

Course 2: Tokenization

What is tokenization?

Turning text...

```
I love playing soccer!
```

...into *tokens*

```
['I', 'love', 'play', 'ing', 'soccer', '!']
```

Historical Notions

Tokenization Origins

The word token comes from linguistics

“ *non-empty contiguous sequence of graphemes or phonemes in a document* ”

≈

Split text on blanks

Tokenization Origins

```
old_tokenize("I love playing soccer!") = ['I', 'love', 'playing', 'soccer!']
```

- Different from *word-forms* ⚠
 - *damélo* → *da/mé/lo* (=give/me/it)

Tokenization Origins

Natural language is split into...

- Sentences, utterances, documents... (*macroscopical*)
that are split into...
 - Tokens, word-forms... (*microscopical*)
- Used for linguistic tasks (POS tagging, syntax parsing,...)

Tokenization & ML

Machine Learning relies on **sub-word** tokenization:

- Gives better performance
- **Fixed-size vocabulary** often required
 - Out-Of-Vocabulary (OOV) issue

Tokenization & ML

Evolution of modeling complexity w.r.t. the sequence length n

Model Type	Year	Complexity
Tf-Idf	1972	$O(1)$
RNNs	~1985	$O(n)$
Transformers	2017	$O(n^2)$

→ Long sequences (e.g. character-level) are **prohibitive**

Modern framework

- **Pre-tokenization**

```
"I'm lovin' it!" -> ["i", "am", "loving", "it", "!" ]
```

- Normalization

- Rules around punctuation (`_:_`, `_!`, ...)
- Spelling correction (`"imo" -> "in my opinion"`)
- Named entities (`"covid" -> "COVID-19"`)
- ...

- Rule-based segmentation

- Blanks, punctuation, ...

Modern framework

- **Tokenization** `-> ["i", "am", "lov", "##ing", "it", "!"]`
 - Split units at subword level
 - Fixed vocabulary
 - **Trained** on text samples
 - Used in inference mode at *pre-processing* time

Sub-word Tokenization

Granularity



Granularity

→ Trade-off between short sequences and reasonable vocabulary size

Fertility

For a string sequence S :

$$\text{fertility}(S) = \frac{\# \text{ tokens}}{\# \text{ words}}$$

Algorithms

Byte-Pair Encoding (BPE)

Let's encode "*aaabdaaabc*" in an optimized way:

- Observed pairs: {*aa*, *ab*, *bd*, *da*, *ba*, *ac*}
- Observed **occurences**: {*aa*: 4, *ab*: 2, *bd*: 1, *da*: 1, *ba*: 1, *ac*: 1}
- Set $X = aa$
- Encode *aaabdaaabc* \rightarrow *XabdXabac*
- Start again from *XabdXabac*

Byte-Pair Encoding (BPE)

(current rules: $aa \rightarrow X$)

Let's encode " $XabdXabac$ " in an optimized way:

- Observed pairs: $\{Xa, ab, bd, dX, ba, ac\}$
- Observed **occurences**: $\{Xa: 2, ab: 2, bd: 1, dX: 1, ba: 1, ac: 1\}$
- Set $Y = ab$
- Encode $XabdXabac \rightarrow XYdXYac$
- Start again from $XYdXYac$

Byte-Pair Encoding (BPE)

(current rules: $aa \rightarrow X$, $ab \rightarrow Y$)

Let's encode " $XYdXYac$ " in an optimized way:

- Observed pairs: $\{XY, Yd, dX, Ya, ac\}$
- Observed occurrences: $\{\textcolor{blue}{XY}: 2, Yd: 1, dX: 1, Ya: 1, ac: 1\}$
- Set $Z = XY$
- Encode $XYdXYac \rightarrow ZdZac$
- Start again from $ZdZac$

Byte-Pair Encoding (BPE)

(current rules: $aa \rightarrow X$, $ab \rightarrow Y$, $XY \rightarrow Z$)

