

Master of Technology in Knowledge Engineering

Text Mining

Preparing Textual Data for Analysis

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ATA/KE-TM/04 TextPreparation/V2.1
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Agenda

- Dealing with different formats of textual data
- From text to words
 - Tokenization
 - Lemmatization/stemming
 - Stopwords
- Indexing document text
 - Frequency-based indexing
 - TF-IDF indexing
- Natural language processing tasks



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Objectives

- To understand the characteristics of textual data
- To introduce the various text pre-processing and transformation tasks
- To learn the common methods for such tasks

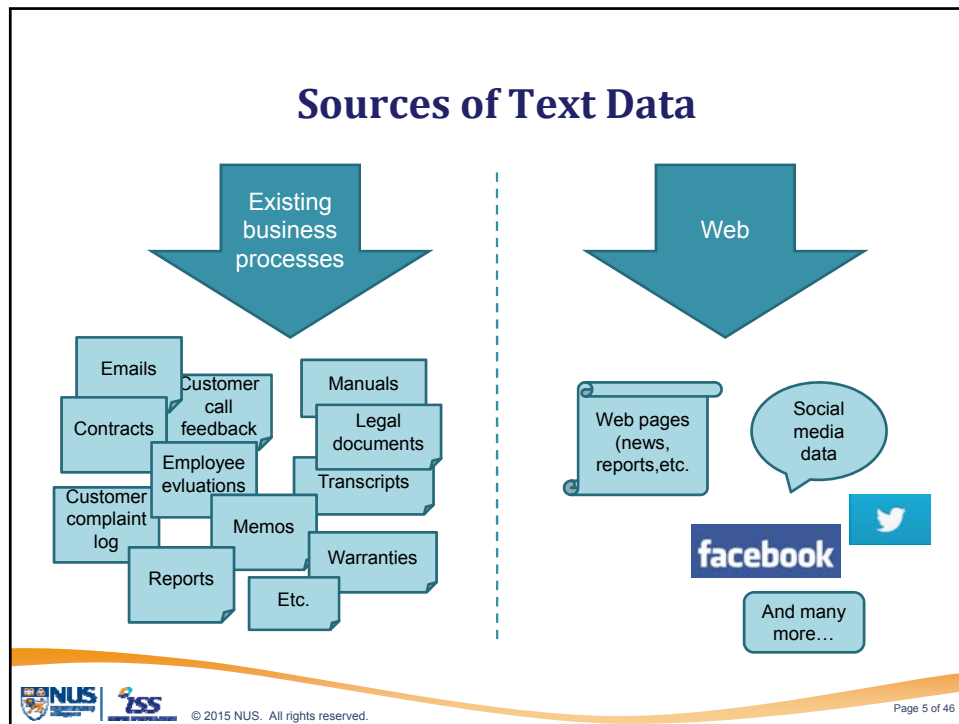
The whole task here is...

Documents

Lost glamor
 Ra
 20
 Ra
 Not what it was, but still a place to go
 We
 to.
 roc
 Rat
 201
 My
 disa
 wh
 to bi
 patr
 in th
 and
 Now
 didn
 Bar
 that
 ever
 nois
 How
 Stayed February 2013

Term Document Matrix

	amazing	service	lost	glamour	disappoint	brilliant	super	expensive	noisy	...
Doc1	1	1	0	0	0	1	0	0	0	
Doc2	0	0	1	1	1	0	0	1	0	
Doc3	0	0	0	1	0	0	1	0	0	
Doc4	0	0	0	0	2	0	0	1	1	
...										

