

Practical Natural Language Processing

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Teaching staff

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2



Textbooks Used

J&M – Jurafsky and Martin



 Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics and Speech Recognition

- Colorado + other contributors

• MRS – Manning, Raghavan, Schütze



- Introduction to Information Retrieval
- Stanford and Yahoo!
- Whole book (.PDF) available from authors website:

– <u>http://www-csli.stanford.edu/~hinrich/information-</u> retrieval-book.html



Course Outline

Day 1

AM

- Applications' Input / Output
- Resources

PM

- Selected Toolkits
- Python Intro
- NLTK Hands-on

Day 2

AM

- Evaluation
- Annotation
- Information
 Retrieval
- ML Intro

PM

- Machine Learning
- SVM Hands-on

Day 3

AM

- Sequence Labeling
- CRF++ Hands-on

PM

- DimensionalityReduction
- Clustering
- Trends & Issues



Acting humanly: Turing Test

- Turing (1950) "Computing machinery and intelligence":
- "Can machines think?" →
 - "Can machines behave intelligently?"
- Operational test for intelligent behavior: the Imitation Game







- Predicted that by 2000, a machine might have a 30% chance of fooling a lay person for 5 minutes
- Anticipated all major arguments against Al in following 50 years
- Suggested major components of AI: knowledge, reasoning, language understanding, learning



NLP from an academic POV: communication

Communication

 Intentional exchange of information brought about by the production and perception of signs drawn from a shared system of conventional signs

Humans use language to communicate most of what is known about the world

- Communication as Action
- Speech act

- Language production viewed as an action

- Speaker, hearer, utterance
- Examples:
 - Query: "Who's going to be elected president in November?"
 - Inform: "I'm teaching a course offsite today."
 - Request: "Please help me make 10 copies." "I could use some help with photocopying."
 - Acknowledge: "OK"
 - Promise: "I'll be there by 9:30 a.m."



Fundamentals of Language

- Formal language: A (possibly infinite) set of strings
- Grammar: A finite set of rules that specifies a language
- Rewrite rules
 - nonterminal symbols (S, NP, etc)
 - terminal symbols (he)
 - $\: S \to NP \: VP$
 - $-\operatorname{NP} \to \operatorname{Pronoun}$
 - Pronoun \rightarrow he



More

powerful

Easier

đ

process

Chomsky Hierarchy

Four classes of grammatical formalisms:



 Unrestricted rules: both sides of the rewrite rules can have any number of terminal and nonterminal symbols

 $\mathsf{AB}\to\mathsf{C}$

Context-sensitive grammars

– The RHS must contain at least as many symbols as the LHS ASB \rightarrow AXB

- Context-free grammars (CFG)
 - LHS is a single nonterminal symbol
 - $S \to XYa$
- Regular grammars

 $X \to a$

 $X \rightarrow aY$



Component Steps of Communication

SPEAKER:

- Intention
 - -Know(H,¬Alive(Wumpus,S3))
- Generation
 - -"The wumpus is dead"
- Synthesis
 - -[thaxwahmpaxsihzdehd]



Component Steps of Communication

HEARER:

• Perception:



-(Semantic Interpretation):

-(Pragmatic Interpretation):

¬Alive(Wumpus, Now)
Tired(Wumpus, Now)
¬Alive(Wumpus1, S3)
Tired(Wumpus1, S3)



Component Steps of Communication

HEARER:

• **Disambiguation**:

-Alive(Wumpus1,S3)

Incorporation:

TELL(KB, ¬Alive(Wumpus1,S3))



Not so great newspaper headlines

- Squad helps dog bite victim.
- Helicopter powered by human flies
- Portable toilet bombed; police have nothing to go on.
- British left waffles on Falkland Islands.
- Teacher strikes idle kids.



Ambiguity!

Core issue in many fields of Al

Ambiguity in every level of NLP. Can you think of some examples?

- Words -
- Syntax -
- Semantics -
- Pragmatics -

• Skewness in the ambiguity (DeRose 88, J&M pp 299)

Unambiguous	1 tag	35340
Ambiguous	2 tags	4100
	3 tags	3760
	4 tags	61
	5 tags	12
	6 tags	2
	7 tags	1 ("still")

"One morning I shot an elephant in my pajamas How he got into my pajamas I don't know" -- Groucho Marx, Animal Crackers 1930



Approaches to Solving NLP problems

Rule Based (Symbolic)

- Developed like traditional expert systems: hand coded rules
- Pro: fast to develop, doesn't require large datasets
- Con: fragile, costly to maintain
- Statistics Based (Empirical)



- Annotate data based on standard tagsets, then machine learn a model
- Pro: current trend, robust, performs better
- Con: extensive up front cost, requires lots of data, improvement may not correct obvious errors
- Hybrid systems
 - Often blend rule-based pre- and post-processing with ML core

Human Intuition

- plays a large role in both, either in coding the rules directly or in deciding what features to use
- can be driven by error analysis



Natural Language Processing – Back to you What is NLP in your context?

