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# N-grams in NLP

Abhishek Jain · [Follow](#)

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N-grams, a fundamental concept in NLP, play a pivotal role in capturing patterns and relationships within a sequence of words. In this blog post, we'll delve into the world of N-grams, exploring their significance, applications, and how they contribute to enhancing language processing tasks.

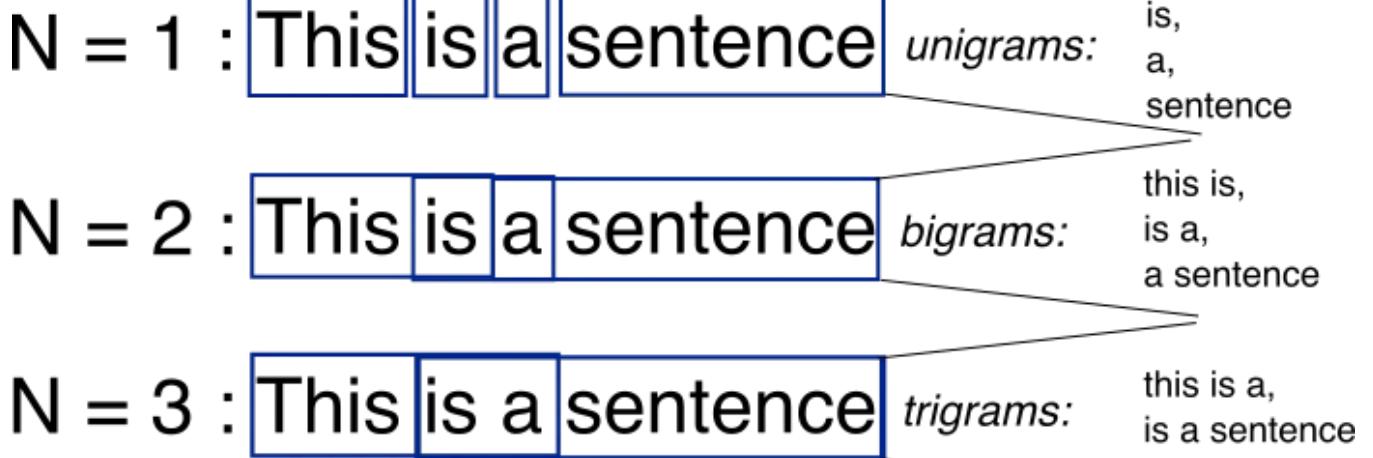
## Understanding N-grams:

### Definition:

N-grams are contiguous sequences of 'n' items, typically words in the context of NLP. These items can be characters, words, or even syllables, depending on the granularity desired. The value of 'n' determines the order of the N-gram.

### Examples:

- **Unigrams (1-grams):** Single words, e.g., "cat," "dog."
- **Bigrams (2-grams):** Pairs of consecutive words, e.g., "natural language," "deep learning."
- **Trigrams (3-grams):** Triplets of consecutive words, e.g., "machine learning model," "data science approach."
- 4-grams, 5-grams, etc.: Sequences of four, five, or more consecutive words.



## Significance of N-grams in NLP:

### 1. Capturing Context and Semantics:

- N-grams help capture the contextual information and semantics within a sequence of words, providing a more nuanced understanding of language.

### 2. Improving Language Models:

- In language modeling tasks, N-grams contribute to building more accurate and context-aware models, enhancing the performance of applications such as machine translation and speech recognition.

### 3. Enhancing Text Prediction:

- N-grams are essential for predictive text applications, aiding in the prediction of the next word or sequence of words based on the context provided by the preceding N-gram.

### 4. Information Retrieval:

- In information retrieval tasks, N-grams assist in matching and ranking documents based on the relevance of N-gram patterns.

### 5. Feature Extraction:

- N-grams serve as powerful features in text classification and sentiment analysis, capturing meaningful patterns that contribute to the characterization of different classes or sentiments.

## Applications of N-grams in NLP:

### 1. Speech Recognition:

- N-grams play a crucial role in modeling and recognizing spoken language patterns, improving the accuracy of speech recognition systems.

## 2. Machine Translation:

- In machine translation, N-grams contribute to understanding and translating phrases within a broader context, enhancing the overall translation quality.