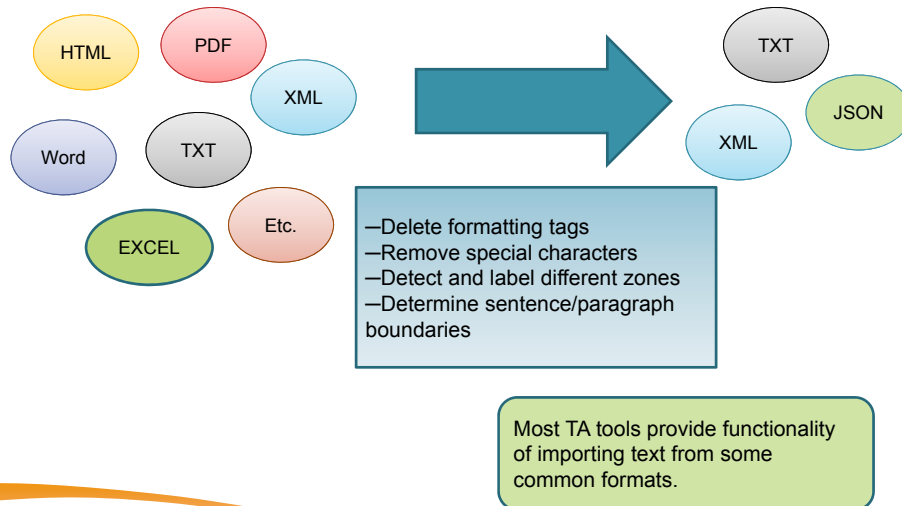


Corpus Data Available

- For R&D of text mining techniques, well-prepared corpora (collection of documents) are available
 - Brown corpus – American English generic texts of varying genres
 - British National Corpus – written and spoken British English
 - Reuters news Corpora - Reuters News stories in English and other languages
 - USENET news group data
 - Biomedical corpus – GENIA, MEDLINE (abstracts on medical subjects)
 - Linguistic Data Consortium Corpora

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File Preprocessing



In a pure text file...

Amazing service

Rated 5 by travel-gini on Feb 26, 2013

Great location with a little bit of history, the staff make this hotel though

Have a drink in the Long Bar, throw your nutshells on the floor, then go to the Tiffin Room for the best curry in the world. About £40a head for food but the choice is brilliant and when my wife mentioned it was her birthday at the end of the meal a cake was presented, what amazing service.

Stayed February 2013

...

XML as Standard Exchange Format

- The trend in industry and text-processing community is to adopt XML as the standard exchange format.
- With XML, we can insert tags onto a text to identify its parts.
 - Eg. <DOC>, <SUBJECT>, <TOPIC>, <TEXT>, etc.
 - Such tags are very useful as they allow selection/extraction of the parts to generate features for subsequent mining.
- Many word processors allow documents to be saved as XML format
- Most TM tools provide functionality of importing text from some common formats.



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What would an XML doc look like?

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<REVIEWS>
  <REVIEW>
    <TITLE>Amazing service</TITLE>
    <RATING>5</RATING>
    <DATE>26/02/2013</DATE>
    <BY>travel-gini</BY>
    <CONTENT>Great location with a little bit of history, the staff make this hotel
    though
    Have a drink in the Long Bar, throw your nutshells on the floor, then go to the Tiffin
    Room for the best curry in the world. About £40a head for food but the choice is
    brilliant and when my wife mentioned it was her birthday at the end of the meal a cake
    was presented, what amazing service. Stayed February 2013 </CONTENT>
  </REVIEW>
  ...
</REVIEWS>
```



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Or as JSON format

