Comp 408 Advanced Topics in Artificial Intelligence

Lecture 2

Regular Expression 2 & Text Processing

15 / 2 / 2025

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Agenda

- Regular Expression
- Python Implementation
- Words and Corpora
- Text Preprocessing
    1. Word Tokenizing
    2. Byte Pair Encoding (BPE)
    3. Normalizing word formats
    4. Lemmatization and stemming
    5. Segmenting sentences.

Summary of RE

• Parenthesis	( )
• Counters	* + ? { }
• Sequences and anchors	the ^myend$
• Disjunction	|, []

- Period (.) Marches any single character.

More operators

RE	Match
*	an asterisk “*”
\.	a period “.”
\?	A question mark
\d	[0-9], any digit
\D	[^0-9], any non-digit
\w	[a-zA-Z0-9_], any alphanumeric or underscore
\W	[^\w], a non-alphanumeric e.g., ? ; + * -
\s	[\r\t\n\f], white space
\S	[^\s], non-whitespace

Example

Write regular expression to matches all computers with the following features:

- at least 6 GHz and
- 500 GB of disk space
- for less than $1000

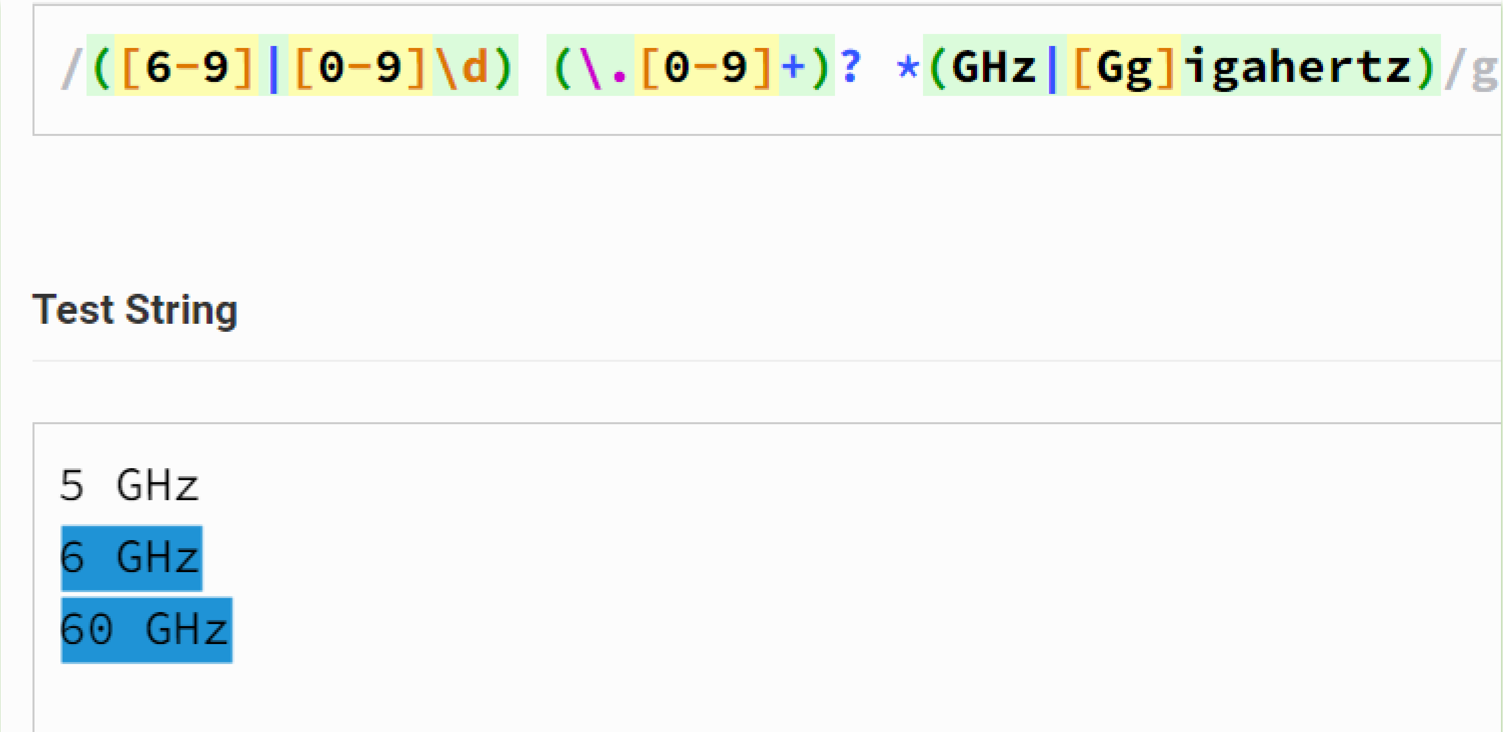
Example (cont.): Give RE to represent numbers less than $1000