## 3. Predictive Text Input:

- Predictive text input on keyboards and mobile devices relies on N-grams to suggest the next word based on the context of the input sequence.

## 4. Named Entity Recognition (NER):

- N-grams aid in identifying and extracting named entities from text, such as names of people, organizations, and locations.

## 5. Search Engine Algorithms:

- Search engines use N-grams to index and retrieve relevant documents based on user queries, improving the accuracy of search results.

## CODE

```
import nltk
nltk.download('punkt')

from nltk import ngrams
from nltk.tokenize import word_tokenize

# Example sentence
sentence = "N-grams enhance language processing tasks."

# Tokenize the sentence
tokens = word_tokenize(sentence)

# Generate bigrams
bigrams = list(ngrams(tokens, 2))

# Generate trigrams
trigrams = list(ngrams(tokens, 3))

# Print the results
print("Bigrams:", bigrams)
print("Trigrams:", trigrams)

'''

Output:
```

Bigrams: [('N-grams', 'enhance'), ('enhance', 'language'), ('language', 'process')]

Trigrams: [('N-grams', 'enhance', 'language'), ('enhance', 'language', 'process')]

'''

## Using N Gram to predict the probability of a sentence

Corpus:

<|s> I am a human </s>

<|s> I am not a stone </s>

<|s> I I live in Mumbai </s>

Check the probability of "I am not" using bigram

$$P(I \text{ am not}) = P(I / \langle s \rangle) \times P(\text{am} / I) \times P(\text{not} / \text{am}) \times P(\langle /s \rangle / \text{not})$$

$$= \frac{\text{Count}(\langle s \rangle | I)}{\text{Count}(\langle s \rangle)} \times \frac{\text{Count}(I | I)}{\text{Count}(I)} \times \frac{\text{Count}(I | \text{am})}{\text{Count}(I)} \times \frac{\text{Count}(\text{am} | \text{not})}{\text{Count}(\text{am})} \times \frac{\text{Count}(\text{not} | \langle /s \rangle)}{\text{Count}(\langle /s \rangle)}$$

$\Rightarrow \text{Count}(\langle s \rangle | I)$   $\Rightarrow$  In our corpus, we have to check the frequency of the combination <|s> I and that in our corpus is 3

$$\text{Count}(\langle s \rangle) = 3$$

$$\frac{3}{3} \times \frac{1}{4} \times \frac{2}{4} \times \frac{1}{2} \times \frac{0}{3} = 0$$

Read as

Prob of "am" given "I"

## Using N grams to predict the next word in the sentence

Consider the following training data

<s> I am Jack </s>  
 <s> Jack I am </s>  
 <s> Jack I like </s>  
 <s> Jack I do like </s>  
 <s> do I like Jack </s>

Assume that we use a bigram language model based on the above data

What is the most probable next word predicted by model

- 1) <s> Jack \_\_\_\_\_
- 2) <s> Jack I do \_\_\_\_\_
- 3) <s> Jack I am Jack \_\_\_\_\_
- 4) <s> do I like \_\_\_\_\_

$$P(I|<s>) = \frac{\text{Count}(<s>|I)}{\text{Count}(<s>)} = \frac{1}{5}$$

$$P(\text{am}|I) = \frac{\text{Count}(I|\text{am})}{\text{Count}(I)} = \frac{2}{5}$$

$$P(\text{Jack}|\text{am}) = \frac{\text{Count}(\text{am}|\text{Jack})}{\text{Count}(\text{am})} = \frac{1}{2}$$

$$P(<\text{s}>|\text{Jack}) = \frac{\text{Count}(\text{Jack}|\text{<s>} )}{\text{Count}(\text{Jack})} = \frac{2}{5}$$

$$P(\text{Jack}|\text{<s>}) = \frac{\text{Count}(<\text{s}>|\text{Jack})}{\text{Count}(<\text{s}>)} = \frac{2}{5}$$

$$P(I|\text{Jack}) = \frac{\text{Count}(\text{Jack}|I)}{\text{Count}(\text{Jack})} = \frac{3}{5}$$

