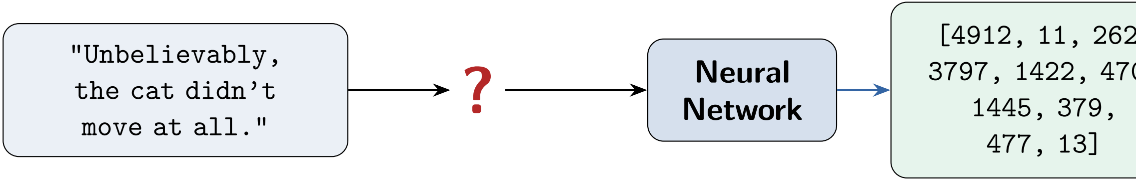
Tokenization

Word · Character · Subword · BPE · WordPiece · SentencePiece

Models need numbers, not text



Tokenization is the first step in any NLP pipeline:
split raw text into discrete units (tokens) and map each to an integer ID.
The choice of tokenizer affects **everything** downstream.

Three levels of granularity

Word-level

`["Unbelievably", "the", "cat", "didn't", "move"]`

Vocab size: ∼100k+

OOV problem

Subword

`["Un", "believ", "ably", ",", "the", "cat", "didn", "'t"]`

Vocab size: ∼30k–50k

The sweet spot

Character

`["U","n","b","e","l","i","e","v","a","b","l","y",...]`

Vocab size: ∼256

Very long sequences

Used by all modern LLMs

Word-level tokenization and the OOV problem

Vocabulary (fixed at training):

`the, cat, sat, on, mat,`
`dog, run, happy, sad, ...`

Size: 50,000–200,000 words

At test time:

`"The cryptocurrency market plummeted after the CEO's tweet."`

Words not in vocab → `[UNK]` [UNK] market [UNK] after the [UNK] tweet.

Problems: • New words, names, typos → `[UNK]` • Huge vocabulary → huge embedding matrix • Morphology lost: "run", "runs", "running" are unrelated tokens

Character-level: no unknowns, but. . .

Input: "The cat sat on the mat."

`The | cat | sat | on | the | mat | .`

7 tokens (word-level)

`T|h|e| |c|a|t| |s|a|t| |o|n| |t|h|e| |m|a|`

23 tokens (character-level)

Drawbacks:

- Sequences are $\sim$4–5$\times$ longer
- Self-attention is $O(n^2)$, so cost grows quadratically
- Each character carries little semantic meaning
- Harder to learn long-range dep

Advantages:

- Tiny vocabulary ($\sim$256)
- Zero unknown tokens
- Works for any language
- Handles typos, code, URLs

Too fine-grained on its own — but the idea of starting from characters inspires **subword** methods

Subword tokenization: the key insight

Common words stay whole: `the`, `cat`, `and`

Rare words are split into known pieces: `un` + `believ` + `ably`

"playing" → `play` + `ing`

"unhappiness" → `un` + `happi` + `ness`

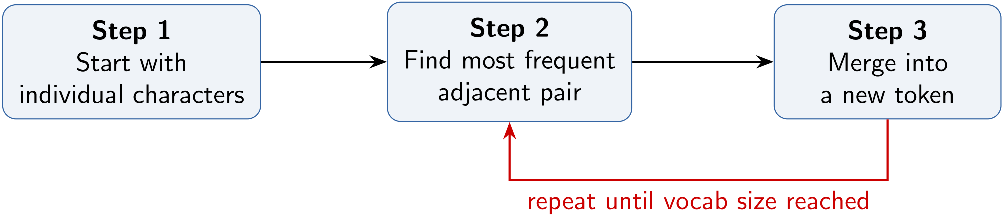
"ChatGPT" → `Chat` + `G` + `PT`

"brrrr" → `br` + `rr` + `r`

Vocab size ∼30k–50k • No `[UNK]` tokens • Reasonable sequence lengths • Morphology is partially captured

Byte-Pair Encoding (BPE): the idea

Training: learn merge rules from a corpus. **Inference:** apply merge rules to new text.



Originally a **data compression** algorithm (Gage, 1994). Adopted for NLP by Sennrich et al. (2016). Used by **GPT**, **GPT-2**, **RoBERTa**, **BART**, **LLaMA**.

BPE: worked example

Corpus: hug (10), pug (5), pun (12), bun (4), hugs (5)

Initial vocab: h, u, g, p, n, b, s
Splits: h u g (10) p u g (5) p u n (12) b u n (4) h u g s (5)

Merge 1: most frequent pair = (u,g) freq = 10+5+5 = 20
Splits: h **ug** (10) p **ug** (5) p u n (12) b u n (4) h **ug** s (5)

Merge 2: most frequent pair = (u,n) freq = 12+4 = 16
Splits: h ug (10) p ug (5) p **un** (12) b **un** (4) h ug s (5)

Merge 3: most frequent pair = (h,ug) freq = 10+5 = 15

Merge rules (ordered):

1. u + g → ug
2. u + n → un
3. h + ug → hug

⋮

Vocab after 3 merges:
h, u, g, p, n, b, s, ug, un, hug

BPE: tokenizing new text

Given the learned merge rules, tokenize a new word:

Tokenize "bugs":

Start: `b u g s`

Rule 1 (`u+g`): `b ug s`

Rule 2 (`u+n`): `b ug s` no match

Rule 3 (`h+ug`): `b ug s` no match

Key point:

Apply merge rule
the *same order* t
were learned.

