

# Preprocessing Steps for Natural Language Processing (NLP): A Beginner's Guide



Maleesha De Silva · Follow

5 min read · Apr 30, 2023



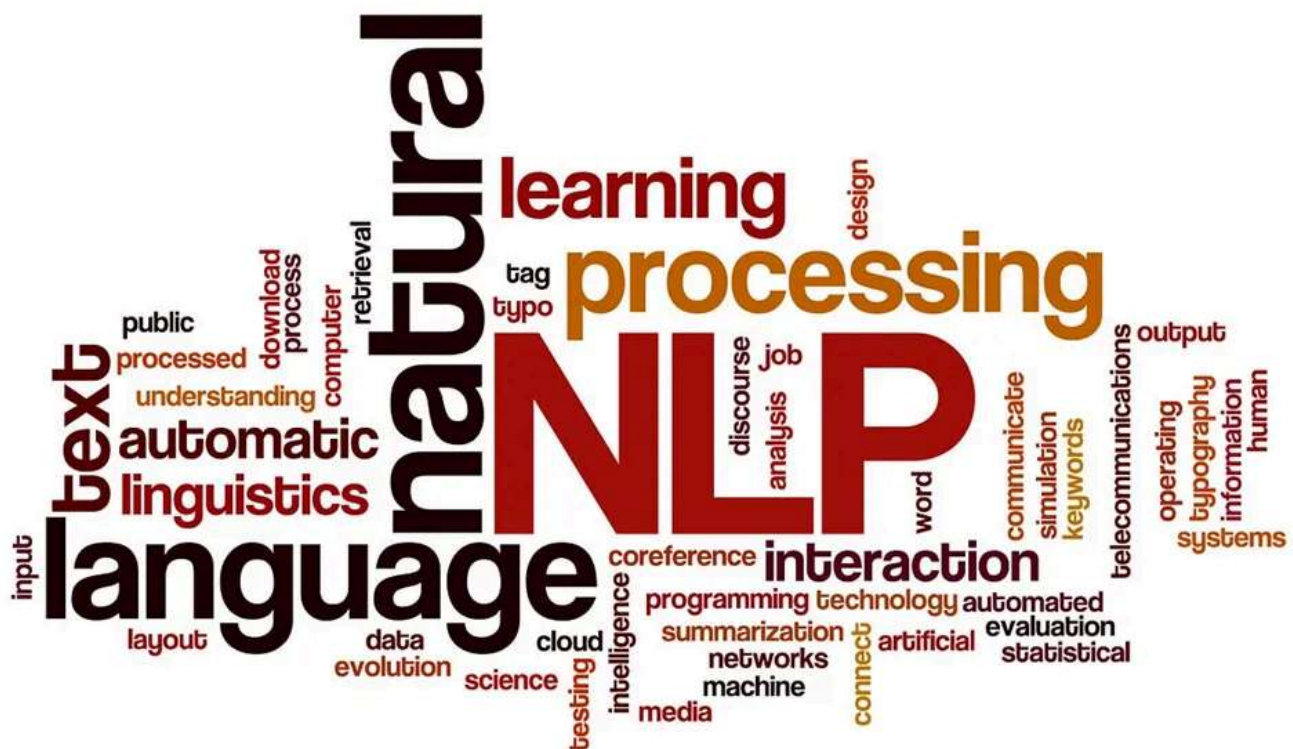
Listen



Share



More



Machine Learning heavily relies on the quality of the data fed into it, and thus, data preprocessing plays a crucial role in ensuring the accuracy and efficiency of the model. In this article, we will discuss the main text preprocessing techniques used in NLP.

## 1. Text Cleaning


In this step, we will perform fundamental actions to clean the text. These actions involve transforming all the text to lowercase, eliminating characters that do not qualify as words or whitespace, as well as removing any numerical digits present.

## I. Converting to lowercase

Python is a case sensitive programming language. Therefore, to avoid any issues and ensure consistency in the processing of the text, we convert all the text to lowercase.

