AI6122 Text Data Management & Analysis

Topic: tokenization, morphology, stem, lemmatization

What to be covered

- Token and Tokenization
- Stop words
- English Morphology
- Stemming and Lemmatization
- Edit Distance

Token

- A **token** is an instance of a sequence of characters in some document that are grouped together as a useful semantic unit for processing.
  - Often loosely referred to as words (or terms)
  - May include punctuations or emojis

- Tokenization: Identifying the tokens in a text that we may want to deal with
  - Also called word segmentation, word tokenization
  - Pretty much a prerequisite to doing anything interesting

- Example input: "*Friends, Romans and Countrymen*"
  - tokens: *Friends, Romans, Countrymen*

- Tokenization is language dependent, e.g., English, Chinese

Tokenization

- For English, why not just use white-space?
  - Mr. Sherwood said reaction to Sea Containers’ proposal has been "very positive." In New York Stock Exchange composite trading yesterday, Sea Containers closed at $62.625, up 62.5 cents.
  - “I said, ‘what’re you? Crazy?’ “ said Sadowsky. “I can’t afford to do that.’’

- Using white-space gives you words like:
  - cents.
  - said,
  - positive.”
  - Crazy?’

Tokenization: issues

- Word-internal punctuation
  - M.P.H. Ph.D. AT&T Google.com Yahoo!

- Other Examples:
  - Finland’s capital → Finland? Finlands? Finland’s?
  - Hewlett-Packard → Hewlett and Packard as two tokens?
  - state-of-the-art: break up hyphenated sequence.
  - co-education, lowercase, lower-case, lower case?

- How about names?
  - San Francisco: one token or two?
  - How do you decide it is one token? Then how about “San Francisco Airport”?

- What about numbers?
  - 3/20/91 Mar. 12, 1991 20/3/91
  - 55 B.C., B-52, My PGP key is 324a3df234cb23e
  - This is my number: (800) 234-2333

Tokenization: Implementation

- Tokenization needs to be run before any other language processing,
  - it needs to be very fast.
  - Standard method for tokenization is to use deterministic algorithms based on regular expressions compiled into very efficient finite state automata.
  - Example Python-based Natural Language Toolkit (NLTK)

```
>>> 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 and 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', '...']
```

Figure 2.11 A python trace of regular expression tokenization in the NLTK (Bird et al., 2009) Python-based natural language processing toolkit, commented for readability; the (?x) verbose flag tells Python to strip comments and whitespace. Figure from Chapter 3 of Bird et al. (2009).

Examples of other issues

- URL segmentation
  - www.dietsthatwork.com
  - www.choosespain.com

- Hashtag segmentation
  - #unitedbrokemyguitar
  - #manchesterunited
  - allows Twitter users to track what many people (especially people whom you aren't already following) are reporting or thinking about a particular topic or event.

What about code?

stackoverflow Questions Tags Tour Users

Stack Overflow is a question and answer site for professional and enthusiast programmers. It's 100% free, no registration required.

EF6 - Value cannot be null. Parameter name: extent

0

I'm using EF6 code first to create my db. Everything was working well last night, now when i run update-database command, I get the following exception:

```
PM> update-database
Specify the '-Verbose' flag to view the SQL statements being applied t
System.ArgumentNullException: Value cannot be null.
Parameter name: extent
   at System.Data.Entity.Utilities.Check.NotNull[T](T value, String pa
   at System.Data.Entity.Core.Mapping.StorageEntitySetMapping..ctor(En
   at System.Data.Entity.ModelConfiguration.Edm.DbDatabaseMappingExten
   at System.Data.Entity.ModelConfiguration.Edm.Services.TableMappingG
   at System.Data.Entity.ModelConfiguration.Edm.Services.DatabaseMappi
   at System.Data.Entity.ModelConfiguration.Edm.Services.DatabaseMappi
   at System.Data.Entity.DbModelBuilder.Build(DbProviderManifest provi
   at System.Data.Entity.DbModelBuilder.Build(DbConnection providerCon
   at System.Data.Entity.Internal.LazyInternalContext.CreateModel(Lazy
   at System.Data.Entity.Internal.RetryLazy`2.GetValue(TInput input)
   at System.Data.Entity.Internal.LazyInternalContext.InitializeContex
   at System.Data.Entity.Internal.LazyInternalContext.get_CodeFirstMod
```