Let's encode "*ZdZac*" in an optimized way:

- Observed pairs: $\{Zd, dZ, Za, ac\}$
- Observed occurrences: $\{Zd: 1, dZ: 1, Za: 1, ac: 1\}$
- **All pairs are unique => END**

Byte-Pair Encoding (BPE)

Final encoding: *aaabdaaabac* \rightarrow *ZdZac*

with **merge rules**:

1. *aa* \rightarrow *X*

2. *ab* \rightarrow *Y*

3. *XY* \rightarrow *Z*

Decoding: follow merge rules in opposite order

BPE Training - pre-tokenization

```
training_sentences = [  
    "Education is very important!",  
    "A cat and a dog live on an island",  
    "We'll be landing in Cabo Verde",  
]
```

=>

```
pretokenized = ["education_", "is_", "very_", "important_", "!", "a_",  
    "cat_", "and_", "a_", "dog_", "live_", "on_", "an_", "island_",  
    "we", "'", "ll_", "be_", "landing_", "in_", "cabo_" "Verde_"  
]
```

BPE Training - iteration 1

```
tokenized = [  
    ['e', 'd', 'u', 'c', 'a', 't', 'i', 'o', 'n', '_'], ..., ['i', 'm', 'p', 'o', 'r', 't', 'a', 'n', 't', '_'], ['!', '_'],  
    ['a', '_'], ['c', 'a', 't', '_'], ['a', 'n', 'd', '_'], ..., ['o', 'n', '_'], ['a', 'n', '_'], ['i', 's', 'l', 'a', 'n', 'd', '_'],  
    ['w', 'e'], [''], ['l', 'l', '_'], ['b', 'e', '_'], ['l', 'a', 'n', 'd', 'i', 'n', 'g', '_'], ..., ['v', 'e', 'r', 'd', 'e', '_']  
]
```

→ Most common pair: "an"

```
tokenized = [  
    ['e', 'd', 'u', 'c', 'a', 't', 'i', 'o', 'n', '_'], ..., ['i', 'm', 'p', 'o', 'r', 't', 'an', 't', '_'], ['!', '_'],  
    ['a', '_'], ['c', 'a', 't', '_'], ['an', 'd', '_'], ..., ['o', 'n', '_'], ['an', '_'], ['i', 's', 'l', 'an', 'd', '_'],  
    ['w', 'e'], [''], ['l', 'l', '_'], ['b', 'e', '_'], ['l', 'an', 'd', 'i', 'n', 'g', '_'], ..., ['v', 'e', 'r', 'd', 'e', '_']  
]
```

BPE Training - iteration 2

```
tokenized = [  
    ['e', 'd', 'u', 'c', 'a', 't', 'i', 'o', 'n', '_'], ..., ['i', 'm', 'p', 'o', 'r', 't', 'a', 'n', 't', '_'], ['!', '_'],  
    ['a', '_'], ['c', 'a', 't', '_'], ['an', 'd', '_'], ..., ['o', 'n', '_'], ['an', '_'], ['i', 's', 'l', 'a', 'n', 'd', '_'],  
    ['w', 'e'], [''], ['l', 'l', '_'], ['b', 'e', '_'], ['l', 'a', 'n', 'd', 'i', 'n', 'g', '_'], ..., ['v', 'e', 'r', 'd', 'e', '_']  
]
```

→ Most common pair: "ca"

```
tokenized = [  
    ['e', 'd', 'u', 'ca', 't', 'i', 'o', 'n', '_'], ..., ['i', 'm', 'p', 'o', 'r', 't', 'a', 'n', 't', '_'], ['!', '_'],  
    ['a', '_'], ['ca', 't', '_'], ['an', 'd', '_'], ..., ['o', 'n', '_'], ['an', '_'], ['i', 's', 'l', 'a', 'n', 'd', '_'],  
    ['w', 'e'], [''], ['l', 'l', '_'], ['b', 'e', '_'], ['l', 'a', 'n', 'd', 'i', 'n', 'g', '_'], ..., ['v', 'e', 'r', 'd', 'e', '_']  
]
```