$$P(<\text{s}>|\text{am}) = \frac{\text{Count}(\text{am}|\text{<s>} )}{\text{Count}(\text{am})} = \frac{1}{2}$$

$$P(\text{like}|I) = \frac{\text{Count}(I|\text{like})}{\text{Count}(I)} = \frac{2}{5}$$

$$P(<\text{s}>|\text{like}) = \frac{\text{Count}(\text{like}|\text{<s>} )}{\text{Count}(\text{like})} = \frac{2}{3}$$

$$P(\text{do}|I) = \frac{\text{Count}(I|\text{do})}{\text{Count}(I)} = \frac{1}{5}$$

$$P(\text{like}|\text{do}) = \frac{\text{Count}(\text{do}|\text{like})}{\text{Count}(\text{do})} = \frac{1}{2}$$

$$P(\text{do}|\text{<s>}) = \frac{\text{Count}(<\text{s}>|\text{do})}{\text{Count}(<\text{s}>)} = \frac{1}{5}$$

$$P(I|\text{do}) = \frac{\text{Count}(\text{do}|I)}{\text{Count}(\text{do})} = \frac{1}{2}$$

$$P(\text{Jack}|\text{like}) = \frac{\text{Count}(\text{like}|\text{Jack})}{\text{Count}(\text{like})} = \frac{1}{3}$$

1) Jack \_

$\Rightarrow P(\text{something}|\text{Jack}) = \text{In our calculated probabilities we got 2 probabilities}$

$$1) P(</s>|\text{Jack}) = \frac{2}{5}$$

$$2) P(I|\text{Jack}) = \frac{3}{5}$$

} Since  $\frac{3}{5} > \frac{2}{5}$ , I is the next word

2) Jack I do \_

$P(\text{something}|do) \rightarrow P(I|do) = 1/2$  } The answer is both

$\rightarrow P(\text{like}|do) = 1/2$  } I and like

Ngrams

Unigram

Bigrams

Trigram

Naturallanguageprocessing



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Sent 2 : good girl  
 Sent 3 : boy girl good

$$TF = \frac{\text{No of rep of words in a sentence}}{\text{No of words in a sentence}}$$

$$IDF = \log \left( \frac{1}{\text{No of sentences}} \right)$$

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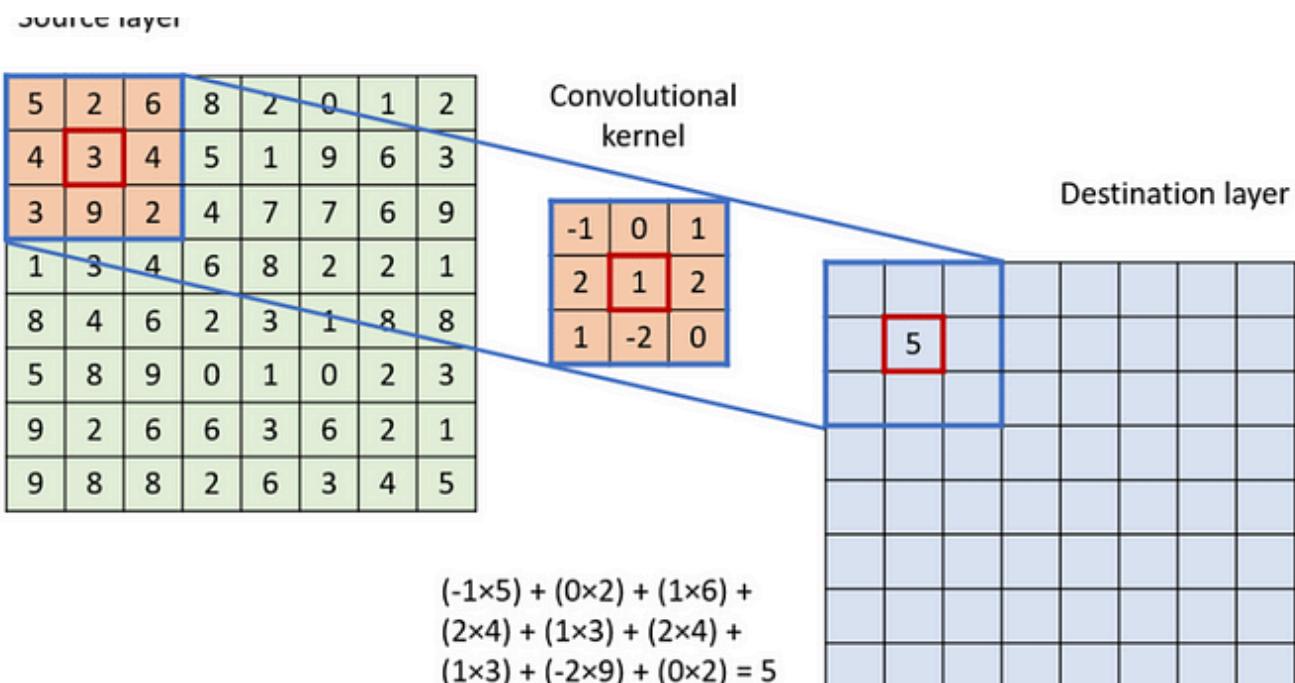
## TF-IDF in NLP (Term Frequency Inverse Document Frequency)