searchcode binarytree lang:Java

Run searchcode locally? Want to run your own version of searchcode

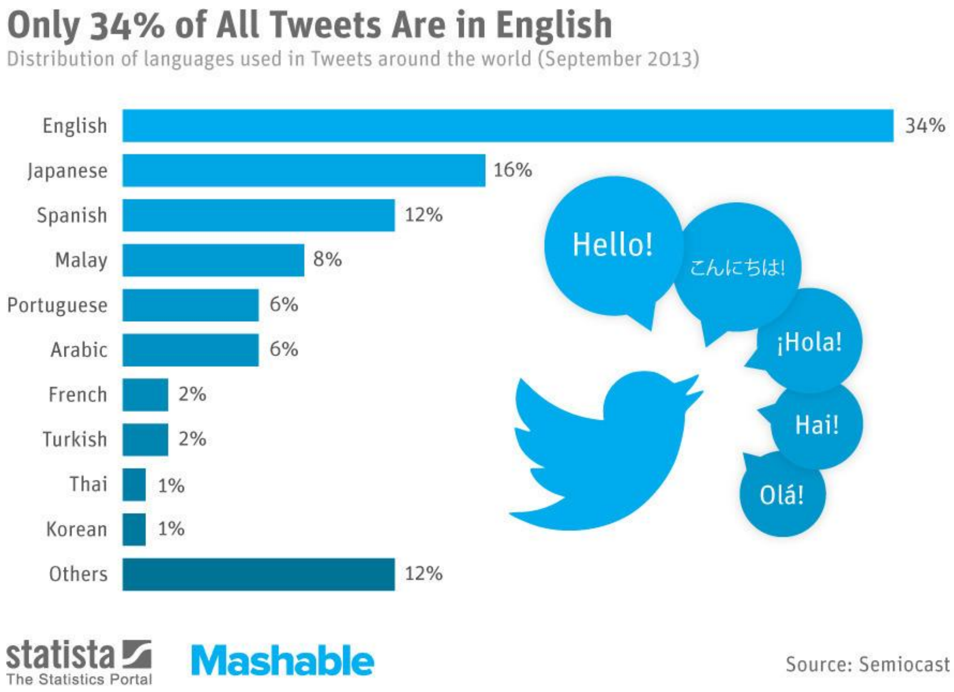
About 419 results

BinaryTree.java in rose_backup https://github.com/dpick/rose_backup.git | 171 lines | Java

```
// BinaryTree class; stores a binary tree.
//

// Also, the following tricky method:
// void merge( Object root, BinaryTree t1, BinaryTree t2 )
//                         --> Construct a new tree

/**
 * BinaryTree class that illustrates the calling of BinaryNode recursive
 * routines and merge.

 */
public class BinaryTree {
        /**
```

Is language really an issue here?

shd, ishould, shudd, shuld, shoud, shud, shld, sould, shouldd



http://languagetime.files.wordpress.com/2013/12/131217_twitter_sprachen_mashable_n.jpg

Words grouping by Brown Clustering

^01110111001 (43)	everything everythin everthing evrything everythang everythinq everythng eveything everythingg everyting evrythng errthang errything #everything errthing erything everythinggg errythang evrythin erthang 1thing erthing everythingggg jony everythig everytin everyhing everithing everythign everythn everyhting everythinqq everythink erythang everything-everythiing everythinggggg errrthang everythg everyword evreything everysong er'thing
^01110111010 (85)	nothing nothin nun nuthin nuttin nuffin 10x noting nthn nowt nuthn nuthing 100x nothingg nothn nothinq nutin notin nuffn nutn whatevers #nodisrespect nuttn nothinggg #dontmeantobrag 1000x zilch nothinn #nothing nothng nutting nufin nuin nout nothinqq nthng nthing nothingggg nufn nofin nothen nthin nottin nttn nought ntg nothinnn nothign n0thing nothig
^011101110110 (108)	something somethin sumthin sumthing sumn somthing sth sumthn sumtin smth somthin suttin sumin somethinq summin treaters somethingg someting sumfin smthn somethn somethng summat smthng smthing sum'n sumthng smthg somn sumtn smething sometin somethign sum10 soemthing somethinn somethinggg somethig sumpin somin sumting something/someone somtin somehting somthn someshit sumptin something- smtg thereabouts
^011101110111 (36)	anything anythin nething anythng anythingg anythinq anyting anythang anyth anytin anthing anythinggg anyfin vaart anythn anythign nethin nything anyhting #anything anything- anythg anythingggg nothing- anythink anythig anythinqq somethingggg nethng anyhing woodsen endsmeat anything/anyone aything anythiing enything

Source: http://www.cs.cmu.edu/~ark/TweetNLP/cluster_viewer.html

Tokenization: language issues

- French
  - **L'ensemble** $\rightarrow$ one token or two?
    - L ? L' ? Le ?
    - Want l'ensemble to match with un ensemble
- German noun compounds are not segmented
  - **Lebensversicherungsgesellschaftsangestellter**
  - 'life insurance company employee'

  - German retrieval systems benefit greatly from a compound splitter module
  - Can give a 15% performance boost for German

Tokenization: language issues

- Chinese and Japanese have no spaces between words:
  - 莎拉波娃现在居住在美国东南部的佛罗里达。
  - Not always guaranteed a unique tokenization

- Japanese is more complicated, with multiple alphabets intermingled
  - Dates/amounts in multiple formats

フォーチュン500社は情報不足のため時間あた$500K(約6,000万円)

Katakana Hiragana Kanji Romaji

End-user can express query entirely in hiragana!