BPE Training - iteration 14 (final)

```
tokenized = [  
    ['e', 'd', 'u', 'cat', 'i', 'on_'], ['is', '_'], ['ver', 'y', '_'], ['i', 'm', 'p', 'o', 'r', 't', 'an', 't', '_'], ['!', '_'],  
    ['a_'], ['cat', '_'], ['and_'], ['a_'], ..., ['on_'], ['an', '_'], ['is', 'l', 'and_'],  
    ['w', 'e'], [''], ..., ['l', 'and', 'i', 'n', 'g_'], ['i', 'n_'], ['ca', 'b', 'o', '_'], ['ver', 'd', 'e_']  
]
```

"Created" tokens:

```
['an', 'ca', 'n_', 've', 'and', 'cat', 'on_', 'is', 'ver', 'a_', 'and_', 'g_', 'e_']
```

→ English common words (a, and, on, is, ...)

→ **and** vs **and_**

BPE Training - iteration 14 (final)

```
tokenized = [  
    ['e', 'd', 'u', 'cat', 'i', 'on_'], ['is', '_'], ['ver', 'y', '_'], ['i', 'm', 'p', 'o', 'r', 't', 'an', 't', '_'], ['!', '_'],  
    ['a_'], ['cat', '_'], ['and_'], ['a_'], ..., ['on_'], ['an', '_'], ['is', 'l', 'and_'],  
    ['w', 'e'], [''], ..., ['l', 'and', 'i', 'n', 'g_'], ['i', 'n_'], ['ca', 'b', 'o', '_'], ['ver', 'd', 'e_']  
]
```

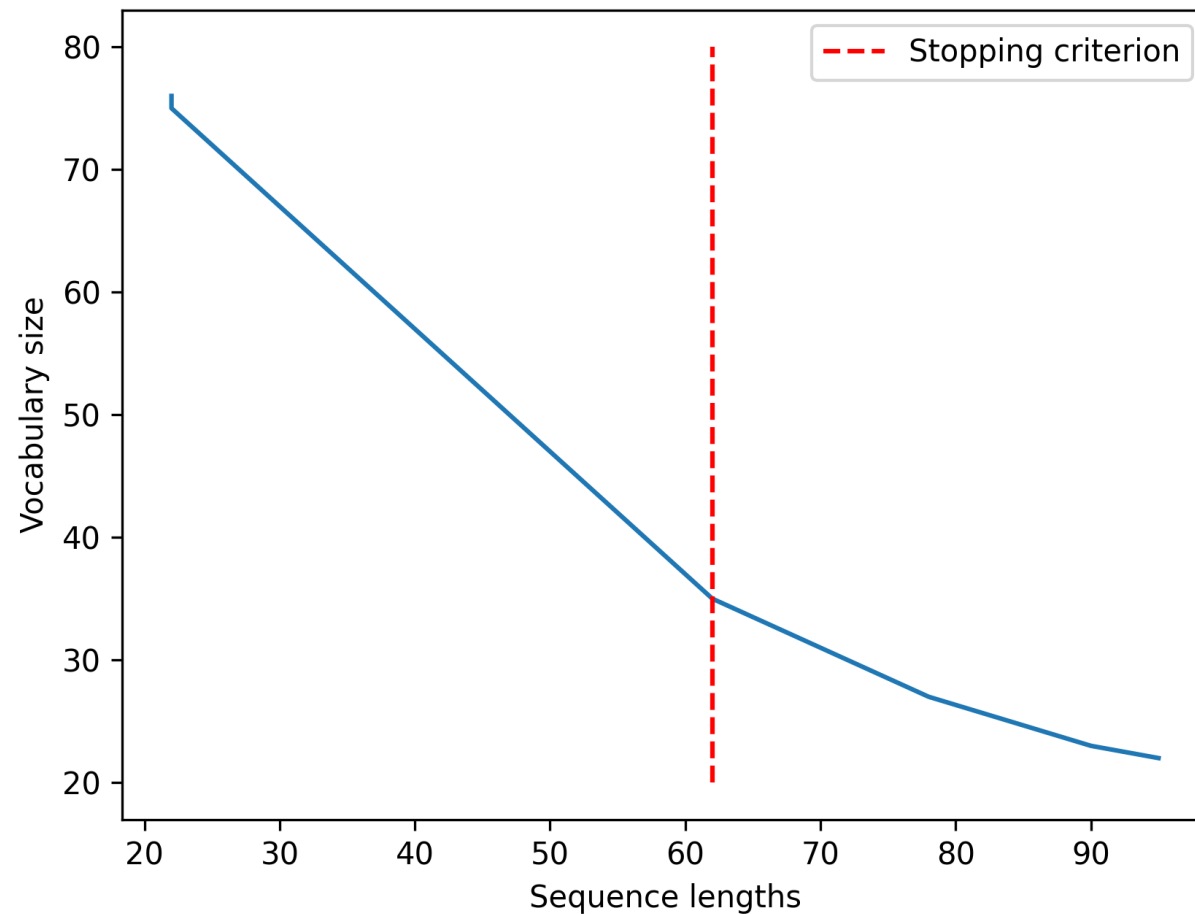
"Created" tokens:

```
['an', 'ca', 'n_', 've', 'and', 'cat', 'on_', 'is', 'ver', 'a_', 'and_', 'g_', 'e_']
```