- To represent numbers beginning with $:
  - /\$[0-9]+/
- For 2 digits decimal number:
  - /\$[0-9]+\.[0-9][0-9]/
- The decimal number can be optional:
  - /\$[0-9]+(\.[0-9][0-9])?/
- The numbers should not be proceeded by letters
  - /(^| \W)\$[0-9]+(\.[0-9][0-9])? \b/
- Numbers should be less than 1000:
  - / (^|\W)\$[0-9]{1, 3}(\.[0-9][0-9])? \b/

Example (cont.): Give RE to represent at Least 6 GHz

- /([6-9]|[1-9][0-9]+)(\.[0-9]+)? *(GHz|[Gg]igahertz)/

6 to 9 10 to 99



Example (cont.): Give RE to represent from 500-999 GB

- /[5-9][0-9][0-9] *(GB|[Gg]igabytes?)/

500 ⟶ 999

/[5-9][0-9][0-9][ ]*(GB|[Gg]bytes?)

Python Implementation

Searching for a given string in python

To search for the string phone in the text ‘My phone number is …’

```
'phone' in 'My phone number is 012-233-23454'
```

```
True
```

To search for a given phone number in the text

```
'012-233-23454' in 'My phone number is 012-233-23454'
```

```
True
```

Searching for a given pattern in python

- If we want to search for any telephone number, we can use regular expression to represent telephone numbers pattern.
- First import the regular expression package (re)

```python
import re
```

```python
text1 = 'My phone number is 012-233-23454,  another number 011 222 22222'
```

```python
pattern = r'\d{3}[ -/]?\d{3}[ -/]?\d{5}'
```

R or r is used before the regular expression pattern to indicate that it is a raw string

```python
re.search(pattern, text1)
```

```
<re.Match object; span=(19, 32), match='012-233-23454'>
```

The telephone number spans from character 19 to 32 in the text

Note

- Function search displays only the first match:

search(pattern, string)	**Scan through a string to find the first match only of the pattern**

Function findall displays all matches

```
import re
```

```
text1 = 'My phone number is 012 233 23454,  another number 01122222222'
```

```
pattern = r'\d{3}[ -/]?\d{3}[ -/]?\d{5}'
```

```
re.findall(pattern, text1)
```

```
['012 233 23454', '01122222222']
```

findall(pattern, string)	**Find all matched strings and returns the result as list.**

Write regular expression to match a valid date of the form 10-02-2024, 10/02/2024, 10/02/24, or 02/10 2024

01/02/2024

```
text1 = "In 10-02-2024  the spring term of the acedimic year 2023-2024 starts. \n Saturday 10/02/2
```

```
print(text1)
```

```
In 10-02-2024  the spring term of the acedimic year 2023-2024 starts.
 Saturday 10/02/24 at 8.00 AM is our first COMP408 Lecture. In 10 2 2024 is our second lecture
```

```
import re
```

```
re.findall(r'\d{1,2}[\s/-]\d{1,2}[\s/-]\d{2,4}', text1)
```

```
]: ['10-02-2024', '10/02/24', '10 2 2024']
```

(0[1-9] | [12][0-9] | 3[01])

(0[12])

Find regular expression to match the strings {heat, cheat, meat, seat, great, eat}

RE: /\b(m|s|c?h|gr)?eat\b/

In python:

```
reg1 = r'\b(m|s|c?h|gr)?eat\b'
```

```
tex2 ='... meat, ... great, ...  eat, heat, cheat, seat'
```

```
re.findall(reg1, tex2)
```

```
]: ['m', 'gr', '', 'h', 'ch', 's']
```

The output contains only the strings inside the parenthesis (,)

Important Note

- Parentheses have double functions in regular expressions:
  1. Used to group items to specify the order in which operators should apply.
  2. Used to capture something is registers.
- If we want to use parenthesis for grouping, we should use the non-capturing group by putting ?: after the parenthesis (?: pattern)
- In the last Pythone example:

```
reg1 = r'\b(?:m|s|c?h|gr)?eat\b'
```

```
tex2 ='... meat, ... great, ...  eat, heat, cheat, seat'
```

```
re.findall(reg1, tex2)
```

```
['meat', 'great', 'eat', 'heat', 'cheat', 'seat']
```