```
{  
  "title": "Amazing service",  
  "rating": 5,  
  "date": "26/02/2013",  
  "by": "travel-gini",  
  "content": "Great location with a little bit of history, the staff make this  
    hotel though Have a drink in the Long Bar, throw your nutshells on the  
    floor, then go to the Tiffin Room for the best curry in the world. About  
    £40a head for food but the choice is brilliant and when my wife  
    mentioned it was her birthday at the end of the meal a cake was  
    presented, what amazing service. Stayed February 2013"  
}
```

From Text to Words

Tokenization

- To break a stream of characters into tokens

Great location with a little bit of history.



Great	location	with	a	little	bit	of	history
-------	----------	------	---	--------	-----	----	---------

- This is done by identifying token delimiters
 - Whitespace characters such as *space, tab, newline*
 - Punctuation characters like *() <> ! ? " "*
 - Other characters *., : - ' ' etc.*

Tokenization Challenges

- It seems simple, but...

- $.$, $:$ between numbers are part of the number

12.34

12,345

12:34

- . can be part of an abbreviation or end of a sentence

U.S.A.

Dr.

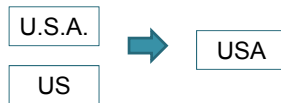
- ' can be a closing internal quote, indicate a possessive, or be part of another token

My friend's

isn't

Lemmatization/Stemming

- A word may come in varied forms and therefore need to be converted into a standard form
 - Inflectional stemming (no change of POS)
 - Derivational Stemming (with change of POS)
 - Other normalisation (including case normalisation)

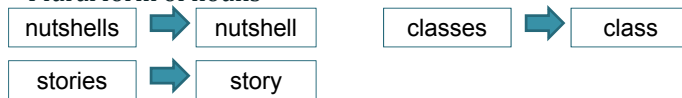


- Stemming can reduce the number of distinct features in a text corpus and increase the frequency of occurrence of some individual features.

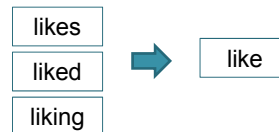
Inflectional Stemming

- Inflections – grammatical variants of the same word

- Plural form of nouns



- Verbs in different tense and aspect



- There are irregular forms and ambiguities!
 - “*corpus*” vs. “*corpora*”, “*seek*” vs. “*sought*”
 - Is “*bore*” the present tense of “*bore*” or past tense of “*bear*”?

Derivational Stemming

- Derivation – forming new words from another word or stem by adding prefixes and/or suffixes
- Thus derivational stemming can change the syntactic category of a root

production → produce

- It may also cause a change of meaning

reapply → apply

unhappy → happy



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How much stemming should be done?

- An inflectional stemmer needs to be partly rule-based and partly dictionary-based.
- Derivational stemming is more aggressive and therefore can reduce the number of features in a corpus drastically. However meaning might be lost in the stemming process.

Too aggressive stemming can result in loss of meaning and non-legitimate words without the support of a dictionary.

[[6]]
battery life portability accessories style

[[7]]
ability store music ability create playlists

[[8]]
portability capacity sound quality durability

[[6]]
batteri life portabl accessori style

[[7]]
abil store music abil creat playlist

[[8]]
portabl capac sound qualiti durabl



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Stemmers

- Some well-known stemming algorithms for English
 - Lovins Stemmer by Julie Beth Lovins, 1968
 - single pass, longest-match
 - removing the longest suffix, ensuring the remaining stem is at least 3 characters long
 - reforming the stem through recoding transformations
 - Porter Stemmer by Martin Porter, 1980
 - Widely used, with implementations in various languages available online (C, java, Perl, python, C#, VB, Javascript, Tcl, Ruby, etc.)
 - Snowball by Porter, a framework for writing Stemming algorithms

Stopword Removal

- Some words are extremely common. They appear in almost all documents and carry little meaning. They are of limited use in text analytics applications.
 - Functional words (conjunctions, prepositions, determiners, or pronouns) like *the, of, to, and, it*, etc.
 - A stopwords list can be constructed to exclude them from analysis.
 - Depending on the domain, other words may need to be included in the stopwords list.

Great

location