→ English common words (a, and, on, is, ...)

→ **and** vs **and_**

BPE - Granularity



WordPiece

- Based on merge rules too
- Initial processing is different:

BPE:

```
["education", "is"] => [{"e", "d", "u", "...", "n", "_"}, {"i", "s", "_"}]
```

WordPiece:

```
["education", "is"] => [{"e", "##d", "##u", "##c", "..."}, {"i", "##s"}]
```

WordPiece

- Pairs are scored using this score function:

$$S((t_1, t_2)) = \frac{freq(t_1 t_2)}{freq(t_1) freq(t_2)}$$

- if t_1 and t_2 are common, less likely to merge
 - ex: *dream/##ing* → not merged
- if t_1 and t_2 are rare but $t_1 t_2$ is common, **more** likely to merge
 - ex: *pulv/##erise* → *pulverise*

Unigram

Unigram is working in the opposite direction:

- Start from a (too) big subword vocabulary
- Gradually eliminate tokens **that won't be missed** 🙌
- **Score** all possible segmentations and take max:
 - Ex: *brew*
 - $S(b/r/e/w) \rightarrow P(b) \times P(r) \times P(e) \times P(w) = 0.024$
 - $S(br/e/w) \rightarrow P(br) \times P(e) \times P(w) = 0.031$
 - ...

Unigram - Inference

⚠ A string of length n has $O(2^n)$ possible segmentations ⚠

→ Unigram is using the **Viterbi** algorithm:

- Observation: $P(S^*(w_{:i+1})) \leq P(S^*(w_{:i}))$ (S^* : best segmentation)

Unigram - Inference

Example: *email*

- Starting from letter *e*
 - For all ending letters, what is the best segmentation if last token starts from *e*?
 - $S(e) = 0.15$
 - $S(em) = 0.02$
 - ...
 - $S(email) = 0.001$

Unigram - Inference

Example: *email*

- Starting from letter m
 - For all ending letters, what is the best segmentation if last token starts from m ?
 - $S(e / m) = 0.1$
 - ...
 - $S(e / mail) = 0.2$
- Remark: we've seen $S(em)$ and $S(e / m) \rightarrow$ we know the best segmentation that ends at m !