Write a regular expression to match a valid date of the form 10 Feb 2024 or 10 February 2024 in a given text

```python
import re
```

```python
text1 = "In 08 Feb 25  the spring term of the academic year 2024-2025 starts. \n Saturday 08 February
```

```python
print(text1)
```

```
In 08 Feb 25  the spring term of the academic year 2024-2025 starts.
 Saturday 08 February 25 at 8.00 AM is our first COMP408 Lecture. In 15 Feb 24 is our second lecture
```

```python
re.findall(r'\d{2} (Jan|Feb|Mar|Apr|May|Jun|Jul|Aug|Sep|Oct|Nov|Dec)[a-z]* \d{2,4}', text1)
```

```
]: ['Feb', 'Feb', 'Feb']
```

Only the string in the parentheses appears, to fix this error add ?: at the beginning of the “(“ parentheses

Write a regular expression to match a valid date of the form 10 Feb 2024 or 10 February 2024 in a given text

Add the non-capturing group: ?:

```
re.findall(r'\d{2} (?:Jan|Feb|Mar|Apr|May|Jun|Jul|Aug|Sep|Oct|Nov|Dec)[a-z]* \d{2,4}', text1)
```

```
['08 Feb 25', '08 February 25', '15 Feb 24']
```

Using RE to capture strings in register

Capturing group is the use of parentheses to store a pattern in memory

Regular Expression

```
/the (.*)er they (.*), the \1er we \2/g
```

\1 matches the first capture group
\2 matches the second capture group

Test String

```
the faster they ran, the faster we ran
```

Test String

No match

```
the faster they ran, the slower we ran
```

Example 1

- Use register to put angle brackets around all integers in a text:
  - for example, change 5 books to <5> books

```
st = 'I bought 5 computer since books, 1 for Artificial intelligence 2 for machine  learning'
```

```
pa1 = r'(\d+)'
```

```
pa2 = r'<\1>'
```

```
re.sub(pa1, pa2, st)
```

```
'I bought <5> computer since books, <1> for Artificial intelligence <2> for machine  learning'
```

Example 2

Regular Expression

Capturing group

```
/(?:some|a few) (people|cats) like some \1/g
```

non capturing group

Test String

```
some people like some people
```

Regular Expression

```
/(?:some|a few) (people|cats) like some \1/g
```

No match

Test String

```
some people like some cats
```

Question

What are the strings matched by each of following regular expressions:

1. /\w+-\w+/
2. \w+@\w+\.\w{3}

\w: [a-zA-Z0-9_]

text_daus12930

Substitutions

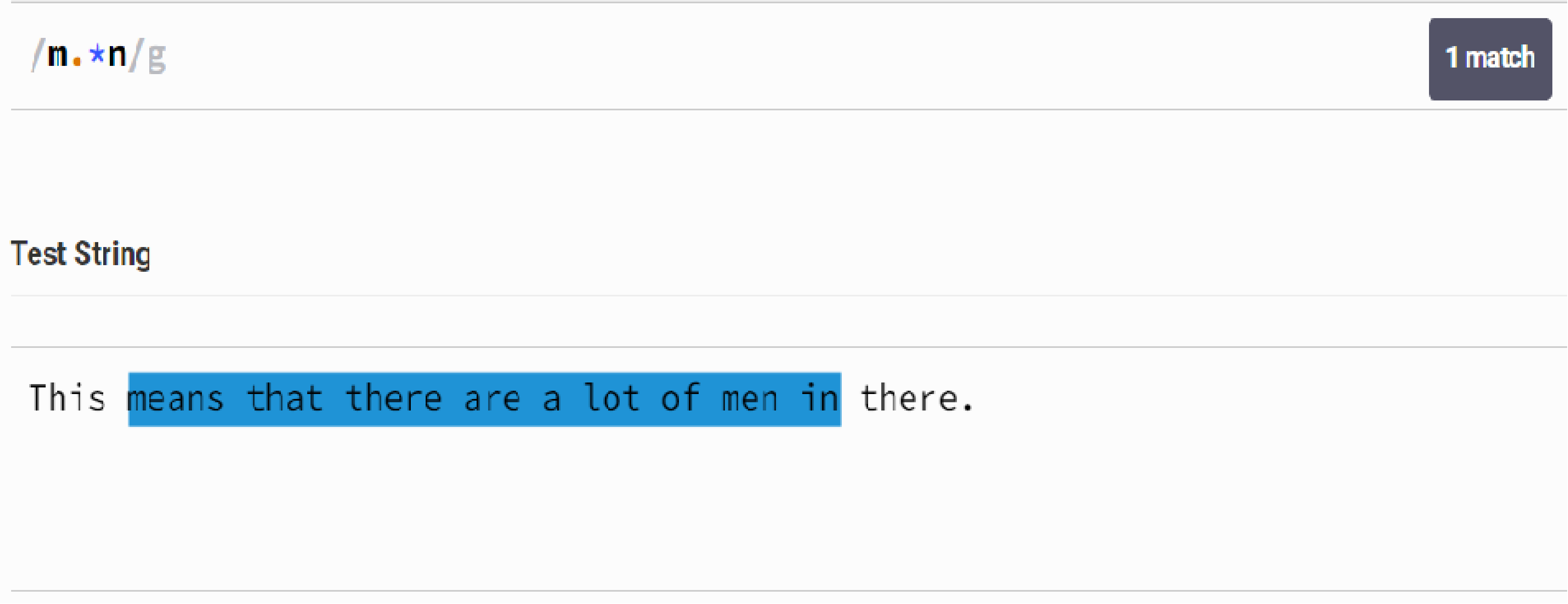
- An important use of regular expression is in substitution
- Python code for substitute the words colour or colours by color

```
import re
pattern = "colours?"
rep = "color"
Str = 'red colours, black colour'
newS = re.sub(pattern, rep, Str)
print(newS)
```