How is it related to Information Retrieval? How is it related to Machine Learning? How is it related to your customers?



Whirlwind Application Tour



Applications – Input and Output

• Words

- Morphological Processing
- Spelling Correction
- Word segmentation
- Language Identification
- Syntax
 - POS Tagging
 - Parsing
- Semantics
 - Word Sense Disambiguation
 - Named Entity Recognition
 - Semantic Role Labeling
- Pragmatics
 - Reference Resolution
 - Generation*

Applications

- Information Extraction
- Summarization
- Machine Translation
- Information Retrieval
 Genre Analysis
 Question Answering
 Sentiment Analysis



Morphological Processing – Ch 3 J&M

- Input : Given a set of words (sentence)
- Output : Decide the stems (lemmas), prefixes and suffixes
- Inflectional syntactic function such as agreement "prices soared"
- Derivational change the class of the word "derive \rightarrow derivational"
- Used in stemming packages for conflating related words
- Morphotactics model of morpheme ordering
- Solve with
 - Orthographic Rules how to combine morphemes
 - Finite State Tranducers (FST)



Spelling Correction – Ch 5 J&M

- Input: Uncorrected sentence / words
- Output: Corrected words (in context?)
- Malapropisms: wards correctly spelled butt incorrectly used
- Solve with
 - Edit distance for operations
 - Incorporate corpus frequency
 - Hidden Markov Model (HMM) to deal with context



Word segmentation – Ch 5, pp 180-4 J&M

- Input: Given a sentence
- Output: Decide where the words are

- 1. 日_(day)本章_(essay)鱼_(fish)怎么_(how)说_(say)?
 2. 日本_(japanese)章鱼_(octopus)怎么_(how)说_(say)?
- More prevalent than you might think:
 - Multiword expressions (MWE) "make a call", "push off", "don't" "as and when", "in terms of"
- Solve with:
 - Sequence Labeling Hidden Markov Mode
 - Be aware of multiple coding points or encoding for Chinese characters)
 - Both dictionary and context as features

What about doubled words in Malay? rumah-rumah (houses)



Language Identification

- Input: Document or segmented document
- Output: detected language of each segment or document
- Code switching: changing languages within document
- Considered a solved problem with a few sentences of text
- Solve with:
 - Encoding
 - Character n-grams as vectors and cosine similar
 - Can sometimes check for genre, dialect of text as well



POS Tagging – Ch 8 J&M

- Input: Segmented word sequence
- Output: Syntactically-labeled word sequence

NN	Noun, sing. or mass
NNS	Noun, plural
NNP	Proper noun, singular
NNPS	Proper noun, plural
PP	Personal Pronoun
PP\$	Possessive Pronoun

Inventory of tags: coarse or fine-grained?

Solve with:

- Rule-Based (pp. 302)
- Transformational based learning (TBL; pp 308-09),
- Sequence labeling



Parsing – Ch 9-12 J&M

- Input: Labeled word sequence
- Output: Sentence structure in some form
- Issues: Long Distance Dependencies (cf morphology)
- Too much ambiguity, must constrain processing
- Solve with:
 - Context Free Grammars (CFG)
 - Constituent / Phrase-Structure Parse relations between constituents
 - Dependency Parse relations between words



Parsing (cont'd)

- Earley vs. CYK vs. GHR
 - Earley (Deterministic Chart)
 - CYK (Probabilistic CFG)
 - Collins (Lexicalized Probabilistic CFG)

Considerations:

- Relationship to programming language compilation:
 - Shift reduce parsers for context free regular languages
 - Is natural language context free?

