Natural Language Processing

AI 3216/UG, AI 5203/PG

Week-2

2.1 Regular Expressions

2.2 Text Normalization

Mahindra™ University
Global Thinkers. Engaged Leaders.

Acknowledgments

These slides are adapted from the book

SPEECH and LANGUAGE PROCESSING: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition

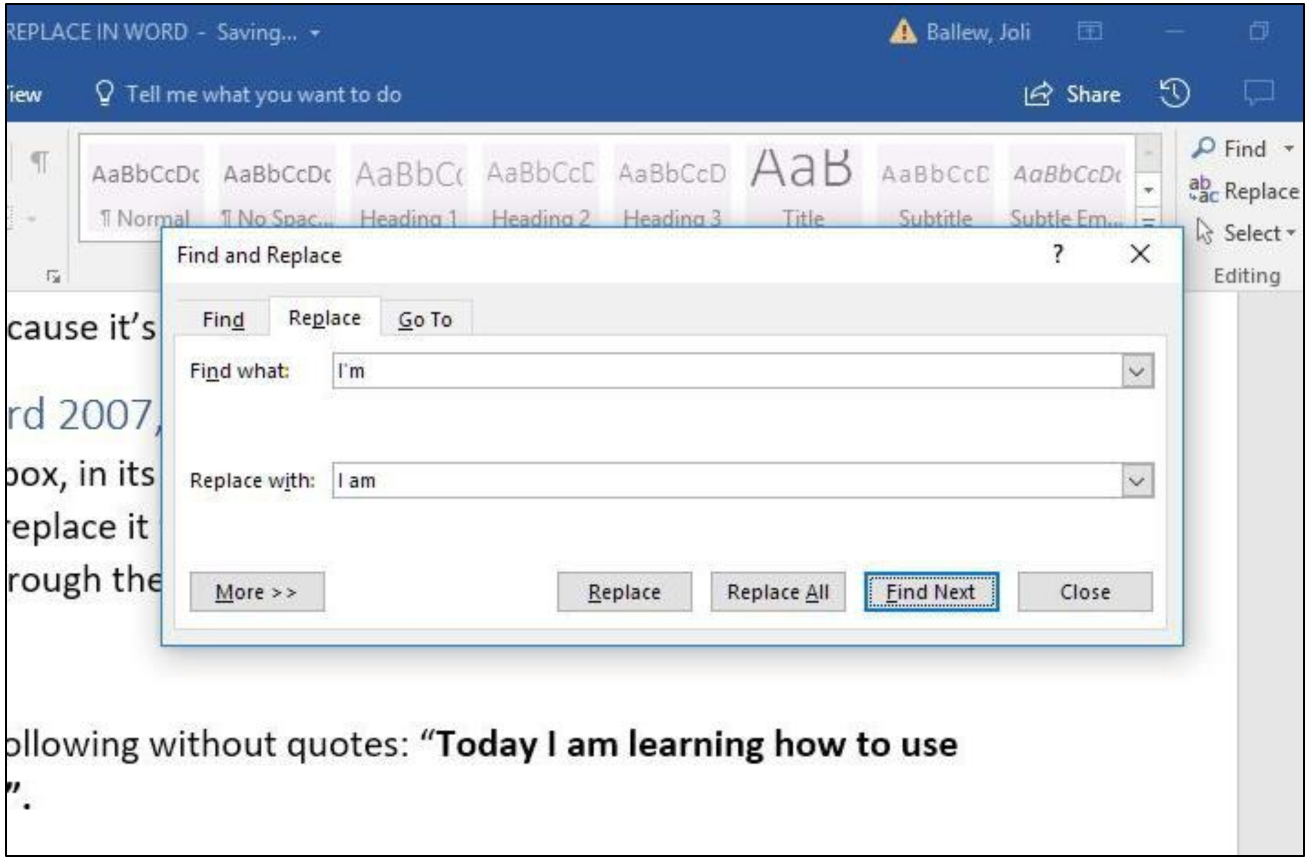
and

Inspired from standard materials, presentations and resources provided online by verified scholars.