Output : red color, black color

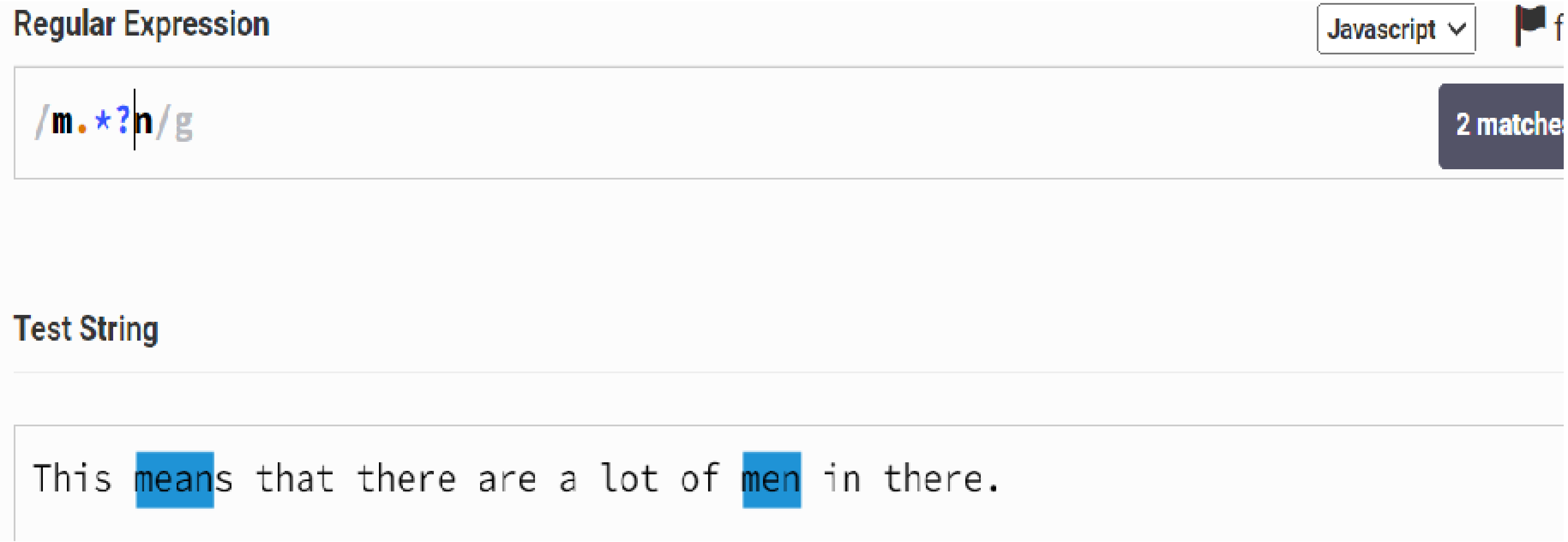
Greedy regular expression match

- Regular expressions always match largest string they can; that pattern is called greedy, expanding to cover as much of a string as they can.



