Marina Sedinkina
- Folien von Desislava Zhekova -

CIS, LMU
marina.sedinkina@campus.lmu.de

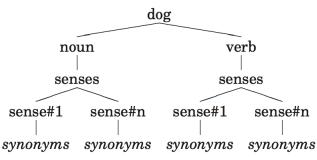
January 9, 2018



Outline

- WordNet
- 2 Lesk Algorithm
- Preprocessing

- WordNet is a large lexical database of English (semantically-oriented)
- Nouns, verbs, adjectives and adverbs are grouped into sets of synonyms (synsets)
- Basis for grouping the words is their meanings.



English WordNet online: http://wordnet.princeton.edu



http://globalwordnet.org/

Wordnets in the World

Language	Resource name	Developer(s)	Contact	Online Browsing	License	Other Resources
Afrikaans	Afrikaans WordNet ₽	North-West University, South Africa @	Gerhard van Huyssteen Ané Bekker	NO	OPEN FOR ACADEMIC USE ₫	
Albanian	AlbaNet ₽	Vlora University, Vlora, Albania &	Ervin Ruci ⊚	YES ₽	OPEN (GPL) 🗗	
Arabic	Arabic WordNet ₽	Arabic WordNet ₽	Horacio Rodriguez ⊚	NO	OPEN	
Multilingual (Arabic/ English/ Malaysian/ Indonesian/ Finnish/ Hebrew/ Japanese/ Persian/ Thail/ French)	Open Multilingual Wordnet &	Linguistics and Multilingual Studies, NTU &	Francis Bond &	NO	OPEN	

- NLTK includes the English WordNet (155,287 words and 117,659 synonym sets)
- NLTK graphical WordNet browser: nltk.app.wordnet()

Current Word:	Next Word:	Search
Help Shutdown		

noun

- S: (noun) wordnet (any of the machine-readable lexical databases modeled after the Princeton WordNet)
- S; (noun) WordNet, Princeton WordNet (a machine-readable lexical database organized by meanings; developed at Princeton University)



Consider the sentence in (1). If we replace the word motorcar in (1) with automobile, to get (2), the meaning of the sentence stays pretty much the same:

- Benz is credited with the invention of the motorcar.
- Benz is credited with the invention of the automobile.

⇒ Motorcar and automobile are synonyms.

Let's explore these words with the help of WordNet

```
1 >>> from nltk.corpus import wordnet as wn
2 >>> wn.synsets("motorcar")
3 [Synset("car.n.01")]
```

- Motorcar has one meaning car.n.01 (=the first noun sense of car).
- The entity car.n.01 is called a synset, or "synonym set", a collection of synonymous words (or "lemmas"):

Synsets are described with a **gloss** (= definition) and some example sentences

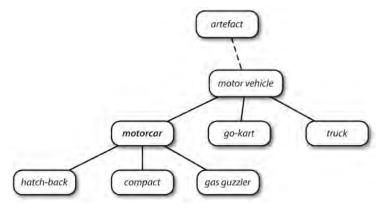
Unlike the words automobile and motorcar, which are unambiguous and have one synset, the word car is ambiguous, having five synsets:

```
>>> wn.synsets("car")
  [Synset("car.n.01"), Synset("car.n.02"), Synset("car.
      n.03"), Synset("car.n.04"), Synset("cable car.n.
      01")]
  >>> for synset in wn.synsets("car"):
   ... print synset.lemma names()
  ["car", "auto", "automobile", "machine", "motorcar"]
  ["car", "railcar", "railway car", "railroad car"]
8 ["car", "gondola"]
9 ["car", "elevator_car"]
  ["cable car", "car"]
```

The WordNet Hierarchy

Hypernyms and hyponyms ("is-a relation")

- motor vehicle is a hypernym of motorcar
- ambulance is a hyponym of motorcar



The WordNet Hierarchy

```
>>> motorcar = wn.synset("car.n.01")
>>> types_of_motorcar = motorcar.hyponyms()
>>> types of motorcar[26]
Synset ("ambulance.n.01")
>>> sorted ([lemma.name() for synset in types of motorcar
    for lemma in synset.lemmas()])
["Model_T", "S.U.V.", "SUV", "Stanley_Steamer", "ambulance"
    , "beach waggon", "beach wagon", "bus", "cab", "
    compact", "compact_car", "convertible", "coupe", "
    cruiser", "electric", "electric automobile", "
    electric car", "estate car", "gas guzzler", "hack", "
    hardtop", "hatchback", "heap", "horseless_carriage", "
    hot-rod", "hot rod", "jalopy", "jeep", "landrover", "
    limo", "limousine", "loaner", "minicar", "minivan", "
    pace_car", "patrol_car", "phaeton", "police_car", "
    police cruiser", "prowl car", "race car", "racer", "
    racing car" ... 1
```