This way, “Free” and “free” will be treated as the same word, and our data analysis will be more accurate and reliable.

```
df = df.applymap(lambda x: x.lower() if isinstance(x, str) else x)
```



| Category |      | Message   |
|----------|------|---|
| 0        | ham  | Go until jurong point, crazy.. Available only ... |
| 1        | ham  | Ok lar... Joking wif u oni...                     |
| 2        | spam | Free entry in 2 a wkly comp to win FA Cup fina... |

| Category |      | Message   |
|----------|------|---|
| 0        | ham  | go until jurong point, crazy.. available only ... |
| 1        | ham  | ok lar... joking wif u oni...                     |
| 2        | spam | free entry in 2 a wkly comp to win fa cup fina... |

Dataset before and after converting all text into lowercase

## II. Removing URLs

When building a model, URLs are typically not relevant and can be removed from the text data.

For removing URLs we can use ‘regex’ library.

```
import pandas as pd
import re

# Define a regex pattern to match URLs
url_pattern = re.compile(r'https?://\S+')

# Define a function to remove URLs from text
def remove_urls(text):
    return url_pattern.sub('', text)
```


```
# Apply the function to the 'text' column and create a new column 'clean_text'  
df['Message'] = df['Message'].apply(remove_urls)
```

### III. Removing remove non-word and non-whitespace characters

It is essential to remove any characters that are not considered as words or whitespace from the text dataset.

These non-word and non-whitespace characters can include punctuation marks, symbols, and other special characters that do not provide any meaningful information for our analysis.

```
df = df.replace(to_replace=r'^[w\s]', value='', regex=True)
```



|   | Category | Message  |
|---|----------|--|
| 0 | ham      | go until jurong point, crazy.. available only in ... |
| 1 | ham      | ok lar... joking wif u oni...                        |
| 2 | spam     | free entry in 2 a wkly comp to win fa cup fina...    |

|   | Category | Message   |
|---|----------|---|
| 0 | ham      | go until jurong point crazy available only in ... |
| 1 | ham      | ok lar joking wif u oni                           |
| 2 | spam     | free entry in 2 a wkly comp to win fa cup fina... |

Dataset before and after removing all non-word and non-whitespace characters


### IV. Removing digits

It is important to remove all numerical digits from the text dataset. This is because, in most cases, numerical values do not provide any significant meaning to the text analysis process.

Moreover, they can interfere with natural language processing algorithms, which are designed to understand and process text-based information.

```
df = df.replace(to_replace=r'\d', value='', regex=True)
```

| Category |      |   | Message |
|----------|------|---|---------|
| 0        | ham  | go until jurong point crazy available only in ... |         |
| 1        | ham  | ok lar joking wif u oni                           |         |
| 2        | spam | free entry in 2 a wkly comp to win fa cup fina... |         |



| Category |      |   | Message |
|----------|------|---|---------|
| 0        | ham  | go until jurong point crazy available only in ... |         |
| 1        | ham  | ok lar joking wif u oni                           |         |
| 2        | spam | free entry in a wkly comp to win fa cup final...  |         |

Dataset before and after removing digits

## 2. Tokenization

Tokenization is the process of breaking down large blocks of text such as paragraphs and sentences into smaller, more manageable units.

**'I see a cup of coffee' → 'I', 'see', 'a', 'cup', 'of', 'coffee'**

Tokenization of text

In this step, we will be applying word tokenization to split the data in the 'Message' column into words.

By performing word tokenization, we can obtain a more accurate representation of the underlying patterns and trends present in the text data.

```
import nltk
from nltk.tokenize import word_tokenize

df['Message'] = df['Message'].apply(word_tokenize)
```

| Category |      |   | Message |
|----------|------|---|---------|
| 0        | ham  | [go, until, jurong, point, crazy, available, o... |         |
| 1        | ham  | [ok, lar, joking, wif, u, oni]                    |         |
| 2        | spam | [free, entry, in, a, wkly, comp, to, win, fa, ... |         |

Dataset after tokenization

## 3. Stopword Removal

Stopwords refer to the most commonly occurring words in any natural language.

