Advanced Methods in Text Analytics

Tokenization

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What is Tokenization?

- Often forgotten/neglected/unglamorous aspect of NLP
  - But **still present in all LMs** (from n-grams to LLMs), thus **important topic**!
  - We assume text is *nicely* "chopped up" into segments before processing it
  - Much like printers, some don't care about the details behind this process
  - They just what it to work!
- Generally, **tokenization** is the process of **splitting text into finite strings** that act as **representation of that text for computers to process it**
  - These substrings often referred to as **tokens** (Webster and Kit, 1992)
- For **example**, take the string "Tokenization won't be neglected anymore."
- If we split it based on whitespace separation (each token is underlined):
  - Tokenization won't be neglected anymore. (5 tokens)
- If we further split punctuation marks:
  - Tokenization won ' t be neglected anymore . (8 tokens)
- Using the Llama3-70B tokenizer (center dot represents whitespace):
  - Token ization ·won 't ·be ·neglected ·anymore . (8 *different* tokens)

Goal of Tokenization (1)

- Why are there different tokenization approaches?
  - Because decision on *how* to split text into tokens isn't trivial
  - Highly depends on what we want those tokens to do/represent
- **The linguistic goal**: traditionally, tokens thought of as words
  - Makes sense in some tasks, e.g. POS tagging
  - But often not clear what a word is
  - E.g. word "won't" was tokenized in three different ways in previous slide
- Hence, **in this lecture** we make **distinction between words and tokens**
  - **Token:** these finite substrings we get as output of tokenization process
  - **Word:** string that is, by itself, semantically meaningful in some language
- Still, **linguistically**, we may want **tokens to be approximations of words**
  - E.g. why break word "won't" into meaningless tokens like "won" and "'t"?
  - Many similar examples, e.g. "copy-paste" makes sense by itself
  - Models may learn the semantics of the same representations used by us
  - Producing *word-like* tokens less common today, known as pre-tokenization

Goal of Tokenization (2)

- **The systems goal:** favor system-level requirements over linguistic motivations
  - E.g. **segmenting text into higher number of tokens increases memory consumption of input sequence of a language model** (LM)
  - Slide 2: different tokenizers split same text into different number of tokens
  - So, if using fewer tokens means we can support longer input sequences at the cost of "tokens being approximations of words", then so be it.
  - E.g. use single token for "tokenization" instead of "token" and "ization"
  - **This perspective more common today**, largely motivated by the success of deep learning methods and the need to scale them
- In short, **goal of tokenization not straightforward**
  - **Linguistically**, we want tokens to be approximation of words
  - From a **systems perspective**, we are happy to drop this linguistic motivation in favor of decisions that improve our systems in any way
- In this lecture, we focus on tokenization as part of pipeline of LMs

Outline

1. Tokenization in Language Models

2. Common Tokenization Methods

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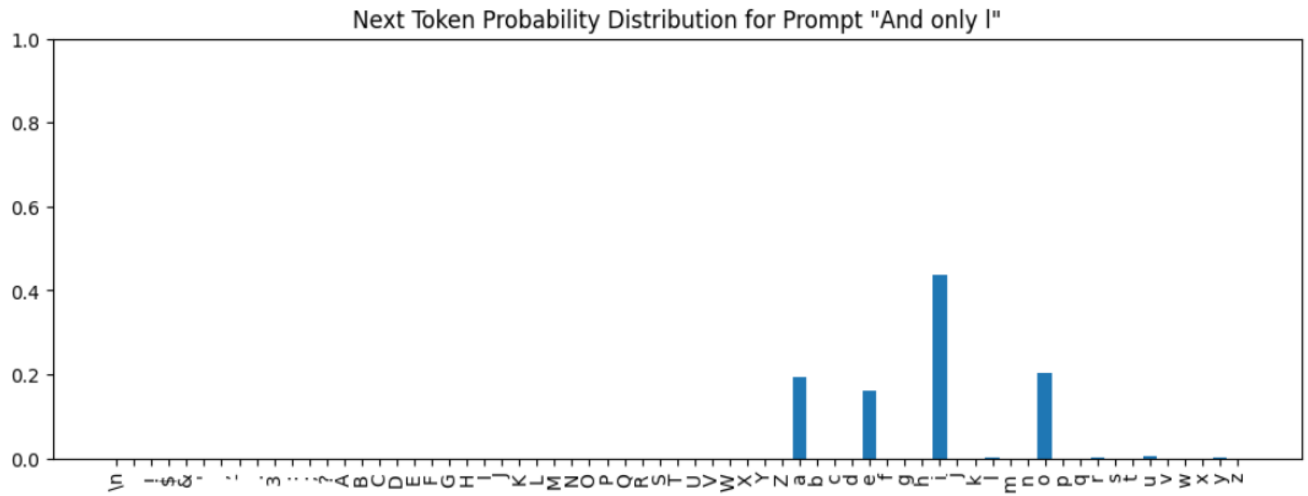
Tokenization in Language Models