Non-greedy (reluctant) match

- To enforce non-greedy matching, use *? Instead of * which matches as little text as possible.
- The operator +? matches as little text as possible.



Greedy and non-greedy RE

Greedy	Non-greedy	
*	*?	Zero or more characters
+	+?	One or more characters
{n, m}	{n, m}?	From n to m characters
?	??	0 or 1 characters

Example 1: search for a string begins with A then any characters then space.

Non greedy

Regular Expression

```
/^A.*? /g
```

Test String

```
Adel went to school.
```

Greedy

Regular Expression

```
/^A.* /g
```

Test String

```
Adel went to school.
```

Example 1 (Cont.):

```
import re
```

```
text = 'Adel went to school. '
```

```
b = re.search('^A.*? ', text)
```

Non greedy match; until the first space

```
b
```

```
<re.Match object; span=(0, 5), match='Adel '>
```

```
b = re.search('^A.* ', text)
```

Greedy match; until the last space

```
b
```

```
<re.Match object; span=(0, 21), match='Adel went to school. '>
```

Example 2: find two characters followed by 1,2, or 3 digits

```
text = 'xy1  xy12 xy345 xy'
```

```
re.findall("[a-z][a-z]\d{1,3}", text)
```

Greedy

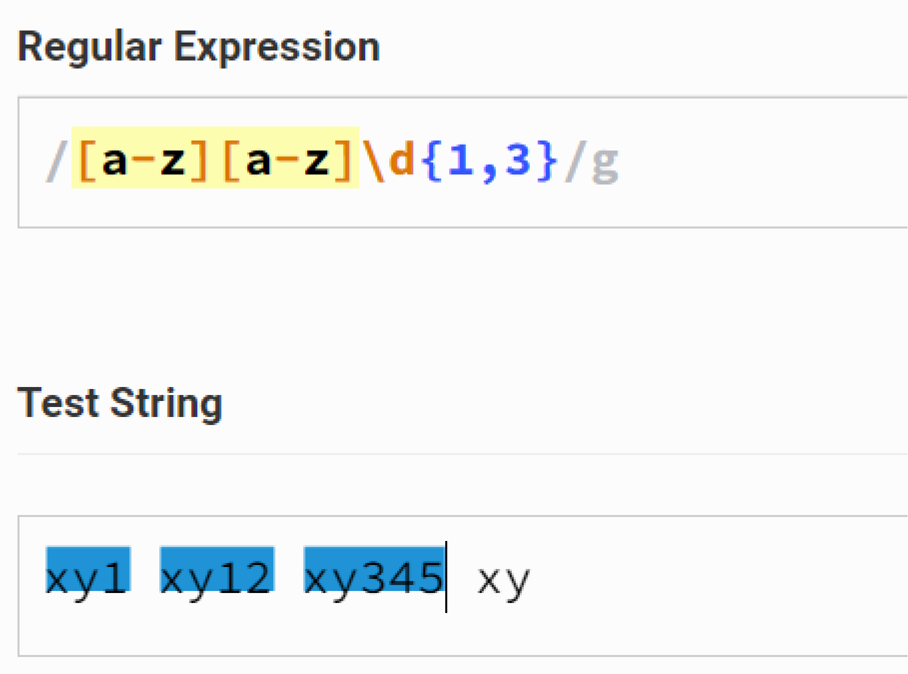
```
['xy1', 'xy12', 'xy345']
```

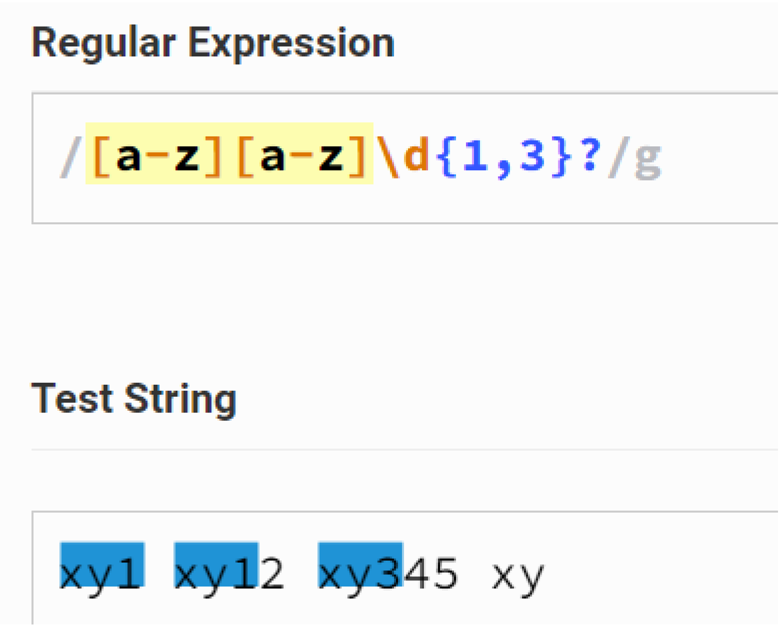
```
re.findall("[a-z][a-z]\d{1,3}?", text)
```

Non-greedy

```
['xy1', 'xy1', 'xy3']
```

Example 2 Cont.





