Social Media & Text Analysis

lecture 9 - Twitter NLP Pipeline
Tokenization, Normalization, POS/NE Tagging

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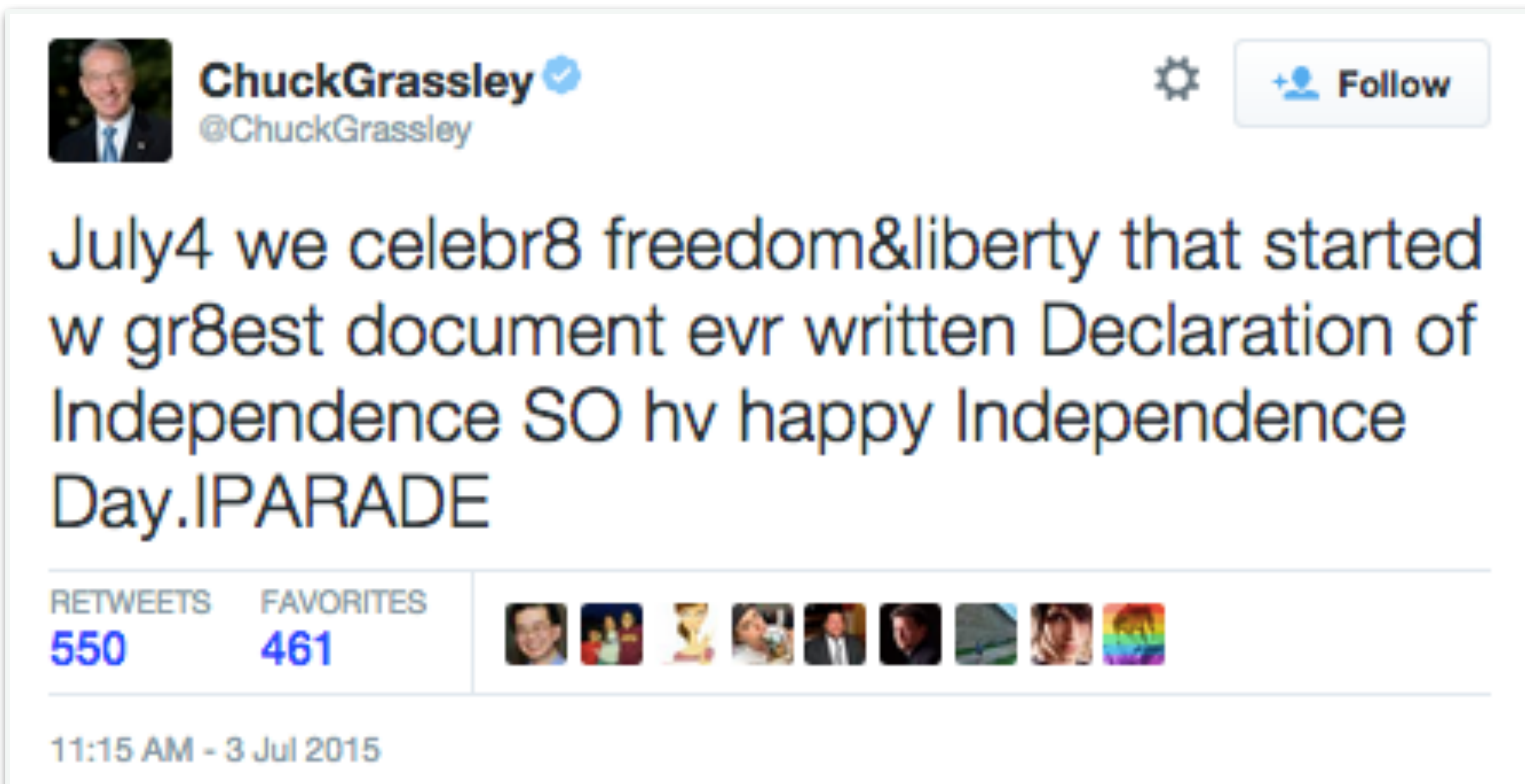
Website: socialmedia-class.org

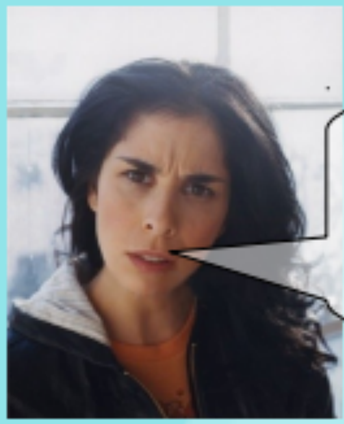
Bad Language?



BAD LANGUAGE!

...on the INTERNET!!

Jacob EISENSTEIN
GEORGIA Institute of TECHnology



Boom! Ya ur website suxx bro

...dats why pluto is pluto it can neva be a star

michelle obama great. job. and. whit all my. respect she. look. great. congrats. to. her.

I now h v an iphone

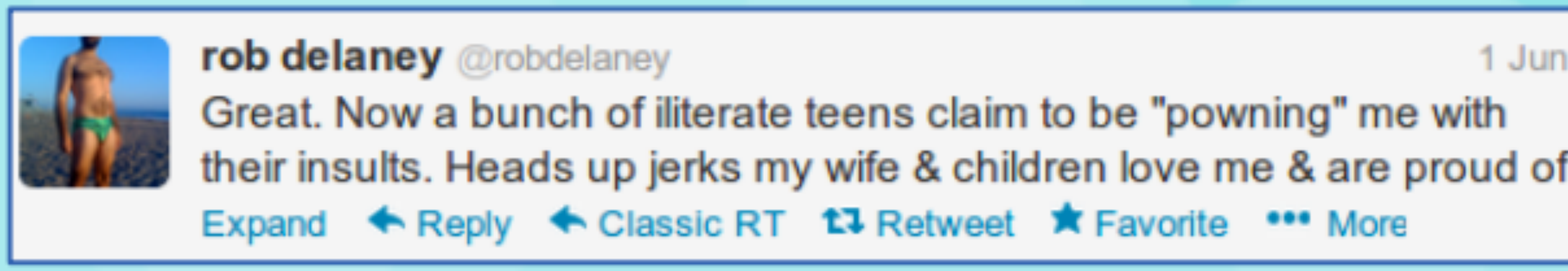
What can we do about it?

Why don't they just write NORMALLY??

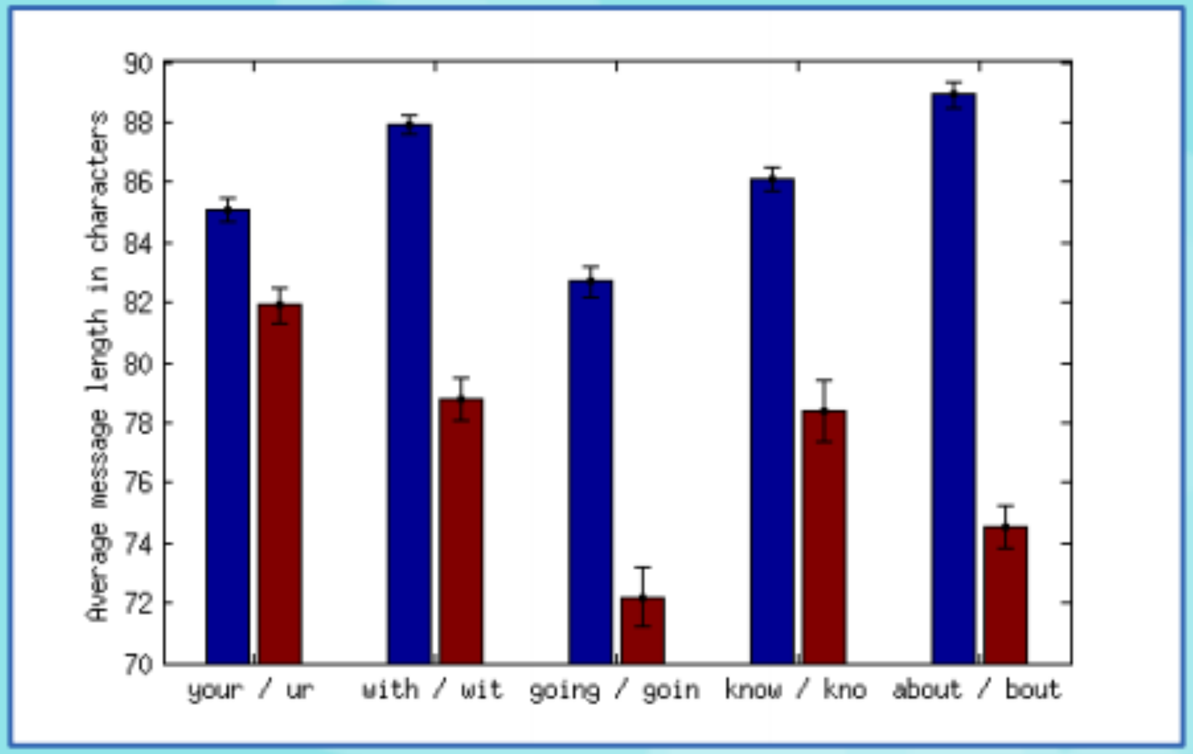
Can our software ever ADAPT???

How does language go bad?

Illiteracy? No.
(Tagliamonte and Denis 2008; Drouin and Davis 2009)



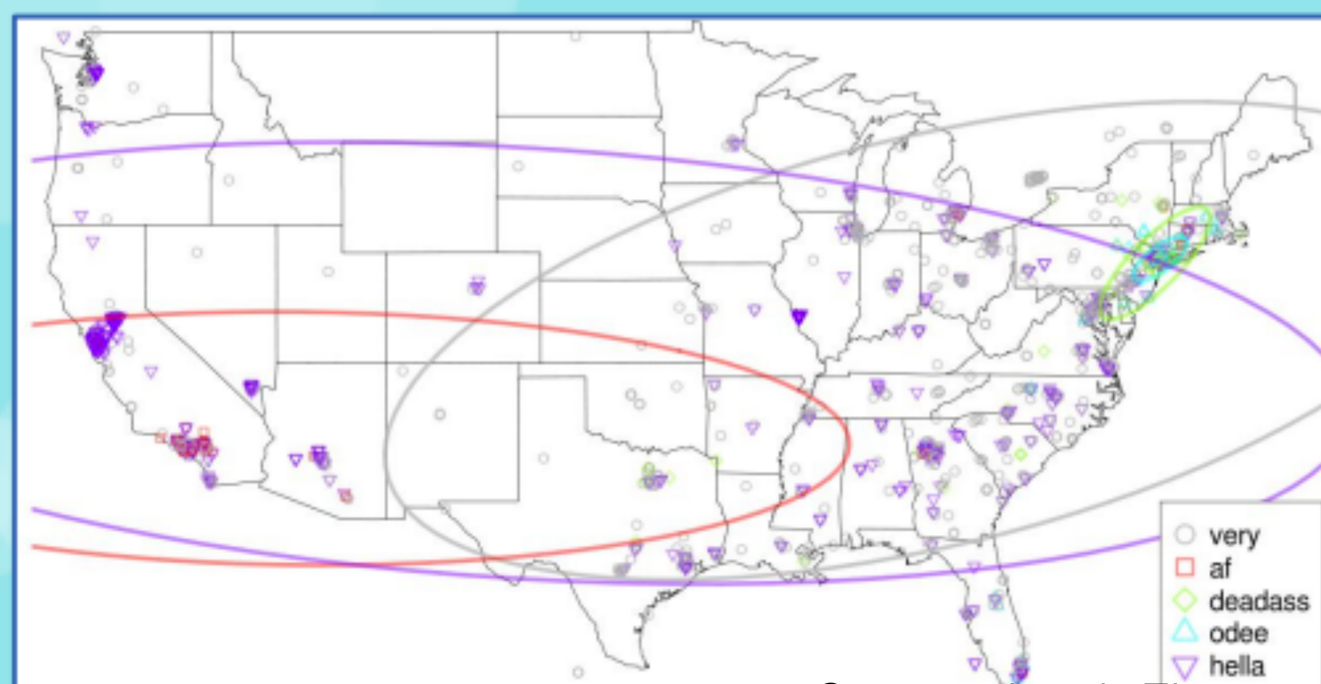
Length limits? (probably not)