In the realm of Natural Language Processing (NLP), TF-IDF (Term Frequency-Inverse Document Frequency) is a powerful technique used to...

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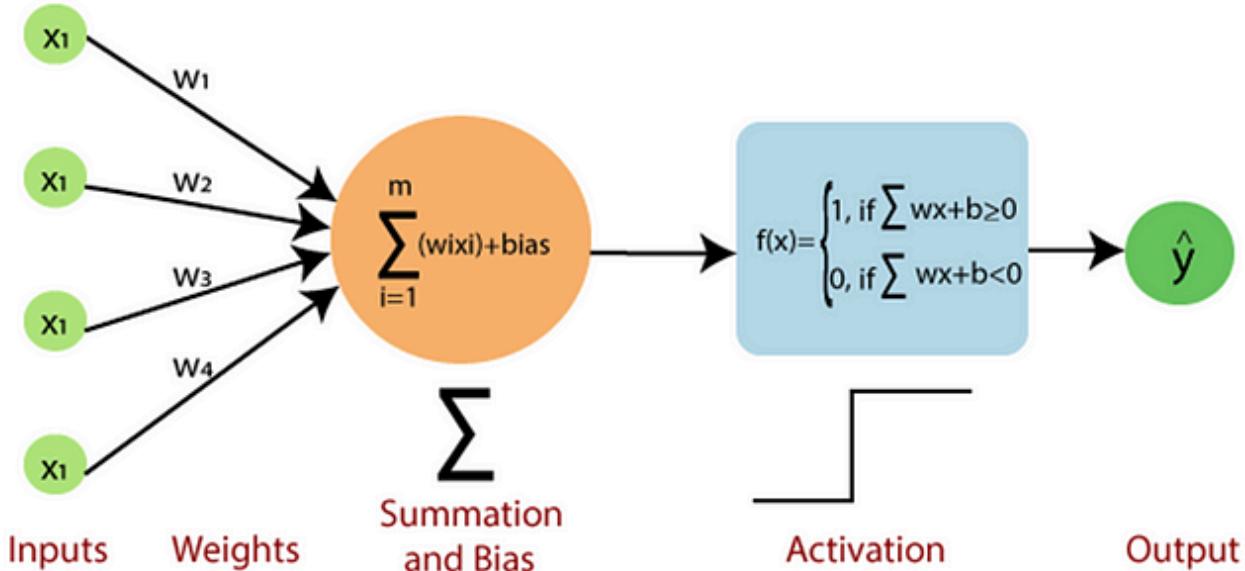
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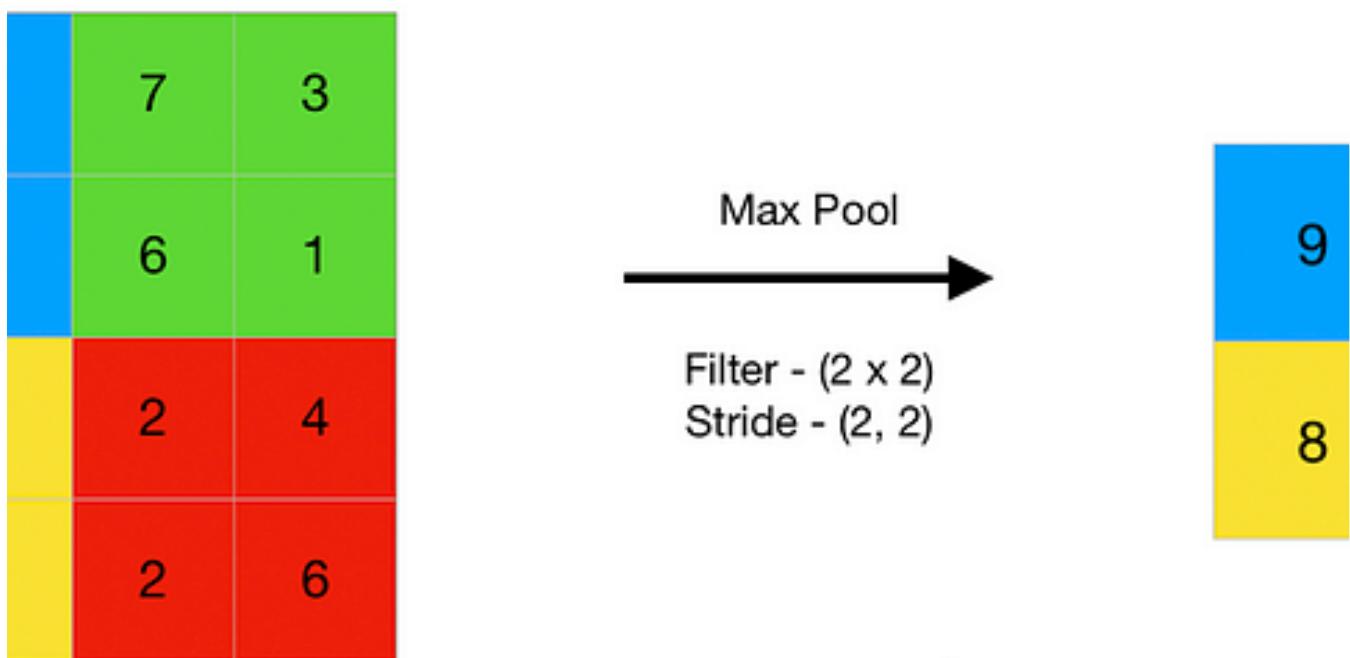
## Perceptron vs neuron, Single layer Perceptron and Multi Layer Perceptron