Example 3: find two characters followed by 0 or 1 digit

```
text = 'ab1 xy34 cd56 yy6'
```

```
re.findall("[a-z][a-z]\d?", text)
```

greedy

```
['ab1', 'xy3', 'cd5', 'yy6']
```

```
re.findall("[a-z][a-z]\d??", text)
```

Non greedy

```
['ab', 'xy', 'cd', 'yy']
```

Words and Corpora

How many words?

- I do uh main- mainly business data processing
  - Fragments (**e.g., main**), filled pauses (**e.g., uh**)
- Seuss's cat in the hat is different from other cats!
  - **Lemma**: the base form of a word, cat and cats have the same lemma cat:
    - the same stem,
    - part of speech (POS)- both are noun,
    - same word sense
  - **Wordform**: the full inflected or derived form of the word
    - cat and cats = different wordforms

Corpus (Plural corpora)

- A computer-readable collection of text or speech.
- The Brown corpus is a million-word collection of samples from 500 written texts from different genres (newspaper, fiction, academic, etc.), assembled at Brawn University in 1963-1964.

How many words?

they lay back on the San Francisco grass and looked at the stars and their

- To count the number of words in an English statement we need to know the difference between types and tokens:
- **Type**: an element of the vocabulary.
  - How many distinct words in a corpus?
- **Token**: an instance of that type in running text.
- How many? (It depends on your counts)
  - 15 **tokens** (or 14 if San Francisco is one word)
  - 13 **types** (or 12 if San Francisco is one word)

    (or 11? If they and their are considered the same lemma)

How many words in a corpus?

N = number of tokens

V = vocabulary = set of types, |***V***| is size of vocabulary

Heaps Law (Herdan's Law), $|V| = kN^{\beta}$ where often .67 < β < .75

i.e., vocabulary size grows with > square root of the number of word tokens

Corpus	Tokens = N	Types = |V|
Switchboard phone conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
COCA	440 million	2 million
Google N-grams	1 trillion	13+ million

Text Preprocessing

Space-based tokenization

- A very simple way to tokenize
  - For languages that use space characters between words
    - Arabic, Cyrillic, Greek, Latin, etc., based writing systems
  - Segment off a token between instances of spaces
- White space is not always sufficient
  - Words like Adel's is considered as one word.
  - I'm need to be separated as I and am.
  - New York is considered as two words.

Issues in Tokenization

- Can't just blindly remove punctuation:
  - m.p.h., Ph.D., AT&T, cap’n
  - prices ($45.55)
  - dates (01/02/06)
  - URLs (http://www.stanford.edu)
  - hashtags (#nlproc)
  - email addresses (someone@cs.colorado.edu)
- **Clitic**: a word that doesn't stand on its own
  - “are" in we're,
  - “am” in I’m. French "je" in j'ai, "le" in l'honneur
- When should multiword expressions (MWE) be words?
  - New York, rock ’n’ roll

Using natural language toolkit (nltk) python library to tokenize text

```
import nltk
```

```
text = 'that U.S.A. poster-print costs $12.40 ...'
```

```
pattern = r'(?:[A-Z]\.)+|\w+(?:-\w+)*| \$?\d+(?:\.\d+)?%?| \.\.\.'
```

```
nltk.regexp_tokenize(text, pattern)
```

```
]: ['that', 'U.S.A.', 'poster-print', 'costs', ' $12.40', ' ...']
```

Notes

- A tokenizer can also be used to **expand clitic** contractions that are marked by apostrophes:
  - Converting we’re   to we are
- Ambiguity that arises from using apostrophe, ’ ,should be handled:
  - Genitive marker: Adam’s book
  - Quotative: ‘The other class’, she said
  - Clitic: they’re

Tokenization in languages without spaces

Many languages (like Chinese, Japanese, Thai) don't use spaces to separate words!

How do we decide where the token boundaries should be?