Unigram - Inference

Example: *email*

- Starting from letter *a*
 - For all ending letters, what is the best segmentation if last token starts from *a*? (**hence after *e / m***)
 - $S(e / m / a) = 0.023$
 - ...
 - $S(e / m / ail) = 0.001$
- Remark: we've seen $S(ema)$, ..., $S(e / m / a) \rightarrow$ we know the best segmentation that ends at *a* ! (here: *e / ma* is best)

Unigram - Inference

Example: *email*

- Starting from letter *i*
 - For all ending letters, what is the best segmentation if last token starts from *i*? (hence after *e / ma*)
 - $S(e / ma / i) = 0.004$
 - $S(e / ma / il) = 0.03$
- Remark: we only have 2 candidates left! (here: *ema / i* is best)

Unigram - Inference

Example: *email*

- Starting from letter */*
 - For all ending letters, what is the best segmentation if last token starts from */*? (hence after *ema / i*)
 - $S(ema / i / I) = 0.002$

Takeaway: At each *start* position, we know what the best segmentation up to *start* is => we just need to explore after *start*


Unigram - Training

- Start from a very big vocabulary
- Infer on all pre-tokenized units $w \in W$ and get total score as:

Unigram - Training

- Start from a very big vocabulary
- Infer on all pre-tokenized units $w \in W$ and get total score as:

$$score(V, W) = \sum_{w=(t_1 \dots t_n) \in W} -\log(P(t_1) \times \dots \times P(t_n))$$

- For all token t , compute $score(V - \{t\}, W)$
- Remove the token that **least decreases** the score when removed
- Iterate  (until you have desired vocabulary size)

Limits & Alternatives

Limits

- Fixed vocabulary...
 - ... leads to OOV (out-of-vocabulary)
 - ... scales poorly to 100+ languages (and scripts)
 - ... can cause over-segmentation
 - ... is not robust to misspellings

```
bpe("artificial intelligence is real bro") => 'artificial', 'intelligence', 'is', 'real', 'bro'
```

```
bpe("aritifical inteligense is reaal bro") =>  
'ari', '##ti', '##fi', '##cial', 'intel', '##igen', '##se', 'is', 're', '##aa', '##l', 'bro'
```

Alternatives - BPE dropout

→ Randomly removes part of the vocabulary during training

u-n-r-e-l-a-t-e-d
u-n re-l-a-t-e-d
u-n re-l-at-e-d
u-n re-l-at-ed
un re-l-at-ed
un re-l-ated
un rel-ated
un-related
unrelated

(a)

u-n-r-e-l-a-t-e-d
u-n re-l-a-t-e-d
u-n re-l-at-e-d
un re-l-at-e-d
un re-l-at-ed
un re-lat-ed
un re-lat-ed
un relat-ed

u-n-r-e-l-a-t-e-d
u-n re-l-a-t-e-d
u-n re-l-at-e-d
u-n re-l-ate-d
u-n rel-ate-d
u-n relate-d