Regular Expressions

- Regular expressions, are sequences of characters that define a search pattern.

- They are used for matching and manipulating text strings based on patterns.



Where to use Regex?

- Data pre-processing
- Rule-based information mining systems
- Pattern matching
- Text feature engineering
- Web scraping
- Data extraction

many more.........

Why?

- Lot of unstructured data
- 1st step is pre-processing
  - Ways to do text pre-processing
    - Regex is one of the tool

Regular Expressions

- Disjunction
  - Negation
  - Pipe |
  - Special characters ? * + .
  - Anchors ^ $

Regular Expressions: Disjunctions

Letters inside square brackets []

Pattern	Matches
[wW]oodchuck	Woodchuck, woodchuck
[1234567890]	Any digit

Ranges

Pattern	Matches	
[A-Z]	An upper case letter	Drenched Blossoms
[a-z]	A lower case letter	my beans were impatient
[0-9]	A single digit	Chapter 1: Down the Rabbit Hole

Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Regular Expressions: Negation in Disjunction

Negations [^Ss]

- Carat means negation only when first in []

Pattern	Matches	
`[^A-Z]`	Not an upper case letter	`Oyfn pripetchik`
`[^Ss]`	Neither 'S' nor 's'	`I have no exquisite reason"`
`[^e^]`	Neither e nor ^	`Look here`
`a^b`	The pattern a carat b	`Look up a^b now`

Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Try Demo tool!!!

[Regex Tester - Javascript, PCRE, PHP (regexpal.com)]

Match the patterns such as

[Ww]

[A-Z]

[a-z]

[A-Za-z]

Regex documentation/Python

Documentation

https://docs.python.org/3/library/re.html#module-re

Regular Expressions: More Disjunction (pipe |)

Pattern	Matches
groundhog|woodchuck	woodchuck
yours|mine	yours
a|b|c	= [abc]
[gG]roundhog|[Ww]oodchuck	Woodchuck

Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Regular Expressions: ? , Kleen operators(*+),.

Pattern	Matches	
colou?r	Optional previous char	color colour
oo*h!	0 or more of previous char	oh! ooh! oooh! ooooh!
o+h!	1 or more of previous char	oh! ooh! oooh! ooooh!
baa+		baa baaa baaaa baaaaa
beg.n		begin begun begun beg3n

Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Regular Expressions: Anchors ^ $

Pattern	Matches
`^[A-Z]`	Palo Alto
`^[^A-Za-z]`	1 "Hello"
`\.$`	The end.
`.$`	The end? The end!

Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Some examples

Find me all instances of the word "the" in a text

the

Misses capitalized examples

[tT]he

Incorrectly returns other or theology

`[^a-zA-Z][tT]he[^a-zA-Z]`

Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Natural Language Processing

AI 3216/UG, AI 5203/PG

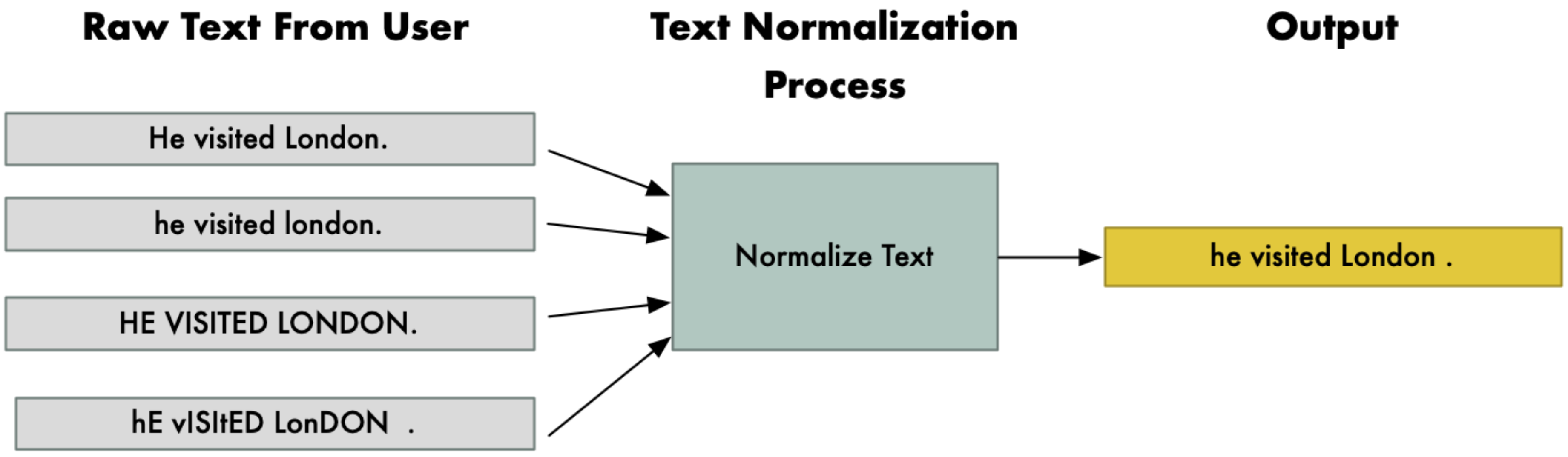
Week-2

2.1 Regular Expressions

2.2 Text Normalization

Mahindra University
Global Thinkers. Engaged Leaders.

Text Normalization



Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Real world issues in text that need Normalization

Industry examples:

[Recruitment Domain]

[E-commerce]

and many more........

Research- Real-world/Industry use-case

KCNet: Kernel-based Canonicalization Network for entities in Recruitment Domain

Nidhi Goyal[1], Niharika Sachdeva[2], Anmol Goel[3], Jushaan Singh Kalra[4], and Ponnurangam Kumaraguru[5*]

[1] Indraprastha Institute of Information Technology, New Delhi, India
nidhig@iiitd.ac.in
[2] InfoEdge India Limited, Noida, India
niharika.sachdeva@infoedge.com
[3] Guru Gobind Singh Indraprastha University, Delhi, India
agoel100@gmail.com
[4] Delhi Technological University, Delhi, India
jushaan18@gmail.com
[5] International Institute of Information Technology, Hyderabad, India
pk.guru@iiit.ac.in

Abstract. Online recruitment platforms have abundant user-generated content in the form of job postings, candidate, and company profiles. This content when ingested into Knowledge bases causes redundant, ambiguous, and noisy entities. These multiple (non-standardized) representation of the entities deteriorates the performance of downstream tasks such as job recommender systems, search systems, and question answering. Therefore, making it imperative to canonicalize the entities to improve the performance of such tasks. Recent research discusses either statistical similarity measures or deep learning methods like word-embedding or siamese network-based representations for canonicalization. In this paper, we propose a Kernel-based Canonicalization Network (KCNet) that

https://cdn.iiit.ac.in/cdn/precog.iiit.ac.in/pubs/2021_July_KCNet-slides.pdf

Basic Normalization steps:

1. Segmenting/tokenizing words in running text
2. Normalizing word formats
3. Segmenting sentences in running text

Slide Reference: 2_TextProc_Mar_25_2021.pdf (stanford.edu)

Tokenization

Input: Mahindra university department

Tokens:

Mahindra

University

Department

A token is a sequence of characters in a document

What are valid tokens?

Hewlett-Packard Company

Are these two tokens "Hewlett" or "Packard" or one token?

Mahindra university -> 1 token or two?

State-of-the-art-> how many tokens?