with

a

little

bit

of

history

Indexing

Indexing

- Many text mining applications are based on vector representation of documents (term-document matrix) using “bag-of-words” approach

$$\begin{pmatrix}
 & T_1 & T_2 & \dots & T_t \\
 D_1 & w_{11} & w_{21} & \dots & w_{t1} \\
 D_2 & w_{12} & w_{22} & \dots & w_{t2} \\
 \vdots & \vdots & \vdots & & \vdots \\
 \vdots & \vdots & \vdots & & \vdots \\
 D_n & w_{1n} & w_{2n} & \dots & w_{tn}
 \end{pmatrix}$$

T : term
 D : document
 w : weight of the term

- Usually only content words (adjectives, adverbs, nouns, and verbs) are used as vector features.

Term Weighting

- Binary
 - 0 or 1, simply indicating whether a word has occurred in the document (but that's not very helpful).
- Frequency-based
 - *term frequency*, the frequency of words in the document, which provides additional information that can be used to contrast with other documents.

	amazing	service	lost	glamour	disappoint	brilliant	super	expensive	noisy	...
Doc1	1	1	0	0	0	1	0	0	0	
Doc2	0	0	1	1	1	0	0	1	0	
Doc3	0	0	0	1	0	0	1	0	0	
Doc4	0	0	0	0	2	0	0	1	1	
...										

Frequent Word List

- With frequency-based TDM, a list of words and their frequencies in the corpus can be generated
 - *Global frequency* – how many times a word appears in the corpus
 - *Document frequency* – how many unique documents contain the word
- This list, sorted by frequency, can give us a rough idea of what the corpus is about.
- Word Cloud is a nice visualization of such information.



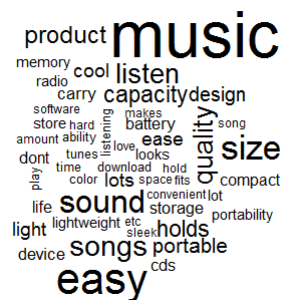
Word Cloud: another example



- Generated from <http://worditout.com/word-cloud/make-a-new-one>

Contrasting Two Groups

- “What do you like most...”
- “What do you like least...”



Other Weighting Methods

- Normalized frequency
 - To deal with varied document length, since a long document definitely has more occurrences of terms than a short document

$$\text{normalized_frequency} = \frac{\text{frequency of a term in a document}}{\text{total number of terms in the document}}$$

- *tf-idf*
 - To modify the frequency of a word in a document by the perceived importance of the word (the *inverse document frequency*), widely used in information retrieval
 - When a word appears in many documents, it's considered unimportant.
 - When the word is relatively unique and appears in few documents, it's important.



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tf-idf Indexing

- *tf-idf* weighting :

$$tf-idf_{t,d} = tf_{t,d} * idf_t$$

- $tf_{t,d}$: term frequency – number of occurrences of term t in document d
- idf_t : inverted document frequency of term t

$$idf_t = \log \frac{N}{df_t}$$

N : the total number of documents in the corpus

df_t : the document frequency of term t , i.e., the number of documents that contain the term.



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tf-idf Indexing – An Example

TERM VECTOR MODEL BASED ON $w_i = tf_i * IDF_i$											
Query, Q: "gold silver truck"											
D ₁ : "Shipment of gold damaged in a fire"											
D ₂ : "Delivery of silver arrived in a silver truck"											
D ₃ : "Shipment of gold arrived in a truck"											
D = 3; IDF = log(D/df _i)											
Terms	Counts, tf_i						Weights, $w_i = tf_i * IDF_i$				
	Q	D ₁	D ₂	D ₃	df _i		Q	D ₁	D ₂	D ₃	
a	0	1	1	1	3	$3/3 = 1$	0	0	0	0	
arrived	0	0	1	1	2	$3/2 = 1.5$	0	0	0.1761	0.1761	
damaged	0	1	0	0	1	$3/1 = 3$	0	0.4771	0	0	
delivery	0	0	1	0	1	$3/1 = 3$	0	0	0.4771	0	
fire	0	1	0	0	1	$3/1 = 3$	0	0.4771	0	0	
gold	1	1	0	1	2	$3/2 = 1.5$	0.1761	0.1761	0	0.1761	
in	0	1	1	1	3	$3/3 = 1$	0	0	0	0	
of	0	1	1	1	3	$3/3 = 1$	0	0	0	0	
silver	1	0	2	0	1	$3/1 = 3$	0.4771	0	0.9542	0	
shipment	0	1	0	1	2	$3/2 = 1.5$	0	0.1761	0	0.1761	
truck	1	0	1	1	2	$3/2 = 1.5$	0.1761	0	0.1761	0.1761	

Note that in this example, stopwords and very common words are not removed, and terms are not reduced to root terms.

<http://www.mislita.com/term-vector/term-vector-3.html>



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Alternative Representation of TDM

- The resulting term document matrix is expected to have most of the values to be zero, since typically a document will only contain a small subset of the vocabulary in a corpus