In deep learning, the terms “perceptron” and “neuron” are related but have distinct meanings, and they are not exactly the same. While both...

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$$\mu_B = \frac{1}{m} \sum_{i=1}^m x_i$$

$$\sigma_B^2 = \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2$$

Here,  $x_i$  are the activations in the mini-batch,  $\mu_B$  is the mean,  $\sigma_B^2$  is the variance, and  $m$  is the mini-batch size.

Jo Wang

## Deep Learning Part 5 -How to prevent overfitting

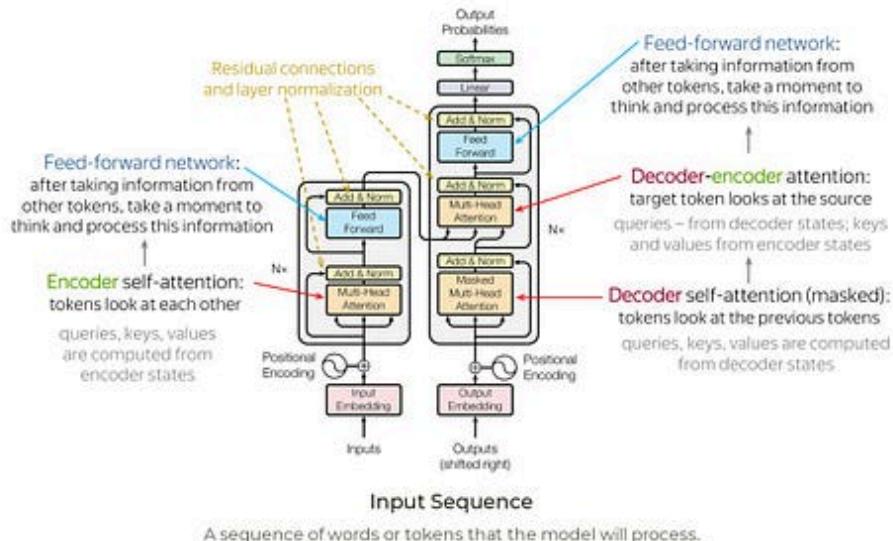
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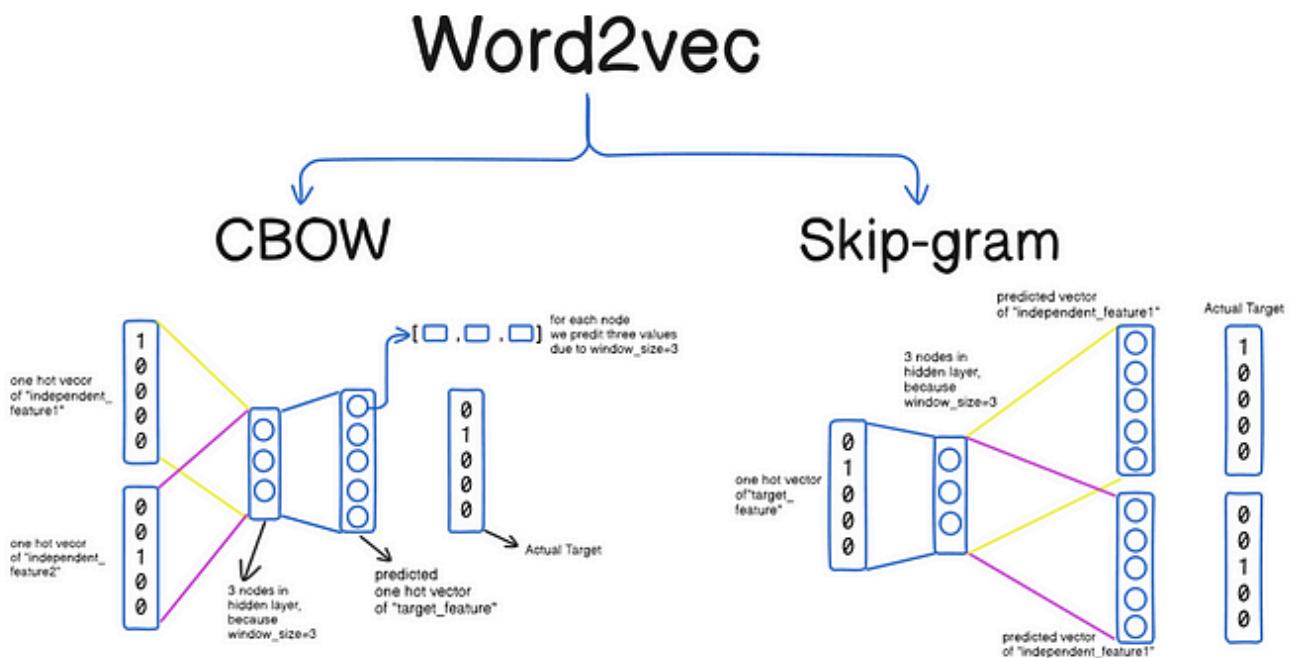
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Fraidoon Omarzai

## Word2Vec (CBOW, Skip-gram) In Depth

Word2Vec is an important model for natural language processing (NLP) developed by researchers at Google.

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## Vector Embeddings

$$\begin{array}{l} \text{Apple} \rightarrow \begin{bmatrix} 0.5 & 0.6 & 0 & 0.1 & 0.4 & \dots & 0.4 & 0 \end{bmatrix} \\ \text{Man} \rightarrow \begin{bmatrix} 0.1 & 0.3 & 0.4 & 0 & 0.5 & \dots & 0.5 & 1 \end{bmatrix} \\ \text{Computer} \rightarrow \begin{bmatrix} 0.4 & 0.5 & 0.4 & 0.1 & 0 & \dots & 0 & 0 \end{bmatrix} \end{array}$$



Mdabdullahalhasib in Towards AI

## A Complete Guide to Embedding For NLP & Generative AI/LLM

Understand the concept of vector embedding, why it is needed, and implementation with LangChain.

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