## Tokenization and datasets

Gustave Cortal

Gustave Cortal 1/30

# Summary

Regular expression

**Tokenization** 

Language diversity

**Definitions** 

Gustave Cortal 2/30

# Regular expression

Gustave Cortal 3/30

### ELIZA, one of the first chatbot

User: I am unhappy.

ELIZA: DO YOU THINK COMING HERE WILL HELP YOU NOT TO BE UNHAPPY

User: I need some help, that much seems certain.

ELIZA: WHAT WOULD IT MEAN TO YOU IF YOU GOT SOME HELP User: Perhaps I could learn to get along with my mother.

ELIZA: TELL ME MORE ABOUT YOUR FAMILY

User: My mother takes care of me.

ELIZA: WHO ELSE IN YOU FAMILY TAKES CARE OF YOU

User: My father. ELIZA: YOUR FATHER

User: You are like my father in some ways.

Gustave Cortal 4/30

## ELIZA, one of the first chatbot

- Uses pattern matching to recognize phrases like "I need X" and translate them into outputs like "What would it mean to you if you got X?"
- ▶ Pattern-based methods play a crucial role in NLP
- ► Famous tool for describing text patterns: the regular expression

Gustave Cortal 5 / 30

# Regular expression (regex)

### What are regular expressions?

A sequence of characters that define a search pattern, primarily used for string matching and manipulation.

### Commonly used symbols

- . (Dot): Matches any single character.
- \d: Matches any digit.
- ▶ \w: Matches any word character (alphanumeric & underscore).
- ▶ \s: Matches any whitespace character.
- \*, +: Match 0 or more, 1 or more occurrences of the preceding element, respectively.
- ^, \$: Start and end of a string, respectively.

Gustave Cortal 6 / 30

# ELIZA's pattern recognition

### Regex example in ELIZA

"^[Ii] (do not|don't) know"

#### Detailed breakdown

- ^[Ii]: Matches "I" in both uppercase and lowercase at the start of a sentence
- (do not|don't): Captures either "do not" or the contraction
   "don't"

### Example interaction

- User: "I don't know what to do."
- ► ELIZA: "Why do you think you don't know what to do?"

Gustave Cortal 7 / 30

# Tokenization

Gustave Cortal 8 / 30

### What is a word?

### Example 1

Hey!! How are you? :)

### Example 2

I do uh main- mainly business data processing.

### Example 3

They are studying because they want to succeed.

### Example 4

We love the cats of Jean, but we don't like this cat.

Gustave Cortal 9 / 30

## Tokenization: principles

- ► Tokenization is splitting text into individual words or *tokens*.
- Essential for NLP tasks
- ► Multiple challenges:
  - ▶ Different delimiters: spaces, punctuation
  - Contractions: "can't" → "can not"
  - Special cases: dates, numbers, URLs, hashtags, email addresses

Gustave Cortal 10 / 30

# Tokenization: basic example

### Input

"Natural language processing enables computers to understand human language."

### Tokenized output

Natural, language, processing, enables, computers, to, understand, human, language, .

Gustave Cortal 11/30

# Tokenization: dealing with contraction

### Input

"I can't believe it's already 2023!"

#### Tokenization with contraction

I, can't, believe, it's, already, 2023, !

### Tokenization with expansion

I, can, not, believe, it, is, already, 2023, !

Gustave Cortal 12 / 30

# Tokenization: complex example

### Input

"Dr. Smith's email, dr.smith@example.com, isn't working since 01/02/2023; try reaching out at (555) 123-4567 in San Francisco."

### Tokenized output

Dr., Smith's, email, "dr.smith@example.com, "isn't, working, since, 01/02/2023, ;, try, reaching, out, at, (, 555, ), 123-4567, in, San Francisco, .

Gustave Cortal 13 / 30

### Tokenization: methods

### Rule-based approach

Use predefined rules, like splitting by spaces or punctuation.

# Machine learning approach

Learn from data to handle complex cases

### Library support

NLTK, SpaCy

Gustave Cortal 14/30

# Tokenization: Byte-Pair Encoding (BPE)

#### Learn the tokenization

Instead of defining tokens as words, or as characters, we can use our data to automatically induce sets of tokens that include tokens smaller than words, called *subwords* 

### Training and testing

NLP algorithms learn some patterns from one corpus (a training set) and then use these patterns to make decisions about a separate corpus (a test set)

Gustave Cortal

# Tokenization: Byte-Pair Encoding (BPE)

#### **Problem**

How to deal with unknown words?

