





# Natural Language Processing IN2361

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# Chapter 2 Regular Expressions, Text-Normalization, Edit-Distance

- content is based on [1] and [2]
- certain elements (e.g. equations or tables) were taken over or taken over in a modified form from [1] or [2]
- citations of [1] and [2] or from [1] or [2] are omitted for legibility
- errors are fully in the responsibility of Georg Groh
- BIG thanks to Dan and James for a great book!

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.

#### **ELIZA Conversation 1966**

```
s/.* I'M (depressed|sad) .*/I AM SORRY TO HEAR YOU ARE \1/
s/.* I AM (depressed|sad) .*/WHY DO YOU THINK YOU ARE \1/
s/.* all .*/IN WHAT WAY/
s/.* always .*/CAN YOU THINK OF A SPECIFIC EXAMPLE/
```

Regular Expression: algebraic notation for characterizing a set of strings
 → simple deterministic classifier / means for search

#### [ ]: disjunction of letters:

Pattern	Matches
[wW]oodchuck	Woodchuck or woodchuck
[1234567890]	a single 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

## caret: [^ ]: negation (if first in [ ]):

Pattern	Matches	
[^A-Z]	not an upper case letter	Oyfn pripetchik
[^Ss]	neither 'S' nor 's'	I have no exquisite reason
[e^]	either e or ^	^^ee Look here
[^e^]	neither e nor ^	^^ee <u>L</u> ook here
a^b	the pattern a caret b	Look up <u>a^b</u> now

#### : disjunction:

Pattern	Matches
yours mine	yours or mine
a b c	same as [abc]
[gG]roundhog [Ww]oodchuck	obvious
<pre>gupp(y ies)</pre>	guppy or guppies

? \* + {} quantifiers (for counting); . wildcards

Pattern	Matches	
colou?r	optional previous char or expr	<u>color</u> or <u>colour</u>
o*h!	zero or more of previous char or expr	<u>h!</u> or <u>oh!</u> or <u>ooh!</u>
o+h!	one or more of previous char or expr	oh! or ooh! or oooh!
a{3,5}	{x,y} : exactly x to y many	aaa or aaaaa or aaaaa
beg.n	. matches any char except \r	begin or begun or beg3n

#### ^ \$ \b \B anchors:

Pattern	Matches	
^[A-Z]	at start of a line	Palo Alto
^[^A-Za-z]		<pre>1 "Hello"</pre>
\.\$	at end of the line	The end.
.\$		The end? The end!
\bthe\b	matches word boundaries	the world but not other

# **Text Normalization**

# Basic (application specific!) tasks:

- Segmenting / tokenizing words in running text
- Normalizing word formats (e.g. lemmatization)
- Segmenting sentences in running text

# **Example: How Many Words?**

#### I do uh main- mainly business data processing

o disfluencies in utterances: fragments, fillers, (similar also: emoticons) etc.

#### Seuss's cat in the hat is different from other cats!

- Lemma: same stem, part of speech, rough word sense
   cat and cats = same lemma
- Wordform: the full inflected surface form
   cat and cats = different wordforms

# **Example: How Many Words?**

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

- Type: an element of the vocabulary V.
- Token: an instance of that type in running text. Number of Tokens: N
- How many in example? 15 tokens, 13 types

#### Corpora:

Corpus	Tokens = N	Types = $ V $
Shakespeare	884 thousand	31 thousand
Brown corpus	1 million	38 thousand
Switchboard telephone conversations	2.4 million	20 thousand
COCA	440 million	2 million
Google N-grams	1 trillion	13 million

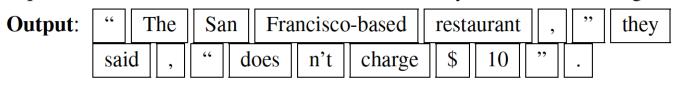
Heran's / Heap's Law:

$$|V| = kN^{\beta}$$
  $0 < \beta < 1$ ,  $k > 0$   $\beta \approx 0.7$ 

#### **Word Tokenization**

- Tokenization: segment text into words
- Issues:
- Finland's capital → Finland Finlands Finland's ?
- what're, I'm, isn't  $\rightarrow$  what are, I am, is not
- \$4.99  $\rightarrow$  \$4.99 \$4.99?
- $state-of-the-art \rightarrow state of the art ?$
- lowercase → lower-case lowercase lower case ?
- San Francisco  $\rightarrow$  one token or two? ( $\leftarrow \rightarrow$  NER)
- m.p.h., Ph.D.,  $AT&T \rightarrow$  keep together?
- www.google.de → http://www.google.de?
- 233,455 → 233.455 ? 233455 ?
- count punctuation as separate words?
- wtf, lol, ⊙, :-) →
- Penn Treebank tokenization stndard:

**Input**: "The San Francisco-based restaurant," they said, "doesn't charge \$10".



# Tokenization – Language Specific Issues

#### French

- clitics example: L'ensemble → one token or two?
  - L?L'?Le?
  - Want *l'ensemble* to match with *un ensemble*

#### German

- noun compounds are not segmented: example: Lebensversicherungsgesellschaftsangestellter ('life insurance company employee')
- $\rightarrow$  German information retrieval needs compound splitter

#### Chinese and Japanese

- no spaces between words:
  - 莎拉波娃现在居住在美国东南部的佛罗里达。
  - 莎拉波娃 现在 居住 在 美国 东南部 的 佛罗里达
  - Sharapova now lives in US southeastern Florida

- treating all issues of tokenization by rules + automata (fast) is complicated → use ML-based sequence processing. but is there a third, more simple, data-driven way?
- ◆ Byte Pair Encoding (BPE):
  - o iteratively merge frequent pairs of characters:
    - start with symbol-vocabulary of characters + end-of-word-character.
    - for most frequent character n-gram pair in words: create new n-gram.
    - iterate. → word segmentation into character n-grams
- benefits: example: low, lowest in training set but lower not in training set but in test set → lower is decomposed as low + er: low and er may be known → compositional representation of unknowns

#### iteratively merge frequent pairs of characters:

- start with symbol-vocabulary of characters + end-of-word-character.
- for most frequent character n-gram pair in words: create new n-gram.
- iterate. → word segmentation into character n-grams

#occ	word
5	low_
2	lowest_
6	newer_
3	wider_
2	new_

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

all characters in vocab

\_ : end of worf token

#### iteratively merge frequent pairs of characters:

- start with symbol-vocabulary of characters + end-of-word-character.
- for most frequent character n-gram pair in words: create new n-gram.
- iterate. → word segmentation into character n-grams

#occ	word
5	low_
2	lowest_
6	n e w e r_
3	wider_
2	n e w _

most frequent pair: r (#occ=9)

#### iteratively merge frequent pairs of characters:

- start with symbol-vocabulary of characters + end-of-word-character.
- for most frequent character n-gram pair in words: create new n-gram.
- iterate. → word segmentation into character n-grams

#occ	word
5	low_
2	lowest_
6	n e w <mark>er</mark> _
3	wider_
2	n e w _

most frequent pair: e r\_ (#occ=9)

#### iteratively merge frequent pairs of characters:

- start with symbol-vocabulary of characters + end-of-word-character.
- for most frequent character n-gram pair in words: create new n-gram.
- iterate. → word segmentation into character n-grams

#occ	word
5	low_
2	lowest_
6	n ew er_
3	wider_
2	n ew _

most frequent pair: ew (#occ=8)

next merge	current "vocabulary"
(n, ew)	_ , d, e, i, l, n, o, r, s, t, w, r_ , er_ , ew, new
(I, o)	_ , d, e, i, l, n, o, r, s, t, w, r_ , er_ , ew, new, lo
(lo, w)	_ , d, e, i, l, n, o, r, s, t, w, r_ , er_ , ew, new, lo, low
(new, er _)	_ , d, e, i, l, n, o, r, s, t, w, r_ , er_ , ew, new, lo, low, newer_
(low, _)	_ , d, e, i, l, n, o, r, s, t, w, r_ , er_ , ew, new, lo, low, newer_ , low_

I o w e r  $\rightarrow$  low er\_ (via greedy longest match first decoding (maximum matching, MaxMatch)) after learning token set

- o algorithm's meta parameter: number k of merge steps: if k large → most words and affixes will get their own character N-gram representation
- alternative: wordpiece algorithm (e.g. used for BERT): merge pairs not based on frequency but in terms of maximizing the likelihood of the resulting language model of word pieces (while minimizing the number of wordpieces)