For the purpose of analyzing text data and building NLP models, these stopwords might not add much value to the meaning of the document. Therefore, removing stopwords can help us to focus on the most important information in the text and improve the accuracy of our analysis.

One of the advantages of removing stopwords is that it can reduce the size of the dataset, which in turn reduces the training time required for natural language processing models.

['This', 'is', 'an', 'example', 'for', 'stop', 'word', 'removal'] ➡ ['This', 'example', 'stop', 'word', 'removal']

Stopword removal

Various libraries such as 'Natural Language Toolkit' (NLTK), 'spaCy', and 'Scikit-Learn' can be used to remove stopwords.

In this example, we will use the NLTK library to remove stopwords in the 'Message' column of our dataset.

```
import nltk
from nltk.corpus import stopwords

stop_words = set(stopwords.words('english'))
df['Message'] = df['Message'].apply(lambda x: [word for word in x if word not in stop_words])
```

| Category |      | Message   |
|----------|------|---|
| 0        | ham  | [go, jurong, point, crazy, available, bugis, n... |
| 1        | ham  | [ok, lar, joking, wif, u, oni]                    |
| 2        | spam | [free, entry, wkly, comp, win, fa, cup, final,... |

Dataset after removal of stopwords

## 4. Stemming/Lemmatization

### What's the difference between Stemming and Lemmatization?

|  |   |
|--|---|
| Stemming is a simple and practical approach that involves cutting off the ends of words with the intention of obtaining the correct root form. | Lemmatization aims to remove inflectional endings only and to return the base or dictionary form of a word, which is known as the ' <i>lemma</i> '. |
| Eg:<br>automate, automatic, automation → automat   | Eg:<br>car, cars, cars', car's → car<br>am, is, are → be  |

Stemming vs Lemmatization

There are various algorithms that can be used for stemming,

- Porter Stemmer algorithm
- Snowball Stemmer algorithm
- Lovins Stemmer algorithm

### Stemming

Let's take a look at how we can use 'Porter Stemmer' algorithm on our dataset.

Some basic rules defined under the Porter Stemmer algorithm are,

sses → ss

Eg: caresses → caress

ies → i

Eg: ponies → poni

ational → ate

Eg: international → internate

tional → tion

Eg: conditional → condition



```

import nltk
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
import pandas as pd

# Initialize the Porter Stemmer
stemmer = PorterStemmer()

# Define a function to perform stemming on the 'text' column
def stem_words(words):
    return [stemmer.stem(word) for word in words]

# Define a function to perform stemming on the 'text' column
def stem_words(words):
    return [stemmer.stem(word) for word in words]

# Apply the function to the 'text' column and create a new column 'stemmed_text'
df['stemmed_messages'] = df['Message'].apply(stem_words)

```

## Lemmatization

Next, let's take a look at how we can implement Lemmatization for the same dataset.

```

import nltk
nltk.download('averaged_perceptron_tagger')
import nltk
nltk.download('wordnet')

import nltk
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
import pandas as pd

# initialize lemmatizer
lemmatizer = WordNetLemmatizer()

# define function to lemmatize tokens
def lemmatize_tokens(tokens):
    # convert POS tag to WordNet format
    def get_wordnet_pos(word):
        tag = nltk.pos_tag([word])[0][1][0].upper()
        tag_dict = {"J": wordnet.ADJ,
                    "N": wordnet.NOUN,
                    "V": wordnet.VERB,
                    "R": wordnet.ADV}

```

```

return tag_dict.get(tag, wordnet.NOUN)

# lemmatize tokens
lemmas = [lemmatizer.lemmatize(token, get_wordnet_pos(token)) for token in

# return lemmatized tokens as a list
return lemmas

# apply lemmatization function to column of dataframe
df['lemmatized_messages'] = df['Message'].apply(lemmatize_tokens)

```

The above code segments will produce outputs as shown below.