The WordNet Hierarchy

```
>>> motorcar.hypernyms()
[Synset("motor vehicle.n.01")]
>>> paths = motorcar.hypernym paths()
>>> len(paths)
2
>>> [synset.name() for synset in paths[0]]
["entity.n.01", "physical entity.n.01", "object.n.01"
    , "whole.n.02", "artifact.n.01", "instrumentality
    .n.03", "container.n.01", "wheeled vehicle.n.01",
     "self-propelled vehicle.n.01", "motor vehicle.n.
   01", "car.n.01"]
>>> [synset.name() for synset in paths[1]]
["entity.n.01", "physical entity.n.01", "object.n.01"
    , "whole.n.02", "artifact.n.01", "instrumentality
    .n.03", "conveyance.n.03", "vehicle.n.01", "
    wheeled vehicle.n.01", "self-propelled vehicle.n.
   01". "motor vehicle.n.01". "car.n.01"1
```

Meronyms and holonyms

- branch is a meronym (part meronym) of tree
- heartwood is a meronym (substance meronym) of tree
- forest is a holonym (member holonym) of tree

```
1 >>> wn.synset("tree.n.01").part_meronyms()
2 [Synset("burl.n.02"), Synset("crown.n.07"), Synset("stump.n.01"), Synset("trunk.n.01"), Synset("limb.n.02")]
3 >>> wn.synset("tree.n.01").substance_meronyms()
4 [Synset("heartwood.n.01"), Synset("sapwood.n.01")]
5 >>> wn.synset("tree.n.01").member_holonyms()
6 [Synset("forest.n.01")]
```

Relationships between verbs:

- the act of walking involves the act of stepping, so walking entails stepping
- some verbs have multiple entailments

```
1 >>> wn.synset("walk.v.01").entailments()
2 [Synset("step.v.01")]
3 >>> wn.synset("eat.v.01").entailments()
4 [Synset("swallow.v.01"), Synset("chew.v.01")]
5 >>> wn.synset("tease.v.03").entailments()
6 [Synset("arouse.v.07"), Synset("disappoint.v.01")]
```

Some lexical relationships can express antonymy:

You can see the lexical relations, and the other methods defined on a synset, using dir(). For example:

```
import nltk
from nltk.corpus import wordnet as wn
print(wn.synsets("motorcar"))
# [Synset( car.n.01 )]
print(dir(wn.synsets("motorcar")[0]))
# [ ... common_hypernyms , definition , entailments , examples
     , frame ids , hypernym distances , hypernym paths ,
    hypernyms , hyponyms , instance_hypernyms ,
    instance hyponyms, jcn similarity, lch similarity,
    lemma_names , lemmas , lexname , lin_similarity ,
    lowest_common_hypernyms , max_depth , member_holonyms ,
    member_meronyms , min_depth , name , offset ,
    part_holonyms , part_meronyms , path_similarity , pos ,
    region domains, res similarity, root hypernyms,
    shortest path distance, similar tos, substance holonyms,
      substance_meronyms , topic_domains , tree , unicode_repr
        usage domains . verb groups . wup similarity l
```

Two synsets linked to the same root may have several hypernyms in common. If two synsets share a very specific hypernym (low down in the hypernym hierarchy), they must be closely related.

```
>>> right = wn.synset("right whale.n.01")
 >>> orca = wn.synset("orca.n.01")
 >>> minke = wn.synset("minke whale.n.01")
 >>> tortoise = wn.synset("tortoise.n.01")
5 >>> novel = wn.synset("novel.n.01")
  >>> right.lowest common hypernyms(minke)
  [Synset("baleen whale.n.01")]
  >>> right.lowest common hypernyms(orca)
  [Synset("whale.n.02")]
  >>> right.lowest common hypernyms(tortoise)
  [Synset("vertebrate.n.01")]
  >>> right.lowest common hypernyms(novel)
  [Synset("entity.n.01")]
```