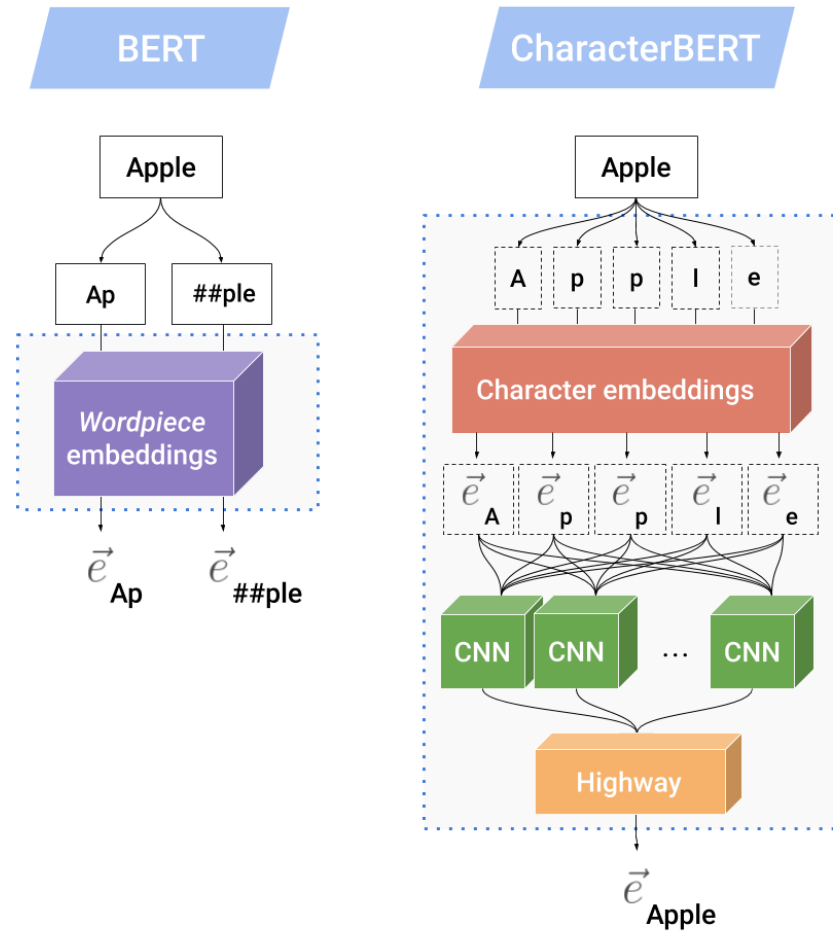
(b)

u-n-r-e-l-a-t-e-d
u-n-r-e-l-at-e-d
u-n-r-e-l-at-ed
un-r-e-l-at-ed
un re-l-at-ed
un re-l-ated
un rel-ated

Figure 1: Segmentation process of the word ‘unrelated’ using (a) BPE, (b) *BPE-dropout*. Hyphens indicate possible merges (merges which are present in the merge table); merges performed at each iteration are shown in green, dropped – in red.

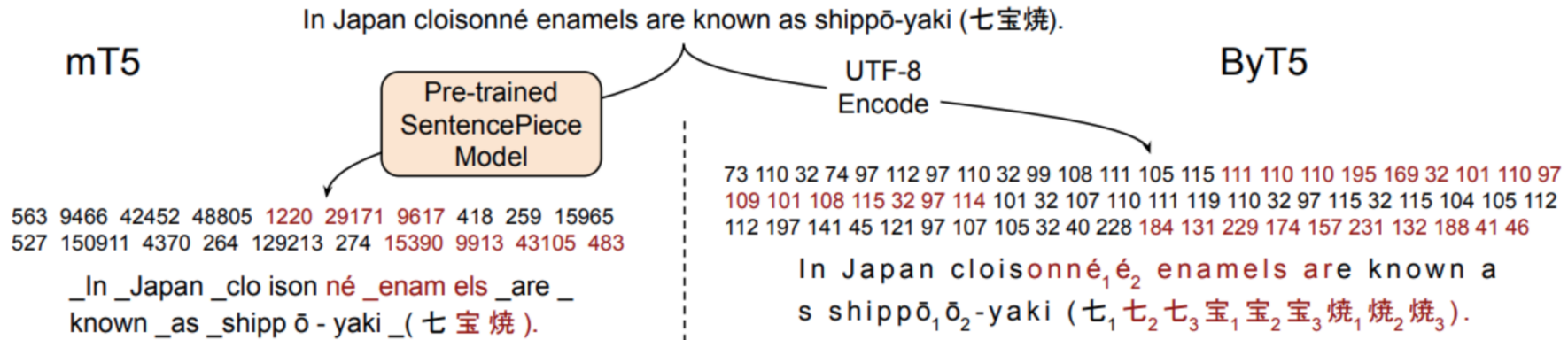
=> makes models more robust to misspellings

Alternatives - CharacterBERT



Alternatives - ByT5

- Gives directly bytes (~characters) as inputs to the model



=> more robust and data efficient BUT ~10 times slower and more hardware consumption