Tokenization: language issues

- Arabic (or Hebrew) is basically written right to left, but with certain items like numbers written left to right

- Words are separated, but letter forms within a word form complex ligatures

استقلت الجزائر في سنة 1962 بعد 132 عاما من الاحتلال الفرنسي.

‘*Algeria achieved its independence in 1962 after 132 years of French occupation.*’

- With Unicode, the surface presentation is complex, but the stored form is straightforward

Segmentation in Chinese

- Words composed of characters; average word is 2.4 characters long.

- A simple segmentation algorithm based on dictionary:
  - Maximum Matching or Maxmatch

  - Given a lexicon of Chinese, and a string
    - Start a pointer at the beginning of the string
    - Find the longest word in dictionary that matches the string starting at pointer
    - Move the pointer over the word in string
    - Go to 2

- State-of-the-art solutions are mostly **probabilistic** and deep learning
  - http://nlpprogress.com/chinese/chinese_word_segmentation.html
  - https://github.com/topics/chinese-text-segmentation

- Recent study: for most Chinese NLP tasks, take characters rather than words as input works better.
  - Characters are at a reasonable semantic level for most applications,
  - Most word standards result in a huge vocabulary with large numbers of very rare words

Maximum Matching Word Segmentation

Lexicon (Dictionary)
the
table
down
there
…

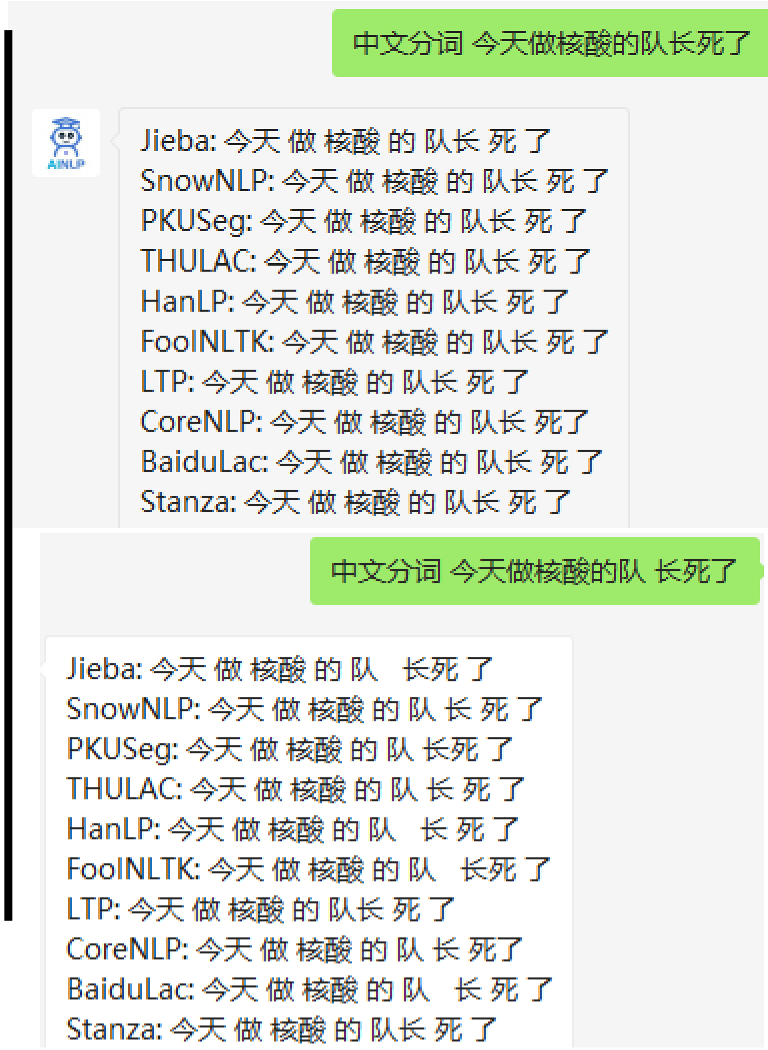
thetabledownthere

the table down there

Lexicon (Dictionary)
the
theta
table
down
there
bled
own

thetabledownthere

theta bled own there



Byte-Pair Encoding for (subword) Tokenization

- Data driven, and not confine to words or characters
  - Resultant **token** could be smaller than words e.g., -est, er,
    - Or larger than words, e.g., New York Times
  - Have **subword** tokens to deal with unknown words.
    - Proposed for machine translation, dealing with rare or new words

- Given training data (words are annotated)
  - BPE starts with the set of symbols equal to the set of characters
  - Each word is represented as a sequence of characters plus a special end-of-word symbol _
  - At each step, the most frequent pair (‘A’, ‘B’) of symbol pairs is merged, and replaced with the newly merged symbol (‘AB’)
  - Repeat the step, until we have done *k* merges (*k* is a parameter)
    - The final symbol vocabulary size is equal to the size of the initial vocabulary, plus the number of merge operations