 Dependency parse: for free word order since constituency doesn't really matter



Named Entity Recognition

- Input: Text
- Output: Labeled text spans
- Related to Parsing via: Chunking, Shallow Parsing
- Solve with:
 - Don't use parsing (poly-time); opt for linear time complexity
 - FASTUS Cascade (pp 580)
 - Sequence labeler



Word Sense Disambiguation

- Input: Word sequence
- Output: Sense marked word sequence
- Issues:
 - Homonymy, polysemy, synonymy (Ch 16.1)
 - Not covered: creativity (metaphor, metonymy, Ch 16.4)
- Solve by:
 - Context, selectional restrictions
 - Machine learning
 - Heuristics "One sense per collocation"
 - Bootstrapping a labeled corpus



Word Sense Disambiguation (cont')

- Considerations:
 - Relationship to conflation dimensionality reduction
 - WSD benchmark tasks
 - Discrepancy between WSD of words varies highly
 - Depends on set of words: All words, set of words



Semantic Role Labeling – Sec 16.3 J&M

- Input: Sentence
- Output: Thematic roles to phrases within sentence

Issues:

- Used on top of (mostly) constituent parsing, chunking
- Related to WSD in problem scope, dependency parsing
- Alternations, Selectional restrictions
- Solve with:
 - ML on annotated data



Reference Resolution – Ch 18 J&M

- Input: Discourse
- Output: Reference resolved discourse

Issues

- Anaphora: indefinite, definite, pronouns
- Centering (cf discourse)
- Pleonastic uses (It is raining)
- Coherence vs. cohesion (*cf* MIT fake conference submissions)

Solve with:

- ML on annotated and processed data



Generation – Ch 20 J&M

- Input: Facts in some symbolic form (logical form) + intention
- Output: Natural Language Output

Considerations:

- Related to machine translation
- An entire pipeline, with many levels of processing
- Used in description generation for museums, personalized course instruction

Solve with:

- Surface / Sentential level:

Functional Unification Grammar (FUG), Forest based scoring (PCFG based) with ML backbone

- Discourse level: RST, Centering



Summarization

- Input: A text
- Output: A shorter version of the input text

Issues:

Multi vs. single, is an update?, Query vs. generic, indicative vs. informative.

- Ordering, Cohensiveness, Content, Fluency (repairs)
- End application or use

Solve with:

- Sentence selection (view as selection or ranking problem)
- Discourse motivated repairs (cf generation)



Information Extraction – Sec 15.5 J&M

- Input: tagged, parsed, NER text
- Output: relationships between NEs, factual tuples suitable for ingestion in a database

Issues:

- usually needs domain specific information
- requires NER as NEs participate in roles
- Solve with:
 - Heuristic systems
 - Machine Learning with heuristic features



Machine Translation – Ch 21 J&M

- Input: input sentence in source language (e)
- Output: output sentence in target language (f)

Architectures

- Interlingua *cf* generation
- Parsing, transfer, generation
- Direct SMT

semantic semantic syntactic surface

•Solve by:

- Large corpora for English
- Example Based MT (memoization for some constituents?)
- Transformation Based Learning (TBL, see Tagging)



Information Retrieval - MRS

- Input: a query
- Output: ranked set of documents relevant to the query

Issues:

ranking words, use of hyperlinks, internal structure of documents

Solve with:

- Vector Space Model, Language Model
- Hyperlink: prestige model (Pagerank) or other model
- Query analysis, customization, clickthrough data



Generic IR Architecture





Question Answering

- Input: a natural language question
- Output: an exact answer

Considerations:

- Factoid vs. List
- Does question have an answer? Equivalent answers?

Solve with:

- Cascaded document retrieval, passage retrieval, exact answer retrieval
- Need both question analysis and answer justification



Register, Genre and Stylistics

- Input: text
- Output: type of text
- Text = Content + Presentation
- Handling different forms of text
 - Email/SMS/IM: threading, emoticons, lexical differences
 - Blog: Link structure, trackback, social network analysis
 - Formal report, web pages: formatting, conventional presentation style → segmentation and segment classification
 - More on this later



Sentiment Analysis

- Input: Text
- Output: Opinionated? Positive or Negative?

Considerations

- Actually a subclass of text classification
- Double negatives infrequent
- Words carry opinion implicitly ("3G" for a mobile phone)

 Recent trends: Attribution to opinion holder, aspect of item being editorialized

Solve with:

- ML on annotated data



Summary

Intro to many issues and parts of NLP

Words \rightarrow Phrases \rightarrow Syntax \rightarrow Semantics \rightarrow Discourse \rightarrow Pragmatics \rightarrow Applications

Many parts can be solved using machine learning techniques

- Critical part of clean annotation and feature engineering

Academic research often doesn't concern

– Memory or time efficiency

 In such cases, rule-based heuristics may be better if limited domain (exploit specific domain characteristics)



NLP Resources

- Corpora
- Lexicons



(English) WordNet

A hierarchical lexicon

<u>S:</u> (v) jump, leap, bound, spring (move forward by leaps and bounds) "The horse bounded across the meadow"; "The child leapt across the puddle"; "Can you jump over the fence?"