Hardware input constraints? (Gouws et al 2011)

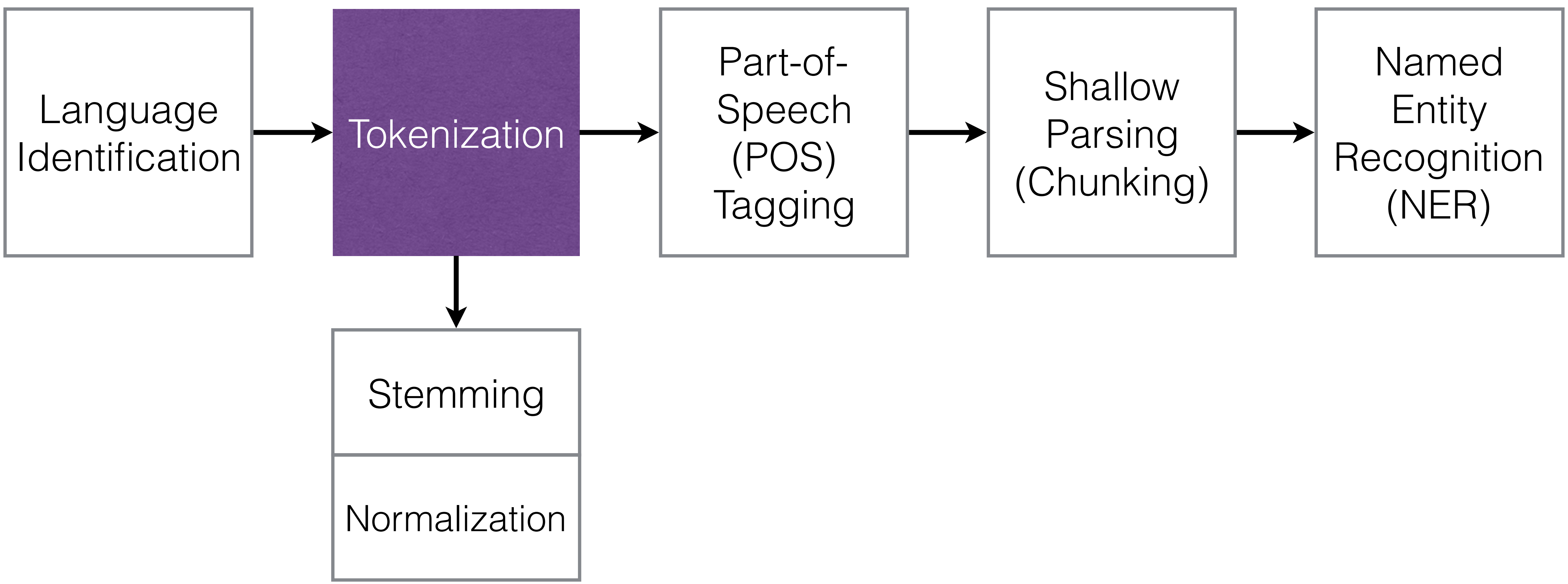
Social variables

- Non-standard language does *identity work*, signaling authenticity, solidarity, etc.
- Social variation is usually inhibited in written language, but social media is less regulated than other written genres.



Source: Jacob Eisenstein

NLP Pipeline



Tokenization

- breaks up the string into words and punctuation
- need to handle:
  - abbreviations ("jr."), number ("5,000") …

```
seas479:training weixu$ ./penn-treebank-tokenizer.perl
Tokenizer v3
Language: en


Ms. Hilton last year called Mr. Rothschild "the love of my life."
Ms. Hilton last year called Mr. Rothschild " the love of my life . "
```

input

output

Tokenization

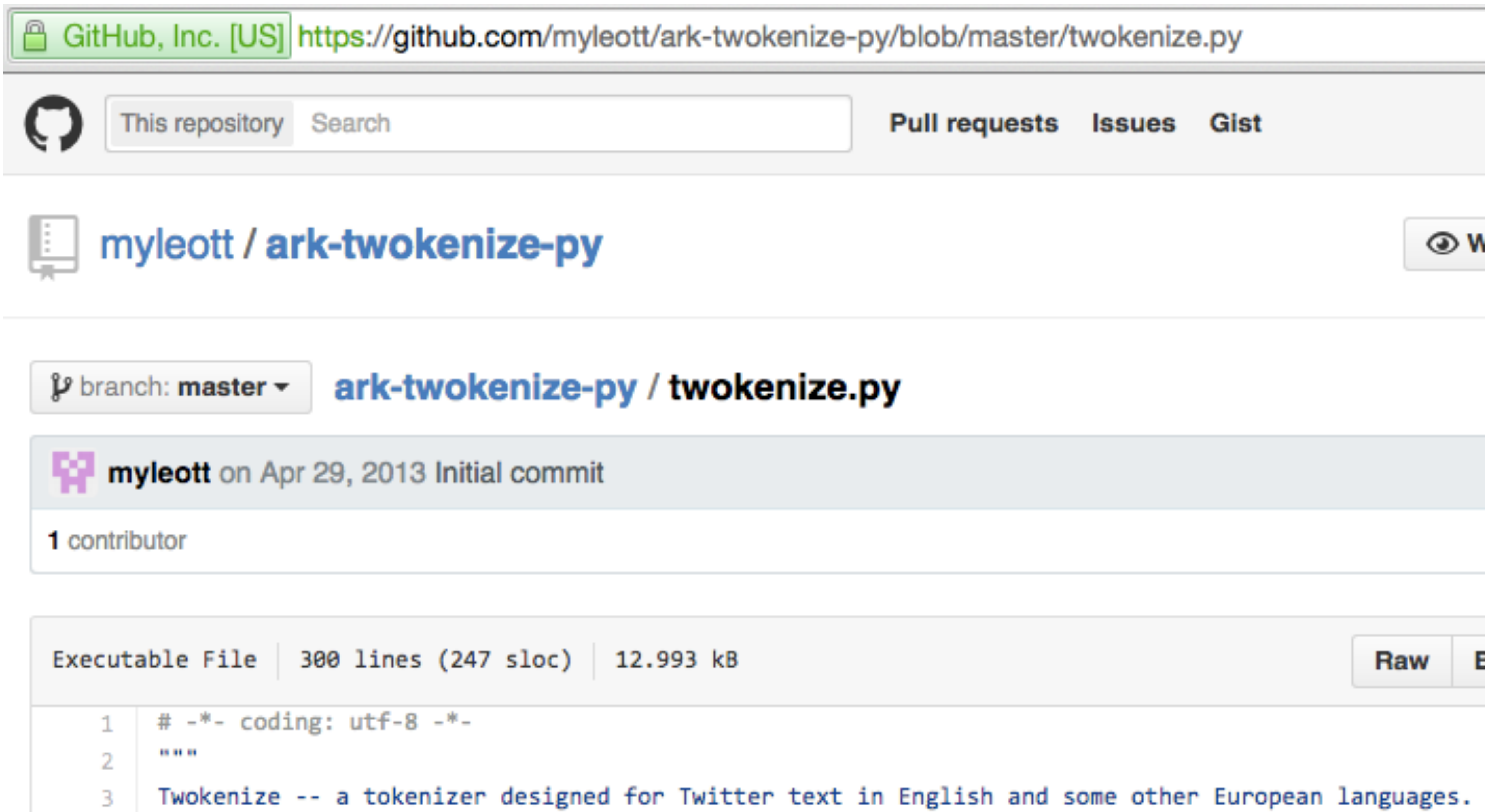
- for Twitter, additionally need to handle:
  - emoticons, urls, #hashtags, @mentions …

```
>>> import twokenize
>>> input = "Clowns are pretty gross tho O.o (I'm afraid of clow
ns :p) ask.fm/a/cc301167"
>>> twokenize.tokenizeRawTweetText(input)
['Clowns', 'are', 'pretty', 'gross', 'tho', 'O.o', '(', "I'm", '
afraid', 'of', 'clowns', ':p', ')', 'ask.fm/a/cc301167']
```

input

output

Tool: twokenize.py



Tool: twokenize.py

```
Twokenize -- a tokenizer designed for Twitter text in English and some other European languages.
This tokenizer code has gone through a long history:

(1) Brendan O'Connor wrote original version in Python, http://github.com/brendano/tweetmotif
       TweetMotif: Exploratory Search and Topic Summarization for Twitter.
       Brendan O'Connor, Michel Krieger, and David Ahn.
       ICWSM-2010 (demo track), http://brenocon.com/oconnor_krieger_ahn.icwsm2010.tweetmotif.pdf
(2a) Kevin Gimpel and Daniel Mills modified it for POS tagging for the CMU ARK Twitter POS Tagger
(2b) Jason Baldridge and David Snyder ported it to Scala
(3) Brendan bugfixed the Scala port and merged with POS-specific changes
    for the CMU ARK Twitter POS Tagger
(4) Tobi Owoputi ported it back to Java and added many improvements (2012-06)

Current home is http://github.com/brendano/ark-tweet-nlp and http://www.ark.cs.cmu.edu/TweetNLP
```

Tokenization

- main techniques:
    - hand-crafted rules as regular expressions

Regular Expression

- a pattern matching language
- invented by American Mathematician Stephen Kleene in the 1950s
- used for search, find, replace, validation … (very frequently used when dealing with strings)
- supported by most programming languages
- easy to learn, but hard to master

Regular Expression

```
Hashtag = "#[a-zA-Z0-9_]+"
```

- [] indicates a set of characters:
  - [amk] will match ‘a’, ‘m’, or ‘k’
  - [a-z] will match any lowercase letter (‘abcdefghijklmnopqrstuvwxyz’)
  - [a-zA-Z0-9_] will match any letter or digit or ‘_’
- + matches 1 or more repetitions of preceding RE

Regular Expression

```
147    Hashtag = "#[a-zA-Z0-9_]+"
```

- will match strings that:
  - start with a ‘#’
  - follow with one or more letters/digits/‘_’

Regular Expression

```
147    Hashtag = "#[a-zA-Z0-9_]+"
```

```
>>> import re
>>> Hashtag = "#[a-zA-Z0-9_]+"
>>> hashtagpattern = re.compile(Hashtag)
>>> hashtagpattern.findall("So that's what #StarWars")
['#StarWars']
```

Regular Expression

```
Hearts = "(?:<+/?3+)+"
```

- will match strings that:
  - start with one or more ‘<‘
  - then maybe a ‘/’
  - then one or more ‘3’
  - and maybe repetitions of the above

Regular Expression

```
Hearts = "(?:<+/?3+)+"
```

- ‘+’ matches 1 or more repetitions of the preceding RE
  - ‘<+’ matches ‘<’, ‘<<’, ‘<<<’ …
  - ‘3+’ matches ‘3’, ‘33’, ‘333’ …
- ‘?’ matches 0 or 1 repetitions of the preceding RE
  - ‘/?’ matches ‘/’ or nothing (so handles ‘</3’)
- (?: …) is a non-capturing version of (…)
- (…) matches whatever RE is inside the parentheses