BEP Example

- BPE runs inside words, we don’t merge across word boundaries
  - The input is a dictionary of words together with their counts

	dictionary	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 $\boxed{\text{r \_}}$	
3	w i d e $\boxed{\text{r \_}}$	
2	n e w _	

  - Count symbol pairs: r _ has highest frequency 9 (6 in newer_ and 3 in wider_)
  - Then r_ is merged

After merging "r _" and then "e r_"

	dictionary	vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, $\boxed{\text{r\_}}$
2	l o w e s t _	
6	n e w $\boxed{\text{e r\_}}$	
3	w i d $\boxed{\text{e r\_}}$	
2	n e w _	

	dictionary	vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, r_, $\boxed{\text{er\_}}$
2	l o w e s t _	
6	n e w $\boxed{\text{er\_}}$	
3	w i d $\boxed{\text{er\_}}$	
2	n e w _	

Continue merging

	dictionary	vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, r_, er_, $\boxed{\text{ew}}$
2	l o w e s t _	
6	n $\boxed{\text{ew}}$ er_	
3	w i d er_	
2	n $\boxed{\text{ew}}$ _	

Merge	Current Vocabulary
(n, ew)	_, d, e, i, l, n, o, r, s, t, w, r_, er_, ew, new
(l, 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_

Apply BEP for (subword) tokenization

- The merging sequence is what we have learned from training data
- To apply BEP for tokenization on test data
  - We run the merges we have learned, greedily, in the order we learned them
  - The frequencies in the test data don't play a role, just the frequencies in the training data.

- Follow the example:
  - Segment each test sentence word into characters.
  - Apply the first rule: replace every instance of "r _" in the test corpus with "r_", and then the second rule: replace every instance of "e r_" in the test corpus with "er_", and so on.
  - By the end, word "n e w e r" , it would be tokenized as a full word.
  - a new (unknown) word like "l o w e r" would be merged into the two tokens "low" and "er"

Sentence Segmentation

- !, ? are relatively unambiguous

- Period "." is quite ambiguous
  - Sentence boundary
  - Abbreviations like Inc. or Dr.

- General idea:
  - Build a binary classifier:
    - Looks at a "."
    - Decides EndOfSentence/NotEOS
    - Could be hand-written rules, sequences of regular expressions, or machine-learning

Now we mainly focus on words

- Stop words
- English Morphology
- Stemming and Lemmatization

Stop words

- With a stop list, you exclude from the dictionary entirely the commonest words. :
  - They have little semantic content: the, a, and, to, be
  - There are a lot of them: ~30% of postings for top 30 words

- But the trend is away from doing this:
  - Good compression techniques means the space for including stopwords in a system is very small
  - Good query optimization techniques mean you pay little at query time for including stop words.
  - You need them for:
    - Phrase queries: “King of Denmark”
    - Various song titles, etc.: “Let it be”, “To be or not to be”
    - “Relational” queries: “flights to London”

English Morphology

- Morphology is the study of the ways that words are built up from smaller meaningful units called **morphemes**

- We can usefully divide morphemes into two categories
  - **Stems**: The core meaning-bearing units
  - **Affixes**: Bits and pieces that adhere to stems to change their meanings and grammatical functions

  - Example
    - cat → cats
    - regular → irregular

English Morphology

- We can further divide morphology up into two broad classes
  - **Inflectional:** has the same word class as the original, cat -> cats
  - **Derivational:** changes of word class, care -> careless

- Word Classes
  - By word class, we have in mind familiar notions like noun and verb
    - We'll go into the details in POS tagging
  - Right now we're concerned with word classes because **the way that stems and affixes combine** is based to a large degree on the word class of the stem

Inflectional Morphology

- Inflectional morphology concerns the combination of stems and affixes where the resulting word:
  - Has the same word class as the original
  - Fill some syntactic function like agreement

  - Nouns are simple
    - Markers for plural and possessive
    - Example: table, tables; children, children’s
  - Verbs are only slightly more complex
    - Markers appropriate to the tense of the verb
    - Example: walk, walks, walking

Regulars and Irregulars

- It is a little complicated by the fact that some words misbehave (refuse to follow the rules)
  - Mouse/mice, goose/geese, ox/oxen
  - Go/went, fly/flew

- The terms regular and irregular are used to refer to words that follow the rules and those that don't

Regular and Irregular Verbs

- Inflectional morphology in English is fairly straightforward
- But is complicated by the fact that there are irregularities

- Regulars…
  - Walk, walks, walking, walked, walked
- Irregulars
  - Catch, catches, catching, caught, caught
  - Cut, cuts, cutting, cut, cut

Derivational Morphology

- More complicated.
- Many paths are possible…
  - Start with compute
    - Computer -> computerize -> computerization
    - Computer -> computerize -> computerizable