Neural tokenization - CANINE

- Downsamples characters into $4\times$ smaller sequences

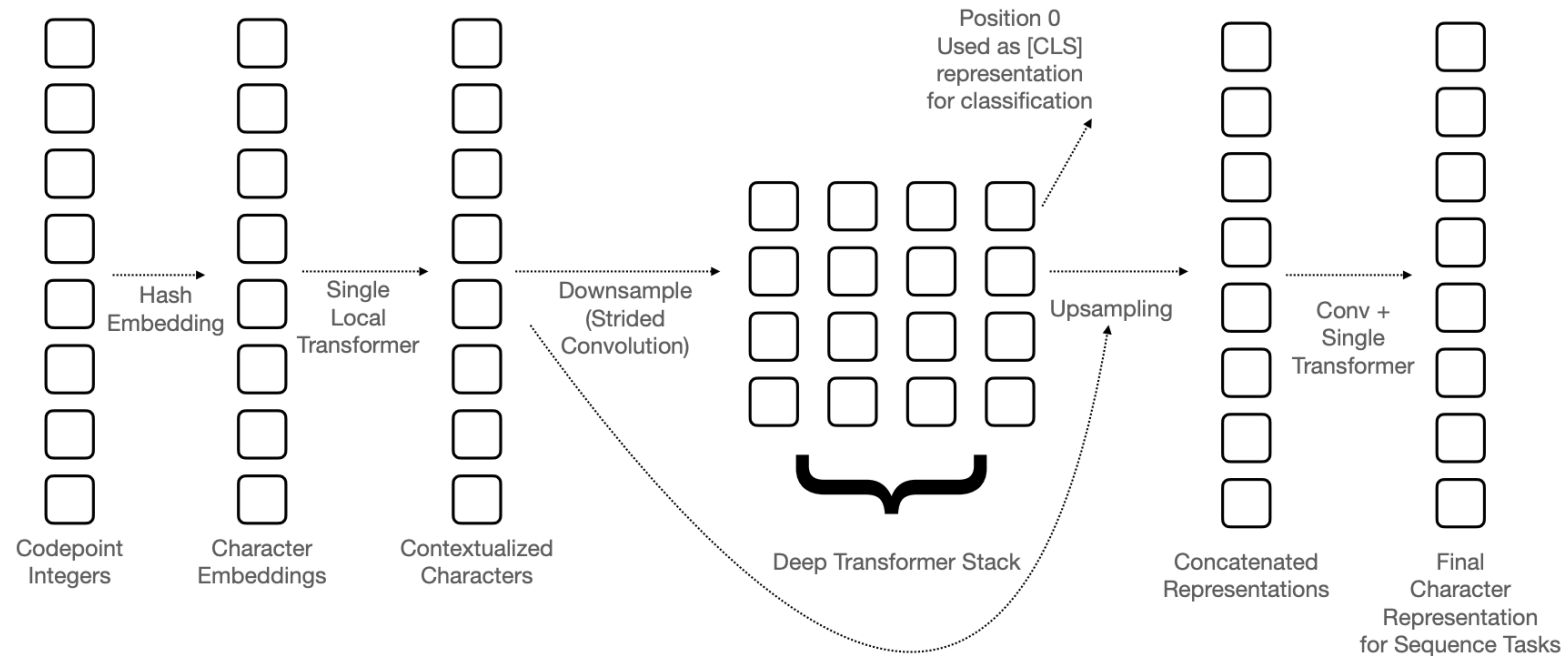
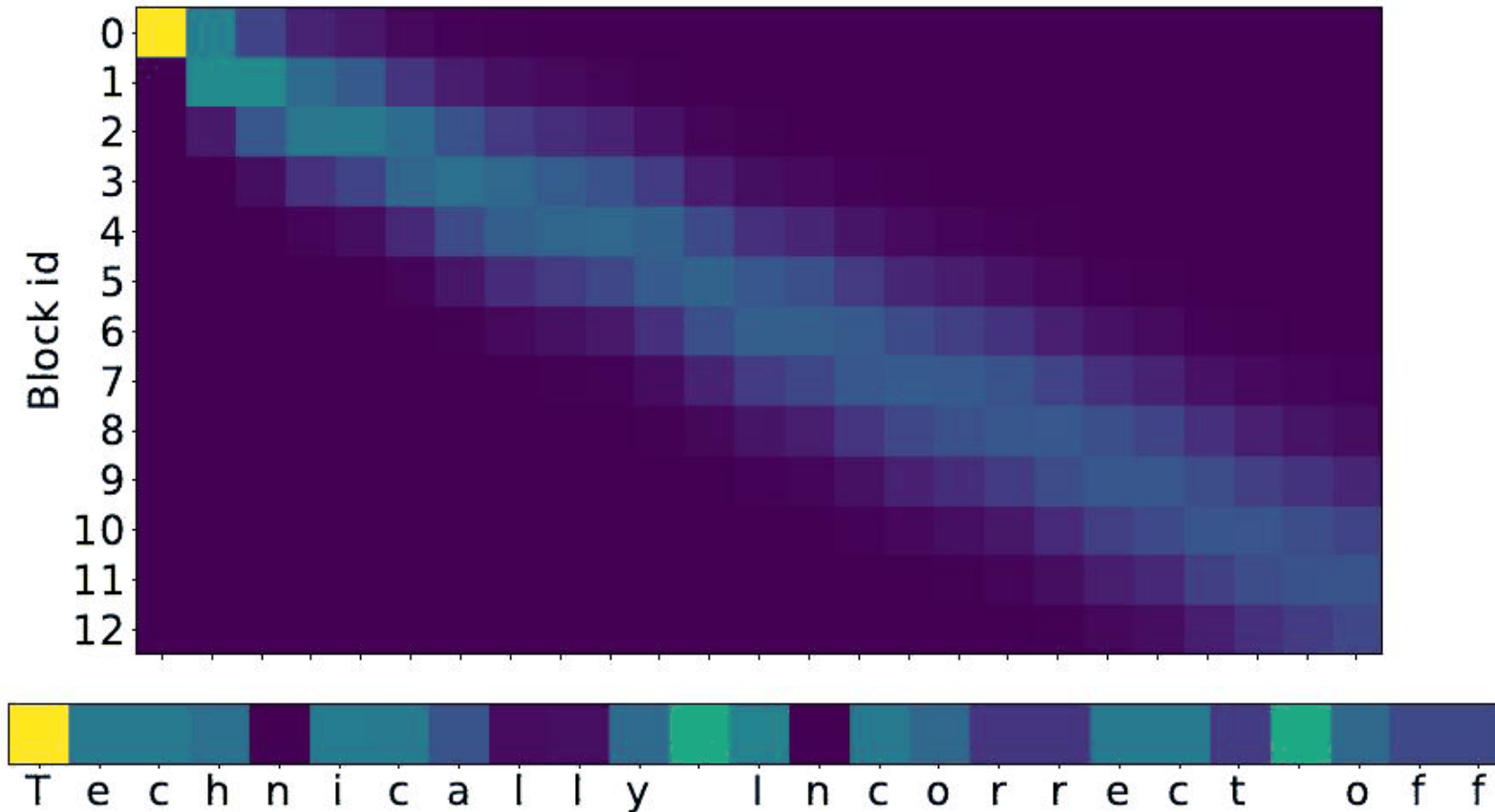


Figure 1: CANINE neural architecture.

Neural tokenization - MANTa

- Allows the language model to learn its *own* mapping



Takeaways

- Tokenization: Art of splitting sentences/words into meaningful smaller units
- In ML: subword tokenization is (very) commonly used
- Three main algorithms
 - **BPE**: iteratively learn most frequent merges
 - **WordPiece**: BPE with adjusted frequency score
 - **Unigram**: Start big and remove tokens that won't be missed
- When facing noisy and/or complex text, alternatives exist