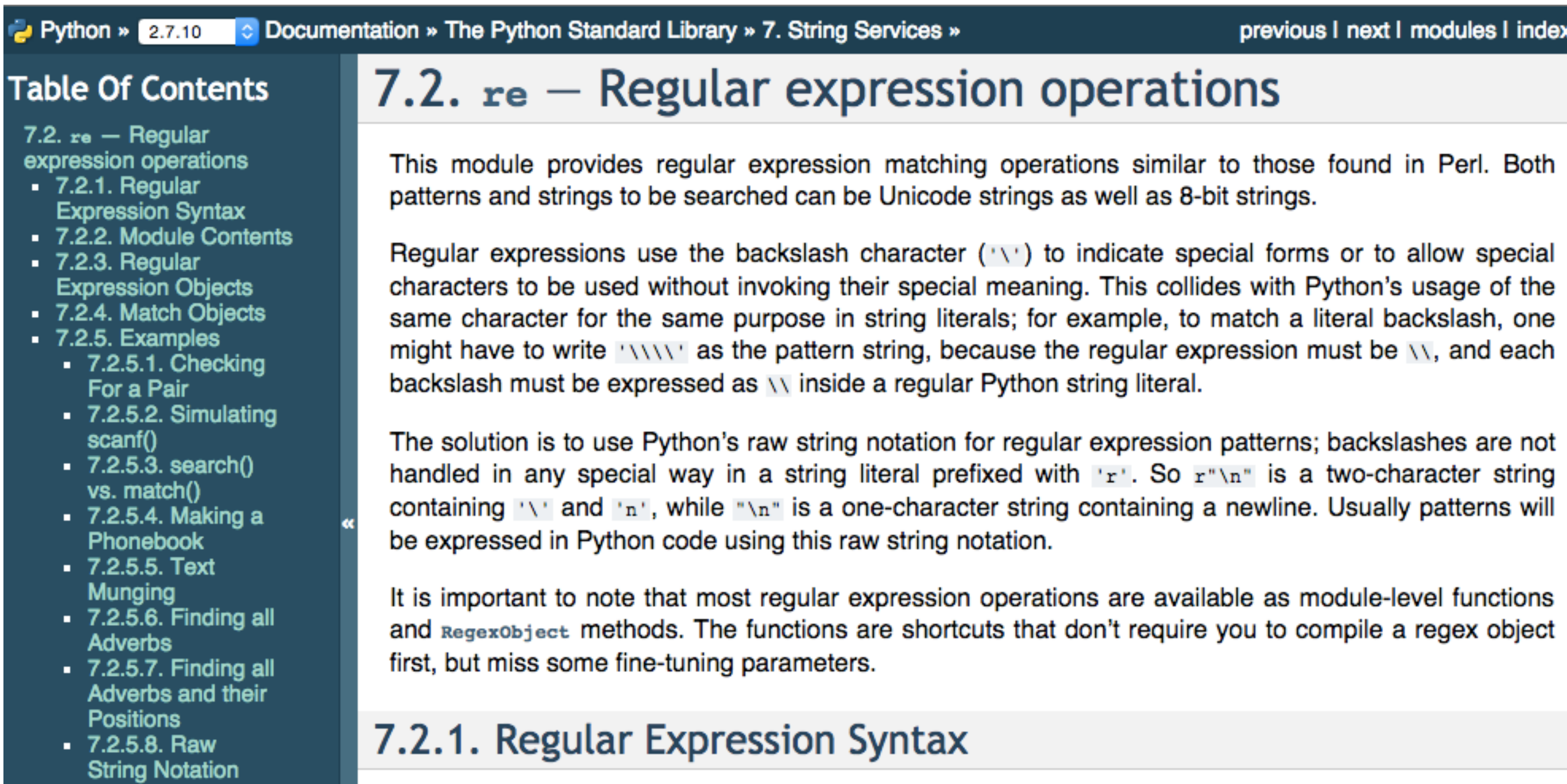
Regular Expression

```
Hearts = "(?:<+/?3+)+"
```

```
>>> import re
>>> Hearts = "(?:<+/?3+)+"
>>> heartspattern = re.compile(Hearts)
>>> heartspattern.findall("I <3 u <3<333333")
['<3', '<3<333333']
>>> heartspattern.findall("sooo sad </3")
['</3']
```

Regular Expression

- learn more (https://docs.python.org/2/library/re.html)



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7.2. `re` — Regular expression operations

This module provides regular expression matching operations similar to those found in Perl. Both patterns and strings to be searched can be Unicode strings as well as 8-bit strings.

Regular expressions use the backslash character (`'\'`) to indicate special forms or to allow special characters to be used without invoking their special meaning. This collides with Python's usage of the same character for the same purpose in string literals; for example, to match a literal backslash, one might have to write `'\\\\'` as the pattern string, because the regular expression must be `\\`, and each backslash must be expressed as `\\` inside a regular Python string literal.

The solution is to use Python's raw string notation for regular expression patterns; backslashes are not handled in any special way in a string literal prefixed with `'r'`. So `r"\n"` is a two-character string containing `'\'` and `'n'`, while `"\n"` is a one-character string containing a newline. Usually patterns will be expressed in Python code using this raw string notation.

It is important to note that most regular expression operations are available as module-level functions and `RegexObject` methods. The functions are shortcuts that don't require you to compile a regex object first, but miss some fine-tuning parameters.

7.2.1. Regular Expression Syntax

Tokenization

- for Twitter, additionally need to handle:
  - emoticons, urls, #hashtags, @mentions …

```
>>> import twokenize
>>> input = "Clowns are pretty gross tho O.o (I'm afraid of clow
ns :p) ask.fm/a/cc301167"
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['Clowns', 'are', 'pretty', 'gross', 'tho', 'O.o', '(', "I'm", '
afraid', 'of', 'clowns', ':p', ')', 'ask.fm/a/cc301167']
```

input

output

Emoticons

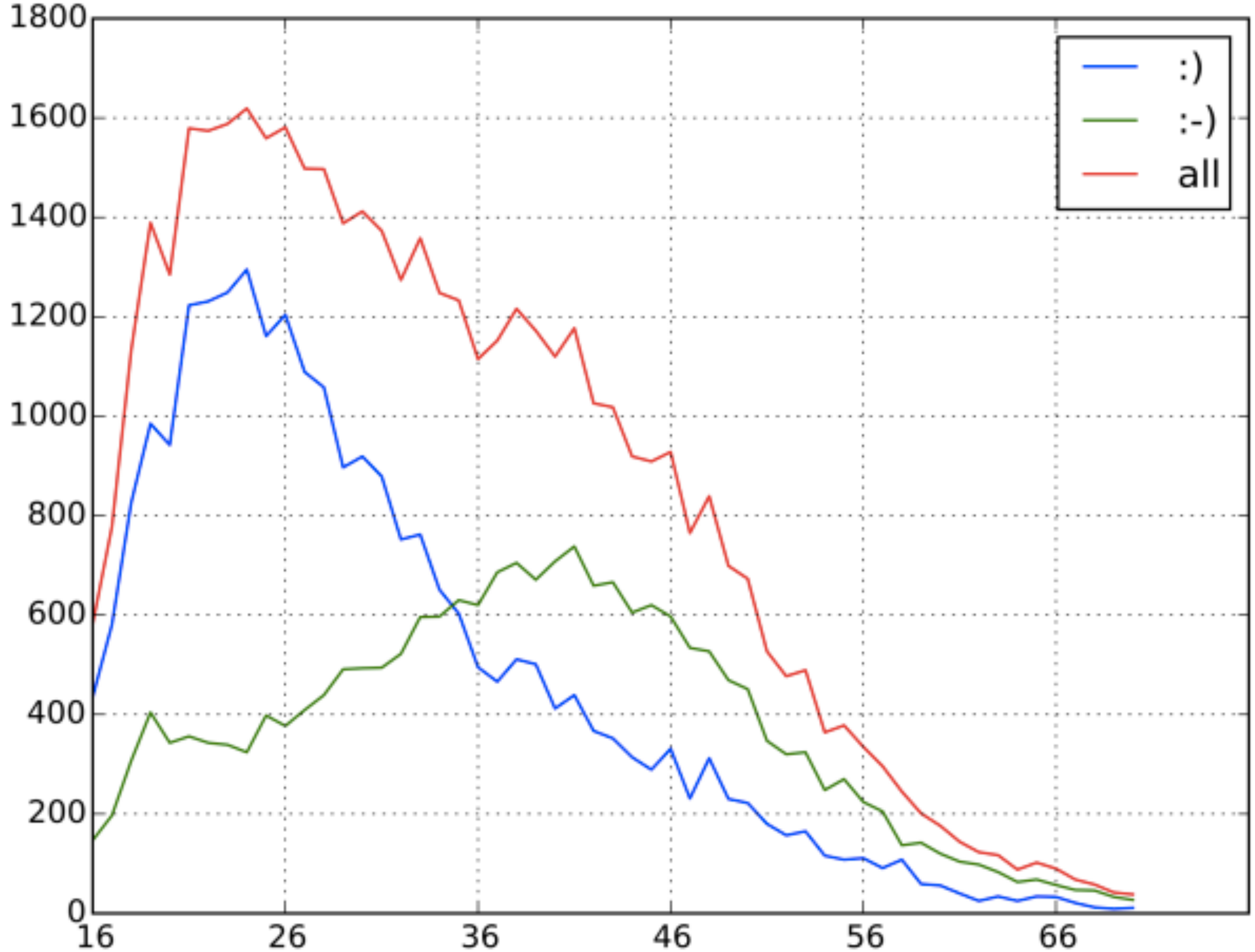


Figure 3: Usage of emoticons with and without nose by age group, aggregated over all countries

Dirk Hovy, Anders Johannsen, and Anders Søgaard.
User review sites as a resource for large-scale sociolinguistic studies. WWW, 2015

Emoticons

With respect to gender, we find that women tend to use the noseless variant significantly more than men, except for France, where the difference between genders is not statistically significant at the chosen level.

country	AGE Spearman ρ	AGE significant	GENDER significant
Denmark	0.89	yes	yes
France	0.63	yes	no
Germany	0.83	yes	yes
UK	0.83	yes	yes
US	0.82	yes	yes

Dirk Hovy, Anders Johannsen, and Anders Søgaard.
User review sites as a resource for large-scale sociolinguistic studies. WWW, 2015

Tokenization

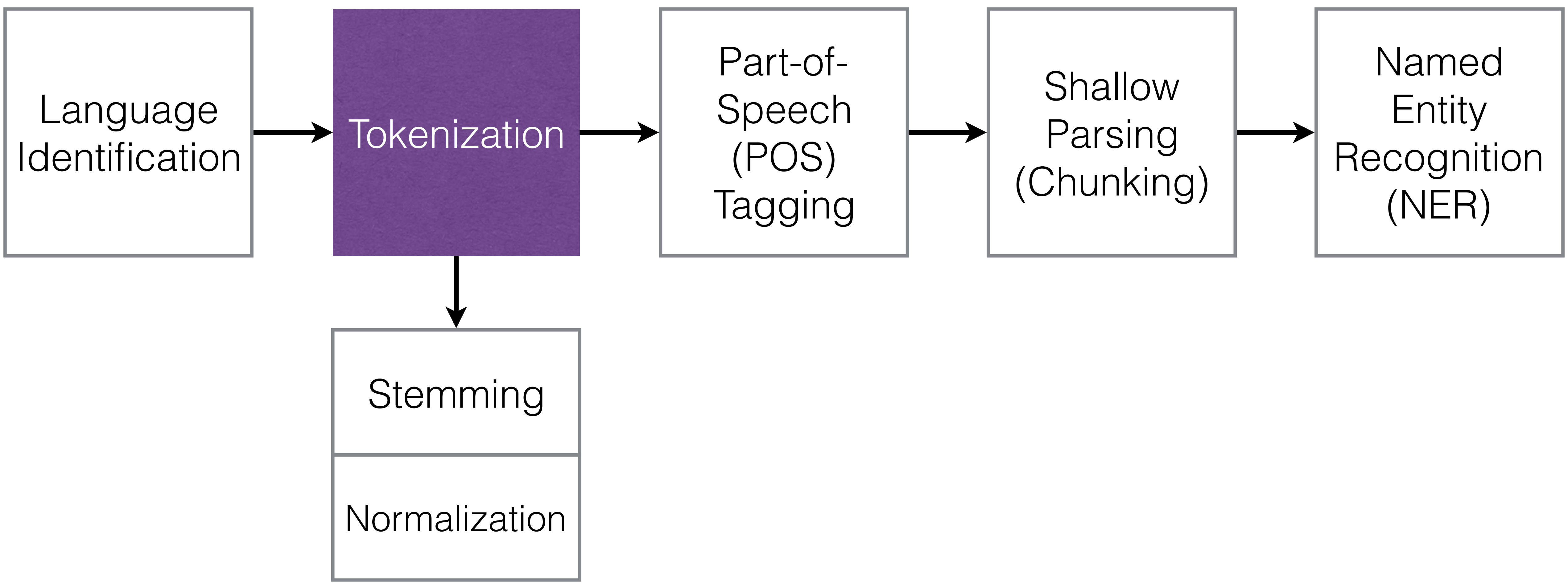
- language dependent

下雨天留客天留我不留	Unpunctuated Chinese sentence
下雨、天留客。天留、我不留！	*It is raining, the god would like the guest to stay. Although the god wants you to stay, I do not!*
下雨天、留客天。留我不？留！	*The rainy day, the staying day. Would you like me to stay? Sure!*