We can quantify this concept of generality by looking up the depth of each synset:

```
1 >>> wn.synset("baleen_whale.n.01").min_depth()
2 14
3 >>> wn.synset("whale.n.02").min_depth()
4 13
5 >>> wn.synset("vertebrate.n.01").min_depth()
6 8
7 >>> wn.synset("entity.n.01").min_depth()
8 0
```

Similarity measures have been defined over the collection of WordNet synsets that incorporate this insight

- path_similarity() assigns a score in the range 0-1 based on the shortest path that connects the concepts in the hypernym hierarchy
- -1 is returned in those cases where a path cannot be found
- Comparing a synset with itself will return 1

```
1 >>> right.path_similarity(minke)
2 0.25
3 >>> right.path_similarity(orca)
4 0.16666666666666666
5 >>> right.path_similarity(tortoise)
6 0.076923076923076927
7 >>> right.path_similarity(novel)
8 0.043478260869565216
```

Similarity between nouns

- ("car", "automobile")
- synsets1("car") = [synset₁₁, synset₁₂, synset₁₃]
 nltk.corpus.wordnet.synsets("car")
- synsets2("automobile") = [synset₂₁, synset₂₂, synset₂₃]
 nltk.corpus.wordnet.synsets("automobile")
- consider all combinations of synsets formed by the synsets of the words in the word pair ("car", "automobile")
 [(synset₁₁, synset₂₁), (synset₁₁, synset₂₂), (synset₁₁, synset₂₃),...]
- determine score of each combination e.g.:
 synset₁₁.path_similarity(synset₂₁)
- determine the maximum score → indicator of similarity

???

Can you think of an NLP application for which semantic similarity will be helpful?



???

Can you think of an NLP application for which semantic similarity will be helpful?

Suggestion

Coreference Resolution:

I saw an orca. The whale was huge.

Polysemy

- The polysemy of a word is the number of senses it has.
- The noun dog has 7 senses in WordNet:

```
from nltk.corpus import wordnet as wn
num_senses=len(wn.synsets("dog","n"))

print(num_senses)
#prints 7
```

 We can also compute the average polysemy of nouns, verbs, adjectives and adverbs according to WordNet.

Polysemy of nouns

We can also compute the average polysemy of nouns.

Fetch all lemmas in WordNet that have a given POS:
 nltk.corpus.wordnet.all_lemma_names (POS)

```
from nltk.corpus import wordnet as wn
all_lemmas=set(wn.all_lemma_names("n"))
print(len(all_lemmas))
#prints 117798
```

Determine meanings of each lemma:
 nltk.corpus.wordnet.synsets(lemma, pos) returns
 list of senses to a given lemma and POS, e.g. for "car"

```
1 from nltk.corpus import wordnet as wn
2 meanings=wn.synsets("car","n")
3 print(meanings)
4 #[Synset( car.n.01 ), Synset( car.n.02 ), ... )]
```

 Sum up the number of meanings of each lemma (restricted to nouns) and devide this by the total number of lemmas

Lesk Similarity

???

Compute the average polysemy of nouns 'car', 'automobile', 'motorcar'

average polysemy

```
average_polysemy = ???
```

Lesk Algorithm

- classical algorithm for Word Sense Disambiguation (WSD) introduced by Michael E. Lesk in 1986
- idea: word's dictionary definitions are likely to be good indicators for the senses they define

Sense Definition

s1: tree a tree of the olive family

s2: burned stuff the solid residue left

when combustible material is burned

Table: Two senses of ash

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Score = number of (stemmed) words that are shared by sense definition and context

Scores Context
s1 s2 This cigar burns slowly and
creates a stiff ash



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Scores	Context			
s1 <mark>s2</mark>	This cigar burns slowly and			
0 1	creates a stiff ash			



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s1 s2 The ash is one of the last trees
??? to come into leaf



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Table: Two senses of ash

Score = number of (stemmed) words that are shared by sense definition and context