```
<<DocumentTermMatrix (documents: 1000, terms: 17887)>>
Non-/sparse entries: 92858/17794142
Sparsity           : 99%
Maximal term length: 56
Weighting          : term frequency (tf)
```

- It saves memory to store the matrix as a set of sparse vectors, where a row is represented by a list of pairs, (ColumnNumber, Value)

Matrix				Sparse Vectors	
0	5	2	0	→	(2, 5) (3, 2)
4	0	0	0		(1, 4)
3	1	0	6		(1, 3) (2, 1) (4, 6)



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Natural Language Processing Tasks

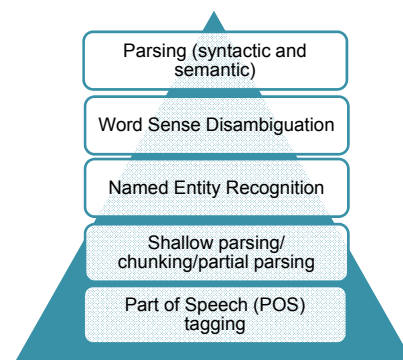


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Natural Language Processing Tasks

- To extract more sophisticated features, additional linguistic analyses of the text is needed.



NLP



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POS Tagging

- To determine POS or grammatical category of a term
 - Nouns, verbs, adjectives, adverbs, pronouns, determiners, prepositions, conjunctions, etc.
 - LDC Penn Tree Bank has 36 categories with detailed information, e.g.

CC	Coordinating conjunction	UH	Interjection
CD	Cardinal number	VB	Verb, base form
DT	Determiner	VBD	Verb, past tense
EX	Existential <i>there</i>	VBG	Verb, gerund or present participle
FW	Foreign word	VBN	Verb, past participle
IN	Preposition or subordinating conjunction	VBP	Verb, non-3rd person singular present
JJ	Adjective	VBZ	Verb, 3rd person singular present
JJR	Adjective, comparative	WDT	Wh-determiner
JJS	Adjective, superlative	WP	Wh-pronoun



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POS Tagging

- Dictionary with word-POS correspondence is needed
- Challenge – POS disambiguation (words with >1 POS)
 - E.g. “book” can be a noun (“my book”) or a verb (“to book a room”)
- Example:
 - About six and a half hours later, Mr. Armstrong opened the landing craft's hatch, stepped slowly down the ladder and declared as he planted the first human footprint on the lunar crust: "That's one small step for man, one giant leap for mankind."

IN/ About CD/ six CC/ and DT/ a JJ/ half NNS/ hours RB/ later ./ , NNP/ Mr. NNP/ Armstrong VBD/ opened DT/ the NN/ landing NN/ craft POS/ 's NN/ hatch ./ , VBD/ stepped RB/ slowly IN/ down DT/ the NN/ ladder CC/ and VBD/ declared IN/ as PRP/ he VBD/ planted DT/ the JJ/ first NN/ human NN/ footprint IN/ on DT/ the NN/ lunar NN/ crust ./ : " " DT/ That VBZ/ 's CD/ one JJ/ small NN/ step IN/ for NN/ man ./ , CD/ one JJ/ giant NN/ leap IN/ for NN/ mankind ./ . " " "

Generated by UIUC POS Tagger



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POS Taggers

- Rule-based - e.g. Brill's tagger by Eric Brill
 - Error-driven transformation-based tagger
 - Initially assign the most frequent tag to each word, based on dictionary and morphological rules
 - Contextual rules are then applied repeatedly to correct any errors
- Stochastic taggers – e.g. CLAWS, Viterbi, Baum-Welch, etc.
 - based on Hidden Markov Models (HMMs) and n-gram probabilities
 - Manually tagged corpus is needed to estimate probabilities
- Many machine learning methods have also been applied
- Stanford's Statistical NLP website lists many free taggers



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Shallow Parsing / Chunking

- To identify phrases in a text (noun phrases, verb phrases, and prepositional phrases, etc.)
- Example:
 - About six and a half hours later, Mr. Armstrong opened the landing craft's hatch, stepped slowly down the ladder and declared as he planted the first human footprint on the lunar crust: "That's one small step for man, one giant leap for mankind."

