

Text Feature Extraction: BoW & TF-IDF



Bag of Words (BoW)

Represents text as word frequency counts

- Ignores word order and grammar
- Only considers word occurrence
- Simple frequency-based representation



TF-IDF

Term Frequency-Inverse Document Frequency weighting

- Balances local and global importance
- Reduces weight of common words
- Increases weight of rare words

TF-IDF Components

TF (Term Frequency)

How often word appears in document (local importance)

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IDF (Inverse Document Frequency)

How rare word is across documents (global importance)

✓ **Advantages:** Simple and interpretable

✗ **Limitations:** Loses semantic and syntactic information



Bag of Words (BoW) - Practical Example

Example Documents:

Doc 1: "I love machine learning"

Doc 2: "Machine learning is amazing"

Doc 3: "I love deep learning"

Step 1: Build Vocabulary

Unique words across all documents:

I love machine learning is amazing deep

Step 2: Count Word Frequencies

Document	I	love	machine	learning	is	amazing	deep
Doc 1	1	1	1	1	0	0	0
Doc 2	0	0	1	1	1	1	0
Doc 3	1	1	0	1	0	0	1

💡 **Result Interpretation:** Each document is represented as a 7-dimensional vector. Example: Doc 1 = [1, 1, 1, 1, 0, 0, 0]
→ Word order and grammar are ignored; only word occurrence counts are considered.

TF-IDF - Practical Example

Same Example Documents:

Doc 1: "I love machine learning"

Doc 2: "Machine learning is amazing"

Doc 3: "I love deep learning"

TF-IDF Formula:

$$\text{TF-IDF}(\text{word}, \text{doc}) = \text{TF}(\text{word}, \text{doc}) \times \text{IDF}(\text{word})$$
$$\text{TF}(\text{word}, \text{doc}) = (\text{word count in doc}) / (\text{total words in doc})$$
$$\text{IDF}(\text{word}) = \log(\text{total documents} / \text{documents containing word})$$

Example: Calculate TF-IDF for "learning" in Doc 1

Step 1: Calculate TF

$$\text{TF}(\text{"learning"}, \text{Doc 1}) = 1 / 4 = 0.25$$

(appears 1 time / total 4 words)

Step 2: Calculate IDF

$$\text{IDF}(\text{"learning"}) = \log(3 / 3) = \log(1) = 0$$

(3 documents / 3 documents containing "learning")

Step 3: Calculate TF-IDF

$$\text{TF-IDF}(\text{"learning"}, \text{Doc 1}) = 0.25 \times 0 = 0$$

→ "learning" appears in all documents, so it has low importance!

Example: Calculate TF-IDF for "deep" in Doc 3

Step 1: Calculate TF

$$\text{TF}(\text{"deep"}, \text{Doc 3}) = 1 / 4 = 0.25$$

Step 2: Calculate IDF

$$\text{IDF}(\text{"deep"}) = \log(3 / 1) = \log(3) \approx 1.099$$

("deep" appears in only 1 document → rare word)

Step 3: Calculate TF-IDF

$$\text{TF-IDF}(\text{"deep"}, \text{Doc 3}) = 0.25 \times 1.099 \approx 0.275$$

→ "deep" is a rare word, so it has high importance!



Key Point: TF-IDF reduces the weight of common words (e.g., "learning") and increases the weight of rare words (e.g., "deep") to better represent document characteristics.