Scores	Context			
s1 s2	The ash is one of the last trees			
10	to come into leaf			



Lesk Algorithm

The definitions for "bank" are:

```
>>> from nltk.corpus import wsordnet as wn
     >>> for ss in wn.svnsets( bank ):
 3
             print(ss. ss.definition())
 4
 5
     Synset( bank.n.01 ) sloping land (especially the slope beside a body of water)
 6
     Synset( depository financial_institution.n.01 ) a financial institution that accepts
           deposits and channels the money into lending activities
     Synset( bank.n.03 ) a long ridge or pile
 8
     Synset( bank.n.04 ) an arrangement of similar objects in a row or in tiers
     Synset( bank.n.05 ) a supply or stock held in reserve for future use (especially in
           emergencies)
10
     Synset( bank.n.06 ) the funds held by a gambling house or the dealer in some gambling
           games
11
     Synset( bank.n.07 ) a slope in the turn of a road or track; the outside is higher than
           the inside in order to reduce the effects of centrifugal force
12
     Synset( savings bank.n.02 ) a container (usually with a slot in the top) for keeping
           money at home
13
     Synset( bank.n.09 ) a building in which the business of banking transacted
14
     Synset( bank.n.10 ) a flight maneuver; aircraft tips laterally about its longitudinal
            axis (especially in turning)
15
     Synset( bank.v.01 ) tip laterally
16
     Synset( bank.v.02 ) enclose with a bank
     Synset( bank.v.03 ) do business with a bank or keep an account at a bank
```

Check implementation via

http://www.nltk.org/_modules/nltk/wsd.html

```
def lesk (context sentence, ambiguous word, pos=None,
       synsets=None):
      context = set(context sentence)
       if synsets is None:
4
           synsets = wordnet.synsets(ambiguous_word)
       if pos:
           synsets = [ss for ss in synsets if str(ss.pos()) ==
                pos 1
       if not synsets:
          return None
      , sense = max(
           (len(context.intersection(ss.definition().split()))
               , ss) for ss in synsets
      return sense
```

Check implementation via

http://www.nltk.org/_modules/nltk/wsd.html

```
def lesk (context sentence, ambiguous word, pos=None,
       synsets=None):
        if not synsets:
4
           return None
       inters = []
       for ss in synsets:
            defin words = ss.definition().split()
            intersec_words = context.intersection(defin words)
            len_iter = len(intersec_words)
            inters.append((len_iter,ss))
       _, sense = max(inters)
14
       return sense
```

- Information derived from a dictionary is insufficient for high quality
 Word Sense Disambiguation (WSD).
- Lesk reports accuracies between 50% and 70%.
- Optimizations: to expand each word in the context with a list of synonyms

Lesk Similarity

- The Lesk similarity of two concepts is defined as the textual overlap between the corresponding definitions, as provided by a dictionary.
- Punctuation in definitions should be eliminated, because they
 do not have a meaning. If two definitions contain punctuation, the
 score increases.
- The larger a text, the higher can its score be. It should be normalized to allow a fair comparison → devide overlap by maximum matching number

Lesk Similarity

```
def lesk_similarity(synset1, synset2):
        #TODO find tokens of wordnet definition of synset1, ignore
            punctuation
        definition words1 = ...
4
        #TODO find tokens of wordnet definition of synset2, ignore
            punctuation
        definition words2 = ...
        #TODO calculate maximum matching number (length of shortest
             definition)
        max match = ...
        #TODO find overlap in definitions, consider words occuring
            twice
        overlap = ...
14
        return overlap/max match
    print(lesk_similarity(wn.synset( car.n.01 ),wn.synset( wheel.n.01
        )))
```

Lesk Similarity

???

Find overlap in definitions, consider word occurring twice?

overlap_number

```
overlap number = ???
```

Preprocessing

Original The boy's cars are different colors.

Tokenized ["The", "boy's", "cars", "are", "different", "colors."]

Punctuation removal ["The", "boy's", "cars", "are", "different", "colors"]

Lowecased ["the", "boy's", "cars", "are", "different", "colors"]

Stemmed ["the", "boy's", "car", "are", "differ", "color"]

Lemmatized ["the", "boy's", "car", "are", "different", "color"]

Stopword removal ["boy's", "car", "different", "color"]

- Tokenization is the process of breaking raw text into its building parts: words, phrases, symbols, or other meaningful elements called tokens.
- A list of tokens is almost always the first step to any other NLP task, such as part-of-speech tagging and named entity recognition.