- Meaning change
    - E.g., care -- careless
- Changes of word class

Derivational Examples

- Nouns and Verbs → Adjectives

-al	computation	computational
-able	embrace	embraceable
-less	clue	clueless

- Verbs and Adjectives → Nouns

-ation	computerize	computerization
-ee	appoint	appointee
-er	kill	killer
-ness	fuzzy	fuzziness

Normalization

- Need to “normalize” terms
  - Information Retrieval: 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

- Alternative: asymmetric expansion:
  - Enter: **window** Search: **window, windows**
  - Enter: **windows** Search: **Windows, windows, window**
  - Enter: **Windows** Search: **Windows**

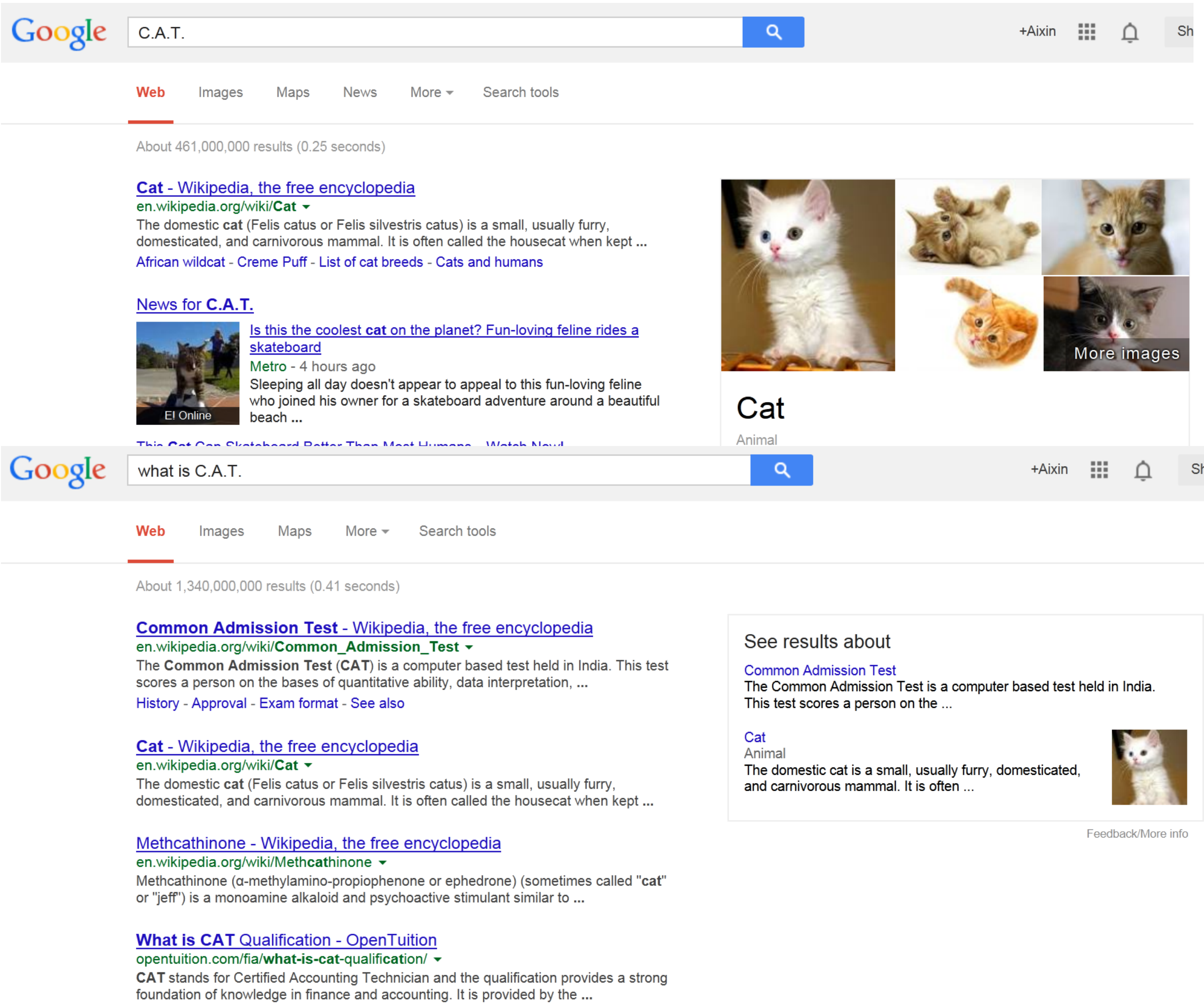
- Potentially more powerful, but less efficient

Case folding

- Applications like IR: reduce all letters to lower case
  - Since users tend to use lower case
  - Possible exception: upper case in mid-sentence?
    - e.g., **General Motors**
    - **Fed** vs. **fed**
    - **SAIL** vs. **sail**

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

Google's answer to query "C.A.T."