#### **Word Normalization**

- Normalization: mapping words / tokens in a standard format  $\rightarrow$  create equivalence classes: {U.S., U.S.A, USA}  $\rightarrow$  USA
- possible element: Case-Folding / Lowercasing: not always helpful:
  - GOOD LORD! it's US, you fool! not you alone!
     (<-> sentiment analysis, information extraction,)
  - The US government announced .. vs. it was us that had the trouble (<-> information extraction, information retrieval...)
- standard algorithms for tokenization + normalization:
  - deterministic algorithms based on regular expressions compiled into very efficient finite state automata.
  - also possible: ML-based algos trained on large hand segmented corpora

#### Lemmatization

- Reduce inflections or variant forms to base form
  - $\circ$  am, are, is  $\rightarrow$  be
  - $\circ$  car, cars, car's, cars'  $\rightarrow$  car
  - $\circ$  the boy's cars are different colors  $\rightarrow$  the boy car be different color
- most sophisticated classic method: morphological parsing
  - Morphology: study of way words are built up from smaller meaningbearing units called
  - o Morphemes:
    - Stems: The core meaning-bearing units
    - Affixes: Bits and pieces that adhere to stems
    - example: cats  $\rightarrow$  stem: *cat*, affix: *s*

# Stemming

- "Poor man's lemmatization": reduce terms to their stems (mostly in / from information retrieval)
- Stemming: crude chopping of affixes (language dependent)

#### Example:

for example compressed and compression are both accepted as equivalent to compress.



for exampl compress and compress ar both accept as equival to compress

# Stemming for English: Porter's Stemmer

Set of term rewriting rules, applied to words repeatedly in passes

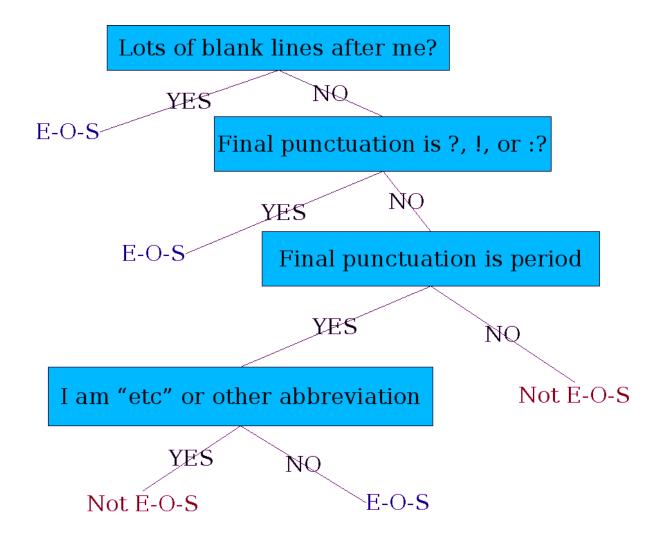
```
Step 1a
                                                          Step 2 (for long stems)
   sses \rightarrow ss caresses \rightarrow caress
                                                             ational \rightarrow ate relational \rightarrow relate
   ies \rightarrow i ponies \rightarrow poni
                                                             izer \rightarrow ize digitizer \rightarrow digitize
   ss \rightarrow ss caress \rightarrow caress
                                                             ator \rightarrow ate operator \rightarrow operate
   s \rightarrow \phi \quad cats \rightarrow cat
                                                             •••
Step 1b
                                                          Step 3 (for longer stems)
    (*v*)ing \rightarrow \emptyset walking \rightarrow walk
                                                             al \rightarrow \emptyset revival \rightarrow reviv
                         sing \rightarrow sing
                                                             able \rightarrow \emptyset adjustable \rightarrow adjust
    (*v*)ed \rightarrow \emptyset plastered \rightarrow plaster
                                                             ate \rightarrow \emptyset activate \rightarrow activ
```

Errors of Co	mmission	<b>Errors of Omission</b>				
organization	organ	European	Europe			
doing	doe	analysis	analyzes			
numerical	numerous	noise	noisy			
policy	police	sparse	sparsity			

# Sentence Segmentation

- !, ? are relatively unambiguous
- Period "." is quite ambiguous
  - Sentence boundary
  - Abbreviations like Inc. or Dr.
  - Numbers like .02% or 4.3
- Build a binary classifier
  - For each ".": apply classifier: features from "."'s neighborhood → class1: endOfSentence or class2: NotEndOfSentence
  - Classifiers: hand-written rules, regular expressions, or machinelearning

# Sentence Segmentation with Decision Tree



# **Edit Distance and Alignment**

#### How similar are two strings?

- Spell correction
  - the user typed "graffe": which word is closest?
    - graf
    - graft
    - grail
    - giraffe