- token is an instance of a sequence of characters in some particular document that are grouped together as a useful semantic unit for processing
- type is the class of all tokens containing the same character sequence

- What is Token?
- Fairly trivial: chop on whitespace and throw away punctuation characters.
- Tricky cases: various uses of the apostrophe for possession and contractions?

Mrs. O'Reilly said that the girls' bags from H&M's shop in New York aren't cheap.

```
Mrs. "Mrs."; "Mrs", "."
O'Reilly "O'Reilly"; "O'", "Reilly"; "O", "'", "Reilly"; aren't "aren't"; "arent"; "are", "n't"; "aren", "t"
```

???

Tokenize manually the following sentence. How many tokens do you get?

Mrs. O'Reilly said that the girls' bags from H&M's shop in New York aren't cheap.

???

Tokenize manually the following sentence:

Mrs. O'Reilly said that the girls' bags from H&M's shop in New York aren't cheap.

Answer

NLTK returns the following 20 tokens:

```
["Mrs.", "O'Reilly", "said", "that", "the",
"girls", "'", "bags", "from", "H", "&", "M",
"'s", "shop", "in", "New", "York", "are",
"n't", "cheap", "."]
```

Most decisions need to be met depending on the language at hand. Some problematic cases for English include:

- hyphenation ex-wife, Cooper-Hofstadter, the bazinga-him-again maneuver
- internal white spaces New York, +49 89 21809719, January 1, 1995, San Francisco-Los Angeles
- apostrophe O'Reilly, aren't
- other cases H&M's

Sentence Segmentation

Tokenization can be approached at any level:

- word segmentation
- sentence segmentation
- paragraph segmentation
- other elements of the text

NLTK comes with a whole bunch of tokenization possibilities:

```
>>> from nltk import word tokenize,
   wordpunct tokenize
>>> s = "Good muffins cost $3.88 \nin New York.
   Please buy me\n two of them.\n\nThanks."
>>> word tokenize(s)
[ Good , muffins , cost , $ , 3.88 , in , New ,
     York, ., Please, buy, me, two, of,
     them , . , Thanks , . ]
>>> wordpunct tokenize(s)
[ Good , muffins , cost , $ , 3 , . , 88 , in
    , New , York , . , Please , buy , me , two
    , of , them , . , Thanks , . 1
```

NLTK comes with a whole bunch of tokenization possibilities:

NLTK comes with a whole bunch of tokenization possibilities:

```
>>> # same as s.split(\n):
2 >>> LineTokenizer(blanklines= keep ).tokenize(s)
  [ Good muffins cost $3.88, in New York. Please buy
      me, two of them., Thanks.]
 >>> # same as [I for I in s.split(\n) if I.strip()
 >>> LineTokenizer(blanklines= discard ).tokenize(s)
  [ Good muffins cost $3.88 , in New York. Please buy
      me, two of them., Thanks.]
 >>> # same as s.split(\t):
8 >>> TabTokenizer().tokenize( a\tb c\n\t d )
 [a, bc\n, d]
```

NLTK PunktSentenceTokenizer: divides a text into a list of sentences

```
>>> import nltk.data
>>> text = "Punkt knows that the periods in Mr. Smith and
    Johann S. Bach do not mark sentence boundaries. And
    sometimes sentences can start with non-capitalized
    words. i is a good variable name."
>>> sent_detector = nltk.data.load( tokenizers/punkt/
    english.pickle )
>>> print \n---\n .join(sent_detector.tokenize(text.
    strip()))
# Punkt knows that the periods in Mr. Smith and Johann S.
    Bach do not mark sentence boundaries.
# ----
# And sometimes sentences can start with non-capitalized
    words.
# -
# i is a good variable name.
```

Normalization

Once the text has been segmented into its tokens (paragraphs, sentences, words), most NLP pipelines do a number of other basic procedures for text normalization, e.g.:

- lowercasing
- stemming
- lemmatization
- stopword removal



Lowercasing

Lowercasing:

```
import nltk

string = "The boy's cars are different colors."

tokens = nltk.word_tokenize(string)

lower = [x.lower() for x in tokens]

print(" ".join(lower))

# prints

# prints

# the boy 's cars are different colors.
```

- Often, however, instead of working with all word forms, we would like to extract and work with their base forms (e.g. lemmas or stems)
- Thus with stemming and lemmatization we aim to reduce inflectional (and sometimes derivational) forms to their base forms.