- Organizes in terms of synset
- Includes gloss definition
- Used to compute similarity between words, sentences
- Other projects to build (manually, automatically)
 WordNets in other languages



WordNet – Ch 16.2 J&M

Semantic relation	Description	Part of speech			ech	Example
		Ν	V	Adj	Adv	
Synonym	A concept that means exactly or nearly the same as another. WordNet considers immediate hypernyms to be synonyms.	×	×	×	×	<pre>{ sofa, couch, lounge } are all synonyms of one another. { seat } is the immediate hypernym of the synset.</pre>
Antonym	A concept opposite in meaning to another.	×	×	×	×	{ love } is the antonym of { hate, detest }.
Hypernym	A concept whose meaning denotes a superordinate.	×	×			A { feline, felid } is a hypernym of { cat, true cat }.
Hyponym	A concept whose meaning denotes a subordinate.	×	×			A { wildcat } is a hyponym of { cat, true cat }.
Substance meronym	A concept that is a substance of another concept.	×		orden et au se de la		A { snowflake, flake } is substance of { snow }.

Used to build the hierarchy



WordNet – Ch 16.2 J&M

Semantic relation	Description	Part of speech				Example
		Ν	v	Adj	Adv	
Part meronym	A concept that is a part of another concept.	×				A { crystal, watch crystal, watch glass } is a part of a { watch, ticker }.
Member meronym	A concept that is a member of another concept.	×				An { associate } is a member of an { association }.
Substance of holonym	A concept that has another concept as a substance.	×				A { <i>tear, teardrop</i> } has { <i>water, H20</i> } as a substance.
Part of holonym	A concept that has another concept as a part.	×				A { school system } has a { school, schoolhouse } as a part.
Member of holonym	A concept that has another concept as a member.	×				{ organized crime, gangland, gangdom } has { gang, pack, ring, mob } as a member.
Attribute	An adjective that is the value of a noun.	×				{ fast (vs. slow) } is a value of { speed, swiftness, fastness}



WordNet – Ch 16.2 J&M

Semantic relation	Description	F	Part of speech			Example
		Ν	v	Adj	Adv	
Cause to	A verb that is the cause of a result.		×			{ give } is the cause of the result { have, have got, hold }
Entailment	A verb that involves unavoidably a result.		×			To { die, decease, perish, go, exit, pass away, expire } involves unavoidably to { leave, leave behind }.
Troponym	A verb that is a particular way to do another.		×			To { samba } is a particular way to { dance, trip the light fantastic }.
Pertainym	An adjective or adverb that relates to a noun.			×	×	{ criminal } relates to { crime }.
Attribute	An adjective that is the value of a noun.	×				<pre>{ fast (vs. slow) } is a value of { speed, swiftness, fastness}</pre>
Value	A noun that has an adjective for a value.			×		<pre>{ weight } has { light (vs. heavy) } as a value.</pre>



Role Labeled Data

Annotated data to learn semantic roles in sentences

- FrameNet case frame representation (lexicalized)
 - semantic roles
- PropBank predicate argument structures
 - more syntactically motivated, centered on the verb, more coarse grained / robust , not lexicalized
- VerbNet Merger of both semantic roles and predicate arguments for limited set of verbs



(Tree) Banks

Structure of language for creating NL algorithms from training data

- Penn Treebank Syntactic information
- Discourse Treebank discourse information
- SenseEval Sense disambiguated data
- NomBank Similar to role labeled data but for nouns
 - "IBM lecture"
 - Lecture about IBM?
 - Lecture given by IBM personnel?



NLP / Speech Corpora

Consortiums that license data for commercial development

- Linguistic Data Consortium (LDC)
 - US based
 - most research on these corpora
 - better tuned to US intelligence interests
 - more diversified genre collection

• Evaluations and Language resources Distribution Agency (ELDA)

- European based
- more language diversity



IR Corpora

• Reuters 21578

- Default classification dataset, too small for today's investigation purposes
- Subsequent work in building Reuters RCV1

•TREC / INEX / CLEF / NTCIR

- Yearly tests of IR systems
- TREC: oldest, most variety, also TRECvid
- INEX: XML retrieval
- CLEF / NTCIR: Multilingual retrieval

WebKB, Open Directory Project

- Web page classification
- Harder to get datasets \rightarrow commercial concerns, AOL gaffe

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Summary

- Resources / corpora necessary if you don't want to reinvent the wheel
- Worth the licensing fee and investigation

 Pulling data from the web as-is without consent may constitute copyright violation