Role of Tokenization in LMs

- **Tokens** are the **atomic units seen/handled by LMs**.
  - Set of tokens known to LM: **vocabulary**
  - **Each token** in vocabulary **mapped to representation vector** of size *d*
  - I.e. the typical (static) embedding table/matrix, impacts model size/costs
- **Input sequences** broken into finite sequence of known tokens
  - E.g. Token ization ·won 't ·be ·neglected ·anymore.
- **Output sequences** are composed of set of these known tokens
  - Next word distribution assigns probability to each of these tokens



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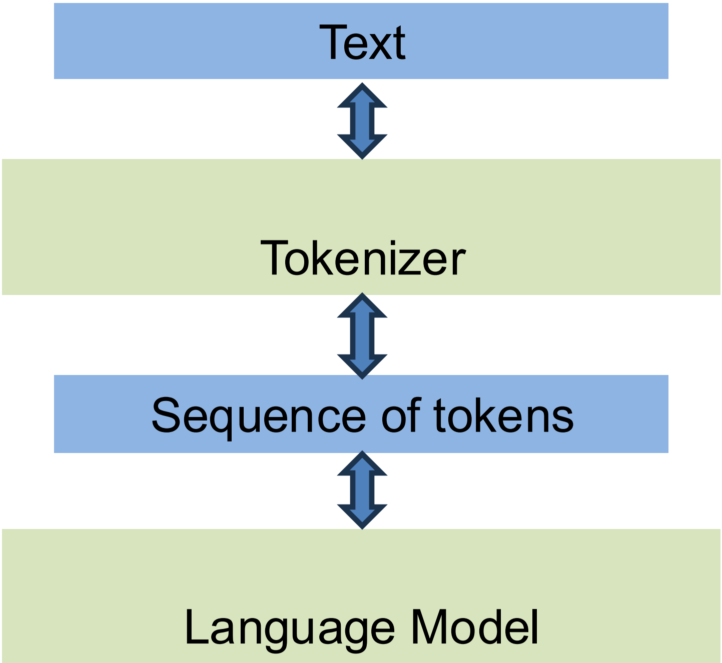
Tokenizers

- Component of NLP system, e.g. LM, in charge of tokenization process
  - *Bidirectional* mapping between text and corresponding sequence of tokens
- Important: **entire separate system from LM**
  - They can also be "trained", separately, different training data (details soon)
  - After that, they act as encoding/decoding function
- **Encoding**
  - **Input:** text
  - **Output:** corresponding sequence of tokens
- **Decoding**
  - **Input:** sequence of tokens
  - **Output:** corresponding text
- Sequence of tokens = sequence of integers
  - IDs mapped to rows of static embedding matrix, e.g. 123, 4673, 56724



Impact of Tokenization in LMs (1)