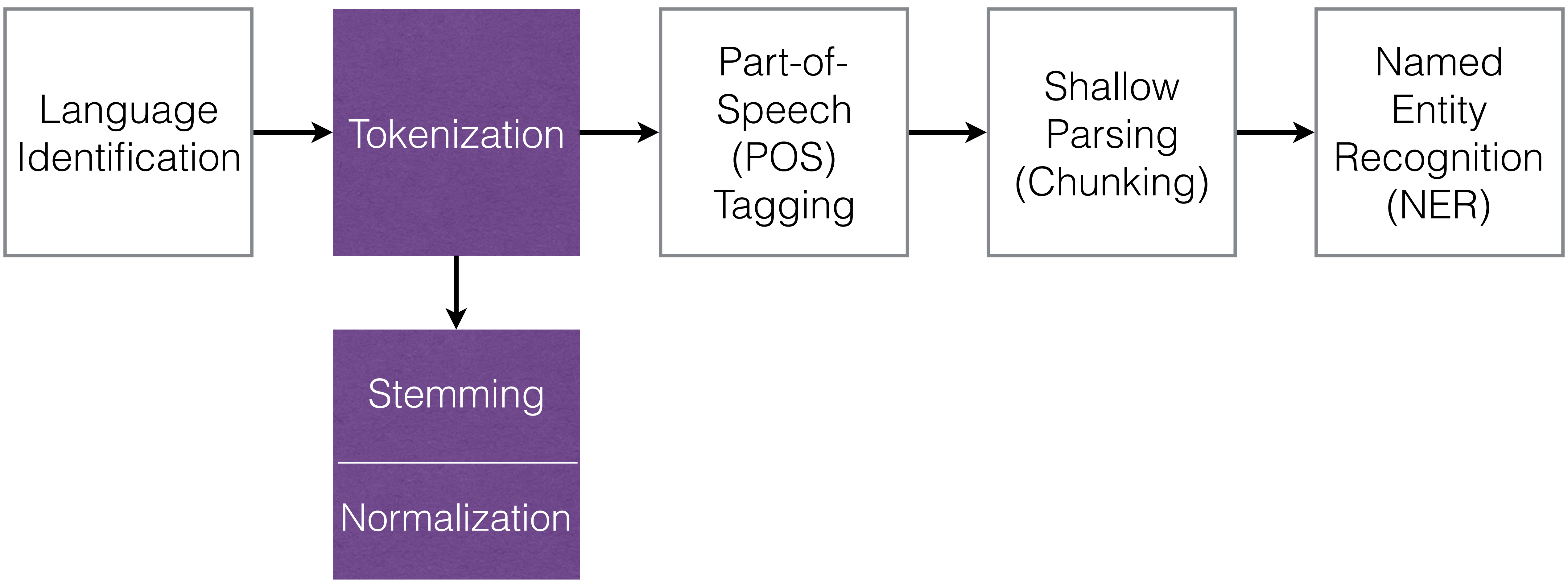
我喜欢新西兰花	Unsegmented Chinese sentence
我　喜欢　新西兰　花	*I like New Zealand flowers*
我　喜欢　新　西兰花	*I like fresh broccoli*

Source: http://what-when-how.com

NLP Pipeline



NLP Pipeline



Stemming

- reduce inflected words to their word stem, base or root form (not necessarily the morphological root)
- studied since the 1960s

```
>>> from nltk.stem.porter import PorterStemmer
>>> stemmer = PorterStemmer()
>>> stemmer.stem('automate')
'autom'
>>> stemmer.stem('automates')
'autom'
>>> stemmer.stem('automation')
'autom'
```

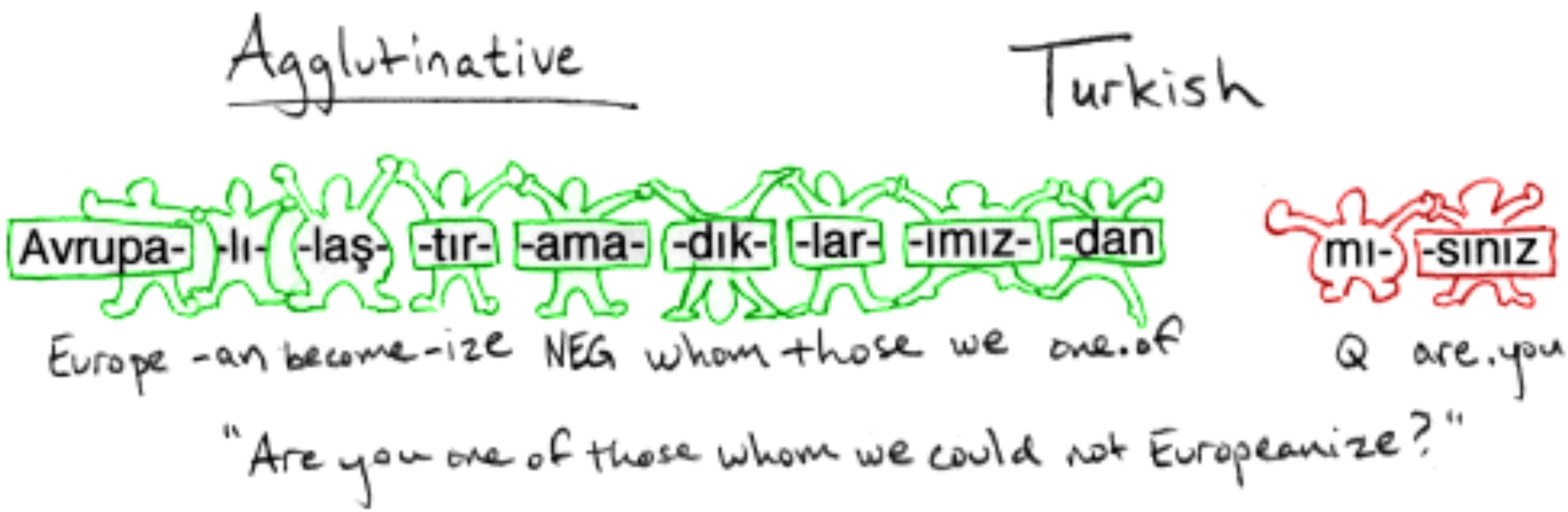
Stemming

- different steamers: Porter, Snowball, Lancaster …
- WordNet's built-in lemmatized (dictionary-based)

```
>>> from nltk.stem import WordNetLemmatizer
>>> wordnet_lemmatizer = WordNetLemmatizer()
>>> wordnet_lemmatizer.lemmatize('leaves', pos='n')
'leaf'
>>> wordnet_lemmatizer.lemmatize('leaves', pos='v')
'leave'
```

Stemming

- language dependent



Source: All Things Linguistic

Text Normalization

- convert non-standard words to standard

Original tweet

@USER, **r u cuming 2** MidCorner **dis** Sunday?

Normalized tweet

@USER, **are you coming to** MidCorner **this** Sunday?

Original tweet

Still have to get up early **2mr thou** so **Gn**

Normalized tweet

Still have to get up early **tomorrow though** so **Good night**

Source: Tim Baldwin, Marie de Marneffe, Han Bo, Young-Bum Kim, Alan Ritter, Wei Xu
Shared Tasks of the 2015 Workshop on Noisy User-generated Text:
Twitter Lexical Normalization and Named Entity Recognition

Text Normalization

- types of non-standard words in 449 English tweets:

Category	Ratio	Example
letter&numer	2.36%	b4 → before
letter	72.44%	shuld → should
number substitution	2.76%	4 → for
slang	12.20	lol → laugh out loud
other	10.24%	sucha → such a

most non-standard words are morphophonemic “errors”

Source: Bo Han and Timothy Baldwin
“Lexical normalisation of short text messages: Makn sens a #twitter” ACL 2011

A Normalization Lexicon

- automatically derived from Twitter data + dictionary

costumess	costumes
nywhere	anywhere
sandwhich	sandwich
aleksander	alexander
juns	jun
showi	showing
washinq	washing
jscript	script
fundin	funding
itxted	fitted
cheeeap	cheap
fawesome	awesome
untalented	talented

<u>Performance</u>

Precision = 0.847

Recall = 0.630

F1-Score = 0.723

Source: Bo Han, Paul Cook and Timothy Baldwin
"Automatically Constructing a Normalisation Dictionary for Microblogs" EMNLP-CoNLL 2012

Phrase-level Normalization

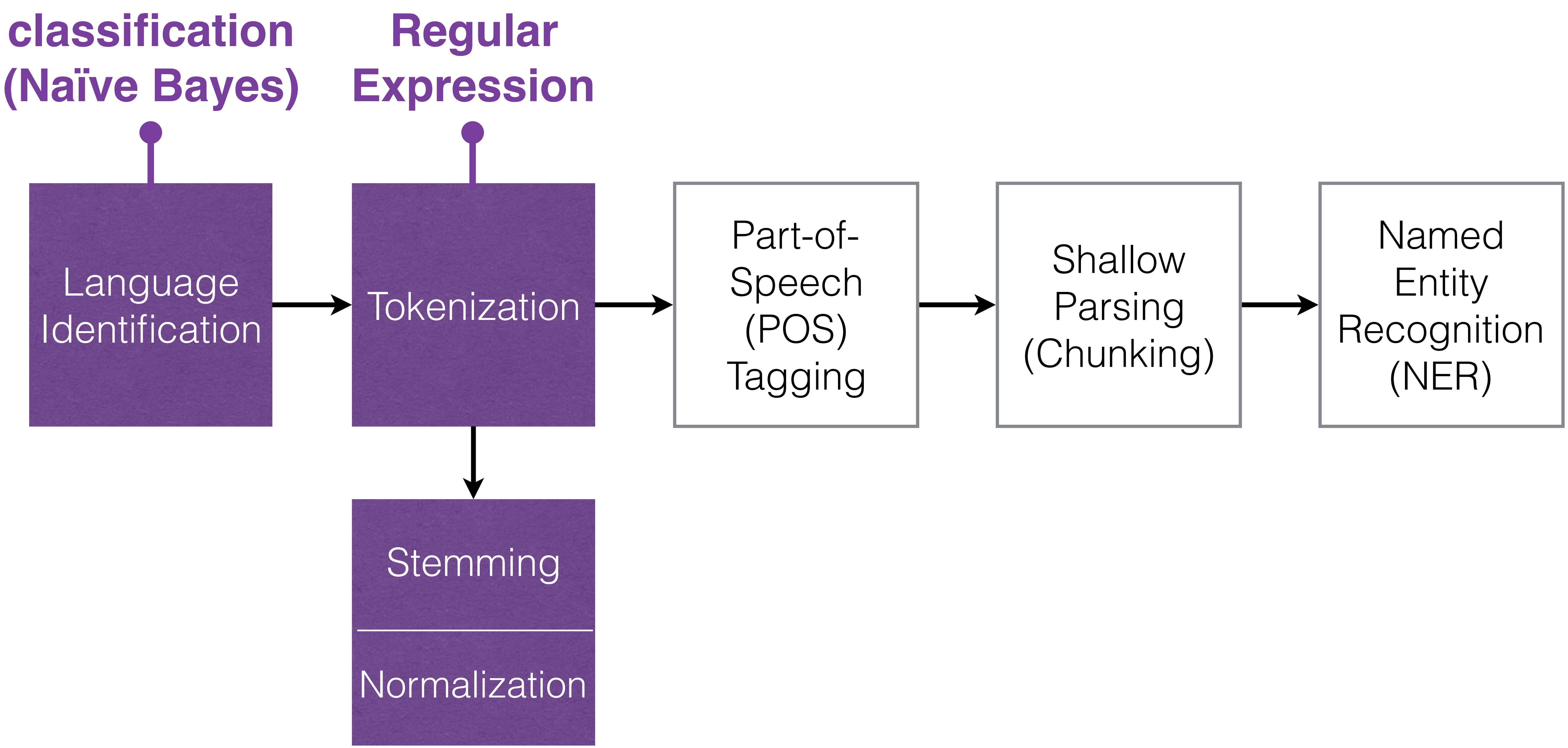
- word-level normalization is insufficient for many cases:

in-vocabulary words

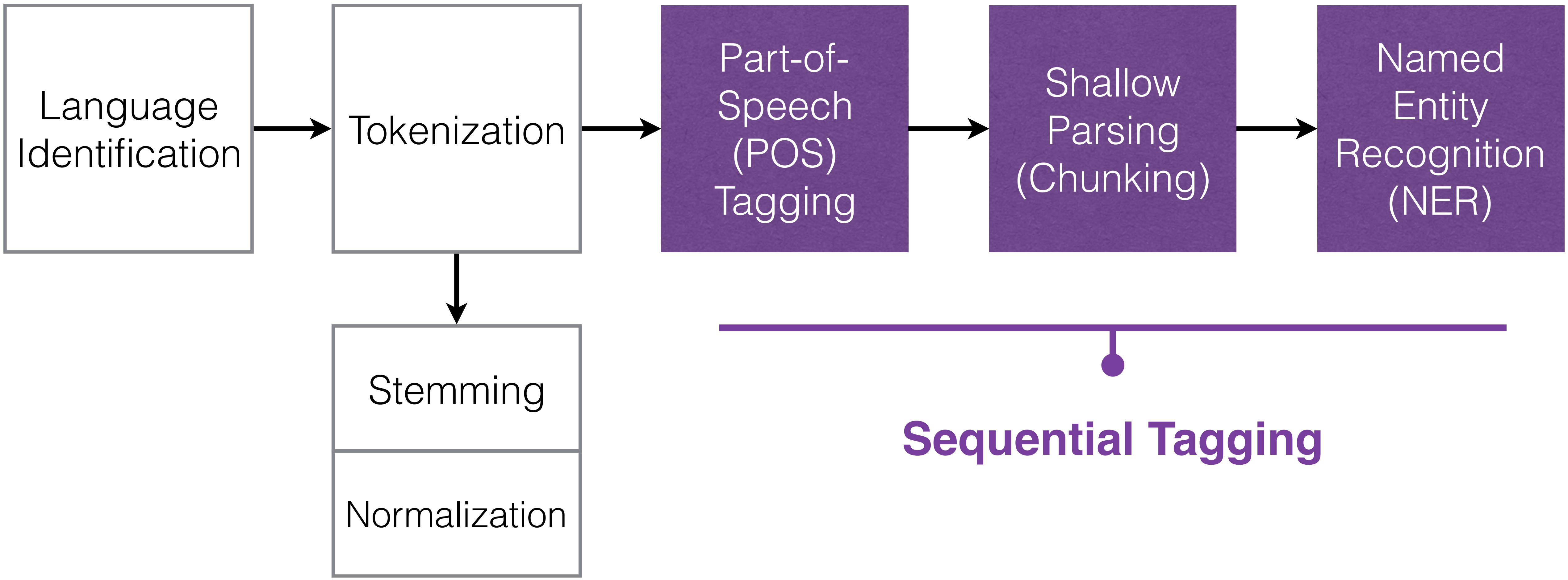
Category	Example
1-to-many	everytime → every time
incorrect IVs	can’t want for → can’t wait for
grammar	I’m going a movie → I’m going to a movie
ambiguities	4 → 4 / 4th / for / four

Source: Wei Xu, Alan Ritter, Ralph Grishman
“Gathering and Generating Paraphrases from Twitter with Application to Normalization” BUCC 2013

NLP Pipeline (summary so far)



NLP Pipeline (next)



Part-of-Speech (POS) Tagging

Cant	MD
wait	VB
for	IN
the	DT
ravens	NNP
game	NN
tomorrow	NN
...	:
go	VB
ray	NNP
rice	NNP
!!!!!!!	.

Penn Treebank POS Tags

1.	CC	Coordinating conjunction
2.	CD	Cardinal number
3.	DT	Determiner
4.	EX	Existential *there*
5.	FW	Foreign word
6.	IN	Preposition/subordinating conjunction
7.	JJ	Adjective
8.	JJR	Adjective, comparative
9.	JJS	Adjective, superlative
10.	LS	List item marker
11.	MD	Modal
12.	NN	Noun, singular or mass
13.	NNS	Noun, plural
14.	NNP	Proper noun, singular
15.	NNPS	Proper noun, plural
16.	PDT	Predeterminer
17.	POS	Possessive ending
18.	PRP	Personal pronoun
19.	PP$	Possessive pronoun
20.	RB	Adverb
21.	RBR	Adverb, comparative
22.	RBS	Adverb, superlative
23.	RP	Particle
24.	SYM	Symbol (mathematical or scientific)
25.	TO	*to*
26.	UH	Interjection
27.	VB	Verb, base form
28.	VBD	Verb, past tense
29.	VBG	Verb, gerund/present participle
30.	VBN	Verb, past participle
31.	VBP	Verb, non-3rd ps. sing. present
32.	VBZ	Verb, 3rd ps. sing. present
33.	WDT	*wh*-determiner
34.	WP	*wh*-pronoun
35.	WP$	Possessive *wh*-pronoun
36.	WRB	*wh*-adverb
37.	#	Pound sign
38.	$	Dollar sign
39.	.	Sentence-final punctuation
40.	,	Comma
41.	:	Colon, semi-colon
42.	(	Left bracket character
43.	)	Right bracket character
44.	"	Straight double quote
45.	‘	Left open single quote
46.	“	Left open double quote
47.	’	Right close single quote
48.	”	Right close double quote

Part-of-Speech (POS) Tagging

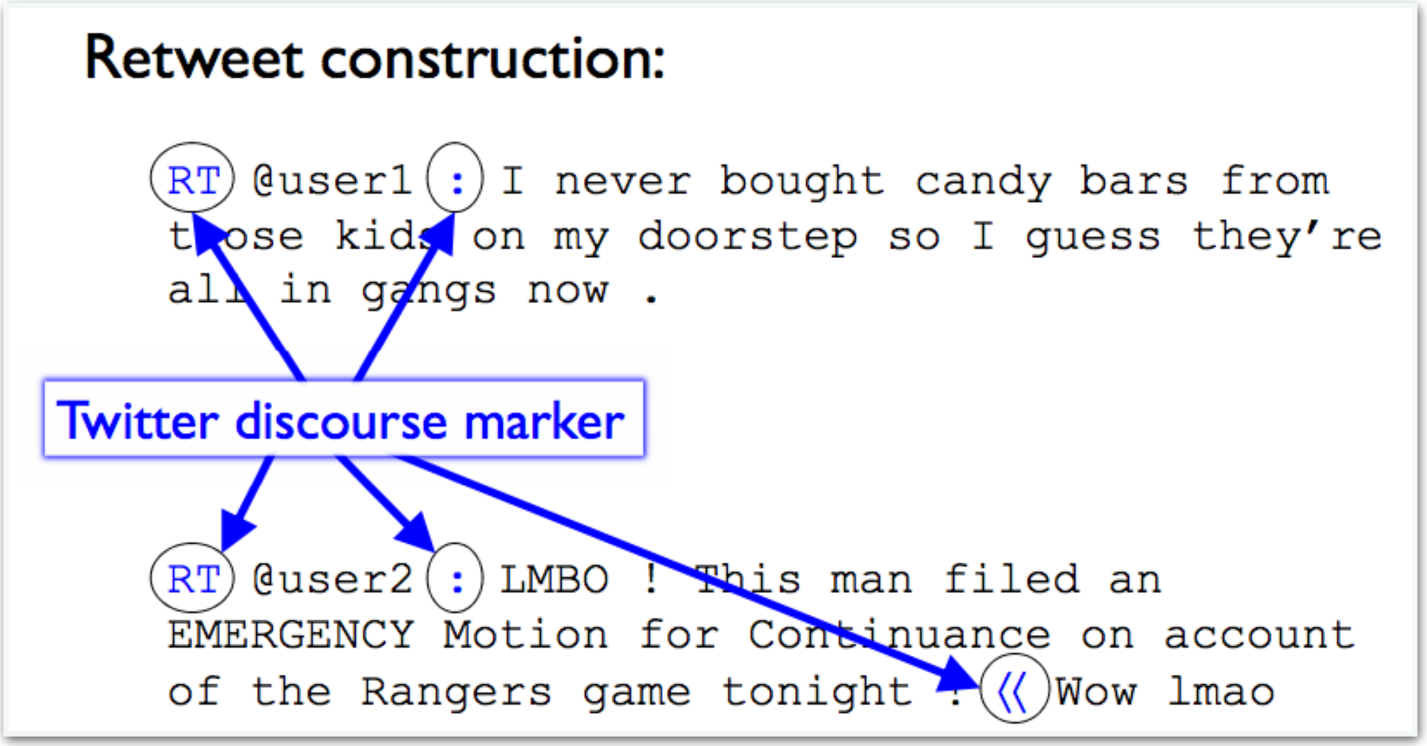
- Words often have more than one POS:
  - The back door = JJ
  - On my back = NN
  - Win the voters back = RB
  - Promised to back the bill = VB

- POS tagging problem is to determine the POS tag for a particular instance of a word.

Source: adapted from Chris Manning

Twitter-specific Tags

- #hashtag
- @metion
- url
- email address
- emoticon
- discourse marker
- symbols
- …



Source: Gimpel et al.
"Part-of-Speech Tagging for Twitter : Annotation, Features, and Experiments" ACL 2011

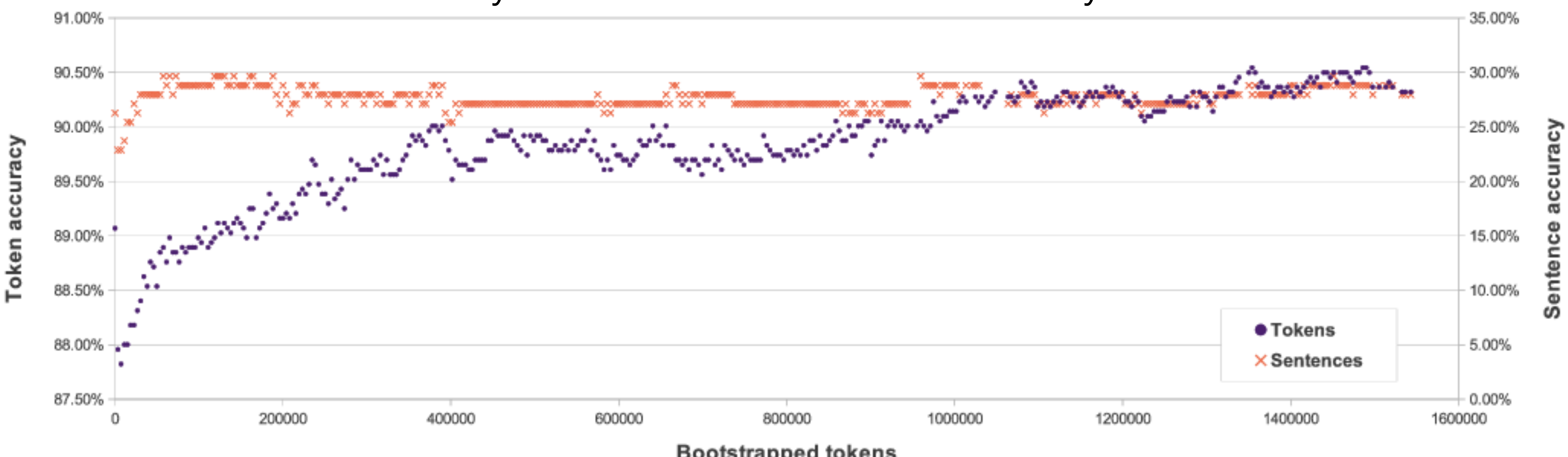
Notable Twitter POS Taggers

- Gimpel et al., 2011
- Ritter et al., 2011
- Derczynski et al, 2013
- Owoputi et al. 2013

(97% on news text)

State-of-the-art:

Token Accuracy: ~ 88%   Sentence Accuracy ~20%



Source: Derczynski, Ritter, Clark, Bontcheva
"Twitter Part-of-Speech Tagging for All: Overcoming Sparse and Noisy Data" RANLP 2013

Chunking

Cant	VP
wait	
for	PP
the	NP
ravens	
game	
tomorrow	NP
...	
go	VP
ray	NP
rice	
!!!!!!!	