Word tokenization in Chinese

Chinese words are composed of characters called "**hanzi**" (or sometimes just "**zi**")

Each one represents a meaning unit called a morpheme.

Each word has on average 2.4 of them.

But deciding what counts as a word is complex and not agreed upon.

How to do word tokenization in Chinese?

- 姚明进入总决赛 “Yao Ming reaches the finals”

How to do word tokenization in Chinese?

- 姚明进入总决赛 “Yao Ming reaches the finals”

- 3 words?
- 姚明　　进入　　总决赛
- YaoMing reaches finals

- 5 words?

How to do word tokenization in Chinese?

•姚明进入总决赛 “Yao Ming reaches the finals”

•3 words?
•姚明 进入 总决赛
•YaoMing reaches finals

•5 words?
•姚 明 进入 总 决赛
•Yao Ming reaches overall finals

•7 characters? (don't use words at all):
•姚 明 进 入 总 决 赛

How to do word tokenization in Chinese?

- 姚明进入总决赛 “Yao Ming reaches the finals”

- 3 words?
- 姚明 进入 总决赛
- YaoMing reaches finals

- 5 words?
- 姚 明 进入 总 决赛
- Yao Ming reaches overall finals

- 7 characters? (don't use words at all):
- 姚 明 进 入 总 决 赛
- Yao Ming enter enter overall decision game

Word tokenization / segmentation

So in Chinese it's common to just treat each character (zi) as a token.

- So the **segmentation** step is very simple

In other languages (like Thai and Japanese), more complex word segmentation is required.

- The standard algorithms are neural sequence models trained by supervised machine learning.

Basic Text Processing

Byte Pair Encoding (BPE)

Another option for text tokenization

Instead of

- white-space segmentation
- single-character segmentation (as in Chinese)

Use the **data** to tell us how to tokenize.

Subword tokenization (because tokens can be parts of words as well as whole words- the token new can be part of the word newer as well as the word new)

Subword tokenization

- Three common algorithms:
  1. Byte-Pair Encoding (BPE) (Sennrich et al., 2016)
  2. Unigram language modeling tokenization (Kudo, 2018)
  3. WordPiece (Schuster and Nakajima, 2012)
- All the three algorithms have 2 parts:
  - A token **learner** that takes a raw training corpus and induces a vocabulary (a set of tokens).
  - A token **segmenter** that takes a raw test sentence and tokenizes it according to that vocabulary

Byte Pair Encoding (BPE) token learner

Let vocabulary be the set of all individual characters

= {A, B, C, D,…, a, b, c, d….}

- Repeat:
  - Choose the two symbols that are most frequently adjacent in the training corpus (say 'A', 'B')
  - Add a new merged symbol 'AB' to the vocabulary
  - Replace every adjacent 'A' 'B' in the corpus with 'AB'.
- Until *k* merges have been done.

BPE token learner algorithm

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 til 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

Byte Pair Encoding (BPE) Addendum

Most subword algorithms are run inside space-separated tokens.

So, we commonly first add a special end-of-word symbol '__' before space in training corpus

Next, separate into letters.

BPE token learner

Original (very simple) corpus:

low low low low low lowest lowest newer newer newer newer newer newer wider wider wider new new

Add end-of-word tokens, resulting in this vocabulary:

vocabulary

`_, d, e, i, l, n, o, r, s, t, w`

BPE token learner

Original (very simple) corpus:

low low low low low lowest lowest newer newer newer newer newer newer wider wider wider new new

Add end-of-word tokens, resulting in this vocabulary:

corpus representation		**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 _	

BPE token learner

corpus

5 l o w _
2 l o w e s t _
6 n e w e r _
3 w i d e r _
2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w

The most frequent pairs of adjacent symbols is e r because it occurs in newer (frequency of 6) and wider (frequency of 3), total is 9 occurrences

Merge e r to er

corpus

5 l o w _
2 l o w e s t _
6 n e w er _
3 w i d er _
2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w, er

Add the merged characters er to vocabulary and modify corpus

BPE

corpus

5 l o w _
2 l o w e s t _
6 n e w er _
3 w i d er _
2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w, er

The most frequent pairs of adjacent symbols is er - total is 9 occurrences

Merge er _ to er_

corpus

5 l o w _
2 l o w e s t _
6 n e w er_
3 w i d er_
2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w, er, er_

BPE

corpus

5 l o w _
2 l o w e s t _
6 n e w er_
3 w i d er_
2 n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w, er, er_