Open in app ↗



Search



|   |     |   |   |   |
|---|-----|---|---|---|
| 3 | ham | [u, dun, say, early, hor, u, c, already, say]     | [u, dun, say, earli, hor, u, c, already, say]     | [u, dun, say, early, hor, u, c, already, say]     |
| 4 | ham | [nah, dont, think, goes, usf, lives, around, L... | [nah, dont, think, goe, usf, live, around, tho... | [nah, dont, think, go, usf, life, around, though] |

Stemmed and Lemmatized dataset

Note that, we only use either Stemming or Lemmatization on our dataset based on the requirement.

## Conclusion

In this article we discussed main preprocessing steps in building an NLP model, which include text cleaning, tokenization, stopwords removal, and stemming/lemmatization. Implementing these steps can help improve model accuracy by reducing the noise in the text data and converting it into a structured format that can be easily analyzed by the model.

## References

### Stemming and lemmatization

Next: Faster postings list intersection Up: Determining the vocabulary of Previous: Other languages. Contents Index For...

nlp.stanford.edu



## NLP Preprocessing Steps in Easy Way

This article was published as a part of the Data Science Blogathon .  
Hello friends, In this article, we will discuss...

[www.analyticsvidhya.com](http://www.analyticsvidhya.com)



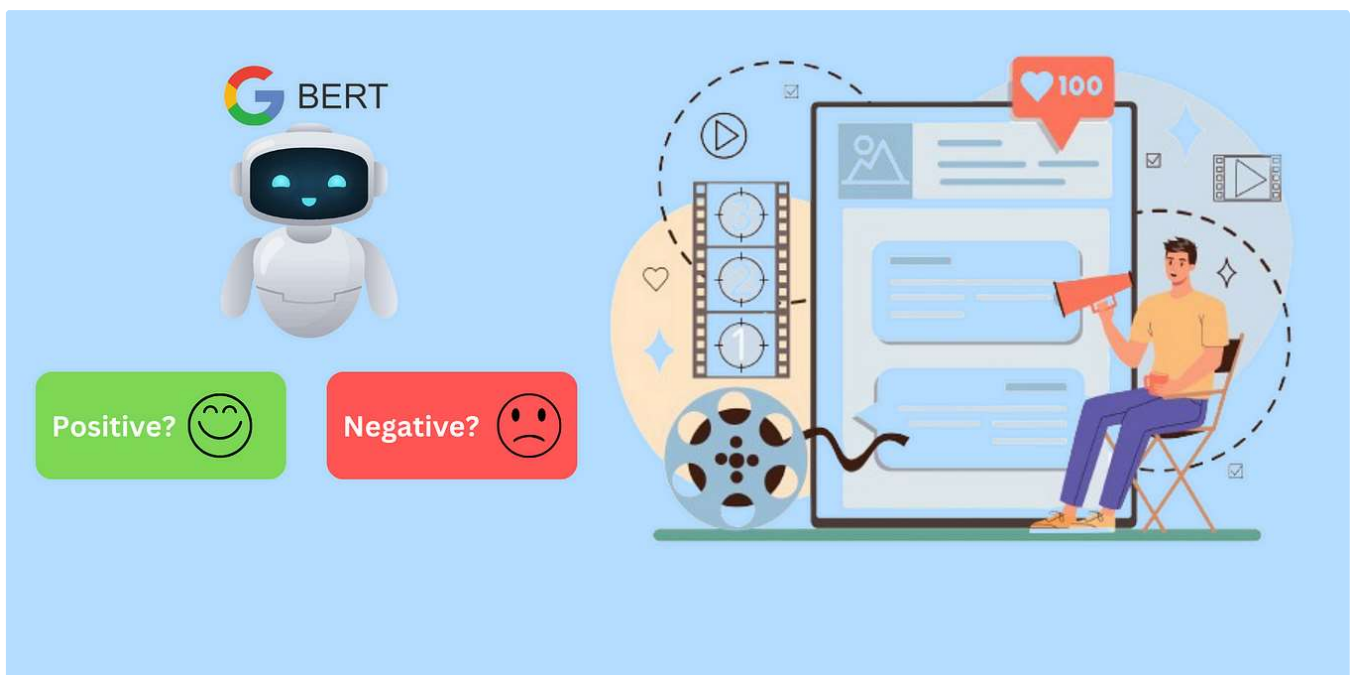
Follow

## Written by Maleesha De Silva

35 Followers

Final Year Data Science Undergraduate | Beta Microsoft Learn Student Ambassador

### More from Maleesha De Silva



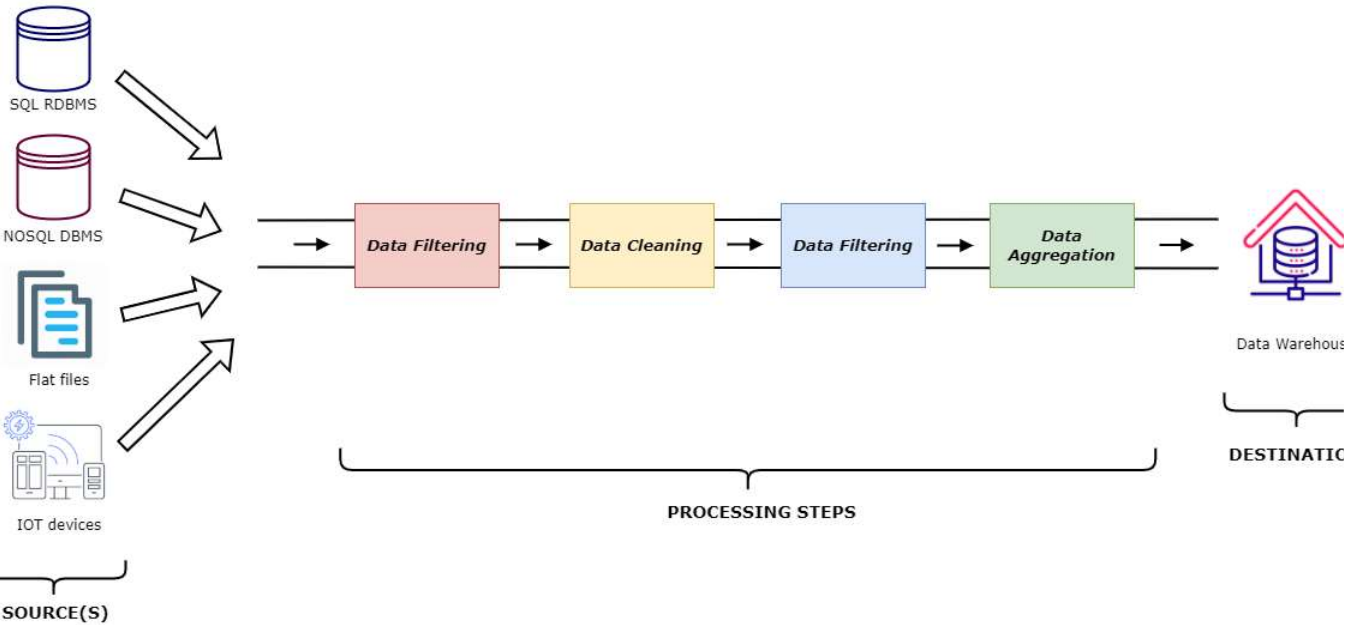
Maleesha De Silva

## Text Classification using BERT: A Complete Guide

# What is BERT?

6 min read · Feb 22, 2024

14

 Maleesha De Silva

## An Introduction to Data Pipelines

What is a data pipeline?