Language issues-> Left-right or right-left (For example: Arabic)

Simple Code Example

```
>>> text = 'That U.S.A. poster-print costs $12.40...'
>>> pattern = r'''(?x)    # set flag to allow verbose regexps
...     (?:[A-Z]\.)+        # abbreviations, e.g. U.S.A.
...   | \w+?:(-\w+)*        # words with optional internal hyphens
...   | \$?\d+(?:\.\d+)?%?  # currency, percentages, e.g. $12.40, 82%
...   | \.\.\.            # ellipsis
...   | [][.,;"'?():_`-]  # these are separate tokens; includes ], [
... '''
>>> nltk.regexp_tokenize(text, pattern)
['That', 'U.S.A.', 'poster-print', 'costs', '$12.40', '...']
```

Source: https://web.stanford.edu/~jurafsky/slp3/2.pdf

Complexity in Word tokenization

Word tokenization is more complex in languages like written Chinese, Japanese, and Thai, which do not use spaces to mark potential word-boundaries

Another Solution-

Byte-pair encoding – [Read the example from book]

Byte pair encoding 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 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

https://web.stanford.edu/~jurafsky/slp3/2.pdf

Implementation

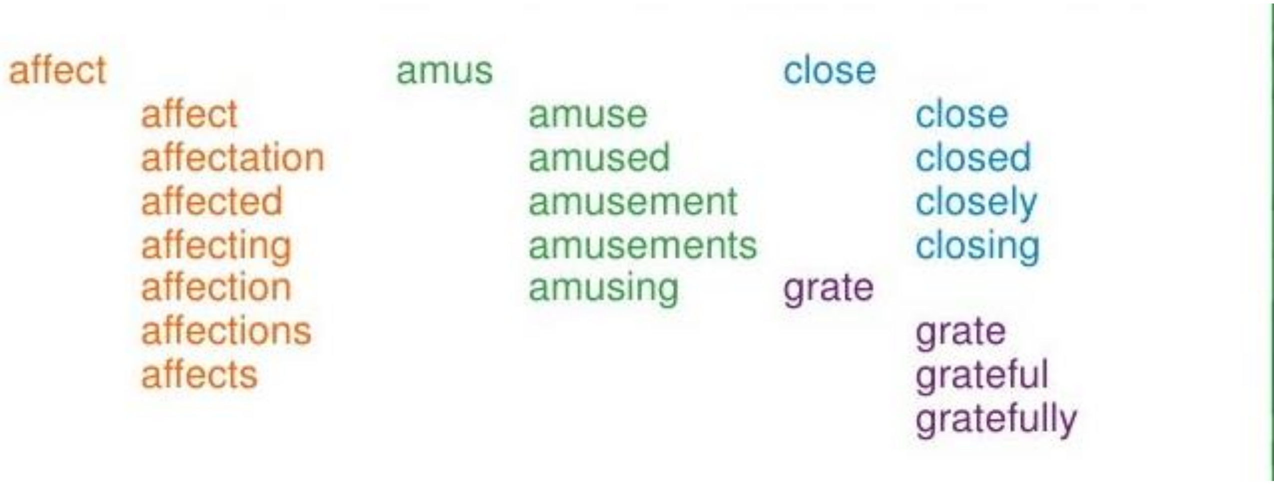
https://huggingface.co/learn/nlp-course/en/chapter6/5

https://github.com/SumanthRH/tokenization

Other tokenizers

- Word piece tokenizers
- Sentence piece tokenizers

Stemming in NLP



Stemming

Stemming

文A 21 languages

Article Talk — Read Edit View history Tools

From Wikipedia, the free encyclopedia

In linguistic morphology and information retrieval, **stemming** is the process of reducing inflected (or sometimes derived) words to their word stem, base or root form—generally a written word form. The stem need not be identical to the morphological root of the word; it is usually sufficient that related words map to the same stem, even if this stem is not in itself a valid root. Algorithms for stemming have been studied in computer science since the 1960s. Many search engines treat words with the same stem as synonyms as a kind of query expansion, a process called conflation.