Words not seen c
training are still t
— just split into
known pieces.

Result: `["b", "ug", "s"]` → IDs `[5, 7, 6]`

Byte-level BPE (GPT-2, GPT-3, LLaMA)

Standard BPE

Base vocab = Unicode characters

Vocab size = ∼30k–50k

Unknown chars → `[UNK]`

Problem: Chinese, emoji, etc. can hit unknown characters

upgrade →

Byte-level BPE

Base vocab = **256 byte values**

Vocab size = 256 + merges (GPT-2: 50,257 total)

No `[UNK]` ever

Any byte sequence is representable

Every text is ultimately a sequence of bytes (UTF-8 encoding).
By starting from **bytes** instead of characters, BPE can tokenize *any* input: English, Chinese, Arabic, code, emoji, binary data — all with the same vocabulary.

WordPiece (BERT, DistilBERT)

BPE

Merge criterion:
most frequent pair

Greedy count-based

Used by: GPT, LLaMA, etc.

WordPiece

Merge criterion:
pair that **maximizes likelihood** of the training corpus

Used by: BERT, DistilBERT

$$\text{score}(a, b) = \frac{\text{freq}(ab)}{\text{freq}(a) \times \text{freq}(b)}$$

Notation: WordPiece marks *continuation* subwords with `##`

“unbelievably” → `["un", "##believ", "##ably"]`

BPE instead marks *word-initial* subwords (e.g., GPT-2 uses `Ġ` = space prefix)

Unigram LM and SentencePiece

Unigram LM

Start with a *large* vocab

Iteratively **remove** tokens
that hurt likelihood the least

Top-down (vs BPE's bottom-up)

Used by: T5, ALBERT, XLNet

Kudo, 2018

SentencePiece

Not an algorithm — a **library**

Treats input as raw byte stream
(no pre-tokenization needed)

Supports both **BPE** and **Unigram**

Language-agnostic: no need for space-based word splitting

Kudo & Richardson, 2018

BPE = bottom-up (merge frequent pairs) vs
Unigram = top-down (prune unlikely tokens)

Both converge to similar subword vocabularies in practice.

Why tokenization matters: LLM quirks

Bad at arithmetic

"12345" → `["123", "45"]`
The model never sees the individual digits together!

Poor non-English efficiency

English "hello" = 1 token
Korean "annyeong" = 3–5 tokens
Same meaning, 3–5× the cost!

Sensitive to formatting

"`Hello World`" and "`Hello  World`" produce different token sequences.

Can't count letters

"How many r's in strawberry?"
"`straw`" + "`berry`" — the model can't see individual letters.

Many apparent "reasoning failures" of LLMs are actually **tokenization artifacts**.
The model literally cannot see what you think it sees.

Visualizing: the same sentence, different tokenizers

Input: “The cat sat on the unbelievably soft mat”

GPT-2 (B The **):** _cat _sat _on _the _un believ ably _soft _mat **10 tok**

BERT (Wo the **ec** cat sat on the un ##bel ##ie ##va ##bly soft mat **12 tok**

Character: `The_cat_sat_on_the_unbelievably_soft_mat` **39 tok**

Same input, very different representations. “unbelievably” = **3 tokens** (GPT-2), **5 tokens** (BERT), **12 tokens** (char).

Special tokens

[CLS]
Classification token (BERT)

[SEP]
Separator between segments

[PAD]
Padding to equal length

[UNK]
Unknown token (fallback)

$\langle$**BOS**$\rangle$
Beginning of sequence

$\langle$**EOS**$\rangle$
End of sequence

[MASK]
Masked position (BERT MLM)

Special tokens are **not** in the original text — they're added by the tokenizer to give the model structural signals: where sequences begin/end, what to predict, etc.

Comparison of tokenization methods

Method	Direction	Criterion	Vocab size	Used by
BPE	Bottom-up	Frequency	30k–50k	GPT, LLaMA
WordPiece	Bottom-up	Likelihood	30k	BERT
Unigram	Top-down	Likelihood	30k–50k	T5, XLNet
Byte BPE	Bottom-up	Frequency	50k–100k	GPT-2/3/4
Character	—	—	256	ByT5

In practice, the differences between BPE, WordPiece, and Unigram are **small**. What matters most: vocab size, training corpus, and whether byte-level is used.

Byte-level BPE is the current default for new large language models.

Practical: tokenizers in action

```python
# GPT-4 tokenizer
import tiktoken
enc = tiktoken.encoding_for_model(
  "gpt-4")
tokens = enc.encode(
  "Hello world!")
# [9906, 1917, 0]
enc.decode(tokens)
# "Hello world!"
```

```python
# BERT tokenizer
from transformers import
  AutoTokenizer
tok = AutoTokenizer.from_pretrained(
  "bert-base-uncased")
tok.tokenize(
  "unbelievably")
# ["un", "##bel", "##ie",
#  "##va", "##bly"]
```

Try it yourself: `https://platform.openai.com/tokenizer`

Paste any text and see how GPT tokenizes it. Pay attention to: numbers, non-English text, code, and whitespace.

Questions?

Next: Evaluation — Perplexity, BLEU, ROUGE