- **Tokenization** is **behind several phenomena observed when using LMs**
  - Sometimes they are a partial explanation for an observation
  - Sometimes they entirely explain an observation
- Let's look at **some examples**
  - This app can help illustrate some of these issues
  - Select tokenizer on top right, each output token has a different color
- **String processing**, e.g. reverse the string "elephant"
  - Llama3's tokenizer breaks word *elephant* into tokens "ele" and "phant"
- **Difficulty in arithmetic**, e.g. "1123 + 245 =" (answer is 1368)
  - Numbers not broken into digits
  - E.g. 1123 split into "112" and "3", 11233 into "1123" & "33"
  - Ongoing research, e.g. Singh et al. 2024
- **Difficulty spelling**, e.g. "how many letters E in the word 'elephant'?"
  - Again, model *sees* tokens "ele" and "phant"

Impact of Tokenization in LMs (2)

- **Performance in languages other than English** usually worse
  - Partly due to lower amount of LM training data in other languages
  - But partly due to lower amount of data when training tokenizer as well
- For example, number of tokens in following words from Llama3-8B:
  - Hello 1 token
  - 안녕하세요 2 tokens
  - नमस्ते 3 tokens
- **Often, words in other languages are split into more tokens**
  - This has to do with the way tokenizers are trained (details soon)
  - Impact?
  - **More memory requirement for same word in different language**
  - **More money spent using LLMs closed behind APIs** (prices per token)
  - Similar arguments behind preferences such as using YAML vs JSON as input
- Next section: we go over some popular tokenization methods.

Common Tokenization Methods

Word-Level Tokenization

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- Referred to tokenizers that **produce *word-like* tokens**
  - **Follows linguistic goal** of tokens being approximations of words
- **Today**, this process referred to as **pre-tokenization**
  - Goal of approximating words no longer a priority
  - But still an important part of pre-processing (more later)
  - May include other steps, e.g. normalization, spell correction
- **Main advantage:** interpretable!
  - Tokens are representations of words/concepts we understand.
- **Main disadvantage:** inability to deal with rare or new words
  - Rare words in training replaced with special **UNK token** (from unknown)
  - During inference, UNK used to represent out-of-vocabulary words
  - **Out-of-vocabulary words (OOV) =** words not seen during training
  - Using UNK during inference bad for: text generation, extracting useful features from OOV words, e.g. "desertification" comes from "desert"
- **Another disadvantage:** large/changing vocab. (hundreds of thousands)

Character-Level Tokenization

- Addresses **main disadvantages** of word-level tokenizers
  - If we **assume a finite set of symbols (a script)**, we **can represent OOV words as sequence of its symbols**, plus **size of vocabulary is small/finite**
- For example, if script is English alphabet, we have 26 symbols.
  - Embedding matrix: *26 x d* (plus whatever words you add to vocabulary)
  - If word "elephant" is OOV, represent it as "e" "l" "e" "p" "h" "a" "n" "t"
- **Disadvantages?**
  - In some languages, **characters may not encode meaning** (linguistic goal)
  - **Vectors per character increases length of representation** (systems goal)
  - E.g. Llama3 breaks "elephant" into "ele" and "phant", i.e. *2 x d*
  - If we break it into characters, it's *8 x d*, so more memory consumption, more costly computations, parameters may have to encode more, etc.
  - Also, **vocabulary may still be large** (e.g. Unicode has 150K characters)
- The *currently accepted* intermediate **sweet spot? Subword tokenizers!**
  - But it's ongoing research; systems change, tokenizers may accommodate

Subword-level Tokenization

- **Split *word-like* tokens into smaller units called subwords**
  - Set of all possible subwords is finite, determined from training data
  - Vocabulary also includes all characters, used to represent OOV words
- **Advantages:**
  - Vocabulary size finite, many tokens still semantically meaningful
  - Can handle OOV words well (breaks them into known subwords)
- **Disadvantage:**
  - Many ways to choose subword units, affects performance
  - E.g. manually constructed, linguistically informed rules, may favor morphologically rich languages (lots of inflections, compounding, etc.)
  - More generally, subword segmentation may not favor non-morphologically rich languages, e.g. arabic or hebrew
- **Most common approach today? Byte-Pair-Encoding (BPE)**
  - Input to BPE is output of pre-tokenization process
  - So, let's have a better look at this first