A computer program or subroutine that stems word may be called a *stemming program*, *stemming algorithm*, or *stemmer*.

Examples [edit]

A stemmer for English operating on the stem *cat* should identify such strings as *cats*, *catlike*, and *catty*. A stemming algorithm might also reduce the words *fishing*, *fished*, and *fisher* to the stem *fish*. The stem need not be a word, for example the Porter algorithm reduces *argue*, *argued*, *argues*, *arguing*, and *argus* to the stem *argu*.

https://en.wikipedia.org/wiki/Stemming#

Stemming

Stemming suggests crude affix chopping

-language dependent

-automation, automatic, automate ---(automat)

Stemming programs are called as Stemmers or Stemming algorithms

[Porter Stemming Algorithm (tartarus.org)]

The Porter Stemmer (Porter, 1980)

- Common Algorithm for English language
- A simple rule-based algorithm for stemming
- An example of a HEURISTIC method
- Based on rules like:
  - ATIONAL -> ATE (e.g., rel**ational** -> rel**ate**)
- The algorithm consists of 7 sets of rules, applied in order

The Porter Stemmer: definitions

- Definitions:
  - **CONSONANTS**: a letter other than A, E, I, O, U, and Y preceded by consonant
  - **VOWEL**: any other letter (if the letter is not a consonant)
- With this definition, all words are of the form: $(C)(VC)^m(V)$
  - C: string of one or more consonants (con+)
  - V: string of one or more vowels
  - m: measure of word or word part which is represented in form of VC
- E.g.
  - **Troubles**
  - $C\ (VC)^m\ V$

Measure of the word

M=0 TREE, BY, TR

M=1 TROUBLE, OATS, TREES, IVY

M=2 TROUBLES, PRIVATE, OATEN

The Porter Stemmer: Rule format

- The rules are of the form:

(condition) S1 -> S2 where S1 and S2 are suffixes

- If the rule (m>1) EMENT->
  - In this S1 is EMENT and S2 is NULL
  - So, this would map REPLACEMENT with REPLAC

Conditions

m	The measure of the stem
*S	The stem ends with S
v	The stem contains a vowel
*d	The stem ends with a double consonant (TT,SS)
*o	The stem ends in CV C (second C not W, X, or Y) Ex: WIL, HOP

The condition may also contains expressions with and, or, or not
Example ((m>1) and (*s or*t)) -tests for a stem with m>1 ending in s or t

The Porter Stemmer: Step 1

- SSES -> SS
  - caresses -> caress
- IES -> I
  - ponies -> poni
  - ties -> ti
- SS -> SS
  - caress -> caress
- S -> €
  - cats -> cat

The Porter Stemmer: Step 2a (past tense, progressive)

- (m>1) EED -> EE
  - **Condition verified**: agreed -> agree
  - **Condition not verified**: feed -> feed
- (*V*) ED -> €
  - **Condition verified**: plastered -> plaster
  - **Condition not verified**: bled -> bled
- (*V*) ING -> €
  - **Condition verified:** motoring -> motor
  - **Condition not verified**: sing -> sing

The Porter Stemmer: Step 2b (cleanup)

- (These rules are ran if second or third rule in 2a apply)
- AT -> ATE
  - Conflat(ed) -> conflate
- BL -> BLE
  - Troubl(ing) - > trouble
- (*d & ! (*L or *S or *Z)) -> single letter
  - **Condition verified**: hopp(ing) -> hop, tann(ed) -> tan
  - **Condition not verified**: fall(ing) -> fall
- (m=1 & *o) -> E
  - **Condition verified**: fil(ing) -> file
  - Condition not verified: fail -> fail

The Porter Stemmer: step 3 and 4

- Step 3: Y elimination (*V*) Y -> I
  - **Condition verified**: happy -> happi
  - **Condition not verified**: sky -> sky
- Step 4: Derivational Morphology, I
  - (m>0) ATIONAL -> ATE
    - Relational -> relate
  - (m>0) IZATION -> IZE
    - Generalization -> generalize
  - (m>0) BILITI -> BLE
    - Sensibiliti -> sensible