5 min read · Jan 18, 2023

1

See all from Maleesha De Silva

## Recommended from Medium

Display options for sense: (gloss) "an example sentence"

## Noun

- **S: (n) dog, domestic dog, *Canis familiaris*** (a member of the genus *Canis* (probably descended from the common wolf) that has been domesticated by man since prehistoric times; occurs in many breeds) *"the dog barked all night"*
- **S: (n) frump, dog** (a dull unattractive unpleasant girl or woman) *"she got a reputation as a frump"; "she's a real dog"*
- **S: (n) dog** (informal term for a man) *"you lucky dog"*
- **S: (n) cad, bounder, blackguard, dog, hound, heel** (someone who is morally reprehensible) *"you dirty dog"*
- **S: (n) frank, frankfurter, hotdog, hot dog, dog, wiener, wienerwurst, weenie** (a smooth-textured sausage of minced beef or pork usually smoked; often served on a bread roll)
- **S: (n) pawl, detent, click, dog** (a hinged catch that fits into a notch of a ratchet to move a wheel forward or prevent it from moving backward)
- **S: (n) andiron, firedog, doa, doa-iron** (metal supports for logs in a fireplace) *"the*



om pramod

## WordNet in Action: Enhancing NLP Capabilities Through NLTK

Words might seem distinct at first glance but often share similarities within certain contexts. Consider the words "big" and "large." At a...

2 min read · Dec 14, 2023



609



# SPELLING CHECKER IN PYTHON



NitinKumar Sharma

## Spell Checker in Python: Create your own spell checker


Spell checking is a crucial component in natural language processing and text analysis. In this blog post, we'll explore a Python...

8 min read · Dec 31, 2023


 6 


Lists

- 


Staff Picks

636 stories · 953 saves
- 

Stories to Help You Level-Up at Work

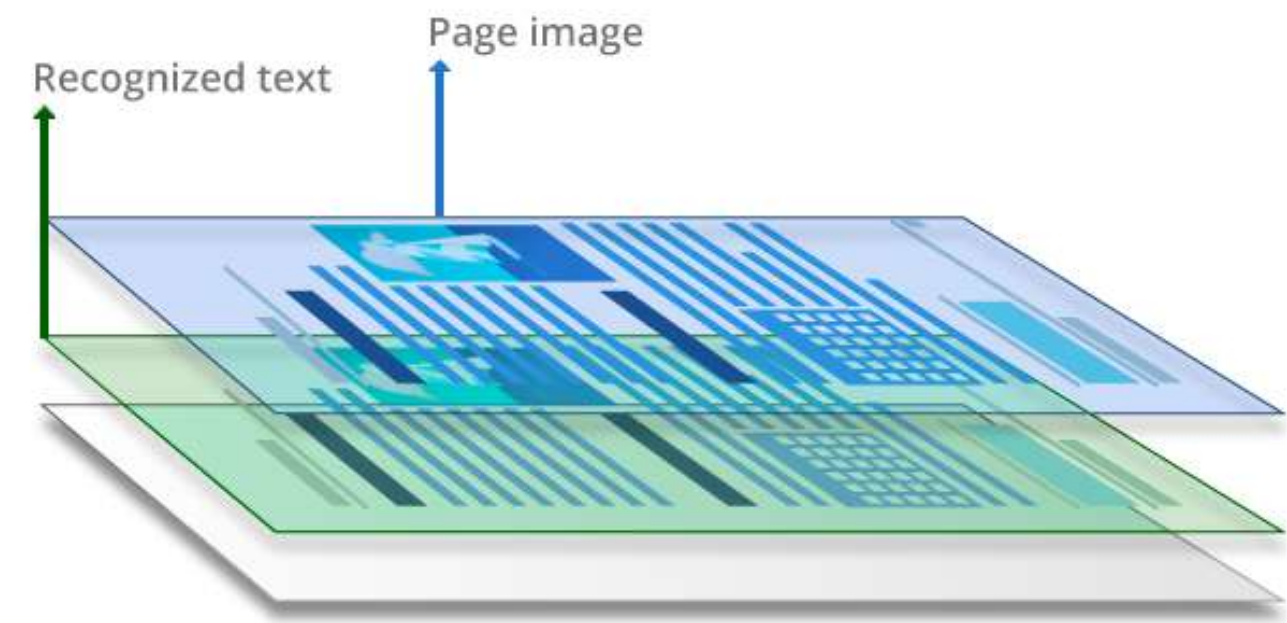
19 stories · 599 saves
- 

Self-Improvement 101

20 stories · 1759 saves
- 

Productivity 101

20 stories · 1623 saves



 Sasha Korovkina in Dev Genius

Building a High Precision Financial PDF Extraction Tool. Part 1.