Pre-Tokenization (1)

- Can be generally described as **classic pre-processing step**
  - Classic: **rule-based**
  - Often forgotten but still present today!
  - Follows normalization step
- **Normalization**:
  - Removing unnecessary whitespaces
  - Turn all characters into lower case
  - Removing accents
  - Etc.
- **Goal of pre-tokenization:** split raw text into word-like segments
  - These segments are foundation to final tokens used by LMs
- **Common pre-tokenization approaches**:
  - Split by whitespace and punctuation (similar to what we do in tutorials)
  - Split by character (e.g. in symbol-based languages like Chinese)
  - More specific rules based on useful linguistic properties

Pre-Tokenization (2)

- Important: **output of pre-tokenization used as input to train tokenizer**
- Examples of rules [used in GPT-2]
  - The following regex pattern:

    's|'t|'re|'ve|'m|'ll|'d|

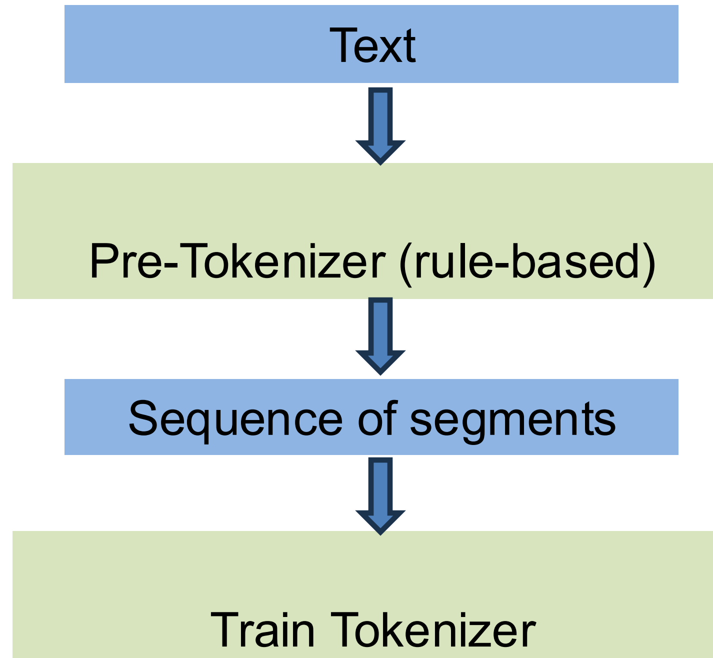
    ?\p{L}+|

    ?\p{N}+|

    ?[^\s\p{L}\p{N}]+

    |\s+(?!\S)|

    \s+



- Details beyond the scope
  - But note rules for contractions, spaces followed by letters or numbers, etc.
- **Important: rules** hand-crafted, **[language dependent]**
  - Character-based languages split by character
  - But [characters often have meaningful parts], require different rules

Byte-Pair-Encoding (1)

- Breakthrough in subword tokenization
  - Originally a data compression algorithm (Gage, 1992)
  - Recently popularized by its use in machine translation (Sennrich, 2016)
- It’s a **fast and simple heuristic**
  - Known to improve downstream performance
- **Idea:** instead of defining tokens a priori, **let data tell us what our tokens should be**
  - A priori: rules, e.g. "each word is a token", or "each character is a token"
  - If we pick the right subwords, we could handle OOV rather well!
- **BPE in short:**
  1. Starting "base vocabulary" V is set of characters
  2. Find most common two-character subword, create token for it, add to V
  3. Replace every instance of two-character subword from Step 1 with its token
  4. Keep finding common and longer subwords until k new tokens are created
- Let's look at this process in more detail.