Category filter: Show All (209)

Acronym	Definition
CAT	Category
CAT	Catalog
CAT	Convention Against Torture *(United Nations;*
CAT	Computerized Axial Tomography *(medical in*
CAT	Centre for Alternative Technology *(Machynlle*
CAT	Catalog *(File Name Extension)*
CAT	Common Admission Test *(India)*
CAT	Caterpillar, Inc.
CAT	Community Action Team
CAT	Catalunya
CAT	Catalyst
CAT	Computer Aided Translation
CAT	Catastrophe *(Claims Office)*
CAT	Catamaran
CAT	Computer-Assisted Translation
CAT	Certified Accounting Technician
CAT	Catastrophic
CAT	Call Any Time
CAT	Catalan Language *(ISO 639-2 Code)*
CAT	Cataract *(ophthalmology)*
CAT	Catalytic Converter *(automobiles)*
CAT	Catapult
CAT	Catalonia *(country identifier)*
CAT	Centre d'Aide par le Travail *(French: Center*
CAT	Catechism
CAT	Computerized Adaptive Testing
CAT	Computer Adaptive Test
CAT	Civil Air Transport *(CIA front airline during 19*
CAT	California Achievement Test
CAT	Concatenate
CAT	Capital Area Transit *(Raleigh, NC)*
CAT	Catalase
CAT	Chloramphenicol Acetyltransferase

Lemmatization

- Reduce inflections or variant forms to base form
  - am, are, is $\rightarrow$ be
  - car, cars, car's, cars' $\rightarrow$ car
- the boy's cars are different colors $\rightarrow$
  - the boy car be different color
- Lemmatization: have to find **correct dictionary headword form**
  - Determining that two words have the same root, despite their surface differences

Light-Weight Morphology

- Sometimes you just need to know the stem of a word and you don't care about the structure.
  - E.g. camera, cameras

- In fact you may not even care if you get the right stem, as long as you get a consistent string—**Stemming**

- Stemming for Information Retrieval
  - Run a stemmer on the documents to be indexed
  - Run a stemmer on users' queries
  - Match to the index

Porter's stemming

- No lexicon needed

- Basically a set of staged sets of rewrite rules that strip suffixes
  - ING → ε (e.g., monitoring → monitor)
  - SSES→ SS (e.g., grasses → grass)

- More Example (recursive)
  - Computerization
    - ization -> -ize computerize
    - ize -> ε computer

Porter’s stemming

- Handles both inflectional and derivational suffixes

- Doesn’t guarantee that the resulting stem is really a stem
  - Lack of guarantee doesn’t matter for IR

- Code:
  - http://tartarus.org/martin/PorterStemmer/
  - Implementations in C, Java, Perl, Python, C#, Lisp, Ruby, VB, javascript, php, Prolog, Haskell, matlab, tcl, D, and erlang

Stemming used in search

- Recall: reduce false negative? (Not matching things that we should have matched)
  - Query: "dog"
  - Doc 1: I love my dog
  - Doc 2: I do not like dogs

Works in this case

- Precision: increase false positives? (Matching strings that we should not have matched)
  - Query: "policy"
  - Doc 3: Singapore policy on gum
  - Doc 4: Singapore police cool

Wrong results here

policy—policies
police—policing

Stemming

- Reduce terms to their stems in information retrieval

- *Stemming* is **crude chopping of affixes**
  - language dependent
  - e.g., ***automate(s), automatic, automation*** all reduced to ***automat***.

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

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

Stemmer vs Dictionary

- Stemming Rules more efficient than a dictionary
  - Algorithmic stemmers can be fast (and lean): 1 Million words in 6 seconds on 500 MHz PC

- No maintenance even if things change

- Better to ignore irregular forms (exceptions) than to complicate the algorithm
  - not much lost in practice
  - 80/20 Rule

Other stemmers

- Other stemmers exist, e.g., Lovins stemmer
  - http://www.comp.lancs.ac.uk/computing/research/stemming/general/lovins.htm
  - Single-pass, longest suffix removal (about 250 rules)

- Full morphological analysis – at most modest benefits for retrieval

- Do stemming and other normalizations help?
  - English: very mixed results. Helps recall for some queries but harms precision on others
    - E.g., operative (dentistry) ⇒ oper
  - Definitely useful for Spanish, German, Finnish, …
    - 30% performance gains for Finnish!

Language-specificity

- Many of the above features embody transformations that are
  - Language-specific and
  - Often, application-specific

- These are “plug-in” addenda to the indexing process

- Both open source and commercial plug-ins are available for handling these

Normalization: other languages

- Accents: e.g., French résumé vs. resume.
- Umlauts: e.g., German: Tuebingen vs. Tübingen
  - Should be equivalent

- Most important criterion:
  - How are **your users like to write** their queries for these words?

- Even in languages that standardly have accents, users often may not type them
  - Often best to normalize to a de-accented term
    - Tuebingen, Tübingen, Tubingen → Tubingen

Normalization: other languages

- Normalization of things like date forms
  - 7月30日 vs. 7/30
  - Japanese use of kana vs. Chinese characters
- Tokenization and normalization may depend on the language and so is intertwined with language detection

- Crucial: Need to "normalize" indexed text and query terms into **the same form**

Morgen will ich in MIT …

Is this German "mit"?