Merge n e (total count of 8) to ne

corpus

5 l o w _
2 l o w e s t _
6 ne w er_
3 w i d er_
2 ne w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w, er, er_, ne

BPE

The next merges are:

Merge		Current Vocabulary
(ne, w)	8	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new
(l, o)	7	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo
(lo, w)	7	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low
(new, er_)	6	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_
(low, _)	5	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_, low_

BPE token **segmenter** algorithm

1. Segment each test sentence into characters.
2. Then apply the rules made in training corpus to test corpus in order:
    1. Replace e r with er
    2. Replace er _ with er_
    3. Replace n e with ne
    4. Replace ne w with new
    5. Replace l o with lo
    6. Replace lo w with low
    7. Replace new er_ with newer_
    8. Replace low _ with low_
    9. …

BPE token **segmenter** algorithm

On the test data, run each merge learned from the training data:

- Greedily
- In the order we learned them
- (test frequencies don't play a role)

So: merge every e r to er, then merge er _ to er_, etc.

- Result:
  - Test set "n e w e r _" would be tokenized as a full word
  - Test set "l o w e r _" would be two tokens: "low er_“, since "l o w e r _" is unknow word (not among the vocabulary)

Properties of BPE tokens

Usually include frequent words

And frequent subwords

- Which are often morphemes like *-est* or *–er*

A **morpheme** is the smallest meaning-bearing unit of a language

- *unlikeliest* has 3 morphemes *un-*, *likely*, and *-est*

Normalization

- Need to "normalize" terms
  - Information Retrieval (IR): indexed text & query terms must have same form.
    - We want to match ***U.S.A.*** and ***USA***
- We implicitly define equivalence classes of terms
  - e.g., deleting periods in a term (deleting dots in ***U.S.A. to match USA)***
- Alternative: asymmetric expansion:
  - Enter: ***window*** Search: ***window, windows***
  - Enter: ***windows*** Search: ***Windows, windows, window***
  - Enter: ***Windows*** Search: ***Windows***

Case folding

- Applications like Information Retrieval: reduce all letters to lower case
  - Since users tend to use lower case
  - Possible exception: upper case in mid-sentence?
    - e.g., ***General Motors*** **(**the beginning of each word is capital**)**
    - ***Fed*** vs. ***fed*** **(**federal reserve system vs. the past of feed**)**
    - ***SAIL*** vs. ***sail*** **(**Stanford Artificial Intelligence laboratory vs the verb sail)

- For sentiment analysis, machine translation-MT, Information extraction
  - Case is helpful (***US*** versus ***us*** is important)

Lemmatization

Represent all words as their lemma, their shared root
= dictionary headword form:

- *am, are, is* → *be*
- *car, cars, car's, cars'* → *car*

- *the boy's cars are different colors* → *the boy car be different color*
- Lemmatization: have to find correct dictionary headword form

Lemmatization is done by Morphological Parsing

- Morphemes:
  - The small meaningful units that make up words
  - **Stems**: The core meaning-bearing units
  - **Affixes**: Parts that adhere to stems, often with grammatical functions
- Morphological Parsers (takes a word and parses it into morphemes)
  - Parse *cats* into two morphemes *cat* and *s*
  - *Parse ذهبوا into two morphemes ذهب and وا*

Stemming

- Reduce terms to stems, chopping off affixes crudely

This was not the map we found in Billy Bones's chest, but an accurate copy, complete in all things-names and heights and soundings-with the single exception of the red crosses and the written notes.

⇒

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Porter Stemmer

- Based on a series of rewrite rules run in series
  - A cascade, in which output of each pass fed to next pass
- Some sample rules:

$$\begin{array}{rcll} \text{ATIONAL} & \rightarrow & \text{ATE} & \text{(e.g., relational} \rightarrow \text{relate)} \\ \text{ING} & \rightarrow & \epsilon & \text{if stem contains vowel (e.g., motoring} \rightarrow \text{motor)} \\ \text{SSES} & \rightarrow & \text{SS} & \text{(e.g., grasses} \rightarrow \text{grass)} \end{array}$$

Sentence Segmentation

!, ? mostly unambiguous but **period** "." is very ambiguous

- Sentence boundary
- Abbreviations like Inc. or Dr.
- Numbers like .02% or 4.3

Common algorithm: Tokenize first: use rules or Machine Learning (ML) to classify a period as either (a) part of the word or (b) a sentence-boundary.

- An abbreviation dictionary can help

Sentence segmentation can then often be done by rules based on this tokenization.

Determining if a word is end-of-sentence: a Decision Tree