

# 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

ML-based NLP (usually) 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 - 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:
  - for all  $i$  and  $j$  indexes:
    - if the optimal segmentation  $S^*(w_{:i})$  is known...
    - ... then all segmentations of type  $S(w_{:i}) + w_{i:j}$  where  $S(w_{:i}) \neq S^*(w_{:i})$  are **suboptimal**

# 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***)
    - $S(e / m / a) = 0.023$
    - ...
    - $S(e / m / ail) = \infty$  (*ail* is not in vocab)
- 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*)
    - $S(ema / i / l) = 0.002$

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


# Unigram - Training ( $\approx$ )

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

# Unigram - Training ( $\approx$ )

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

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

- For all token  $t$ , compute  $score(V - \{t\}, W)$
- Get rid of the 20% tokens that **least decrease** 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") => 'artificial', 'intelligence', 'is', 'real'
```

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

# Alternatives - BPE dropout (Provilkov et al.)

→ 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

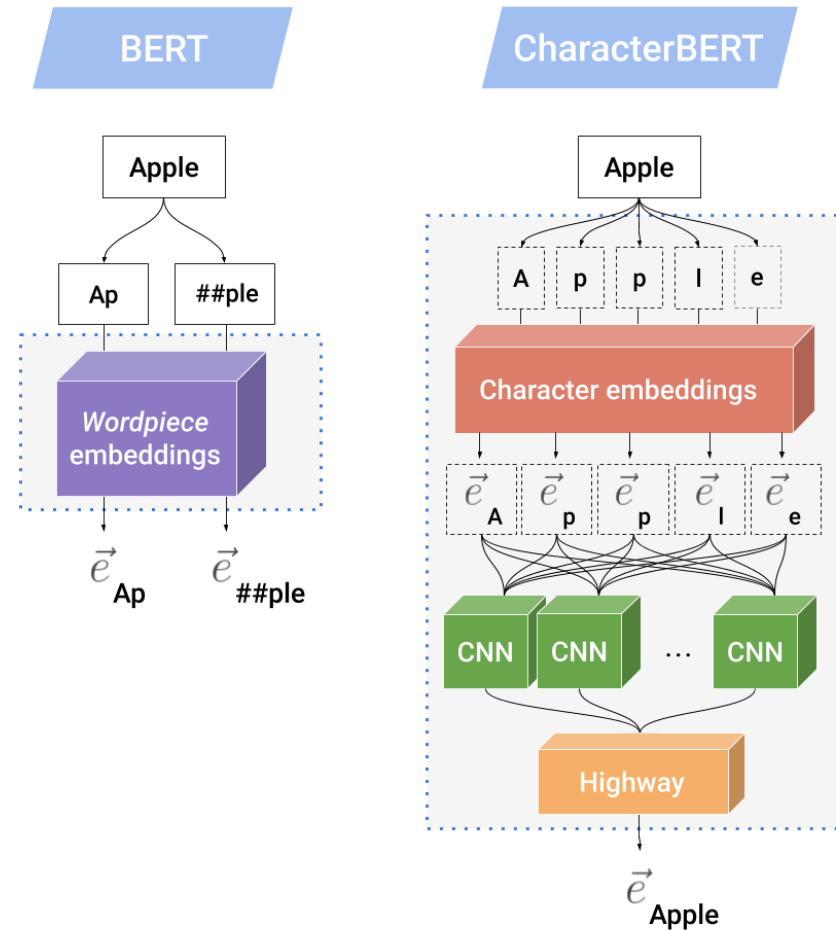
(b)

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 (El Boukkouri et al.)



# Alternatives - ByT5 (Xue et al.)

- 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 (Clark et al.)

- Downsamples characters into  $4\times$  smaller sequences

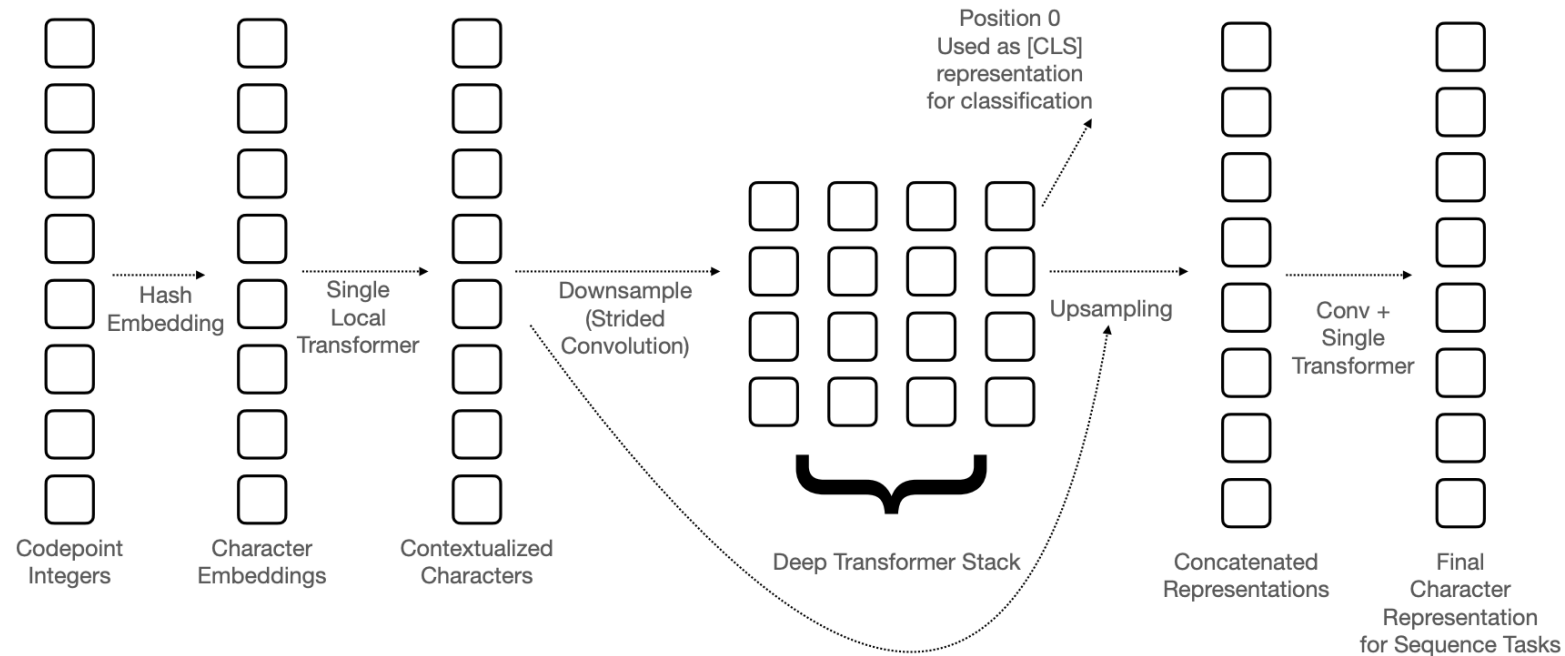
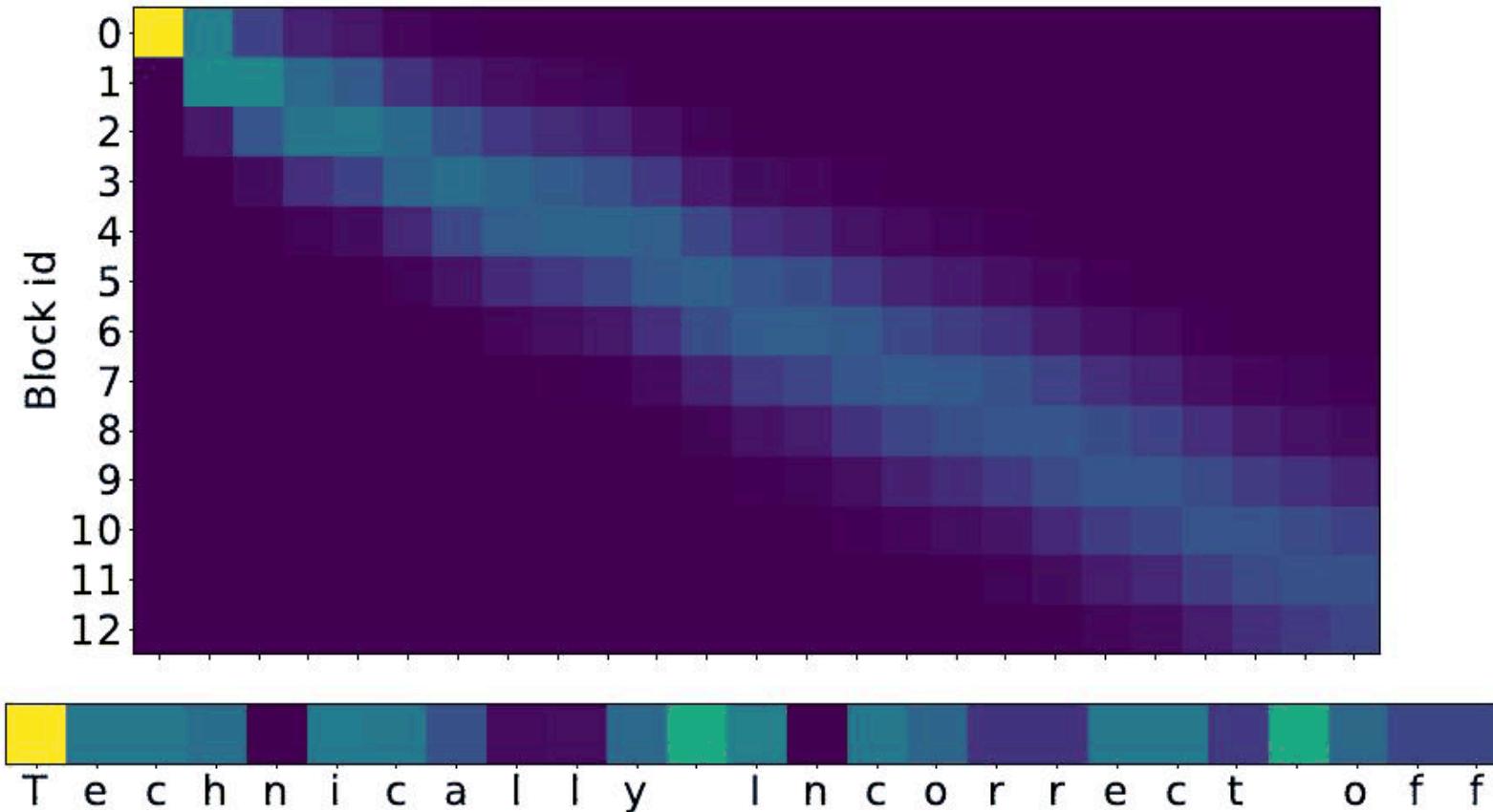


Figure 1: CANINE neural architecture.

# Neural tokenization - MANTa (Godey et al.)

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



# Neural tokenization - MEGABYTE (Yu et al.)

- Encode and then decode autoregressively



# 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