.



Document 3:

"programming" is present, so the third element is 1.

"is" is present, so the fourth element is 1.

"coding" is present, so the sixth element is 1.

"interesting" is present, so the seventh element is 1.

The rest of the elements are 0 because those words are not present.



Thanks!