[NP About six and a half hours] [ADVP later] , [NP Mr. Armstrong] [VP opened] [NP the landing craft] [NP 's hatch] , [VP stepped] [ADVP slowly] [PP down] [NP the ladder] and [VP declared] [SBAR as] [NP he] [VP planted] [NP the first human footprint] [PP on] [NP the lunar crust] : "[NP That] [VP 's] [NP one small step] [PP for] [NP man] , [NP one giant leap] [PP for] [NP mankind] ."

Generated by UIUC chunker



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Shallow Parsing / Chunking

- After morphological analysis and disambiguation, using information of lemmata, morphological information, and word order configuration
- Largely stochastic techniques based on probabilities derived from an annotated corpus
- Avoiding the complexity of full parsing, faster, more robust
- Useful in Information Extraction, Summary Generation, and Question Answering



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Name Entity Recognition

- Recognition of particular types of proper noun phrases, specifically persons, organizations, locations, and sometimes money, dates, times, and percentages.
- Very useful in text mining applications, by turning verbose text data into a more compact structural form
- **More details in another module later**

[LOC Houston] , Monday, July 21 -- Men have landed and walked on the moon. Two [MISC Americans] , astronauts of [ORG Apollo] 11, steered their fragile four-legged lunar module safely and smoothly to the historic landing yesterday at 4:17:40 P.M., Eastern daylight time. [PER Neil A. Armstrong] , the 38-year-old civilian commander, radioed to earth and the mission control room here: "[LOC Houston] , [ORG Tranquility Base] here; the Eagle has landed."

Generated by UIUC NER system



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Word Sense Disambiguation

- English words are also ambiguous as to their meaning or reference
 - E.g. *table*: 1. a piece of furniture with a flat top supported by legs
2. A list of numbers, facts, or information arranged in rows across and down a page
- Disambiguation of meanings in context has not been well solved, partly due to the lack of corpus of disambiguated text to serve as training corpus for machine learning algorithms
- Usually not applied in a typical text mining project



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Parsing

- Or Syntactic Analysis, the more sophisticated kind of text processing
- To produce a full parse of a sentence, typically as a tree, with syntactic functions of each word (e.g. subject, object, etc.)
- Many different kinds of parses associated with different linguistic theories
 - E.g. Context-Free Grammar, Lexical-Functional Grammar, Head-driven Phrase-Structure Grammar, Dependency Grammar, etc.
 - Grammar-driven as well as statistical methods, constructing parsers from a statistical analysis of tree banks of sentences parsed by hand

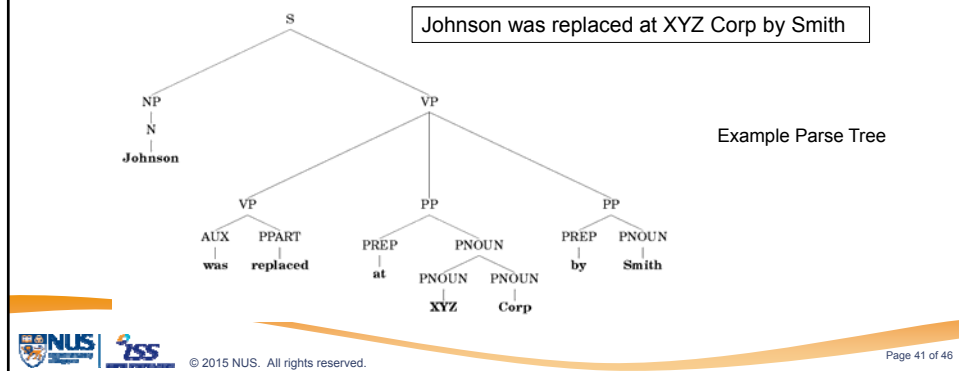


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Parse Tree

- A parse - a tree of nodes
 - Leaf nodes: words of a sentence
 - Internal nodes: the phrases into which the words are grouped
 - One top node: the root of the tree, S, representing sentence



Parsing

- Tree can be represented in another way:

Tagging

John/NNP was/VBD replaced/VBN at/IN XYZ/NNP Corp/NNP by/IN Smith/NNP ./.

Parse