Porter Stemmer Step 5 and Step 6

- Derivational Morphology II
    - (m>0) ICATE-> IC
        - Triplicate-> Triplic
    - (m>0) FUL -> €
        - hopeful-> hope
    - (m>0) NESS-> €
        - goodness->good
- Derivational Morphology III
    - (m>0) ANCE-> €
        - allowance-> allow
    - (m>0) ENT -> €
        - dependent-> depend
    - (m>0) IVE-> €
        - effective->effect

The porter stemmer Step 7 (cleanup)

- Step 7a
  - (m>1) E -> €
    - Probate -> probat
  - (m=1 & !*o) NESS -> €
    - Goodness -> good
- Step 7 b
  - (m>1 & *d & *L) -> single letter
    - **Condition verified**: controll -> control
    - **Condition not verified:** roll -> roll

Lemmatization

Lemmatization

18 languages

Article Talk Read Edit View history Tools

From Wikipedia, the free encyclopedia

Lemmatization (or less commonly **lemmatisation**) in linguistics is the process of grouping together the inflected forms of a word so they can be analysed as a single item, identified by the word's lemma, or dictionary form.[1]

In computational linguistics, lemmatization is the algorithmic process of determining the lemma of a word based on its intended meaning. Unlike stemming, lemmatization depends on correctly identifying the intended part of speech and meaning of a word in a sentence, as well as within the larger context surrounding that sentence, such as neighbouring sentences or even an entire document. As a result, developing efficient lemmatization algorithms is an open area of research.[2][3][4]

Description [edit]

In many languages, words appear in several *inflected* forms. For example, in English, the verb 'to walk' may appear as 'walk', 'walked', 'walks' or 'walking'. The base form, 'walk', that one might look up in a dictionary, is called the *lemma* for the word. The association of the base form with a part of speech is often called a *lexeme* of the word.

https://en.wikipedia.org/wiki/Lemmatization

Lemmatization

Task of determining whether two words have same root despite surface differences

Lemmatization

The most sophisticated methods for lemmatization involve complete **morphological parsing** of the word.

Morphology is the study of morpheme the way words are built up from smaller meaning-bearing units called **morphemes**.

Two broad classes of morphemes can be distinguished:

stems—the central moraffix pheme of the word, supplying the main meaning—

and **affixes**—adding “additional” meanings of various kinds.

So, for example, the word **fox** consists of one morpheme (the morpheme **fox**) and

the word **cats** consists of two: the morpheme **cat** and the morpheme -**s**.

Stemming vs Lemmatization

Stemming

achieve -> achiev
achieving -> achiev

- Can reduce words to a stem that is not an existing word
- Operates on a single word without knowledge of the context
- Simpler and faster

Lemmatization

achieve -> achieve
achieving -> achieve

- Reduces inflected words to their lemma, which is always an existing word
- Can leverage context to find the correct lemma of a word
- More accurate but slower

In-class activity

Exercise1:

Convert these list of words into base form using Stemming and Lemmatization and observe the transformations

['running', 'painting', 'walking', 'dressing', 'likely', 'children', 'whom', 'good', 'ate', 'fishing']

Write a short note on the words that have different base words using stemming and Lemmatization

In class activity

Write a python code to use NLTK library and convert the base forms using different Stemmers and Lemmatizers

#use different stemmers and lemmatizers provided by NLTK

#see

https://www.nltk.org/howto/stem.html

for full NLTK stemmer module documentations

Reference materials

- https://vlanc-lab.github.io/mu-nlp-course/
- Lecture notes
- (A) Speech and Language Processing by Daniel Jurafsky and James H. Martin
- (B) Natural Language Processing with Python. (updated edition based on Python 3 and NLTK 3) Steven Bird et al. O'Reilly Media