Byte-Pair-Encoding (2)

- The algorithm runs "inside words", i.e. no merges across words
  - These "words" first determined by pre-tokenization step
  - I.e. word boundaries depend pre-tokenization rules
  - Boundary represented by added special symbol, e.g. an underscore _
- So, for a tiny input corpus of 18 word tokens, we have the following frequencies for each word, as well as our base vocabulary:

corpus		**vocabulary**
5	l o w _	_, d, e, i, l, n, o, r, s, t, w
2	l o w e s t _	
6	n e w e r _	
3	w i d e r _	
2	n e w _	

- The algorithm then counts all pairs of *adjacent* symbols
  - Most common is "er" (appears in *newer* and *wider*, so 9 times in corpus)
- It then merges the two symbols into new token, adds it to vocabulary

Byte-Pair-Encoding (3)

- We count adjacent tokens again (note "er" is now a token)

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er
2	l o w e s t _	
6	n e w er _	
3	w i d er _	
2	n e w _	

- Most common adjacent tokens are now "er" and "_", which we add to *V*

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er, er_
2	l o w e s t _	
6	n e w er_	
3	w i d er_	
2	n e w _	

- The process continues until we add *k* tokens to our base vocabulary
  - *k* is a hyperparameter,
  - This loop often referred to as **training the tokenizer**

Byte-Pair-Encoding (4)

- In the end, for *k = 8*, we would derive the following merge rules:

merge	current vocabulary
(ne, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new
(l, o)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo
(lo, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low
(new, er_)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_
(low, _)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_, low_

  - Note that we added two full words: *newer_* and *low_*.
  - In real-world settings, *k* is in the thousands, so many words get full tokens.
- Then, for **encoding a word into tokens**, we proceed as follows:
  - We **break input sequence into characters**
  - **Apply merges in learned order**, e.g. first merge "e" and "r" into "er"
- Note that encoding ensures we use tokens of highest possible level
  - Thus, **many words tokenized as full word**
  - **Only OOV words would be represented by subword tokens**
  - E.g. "lower" in our toy setting would be "low" and "er_"

Byte-Pair-Encoding (5)

- The algorithm for "learning" the tokenizer is thus the following.

function BYTE-PAIR ENCODING(strings C, number of merges k) **returns** vocab V

$V \leftarrow$ all unique characters in C # initial set of tokens is characters
for $i = 1$ **to** k **do** # merge tokens k times
  $t_L, t_R \leftarrow$ Most frequent pair of adjacent tokens in C
  $t_{NEW} \leftarrow t_L + t_R$ # make new token by concatenating
  $V \leftarrow V + t_{NEW}$ # update the vocabulary
  Replace each occurrence of t_L, t_R in C with t_{NEW} # and update the corpus
return V

- Several methods exist that are similar to BPE.
- **WordPiece** (Schuster and Nakajima, 2012) focused on Japanese and Korean (can't be relied on space-separated tokens)
  - Instead of merging most common pairs of tokens, **merged pairs that increase data likelihood of an n-gram LM** trained with this updated vocabulary

UnigramLM and SentencePiece

- **Another common approach:** UnigramLM (Kudo, 2018)
    - Adopts same idea of evaluating subword candidates by impact on LM
- **UnigramLM in short:**
    - Starts with very large vocabulary, much larger than what we would want
    - At every iteration, trains unigram LM on current vocabulary, then drops lowest probability items from vocabulary
    - Process is repeated until desired vocabulary size is reached
- Their **probabilistic approach** allowed for **interesting observations**:
    - A string can be broken down into different equally probable segmentations
    - They found that using "sampled segmentation" instead of a deterministic mapping between string and set of tokens improved performance on MT
    - Similar idea adopted by **BPE-Dropout** (Provilkov et al. 2020): token merges are randomly skipped to produce segmentation variety.
- **SentencePiece** (Kudo and Richardson, 2018):
    - Software library for BPE and UnigramLM, thus often ambiguous reference

The Tokenization Spectrum

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- **Word-level tokens**:
  - Meaningful representations, interpretable, **often helps LM performance**
  - Why? Intuition: easier for models to learn since **representation units closer to language being learned**, learned relations between representations similar to relations between words
  - Larger, potentially infinite vocabulary, difficult to handle OOV words
- **Character-level tokens**:
  - Smaller vocabulary but potentially meaningless representations, often associated with lower LM performance
  - **May require higher capacity models to learn to use representations well**
  - BPE-like processes require more merges/data (i.e. larger vocabulary, more parameters) to get to meaningful subwors/words