Thesauri and soundex

- Do we handle synonyms and homonyms?
  - E.g., by hand-constructed equivalence classes
    - ***car*** = ***automobile*** ***color*** = ***colour***
  - We can rewrite to form equivalence-class terms
    - When the document contains ***automobile***, index it under ***car-automobile*** (and vice-versa)
  - Or we can expand a query
    - When the query contains ***automobile***, look under ***car*** as well

- What about spelling mistakes?
  - One approach is soundex, which forms equivalence classes of words based on phonetic heuristics

Basic concepts: Phrase Detection

- Important for English
  - New York City Police Department
  - Bill Gates spoke on the benefits of Windows

- Essential for CJK (Chinese, Japanese, Korean)
  - 新加坡是个美丽的城市 [Singapore is a beautiful city]

- Approaches
  - Dictionary Based
    - Most Accurate; Needs maintenance (by humans)
  - Learnt/Extracted from Corpus
    - Hidden Markov Model; N-Grams; Statistical Analysis
    - Suffix Tree Phrase Detection (via statistical counting)

Example of Extracted Phrases on 20 Newsgroup dataset

south
south africa
south africa internet
south africa po
south african
south african government
south african intelligence
south african libertarian
south america
south atlantic
south dakota
south dakota writes
south georgia
south georgia island
south pacific
south pacific island

san diego
san diego ca
san francisco
san francisco bay
san francisco chronicle
san francisco giants
san francisco police
san francisco police inspector
san francisco police inspector ron
san francisco police intelligence
san francisco police intelligence unit
san francisco police officer
san jose
san jose ca
san jose mercury

high
high density
high end
high enough
high frequency
high hockey
high just
high level
high performance
high power
high quality
high ranking
high ranking crime
high ranking initiate
high resolution
high school
high school students
high speed
high speed collision
high sticking
high tech
high voltage
highend
higher

united
united kingdom
united nations
united nations quite
united states
united states attempt
united states code
united states government
united states holocaust
united states officially
united states senate

Edit Distance

- The minimum edit distance between two strings is the minimum number of editing operations needed to transform one into the other
  - Insertion
  - Deletion
  - Substitution

- Spell correction
  - The user typed "**graffe**"
  - Which is closest?
    - graf
    - graft
    - grail
    - giraffe

Minimum Edit Distance

- Two strings and their **alignment**:

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
```

Minimum Edit Distance

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
d s s   i s
```

- If each operation has cost of 1
  - Distance between these is 5
- If substitutions cost 2 (Levenshtein)
  - Distance between them is 8

Other uses of Edit Distance in NLP

- Evaluating Machine Translation and speech recognition
  - Spokesman confirms senior government adviser was shot
  - Spokesman said the senior adviser was shot dead

    S I D I

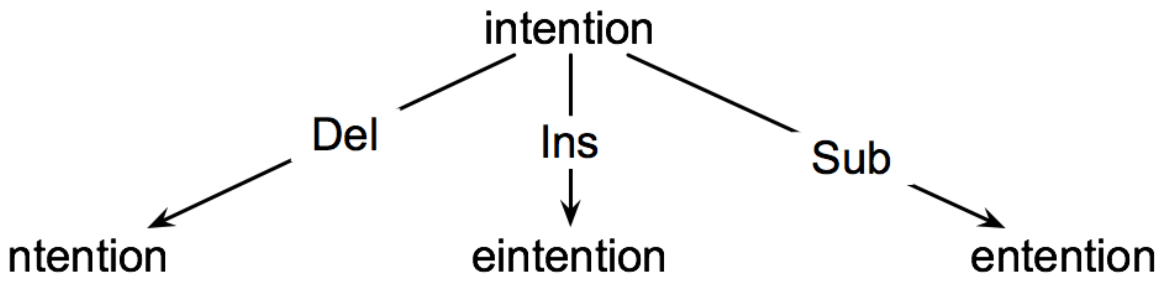
- Named Entity Extraction and Entity Coreference
  - IBM **Inc.** announced today
  - IBM profits

  - Stanford President John Hennessy announced yesterday
  - for Stanford **University** President John Hennessy

How to find the Min Edit Distance?

- Searching for a path (sequence of edits) from the start string to the final string:
  - Initial state: the word we're transforming
  - Operators: insert, delete, substitute
  - Goal state: the word we're trying to get to

  - Path cost: what we want to minimize: the number of edits



Minimum Edit as Search

- But the space of all edit sequences is huge!
  - We can't afford to navigate naïvely

  - Lots of distinct paths wind up at the same state.
    - We don't have to keep track of all of them
    - Just the shortest path to each of those re-visted states.

```
i n t e n t i o n
                    ← delete i
n t e n t i o n
                    ← substitute n by e
e t e n t i o n
                    ← substitute t by x
e x e n t i o n
                    ← insert u
e x e n u t i o n
                    ← substitute n by c
e x e c u t i o n
```

Defining Min Edit Distance

- For two strings
  - X of length n
  - Y of length m

- We define $D(i, j)$ to be the edit distance between $X[1..i]$ and $Y[1..j]$, i.e., the first i characters of X and the first j characters of Y
  - The edit distance between X and Y is thus $D(n, m)$

Dynamic Programming for Minimum Edit Distance

- Dynamic programming: A tabular computation of $D(n, m)$
  - Solving problems by combining solutions to subproblems.