```
(ROOT
 (S
  (NP (NNP John))
  (VP (VBD was)
   (VP (VBN replaced)
    (PP (IN at)
     (NP (NNP XYZ) (NNP Corp)))
    (PP (IN by)
     (NP (NNP Smith)))))
  (. .)))
```

From Stanford Parser

Typed dependencies, collapsed

```
nsubjpass(replaced-3, John-1)
auxpass(replaced-3, was-2)
root(ROOT-0, replaced-3)
nn(Corp-6, XYZ-5)
prep_at(replaced-3, Corp-6)
agent(replaced-3, Smith-8)
```

- Comparatively expensive process, but can provide information that shallow parsing can not provide.

From Syntax to Semantics

- Semantic analysis can be applied on top of parsing result to help identify the right entity for the text mining task.

SRL		Charniak	
John	old thing [A1]	(S1 (S (NP (NNP John))	
was		(VP (AUX was)	
replaced	V: replace	(VP (VBN replaced)	
at		(PP (IN at)	
XYZ	location [AM-LOC]	(NP (NNP XYZ)	
Corp		(NNP Corp)))	
by		(PP (IN by)	
Smith	replacer [A0]	(NP (NNP Smith))))	
.		(. .)))	

Generated by UIUC Semantic Role Labeling system



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Challenges in Parsing

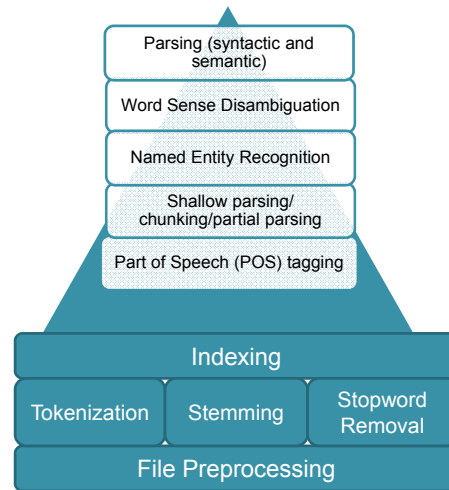
- Robustness – graceful degradation
 - The input may not conform to what is normally expected
 - Ill-formed input or lack of coverage of grammars
 - To recover as much meaningful information as possible
- Disambiguation
 - Ambiguity accumulated from earlier steps can result in combinatorial increase of possible parses
 - Return the n best analyses, if not one, to the next level of processing
- Efficiency
 - Theoretical time complexity of most formalisms are polynomial



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Summary



Reference & Resources

- Weiss, Indurkha, & Zhang. Chapter 2 “From Textual Information to Numerical Vectors”, *Fundamentals of Predictive Text Mining*, Springer, 2010.
- Porter Stemmers: <http://tartarus.org/~martin/PorterStemmer/>
- List of online word cloud generators
 - <http://www.techlearning.com/default.aspx?tabid=67&entryid=364>
- UIUC POS Tagger, Chunker, etc.
 - <http://cogcomp.cs.illinois.edu/page/demos>
- NLP resources: <http://nlp.stanford.edu/links/statnlp.html>