Character-level tokens

Word-level tokens

Handling OOV Words

- How does BPE handle OOV words?
  - Breaks them down into subwords
  - Can go as far "down" as base vocabulary
- Thus, **BPE dependent on base vocabulary to handle OOV words**
  - If we still can't identify a character in a word, we assign UNK token
- Common choices of base vocabulary:
  - Unicode (database for all symbols in all languages and beyond)
  - Raw Bytes (used by OpenAI's models, META's Llama models, etc.)
- **Unicode**:
  - **PROs:** lookup table for "all" symbols (or subsets thereof), ~150K entries
  - **CONs:** still a finite lookup table, changes over time, e.g. emojis were added
- **Raw Bytes**:
  - **PROs:** tiny base vocabulary, impossible to find OOV words
  - **CONs:** meaningless base vocabulary, likely requires stronger models
- Why impossible to find OOV? Let's discuss this in a bit more detail

Falling Back to Bytes

- **Unicode**:
  - Mapping from real-world symbol to unique ID

- **UTF-8** (stands for **U**nicode **T**ransformation **F**ormat):
  - How to encode Unicode IDs into bytes, i.e. blocks of 8-bits
  - English alphabet dominant due to US role in Computer Science history
  - Thus, such characters typically use single byte: *a-z, A-Z, 0-9,* etc.
  - Languages with other scripts added later
  - Thus, single characters from other languages often require more bytes, e.g. japanese symbol か used to make questions (i.e. common) uses 3 bytes
- So, starting with raw bytes as base vocabulary is a clever idea
  - All text boils down to byte patterns established by both Unicode and UTF-8
  - I.e. base vocabulary only has 256 tokens
  - This approach taken by GPT-2 and other OpenAI models, many LLMs since
  - Note: for fixed vocabulary size *K*, English has benefits
- We'll come back to this in future lectures

How to Select Number of Merges?

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- Do we simply choose a desired vocabulary size?
  - Usually the standard approach
  - But how to reason about this?
- More and larger subwords may lead to more memorization, less fundamental understanding (Kharitonov et al. 2021)
- Optimal choice may depend on task and language (Mielke et al. 2019)
  - Always challenging to develop general solutions
- This **choice directly relates to** where in **tokenization spectrum** we lie

Can We Get Rid of Tokenization?

- E.g. by simply using characters as tokens, i.e. we never merge anything
  - Something like Unicode encodes all symbols from past and present
  - Some language models designed around processing bytes
- But what about semantics?
  - Deep-enough transformers may be able to pick up semantics enough to outperform subword-based models (Al-Rfou et al. 2019)
  - But more work is needed to understand this better
- And what about input length?
  - Lots of characters still need longer input sequence in terms of memory/parameters/cost
  - But this may become less of an issue with recent work on infinite attention
- **Another alternative:** learn tokens based on visual representations, i.e. symbols (e.g. Rust et al. 2022)

Summary

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- **Tokenization** is often neglected, described as unglamorous
- But it has a **clear impact on the representations learned by models**
  - Thus, also a **clear impact on downstream applications**
- Several types of tokenization approaches exist
  - Word-level
  - Character-level
  - Subword-level
- Difficult to learn/advocate for one single approach
  - **Subword is most common today** (esp. **BPE** and UnigramLM)
  - But **research is ongoing to better understand impact** of different methods
- Tokenization has a **direct impact** on **evaluating model performance** and on models' ability to **perform in different languages**
  - More in future lectures

References

- Speech and Language Processing, Jurafsky et al., 2024
  - Chapter 2
- Between words and characters: A Brief History of Open-Vocabulary Modeling and Tokenization in NLP, Mielke et al, 2021
- Let's build the GPT Tokenizer, Andrej Karpathy, 2024
- References linked in corresponding slides