### Unknown word as composed of known subwords

Every unknown word like *lower* can be represented by some sequence of known subword units, such as *low* and *er* 

Gustave Cortal 16 / 30

# Tokenization: Byte-Pair Encoding (BPE)

#### Initialization

The BPE token learner begins with a vocabulary that is the set of all individual characters

### Algorithm

Examines the training corpus, chooses the two symbols that are most frequently adjacent (say 'A', 'B'), adds a new merged symbol 'AB' to the vocabulary, and replaces every adjacent 'A' 'B' in the corpus with the new 'AB'. It continues to count and merge, creating new longer and longer character strings, until k merges have been done

Gustave Cortal

# Applying BPE on an example

# Corpus vocabulary with frequencies

```
5 1 o w
2 1 o w e s t
6 n e w e r
3 w i d e r
2 n e w
```

## Initial vocabulary

```
Unique characters: I, o, w, d, e, i, n, r, s, t
```

Gustave Cortal 18 / 30

## Most frequent pair (e, r)

Merge 'e' and 'r' into 'er'. New vocabulary: I, o, w, d, e, i, n, r, s, t, er Updated corpus:

```
5 1 o w
2 1 o w e s t
6 n e w er
3 w i d er
2 n e w
```

## Next frequent pair (n, e)

Merge 'n' and 'e' into 'ne'. New vocabulary: I, o, w, d, e, i, n, r, s, t, er, ne Updated corpus:

```
5 l o w
2 l o w e s t
6 ne w er
3 w i d er
2 ne w
```

Gustave Cortal 19 / 30

### Sequence of merges

- 1. Merge (ne, w). New vocabulary: d, e, i, l, n, o, r, s, t, w, er, ne, new
- 2. Merge (I, o). New vocabulary: d, e, i, I, n, o, r, s, t, w, er, ne, new, lo
- 3. Merge (lo, w). New vocabulary: d, e, i, l, n, o, r, s, t, w, er, ne, new, lo, low
- 4. Merge (new, er). New vocabulary: d, e, i, l, n, o, r, s, t, w, er, ne, new, lo, low, newer

Gustave Cortal 20 / 30

To tokenize a text, always apply the merge rules in the order they were learned during training

This fixed, sequential order is what makes the tokenization deterministic

Gustave Cortal 21 / 30

Language diversity

Gustave Cortal 22 / 30

### Beyond English

Current trends often focus on English, overlooking the necessity of testing algorithms on a diverse range of languages

### Varieties of language

Most languages have multiple dialects or varieties influenced by regions or social groups

### Variation in genre

Algorithms encounter text from various genres: newswires, books, scientific articles, Wikipedia, religious texts, spoken conversations, etc

### Demographic influence

The demographic characteristics of writers or speakers (age, gender, race, socioeconomic class) impact the linguistic properties of texts

### Temporal influence

Language evolves over time (Old French vs. Current French)

Gustave Cortal 23 / 30

### **Datasheet**

A datasheet specifies the properties of a dataset:

- Motivation: Why was the corpus collected, by whom, and who funded it?
- ➤ **Situation:** When and in what situation was the text written/spoken? For example, was there a task? Was the language originally spoken conversation, edited text, or social media communication?
- Language variety: What language was the corpus in?
- Speaker demographics: What was, e.g., the age or gender of the text's authors?
- ➤ Collection process: How big is the data? If it is a subsample, how was it sampled? Was the data collected with consent? How was the data pre-processed, and what metadata is available?
- ► Annotation process: What are the annotations, what are the demographics of the annotators, how were they trained, and how was the data annotated?
- Distribution: Are there a copyright or other intellectual property restrictions?

Gustave Cortal 24 / 30

# **Definitions**

Gustave Cortal 25 / 30

### **Definitions**

#### Text normalization

The process of transforming text into a more uniform format, facilitating easier processing

#### Lemma

The base form of a word. Lemmatization involves reducing inflected words to their lemma form (e.g., "running" to "run")

### Corpus

A structured collection of texts. It serves as a dataset for various language processing tasks

#### Token

A single, meaningful element in a text. Tokenization is the process of splitting text into tokens

Gustave Cortal 26 / 30

### **Definitions**

### Training corpus

### Test corpus

A separate dataset used to evaluate the model performance

### Vocabulary

The set of unique tokens a model uses for processing

Gustave Cortal 27 / 30

## Exercices

Gustave Cortal 28 / 30

#### Exercices

- ▶ Using regular expressions, create a tokenizer handling some complex examples ( $\sim$ 30m)
- ▶ Using regular expressions, create an ELIZA-like system ( $\sim$ 30m)
- ▶ Implement Byte-Pair Encoding from scratch (~1h)

Gustave Cortal 29 / 30

### Pseudo-code for BPE

```
function BYTE-PAIR ENCODING(strings C, number of merges k) V \leftarrow \text{ all unique characters in C \# initial set of tokens} \\ \text{for } i \leftarrow 1 \text{ to k do \# merge tokens k times} \\ \text{ $tL$, $tR$ } \leftarrow \text{ Most frequent pair of adjacent tokens in C} \\ \text{ $tNEW$ } \leftarrow \text{ $tL$ } + \text{ $tR$ \# make new token by concatenating} \\ \text{ $V$ } \leftarrow \text{ $V$ } + \text{ $tNEW$ \# update the vocabulary} \\ \text{ $Replace each occurrence of $tL$, $tR$ in $C$ with tNEW} \\ \text{ $\#$ update the corpus} \\ \text{ $return $V$} \\ \text{}
```

Gustave Cortal 30 / 30