Chunking

- recovering phrases constructed by the part-of-speech tags
- a.k.a shallow (partial) parsing:
  - full parsing is expensive, and is not very robust
  - partial parsing can be much faster, more robust, yet sufficient for many applications
  - useful as input (features) for named entity recognition or full parser

Named Entity Recognition(NER)

Cant	
wait	
for	
the	
ravens	ORG
game	
tomorrow	
...	
go	
ray	PER
rice	PER
!!!!!!!	.

ORG: organization

PER: person

LOC: location

NER: Basic Classes

Cant	
wait	
for	
the	
ravens	ORG
game	
tomorrow	
...	
go	
ray	PER
rice	
!!!!!!!	.

ORG: organization

PER: person

LOC: location

NER: Rich Classes

Source: Strauss, Toma, Ritter, de Marneffe, Xu
Results of the WNUT16 Named Entity Recognition Shared Task (WNUT@COLING 2016)

NER: Genre Differences

	News	Tweets
PER	Politicians, business leaders, journalists, celebrities	Sportsmen, actors, TV personalities, celebrities, names of friends
LOC	Countries, cities, rivers, and other places related to current affairs	Restaurants, bars, local landmarks/areas, cities, rarely countries
ORG	Public and private companies, government organisations	Bands, internet companies, sports clubs

Source: Kalina Bontcheva and Leon Derczynski
"Tutorial on Natural Language Processing for Social Media" EACL 2014

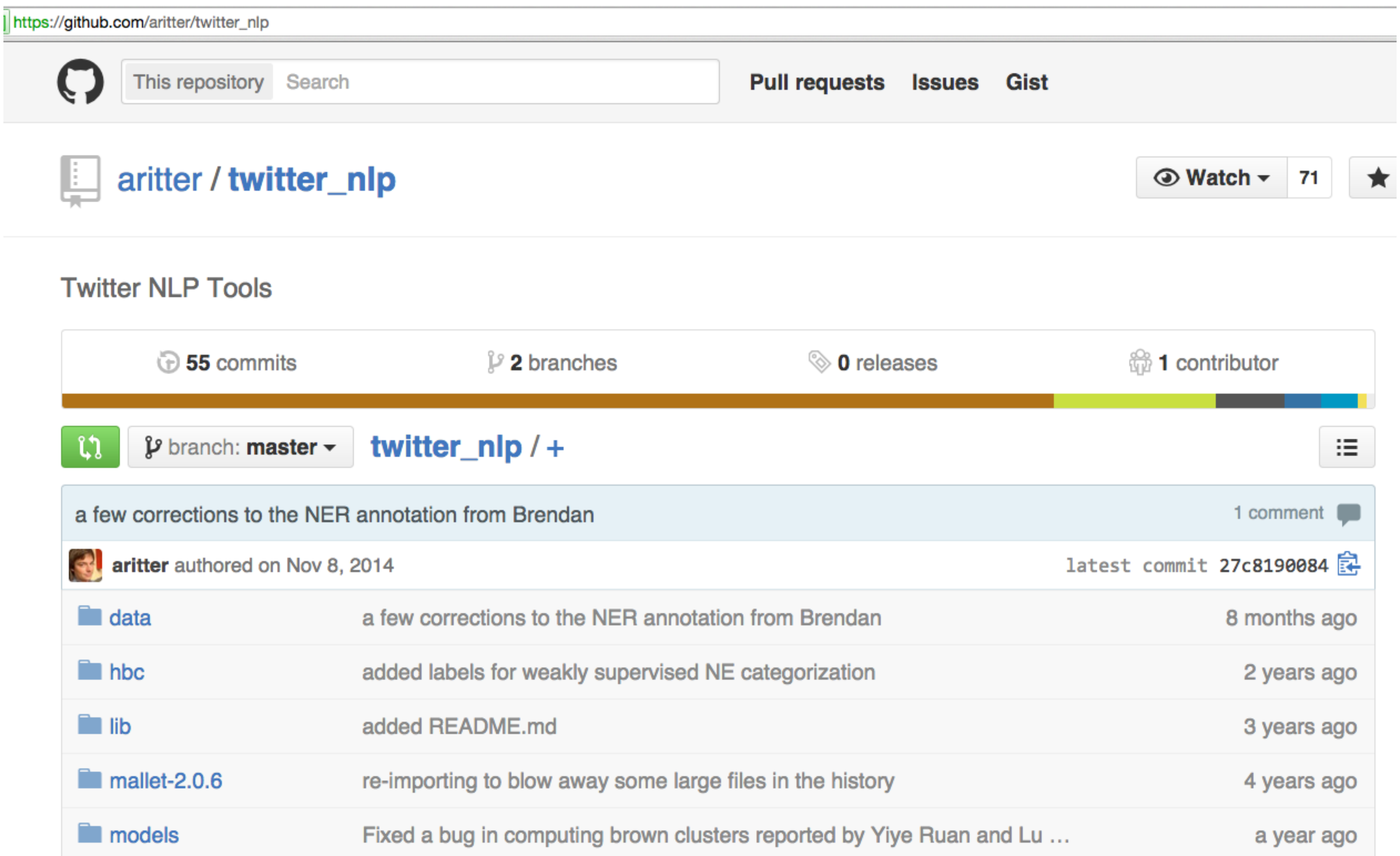
Notable Twitter NE Research

- Liu et al., 2011
- Ritter et al., 2011
- Owoputi et al. 2013
- Plank et al, 2014
- Cherry & Guo, 2015

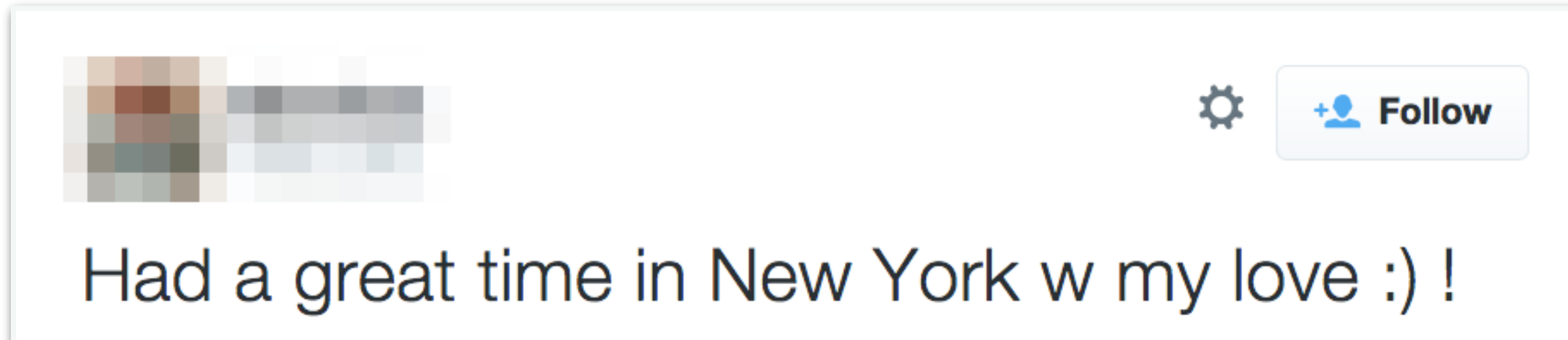
System	P	R	F_1
COTRAIN-NER (10 types)	0.55	0.33	0.41
T-NER(10 types)	0.65	0.42	**0.51**
COTRAIN-NER (PLO)	0.57	0.42	0.49
T-NER(PLO)	0.73	0.49	**0.59**
Stanford NER (PLO)	0.30	0.27	0.29

Table 12: Performance at predicting both segmentation and classification. Systems labeled with PLO are evaluated on the 3 MUC types *PERSON*, *LOCATION*, *ORGANIZATION*.

Tool: twitter_nlp



Tool: twitter_nlp




```
xuwei@proteus100[twitter_nlp]$ export TWITTER_NLP=./
xuwei@proteus100[twitter_nlp]$
xuwei@proteus100[twitter_nlp]$ echo "Had a great time in New York w my
love :) ! " | python python/ner/extractEntities2.py

Had/O a/O great/O time/O in/O New/B-ENTITY York/I-ENTITY w/O my/O love/
O :)/O !/O
Average time per tweet = 3.04769945145s
xuwei@proteus100[twitter_nlp]$
xuwei@proteus100[twitter_nlp]$ echo "Had a great time in New York w my
love :) ! " | python python/ner/extractEntities2.py --pos --chunk

Had/O/VBD/B-VP a/O/DT/B-NP great/O/JJ/I-NP time/O/NN/I-NP in/O/IN/B-PP
New/B-ENTITY/NNP/B-NP York/I-ENTITY/NNP/I-NP w/O/IN/B-PP my/O/PRP$/B-NP
 love/O/NN/I-NP :)/O/UH/B-INTJ !/O/./I-INTJ
Average time per tweet = 5.49846148491s
xuwei@proteus100[twitter_nlp]$ _
```

IO tag encoding

Cant	VP		
wait			
for	PP		
the	NP		
ravens			
game			
tomorrow	NP		
…			
go	VP		
ray	NP		
rice			
!!!!!!!			