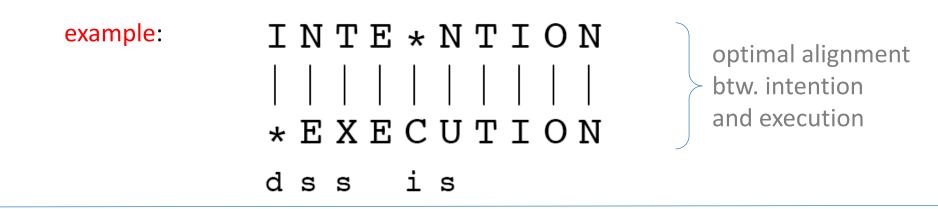
- Computational Biology
  - Align two sequences of nucleotides
     AGGCTATCACCTGACCTCCAGGCCGATGCCC
     TAGCTATCACGACCGCGGTCGATTTGCCCGAC
  - Resulting alignment:
    - -AGGCTATCACCTGACCTCCAGGCCGA--TGCCC--TAG-CTATCAC--GACCGC--GGTCGATTTGCCCGAC

Also for Machine Translation, Information Extraction, Speech Recognition

## **Edit Distance**

- Minimum Edit Distance between two strings is the minimum number of editing operations
  - o insertion
  - o deletion
  - o substitution

needed to transform one into the other



Levenshtein distance: assign costs:

if each operation has cost of  $1 \rightarrow \text{dist} = 5$  if substitutions cost  $2 \rightarrow \text{dist} = 8$ 

# Algorithm for MinEditDistance

- Todo: search for shortest weighted path
   (sequence of edits with minimal overall cost)
   from start string X (length n) to target string Y (length m)
- Define: D[i,j] = minEditDist btw. first i characters of X (X[1..i]) and first j characters of Y (Y[1..j])
- → minEditDist(X, Y) = D[m,n]
- Approach: Dynamic Programming: compute D(i,j) for small i,j and compute larger D(i,j) based on previously computed smaller values

# Algorithm for MinEditDistance

```
function MIN-EDIT-DISTANCE(source, target) returns min-distance
```

```
n \leftarrow \text{LENGTH}(source)
m \leftarrow \text{LENGTH}(target)
Create a distance matrix distance [n+1,m+1]
# Initialization: the zeroth row and column is the distance from the empty string
     D[0,0] = 0
     for each row i from 1 to n do
         D[i,0] \leftarrow D[i-1,0] + del-cost(source[i])
     for each column j from 1 to m do
         D[0,j] \leftarrow D[0,j-1] + ins-cost(target[j])
# Recurrence relation:
for each row i from 1 to n do
     for each column j from 1 to m do
        D[i,j] \leftarrow MIN(D[i-1,j] + del-cost(source[i]),
                         D[i-1,j-1] + sub\text{-}cost(source[i],target[j]),
                         D[i,j-1] + ins-cost(target[j])
  Termination
return D[n,m]
```

# Algorithm for MinEditDistance

function MIN-EDIT-DISTANCE(sour

option: may want to choose

non-uniform costs here

listance[n

# Introduced the zeroth row and

Confusion matrix for spelling errors

sub[X, Y] = Substitution of X (incorrect) for Y (correct)

# Recurrence relation:

for each row i from 1 to n do

for each column j from 1 to m and

 $D[i,j] \leftarrow \text{MIN}(D[i-1,j] + del\text{-}cost(source[i]),}$  D[i-1,j-1] + sub-cost(source[i], target[j]),D[i,j-1] + ins-cost(target[j]))

# Termination return D[n,m]

# Algorithm for MinEditDistance (Levenshtein)

Initialization

$$D(i,0) = i$$
  
 $D(0,j) = j$ 

Recurrence Relation:

```
For each i=1...M

For each j=1...N

D(i,j)=\min \begin{cases} D(i-1,j)+1 & \text{$i\to i-1: a \ deletion \ from \ source \ is \ necessary} \\ D(i,j-1)+1 & \text{$j-1\to j: an \ insertion \ into \ target \ is \ necessary} \\ D(i-1,j-1)+1 & \text{$0: if \ } X(i)\neq Y(j) \\ 0; \text{ if } X(i)=Y(j) \end{cases}
```

Termination:

D(N,M) is distance

# Algorithm for MinEditDistance (Levenshtein)

Src\Tar	#	e	X	e	c	u	t	i	0	n
#	0	1	2	3	4	5	6	7	8	9
i		2	3	4	5	6	7	6	7	8
n	2	3	4	5	6	7	8	7	8	7
t	3	4	(5)	6	7	8	7	8	9	8
e	4	3	4	5	6	7	8	9	10	9
n	5	4	5	6	7	8	9	10	11	10
t	6	5	6	7	8	9	8	9	10	11
i	7	6	7	8	9	10	9	8	9	10
0	8	7	8	9	10	11	10	9	8	9
n	9	8	9	10	11	12	11	10	9	8

$$D(i,j) = \min \begin{cases} D(i-1,j) + 1 \\ D(i,j-1) + 1 \\ D(i-1,j-1) + \end{cases} \begin{cases} 2; & \text{if } X(i) \neq Y(j) \\ 0; & \text{if } X(i) = Y(j) \end{cases}$$

# Extension of Algorithm: Compute Alignment

 Alignment of X and Y: from (n,m): reconstruct non-decreasing path through matrix ("backtrace"): remember in each step "where we came from" tar i =>

src .		#	e	X	e	c	u	t	i	0	n
510	#	0	1	2	3	4	5	6	7	8	9
i	i	1	<u> </u>	<b>\</b> ←↑3	<u> </u>	<u> </u>	<u> </u>	<u> </u>	<u> </u>	←7	← 8
$\prod$	n	2	$\nwarrow \leftarrow \uparrow 3$	<b>₹</b> ←↑4	<u> </u>	<u> </u>	<u> </u>	<u> </u>	<b>↑7</b>	<u>~</u> ←↑8	<b>人</b> 7
Ĭ	t	3	<u> </u>	<b>₹</b> ←↑ <b>5</b>	<u> </u>	<u> </u>	<u> </u>	₹7	←↑8	<b>~</b> ←↑9	<b>† 8</b>
	e	4	₹ 3	← 4	<b>₹</b> ← <b>5</b>	<b>← 6</b>	<b>←7</b>	<b>←</b> ↑ 8	<u> </u>	<b>\</b> ←↑ 10	<b>↑9</b>
	n	5	<b>↑4</b>	<b>\</b> ←↑ 5	<u> </u>	<u> </u>	<u> </u>	<u> </u>	<b>△</b> ←↑ 10	<b>\←</b> ↑11	<b>₹</b> ↑ 10
	t	6	† <b>5</b>	<u> </u>	<u> </u>	<u> </u>	<u> </u>	₹ 8	<b>←</b> 9	← 10	<b>←</b> † 11
	i	7	† 6	<u> </u>	<u> </u>	<u> </u>	<b>&lt;</b> ←↑ 10	<b>↑9</b>	₹ 8	<b>←</b> 9	← 10
	0	8	<sub>†</sub> 7	<b>₹</b> ←↑8	<u> </u>	<b>△</b> ↑ 10	<b>△</b> ←↑ 11	↑ 10	<b>↑9</b>	₹ 8	←9
	n	9	† 8	<b>\←</b> ↑9	<b>₹</b> ←↑ 10	<b>\</b> ←↑11	<b>△</b> ←↑ 12	↑11	↑ 10	<b>↑9</b>	₹ 8

$$D(i,j) = \min \begin{cases} D(i-1,j) + 1 & \text{deletion} \\ D(i,j-1) + 1 & \text{insertion} \\ D(i-1,j-1) + \begin{cases} 2; & \text{if } X(i) \neq Y(j) \\ 0; & \text{if } X(i) = Y(j) \end{cases}$$
 id deletion

deletion insertion substitution or id



# Bibliography

- (1) Dan Jurafsky and James Martin: Speech and Language Processing (3<sup>rd</sup> ed. draft, version October, 2019); Online: <a href="https://web.stanford.edu/~jurafsky/slp3/">https://web.stanford.edu/~jurafsky/slp3/</a> (URL, Oct 2019) (this slideset is especially based on chapter 2)
- (2) Powerpoint slides from Dan Jurafsky and James Martin: Speech and Language Processing (3<sup>rd</sup> ed. draft); Online: <a href="https://web.stanford.edu/~jurafsky/slp3/">https://web.stanford.edu/~jurafsky/slp3/</a> (URL, Oct 2018)

# Recommendations for Studying

minimal approach:

work with the slides and understand their contents! Think beyond instead of merely memorizing the contents

standard approach:

minimal approach + read the corresponding pages in Jurafsky [1]

interested students

== standard approach