Stemming: removing morphological affixes from words, leaving only the word stem.

```
import nltk
string = "The boy's cars are different colors."
tokens = nltk.word tokenize(string)
lower = [x.lower() for x in tokens]
stemmed = [stem(x) for x in lower]
print(" ".join(stemmed))
def stem(word):
    for suffix in ["ing", "ly", "ed", "ious", "ies", "ive",
         "es", "s", "ment"]:
        if word.endswith(suffix):
            return word[:-len(suffix)]
   return word
# prints
# the boy 's car are different color .
```

Stemming:

```
import nltk
  import re
4
   string = "The boy's cars are different colors."
  tokens = nltk.word tokenize(string)
  lower = [x.lower() for x in tokens]
  stemmed = [stem(x) for x in lower]
  print(" ".join(stemmed))
  def stem(word):
       regexp = r"^(.*?) (ing | ly | ed | ious | ies | ive | es | s | ment) ?$"
       stem, suffix = re.findall(regexp, word)[0]
       return stem
  # prints
  # the boy 's car are different color .
```

NLTK's stemmers:

 Porter Stemmer is the oldest stemming algorithm supported in NLTK, originally published in 1979.

```
http:
//www.tartarus.org/~martin/PorterStemmer/
```

- Lancaster Stemmer is much newer, published in 1990, and is more aggressive than the Porter stemming algorithm.
- Snowball stemmer currently supports several languages:
 Danish, Dutch, English, Finnish, French, German, Hungarian,
 Italian, Norwegian, Porter, Portuguese, Romanian, Russian,
 Spanish, Swedish.
- Snowball stemmer: slightly faster computation time than porter.



NLTK's stemmers:

```
import nltk
   string = "The boy's cars are different colors."
   tokens = nltk.word_tokenize(string)
   lower = [x.lower() for x in tokens]
   porter = nltk.PorterStemmer()
   stemmed = [porter.stem(t) for t in lower]
   print(" ".join(stemmed))
   # prints
   # the boy 's car are differ color .
   lancaster = nltk.LancasterStemmer()
14
   stemmed = [lancaster.stem(t) for t in lower]
   print(" ".join(stemmed))
   # prints
   # the boy 's car ar diff col .
```

NLTK's stemmers:

```
import nltk

string = "The boy's cars are different colors."

tokens = nltk.word_tokenize(string)

lower = [x.lower() for x in tokens]

snowball = nltk.SnowballStemmer("english")

stemmed = [snowball.stem(t) for t in lower]

print(" ".join(stemmed))

# prints

# the boy 's car are differ color.
```

Lemmatization

- stemming can often create non-existent words, whereas lemmas are actual words
- NLTK WordNet Lemmatizer uses the WordNet Database to lookup lemmas

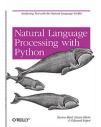
```
import nltk
string = "The boy's cars are different colors."
tokens = nltk.word_tokenize(string)
lower = [x.lower() for x in tokens]
porter = nltk.PorterStemmer()
stemmed = [porter.stem(t) for t in lower]
print(" ".join(lemmatized))
# prints the boy 's car are differ color .
wnl = nltk.WordNetLemmatizer()
lemmatized = [wnl.lemmatize(t) for t in lower]
print(" ".join(lemmatized))
# prints the boy 's car are different color .
```

Stopword removal:

Stopword removal:

```
import nltk
   string = "The boy s cars are different colors."
   tokens = nltk.word tokenize(string)
   lower = [x.lower() for x in tokens]
   wnl = nltk.WordNetLemmatizer()
   lemmatized = [wnl.lemmatize(t) for t in lower]
   content = [x for x in lemmatized if x not in nltk.
       corpus.stopwords.words("english")]
   print(" ".join(content))
10
   # prints
   # boy 's car different color .
```

References



- http://www.nltk.org/book/
- https://github.com/nltk/nltk
- Christopher D. Manning, Hinrich Schütze 2000. Foundations of Statistical Natural Language Processing. The MIT Press Cambridge, Massachusetts London, England.

```
http://ics.upjs.sk/~pero/web/documents/
pillar/Manning_Schuetze_StatisticalNLP.pdf
```