IO tag encoding

Cant	VP	VP
wait		VP
for	PP	PP
the	NP	NP
ravens		NP
game		NP
tomorrow	NP	NP
…		O
go	VP	VP
ray	NP	NP
rice		NP
!!!!!!!		O

IO tag encoding

Cant	VP	VP	B-VP
wait		VP	I-VP
for	PP	PP	B-PP
the		NP	B-NP
ravens	NP	NP	I-NP
game		NP	I-NP
tomorrow	NP	NP	B-NP
…		O	O
go	VP	VP	B-VP
ray	NP	NP	B-VP
rice		NP	I-VP
!!!!!!!		O	O

I: Inside

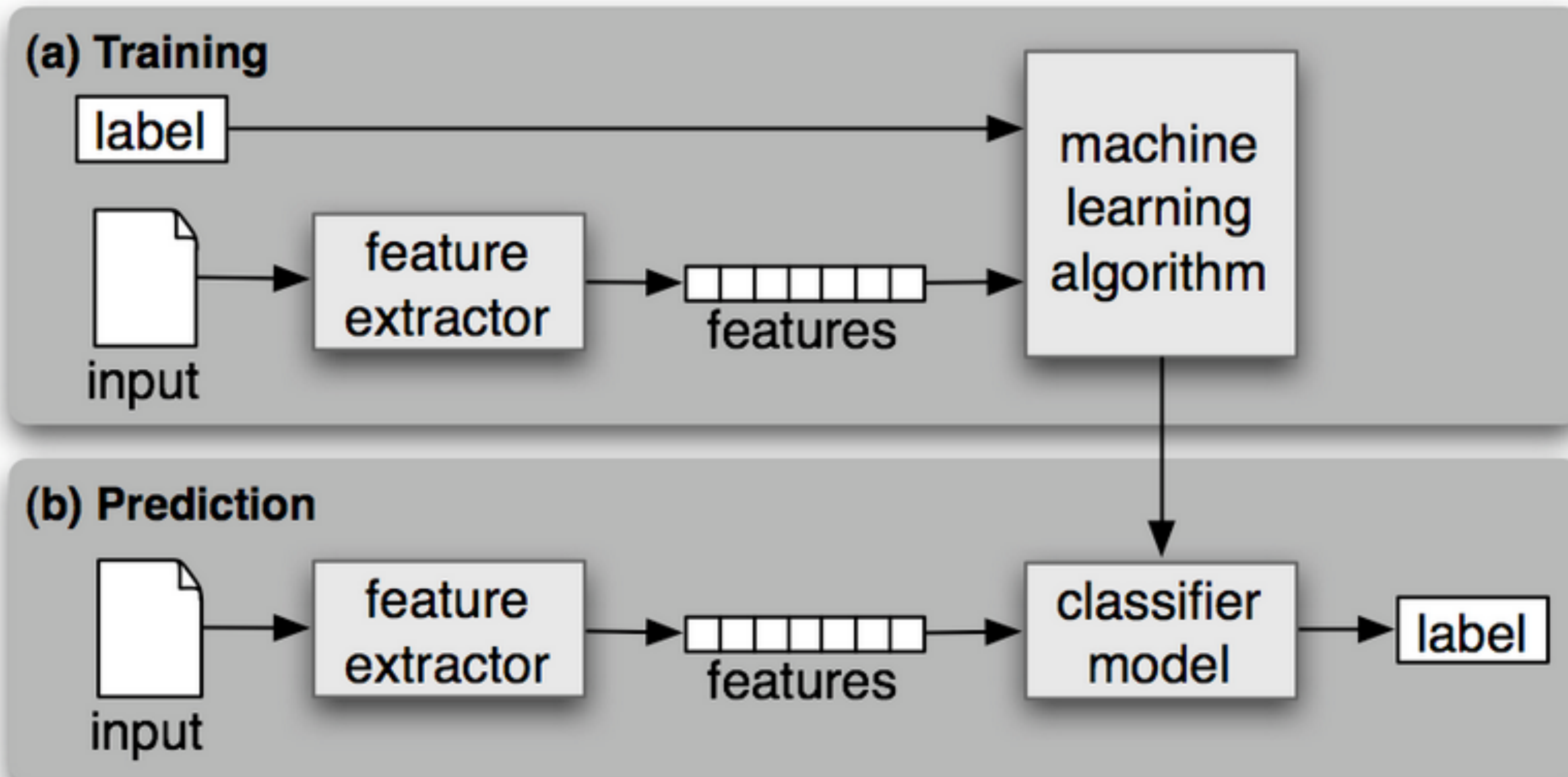
O: outside

B: Begin

BIO allows separation of adjacent chunks/entities

[Recap] Classification Method:

Supervised Machine Learning



Source: NLTK Book

Classification Method:

Supervised Machine Learning

- Naïve Bayes
- Logistic Regression
- Support Vector Machines (SVM)
- …
- Hidden Markov Model (HMM)
- Conditional Random Fields (CRF)
- …

sequential models

Classification Method:

Sequential Supervised Learning

- Input:
  - rather than just individual examples ***(w_1 = the, c_1 = DT)***
  - a training set consists of ***m*** sequences of labeled examples ***(x_1, y_1), … , (x_m, y_m)***

    x_1 = <the back door> and y_1= <DT JJ NN>

- Output:
  - a learned classifier to predict label sequences ***$\gamma : x \rightarrow y$***

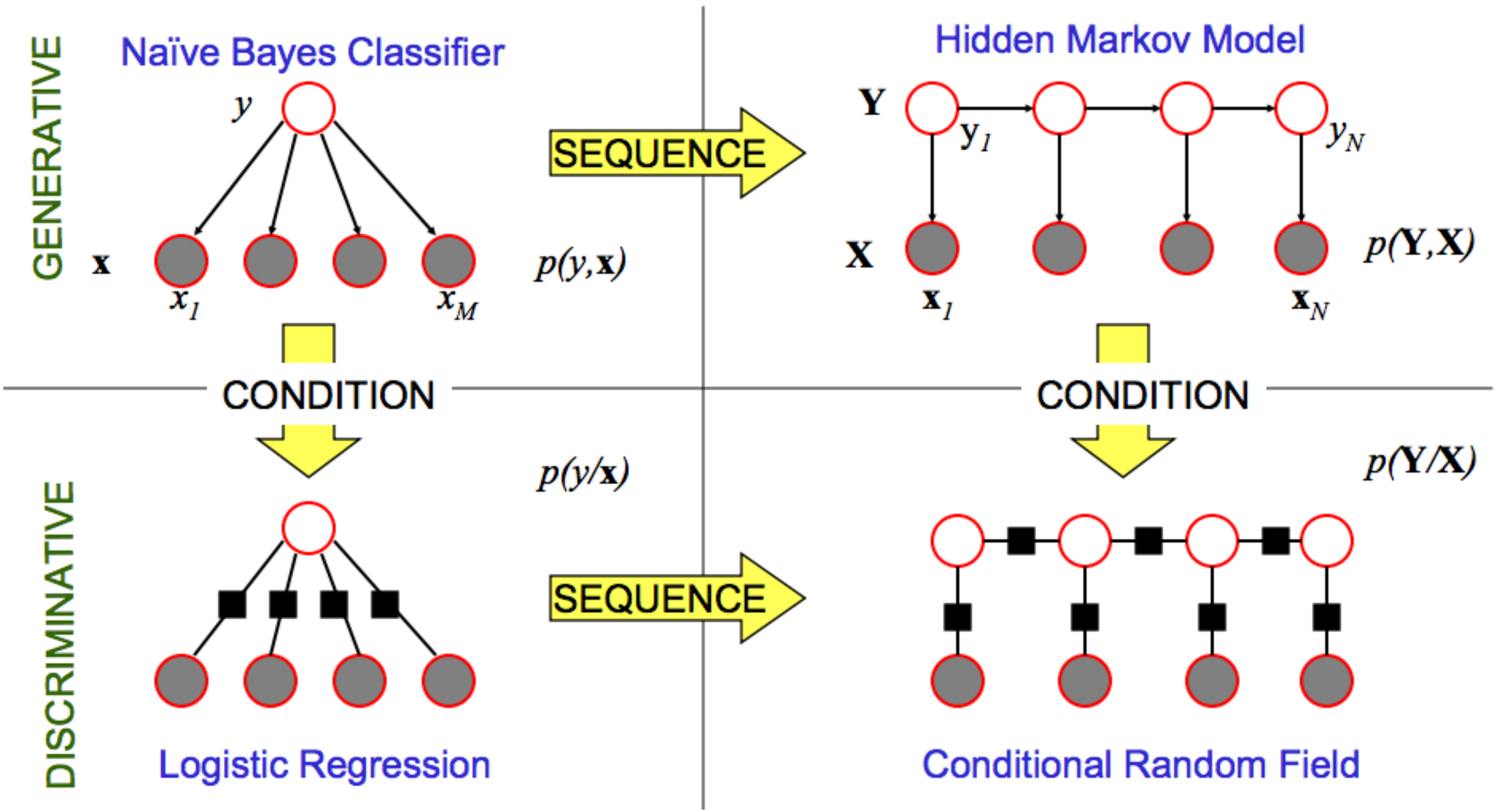
Features for Sequential Tagging

- Words:
  - current words
  - previous/next word(s) — context
- Other linguistic information:
  - word substrings
  - word shapes
  - POS tags
- Contextual Labels
  - previous (and perhaps next) labels

word shapes

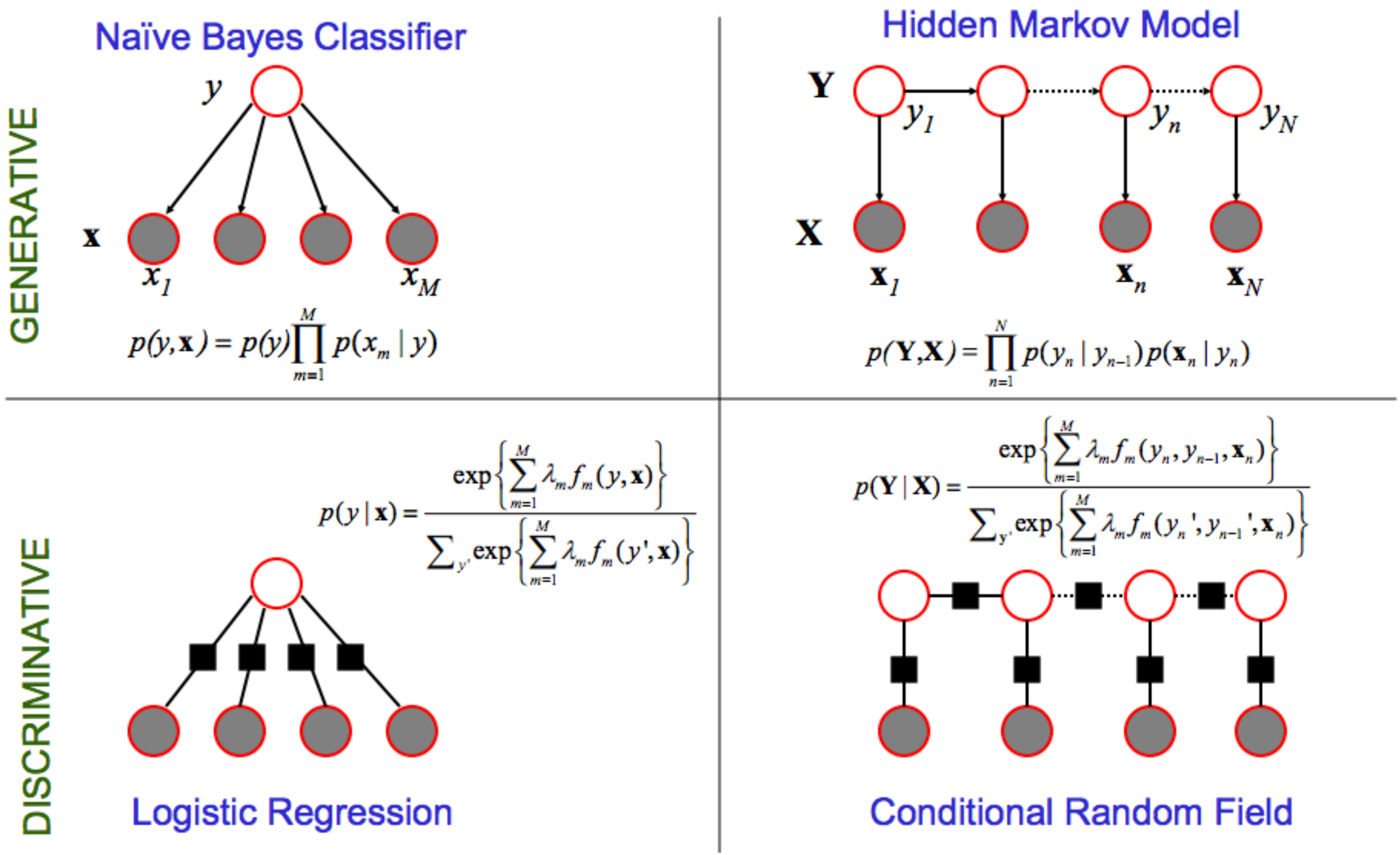
Varicella-zoster	Xx-xxx
mRNA	xXXX
CPA1	XXXd