- Bottom-up
  - We compute $D(i, j)$ for small i, j , then compute larger $D(i, j)$ based on previously computed smaller values

  - That is: we compute $D(i, j)$ for all i $(0 < i < n)$ and j $(0 < j < m)$

Defining Min Edit Distance (Levenshtein)

$D(i, j)$ to be the edit distance between $X[1..i]$ and $Y[1..j]$, i.e., the first i characters of X and the first j characters of Y

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

- Recurrence Relation:

  For each $i = 1 \ldots M$

  For each $j = 1 \ldots N$

$$D[i,j] = \min \begin{cases} D[i-1,j] + \text{del-cost}(source[i]) \\ D[i,j-1] + \text{ins-cost}(target[j]) \\ D[i-1,j-1] + \text{sub-cost}(source[i], target[j]) \end{cases}$$

- Termination:
  - D(N,M) is distance

$$D[i,j] = \min \begin{cases} D[i-1,j] + 1 \\ D[i,j-1] + 1 \\ D[i-1,j-1] + \begin{cases} 2; & \text{if } source[i] \neq target[j] \\ 0; & \text{if } source[i] = target[j] \end{cases} \end{cases}$$

The Edit Distance Table

N	9									
O	8									
I	7									
T	6									
N	5									
E	4									
T	3									
N	2									
I	1									
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

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The Edit Distance Table

$$D[i,j] = \min \begin{cases} D[i-1,j]+1 \\ D[i,j-1]+1 \\ D[i-1,j-1] + \begin{cases} 2; & \text{if } source[i] \neq target[j] \\ 0; & \text{if } source[i] = target[j] \end{cases} \end{cases}$$

N	9	8	9	10	11	12	11	10	9	**8**
O	8	7	8	9	10	11	10	9	8	9
I	7	6	7	8	9	10	9	8	9	10
T	6	5	6	7	8	9	8	9	10	11
N	5	4	5	6	7	8	9	10	11	10
E	4	3	4	5	6	7	8	9	10	9
T	3	4	5	6	7	8	7	8	9	8
N	2	3	4	5	6	7	8	7	8	7
I	1	2	3	4	5	6	7	6	7	8
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

Computing alignments

- Edit distance isn't sufficient
  - We often need to **align** each character of the two strings to each other
- We do this by keeping a "backtrace"
- Every time we enter a cell, remember where we came from
- When we reach the end,
  - Trace back the path from the upper right corner to read off the alignment

MinEdit with Backtrace

n	9	↓ 8	↙←↓ 9	↙←↓ 10	↙←↓ 11	↙←↓ 12	↓ 11	↓ 10	↓ 9	↙ **8**	
o	8	↓ 7	↙←↓ 8	↙←↓ 9	↙←↓ 10	↙←↓ 11	↓ 10	↓ 9	↙ **8**	← 9	
i	7	↓ 6	↙←↓ 7	↙←↓ 8	↙←↓ 9	↙←↓ 10	↓ 9	↙ **8**	← 9	← 10	
t	6	↓ 5	↙←↓ 6	↙←↓ 7	↙←↓ 8	↙←↓ 9	↙ **8**	← 9	← 10	←↓ 11	
n	5	↓ 4	↙←↓ 5	↙←↓ 6	↙←↓ 7	↙←↓ **8**	↙←↓ 9	↙←↓ 10	↙←↓ 11	↙↓ 10	
e	4	↙ 3	← 4	↙← **5**	← **6**	← 7	←↓ 8	↙←↓ 9	↙←↓ 10	↓ 9	
t	3	↙←↓ 4	↙←↓ **5**	↙←↓ 6	↙←↓ 7	↙←↓ 8	↙ 7	←↓ 8	↙←↓ 9	↓ 8	
n	2	↙←↓ **3**	↙←↓ 4	↙←↓ 5	↙←↓ 6	↙←↓ 7	↙←↓ 8	↓ 7	↙←↓ 8	↙ 7	
i	**1**	↙←↓ 2	↙←↓ 3	↙←↓ 4	↙←↓ 5	↙←↓ 6	↙←↓ 7	↙ 6	← 7	← 8	
#	**0**	1	2	3	4	5	6	7	8	9	
	#	**e**	**x**	**e**	**c**	**u**	**t**	**i**	**o**	**n**	

Result of Backtrace

- Two strings and their **alignment**:

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
```

Topics covered

- Token and Tokenization
- Stop words
- English Morphology
- Stemming and Lemmatization
- Edit Distance