Parsing Text from PDF Files

10 min read · Apr 29, 2024





97



Jason Roell in Stackademic

## Ultimate Python Cheat Sheet: Practical Python For Everyday Tasks

(My Other Ultimate Guides)

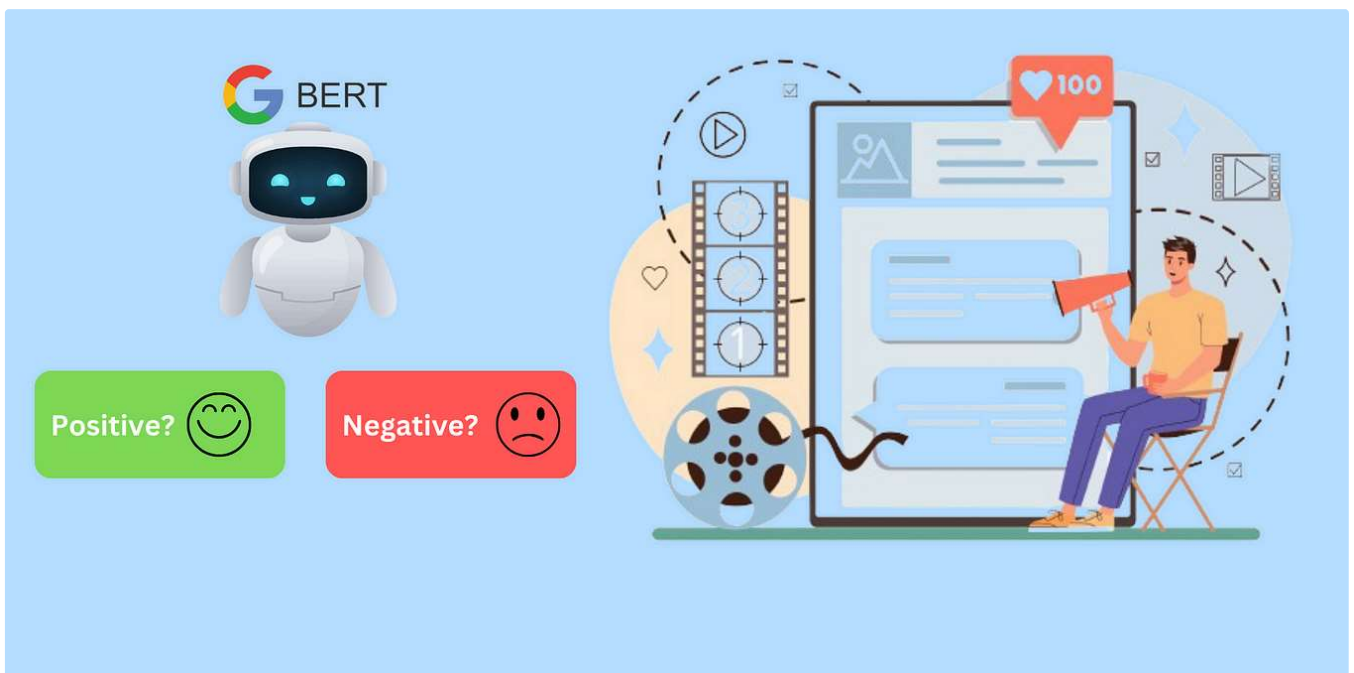
34 min read · Jan 30, 2024



4.4K



38





Maleesha De Silva

## Text Classification using BERT: A Complete Guide

What is BERT?

6 min read · Feb 22, 2024



14



Furkan Ayık

## Mastering Text Classification with BERT: A Comprehensive Guide

Understand how to build advanced classifiers with fine-tuning BERT and its variants.

10 min read · Dec 17, 2023



62



See more recommendations