Probabilistic Graphical Models



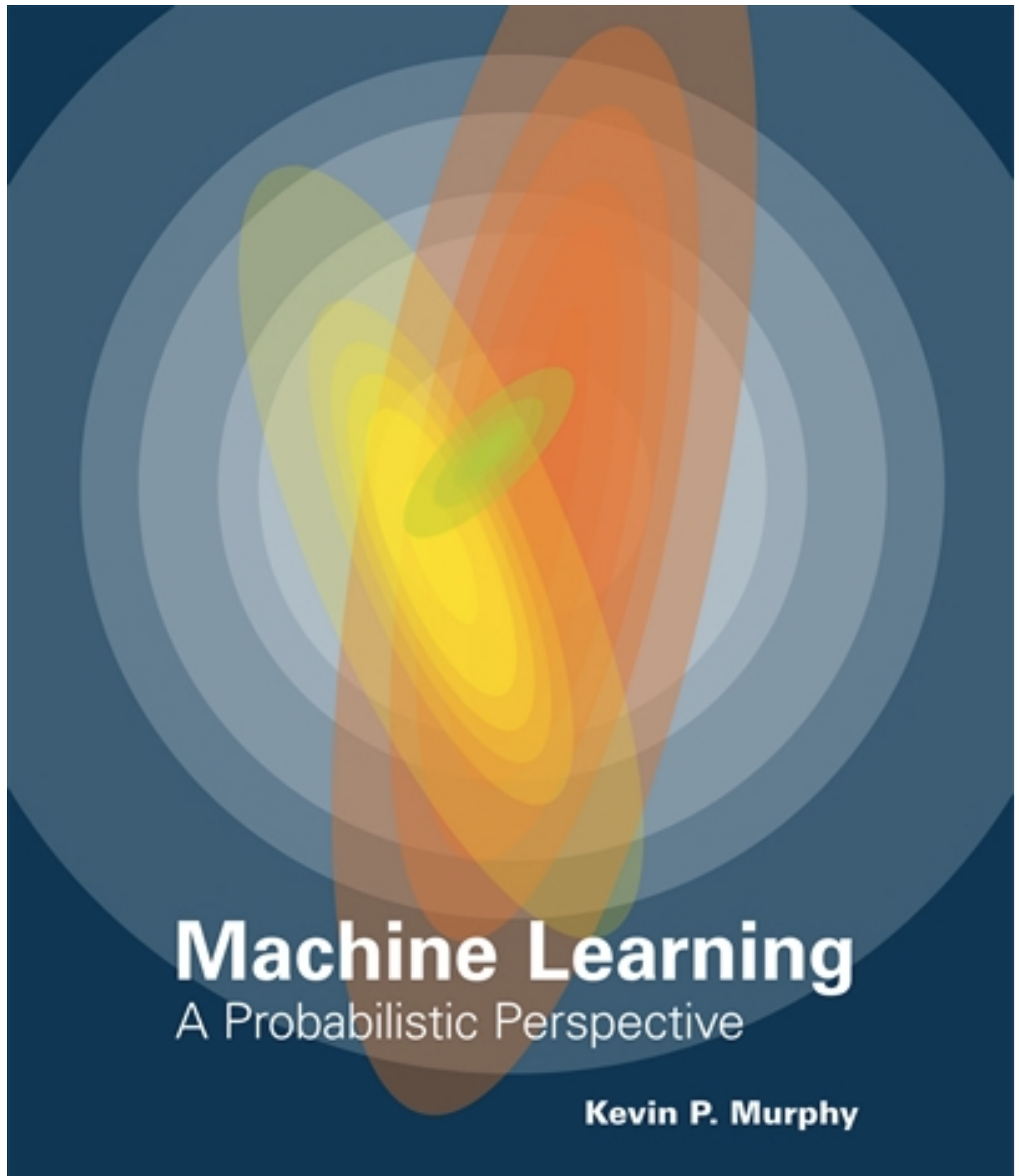
Source: Andrew McCallum, Sargur Srihari

Probabilistic Graphical Models

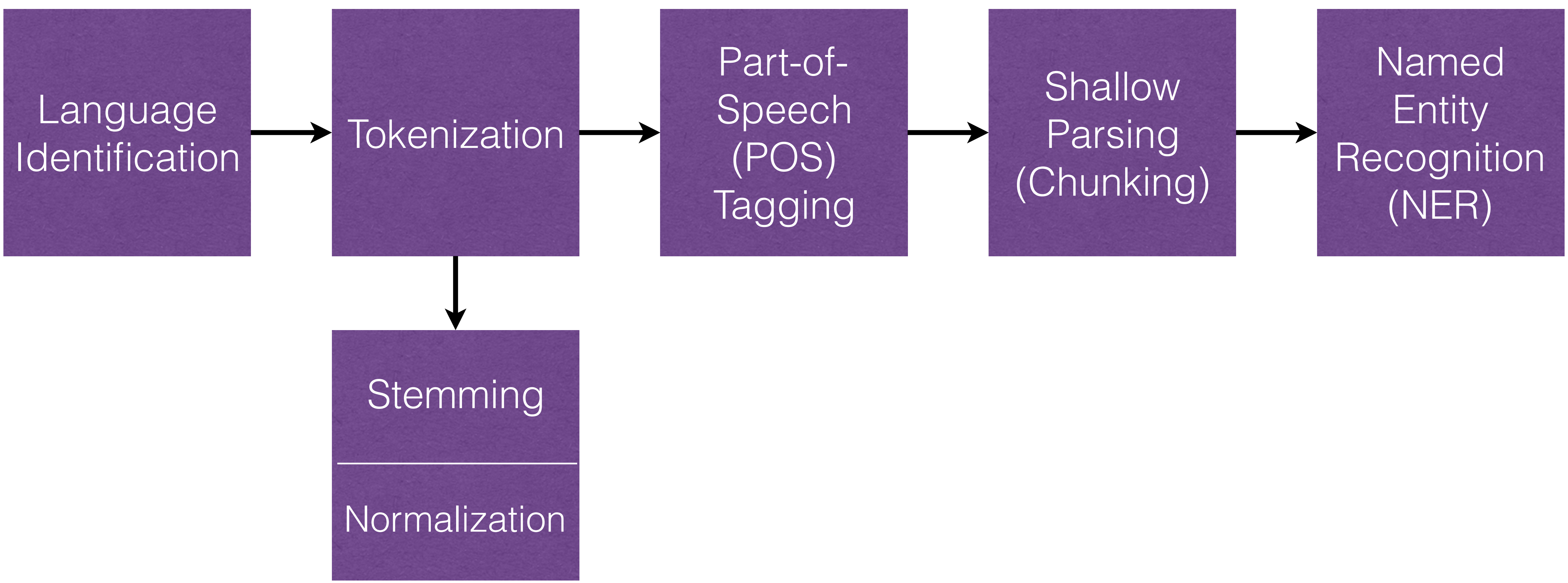


Source: Andrew McCallum, Sargur Srihari

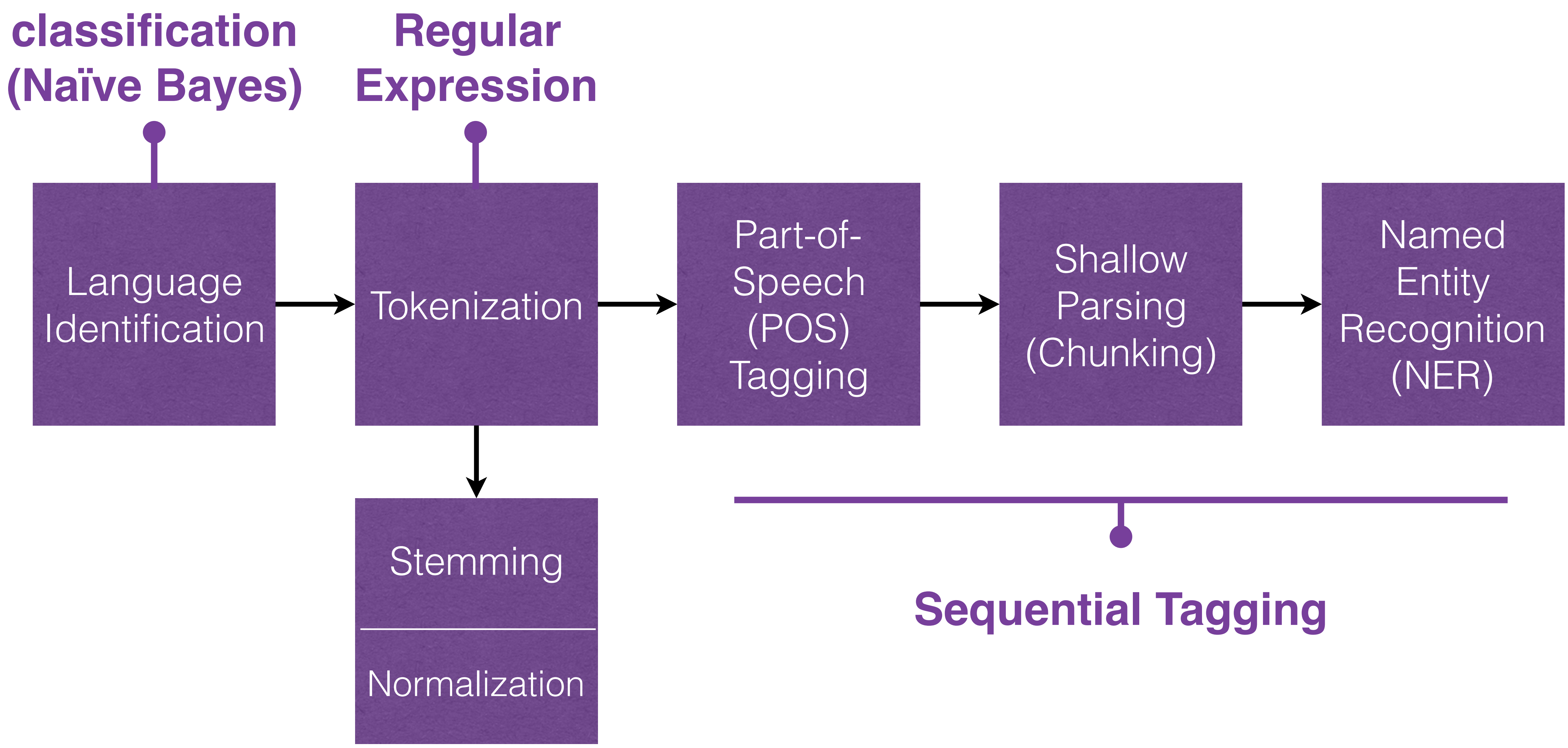
Probabilistic Graphical Models



Summary


Language Identification
Tokenization
Part-of-Speech (POS) Tagging
Shallow Parsing (Chunking)
Named Entity Recognition (NER)
Stemming
Normalization

Summary



classification
(Naïve Bayes)
Regular
Expression
Language
Identification
Tokenization
Part-of-
Speech
(POS)
Tagging
Shallow
Parsing
(Chunking)
Named
Entity
Recognition
(NER)
Stemming
Normalization
Sequential Tagging

(Next Class)
Challenges in Twitter

2m 2ma 2mar 2mara 2maro 2marrow 2mor 2mora 2moro 2morow 2morr 2morro 2morrow 2moz 2mr 2mro 2mrrw 2mrw 2mw tmmrw tmo tmoro tmorrow tmoz tmr tmro tmrow tmrrow tmrrw tmrw tmrww tmw tomaro tomarow tomarro tomarrow tomm tommarow tommarrow tommoro tommorow tommorrow tommorw tommrow tomo tomolo tomoro tomorow tomorro tomorrw tomoz tomrw tomz

Thank You!

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www.cis.upenn.edu/~xwe/

Course Website: socialmedia-class.org